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Invited Review Article

Nonlinearity in thermal comfort-based control systems: A systematic review

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ABSTRACT

This work presents an in-depth systematic literature review of the strategies used to characterise and quantify thermal comfort conditioned by mechanical HVAC systems. The model development is paramount for the study on the stability and robustness of the ventilation process control. They are required to establish supervisory and local control loops to improve the component sequence of the HVAC systems, and the interaction among the indoor environment, occupants, and the HVAC system response. Over the past decade, innovative technologies and artificial intelligence revamped the HVAC control research with a reluctancy of application in practice due to complex computations and lack of understanding for these innovations. However, the need to find the balance between the functionality of the HVAC system and suitable comfort levels of occupants still persisted. This work examines three research clusters of HVAC systems: ***zone thermal conditions representation, the inherent nonlinearity of HVAC complex systems and model reduction strategies,*** *and* ***HVAC processes optimisation and control methods***. This enables a holistic view of the complexities folded in delivering occupants' thermal comfort. Central to constructing these research clusters, existing studies were investigated following the four-step protocol based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines: identification of relevant literature based on keywords, screening of the chosen literature quality, setting eligibility criteria for scoping the objectives of the study and lastly inclusion of literature categories into one set. Based on the findings of this work, the application of linearisation and model reduction is found to be a promising area of research in the field of HVAC system control and optimisation. This is because emerging deep learning methods could facilitate the integration of linearisation to high-dimensional data of zone thermal interactions presented by computational fluid dynamics. Finally, this work discusses the challenges faced in the data-driven control strategies of HVAC systems, opens future direction of evaluating occupants' comfort and highlights the importance of interpretability and tracking of control process in relation to thermal comfort.

1. Introduction

Amidst the backdrop of energy crises and the urgent need for temperature regulations to combat skyrocketing energy costs, a pressing question emerges: Do HVAC systems truly offer occupants the ultimate thermal comfort while minimising energy waste? In proportion, the effects of climate change have led to more frequent and severe warm spells, resulting in an increased population reliance on mechanical cooling systems with the space cooling energy trend tripling since 1990 and a predicted projection doubling by 2050 if there is no action taken [1,2] as shown in Fig. 1, where it presents the portion of the population in need of mechanical air conditioning, the percentage of each population living in hot climate and the increased demand of AC installation. 2022 was recorded as the fourth warmest year on record since the late 1800s [3], with the lack of access to space cooling causing global risk for heat stress, adverse thermal discomfort, labour productivity and human health. This alarming increase signifies the need for improvement and management of HVAC systems' performance. While the range of these improvements is growing, gaps for thermal nonuniformity representation, accurate nonlinearity identification and regulating overall thermal comfort with control signal accounting for both nonlinearity and nonuniformity remain as obstacles in the path of achieving a balance the energy consumption with occupants' thermal comfort.

Understanding what constitutes thermal comfort and developing approaches to forecast and quantify whether a given scenario represents thermal satisfaction or dissatisfaction has been the subject of extensive research for almost five decades. Studies in climatic chambers, created by Fagner in the late 1960s, made it possible to standardise

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physiological and environmental factors using an analytical categorisation approach. In this approach, the human body is aimed at achieving thermal equilibrium by diffusion and evaporation with an average core body temperature of 37 °C. Fagner specified three requirements for steady state thermal comfort as; the human body is in a state of thermal equilibrium, mean skin temperature and sweat rate are within a specified range and no local discomfort exists [5]. In addition, high fluctuation in temperature should be minimised. This analytical approach was derived from experiments conducted on college-age students in a climate chamber during winter while performing common activities and wearing standardised clothing, leading to an empirical comfort equation [6]. Then Fagner expanded this comfort equation into the current Predicted Mean Vote (PMV) model with various groups, deviating from what he defined as optimal thermal comfort to thermoneutrality. The PMV model comprises all major variables influencing the thermal sensation and quantifies the absolute and relative influence of these six factors as; air temperature, mean radiant temperature, air velocity, relative humidity, activity level for occupants, and clothing insulation.

Once this model was introduced, it faced with numerous criticisms for its geographic and demographic limited and reductive application, and its narrow application on types of buildings. These studies geared the interest toward the adaptive thermal approach, which relies on the adaptability of humans to a given thermal environment and reaction to achieve thermal satisfaction. According to [7], the adaptive thermal comfort definition is "If a change occurs as to produce discomfort, people react in ways which tend to restore their comfort". This approach has been studied in terms of the behaviour of the occupants. However, PMV model is standing as the only analytical quantification index for thermal comfort close to reality. Subsequently, the American Society of Heating, Refrigeration, and Air Conditioning (ASHRAE) adopted it as a thermal comfort model [8]. Then, ISO 7730 implemented PMV index with a seven-point thermal sensation scale as shown in Table 1, which advised to keep PMV index value close to 0 to achieve thermoneutrality with a tolerance of 0.5 for the ultimate thermal comfort sensation. In this work, we are utilising the analytical and quantification abilities of the PMV index as the focus of our study.

Table 1
Seven-point thermal comfort categories (.

Sensation	Cold	Cool	Slightly cool	Neutral	Slightly warm	Warm	Hot
Vote	−3	−2	−1	0	1	2	3

Source: ISO 7730)

To adjust the indoor thermal conditions, many technological solutions have been proposed. With these technologies, it is assumed that the occupants are assumed to be an expert with the complexity of these technologies tuning and adjustment, challenging the accessibility of them and creating the need for smart regulating technologies equipped with sensors and control systems. Consequently, there is a growing demand for smart control technologies equipped with sensors and automated systems. As a result, researchers have turned their attention to HVAC control systems, ranging from basic ON/OFF reactive control models to those supported by artificial intelligence (AI) predictive controls, in order to accommodate occupants' preferences and improve the efficiency of HVAC system operation. Initial efforts to integrate AI for building controllers began in the 1990s. The first instance suggested the application of neural network and fuzzy logic was introduced to incorporate thermal comfort preferences into air conditioning operation by Matsushita Electric and to define a heater firing time based on room size and absorption specifications [9]. Since then, intelligent controllers have employed the synergy between the neural networks and advanced algorithms to overcome the nonlinearity and complexity of thermal conditions, time delays and zone disturbances.

The literature review indicated that significant survey studies and previous research examined the optimisation of HVAC controllers for enhancing comfort, and some studies combined the balance of comfort with the reduction of energy consumption. Yet, none of these studies closely explored in depth the nonlinearity associated with HVAC systems, considering the individual interactions in the comfort-energy control process. In Table 2, an outline and comparison of the key survey papers are provided, besides their limitations. With control systems divided into reactive and predictive models, model predictive control

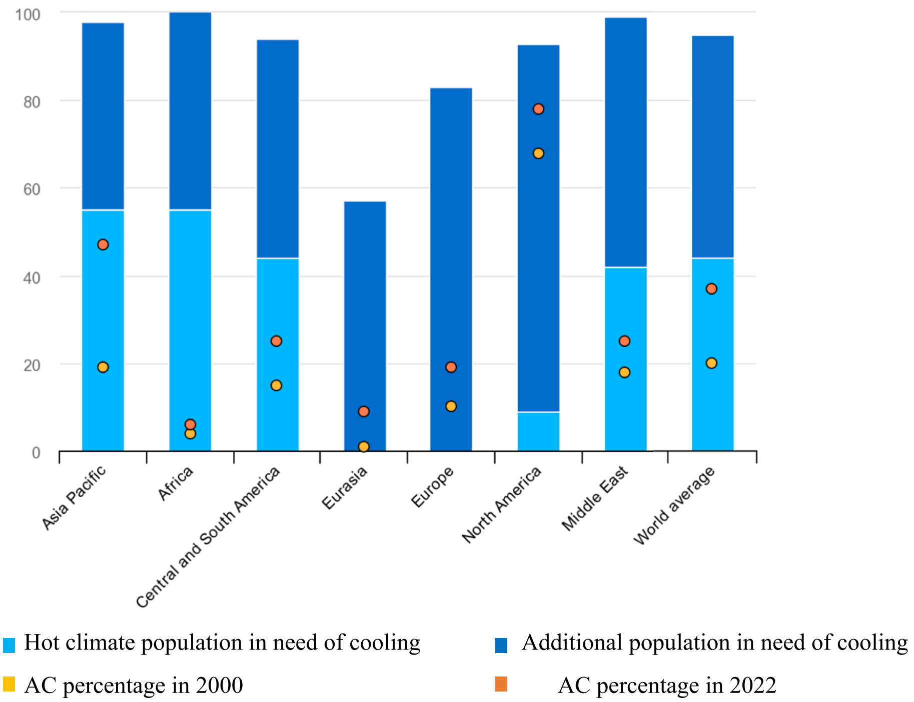


Fig. 1. Percentage of population living in a hot climate 2022, and percentage of air conditioning systems installed 2000–2022 ().
Source: adopted from IEA [4]

Table 2
Comparison of similar previous systematic literature review works.

