

Review

Smart HVAC Control Strategies for Optimizing Thermal Comfort and Energy Efficiency in Omani Residential Buildings Under Extreme Heat Conditions

Mohammed Abu Safaqah ^{1,*}, Jeyaprakash Natarajan ² and Khalid Anwar ²

¹ Building Services Engineering, Global College of Engineering and Technology (GCET), Muscat P.O. Box 2546, Oman

² Mechanical Engineering Department, Global College of Engineering and Technology (GCET), Muscat P.O. Box 2546, Oman; jeyaprakash.n@gcet.edu.om (J.N.); khalid.a@gcet.edu.om (K.A.)

* Correspondence: mohammed.s@gcet.edu.om; Tel.: +968-2422-7906

Abstract

Heating, Ventilation, and Air Conditioning (HVAC) systems account for 60–70% of residential electricity consumption in Oman, where extreme desert climate, with temperatures regularly exceeding 45 °C create substantial cooling demands. Unlike general reviews of smart HVAC controls, this study specifically evaluates the applicability and performance of advanced control strategies for Omani residential buildings operating under extreme heat conditions, synthesizing evidence from international research, the Gulf Cooperation Council (GCC) region, and Oman. Based on a systematic review of peer-reviewed literature published between 2015 and 2025, this analysis examines Model Predictive Control (MPC), Deep Reinforcement Learning (DRL), Fuzzy Logic Control, and Internet of Things-based integrated approaches. International studies demonstrate that MPC strategies achieve energy savings of 16–40% compared to conventional thermostatic control by utilizing dynamic building thermal models to optimize control sequences over finite prediction horizons. DRL-based controllers achieve energy reductions of 17–23% through adaptive learning of optimal policies without requiring explicit system models, offering adaptability to dynamic occupancy patterns. Real-world implementation case studies from Oman and the GCC region—including the GUTech EcoHaus net-zero energy building and national-scale retrofit programs—demonstrate realized energy savings ranging from 25–75%, with higher savings achieved through comprehensive interventions that combine advanced controls with high-performance building envelopes. These findings suggest that substantial potential for reducing residential energy consumption while maintaining occupant thermal comfort under Oman’s extreme climatic conditions is achieved through the integration of advanced HVAC control strategies with high-performance building envelopes. Future research may address the development of occupant-centric adaptive comfort models calibrated for extreme heat conditions and context-specific control strategies that account for regional occupancy patterns and cultural preferences.

Keywords: smart HVAC control; thermal comfort; energy efficiency; Model Predictive Control; Deep Reinforcement Learning; extreme heat; Oman; GCC region; building automation

Academic Editors: Alan Fong and Yan Pan

Received: 27 May 2026

Revised: 24 August 2026

Accepted: 30 August 2026

Published: 9 September 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Buildings account for approximately 40% of global energy consumption and 36% of greenhouse gas emissions, making the built environment a critical target for climate change mitigation efforts [1,2]. Within buildings, Heating, Ventilation, and Air Conditioning (HVAC) systems represent the largest single energy end-use, particularly in extreme climates where maintaining indoor thermal comfort is essential for occupant health and productivity [3]. As global temperatures rise due to climate change, cooling degree days are increasing across many regions, intensifying the energy demand from air conditioning systems and creating a feedback loop that further exacerbates environmental challenges [4].

The Sultanate of Oman, located in the southeastern Arabian Peninsula, exemplifies these challenges in acute form. The country experiences one of the world's extreme hot desert climates, with summer temperatures regularly exceeding 45 °C and the coastal city of Quriyat recording a global high of 50.8 °C in 2018 [5]. In this context, air conditioning has transitioned from a luxury to a necessity, substantially reshaping building energy demand patterns. The residential sector accounts for approximately 40% of total electricity consumption in Oman, with HVAC systems responsible for 60–70% of residential electricity use [6]. This heavy reliance on mechanical cooling creates a self-reinforcing cycle: increased electricity demand drives greater fossil fuel combustion, contributing to greenhouse gas emissions that intensify cooling requirements. Breaking this cycle requires approaches to building energy management that prioritize both efficiency and occupant well-being.

The challenges faced by Oman are shared across the Gulf Cooperation Council (GCC) region, where extreme desert climates and rapid urbanization have created similar patterns of high residential energy consumption. Across the GCC, residential buildings account for 58–75% of national electricity consumption, with cooling representing the dominant end-use [7]. Saudi Arabia, the largest GCC economy, has implemented energy efficiency initiatives under Vision 2030, including the Saudi Building Code and the Saudi Energy Efficiency Centre's programs targeting 30% reduction in power intensity by 2030 [8]. The Kingdom's residential sector accounts for approximately 50% of total electricity consumption, with cooling demands driving peak loads that strain grid infrastructure during summer months [8]. The United Arab Emirates has implemented green building standards through the Estidama Pearl Rating System and Dubai's Al Sa'fat Green Building System, mandating energy performance requirements that have accelerated the adoption of building automation systems and smart HVAC controls in residential developments [9]. Qatar has invested in district cooling infrastructure with centralized plant optimization systems serving residential areas, while Kuwait and Bahrain face comparable climatic extremes with summer temperatures regularly exceeding 50 °C and residential buildings consuming 60–80% of national electricity generation during peak cooling periods [7,10].

Despite these shared climatic challenges, important differences exist across the GCC region that affect the applicability of smart HVAC control strategies. The UAE and Saudi Arabia have advanced building automation markets supported by higher GDP per capita and greater availability of technical expertise, supporting implementations of model predictive control and IoT-based systems [9]. Qatar and Kuwait have invested heavily in district cooling infrastructure, which shifts the control paradigm from individual building systems to centralized plant optimization [11]. Field studies in Kuwait have demonstrated that thermal comfort-based control strategies can achieve energy reductions of 33–39% in residential buildings, providing important reference data for similar climates [12]. Oman occupies a unique position within this regional context: while sharing the extreme heat conditions and high cooling demands of its neighbors, the Sultanate's building stock,

policy framework, and technical capacity differ in ways that affect the feasibility and performance of advanced control strategies. Oman's residential buildings typically feature lower insulation levels and higher air infiltration rates (approximately 0.7 air changes per hour) than buildings in the UAE or Saudi Arabia, potentially limiting the effectiveness of model-based predictive strategies that assume tighter building envelopes [13,14]. The country's developing technical infrastructure and emerging regulatory framework present both opportunities for leapfrogging to advanced technologies and challenges for implementation and maintenance.

The performance data reported from international smart HVAC research must be interpreted cautiously when considering Omani applications. International studies demonstrating MPC energy savings of 16–40% and DRL reductions of 17–23% are typically conducted in buildings with high-performance envelopes, stable occupancy patterns, and well-maintained equipment—conditions that differ substantially from the Omani context. Oman's climate severity, characterized by higher peak temperatures and greater diurnal temperature swings than many study locations [5], increases cooling loads and may reduce the relative effectiveness of predictive control strategies. The country's residential building stock exhibits greater air infiltration rates and lower thermal insulation compared to buildings in North American or European studies, increasing thermal loads and potentially diminishing the proportional savings achievable through control optimization alone. Occupant behavior patterns in Oman, influenced by cultural practices including prayer schedules, extended family structures, and Ramadan observances [14], differ significantly from the Western office-building contexts common in international research. Additionally, Oman's developing technical infrastructure, including limited local availability of building automation components and shortage of qualified commissioning and maintenance professionals, presents implementation barriers not captured in laboratory or simulation studies from more developed markets [13,14].

The evolution of HVAC control strategies has progressed through several generations of technological advancement. Traditional thermostatic control, which maintains fixed indoor temperature setpoints regardless of occupancy or external conditions, remains the dominant approach in residential buildings worldwide [15]. While simple to implement, this method fails to capitalize on energy optimization opportunities during unoccupied periods or when outdoor conditions permit reduced mechanical cooling loads. The second generation introduced programmable thermostats and time-based scheduling, offering modest improvements but lacking adaptability to dynamic conditions [16].

The current research frontier focuses on intelligent control systems that leverage real-time data, predictive models, and machine learning algorithms. Model Predictive Control (MPC) has been widely adopted as a paradigm, utilizing dynamic building thermal models to anticipate future conditions and optimize control actions over finite prediction horizons [17,18]. MPC strategies have demonstrated energy savings of 16–40% compared to conventional approaches while maintaining acceptable thermal comfort levels [19,20]. Concurrently, Deep Reinforcement Learning (DRL) has been studied for its ability to learn optimal control policies through interaction with building environments without requiring explicit system models, achieving reported energy reductions of 17–23% [21,22].

Despite these advances, significant controversies and diverging hypotheses persist within the research community. A fundamental debate concerns the appropriate framework for assessing thermal comfort in extreme heat conditions. The Predicted Mean Vote (PMV) model developed by Fanger [23] remains the most widely adopted international standard, yet its applicability in hot environments has been questioned, with studies demonstrating reduced prediction accuracy when outdoor temperatures exceed 35 °C [24]. Alternative adaptive comfort models, which recognize that occupants can

acclimatize to different temperature ranges based on outdoor conditions and past thermal experiences, have gained traction in hot climate research [25,26]. However, the lack of consensus on which framework best serves extreme heat applications creates uncertainty for control system designers and policymakers.

Another divergence concerns the relative merits of model-driven versus model-free control approaches. MPC offers interpretability and theoretical guarantees but requires accurate building thermal models that can be costly to develop and maintain [27]. DRL provides adaptability to changing conditions and requires no prior system knowledge, but suffers from the “black box” problem of limited interpretability and potential instability during learning [28]. The optimal balance between these approaches remains an open question, particularly for residential buildings where occupant behavior introduces significant stochasticity.

The architectural design of smart building systems also presents competing paradigms. Centralized control architectures enable global optimization but create single points of failure and may not scale efficiently to large building portfolios [29]. Distributed IoT-based approaches offer scalability and fault tolerance but face challenges in coordinating actions across multiple autonomous agents [30]. Recent research has explored hybrid architectures that combine local intelligence with centralized oversight, though optimal configuration remains context-dependent [31].

While the global literature on smart HVAC control strategies is extensive, existing reviews typically address temperate climates [3], commercial building applications [16], or general principles without specific consideration for extreme heat conditions and regional implementation contexts. This review addresses a gap in the literature by providing a dedicated comprehensive analysis of smart HVAC control strategies specifically applicable to Omani residential buildings operating under extreme heat conditions. Unlike general reviews that present control technologies in isolation from implementation context, this study systematically evaluates the applicability, performance potential, and practical challenges of advanced control strategies within Oman’s unique climatic, regulatory, and technical environment. The review synthesizes evidence from international research, GCC regional case studies, and Omani implementation experiences to provide insights for researchers, practitioners, and policymakers seeking to advance residential energy efficiency in extreme heat climates. By bridging the gap between global control research and regional implementation realities, this study contributes to understanding of context-appropriate solutions that address both the universal challenges of smart building control and the specific constraints of Oman’s extreme heat environment.

The purpose of this paper is to provide a comprehensive review of smart HVAC control strategies specifically applicable to Omani residential buildings operating under extreme heat conditions. We systematically analyze four primary control paradigms—Model Predictive Control, Deep Reinforcement Learning, Fuzzy Logic Control, and IoT-based integrated approaches—examining their underlying principles, implementation requirements, and performance characteristics within the Omani context. Our analysis reveals that advanced control strategies offer significant potential for energy reduction, with MPC achieving 16–40% savings [19,20], DRL demonstrating 17–23% reductions [21,22], and integrated case studies showing realized savings of 25–75% depending on intervention comprehensiveness [14,32,33]. We further contextualize these technical solutions within Oman’s evolving policy framework, including the Oman Building Code, Energy Efficiency and Sustainability Code, and Oman Vision 2040 objectives. Finally, we identify research gaps, including the need for occupant-centric adaptive comfort models calibrated for extreme heat, integration of distributed energy resources with HVAC systems, and development of culturally appropriate control strategies that account for regional occupancy patterns.

2. Materials and Methods

This systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [34] and established systematic review methodologies for engineering research [35]. The review protocol was developed to ensure transparency, reproducibility, and comprehensive coverage of the literature on smart HVAC control strategies for residential buildings in extreme heat climates.

2.1. Review Protocol and Research Questions

A systematic review protocol was developed prior to conducting the review, defining the research questions, search strategy, inclusion and exclusion criteria, and data extraction procedures. This review addresses the following research questions:

- a. What smart HVAC control strategies have been developed and evaluated for residential buildings in extreme heat climates?
- b. What are the quantitative energy savings and thermal comfort performance outcomes of these control strategies?
- c. What are the implementation requirements, advantages, and limitations of each control paradigm?
- d. What is the applicability of international research findings to Omani residential buildings under extreme heat conditions?

The protocol was structured following systematic review best practices to ensure methodological rigor.

2.2. Literature Search Strategy

A comprehensive literature search was conducted across multiple electronic databases to identify peer-reviewed publications on smart HVAC control strategies. The search strategy was developed to maximize retrieval of relevant literature across multiple databases, employing a combination of controlled vocabulary and free-text terms related to HVAC control, building energy efficiency, and extreme heat climates.

2.2.1. Databases Searched

- Web of Science (Core Collection)
- Scopus (Elsevier)
- IEEE Xplore Digital Library
- Google Scholar (for grey literature and additional sources)

2.2.2. Search Terms and Boolean Operators

Keywords and Boolean operators were combined to develop a search strategy targeting studies related to smart HVAC control strategies, energy efficiency, and thermal comfort in residential buildings located in hot climates. The search string was modified where necessary to accommodate the specific syntax of each database. The general search strategy applied across the electronic databases was:

- (“smart HVAC control” OR “intelligent HVAC” OR “advanced HVAC control” OR “building automation system” OR “BAS”)
- AND (“model predictive control” OR “MPC” OR “deep reinforcement learning” OR “DRL” OR “fuzzy logic control” OR “FLC” OR “Internet of Things” OR “IoT”)
- AND (“energy efficiency” OR “energy savings” OR “thermal comfort” OR “demand response”)
- AND (“residential building” OR “house” OR “dwelling” OR “home”)

- AND (“extreme heat” OR “hot climate” OR “arid climate” OR “desert climate” OR “GCC” OR “Gulf” OR “Middle East” OR “Oman”)

The systematic literature search primarily focused on publications from January 2015 to December 2025 to ensure coverage of recent advances in machine learning and IoT-based control strategies while maintaining relevance to current technologies. The search was conducted in February 2026. In addition, seminal and foundational studies published prior to 2015 were retained where necessary to provide theoretical background, establish fundamental concepts (e.g., thermal comfort models and control theory foundations), or support the interpretation of findings.