Ref. of the work	Year	Purpose of the work	Limitations of the work
[10]	2013	Examines MPC models for air handling units with components modelled as linearised bilinear models.	The majority of MPC cost functions were evaluated based on the energy cost while ignoring thermal comfort assessment.
[11]	2014	Reviews strategies for modelling HVAC supervisory and local control loops while highlighting the importance of system definition in the performance on HVAC controllers.	Lacks the definition of intelligent control systems and the recency of AI/ML in the definition of black box
[13]	2016	Provides a selected review and evaluation for ten intelligent/ predictive HVAC controllers in terms of their thermal comfort effectiveness and minimisation of operational costs.	A general comparison of the controller's performance was lacking due to its scarcity of testing and application of these specific models
[12]	2018	Provides an overview of different control strategies and divide them into three categories: hard, soft and hybrid categories, while introducing a new framework for system identification as fuzzy cognitive mapping to solve HVAC nonlinearity.	Does not analyse the advantages and disadvantages of each control strategy in terms of occupant's perception of thermal comfort
[14]	2019	Categorises the application of AI in HVAC systems for weather forecast, optimisation, and predictive control, while highlighting how the performance of these AI aided systems fail due to the lack of high sensors resolutions.	Targets only the energy savings as a metric of performance without the consideration of thermal comfort improvement.
[15]	2021	Reviews comprehensively and classifies existing AI/ML aided tools specifically targeting enhancement of thermal comfort for building occupants.	Reviews mainly AI/ML assisted tools as black box models lacking the discussion of the interpretability traceability of the HVAC system.
[16]	2021	Reviews occupant-based HVAC controls in terms of occupants' resolution definition such as user-defined schedules and occupancy detection and monitoring, types of test bands and performance evaluation methods.	Highlighted the benefits of occupancy- based controls mainly on offices and residential buildings without evaluating the performance and validity of these models in highly occupied areas such as schools and conference halls
[17]	2022	Reviews existing ML applications in thermal comfort evaluation against group and personal based thermal comfort models while ranking the performance of each ML technique for predictions accuracy	Investigated the predictions and accurate evaluation of thermal comfort sensation of the occupants with no direction of the integration of the identified systems with controllers
[18]	2023	Reviewed how ML applications are extended to thermal comfort studies with the focus of personal thermal comfort while highlighting the need of more studies targeting controllers regulating thermal comfort identified by ML schemas	Presented the challenges of ML comfort-based models in terms of modelling selection, sample size and real-world application with the ambiguity of black box models
[19]	2023	Reviewed how research advanced Building Automation Systems (BAS) in green buildings mitigate energy waste in buildings in terms of the building's life cycle and supporting the building functions of thermal comfort, ventilation comfort and acoustic comfort.	Focused on the BAS investigation with potential control strategies and touched on the different modelling techniques for MPC and PID controllers without detailing the mathematical challenges and opportunities for these models and their impact on the BAS performance.
[20]	2023	Presented a review for demand-based controllers supported by indirect data collected by IT equipment usage and direct data from infrared and wearable sensors.	Highlighted existing research in the field of human detection combined with zone ventilation control signal. The study focused on the technology implementations without the consideration of fitting the purpose of thermal comfort.

model (MPC) grew as an interesting scheme that balances between the optimisation of thermal comfort and minimises operational cost of reviewing the application of MPC on the air side of an HVAC system as well as the water side, while highlighting the importance of the system identification in the performance of the MPC model [10]. [11] took over the critical analysis of the three categories of system identification of HVAC such as white box physics-based models, black box machine learning models and grey hybrid models. Similarly, [12] reviewed the strategies of system identification of the HVAC components while proposing a hybrid model such as fuzzy cognitive mapping, whereas [13,14] specifically evaluate the performance of intelligent black box in achieving energy consumption reduction. [15] extensively reviews AI/ML aided controllers to optimise and assess thermal comfort and occupant satisfaction. Lastly, with the growing demand for personalised HVAC systems, [16] review occupant based controllers for HVAC systems in terms of the resolution definition for user defined schedules and occupant monitoring approaches with the emphasis on thermal comfort predictive models.

To best of the authors knowledge, this work is the first to cover the role of system identification of thermal conditions combined with AI/ML aided HVAC control to achieve thermal comfort optimisation in buildings. This work main contributions are:

- Exploring the role of thermal comfort representation through computational fluid dynamics (CFD) in improving the thermal sensation of occupants.
- Covering the existing methods and strategies of HVAC system identification, their functionalities with the HVAC control systems.
- Identifying various challenges in representing the thermal condition and directions on how linearisation and model reduction can contribute to a real time representation of dynamical and nonlinear systems.

This article describes the process of conducting systematic literature review in Section 2 and analysis to the existing research targeting our aim of research given in Section 1. Section 3 examines the outcome of the clusters analysis of popular system identification strategies of HVAC dynamical systems accounting for nonlinearity and the performance of thermal comfort. Section 4 discusses the key insights, synthesises further research directions and challenges. Finally, the article concludes with a summary of our finding in Section 5.

2. Method

2.1. Systematic literature review SLR and selection method

The systematic literature review followed a clear four-step protocol based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines proposed by [21]. These four steps shown in Fig. 2 included: first, finding relevant research articles through a database search; second, setting criteria for screening the articles; third, checking which articles met the criteria for eligibility; and finally, reviewing and analysing the articles that passed the eligibility criteria. To examine the multi-disciplinary frameworks of HVAC systems controls and the deep learning models proposed in the literature, the following keywords search string was used for peer-reviewed articles as: (System identification OR HVAC controls OR Thermal comfort OR zone level controls OR Computational fluid dynamics OR Indoor environment OR Buildings OR Machine learning OR Deep learning OR Autoencoder OR Koopman operator OR Predicted mean vote OR Linear quadratic regulator OR Hybrid HVAC control) AND (model reduction OR linearisation theories OR air distribution). When OR was replaced with AND, no relevant articles were found. While the focus of this research effort is HVAC control systems, thermal comfort modelling strategies, and hybrid HVAC controls, other terms such as machine learning, linearisation theories, computational fluid dynamics, zone level controls were included as they are built upon their interrelation with the thermal comfort of the built environment. Despite their interrelation in some of the literature, the different concepts lack clear definition for their roles and interchangeable contribution to the overall performance of the systems, and were once recently reviewed and examined in [15]. That is why these keywords were included in the search string with OR operator in order to provide a holistic assessment of the proposed control strategies.

Web of science was selected as the primary database for its comprehensive high impact publications while supplemented by IEEE Xplore Online, ProQuest and Compendex for their relevance to building specific publications over the period from 1967 to 2023. The search yielded 1001, 98 and 135 articles from Web of Science, ProQuest and Compendex, respectively. Nonpeer review articles were removed as well as duplicates resulting in 889 journal papers. The following eligibility criteria were applied as (1) studies conducted for the indoor environment; (2) review work included typical and advanced HVAC and thermal comfort control; and (3) review work focused on indoor thermal conditions representation. As a result of applying these criteria, the 889 articles were reduced to 118 study. The reviewed studies were arranged into clusters as shown in Fig. 3 to present the themes involved in presenting thermal comfort, modelling HVAC systems and their usability to improve the occupants' sensation. This allows to establish the added value of the controller to the building performance. Moreover, the prime consideration was given to the diversity of the thermal comfort analysis and assessment techniques, space control devices, load control, occupant interactions, study cases of system identification with the model input, and controlled parameters in the next section.

2.2. Research clusters

How did existing literature target the integration of thermal comfort nonlinearity with control modelling? To answer and analyse this question, this review adopted bibliometric analysis for evaluating the trends of the publications and keywords co-occurrence resulting from the research selection framework [22]. VOSviewer software [23] was used to generate a bibliometric network of the key research themes related to thermal comfort of HVAC controllers based on the output of the databases mentioned in Section 2. Authors' keywords were selected as the primary clusters as they indicate the importance in conveying their research foci. Fig. 3 illustrates the interconnectedness of the keywords in

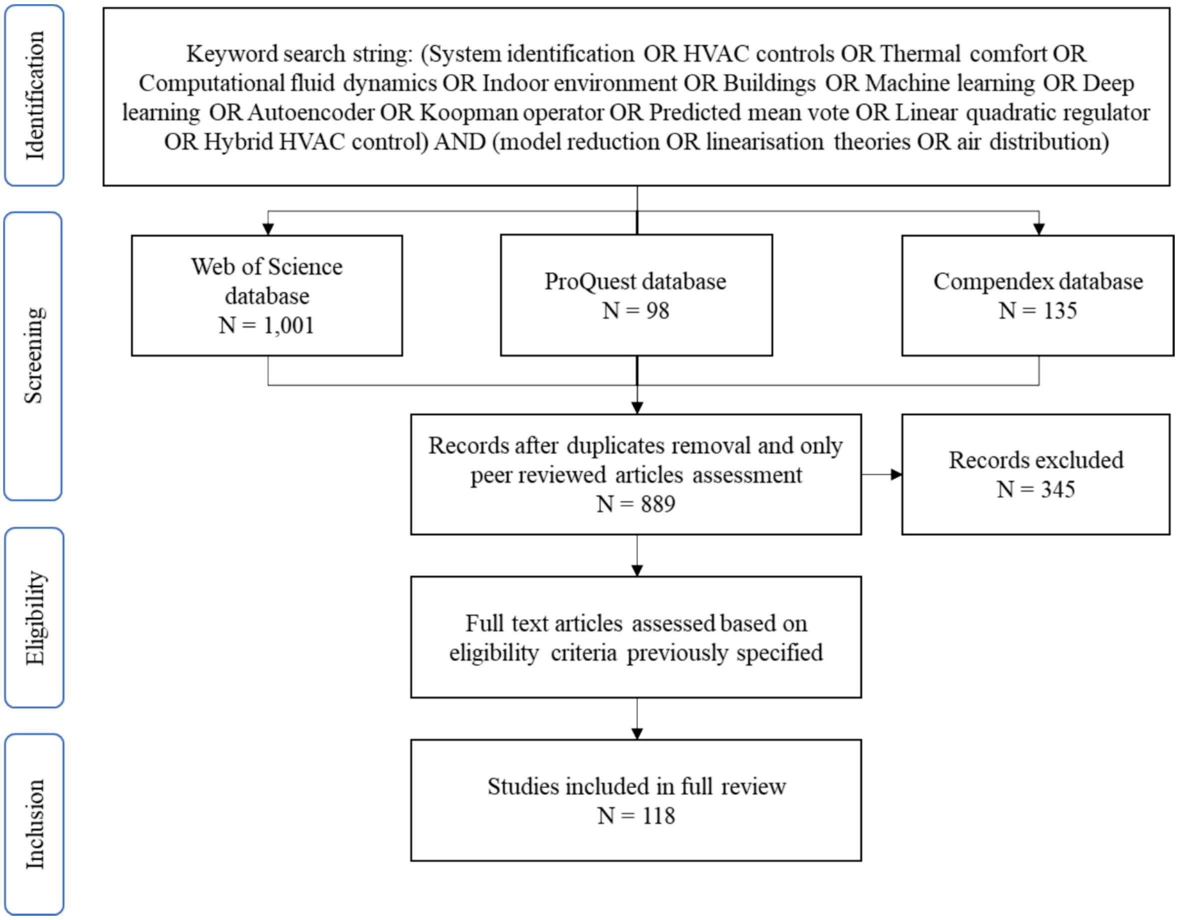


Fig. 2. Flowchart of the articles' selection process.

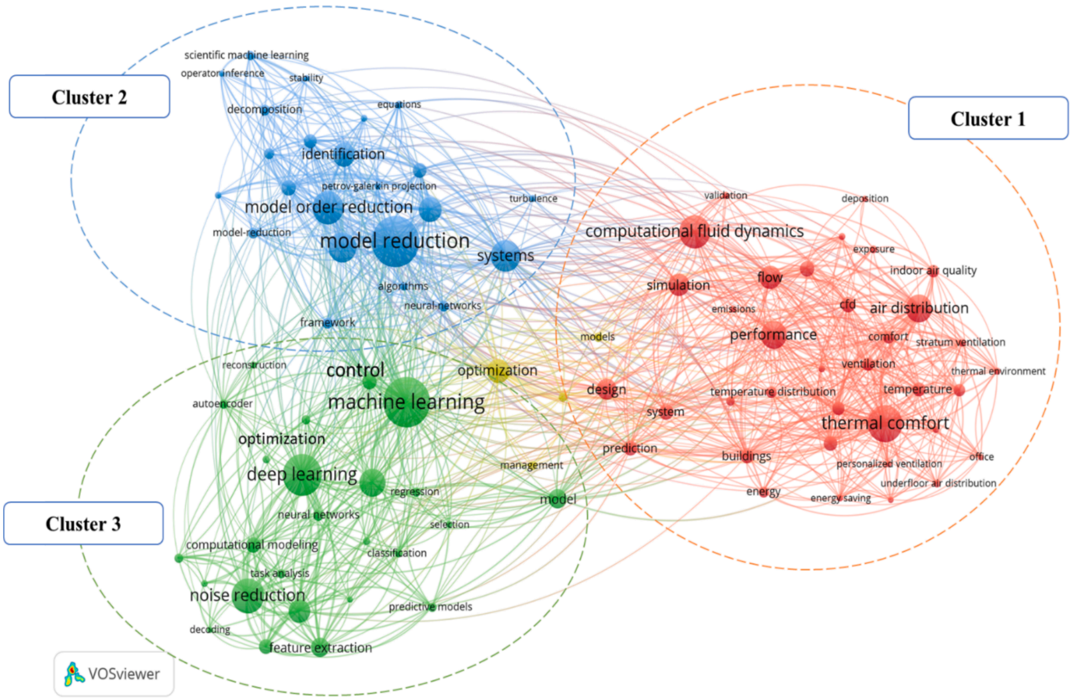


Fig. 3. Research clusters.

the analysed articles. As mentioned before, co-occurrence is presented through links and the links' strength in the number of publications. The greater the commonality in usage between words, the higher the correlation which consecutively determines their cluster [24]. Based on the association of the keywords, an evident connection of thermal comfort, air distribution and computational fluid dynamics (CFD) creates the first cluster in examining the thermal comfort evaluation in energy efficient HVAC cooling systems. The second cluster targets model order reduction, system identification, linearisation theories combined with algorithms, where there is a predominant link between system identification with CFD simulations and no connection between this cluster and thermal comfort performance. This highlights the gap this review targets. Cluster 3 indicates the role of deep learning and neural networks and predictive models as tools for applying the buildings' control strategies and system identification. These clusters are expanded in the next sections.

3. Indoor environment thermal comfort

3.1. *Thermal comfort assessment and simulation*

As it was mentioned in Section 1, recent research highlights the growing importance of indoor air quality in commercial buildings for employees' health and productivity. This section explores the link between Indoor Air Quality (IAQ) and its economic impact. People spend a significant portion of their week in commercial buildings, making it essential to provide just and favourable working conditions. Various studies have shown that poor IAQ and thermal discomfort can negatively affect employees, causing short-term and long-term health issues [25,26]. According to the Australian department of water, agriculture and environment, people spend an average of 40 h weekly in the working environment inside commercial buildings, and according to the Universal Declaration on Human Rights, people are entitled to have just and favourable conditions at work. In accordance with Epidemiological studies conducted by the World Health Organization (WHO) and several other research institutions [27,28], poor IAQ and thermal discomfort are classified as environmental stressors, impacting the cognitive ability of employees, producing negative stress on the occupants and causing short-term illness and long term mental and physical problems [29]. In this research cluster, we are providing insights into the nonuniformity, nonlinearity and assessment of thermal comfort in the indoor environment using computational fluid dynamics, case studies and simulations.

Traditional thermal comfort evaluation research [6] was developed with the assumption of uniform environments where thermal convective and radiation heat transfer is considered equal from all directions. In ideal conditions, thermal equilibrium is considered the primary condition for achieving thermal comfort sensation for occupants, with the target to create a moderate environment to satisfy a group of occupants through the adjustment of thermal parameters. However, thermal comfort conditions are nonuniform with variation in radiation and convection patterns from different directions and different surfaces. The overall thermal comfort varies significantly with the increase of thermal asymmetries [30], indicating that considering only heat transfers and mean skin temperature are insufficient in describing thermal sensation. Besides achieving thermal comfort, realising nonuniform local and overall thermal comfort distribution is a goal for thermal comfort research. The nonuniformities of thermal environments induce various heat exchange rate in multiple segments of the human body. Hence, the multi segment model was proposed by Stolwijk [31] to regulate thermoregulate the process of sweating, and shivering through experimental data. As a result, considering angular heat conduction, arterial blood temperature and clothing insulation at local segments were defined as major contributors to local thermal sensation. By assessing local body regions sensation, a comprehensive picture of comfort perception can be drawn in non-uniform conditions. Types of nonuniform environments are categorised as adverse non uniform radiant environment caused by longwave direct shortwave and diffuse shortwave radiation and creation of non-uniform environments. The indoor radiation field is generated by the longwave and shortwave solar radiation through opaque fenestration structures and warm and cold external enclosures contributing to the nonlinearity of the thermal conditions distribution within the zone [32,33]. Quantitative studies on the impact of radiation asymmetries and multiple environment analysis were conducted such as [34] where an experiment chamber was used to experiment the effect of cold and warm walls radiation on thermal comfort. It was found that cold radiation had more impact on the thermal comfort and skin temperatures in comparison to warm walls. In another study [35] investigated the thermal comfort in two nonuniform environments: equal inner surface temperature and varying radiant and air temperature and one that considered a single wall temperature varying across the wall surface. The findings proposed a thermal dissatisfied percentage models to consider the impact of nonuniformity on participants thermal sensation. In addition to experiment-based evaluation, several studies adopted computational fluid dynamics (CFD) to evaluate thermal conditions.

Mathematically, the principles governing air distribution have been expressed through a collection of differential equations referred to as the Navier-Stokes equations. These equations have been addressed in various ways: analytically for ideal situations, illustrated with examples like calculations of turbulent jets by Rajaratnam [36], empirically through relations derived from experiments conducted in test chambers [37,38], and most recently, numerically for general scenarios, including the distribution of air within ventilated rooms, as observed since Nielsen's initial study on ventilation [39]. and most recently, numerically for general scenarios, including the distribution of air within ventilated rooms, as observed since Nielsen's initial study on ventilation. To understand CFD, it is important to be familiar with the equations contributing to the nonlinearity of airflow in the indoor environment for continuity equation based on the principles of mass conservation where within a controlled volume such as a room the mass within this volume is equal to the mass flow into or out of the control volume presented. In addition to the continuity equation, momentum equation is another equation that describes the velocity vectors of the airflow in the x, y and z directions. Equations for the y and z momentum equations with further description and analysis can be found in [34]. Lastly, the energy presented in heat transferred by the airflow is solved with the energy equation due to convection, conduction and radiation.