2.2.3. Supplementary Search Methods

In addition to database searches, the reference lists of included studies and relevant review articles were manually screened to identify additional studies (backward snowballing: $n = 19$). Key journals in the field (Energy and Buildings, Building and Environment, Applied Energy, Sustainable Cities and Society) were hand-searched for recent publications ($n = 12$).

The systematic literature search and study selection process is illustrated in Figure 1 (PRISMA 2020 flow diagram), showing the identification of records from four databases and supplementary sources, screening procedures, eligibility assessment, and final study inclusion.

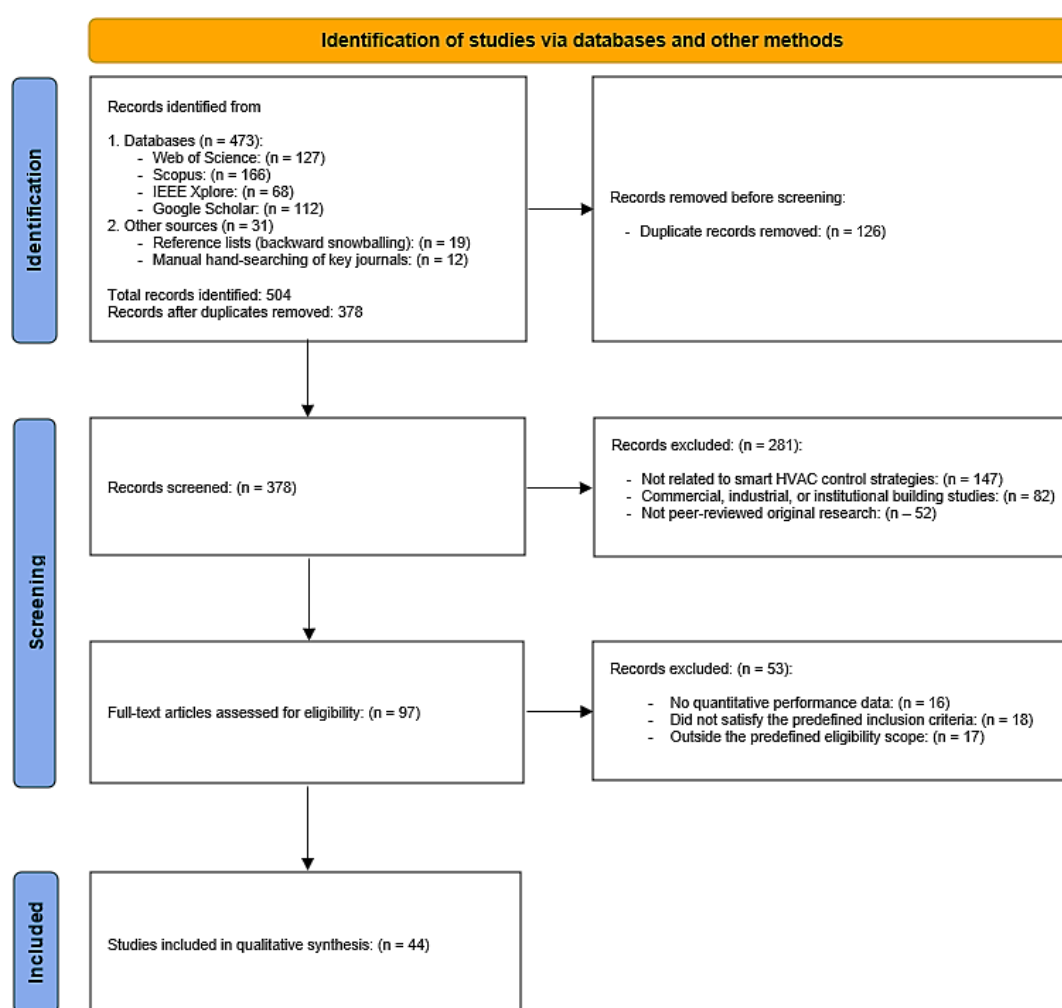


Figure 1. PRISMA 2020 flow diagram showing the systematic literature search and study selection process.

2.3. Study Selection Process

The study selection process followed a two-phase screening procedure: (1) title and abstract screening, and (2) full-text eligibility assessment. Records were initially identified from four electronic databases (Web of Science, Scopus, IEEE Xplore, and Google Scholar) and supplementary sources including backward snowballing and manual hand-searching. After duplicate removal, records underwent screening against the defined inclusion and exclusion criteria. Full-text articles were assessed for eligibility, with reasons for exclusion documented. The complete PRISMA 2020 flow diagram illustrating the identification, screening, eligibility assessment, and inclusion phases is presented in Figure 1.

2.4. Inclusion and Exclusion Criteria

2.4.1. Inclusion Criteria

Studies were included if they met all of the following criteria:

- a. Investigated smart or advanced control strategies for HVAC systems in buildings;
- b. Reported quantitative performance metrics including energy savings (kWh, percentage reduction, EUI) and/or thermal comfort indices (PMV, PPD, operative temperature);
- c. Focused primarily on residential building applications (single-family, multi-family, or residential prototypes);
- d. Published in English in peer-reviewed journals or conference proceedings;
- e. Published between 2015 and 2025 (for the systematic search); seminal foundational studies published prior to 2015 were also considered for theoretical background where appropriate;
- f. Employed research methods including simulation, experimental testing, or field studies with empirical data.

2.4.2. Exclusion Criteria

Studies were excluded if they met any of the following criteria:

- a. Focused exclusively on commercial, industrial, or institutional buildings without relevance to residential applications;
- b. Lacked quantitative performance data or reported only qualitative outcomes;
- c. Addressed only hardware improvements (e.g., equipment efficiency upgrades) without control strategy innovations;
- d. Focused solely on building envelope improvements without HVAC control components;
- e. Were review papers, editorials, or conference abstracts without original data;
- f. Duplicate publications of the same study (only the most comprehensive version was retained)

2.5. Data Extraction and Synthesis

A standardized data extraction form was developed to capture relevant information from each included study [36]. Data extraction was performed following a standardized protocol to ensure consistency.

2.5.1. Data Extracted

- a. Study Characteristics: Author(s), publication year, country/region, funding source;
- b. Methodological Information: Research design (simulation, experimental, field study, hybrid), sample size (number of buildings, zones, or simulation runs), study duration;

- c. Building Characteristics: Building type, climate zone, floor area, construction vintage, envelope characteristics, HVAC system type;
- d. Control Strategy: Control paradigm (MPC, DRL, FLC, IoT-based), algorithm details, sensor configuration, occupancy model, optimization objectives;
- e. Performance Metrics:
 - Energy metrics: Energy consumption (kWh), Energy Use Intensity (kWh/m²/year), percentage savings, peak demand reduction;
 - Thermal comfort metrics: PMV, PPD, operative temperature, discomfort hours, thermal sensation votes;
 - Additional metrics: Indoor air quality (CO₂, VOCs), cost savings, payback period.

2.5.2. Data Synthesis

Data synthesis employed a combination of narrative synthesis and tabular presentation to identify common patterns, implementation challenges, and research gaps across the reviewed literature [37]. Due to the heterogeneity of study designs, building types, climates, and outcome measures, quantitative meta-analysis was not deemed appropriate. Instead, performance outcomes were synthesized by control paradigm, with ranges and descriptive statistics reported where applicable. Table 1 provides a detailed classification of the studies included in this review.

2.6. Quality Assessment

Study quality was assessed using a customized quality assessment tool adapted from the Critical Appraisal Skills Program (CASP) checklist for systematic reviews [38] and the guidelines for quality assessment in energy efficiency studies. Each included study was evaluated across the following domains:

- a. Study Design Appropriateness: Was the research design (simulation, experimental, field study) appropriate for the research question?
- b. Methodological Rigor: Was the methodology clearly described and reproducible?
- c. Data Quality: Were input data (weather, occupancy, building parameters) clearly specified and justified?
- d. Validation: Were simulation models or experimental setups validated against measured data?
- e. Reporting Completeness: Were results reported with sufficient detail (sample size, statistical significance, uncertainty)?

Each of the five quality assessment domains was evaluated independently and rated as high, medium, or low based on predefined criteria. The overall study quality was determined by aggregating ratings across all five domains: studies rated as satisfactory (high or medium) in at least four domains, with no domain rated as low, were classified as high quality; studies with satisfactory ratings in two to three domains, with no more than two domains rated as low, were classified as medium quality; and studies with fewer than two satisfactory ratings, or with three or more domains rated as low, were classified as low quality. Studies were not excluded based on quality assessment; however, quality ratings were considered during data synthesis and interpretation, with greater weight given to findings from higher-quality studies.

Table 1. Characteristics of Included Studies.

Reference	Country/Region	Building Type	Climate	HVAC System Type	HVAC Control Strategy	Research Method	Validation Approach	Main Performance Metric(s)
Eini & Abdelwahed [39]	USA (Chicago)	Office (4-zone, 1600 m ²)	Temperate (Cfa)	Multi-zone HVAC (4 systems)	MPC with ANN occupancy estimation	Simulation	Comparison with conventional MPC (EnergyPlus)	Energy savings (%), Cooling/heating power
Sha et al. [40]	Not reported	Residential building	Not reported	Central HVAC	MPC (online learning-enhanced)	Simulation	Simulation validation (EnergyPlus)	Energy consumption, IAQ, Thermal comfort
Yang et al. [41]	Singapore	Office and lecture theatre (university)	Tropical (Af)	ACMV system	MPC (adaptive ML-based)	Experimental	Experimental validation in real testbeds	Cooling energy reduction (%), Thermal comfort
Zhuang et al. [42]	Singapore	Multi-zone building	Not reported	Central HVAC	DRL + LSTM time-series forecasting	Simulation	Comparison with rule-based control	Energy savings (%), Thermal comfort
Liu et al. [43]	Not reported	Office building	Not reported	VRF system	MSP-DRL	Simulation	Simulation validation	Energy consumption, Learning stability
Al Sayed [44]	Luxembourg	University amphitheater	Not reported	Air Handling Unit (AHU)	Hybrid DRL (DDQN + TD3)	Simulation	Comparison with DDQN and TD3 benchmark controllers	Energy consumption, AHU control performance
Gouda et al. [45]	UK	Office/laboratory	Temperate (Cfb)	Central HVAC	Fuzzy Logic (PMV-based)	Experimental	Experimental validation with environmental test chamber	PMV index, Energy consumption
Kang et al. [46]	South Korea	Residential apartment	Temperate (Cwa/Cfa)	Split AC system	Fuzzy Logic (advanced on-off)	Simulation	Comparison with conventional on-off control	Energy consumption, Thermal comfort
Su & Wang [47]	Hong Kong	Office building	Subtropical (Cwa)	VAV system	IoT-based (agent-based distributed)	Simulation	Simulation validation (computation load analysis)	Energy savings (%), Computational efficiency
Liang et al. [48]	Australia (Melbourne, Victoria)	Residential/office	Not reported	Split AC system (3.5 kW)	IoT-based (HITL with occupancy prediction)	Simulation	Comparison with rule-based baseline controllers	Cost reduction, Thermal comfort
Rudolph et al. [32]	Oman (Muscat)	Residential (EcoHaus, 242 m ²)	Hot arid (BWh)	VRF + ERV + Solar cooling	Integrated smart controls (MPC-based)	Field Study	Field validation with 2-year monitoring data	EUI (kWh/m ² /yr), PMV, Temperature
Krarti & Dubey [33]	Oman/GCC	Residential (national stock)	Mixed GCC (BWh/BSk)	Various conventional systems	Retrofit + smart controls	Analysis	Comparative analysis of national retrofit scenarios	Energy savings (%), Peak demand reduction
Alalouch et al. [14]	Oman (Three climatic zones)	Residential (villa prototype)	Hot arid (BWh)	Split AC systems	Smart design strategies + scheduling	Simulation	Simulation validation against baseline (Design-Builder)	Energy savings (%), EUI

2.7. Case Study Selection

In addition to the systematic literature review, representative case studies from Oman and the GCC region were selected to provide practical implementation context. Case study selection followed these criteria:

- a. Geographic Location: Located within Oman or the GCC region;
- b. Data Availability: Published performance data available in peer-reviewed literature or official reports;
- c. Building Typology: Relevance to residential building applications;
- d. Control Strategy Diversity: Representation of different control paradigms;
- e. Empirical Validation: Preference for studies with measured (not just simulated) performance data.

The GUTech EcoHaus was selected as a flagship demonstration project representing integrated design with comprehensive monitoring data. The large-scale retrofit program analysis was included to represent aggregate potential at the national level. Simulation-based studies were included where empirical validation data were available.

2.8. Limitations

This systematic review is subject to several limitations:

- a. Publication Bias: Positive results may be overrepresented in the published literature, potentially inflating reported energy savings;
- b. Heterogeneity: The diversity of study designs, building types, climates, and performance metrics limits direct comparability across studies;
- c. Regional Specificity: While global literature on smart HVAC controls is extensive, region-specific studies targeting extreme heat climates, particularly within the Oman context, remain relatively scarce;
- d. Temporal Validity: Rapid technological advancement in machine learning and IoT may limit the applicability of older studies (pre-2020) to current implementations;
- e. Generalizability: The performance metrics reported represent outcomes from diverse climatic conditions, building typologies, and occupancy patterns; actual performance in Omani residential buildings may vary based on specific implementation conditions.