With this description of the Navier Stokes equations and the rapid growth in the application of using CFD, ventilation parameters and different building systems can be examined flexibly for the indoor occupied interactions with increasing speed of supercomputers [40]. Thermal comfort assessment has been investigated using CFD simulations. In 1990, thermal comfort was examined with the variations of acceptable indoor temperature in transient conditions with the focus of thermoregulatory system for occupants while conducting experiments to categories the predictions in the transient changes to cyclical, drifts and steps changes [41], which highlighted the importance of full assessment for thermal comfort in transient conditions. [42] was one of the first studies to provide a full assessment of indoor thermal comfort, while examining the role of radiant temperature and vapour pressure for thermal dissatisfaction. While previous studies focused on addressing thermal comfort on mechanically conditioned buildings [43], investigated the adaptability of occupants through insulation and activity for naturally ventilated buildings. Moreover [44], critically evaluated 22,346 comfort studies and 160 buildings statistically with regressive models for thermal neutrality, revising the ASHRAE comfort standard 55 for its thermal comfort questionnaires. The studies reported that a clear dependence of indoor comfort on outdoor air temperatures specifically for naturally ventilated buildings. Back to mechanically ventilated spaces, CFD model was applied to test the Air Diffusion Performance Index (ADPI) for three inlet/outlet configurations to determine their impact on the gradient of the temperature between the head and ankle temperatures [45]. To be more specific of local thermal discomfort [46], examined the human body with 16 segments under transient conditions in terms of sensible and latent heat transfers, through modelling the human body with thermal resistance network, representing the heat transfer from the skin to the environment by radiation, convection and evaporation of the sweat. Thermoregulation model was developed in [47] segmenting the human manikin to 65 node, detailing further the 16 segment model proposed by the TSENS and DISC models, incorporating a radiation exchange model and CFD modelling. Thermal comfort in this study was predicted with empirical expressions named TSENS and DISC, based on body temperatures and the heat transfer rates. The study concluded that wetness of the skin increases in hot climates, increasing the thermal discomfort specifically at the feet and pelvis skin, which can be reversed by increasing the air velocity. As office spaces were studied for their thermal conditions in hot and humid climates, transitional spaces such as lifts and lobbies were investigated for their occupants' thermal preference. [48] studied thermal comfort of occupants with CFD modelling as well as occupants' surveys and environment measurements. The study indicated the importance of supplemented PMV index with occupants' thermal preferences to reach acceptable thermal performance of the system. With the rise of CFD popularity in presenting thermal comfort, a significant investigation of the dependency on the grid size and turbulence model was conducted in [49]. [50] utilised CFD thermal comfort modelling in determining thermal comfort levels for immunity compromised patients and children in a hospital and schools. Further analysis and investigation of the PMV index condonement of human adaptability in [51] where adaptive PMV and Human Thermal Model (HTM) based on the local segment of the body sensation and weighing the impact of them as a total in estimating thermal discomfort. The results showed lower dissatisfaction levels in comparison to typical PMV calculations. Air distribution systems for passenger compartments were assessed in terms of temperature distribution through Computational Fluid Dynamics (CFD) modelling in [52]. Similarly, [53] conducted an analysis of indoor air quality, focusing on air age and temperature fields in residential applications using CFD simulations. Human exergy rate has been studied using CFD to evaluate the thermal comfort conditions using destroyed exergy and exergy transfer to the environment by [54]. Additionally [55], addressed the advantageous coupling of thermoregulatory model of human body and CFD modelling as a numerical assessment tool needing further development. Further validation of thermal comfort indices in ISO 7730 through surveys carried out in a classroom and CFD simulation, with results showing that thermal sensation is in line with PMV index calculation in the absence of the direct component of solar radiation [56]. HVAC equipment specific studies were conducted to test air handling unit performance in the office environment. [57] presented the impact of fan coil HVAC system at an office with a 3D CFD model of an office at a masonry historical building and single glass windows and a validated experimental set up. The lack of control was highlighted in previous articles. With the growing trend of "intelligent" buildings and AI, indoor environments in two intelligent buildings were investigated in [58] with the thermal comfort addressed with 1369 questionnaires. The investigation targeted the dependency of thermal comfort on operative temperature, which proved to be very strong. The integration of CFD with BIM model was proposed with the ability of BIM in providing geometrical and semantic information to the CFD model as proposed by [59]. BIM-CFD model provided sufficient information for training a neural network to predict optimal thermal comfort conditions. Table 3 summarises the literature relevant to thermal comfort assessment models and simulation tools. While Table 4 details the features of the software applied in these studies with their strengths and limitations.

3.2. *Thermal comfort of cold air distribution*

With the recommendation from previous section, reduced cooling temperature and supply air velocity are thermally preferred for cooling systems. Unlike conventional cooling systems (delivering air at 13 °C), cold air distribution systems supply air within the range of 4 °C to 10 °C. Introducing lower temperature supply air results in a proportional reduction in the required supply air volume for a given air conditioning load, consequently reducing the supply duct size, fan speed, and overall energy consumption [63]. Thus, the supply duct size, fan speed and energy consumption will be reduced. According to [64], the supply airflow for a cold air distribution system can be reduced 30–40 % compared to conventional cooling systems. Although introduced since 1992, cold air distribution systems have been extensively studied, particularly with two-dimensional cavity models. Researchers have

Table 3
Summary of the works focusing on thermal comfort assessment and simulation tools.

Ref.	Year	Purpose	Simulation tools	Outcomes and Key results
[41]	1990	With restricting the study to homes and offices, the study focused on transient thermal sensation on occupants with cyclical, drifts and steps fluctuations in the ambient temperature.	Not specified	Experiments indicated that cyclical ambient temperature changes impact peak variations when operative temperature exceeds 1.1 K rate of change and doesn't exceed 2.2 K/h, in line with ASHRAE standard.
[42]	1994	CFD was deployed for solving the airflow equations with $k-\varepsilon$ turbulence model for a room with two fenestration openings, and with the distribution of mean radiant temperature attained with a radiation heat exchange model. PMV and PPD were calculated after obtaining the solution of the CFD model.	QUICK simulation scheme for transport and momentum PDEs	Assumptions of a constant radiant temperature creates an error of 7.5 % for the estimation of PPD. In addition, disregarding the variation of vapour pressure variation creates 4 % of the PPD index.
[45]	1996	Turbulence impact was evaluated using Air Diffusion Performance Index (ADPI) for different configurations of supply inlets and outlets. CFD solutions was applied to calculate the ADPI.	Not specified	ADPI is inadequate to describe the air diffusion performance or the draft risk with the importance of the inlet/outlet location highlighted.
[47]	2002	The study developed a 65-node thermoregulation model. With the 16-body segment model segment to further 4 layers of core, muscle, fat and skin, thermal manikin was used for conducting experiments. CFD model was created to determine the impact of radiation and convection on the local thermal comfort.	Not specified	According to the CFD model, air temperature near window was 1–2 °C higher than other spaces in the occupied zone. Comprehensive 65 node analysis provided in depth evaluation of the thermal comfort.
[60]	2004	The study evaluated the impact of cold surfaces on the thermal dissatisfaction and draught risk for occupants. Five cases with different heat loads with/without furniture were simulated with 3D steady state CFD modelling and surface to surface radiation exchange model	FLOVENT simulation code with SIMPLE algorithm	Heat loads in the room influence the maximum air speed near the cold wall and floor with the buoyancy momentum of the heat sources boosts the motion of downward flow near the cold wall. It was concluded that the draught is critical in the thermal discomfort than reduced operative temperatures or radiation asymmetry.
[48]	2009	The study aimed at investigating the thermal comfort for transitional spaces such as enclosed lifts and lobbies. The study verified predicted CFD solution with surveys conducted for the occupants in relation to thermal comfort based on PMV index and measurement of the indoor temperature utilising thermo-anemometer.	ANSYS Fluent v 6.3 with transient solver	80 % of the transitional space occupants perceived it as thermally acceptable, with a preference for cooler environment, and highlighted the importance of supplementing the PMV-CFD index results with occupants' preference.
[49]	2013	The study investigated the shape of computer-simulated person (CSP) and its impact to the calculation of the thermal comfort for PMV index and equivalent homogeneous temperature (EHT) with the CFD models.	ANSYS Fluent solver and code for PMV model	The study concluded that CSP shape and grid features do not impact the global flow fields or the PMV index evaluation, but with a detailed human model with prism grid improves the thermal comfort prediction estimated by EHT.
[50]	2014	A CFD study was conducted to calculate the impact of cooling systems for children and patients in hospitals.	Not specified	The study highlighted the importance of validating the CFD results with field measurements with recommendations provided as a state program of the Russian Federation.
[53]	2014	Indoor air quality (IAQ) was assessed by CFD model with indices such as wind velocity fields, temperature fields and air age fields.	Airpak simulation model	The results of this study showed that the air age in the area where occupants' heads are located is too large, indicating the need for effective measures to improve the air quality for occupants.
[54]	2014	Human exergy analysis was first introduced in this study to be added to indicators of thermal comfort as destroyed exergy and exergy transfer to environment while adding respiration energy transfer to the convection, radiation and evaporation.	Not specified	The results showed that with relative humidity ranges from 40 % to 60 %, destroyed exergy's impact is minimal to the thermal comfort conditions. For lower relative humidity and higher temperatures, the destroyed exergy is also minimal.
[52]	2015	The study investigated the thermal sensation of travellers in compartments using CFD modelling combined with solar radiation modelling. The thermal sensation was assessed by PMV index and equivalent temperature model (ETM).	ANSYS Fluent V13.0	It was found that spectral solar radiation had significant impact on both thermal comfort models with ETM being superior in the assessment of thermal comfort involving radiation model.
[55]	2015	The article reviewed thermal comfort assessment	Not specified	The paper depicted the shortcomings of thermal comfort

(continued on next page)

Table 3 (*continued*)