3. Results

This section presents the quantitative performance findings from the systematic review, organized to show the progression from international evidence through GCC regional studies to Oman-specific case studies. The results are structured to facilitate comparison across control paradigms and geographic contexts.

3.1. Performance of Smart HVAC Control Strategies: International Evidence

This subsection presents performance data from peer-reviewed studies conducted across diverse global contexts, providing the foundation for understanding control strategy capabilities before contextualizing findings for Oman and the GCC region.

3.1.1. Model Predictive Control (MPC)

Operating Principle

Model Predictive Control utilizes dynamic building thermal models to anticipate future conditions and optimize control actions over finite prediction horizons. The predictive model typically takes the form of a state-space representation:

$$x_{k+1} = Ax_k + Bu_k + Ed_k$$

where x_k represents the state vector (zone temperatures), u_k represents control inputs (HVAC setpoints), and d_k represents disturbance inputs (outdoor temperature, solar radiation, occupancy) [17,18].

The fundamental architecture of MPC involves three core components: a predictive model of building thermal dynamics, an optimization algorithm determining optimal control sequences, and a receding horizon implementation applying only the first control action before re-optimizing.

Reported Energy Savings

MPC strategies achieve energy savings ranging from 16% to 40% compared to conventional thermostat control [19,20]. Eini and Abdelwahed [39] reported a 40.56% reduction in cooling power consumption and a 16.73% reduction in heating power consumption using learning-based MPC with ANN occupancy estimation. Building upon these findings, Sha et al. [40] demonstrated simultaneous optimization of HVAC energy consumption, indoor air quality, and thermal comfort through online learning-enhanced data-driven MPC. Furthermore, Yang et al. [41] experimentally validated MPC with adaptive machine-learning-based models in two real testbeds (an office and a lecture theatre) in tropical Singapore, achieving a 58.5% reduction in cooling thermal energy consumption in the office and a 36.7% reduction in cooling electricity consumption in the lecture theatre compared with their respective original reactive control systems, while improving thermal comfort. Collectively, these studies demonstrate that MPC approaches consistently deliver substantial energy savings across diverse building types and climate conditions, with particular efficacy when enhanced by machine learning techniques for occupancy prediction and adaptive modeling.

Thermal Comfort Performance

MPC maintains thermal comfort within acceptable Predicted Mean Vote (PMV) ranges (± 0.5) while optimizing energy consumption [39,40]. The precooling capability of MPC allows buildings to shift cooling loads to off-peak periods while maintaining occupant comfort during occupied hours. This predictive capability distinguishes MPC from reactive control strategies, enabling proactive thermal management that anticipates comfort requirements before they arise.

Advantages

The theoretical rigor of MPC offers distinct advantages that explain its higher energy savings potential (16–40%) compared to other control paradigms. The explicit system models provide interpretability that enables building operators and commissioning engineers to verify control behavior before deployment, addressing the trust barriers that often impede adoption of automated control systems [17,18]. This interpretability contrasts with the “black box” nature of DRL, making MPC more acceptable in contexts where stakeholders require transparency in decision-making processes. The precooling capability represents a significant advantage in peak-load-constrained grids such as Oman’s, where shifting cooling loads to off-peak periods can reduce both electricity costs and grid stress while maintaining occupant comfort during occupied hours [19]. Unlike FLC, which operates reactively based on current conditions, MPC’s predictive framework enables proactive thermal management that anticipates future comfort requirements and energy price fluctuations. The multi-objective optimization capability simultaneously addresses energy consumption, thermal comfort, and indoor air quality within a unified mathematical framework [39,40], providing optimization sophistication that rule-based approaches

does not achieve. Furthermore, the extensive theoretical foundation and substantial literature support facilitate knowledge transfer and implementation by practitioners with control engineering expertise, reducing the knowledge barriers that constrain deployment of emerging control technologies [20].

Limitations

Despite its performance advantages, MPC faces implementation challenges that constrain its applicability across the residential building stock. The requirement for accurate building thermal models creates a significant barrier to entry, as model development demands detailed building characterization that is often unavailable for existing buildings lacking as-built documentation [17]. This limitation sharply distinguishes MPC from DRL, which learns control policies without prior system identification, and from FLC, which relies on expert knowledge rather than mathematical models. The computational intensity of solving optimization problems at each control interval necessitates dedicated hardware or cloud-based computation that may be economically unviable in residential settings [18], particularly compared to FLC's minimal computational requirements. Model accuracy degradation over time as buildings age or undergo modifications creates ongoing maintenance burdens that exceed typical homeowner capabilities, potentially compromising performance when actual building behavior deviates from model predictions [19]. In addition, MPC's limited adaptability to unmodeled disturbances—such as unexpected occupancy patterns or equipment malfunctions—represents a critical vulnerability in residential contexts where such disturbances are common. These limitations collectively explain why MPC, despite its theoretical advantages, remains predominantly deployed in commercial buildings with dedicated facility management rather than in typical residential applications.

Suitability for Omani Residential Buildings

The suitability of MPC for Omani residential applications reflects a fundamental trade-off between performance potential and implementation feasibility. MPC is well-suited for new construction or major renovations where accurate thermal models can be developed during the design phase, leveraging the availability of building information modeling (BIM) data and commissioning resources [17]. The high computational requirements and need for professional commissioning may limit applicability in Oman's residential sector, where technical infrastructure and expertise are still developing. Compared to DRL, MPC provides greater interpretability and theoretical guarantees but requires substantially more upfront modeling effort and ongoing maintenance; this trade-off favors MPC in institutional settings with dedicated technical staff but disadvantages it in typical residential contexts. Compared to FLC, MPC achieves higher energy savings (16–40% versus 12–25%) but demands significantly greater computational resources, technical expertise, and implementation costs, making FLC appropriate for cost-sensitive retrofit applications. The potential for MPC in Oman's residential sector lies primarily in high-performance buildings with integrated building management systems, where the infrastructure investments can be amortized across substantial energy savings and where technical support is available for ongoing model maintenance.

3.1.2. Deep Reinforcement Learning (DRL)

Operating Principle

Deep Reinforcement Learning learns optimal control policies through interaction with building environments without requiring explicit system models. DRL agents receive feedback (rewards) based on energy consumption and comfort metrics, gradually improving control strategies through trial and error [21,22]. This model-free approach

contrasts with MPC, which relies on pre-defined thermal models. The agent explores control actions, observes environmental responses, and updates its policy to maximize cumulative rewards, enabling adaptation to building-specific dynamics without prior system identification.

Reported Energy Savings

DRL strategies demonstrate reported energy reductions in the range of 17–23% across different climate conditions [21,22]. Zhuang et al. [42] achieved 17.4% energy savings and 16.9% improvement in thermal comfort using data-driven predictive control combining time-series forecasting with reinforcement learning. Liu et al. [43] demonstrated improved learning stability and control performance using multi-step predictive DRL (MSP-DRL), addressing temporal credit assignment problems that plague conventional DRL implementations. Al Sayed [44] demonstrated a hybrid DRL approach combining discrete and continuous control actions (DDQN + TD3) in an EnergyPlus-simulated university amphitheater in Luxembourg, achieving a 16.24% reduction in energy consumption relative to TD3 and a 23.68% reduction relative to DDQN baseline controllers. Zhuang et al. [42] and Liu et al. [43] demonstrate DRL energy savings comparable to MPC in building applications, while Al Sayed [44] shows hybrid DRL effectiveness in AHU control for a university amphitheater, though with different baselines (TD3 and DDQN controllers rather than conventional HVAC).

Thermal Comfort Performance

DRL demonstrates greater adaptability to dynamic occupancy patterns and weather conditions, achieving 16.9% improvement in thermal comfort [42]. The learning-based approach can adapt to occupant preferences and behavior patterns over time, continuously refining control policies based on observed comfort responses. Unlike MPC, which requires explicit comfort models, DRL learns comfort preferences implicitly through reward signals, potentially capturing subjective comfort variations that standardized PMV models miss.

Advantages

The model-free learning paradigm of DRL offers advantages that address key limitations of conventional control approaches. The absence of requirements for prior building models eliminates the costly and time-consuming system identification phase that constrains MPC deployment, enabling faster implementation in existing buildings without detailed thermal characterization [21]. This advantage is significant in retrofit applications where building documentation is incomplete or unavailable. The superior adaptability to changing conditions and occupancy patterns allows DRL to handle the inherent variability of residential environments differently than MPC, which relies on fixed models that may become outdated [22]. Unlike FLC, which applies static rules regardless of changing building dynamics, DRL continuously refines its policy based on observed performance, potentially improving over time as it learns building-specific behaviors. DRL's natural handling of stochasticity in occupant behavior and weather through probabilistic policy representations enables robust performance under uncertainty, addressing scenarios that challenge deterministic MPC formulations. Additionally, DRL can optimize complex multi-objective problems without explicit mathematical formulation, learning energy-comfort trade-offs through experience rather than requiring pre-defined optimization functions [42]. This capability enables optimization of objectives that may be difficult to formalize mathematically, such as occupant satisfaction or equipment longevity.

Limitations

The practical deployment of DRL faces significant limitations that temper its theoretical promise for residential HVAC control. The “black box” nature of deep neural networks creates fundamental interpretability challenges, making it difficult for building operators to verify control logic, diagnose anomalous behavior, or understand why particular control decisions were made [21]. This opacity contrasts sharply with MPC’s interpretable models and FLC’s explicit rules, potentially limiting acceptance in contexts where trust and transparency are valued. Potential instability during initial learning phases can produce uncomfortable indoor conditions or excessive energy consumption before the policy converges, representing a significant risk in residential applications where occupant complaints may lead to system abandonment. The training process requires extensive data collection and computational time to converge to optimal policies, potentially taking weeks or months in real buildings [22], during which performance may be suboptimal. Furthermore, performance depends critically on reward function design; poorly specified rewards can produce unintended behaviors that optimize measured metrics at the expense of actual comfort or efficiency [44]. Compared to FLC, which provides predictable behavior from initial deployment, DRL’s learning phase introduces uncertainty that may be unacceptable in comfort-critical applications.

Suitability for Omani Residential Buildings

DRL presents a distinctive value proposition for Omani residential applications that reflects the trade-offs between adaptability and predictability. DRL is well-suited for applications with dynamic occupancy patterns, such as extended family homes or vacation properties, where the ability to adapt to varying conditions outweighs the need for interpretable control logic. The adaptability to Oman’s diverse climate conditions—ranging from coastal humidity to interior aridity—aligns with DRL’s strength in handling environmental variability without requiring climate-specific model development. Cultural occupancy patterns, including Ramadan fasting schedules and prayer times that alter typical building usage, favor DRL’s learning-based approach over MPC’s fixed models that assume regular occupancy schedules. However, the computational requirements and need for stable learning environments present challenges in residential settings with limited technical support, where system troubleshooting may be difficult when control behavior appears anomalous. Unlike MPC, DRL requires minimal upfront modeling but sacrifices interpretability, making it appropriate when building characterization is infeasible but trust in automated decisions is established. Compared to FLC, DRL offers superior adaptability and potentially higher savings but demands greater computational resources and longer commissioning periods, making FLC appropriate in cost-sensitive applications with stable operating conditions.

3.1.3. Fuzzy Logic Control (FLC)

Operating Principle

Fuzzy Logic Control uses rule-based systems that process linguistic variables (e.g., “cold,” “comfortable,” and “hot”) rather than precise numerical values. The control system fuzzifies crisp input values, applies inference rules, and defuzzifies the output to generate control signals [45]. This approach mimics human reasoning processes, enabling intuitive control strategies that incorporate expert knowledge without requiring mathematical models of building thermal dynamics.

Reported Energy Savings

FLC studies report energy savings ranging from 12% to 25% compared to conventional on/off control. Gouda et al. [45] demonstrated 15–20% energy savings compared to conventional on/off control using PMV as a direct control input. Kang et al. [46] showed 12–18% reduction in HVAC energy consumption while maintaining thermal comfort through advanced on-off control methods addressing system time-lag. Additional studies in the literature report variable results (10–25%) depending on rule base complexity and system integration [45,46]. While FLC achieves lower energy savings than MPC or DRL, the moderate but consistent performance highlights the value of interpretability in contexts where model-based optimization is impractical.

Thermal Comfort Performance

FLC demonstrates improved PMV maintenance within acceptable ranges (± 0.5) compared to conventional temperature-based control [45]. The rule-based approach enables faster response to comfort violations and reduced temperature fluctuations through anticipatory control actions. Unlike MPC, which relies on predictive models, or DRL, which learns through trial and error, FLC applies expert-derived rules that encode established thermal comfort principles, potentially providing more predictable comfort outcomes.

Advantages

FLC offers a combination of accessibility and interpretability that explains its enduring relevance despite lower energy savings potential compared to optimization-based approaches. The transparency and interpretability provided by explicit rules enable stakeholders—including homeowners, facility managers, and commissioning engineers—to understand and verify control logic, facilitating acceptance and trust that may be difficult to achieve with “black box” DRL systems [45]. This interpretability advantage is valuable in contexts where control decisions must be explainable for regulatory compliance or occupant satisfaction. FLC enables direct incorporation of expert knowledge and heuristics without requiring translation into mathematical models, allowing domain experts to contribute control strategies without control engineering expertise. The absence of complex mathematical model requirements substantially reduces development costs and time compared to MPC implementations, making FLC economically viable for smaller projects where MPC development costs would be prohibitive. FLC’s robustness to sensor noise and measurement uncertainty through fuzzy membership functions provides reliable operation in environments with lower-quality instrumentation [46]. Importantly for residential applications, FLC requires lower computational resources than MPC or DRL, enabling implementation on inexpensive microcontrollers without dedicated computing infrastructure, a critical advantage for cost-sensitive residential retrofits.