Ref.	Year	Purpose	Simulation tools	Outcomes and Key results
		approaches starting from the physiological reaction of the body in thermal stress conditions and ending with implementation and testing through CFD modelling.		indices and models with the lack of assessment in transient and non-uniform environments and addressing different categories of the occupants such as children and elderly. In addition, the article signified CFD modelling as a numerical tool in showing environment asymmetry.
[56]	2017	CFD thermal comfort model in ISO 7730 was validated with classroom surveys.	ANSYS Fluent	The results showed that thermal sensation is in line with PMV index calculation in the absence of the direct component of solar radiation.
[57]	2019	Fan coil HVAC system was assessed at an office with 3D CFD model and validated office measurements conducted with a patented measurement system which measures the distance of the temperature sensor from a know point similar to the GPS.	ANSYS Fluent and Gambit software	The results showed that even with uniform air temperature, low insulated envelope leads to lower radiant temperature during winter leading to thermal discomfort. Furthermore, the lack of a local control system causes large variation in comfort conditions during working days. It concluded that CFD is an important tool in evaluating local thermal comfort sensation.
[61]	2019	The study proposed pairing the building performance simulation conducted by EnergyPlus with the multi-objective optimisation applied with MATLAB. PMV index was considered as one objective of the simulation objective functions formulation.	EnergyPlus coupled with MATLAB	The results presented the PMV index and PPD%, resulting from the retrofits applied by EnergyPlus. The study calculated one averaged value of PPD % for large scale offices against the energy consumption.
[59]	2021	The study proposed a framework in integrating BIM and CFD modelling, to provide geometrical and envelope relevant information. Thermal comfort PMV index was assessed based on the CFD model. In addition, the information generated was utilised for a predictive neural network to optimise thermal comfort conditions.	Autodesk Revit CFD	The results showed that natural ventilation can save cooling power consumption, but it cannot be a sufficient alternative of mechanical ventilation to fulfil thermal comfort. The neural network can examine thermal comfort conditions and predictions efficiently.
[62]	2023	A comparative study was conducted to verify the performance of two software in estimating PMV index of a simplified residential building.	EnergyPlus and Ansys Fluet	Both software showed that thermal sensation inside a building is greatly impacted by outside air temperature, with no discrepancies in estimating the averaged PMV values of the zone.

examined air movement in commercial zones, calculated potential energy savings, and identified challenges, including condensation, cold drafts, the lack of control systems, and thermal discomfort.

Concerns about thermal comfort in cold air distribution applications arise from drafts and significant vertical zone temperature differences. The Air Diffusion Performance Index (ADPI) assesses the performance of cold air distribution systems, representing the percentage of points in the occupied zone with Effective Draft Temperature (EDT) ranging from −1.7 to 1.1 K, based on air velocity and effective draft temperature. [65] analysed the air motion with parameters collected from previous studies calculating the momentum number of the supply air and correlating it with existing ADPI data. The relationship between ADPI and room air velocities was identified as a method for evaluating the comfort of cold air distribution systems. The study highlighted potential discomfort caused by the lack of control conditions when using low temperatures for thermal comfort, emphasising dependence on mean air velocities without considering relative humidity and zone temperature variations. Comparing temperature distributions and heat dissipation in two-dimensional rooms, [66], it was found that despite the reduced airflow rate provided by the cold air distribution, carbon dioxide concentration and heat dissipation were approximately similar to the conventional supply systems for ceiling diffusers. Although cold air systems gained popularity in the late twentieth-century, recent studies use advanced simulations to investigate their performance. Thermal comfort was investigated in a more recent study by using Computational Fluid Dynamics modelling (CFD) with ADPI index to quantitively estimate the indoor air quality inside the zone. A 2D cavity zone model was created to understand the variations of velocities, hence the averaged effective draft temperature was calculated and indicated the thermal comfort level. After simulating three different cases of inlet temperatures of 14 °C, 10 °C, and 6 °C, the 6 °C scenario was concluded to provide adequate thermal comfort based on the ADPI value in the zone, with no cold spots' formation in the 2D plan. Following the same steps [67], concluded the importance of using appropriate air distribution inlets and outlets configuration to meet the criteria of APDI. In addition, the importance of supply air diffusers selection was highlighted based in [68] experimental setup with a testing chamber to avoid condensation and regulate airflow. Conversely, studies [69–71] have highlighted the inability of ADPI to judge thermal comfort based on the link between draught and air temperature without considering other thermal comfort parameters. With these short comings of the thermal assessment of cold air distribution system and the lack of proper demand driven control for this system, the need for thermal comfort demand-based controller arises as we can find in clusters 2 and 3, along with the consideration of addressing the non-uniformity of thermal condition distribution.

4. Nonlinearity, linearisation and model reduction

The inherent nonlinearity of HVAC systems imposes a challenge on implementing thermal comfort indicators on the zone conditioning. Nonlinearity in HVAC systems refers to the fact that the relationship between inputs and outputs is not proportional or additive, and small changes in input conditions may lead to disproportionate or unpredictable changes in the system's response. HVAC operations change in the range of several hundred during seconds of the operation time.

Table 4
Primary features of CFD software for HVAC systems and airflow investigation.

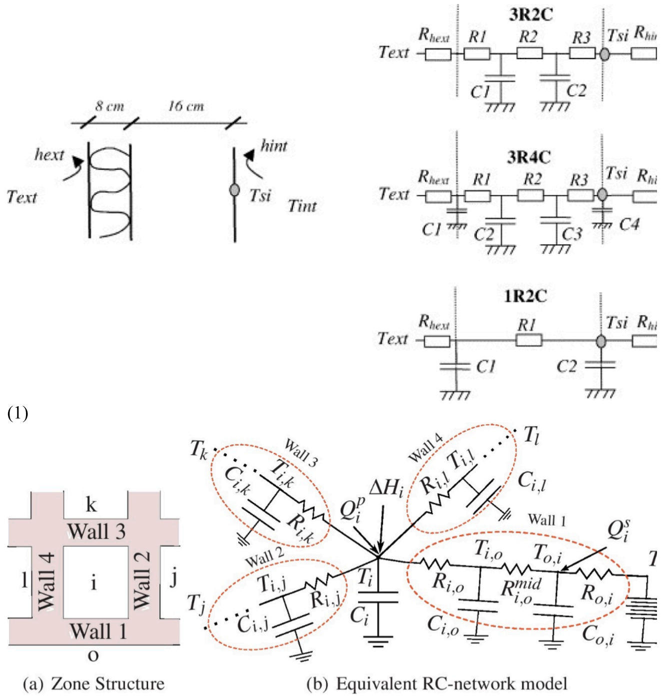
	QUICK [42]	FloVENT [60]	OpenFOAM	Airpak [53]	ANSYS Fluent [56]	Autodesk REVIT CFD [59]
User-friendliness	Simplified interface for beginners	Intuitive GUI User-friendly	Learning curve for beginners with GUI variations	User-friendly and simplified interface	Comprehensive GUI and extensive feature	Integrated with BIM user-friendly for Revit users
Mesh generation	Automatic mesh generation	Automated meshing	Powerful meshing capabilities	Simplified meshing tools	Robust meshing features and fine control	Relies on Revit for geometry and meshing
Solver performance	Efficient solver	Good performance for HVAC simulations	Parallel processing capabilities	Efficient for HVAC simulations	High-performance solver and parallel processing	Solver performance may be limited
Physics modelling	Limited physics models	Focused on HVAC simulations	Extensive physics models	Specialized in HVAC applications	Broad range of physics models	HVAC-focused physics models
Pre and post processing	Basic pre-processing tools	Robust pre- and post-processing capabilities	Varied pre-processing tools and limited post-processing	Streamlined pre-processing	Comprehensive pre- and post-processing tools	Integrates with Revit for geometry and setup
Multiphysics capabilities	Limited Multiphysics capabilities	Focused on HVAC and thermal comfort	Supports Multiphysics simulations	Primarily HVAC-focused	Strong Multiphysics capabilities	Limited Multiphysics capabilities
Cost and licensing	May offer cost-effective options	Commercial licensing	Open source with options for support plans	Discontinued commercial licensing	Commercial licensing	Part of Autodesk suite commercial licensing
Integration with other tools	Limited integration options	Integrates with other Autodesk tools	Integrates with various CAD software	Integration with AutoCAD	Interfaces with CAD software, User Defined Functions and ACSII and Excel outputs	Integrates seamlessly with Revit
Simulation accuracy	Limited accuracy for certain applications	Accurate for HVAC simulations	Accurate results for a range of applications	Accurate for HVAC simulations	Generally accurate	Accuracy depends on Revit model quality
Scalability	May have limitations for large-scale simulations	Scales well for HVAC simulations	Good scalability for parallel computing	Well-suited for HVAC simulations	Scales well for large simulations	Scalability depends on Revit model complexity

Model linearisation and model reduction can address the challenges posed by nonlinearity. These techniques entail dividing a flow pattern into distinct modes, and the progression of the operator spectrum demonstrates the complete dynamics. This method enables the effective utilisation of algorithms tailored for linear systems.