Limitations

The accessibility of FLC comes at the cost of optimization capability that constrains its performance relative to more sophisticated approaches. Rule development requires domain expertise and iterative tuning, creating barriers for implementation without experienced practitioners who understand both HVAC systems and fuzzy logic principles [45]. This expertise requirement, while less demanding than MPC’s modeling expertise or DRL’s machine learning knowledge, nonetheless limits scalability in markets with limited technical workforce. The optimization capability is limited compared to MPC, which can explore control sequences globally through mathematical optimization rather than following fixed rule sets; this limitation explains why FLC typically achieves 12–25% savings compared to MPC’s 16–40%. Performance depends heavily on rule base quality and

completeness, with incomplete rules potentially failing to address unusual operating conditions that fall outside anticipated scenarios. FLC encounters particular difficulty handling multi-variable optimization problems requiring simultaneous balancing of competing objectives, whereas MPC's multi-objective framework naturally accommodates such trade-offs. In addition, rule base maintenance is required as building conditions change, necessitating ongoing expert involvement [46] that may be unsustainable in residential contexts without local technical support infrastructure.

Suitability for Omani Residential Buildings

FLC represents a pragmatic compromise between performance and practicality that aligns well with current conditions in Oman's residential sector. FLC is appropriate for applications where interpretability is valued, computational resources are limited, and expert knowledge is available for initial rule development. The lower cost and simpler implementation make FLC accessible for retrofit applications in existing buildings, where the infrastructure requirements of MPC or the computational demands of DRL may be impractical. Compared to MPC, FLC sacrifices some energy savings potential (12–25% versus 16–40%) in exchange for substantially lower implementation costs, reduced technical complexity, and greater interpretability—a trade-off that favors FLC in cost-sensitive residential retrofits where the additional savings of MPC may not justify its higher costs. Compared to DRL, FLC offers greater transparency and predictable behavior from initial deployment but less adaptability to changing conditions; this trade-off favors FLC in stable operating environments with limited technical support for troubleshooting learning-based systems. The primary constraint on FLC scalability in Oman is the need for expert tuning and rule maintenance, which may limit widespread deployment without development of local technical expertise or standardized rule bases for common building types.

3.1.4. IoT-Based Integrated Approaches

Operating Principle

Internet of Things (IoT)-based integrated control systems utilize distributed sensor networks and edge computing to enable real-time monitoring and control of HVAC systems. These systems often employ agent-based architectures where multiple intelligent agents coordinate control actions across building zones [47,48]. The distributed nature enables localized decision-making while maintaining system-wide coordination through communication protocols between agents.

Reported Energy Savings

IoT-based integrated control systems demonstrate energy savings of up to 20% compared to conventional control [47,48]. Su and Wang [47] reported up to 20% energy savings using agent-based distributed real-time optimal control on IoT sensor networks. Liang et al. [48] demonstrated significant cost reductions while maintaining or enhancing occupant comfort through Human-in-the-Loop (HITL) approaches incorporating real-time occupant feedback. These savings, while moderate compared to MPC's upper range, are achieved with lower infrastructure requirements and greater scalability than centralized optimization approaches.

Thermal Comfort Performance

IoT-based systems maintain or enhance occupant comfort through real-time data integration and feedback loops [48]. The distributed nature allows for zonal comfort optimization based on actual occupancy and preferences. Unlike centralized MPC

implementations, IoT systems can respond to local comfort variations at the zone level, potentially achieving more granular comfort control than building-wide optimization strategies.

Advantages

IoT-based approaches offer architectural characteristics that address scalability challenges inherent in centralized control paradigms. The scalability over centralized MPC implementations enables deployment across building portfolios without proportional increases in computational infrastructure, supporting applications from single-family homes to large residential complexes [47]. This scalability contrasts with MPC's centralized optimization, which faces computational bottlenecks as building complexity increases. The distributed architecture provides fault tolerance that centralized systems does not provide; failure of individual agents compromises only local control rather than entire building operation, improving reliability in critical applications. Real-time data integration from multiple sources enables more responsive control than periodic optimization cycles typical of MPC implementations, potentially improving comfort responsiveness. Human-in-the-loop capabilities support occupant engagement and preference learning [48], enabling personalization that purely automated systems may not achieve. Lower infrastructure costs with wireless sensor networks reduce barriers to entry compared to wired BMS installations required for MPC, making IoT approaches economically viable for retrofit applications where wiring costs would be prohibitive.

Limitations

The distributed nature of IoT-based control introduces challenges that centralized approaches avoid. Coordination across multiple autonomous agents requires careful protocol design to prevent conflicting control actions that could waste energy or compromise comfort [47], adding complexity absent from MPC's centralized decision-making. Security concerns with networked devices create vulnerability to cyberattacks that could compromise building operations, a risk that increases with system connectivity and requires ongoing security maintenance. Data privacy considerations arise with occupant monitoring, particularly for behavioral tracking and preference learning [48], potentially limiting acceptance in privacy-sensitive residential contexts. Network reliability dependencies mean that control performance degrades with communication failures, creating vulnerabilities in regions with developing internet infrastructure. Integration complexity with legacy systems may require substantial retrofitting for older buildings, potentially negating the installation cost advantages of wireless sensors. Compared to MPC's deterministic optimization, IoT-based distributed control achieves scalability at the cost of optimization rigor, potentially producing suboptimal control decisions that centralized optimization would avoid.

Suitability for Omani Residential Buildings

IoT-based approaches align well with the developing nature of Oman's residential building stock and infrastructure. These approaches are well-suited for Oman's market, offering scalability and lower upfront costs compared to centralized BMS solutions that require substantial infrastructure investment. The wireless infrastructure reduces installation complexity in existing buildings, enabling retrofit applications where wiring costs would make MPC or FLC implementation uneconomical. However, network reliability and cybersecurity considerations require attention in Oman's developing technical infrastructure, where internet connectivity may be intermittent and cybersecurity expertise limited. Compared to MPC, IoT offers greater scalability and lower infrastructure costs but sacrifices optimization rigor and theoretical performance guarantees, making IoT

appropriate for distributed applications where centralized control is impractical. Compared to DRL, IoT provides distributed sensing capabilities that can enhance learning-based control through richer environmental data, though coordination complexity increases with system scale. Compared to FLC, IoT enables more sophisticated coordination between multiple control zones and greater scalability, though at the cost of increased complexity and network dependencies (Figure 2).

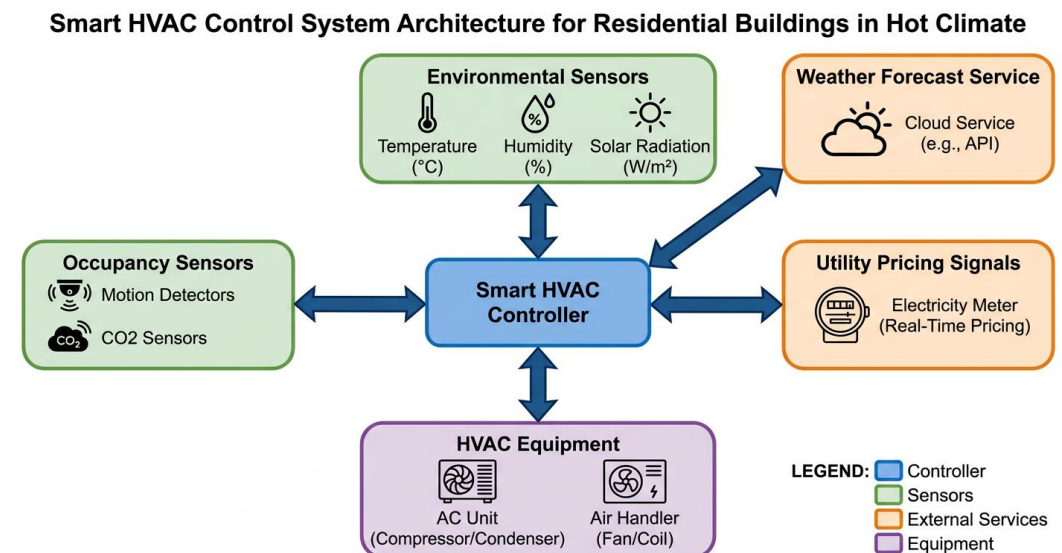


Figure 2. Smart HVAC control system architecture for residential buildings in hot arid climates, showing integration of sensors, external data sources, and HVAC equipment through a central intelligent controller.

3.2. Comparative Summary of International Evidence

The comparative analysis reveals that MPC offers the highest energy savings potential (16–40%) but requires significant infrastructure and expertise. DRL provides excellent adaptability (16–23% savings) but faces interpretability challenges. FLC offers moderate savings (12–25%) with lower implementation barriers. IoT-based approaches provide scalability with moderate savings (up to 20%). All studies used simulation-based validation except [45], which employed experimental test chamber validation. Baseline comparisons varied across studies, with most comparing against conventional rule-based or on/off control strategies (Table 2).

Table 2. Consolidated Performance Comparison of HVAC Control Strategies.

Control Paradigm	Study	Energy Savings	Baseline for Comparison	Dataset/Case Study	Control Variables	Validation Approach	Thermal Comfort Constraints	Implementation Complexity
MPC	Eini & Abdelwahed (2019) [39]	40.6% cooling, 16.7% heating	Conventional MPC (w/o learning)	EnergyPlus simulation of 4-zone office building (Chicago)	Temperature setpoint, occupancy profile (ANN-predicted), weather data	EnergyPlus simulation with RLS parameter identification	Comfort temperature 20–25 °C	High
	Sha et al. (2025) [40]	10.2% energy reduction	Baseline feedback control strategy	EnergyPlus simulation (residential building)	HVAC energy consumption, IAQ parameters, thermal comfort variables	Online learning-enhanced data-driven simulation	Energy, IAQ, and comfort optimization	High
	Yang et al. (2020) [41]	58.5% (office thermal energy), 36.7% (lecture theatre electricity)	Original thermostat control (office), original BMS control (lecture theatre)	Two real testbeds: office and lecture theatre (university campus, Singapore)	ACMV system control via adaptive ML-based MPC	Experimental validation in real testbeds	Improved thermal comfort vs. original controls	High
DRL	Zhuang et al. (2023) [42]	17.40%	Rule-based control	IoT-integrated multi-zone building simulation	Temperature, occupancy, sensor data (TSF + RL)	Comparison with rule-based baseline	16.9% thermal comfort improvement	Medium-High
	Liu et al. (2022) [43]	>12% cost savings	Comparison with counterpart control approaches	Office building with VRF system	HVAC control actions (multi-step predictive)	Simulation with learning stability analysis	Energy and learning stability metrics	Medium-High
	Al Sayed (2025) [44]	16.24% (vs. TD3), 23.68% (vs. DDQN)	TD3 and DDQN benchmark controllers	EnergyPlus-simulated university amphitheater (Luxembourg)	Discrete AHU ON/OFF action, continuous supply-air-temperature setpoint	Comparison with TD3 and DDQN controllers	Not reported	Medium-High
FLC	Gouda et al. (2001) [45]	15–20%	Conventional on/off control	UK office/laboratory test chamber	PMV-based compressor cycling, temperature setpoint	Experimental validation with environmental test chamber	PMV-based direct control input	Low-Medium

	Kang et al. (2015) [46]	12–18%	Conventional on/off control	Residential apartment simulation (South Ko- rea)	ON/OFF timing (time-lag compensation)	Simulation compari- son with conventional on-off	Thermal comfort maintenance	Low-Me- dium
IoT-Based	Su & Wang (2020) [47]	Up to 20%	Conventional centralized con- trol	Multi-zone office build- ing (Hong Kong)	Zone temperature setpoints (agent-based distributed)	EnergyPlus simulation with computation load analysis	Comfort con- straints via distributed optimi- zation	Medium
	Liang et al. (2025) [48]	Significant cost Reduction *	Rule-based base- line controller	Residential/office building simulation	HVAC ON/OFF (3.5 kW sys- tem), occupancy feedback, electric- ity price	Simulation compari- son with rule-based controllers	Thermal comfort via HITL feedback	Medium

* Note: Liang et al. (2025) [48] focuses on cost reduction rather than direct energy savings percentage; maintains/enhances occupant comfort through HITL ap-
proach.

3.3. Performance Evidence from GCC Region

The synthesis of GCC-specific evidence reveals both the potential and the constraints of applying international control strategy research to this distinctive climatic context. While the international literature provides extensive evidence on smart HVAC control strategies, studies specifically targeting the GCC region remain relatively limited, creating uncertainty about the transferability of findings from temperate climates to extreme heat conditions. The extreme heat conditions, high cooling demands, and unique building characteristics of the GCC create a distinct context that affects control strategy performance, potentially amplifying the benefits of optimization in high-consumption environments.

The regional evidence that does exist suggests performance potential. Kuwaiti studies by Park et al. [12] demonstrated that thermal comfort-based control strategies can achieve 33–39% energy reductions in residential buildings under hot climate conditions, providing important reference data for similar climates. These findings suggest that smart control strategies may achieve even higher savings in GCC conditions than reported in temperate climate studies, likely due to the greater baseline energy consumption providing more optimization opportunity—when cooling loads are high, even modest percentage improvements yield substantial absolute savings. The UAE and Saudi Arabia have implemented building automation systems in commercial and high-end residential developments, though published performance data for residential applications remain scarce, limiting evidence-based assessment of real-world performance.

The convergence of high cooling loads, distinct occupancy patterns during Ramadan and prayer times, and rapidly developing building stock creates both opportunities and challenges for smart control deployment that differ from established markets in Europe and North America. Qatar's district cooling infrastructure with centralized plant optimization provides a different control paradigm than individual building systems, suggesting that GCC-specific control strategies may need to accommodate centralized cooling distribution rather than individual building optimization. The limited GCC-specific residential HVAC control literature highlights the need for region-specific research that accounts for local climate conditions, building stock characteristics, and occupancy patterns, as control strategies optimized for temperate climates may not perform equivalently in extreme heat conditions with different thermal dynamics and occupancy behaviors.

3.4. Oman-Specific Evidence

This subsection presents empirical evidence from Oman and Oman-focused analyses, providing context-specific performance data for smart HVAC control strategies under local conditions.

3.4.1. GUtech EcoHaus Performance

The GUtech EcoHaus case study demonstrates the combined potential of integrating smart controls with high-performance building design, achieving results that exceed what control strategies alone can accomplish. Based on two years of monitoring data [32], the EcoHaus achieved total building energy consumption of 42 kWh/m²/year and HVAC energy consumption of 28 kWh/m²/year (67% of total), representing strong performance for Oman's hot arid climate where conventional buildings typically consume 160–200 kWh/m²/year. The Energy Use Intensity (EUI) reduction of 75% compared to conventional Omani residential buildings substantially exceeds the 16–40% savings reported for MPC strategies alone in international literature, demonstrating that envelope improvements and smart controls together achieve far greater savings than either intervention alone.

This finding has implications for control strategy selection: when building envelopes are optimized, the relative contribution of advanced control strategies diminishes, potentially making simpler and less expensive control approaches economically preferable to sophisticated MPC or DRL implementations. Indoor temperatures maintained within the 22–26 °C range during occupied hours and average PMV values of -0.3 to $+0.5$ during summer confirm that comfortable conditions are achievable in Oman's extreme heat, but only with comprehensive interventions that address both building fabric and control systems. The EcoHaus experience suggests that control strategy investment should be proportionate to envelope performance; deploying expensive MPC in poorly insulated buildings may yield lower returns than upgrading envelopes while using simpler FLC or IoT-based controls.

3.4.2. Large-Scale Retrofit Program Analysis (National Assessment)

The national-scale retrofit analysis by Krarti and Dubey [33] provides evidence that control strategies can contribute meaningfully to national energy efficiency targets when deployed at scale, even when individual per-building savings are modest. Projected energy savings of 25–40% for retrofitted buildings align with the upper range of international MPC studies, suggesting that Omani building stock offers significant optimization potential comparable to international benchmarks. This alignment is significant because it suggests that the extreme heat conditions in Oman do not inherently limit control strategy effectiveness; rather, the high cooling loads may provide greater absolute savings potential.

The projected peak electricity demand reductions of 15–25% would support grid stability in Oman's rapidly growing electricity market, where peak cooling loads drive infrastructure investment. The simple payback period of 3–7 years depending on measure combination indicates economic viability for residential investment, though this payback period reflects combined measures rather than controls alone. Notably, control measures alone contribute only 8–15% of total savings in the comprehensive retrofit packages analyzed, reinforcing the EcoHaus finding that envelope improvements dominate energy savings while controls optimize the remaining consumption. The national energy savings potential of 3.5 TWh/year by 2030 demonstrates that even modest per-building savings aggregate to substantial national impact, supporting policy consideration for smart control deployment. These projections suggest that FLC and IoT-based approaches, with their lower costs and faster deployment potential, may be preferable to MPC or DRL for achieving national-scale impact within constrained implementation timelines.

3.4.3. Energy-Efficient Design Strategies (Simulation-Based Analysis)

The simulation-based analysis by Alalouch et al. [14] provides systematic evidence that Oman-specific conditions support energy savings across the full range reported internationally, with control strategies contributing incrementally to envelope-based improvements. Energy-efficient designs achieved 13.2% to 48.2% energy savings across various configurations, with the upper range approaching the 75% reduction demonstrated by the GUTech EcoHaus. This convergence between simulation predictions and measured performance supports the use of simulation-based design optimization for Omani residential buildings.

The disaggregation of savings sources reveals insights for control strategy prioritization. Smart thermostat scheduling contributed 10–15% of total savings, comparable to standalone FLC performance in international studies, suggesting that relatively simple control interventions can capture significant value. Zonal control provided additional 5–8% savings with improved comfort, illustrating the incremental value of advanced control strategies beyond basic scheduling but also indicating diminishing returns as control

complexity increases. Natural ventilation integration reduced cooling loads by 8–12% during shoulder seasons, highlighting the importance of climate-appropriate control strategies that leverage available environmental conditions rather than relying solely on mechanical cooling.

These findings collectively demonstrate that Oman-specific conditions support energy savings across the full range reported internationally (12–48%), with integrated approaches achieving the highest performance. The pattern of results—envelope improvements providing base savings (13–48%), smart scheduling capturing additional savings (10–15%), and zonal controls adding further incremental value (5–8%)—suggests a staged implementation strategy: optimize envelopes first, then implement basic smart controls, and finally add advanced control features as justified by marginal returns.

Table 3 summarizes the performance metrics from the Oman-specific studies reviewed, including the GUTech EcoHaus case study, national-scale retrofit program analysis, and simulation-based energy-efficient design studies.

Table 3. Summary of Oman-Specific Case Study Performance Metrics.

Case Study	Energy Savings	HVAC EUI	Comfort Metric	Climate
GUTech EcoHaus [32]	75% vs. baseline	28 kWh/m ² /yr	PMV: −0.3 to +0.5	Hot arid
Retrofit Program [33]	25–40%	Not reported	Standard PMV	Mixed GCC
Alalouch et al. [14]	13–48%	35–55 kWh/m ² /yr	Adaptive comfort	Hot arid

3.5. Thermal Comfort Performance

The Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) models remain the most widely adopted standards for indoor thermal comfort assessment [49]. However, the applicability of standard PMV models in extreme heat conditions shows reduced prediction accuracy when outdoor temperatures exceed 35 °C [24].

Adaptive thermal comfort models extend acceptable temperature ranges beyond standard PMV recommendations for hot climates [50]. Studies demonstrate that PMV-based control maintains comfort within the acceptable range of −0.5 to +0.5 for conventional HVAC systems, while adaptive comfort models allow extended temperature ranges of 23–28 °C for naturally ventilated buildings in hot climates [50,51]. Region-specific comfort models for the GCC remain underdeveloped due to limited field studies, representing a critical research gap for extreme heat applications.

The GUTech EcoHaus case study achieved average PMV values of −0.3 to +0.5 during summer, demonstrating that comfortable conditions can be maintained in Oman’s extreme heat with appropriate control strategies and building design integration.

3.6. Summary of Key Findings

The quantitative analysis reveals the following key findings:

- MPC demonstrates the higher energy savings potential (16–40%) among individual control paradigms in international studies, though implementation requires accurate thermal models and computational infrastructure;
- DRL shows adaptability with 17–23% energy reductions and 16.9% comfort improvement, particularly suited to dynamic occupancy patterns;
- FLC offers accessible energy savings (12–25%) with lower implementation barriers, making it suitable for retrofit applications where interpretability is valued;

- d. IoT-based approaches provide scalability with up to 20% energy savings and advantages in distributed control architectures;
- e. Oman-specific case studies demonstrate higher realized savings (13–75%) than individual control strategies alone, indicating the importance of integrated design approaches that combine smart controls with high-performance building envelopes;
- f. Thermal comfort maintenance within acceptable PMV ranges (−0.5 to +0.5) is achievable across all paradigms in extreme heat conditions;
- g. The GUtech EcoHaus demonstrates that integrated design combining high-performance envelopes with smart controls can achieve 75% EUI reduction, exceeding savings from control strategies alone;
- h. Region-specific thermal comfort models for extreme heat conditions remain under-developed, representing a research gap for Omani and GCC applications.

Figure 3 presents the energy performance data from Oman case studies, showing both the energy use intensity comparison and the breakdown of residential energy consumption by end-use.

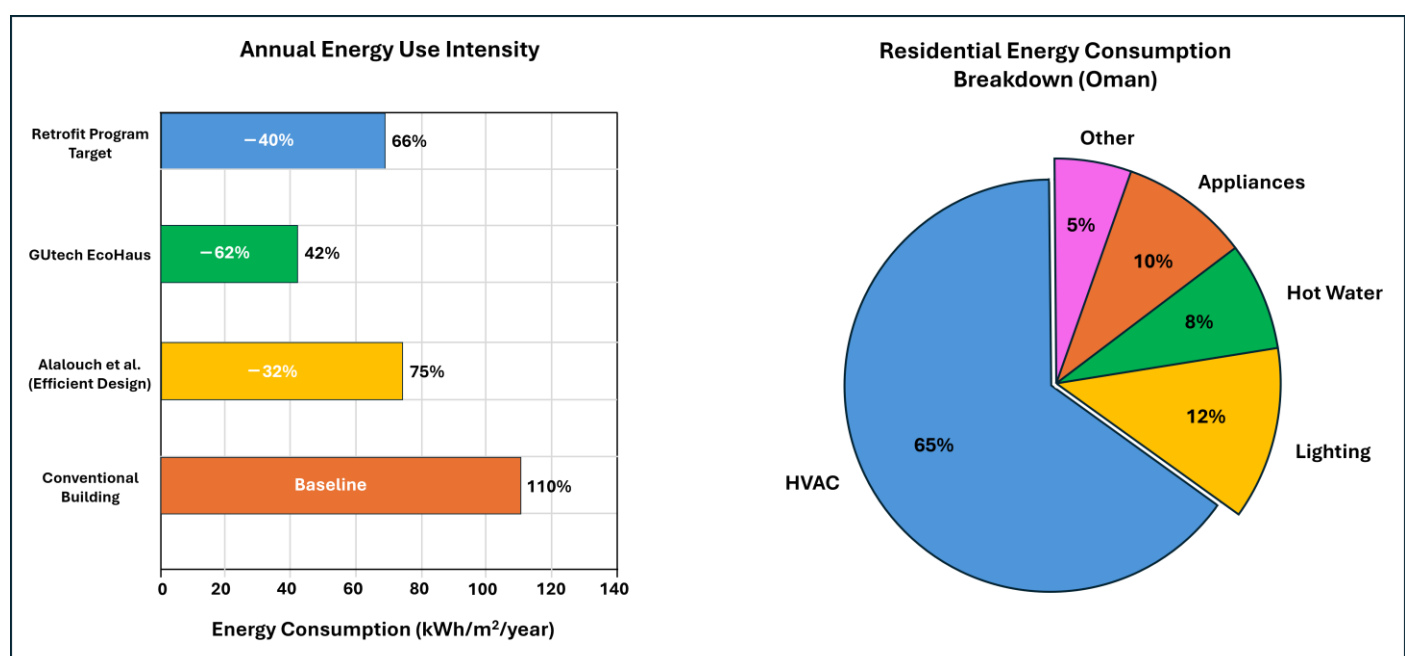


Figure 3. Annual energy use intensity comparison across Omani residential building case studies showing percentage savings (left) and typical residential energy consumption breakdown in Oman (right), with HVAC accounting for 65% of total consumption.

4. Discussion

The results presented in Section 3 demonstrate that smart HVAC control strategies offer significant potential for energy reduction in Omani residential buildings. This section critically interprets these technical findings within the context of Oman's extreme climate conditions, building stock characteristics, and unique occupancy patterns, while distinguishing evidence-based conclusions from the policy frameworks that may support their implementation.

4.1. Interpretation of Control Strategy Performance for Oman

The systematic review findings require careful interpretation when applied to Omani residential buildings. While international studies demonstrate impressive energy savings potential (12–40% across control paradigms), the specific characteristics of Oman's built

environment, climate, and occupancy patterns influence the relative suitability and expected performance of each approach.

4.1.1. Comparative Analysis of Control Paradigms

Model Predictive Control (MPC)

MPC demonstrates the higher theoretical energy savings potential (16–40%) among the reviewed strategies [39–41], making it an attractive option for Oman’s energy-intensive residential sector. The precooling capability of MPC is valuable in Oman’s context, where shifting cooling loads to off-peak periods could reduce both energy costs and grid strain during extreme summer afternoons.

However, several factors limit MPC’s applicability in Oman. The strategy requires accurate thermal models of building dynamics, which are costly to develop and maintain. In Oman’s residential sector, characterized by variable construction quality across the existing building stock [21,22] and limited availability of as-built documentation, developing reliable predictive models presents challenges. Furthermore, MPC’s computational intensity demands professional commissioning and ongoing technical support, which may exceed the capacity of Oman’s developing technical infrastructure for residential applications.

The evidence suggests MPC is best suited for new high-end residential developments with integrated building management systems, where accurate models can be developed during design and construction. For retrofits, the modeling costs and expertise requirements may render MPC economically unfeasible, particularly given that Oman’s existing residential buildings typically exhibit higher air infiltration rates (approximately 0.7 ACH [21,22]) and lower insulation levels than the well-characterized buildings in international MPC studies. These envelope deficiencies may reduce the proportional benefits of optimized control, as a significant portion of cooling energy is consumed compensating for thermal losses that predictive control cannot eliminate.

Deep Reinforcement Learning (DRL)

DRL offers advantages for Omani residential applications, particularly given the region’s dynamic occupancy patterns. Zhuang et al. [42] and Liu et al. [43] demonstrated 16–23% energy savings against conventional HVAC controls in building applications, with Zhuang et al. reporting a 16.9% improvement in thermal comfort, which aligns well with Oman’s need for both efficiency and occupant satisfaction. Al Sayed [44] provides international evidence of hybrid DRL effectiveness for AHU control in a university amphitheater, demonstrating the approach’s potential for adaptive control, though with different baselines (TD3 and DDQN controllers) and building type. The strategy’s key advantage—learning optimal control policies without requiring explicit building models—addresses the modeling challenges that limit MPC applicability in Oman’s heterogeneous building stock.

The adaptability of DRL is relevant to Omani household dynamics. Extended family structures create variable occupancy with unpredictable heat gains; prayer schedules establish five-times-daily occupancy patterns that differ from Western residential assumptions; and Ramadan observances shift activity patterns and thermal expectations for extended periods. DRL’s ability to learn from interaction with the environment, rather than relying on pre-programmed assumptions, enables optimization for these culturally specific patterns.

Nevertheless, DRL presents implementation challenges in Oman’s context. The “black box” nature of learned policies conflicts with local preferences for interpretable systems, particularly given limited technical expertise for troubleshooting complex control strategies. The initial learning period requires stable operation, which may be difficult

to guarantee in residential settings with limited technical support infrastructure. Additionally, the computational requirements, while manageable with modern edge devices, still exceed the capabilities of the simplest thermostat replacements that might be feasible for widespread residential deployment.