Since 1988, the optimisation and modelling of HVAC plant components have been questioned [72], where a component-based technique is used to define the system's process with heat and mass transfer balance equations and optimisation problem is applied by designating the links between each component with objective functions based on net energy consumption, primary energy consumption, first cost, annual operating cost, net present value and discounted payback period. One of the first optimisation models of HVAC system performance was proposed in that article; however, it built the optimisation on white-box equations that simplified the processes of each component. From there, several studies branched out to model the process of specific HVAC components. For instance [73], developed a four-parts component model for steady fan flow: the performance model, which relied on the pressure–volume flow characteristic presented by constant-speed curves vs volume flowrate and the absorbed power-volume flow characteristic, the energy model, which reproduces the absorbed power by the fan, the constraint model which limited the solution of the optimisation problem to performance of the fan curves and lastly the cost model for both the capital and operational costs. With time, the scope of nonlinearity evolved beyond components of HVAC system to including the entire air handling unit of the zone. [74] examined deriving dynamic models for transient conditions in a zone, heating coil, cooling and dehumidifying coil, humidifier, ductwork, fan and mixing box. The proposed model for each component was developed using heat and mass transfer equations, Laplace transform, and the Ziegler Nichols rule for tuning the K gain parameters of the PID controller. The study concluded that the zone temperature approaches steady-state conditions after 8000 s for summer and winter operation, while humidity ratio takes 3000 s for summer operation/ 2000 s for winter operation to reach a steady state. PID controller was capable of rejecting disturbances with small errors for a limited control horizon.

Resistor-capacitor networks are commonly used for constructing a reduced order model for transient heat through the zone where a wall is modelled with a set of linear differential equations with an order equal to the number of capacitors and with a set of ordinary differential equations modelling the heat and moisture exchange which can be nonlinear if latent heat is considered. Linking the linear RC models for solid surfaces to the nonlinear ODE of air enthalpy dynamics would create a full-scale model. Several studies adopted the RC model as the basis of feedback controllers since the early 2000s in [75,76]. [77] recently detailed and proposed a method of reducing the order of the full-scale model of the thermal dynamics of a multizone building for predicting space temperatures and humidities of the zone, employing outside temperature and humidity, heat gains and supply airflow characteristics with a 3R2C model as shown in Fig. 4 and a focus on the downstream side of air conditioning as the zone and ignoring the upstream side of the air handling unit dynamics due to the complexity of the zone interactions. It is assumed in the article that the air is well mixed with only one value reading averaged at each time step. Balanced truncation is used for model reduction of linear time invariant systems by ensuring that the controllability and observability Gramains are both equal and diagonal and ignoring the smallest eigenvalues of them. The results showed that the model can predict the temperatures and humidities with minimal error through simulating full-scale model of 40 model order and a reduced 14 and 8 model order using MATLAB of a 4-zone building for 24 h. To categorise the HVAC modelling strategies with their strengths and weaknesses, literature surveys [78,79] divided HVAC control techniques into three categories: white box physics based models elaborated in this cluster, black box model free models further explained in cluster 3, and hybrid models, where the review studies indicated the scarcity of state space system identification models for HVAC systems.

In response to the limited literature on HVAC system identification techniques, we delve into the exploration of computationally traceable approximations for generic airflow dynamics [80]. The modelling of airflow using nonlinear partial differential equations has the potential to result in the discretisation of over 10^6 states. One method, the Generalised Laplace Analysis (GLA), has been utilised to approximate a reduced order set of modes. However, its application requires prior



(a) Zone Structure (b) Equivalent RC-network model

Fig. 4. Lumped RC networks different configurations for conductive interaction in walls [76,77].

knowledge of eigenvalues for the reconstruction of eigenfunctions and modes [81]. Another approach to model reduction, Galerkin projection [82], based on Proper Orthogonal Decomposition (POD), dissects the flow field, concentrating on its most energetic features, such as the flow velocity field. This aims to obtain a lower-dimensional representation of flow sub-states. POD identifies basic functions used in Galerkin projection, producing finite-dimensional approximations of the Perron-Frobenius operator [83,84]. The resulting discrete finite-dimensional Perron-Frobenius operator, known as a Markov matrix, characterises the probabilistic transition from an initial state to all other states [85].

Furthermore, the discrete Fourier transformation serves as a common technique for analysing nonlinear flow dynamics. Dynamic Mode Decomposition (DMD) has been employed to extract dynamic modes, offering a generalisation of global stability modes in fluid flow, and providing insights into the underlying mechanisms captured in the flow data [84,86,87]. Nevertheless, DMD and Markov matrices have been deemed insufficient in capturing nonlinear transients, leading to the development of Extended Dynamic Mode Decomposition (eDMD). Presented as a numerical approximation, eDMD improves upon the classical DMD approach by introducing an additional set of observables spanning a finite-dimensional space. This initiates the approximation of the Koopman operator [88,89]. Despite the feasibility of approximating Koopman eigenvalues, the cross-validation process incurs a high error, necessitating the incorporation of deep learning. It is noteworthy that these model reduction methods have exclusively explored the dynamics of airflow properties and have not extended to the application of model reduction in indoor thermal performance and control.

5. Thermal comfort and airflow prediction, optimisation and control

Deep learning (DL), machine learning (ML), and optimisation were the terms composing the third research cluster. Central to thermal comfort control modelling is model free black box controllers, as mentioned in the second cluster. The integration of Artificial Intelligence (AI) tools in thermal comfort control systems has gained significant attention since the 1990s, offering the potential for adaptive and energy-efficient solutions. [90] indicated that the “sick building syndrome” motivated the construction of intelligent operation support system for HVAC processes for operation sequence planning, comfort settings and conflict reasoning. In addition, backpropagation was introduced for a two neural network controller into an air conditioner to ensure that the system is adapted to customer’s thermal preferences [91]. After a decade of the optimisation algorithms revolution [92], proposed a two objectives optimisation genetic algorithm for thermal comfort and energy consumption. The article demonstrated that energy consumption and thermal comfort can pose as conflicting optimisation objectives, however; Pareto optimal solution method put forward multiple solutions with metric criteria of front-generation distance method and diversity among non-dominated solutions spread method. The results showed that online implementation of the optimisation program for a supervisory controller saved 19.5 % of energy and provided minimum zone thermal comfort for one summer week. Optimisation of CO_2 as a parameter of the indoor air quality was considered along with thermal comfort and energy consumption of the cooling and heating coils and fan with genetic algorithm. The optimisation algorithm was implemented using MATLAB simulation for two air handling units supplying for a university campus. The results indicated that the optimisation algorithm was capable to reduce the energy consumption by 30.4 % [93]. [94] targeted the thermal comfort index using fuzzy optimisation logic with PID controller, hierarchical structure and dynamic matrix control (DMC), with limited results on the impact of the fuzzy control on the thermal comfort index.

Along with optimisation, predictions became advent benefit of machine learning algorithms, [95] offered one of the first prediction models to predict indoor air temperature based on outside air temperature, global solar radiation, wind speed, outside relative humidity and perturbation using autoregressive models with external input (ARX). Predictions of occupancy satisfaction probability was another investigated scheme of the AI tools capabilities. [96] applied Bayesian networks based on the compilation of subjective thermal sensation data from occupants to infer the probability distribution of thermal satisfaction calculations using MATLAB simulation for both a mechanically ventilated zone and naturally ventilated zone. [97] combined both optimisation and prediction advantages of AI models in a two-layer controller that utilises practical nonlinear model predictive controller (PNMPC) as an upper layer. The PNMPC was based on a classical hierarchical control scheme with a reference governor to provide impulse temperature reference, optimising the indoor PMV index. This reference posed an input for the PID lower layer of the fan coil unit. The results showed that the two-layer controller could reduce the energy consumption by 53 % while maintaining acceptable thermal comfort in office space implementation. With existing buildings retrofit popularity growth, studies were developed to characterise the thermal building performance before applying extensive retrofit processes. [98] aimed to develop a surrogate model to accelerate thermal comfort prediction verified with real data measurements by an artificial neural network. The ANN thermal characterisation reduced computational times by 98 %.

Other models diverted from the optimisation and prediction categories to replace existing indices and identifying new thermal comfort models tackling nonlinearity. Two data driven models in [99,100] developed learning methods that replace PMV index with a personalised thermal comfort models, one using the feedback data from information system in a real office environment, and the other proposing a Bayesian comfort model (BCM). The first model showed that simulation and experimental results demonstrate high accuracy in investigating personal energy savings. The latter model increased the accuracy of the personal thermal comfort predictions 13.2 % to 25.8 % more accurate than existing thermal comfort indicators. In [101], an alternative data-centric model collected sensor data from an experimental room and combined it with a data-based Neuro Fuzzy Inference System (ANFIS) and Particle Swarm algorithm. This combination sought to account for the nonlinear aspects of the PMV index. The study provided valuable findings on the assessment of thermal comfort using extensively distributed sensors for real-time algorithmic training. In a different investigation [102] a PMV controller was created, employing a genetic algorithm to maintain equilibrium among environmental factors using only a single room temperature and humidity sensor. This approach aimed to create balance between thermal comfort and energy consumption. In contrast to [101], the use of a lone sensor provided restricted insights into zone interactions.

Neural networks were employed in conducting a sensitivity analysis of the PMV index to its six variables as another trajectory of leveraging machine learning in thermal comfort assessment, with findings suggesting that occupants' physiological conditions exert the most substantial influence on the PMV index [103]. Investigations into the impact of Mean Radiant Air Temperature (MRT) on PMV estimation have been pursued using neural network predictions in Kuwait [104] and through inverse feedback controller approaches in [105]. Another investigation of MRT impact on PMV index estimation was developed using smart Wi-Fi thermostat based on a nonlinear autoregressive exogenous model (NARX) [106]. The model was used to calculate the temperature and humidity setpoints needed to achieve minimum thermal comfort, with initial results showing colling energy savings of 83 %. As technological advancements, particularly within the Internet of Things (IoT), continue to flourish, several studies have integrated data collected from smart devices. These studies employ a range of neural network architectures, including backpropagation, Multilayer Perception, and Recurrent neural networks [107,108]. In [109], the article highlighted the importance of integrating users' feedback corrections into the IoT feeding support vector machine (SVM). Most recently, IoT devices supported by predictive machine learning frameworks were developed for detecting HVAC systems faults but failed to detect the causes of such faults and errors in [110]. [111] Nanocoated rooms were considered for Microclimatic data-based HVAC control aided by a thermal camera, accounting for human skin and walls temperature and CO_2 concentration for optimising thermal setpoint temperature through regression analysis. In [104], PMV based online controller was applied to a residential building in Kuwait based on the sensors collected data combined with estimated mean radiant temperatures while sending the signal to the air conditioning system based on linear regression learning. One of the most recent innovations relevant to machine learning aided HVAC control systems is natural language processing as constraints for controller performance. [112] showcased the processing of game theory Shapley values in the context of HVAC MPC thermal comfort regulation to interpret the control signal for demand response events. While these advancements enable online thermal comfort-based control, they often struggle to establish precise system identification models due to the constant reliance on reading state space information for signal transmission. Consequently, achieving real-time responsiveness and accurate tracking of indoor conditions faces significant challenges and delays. Furthermore, some studies have explored the convergence between the PMV index and Computational Fluid Dynamics, incorporating simple embedded feedback control models without system identification applications [113]. This coupling of control mechanisms with ongoing system modelling demands extensive computational resources. The summary of works focusing on thermal conditions assessment, prediction and control supported by machine learning is given in Table 5.

For the development of linearisation and system identification techniques mentioned in Section 4 deep neural networks offer a solution by efficiently representing and autonomously learning complex functions derived from data. These models, initially explored in unrelated fields like molecular conformations [114], operate through sequential layers performing simple operations on previous layer outputs to extract higher-level features [115,116]. Among these, the autoencoder stands out—a self-supervised deep neural network characterised by a symmetric layer structure with a central bottleneck. Its encoder-decoder setup extends beyond deterministic functions to encompass stochastic mapping. In various applications, deep neural networks have tackled fluid dynamics problems. For instance, [117] introduced an attention mechanism into a stacked autoencoder to construct a data-driven reduced-order model for the 2D flow past a cylinder, while similar architectures [118], have employed autoencoder networks to unveil Koopman operator eigenfunctions. These efforts aim to avoid overfitting, handle continuous spectrums, and diminish nonlinearities in nonlinear systems, including pendulum movements and nonlinear fluid flow problems.

6. Discussion and future research directions

The section focuses on assessing the findings of the question proposed as how existing literature targeted the integration of thermal comfort nonlinearity with control modelling to assist in the design of optimal control solution. Nonlinearity of thermal conditions attributed to the HVAC system's complexity. The synthesis of existing literature defined five schemes contributing to thermal comfort conditions as shown in Fig. 5, including thermal comfort assessment models, thermal comfort parameters, air conditioning control devices, linearisation and model reduction techniques and HVAC systems modelling. It was noted that most of the existing literature had the aim of balancing the two conflicting objectives of thermal comfort optimisation and energy consumption reduction. According to literature, thermal comfort of energy efficient HVAC systems require proper and accurate assessment with indices, measurements and CFD models. In addition, it requires feasible interpretable and tractable HVAC system identification and modelling strategies while highlighting the challenges in AI aided tools. These requirements are detailed in the following subsections.

6.1. Requirement of thermal comfort assessment indicators and modelling tools

Thermal comfort indices and assessment tools ranged from static to adaptive models to assess and measure thermal comfort in various environments. Three frameworks appeared repeatedly in existing literature and verified with simulations and experiments: PMV-PPD index, Adaptive thermal comfort model and air diffusion performance index (ADPI). PMV index was found to be the most utilised index for its ability to quantify thermal sensation for averaged values and assumptions. However, several studies were capable of demonstrating the distribution of PMV index by CFD modelling, as shown in Table 5. While PMV index standardises and categorises thermal sensation through ISO 7730 scale, it lacked the subjectivity of age, gender and acclimatisation, which prompted the suggestion of adaptive PMV index that factors and weighs the impact of these factors. While PMV index is criticised for subjectivity, ADPI is criticised for its simplification for judging the draught and diffusion impact of the overall thermal sensation. Adaptive thermal comfort model considered adaptation and the behavioural acclimatisation of occupants. However, applicability to real environments is hindered due to the dynamic nature of the index and the lack of communication between the behavioural model and HVAC components. It was noted that operative temperature, mean radiant temperature (MRT) and skin wetness are the most influential factors in causing thermal discomfort. As previously mentioned, CFD modelling posed as a significant tool in presenting the thermal comfort for the indoor environment. For CFD modelling of thermal comfort indices, it was found that constant radiant temperature creates high error in estimating thermal comfort index. It was also found that occupants preferred cooler indoor environment, in addition to the significance of defining local thermal discomfort nodes. With the review of CFD simulation tools, it was found that OpenFOAM and ANSYS Fluent are robust tools to conduct multiphysics CFD model with high simulation accuracy, powerful meshing capacities and parallel processing potential. With the preference of occupants of lower cooling temperature and lower supply

Table 5
Summary of works discussing thermal comfort assessment, predictions and control aided with machine learning frameworks.

Ref.	Year	Study case	Underlying DL/ML tools	Thermal comfort model	Optimisation objective	Outcomes and results
[90]	1993	A *meta*-system providing a framework for the integration management of intelligent operation support system (IOSS) through four subsystems: operation mode consulting, indoor comfort setting, conflict reasoning and system introduction.	Knowledge base automation	PMV index	Operation sequence, comfort parameters, responding time, energy conservation	The results indicated that the system can easily control real time sequence with the potential to be applied in HVAC industrial scale
[92]	2004	Two VAV systems investigated for a university campus with a two-objective optimisation for finding a Pareto optimal solution of HVAC control between energy consumption and building thermal comfort.	Non-dominated Sorting Genetic algorithm (NSGA)	PMV-PPD indices	Energy consumption and thermal comfort parameters	The results showed that two objective optimisation is capable of reducing the energy consumption for 19.5 % with minimum zone thermal comfort.
[95]	2007	Predictions of the indoor temperature were investigated using ARX and ARMAX models using outside air temperature, global solar radiation, wind speed, outside relative humidity and perturbation.	Autoregressive model with external input and offline parameter identification methods	Black-box prediction model	Indoor temperature prediction accuracy	Results presented the performance of the two models in indoor temperature predictions with ARX model providing 0.94 coefficient of determination
[93]	2009	The study examines two control strategies; one based on fresh air supply rate and the supply air temperature, and the other is based on controlling the fresh air rate.	Genetic algorithm	PMV index	Indoor air quality parameters, energy consumption and thermal comfort	The results showed that energy consumption was reduced by 30.4 % during summer season for four months.
[96]	2009	The article investigates the capacity of Bayesian network for prediction the probability distribution of occupant's thermal satisfaction in tropical, subtropical and temperate climate regions.	Bayesian network	Adaptive thermal comfort model and PMV model	Thermal comfort and energy consumption	The findings indicate that adaptive comfort model is capable to balance energy savings with the thermal sensation of the occupants without compromising their mental performance,
[94]	2012	Fuzzy control algorithms and model predictive control algorithms are used in the hierarchical structure of climate comfort control system.	Fuzzy control algorithm	PMV index	PMV index and energy consumption	The results showed that DMC and GPC fuzzy models had only small differences in impacting thermal comfort
[99]	2014	A data driven model was proposed for personalised thermal comfort model that focuses on the personal differences and heat balance with a model called personalised thermal vote PTV.	Recursive least square estimation	PTV index	Personal thermal comfort and energy consumption	The simulation and experimental results demonstrate high accuracy in investigating personal energy savings
[97]	2014	Two layers control system was developed utilising the predictive abilities of neural network to develop the first layer of the practical nonlinear model predictive controller and the second layer applies the temperature setpoints on the fan coil unit.	Nonlinear predictive optimiser	PMV index	Thermal comfort and energy consumption	The results showed that the two-layer controller was capable of reducing the energy consumption by 53 % while maintaining acceptable thermal comfort in office space implementation.
[101]	2015	The article presented a wireless sensor network based on PMV index to regulate the temperature of the air conditioner with an adaptive neurofuzzy inference system (ANFIS) and particle swarm algorithm. The network solves the multivariable inverse PMV problem as feedforward-feedback control to determine thermal comfort temperature.	ANFIS and particle algorithm	PMV index	Thermal comfort, operating temperature and energy consumption	The results showed that the algorithm is capable to maintain the PMV value within the range of acceptable thermal comfort range between + 0.5 and −0.5
[100]	2017	A Bayesian comfort model was developed for estimating personal thermal comfort in comparison to existing thermal indices	Bayesian network model	Personal thermal comfort model combining static and adaptive indicators	Thermal comfort and energy consumption	The proposed model was able to predict the individual thermal comfort 13.2–25.8 % more accurate in comparison to existing PMV index
[98]	2019	The article employed ANN model with MATLAB modelling toolbox to predict a building thermal comfort and verify the predictions with real life data for a linear-type multi-family social housing.	ANN	Discomfort hours	Thermal comfort characteristics	The developed model provided a regression coefficient between simulated data and ANN predictions of 0.96 with a relative error of 9 %
[106]	2020	Thermal comfort controller with nonlinear autoregressive exogenous mode (NARX) was designed to	nonlinear autoregressive exogenous model (NARX)	PMV index	Thermal comfort parameters such as temperature and	The initial results indicated cooling energy savings ranging from 85 % to 95 % for high and low efficiency