DRL appears best suited for grid-interactive applications and homes with highly variable occupancy where its learning capabilities provide advantage. For these applications, the strategy's adaptability to Oman's diverse climate zones (coastal humidity vs. interior aridity) and cultural occupancy patterns supports consideration of the additional complexity.

Fuzzy Logic Control (FLC)

FLC occupies a middle ground in terms of performance (12–25% energy savings [45,46]) but offers distinct implementation advantages for Oman. The interpretability of rule-based systems aligns with local maintenance capabilities and preferences for understandable technology. Unlike DRL's opaque learned policies, FLC rules can be explicitly documented, reviewed, and modified by local technicians.

The lower cost and simpler implementation of FLC make it accessible for the retrofit market, which represents the largest segment of Oman's residential building stock. The strategy's robustness to sensor noise and measurement uncertainty is valuable in environments where sensor quality and calibration may be variable. Furthermore, FLC's incorporation of expert knowledge allows integration of local insights about appropriate temperature setpoints, cooling load patterns, and comfort expectations.

The primary limitation of FLC is its limited optimization capability compared to MPC. While rules can be tuned for specific conditions, they cannot achieve the mathematically optimal control sequences that MPC generates. For Omani applications, this trade-off may be acceptable given FLC's lower cost and greater accessibility. The strategy is appropriate for mid-range residential applications where cost constraints prevent MPC deployment but occupants desire improved comfort and efficiency beyond conventional thermostats.

FLC's requirement for rule development expertise presents a barrier, but one that can be addressed through knowledge transfer and standardized rule libraries developed for Oman's climate zones. Unlike MPC's requirement for building-specific models or DRL's need for stable learning environments, FLC's rule bases can be developed once and applied across similar building types with minor customization.

IoT-Based Integrated Approaches

IoT-based approaches demonstrate moderate energy savings (up to 20% [47,48]) but offer unique advantages in scalability and distributed control that align with Oman's developing residential market. The wireless infrastructure reduces installation complexity, particularly in existing buildings where running control wiring would be prohibitively expensive or architecturally invasive.

The scalability of IoT approaches—from single rooms to building portfolios—enables portfolio-level energy management strategies that could support Oman's national efficiency targets. As Oman's smart city initiatives expand, IoT-based HVAC controls can integrate with broader building and urban management systems. The human-in-the-loop capabilities identified by Liang et al. [48] address the occupant engagement challenges that limit effectiveness of fully automated systems.

Network reliability and cybersecurity represent significant concerns for IoT deployment in Oman's developing technical infrastructure. Residential internet connectivity may be intermittent, and the cybersecurity expertise required to secure networked building systems may exceed local capacity. These limitations suggest that IoT-based

approaches are well-suited for new developments with reliable network infrastructure and professional management, rather than retrofits in areas with uncertain connectivity.

Table 4 summarizes the suitability of the reviewed smart HVAC control strategies for different residential applications in Oman, providing practical guidance for technology selection based on building characteristics and constraints.

Table 4. Suitability of Smart HVAC Control Strategies for Omani Residential Applications.

Application Type	MPC	DRL	FLC	IoT-Based	Key Considerations
New buildings	Most suitable	Suitable	Suitable	Suitable	BMS integration enables all strategies; MPC offers highest savings potential for well-instrumented buildings [39–41]
Retrofit projects	Less suitable	Suitable	Most suitable	Suitable	FLC's lower cost and simpler implementation ideal for existing stock; MPC modeling costs prohibitive for retrofits [45–47]
Low-cost housing	Less suitable	Less suitable	Most suitable	Suitable	Cost constraints favor FLC and IoT-based approaches; MPC/DRL complexity and expertise requirements may be prohibitive [45,46,48]
High-performance buildings	Most suitable	Suitable	Suitable	Suitable	BMS-equipped buildings can leverage MPC's optimization capabilities; envelope-control integration maximizes benefits [32,39]
Dynamic occupancy patterns	Suitable	Most suitable	Suitable	Suitable	DRL's adaptability excels with variable occupancy; FLC rules can incorporate predictable schedule patterns [42,43]

Note: Suitability categories: Most suitable = optimal combination of performance and practicality; Suitable = effective application with standard considerations; Less suitable = significant barriers limit applicability. Assessment based on energy performance (12–40% savings range), implementation complexity, computational requirements, cost, and practicality for Omani residential context as discussed in Section 4.1.1.

This comparison highlights that no single control strategy is appropriate for all applications; rather, selection should be guided by specific building characteristics, budget constraints, and operational requirements. For Oman's diverse residential building stock, FLC offers the broadest applicability across retrofit and low-cost segments, while MPC and DRL provide maximum performance potential in new construction and high-occupancy-variability applications, respectively.

4.1.2. Integration with Building Envelope Performance

A critical interpretation of the Oman-specific evidence (Section 3.4) concerns the relationship between control strategies and building envelope performance. The realized savings in Oman (13–75%) exceed the theoretical performance of individual control strategies, highlighting a key insight: control optimization cannot fully compensate for poor building envelope performance, but integrated design combining envelope improvements with smart controls achieves combined benefits.

The GÜtech EcoHaus [32] demonstrates this integration clearly, achieving 75% EUI reduction through a combination of high-performance envelope (reducing cooling loads at the source) and intelligent controls (optimizing delivery of the remaining loads). This performance exceeds what controls alone could achieve, regardless of control paradigm.

Krarti and Dubey's [33] national retrofit analysis further illuminates this relationship, finding that control measures contribute only 8–15% of total savings in comprehensive retrofit programs. The remaining savings derive from envelope improvements, equipment upgrades, and operational changes. This distribution suggests that for Oman's existing building stock, envelope improvements should precede or accompany control upgrades to maximize return on investment.

Alalouch et al.'s [14] simulation studies demonstrate that smart design strategies (including appropriate orientation, shading, and envelope specifications) achieve 13–48% savings, with smart thermostat scheduling adding 10–15% and zonal control providing 5–8% additional savings. The hierarchy is clear: design determines the cooling load; controls optimize the delivery.

For Oman, where existing residential buildings typically exhibit higher infiltration and lower insulation than international standards [21,22], this finding has implications. Implementing MPC, DRL, or other advanced controls in buildings with poor envelopes may yield disappointing results, as the controls optimize delivery of unnecessarily large cooling loads. Attention should be given to envelope improvements in such buildings, with controls implemented as part of integrated retrofits rather than standalone measures.

4.1.3. Thermal Comfort Considerations in the Omani Context

The interpretation of thermal comfort findings requires particular attention to Oman's extreme climatic conditions and cultural context. While the reviewed studies demonstrate that acceptable PMV ranges (± 0.5) are achievable with smart controls [39,40,45], the broader question concerns whether conventional PMV-based approaches are appropriate for Omani residential applications.

Limitations of PMV in Extreme Heat

The Predicted Mean Vote model [23], derived from studies in temperate climates, shows reduced accuracy when outdoor temperatures exceed 35 °C [24]. In Oman's climate, where summer temperatures regularly exceed 45 °C and peak above 50 °C [5], this limitation is significant. The physiological and psychological responses of occupants in such extreme conditions may not follow the relationships embedded in the PMV model, which was validated primarily on data from Western office environments with moderate outdoor conditions.

Cheung et al.'s [24] research on PMV limitations in hot conditions suggests that the model underestimates thermal sensation in extreme heat, potentially leading to overcooling when PMV-based controls target neutral comfort. Overcooling not only wastes energy but may create thermal shock when occupants transition between extreme outdoor heat and excessively cool indoor environments.

Adaptive Comfort Opportunities

Adaptive comfort models [25,26] offer an alternative framework that recognizes occupants' ability to adapt to different temperature ranges based on outdoor conditions and cultural expectations. For Oman, adaptive models present several opportunities:

Seasonal variations in Oman's climate create wide adaptation ranges. Winter temperatures (15–25 °C) contrast sharply with summer extremes (>45 °C), and occupants naturally adjust expectations and behaviors across these ranges. Adaptive models permit expanded acceptable temperature ranges (23–28 °C for naturally ventilated buildings

[50,51]), potentially allowing elevated cooling setpoints during extreme outdoor conditions when occupants expect and accept warmer indoor environments relative to the outdoor extreme.

However, the application of adaptive models in fully air-conditioned Omani residences requires careful consideration. Unlike naturally ventilated buildings where occupants actively adapt through clothing and behavior changes, air-conditioned environments may foster expectations of constant thermal conditions regardless of outdoor extremes. The cultural preference for thermal “refuge” from outdoor heat—a psychological need to escape the oppressive outdoor environment—may override the physiological adaptability that adaptive models assume.

Local Factors Influencing Comfort and Control Performance

Several Omani-specific factors influence thermal comfort and should inform the design of intelligent HVAC controls:

- **Occupant Behavior Patterns:** Prayer schedules create predictable five-times-daily occupancy variations that differ from Western assumptions of morning departure and evening return. Homes may be fully occupied during midday peak heat periods when Western office buildings are vacant. Ramadan observances shift eating, sleeping, and activity patterns for extended periods, requiring control strategies that adapt to these predictable but significant variations.
- **Extended Family Structures:** Omani households often include extended family members, creating dynamic occupancy with variable heat gains from additional occupants. Control strategies must accommodate unpredictable visitation patterns and varying occupancy density rather than assuming nuclear family occupancy profiles.
- **Clothing Practices:** Traditional attire (dishdasha for men, abaya for women) provides different insulation and moisture permeability than Western business or casual clothing assumed in PMV calculations. The metabolic heat generation and evaporative cooling characteristics differ, potentially affecting thermal sensation at given air temperatures and humidity levels.
- **Cultural and Lifestyle Characteristics:** The social importance of hospitality spaces (majlis) may create areas with higher cooling expectations than private family spaces. Gender-segregated spaces may have different occupancy patterns and comfort requirements. Sleeping patterns may involve different thermal zones within homes, with some occupants preferring cooler sleeping environments while others maintain higher temperatures.
- **Seasonal Variations and Extreme Summer Conditions:** Oman’s climate includes not only extreme summer heat but also relatively mild winters where heating is unnecessary and natural ventilation might be feasible. Control strategies should accommodate seasonal mode switching and integration of natural ventilation during shoulder seasons, as demonstrated by Alalouch et al.’s [14] finding that natural ventilation integration reduced cooling loads by 8–12% during appropriate periods.

Implications for Control Strategy Design

These factors suggest that intelligent HVAC controls for Omani residences should move beyond conventional PMV-based approaches toward more nuanced strategies:

- **Adaptive setpoint algorithms** that adjust targets based on outdoor conditions, time of day, and occupancy patterns, rather than maintaining fixed PMV targets. Such algorithms might permit elevated indoor temperatures during extreme outdoor heat events when the psychological need for thermal refuge is satisfied by any significant temperature differential, not necessarily by achieving neutral thermal sensation.

- Zonal control systems that accommodate different comfort requirements across hospitality spaces, family areas, and sleeping quarters, recognizing that a single setpoint may not satisfy diverse activities and preferences within the same home.
- Schedule-aware controls that anticipate prayer-time occupancy variations and Ramadan-adjusted patterns, pre-cooling or adjusting ventilation proactively rather than reactively.
- Learning-based approaches (DRL or advanced FLC) that adapt to individual household patterns and preferences rather than assuming standardized occupant models derived from Western contexts.
- The GUTech EcoHaus case study [32], which achieved average PMV values of -0.3 to $+0.5$ during summer, demonstrates that comfortable conditions are achievable in Oman's extreme heat. However, the opportunity lies in developing control strategies that recognize when strict PMV neutrality is unnecessary and when expanded acceptable ranges can satisfy occupant expectations while reducing energy consumption.

4.2. Policy Context and Implementation Drivers

The policy landscape in Oman, including Oman Vision 2040 [52] and the Oman Building Code [53], creates enabling conditions for smart HVAC adoption. However, these policy initiatives represent contextual drivers rather than technical validation of control strategy performance. The following discussion examines how policy frameworks can support the technical solutions identified in Section 4.1, while acknowledging that realizing energy efficiency potential requires addressing implementation barriers beyond policy mandates.

4.2.1. Oman Vision 2040 and Energy Strategy

Oman Vision 2040 establishes sustainability and environmental stewardship as core pillars of national development [52], with the National Energy Strategy targeting 20% improvement in energy efficiency by 2030. These targets create market demand for efficiency solutions, including smart HVAC controls, but do not guarantee their technical performance in specific applications.

The policy context is important for market development: rising electricity tariffs referenced in the Vision framework improve the economics of efficiency investments, while government incentives can accelerate adoption. However, the technical findings of this review indicate that achieving the 20% efficiency target will require careful attention to implementation quality, integration with envelope improvements, and adaptation to local conditions—factors that policy alone cannot ensure.

4.2.2. Oman Building Code Framework

The Oman Building Code (OBC) [53], particularly the Oman Energy Efficiency and Sustainability Code, establishes regulatory requirements that influence HVAC control adoption. The code encourages advanced control strategies including building automation systems, energy management systems, and demand-controlled ventilation, though it does not mandate them for residential applications.

This regulatory context matters for implementation: as the code becomes enforced, developers may increasingly specify smart controls to demonstrate compliance or achieve voluntary certifications. However, the technical evidence reviewed in this paper indicates that code-compliant installation does not guarantee optimal performance. Controls must be properly commissioned, integrated with appropriate envelope performance, and adapted to occupancy patterns to achieve the energy savings demonstrated in research studies.

4.2.3. Barriers and Enablers

The barriers identified in Section 4.1 (high initial costs, limited technical expertise, market awareness, fragmented supply chain) operate within this policy context. Policy initiatives can address some barriers—government incentives reduce cost barriers, capacity building addresses expertise gaps—but others require market development and technological maturation that policy can only indirectly influence.

The enablers (rising energy prices, government incentives, technology maturation, regional knowledge transfer) similarly benefit from policy support but ultimately depend on technical solutions that perform as demonstrated in the reviewed studies. The policy context creates favorable conditions for adoption, but the technical performance findings from Section 3 provide the evidence base for what can be achieved when these enablers align with proper implementation.