(*continued on next page*)

Table 5 (*continued*)

Ref.	Year	Study case	Underlying DL/ML tools	Thermal comfort model	Optimisation objective	Outcomes and results
		calculated temperature and humidity setpoints based on Wi-Fi sensors input data			humidity and cooling energy savings	buildings respectively with PMV values maintained between 0 and −0.5 for cooling conditions.
[110]	2022	The article addresses the limitations of obtaining building performance data by IoT driven fault detection system for the indoor thermal comfort. The IoT device is used to monitor perceptual information from the physical site as system input. The processing and prediction of the IoT detection data was tested by several machine learning tools.	ANN, KNN, SVM, Decision Tree Naïve Bayes	HVAC faults detection	Thermal comfort parameters	The results showed that the models based on the IoT sensors reached acceptable predictive performance for monitoring and detecting HVAC problems. However, the models couldn't detail how and why such events were caused.
[119]	2022	The study proposed deep reinforcement learning for a control framework, aimed at occupant centric and personalised thermal comfort. The deep learning algorithm utilised branching dueling Q network (DQN) for pretraining the control framework based on Modelica virtual environment data, followed by the deployment for online office control.	Branching dueling Q-network algorithm	Occupant centric and personalised thermal comfort index	Occupant presence, room temperature and air velocity	The results indicated a reduction of 14 %in cooling energy with 11 % thermal acceptability for occupants.
[120]	2024	The article targeted the challenges to control indoor environment based on different thermal comfort requirements. While estimating the control system coefficients by experimental data, the study proposed the application of deep learning control framework applied with Modelica.	Dueling DQN algorithm	Control system identification	Reward function based on PMV index	The results of the experimental control application achieved 5–40 % reduction in heating consumption while maintaining thermal comfort. However, the coefficients learned from experimental data cannot be used for the control in a real building while not considering uncertainties.

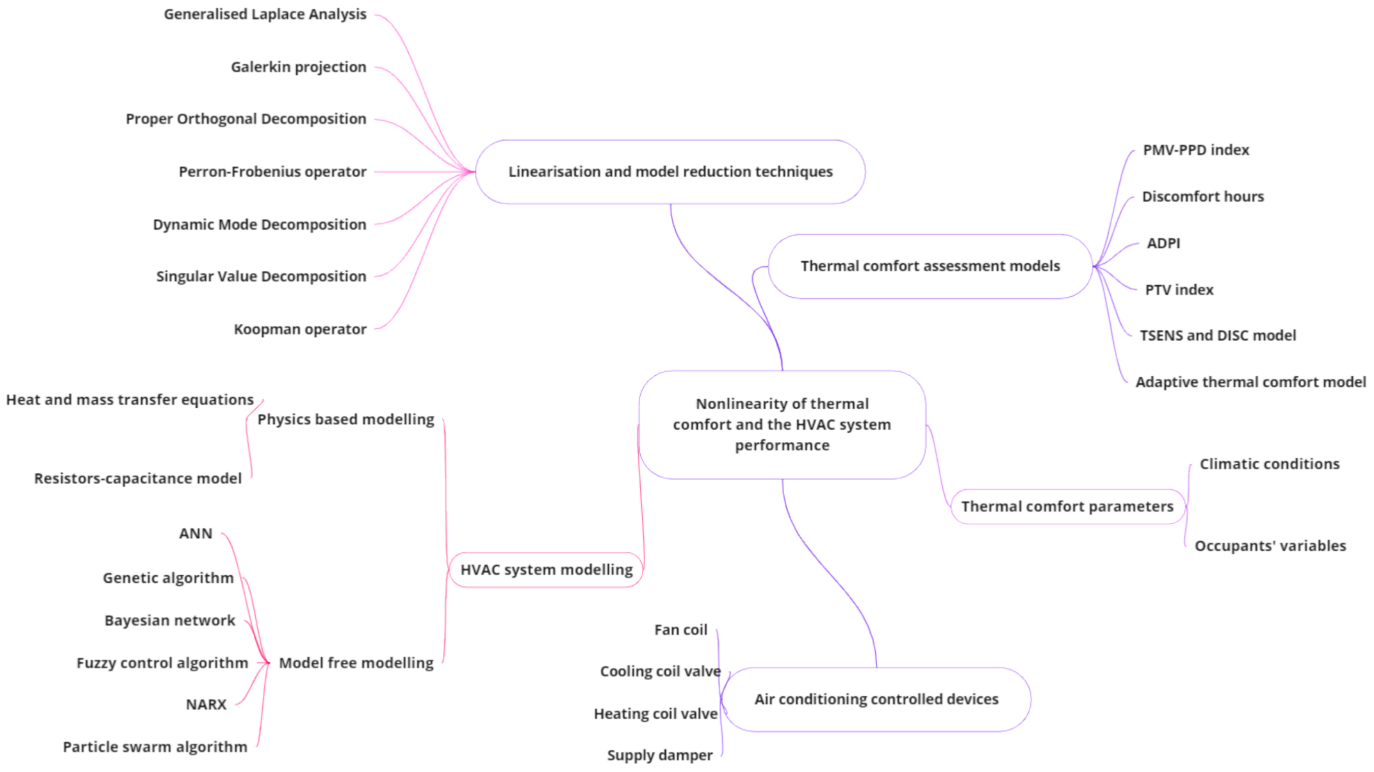


Fig. 5. Nonlinearity of HVAC systems thermal comfort assessment, modelling and control schemes.

velocities, cold air distribution systems were proposed as an energy efficient HVAC system with a controversial thermal comfort application, with the systems supply air with low velocity and relatively low cooling temperature. However, the cold air systems were not assessed thoroughly with verified thermal comfort and CFD models and indicated a lack of proper control systems for overall thermal conditions.

6.2. Requirement of HVAC control and optimisation identification

Addressing thermal comfort nonlinearity was reviewed in two schemes: physics based and model free modelling. Central to the physics-based models is the definition of heat and mass transfer models for several HVAC components. Physics based model limitations were determined by its reliance on assumptions and simplified mathematical equations, leading to discrepancies between model performance and actual performance. RC lumped model was one of methods of applying physics-based HVAC modelling, representing the zone interactions. However, the model considered averaged readings of each heat transfer elements. On the other hand, model free HVAC modelling scheme has been extensively applied with several AI tools. Each of these AI tools has advantages and disadvantages. ANN modelling can handle large number of input data and variables and the ability to represent any function, but ANN modelling lacks the systematic method of defining a structure for its purpose as well as suffering the risk of overfitting. For fuzzy logic, there is the advantage of not requiring a model and the use of fast processing with the ability to manage uncertainty; however, fuzzy modelling does not guarantee the consistency of inferences with sometimes creating contradicting inference rules. Genetic and particle swarm algorithms are known for their robustness in managing several parameters and solving optimisation problems, as well as their quick responsiveness and adaptability to changes in input. However, costly computation is required for these algorithms with the challenge of establishing evaluation functions, incorrect local optimums. With these challenges of representing nonlinearity of thermal conditions and HVAC processes, solutions borrowed from linearisation and model reduction along with AI tools can provide interpretable and trackable HVAC control systems to balance between thermal sensation, indoor air quality and energy consumption.

6.3. Future direction

To address the challenges and shortcomings mentioned above for thermal comfort assessment and control, further works are recommended in future works. The key directions are the following:

- Development of a proper thermal assessment framework of controversial yet energy efficient HVAC systems must be conducted to further realise the opportunities and savings offered for space cooling.
- Accurate and tractable system identification of HVAC processes is significantly needed with the barriers of nonlinearity and high computation cost of HVAC model free schemes and over-simplification of HVAC physics-based methods.
- Integration of near linear and order reduced identified HVAC system with existing feedback controllers is essential to check the overall stability, controllability, and robustness of these methods.
- Consideration of near linear zone dynamics with overall HVAC system optimisation to detect potential energy savings with other system's components.
- Optimal sensors placement can utilise the tractable system identification.

7. Conclusions

This work presented a systematic multidisciplinary literature review for nonlinearity of thermal comfort and HVAC modelling techniques with their potential of providing optimal thermal comfort through intelligent control and energy savings. The study was set out to investigating how using computational fluid dynamics (CFD) can enhance occupants' thermal comfort by better representing thermal sensations. This was deployed by reviewing current approaches and tactics for identifying HVAC systems, understanding their functions within HVAC control systems, recognising obstacles in accurately depicting thermal conditions and suggesting ways such as linearisation and model simplification to create real-time representations of dynamic and complex systems. Through conducting clusters analysis for existing literature, accommodating the multidisciplinary nature of this topic, thermal comfort assessment cluster indicated that adaptive PMV index is widely spread in quantifying the thermal sensation as a finding while considering occupant's subjectivity. In addition, operative temperature, skin wetness, draught and mean radiant temperature are the most important factors contributing to thermal discomfort. Another significant finding emerged from scoping linearisation and model reduction techniques in other fields of research, where linearisation techniques plays a role in accurate estimation of controlled system conditions. Lastly, the study highlight how model free black box AI tools can impose challenges for HVAC control systems. This study lays the groundwork for future research into creating thermal assessment framework of cooling systems, identify HVAC systems and processes with linearisation techniques and investigating the impact of such models on well-developed feedback controllers.

CRediT authorship contribution statement

Nourehan Wahba: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Behzad Rismanchi:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Ye Pu:** Writing – review & editing, Supervision. **Lu Aye:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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