4.3. Research Implications and Future Directions

The review of smart HVAC control strategies and their application in Oman reveals opportunities for improving residential building energy efficiency. However, realizing this potential requires addressing critical gaps that emerge from the interpretation of findings in Section 4.1.

4.3.1. Research Gaps

A primary research gap concerns the development of thermal comfort models specifically calibrated for extreme heat conditions prevalent in Oman. While the PMV and adaptive comfort models provide general frameworks, their accuracy in predicting occupant satisfaction at the upper extremes of the temperature spectrum remains uncertain. The local factors identified in Section 4.1.3—occupant behavior, clothing practices, occupancy patterns, and cultural characteristics—require systematic study to develop region-specific comfort models that can inform control strategy design.

The integration of smart HVAC controls with building envelope performance represents another significant gap. The evidence reviewed suggests that controls achieve maximum benefit when integrated with high-performance envelopes, yet the specific relationships between envelope characteristics and control strategy effectiveness in Oman's climate remain underexplored. Research is needed to determine optimal sequencing of envelope and control improvements in retrofit applications.

Occupant behavior modeling for the Omani context remains underdeveloped. Most smart control strategies assume occupancy patterns derived from Western settings, which may not accurately reflect Omani household dynamics, prayer schedules, Ramadan observances, and extended family visitation patterns. Developing culturally appropriate occupancy models would improve the effectiveness of demand-responsive HVAC controls.

4.3.2. Future Research Directions

Research directions include:

- a. Field Studies: Long-term monitoring of residential buildings with smart HVAC controls in Oman to validate simulation results and develop empirical performance databases that account for local climate, construction practices, and occupancy patterns.
- b. Adaptive Comfort: Development of adaptive comfort models specific to Oman's climate and cultural context, including studies of occupant thermal sensation across the full range of outdoor conditions and cultural activities.
- c. Grid Integration: Investigation of HVAC demand response potential and grid-interactive efficient buildings, recognizing Oman's expanding renewable energy capacity

and the opportunities for coordinated control of HVAC systems with on-site generation and storage.

- d. **Occupant-Centric Controls:** Development of personalized comfort systems that account for individual preferences within shared residential spaces, accommodating the diverse needs of extended family structures.
- e. **Cost–Benefit Analysis:** Comprehensive economic assessments accounting for lifecycle costs, including maintenance and system upgrades, specific to Oman’s technical infrastructure and market conditions.

4.3.3. Policy Recommendations

To accelerate the adoption of smart HVAC control technologies in Oman, informed by the technical findings of this review:

- a. **Integrated Requirements:** Rather than mandating controls alone, require integrated approaches that combine envelope improvements with control upgrades in retrofit applications, recognizing that controls achieve maximum benefit when cooling loads are minimized at the source.
- b. **Performance Standards:** Establish minimum energy performance standards for HVAC control systems that account for local climate conditions, including requirements for adaptive setpoint capabilities that respond to extreme outdoor temperatures.
- c. **Capacity Building:** Invest in technical training programs specifically focused on commissioning and maintenance of smart control systems, addressing the expertise gap that limits performance realization.
- d. **Demonstration Projects:** Fund additional demonstration projects showcasing different control strategies across Oman’s climate zones (coastal, interior, mountain), building types, and occupancy patterns to build empirical evidence and market awareness.
- e. **Research Support:** Support development of region-specific thermal comfort models and occupant behavior databases that can inform control strategy design for Omani residential applications.

Figure 4 illustrates the evolution of building energy efficiency policy in Oman, from the initial research initiatives through the comprehensive Oman Building Code framework.

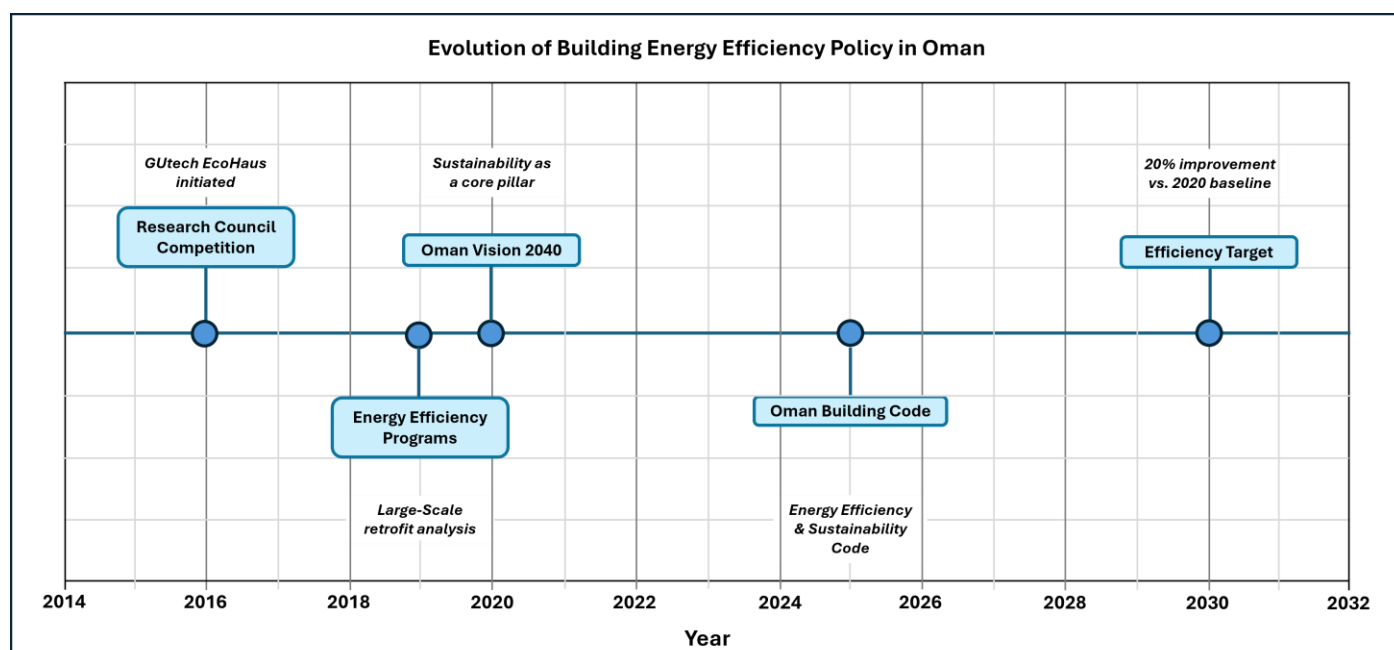


Figure 4. Timeline of key policy milestones in Oman’s building energy efficiency landscape, from the GUtech EcoHaus initiative (2016) through the Oman Vision 2040 efficiency targets (2030).

5. Conclusions

This systematic review demonstrates that smart HVAC control strategies are achievable pathways for reducing residential energy consumption in Oman’s extreme heat climate, though the magnitude of benefits depends critically on the specific control paradigm selected and its integration with building envelope performance. The evidence demonstrates a hierarchy of energy savings potential: Model Predictive Control achieves higher theoretical performance (16–40% [39–41]), followed by Deep Reinforcement Learning (16–23% energy savings with 16.9% comfort improvement [42,43]), Fuzzy Logic Control (12–25% [45,46]), and IoT-based integrated approaches (up to 20% [47,48]). Al Sayed [44] provides international evidence of hybrid DRL for AHU control in a university amphitheater, with energy reductions of 16.24% relative to TD3 and 23.68% relative to DDQN baseline controllers. However, the Oman-specific evidence reveals that these individual control savings are substantially exceeded when controls are implemented as part of integrated design strategies combining high-performance building envelopes with intelligent control systems, with realized savings ranging from 13% to 75% across case studies [14,32,33]. This finding indicates that control optimization alone cannot overcome poor building envelope performance, and that maximum energy efficiency in Omani residential buildings requires coordinated investment in both demand reduction (through envelope improvements) and demand optimization (through smart controls).

The practical implications of these findings are relevant for Oman’s residential building sector and its broader energy efficiency objectives under Oman Vision 2040. For the approximately 65% of residential energy consumption attributable to HVAC systems in Oman, widespread deployment of appropriate smart controls could reduce cooling energy by 12–40% depending on the strategy selected, with reductions in peak electricity demand and carbon emissions. Importantly, the review demonstrates that acceptable thermal comfort (PMV within ± 0.5) is achievable even under extreme summer conditions exceeding 45 °C when appropriate control strategies are implemented. The adaptability of advanced controls to Omani-specific occupancy patterns—including prayer schedules, Ramadan observances, and extended family structures—offers opportunities for optimization that conventional thermostats cannot achieve. These findings provide evidence for

policymakers and practitioners seeking to improve building performance while maintaining or enhancing occupant comfort in challenging climates for residential HVAC operation.

This review makes a contribution to the literature by providing the systematic synthesis of smart HVAC control evidence specifically contextualized for Omani residential buildings operating under extreme heat conditions. While international literature has extensively documented control strategy performance in temperate and moderately hot climates, this review addresses the gap between global research and regional implementation needs by analyzing the suitability of each control paradigm for Oman's specific building stock characteristics, technical infrastructure, and cultural occupancy patterns. The review integrates international evidence (primarily from 2019–2025), GCC regional studies, and Oman-specific case studies to provide a comprehensive evidence base that accounts for the unique challenges of extreme heat climates. By identifying important factors such as the importance of envelope-control integration, the limitations of conventional PMV-based approaches in extreme heat, and the need for culturally appropriate occupancy models, this review contributes to understanding beyond generic control strategy assessments toward context-specific implementation guidance.

Future research priorities should focus on five areas to translate the theoretical benefits identified in this review into realized energy savings across Oman's residential building stock. First, field implementation studies are warranted to validate simulation-based performance estimates under actual Omani operating conditions, as the majority of reviewed evidence derives from simulations rather than measured performance in extreme heat environments. Second, comparative field evaluations of different control paradigms (MPC, DRL, FLC, IoT-based) in identical Omani residential settings could help address uncertainties about relative performance that persist due to variations in study methodologies and building characteristics across the existing literature. Third, research on integration of HVAC controls with renewable energy systems and thermal storage is important as Oman expands its solar capacity, with particular attention to grid-interactive controls that can optimize building energy use while supporting grid stability. Fourth, development of adaptive thermal comfort models and occupant-centric control strategies calibrated for Omani cultural contexts—including extended family occupancy patterns, traditional clothing practices, and thermal expectations under extreme outdoor conditions—could enable controls that respond to actual occupant needs rather than generic PMV assumptions derived from Western office environments. Fifth, investigation of AI-driven optimization approaches that can learn and adapt to individual household patterns while maintaining interpretability for local maintenance capabilities could address the trade-offs between performance and practicality that currently limit control strategy selection.

Addressing these research priorities would provide the empirical foundation needed for widespread deployment of smart HVAC controls as a central component of Oman's strategy for achieving its 20% energy efficiency improvement target by 2030.

Author Contributions: Conceptualization, M.A.S. and J.N.; methodology, M.A.S., J.N. and K.A.; investigation, M.A.S. and J.N.; data curation, M.A.S.; writing—original draft preparation, M.A.S.; writing—review and editing, J.N. and K.A.; visualization, M.A.S.; supervision, J.N. and K.A.; project administration, J.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created in this study. Data supporting the reported results can be found in the cited publications and publicly available databases including Web of

Science, Scopus, IEEE Xplore, and Google Scholar. Performance data from the GUTech EcoHaus case study are available from the German University of Technology in Oman upon reasonable request.

Acknowledgments: The authors acknowledge the support of the Ministry of Housing and Urban Planning, Sultanate of Oman, for providing access to building code documentation and policy materials. We also thank the German University of Technology in Oman for sharing performance data from the EcoHaus project.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

HVAC	Heating, Ventilation, and Air Conditioning
ACMV	Air-Conditioning and Mechanical Ventilation
LSTM	Long Short-Term Memory
MPC	Model Predictive Control
DRL	Deep Reinforcement Learning
FLC	Fuzzy Logic Control
IoT	Internet of Things
ANN	Artificial Neural Network
RLS	Recursive Least Squares
TSF	Time-Series Forecasting
RL	Reinforcement Learning
PMV	Predicted Mean Vote
IAQ	Indoor Air Quality
BAC	Building Automation Control
PPD	Predicted Percentage of Dissatisfied
GCC	Gulf Cooperation Council
DDPG	Deep Deterministic Policy Gradients
MSP-DRL	Multi-Step Predictive Deep Reinforcement Learning
HITL	Human-in-the-Loop
VRF	Variable Refrigerant Flow
DDQN	Double Deep Q-Network
TD3	Twin Delayed Deep Deterministic Policy Gradient
AHU	Air Handling Unit
VAV	Variable Air Volume
EUI	Energy Use Intensity
AER	Authority for Electricity Regulation
OBC	Oman Building Code
MoHUP	Ministry of Housing and Urban Planning
BAS	Building Automation System
EMS	Energy Management System
LEED	Leadership in Energy and Environmental Design
PV	Photovoltaic
AI	Artificial Intelligence
CO ₂	Carbon Dioxide
kWh	kilowatt-hour
m ²	Square meter
yr	Year

References

1. International Energy Agency (IEA). *World Energy Outlook 2023*; IEA: Paris, France, 2023. Available online: <https://www.iea.org/reports/world-energy-outlook-2023> (accessed on 14 February 2026).
2. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Shukla, P.R., Skea, J., Slade, R., Fradera,

- R., Pathak, M., Al Khourdajie, A., Belkacemi, M., van Diemen, R., Hasija, R., Lisboa, G., et al., Eds.; Cambridge University Press: Cambridge, UK, 2023. <https://doi.org/10.1017/9781009157926>.
3. Pérez-Lombard, L.; Ortiz, J.; Pout, C. A review on buildings energy consumption information. *Energy Build.* **2008**, *40*, 394–398. <https://doi.org/10.1016/j.enbuild.2007.03.007>.
4. International Energy Agency (IEA). *The Future of Cooling: Opportunities for Energy-Efficient Air Conditioning*; IEA: Paris, France, 2018. Available online: <https://www.iea.org/reports/the-future-of-cooling> (accessed on 14 February 2026).
5. Directorate General of Meteorology, Oman. Climate Data and Extreme Weather Records. Available online: <https://met.caa.gov.om> (accessed on 14 February 2026).
6. Authority for Public Services Regulation (APSR), Oman. *Annual Report 2022*; APSR: Muscat, Oman, 2023. Available online: <https://apsr.om> (accessed on 14 February 2026).
7. Almasri, R.A.; Alshitawi, M.S. Electricity consumption indicators and energy efficiency in residential buildings in GCC countries: Extensive review. *Energy Build.* **2022**, *267*, 112133. <https://doi.org/10.1016/j.enbuild.2021.111664>.
8. Felimban, A.; Prieto, A.; Knaack, U.; Klein, T.; Qaffas, Y. Assessment of current energy consumption in residential buildings in Jeddah, Saudi Arabia. *Buildings* **2019**, *9*, 163. <https://doi.org/10.3390/buildings9070163>.
9. Abu-Hijleh, B.; Jaheen, N. Energy and economic impact of the new Dubai municipality green building regulations and potential upgrades of the regulations. *Energy Strategy Rev.* **2019**, *26*, 100419. <https://doi.org/10.1016/j.esr.2019.100419>.
10. Krarti, M.; Dubey, K. Benefits of energy efficiency programs for residential buildings in Bahrain. *J. Build. Eng.* **2018**, *20*, 70–79. <https://doi.org/10.1016/j.job.2018.07.005>.
11. Saffouri, F.; Bayram, I.S.; Koc, M. Quantifying the cost of cooling in Qatar. In Proceedings of the 2017 9th IEEE-GCC Conference and Exhibition (GCCCE), Manama, Bahrain, 8–11 May 2017; pp. 1–6. <https://doi.org/10.1109/IEEEGCC.2017.8448269>.
12. Park, J.; Kim, T.; Lee, C. Development of thermal comfort-based controller and potential reduction of the cooling energy consumption of a residential building in Kuwait. *Energies* **2019**, *12*, 3348. <https://doi.org/10.3390/en12173348>.
13. Al-Saadi, S.N.J.; Al-Jabri, K.S. Energy-efficient envelope design for residential buildings: A case study in Oman. In Proceedings of the 2017 IEEE Smart City Symposium Prague (SCSP), Prague, Czech Republic, 25–26 May 2017; pp. 1–6. <https://doi.org/10.1109/SCSP.2017.7973853>.
14. Alalouch, C.; Al-Saadi, S.; AlWaer, H.; Al-Khaled, K. Energy saving potential for residential buildings in hot climates: The case of Oman. *Sustain. Cities Soc.* **2019**, *46*, 101442. <https://doi.org/10.1016/j.scs.2019.101442>.
15. Gyalistras, D.; Gwerder, M. (Eds.). *Use of Weather and Occupancy Forecasts for Optimal Building Climate Control (OptiControl): Two Years Progress Report*; Terrestrial Systems Ecology, ETH Zurich: Zurich, Switzerland; Building Technologies Division, Siemens Switzerland Ltd.: Zug, Switzerland, 2010; p. 158. Available online: <https://www.sysecol2.ethz.ch/pdfs/Gy028.pdf> (accessed on 14 February 2026).
16. Pérez-Lombard, L.; Ortiz, J.; Coronel, J.F.; Maestre, I.R. A review of HVAC systems requirements in building energy regulations. *Energy Build.* **2011**, *43*, 255–268. <https://doi.org/10.1016/j.enbuild.2010.10.025>.
17. Köhler, J.; Müller, M.A.; Allgöwer, F. Analysis and design of model predictive control frameworks for dynamic operation—An overview. *Annu. Rev. Control* **2024**, *57*, 100929. <https://doi.org/10.1016/j.arcontrol.2023.100929>.
18. Sturzenegger, D.; Gyalistras, D.; Morari, M.; Smith, R.S. Model Predictive Climate Control of a Swiss Office Building: Implementation, Results, and Cost-Benefit Analysis. *IEEE Trans. Control Syst. Technol.* **2016**, *24*, 1314–1324. <https://doi.org/10.1109/TCST.2015.2415411>.
19. Ma, Y.; Borrelli, F.; Hencsey, B.; Coffey, B.; Benga, S.; Haves, P. Model Predictive Control for the Operation of Building Cooling Systems. *IEEE Trans. Control Syst. Technol.* **2012**, *20*, 796–803. <https://doi.org/10.1109/TCST.2011.2124461>.
20. Oldewurtel, F.; Parisio, A.; Jones, C.N.; Gyalistras, D.; Gwerder, M.; Stauch, V.; Lehmann, B.; Morari, M. Energy efficient building climate control using stochastic model predictive control and weather predictions. In Proceedings of the 2010 American Control Conference (ACC 2010), Baltimore, MD, USA, 30 June–2 July 2010; pp. 5100–5105. <https://doi.org/10.1109/ACC.2010.5530680>.
21. Gao, G.; Li, J.; Wen, Y. Energy-Efficient Thermal Comfort Control in Smart Buildings via Deep Reinforcement Learning. *arXiv* **2019**, arXiv:1901.04693.
22. Wei, T.; Wang, Y.; Zhu, Q. Deep Reinforcement Learning for Building HVAC Control. In Proceedings of the 54th Annual Design Automation Conference (DAC 2017), Austin, TX, USA, 18–22 June 2017; pp. 1–6. <https://doi.org/10.1145/3061639.3062224>.
23. Fanger, P.O. *Thermal Comfort: Analysis and Applications in Environmental Engineering*; Danish Technical Press: Copenhagen, Denmark, 1970. Available online: <https://books.google.com/books?id=50FSAAAAMAAJ> (accessed on 14 February 2026).

24. Cheung, T.; Schiavon, S.; Parkinson, T.; Li, P.; Brager, G. Analysis of the accuracy of the PMV-PPD model using the ASHRAE Global Thermal Comfort Database II. *Build. Environ.* **2019**, *153*, 205–217. <https://doi.org/10.1016/j.buildenv.2019.01.055>.
25. Humphreys, M.A.; Nicol, J.F. The validity of ISO-PMV for predicting comfort votes in everyday thermal environments. *Energy Build.* **2002**, *34*, 667–684. [https://doi.org/10.1016/S0378-7788\(02\)00018-X](https://doi.org/10.1016/S0378-7788(02)00018-X).
26. de Dear, R.J.; Brager, G.S. Developing an adaptive model of thermal comfort and preference. *ASHRAE Trans.* **1998**, *104*, 145–167. Available online: <https://escholarship.org/uc/item/4qq2p9c6> (accessed on 14 February 2026).
27. Privara, S.; Siroký, J.; Ferkl, L.; Cigler, J. Building modeling as a crucial part for building predictive control. *Energy Build.* **2013**, *56*, 8–22. <https://doi.org/10.1016/j.enbuild.2012.10.024>.
28. Zhang, Z.; Chong, A.; Pan, Y.; Zhang, C.; Lu, S.; Lam, K.P. A deep reinforcement learning approach to using whole building energy model for HVAC optimal control. In Proceedings of the 16th Conference of the International Building Performance Simulation Association (IBPSA), Building Simulation 2019, Rome, Italy, 2–4 September 2019; pp. 675–682. <https://doi.org/10.26868/25222708.2019.210763>.
29. Wang, Y.; Chen, Q.; Xu, C.; Li, Z.; Feng, X. Real-time building control: Challenges and opportunities for enabling digital twin-based HVAC control. *Build. Environ.* **2023**, *236*, 110198. <https://doi.org/10.1016/j.buildenv.2023.110198>.
30. Dong, B.; O'Neill, Z.; Li, Z.; Zhang, A.; Brahme, R.; Bailey, T.; Joo, I.; Kar, P.; Lam, K.P.; Ouf, M.M.; et al. Real-time model predictive control for building heating and cooling systems based on occupancy information. *Energy Build.* **2017**, *142*, 236–249. <https://doi.org/10.1016/j.enbuild.2017.03.012>.
31. Lin, Y.; Barooah, P.; Meyn, S.; Middelkoop, T. Experimental validation of a feedback linearization control for commercial building HVAC systems. In Proceedings of the ASME 2012 5th Annual Dynamic Systems and Control Conference (DSCC), Joint with JSME 2012 11th Motion and Vibration Conference, Fort Lauderdale, FL, USA, 17–19 October 2012; pp. 149–156. <https://doi.org/10.1115/DSCC2012-MOVIC2012-8530>.
32. Rudolph, M.; Knebel, N.; Reisi, E. Monitoring and evaluating the performance of a net-zero-energy building in Oman: A case study of the GUtech EcoHaus. In Proceedings of the 32nd International Conference on Passive and Low Energy Architecture (PLEA 2016), Los Angeles, CA, USA, 11–13 July 2016; Volume 2, pp. 1067–1074. Available online: https://www.researchgate.net/publication/317043718_Monitoring_and_Evaluating_the_Performance_of_a_Net-Zero-Energy_Building_in_Oman_-_A_case_study_of_the_GUtech_ECOHAUS (accessed on 14 February 2026).
33. Krarti, M.; Dubey, K. Energy productivity evaluation of large-scale building energy efficiency programs for Oman. *Sustain. Cities Soc.* **2017**, *29*, 12–22. <https://doi.org/10.1016/j.scs.2016.11.009>.
34. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. <https://doi.org/10.1136/bmj.n71>.
35. Kitchenham, B.; Charters, S. Guidelines for Performing Systematic Literature Reviews in Software Engineering; EBSE Technical Report EBSE-2007-01; Keele University and Durham University: Keele, UK, 2007. Available online: <https://www.cin.ufpe.br/~in1037/leitura/kitchenham2007guidelines.pdf> (accessed on 8 August 2026).
36. Higgins, J.P.T.; Thomas, J.; Chandler, J.; Cumpston, M.; Li, T.; Page, M.J.; Welch, V.A. (Eds.) *Cochrane Handbook for Systematic Reviews of Interventions*, Version 6.3; Cochrane: London, UK, 2022. Available online: <https://training.cochrane.org/handbook> (accessed on 18 February 2026).
37. Popay, J.; Roberts, H.; Sowden, A.; Petticrew, M.; Arai, L.; Rodgers, M.; Britten, N.; Roen, K.; Duffy, S. *Guidance on the Conduct of Narrative Synthesis in Systematic Reviews: A Product from the ESRC Methods Programme*; Lancaster University: Lancaster, UK, 2006. <https://doi.org/10.13140/2.1.1018.4643>
38. Critical Appraisal Skills Programme (CASP). *CASP Systematic Review Checklist*; CASP: Oxford, UK, 2018. Available online: <https://casp-uk.net/casp-tools-checklists/> (accessed on 11 July 2026).
39. Eini, R.; Abdelwahed, S. Learning-Based Model Predictive Control for Smart Building Thermal Management. *arXiv* **2019**, arXiv:1909.05331.
40. Sha, X.; Ma, Z.; Sethuvenkatraman, S.; Li, W. Online learning-enhanced data-driven model predictive control for optimizing HVAC energy consumption, indoor air quality and thermal comfort. *Appl. Energy* **2025**, *383*, 125341. <https://doi.org/10.1016/j.apenergy.2025.125341>.
41. Yang, S.; Wan, M.P.; Chen, W.; Ng, B.F.; Dubey, S. Model predictive control with adaptive machine-learning-based model for building energy efficiency and comfort optimization. *Appl. Energy* **2020**, *271*, 115147. <https://doi.org/10.1016/j.apenergy.2020.115147>.

42. Zhuang, D.; Gan, V.J.L.; Tekler, Z.D.; Chong, A.; Tian, S.; Shi, X. Data-driven predictive control for smart HVAC systems in IoT-integrated buildings with time-series forecasting and reinforcement learning. *Appl. Energy* **2023**, *338*, 120936. <https://doi.org/10.1016/j.apenergy.2023.120936>.
43. Liu, X.; Ren, M.; Yang, Z.; Yan, G.; Guo, Y.; Cheng, L.; Wu, C. A multi-step predictive deep reinforcement learning algorithm for HVAC control systems in smart buildings. *Energy* **2022**, *259*, 124857. <https://doi.org/10.1016/j.energy.2022.124857>.
44. Al Sayed, K. Deep Reinforcement Learning Techniques for Adaptive HVAC Control Systems in Smart Buildings. Ph.D. Thesis, Arts et Métiers Institute of Technology, Paris, France, 2025. Available online: <https://theses.fr/2025ENAME098> (accessed on 9 March 2026).
45. Gouda, M.M.; Danaher, S.; Underwood, C.P. Thermal comfort based fuzzy logic control. *Build. Serv. Eng. Res. Technol.* **2001**, *22*, 237–253. <https://doi.org/10.1177/014362440102200403>.
46. Kang, C.S.; Hyun, C.H.; Park, M. Fuzzy logic-based advanced on–off control for thermal comfort in residential buildings. *Appl. Energy* **2015**, *155*, 270–283. <https://doi.org/10.1016/j.apenergy.2015.05.119>.
47. Su, B.; Wang, S. An agent-based distributed real-time optimal control strategy for building HVAC systems for applications in the context of future IoT-based smart sensor networks. *Appl. Energy* **2020**, *274*, 115322. <https://doi.org/10.1016/j.apenergy.2020.115322>.
48. Liang, X.; de Nijs, F.; Say, B.; Wang, H. Human-in-the-Loop AI for HVAC Management: Enhancing Comfort and Energy Efficiency. *arXiv* **2025**, arXiv:2505.05796.
49. Parsons, K. The Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD). In *Human Thermal Comfort*; CRC Press: Boca Raton, FL, USA, 2019; pp. 165–184. <https://doi.org/10.1201/9780429294983-3>.
50. Nguyen, A.T.; Singh, M.K.; Reiter, S. An adaptive thermal comfort model for hot humid South-East Asia. *Build. Environ.* **2012**, *56*, 291–300. <https://doi.org/10.1016/j.buildenv.2012.03.021>.
51. Carlucci, S.; Bai, L.; de Dear, R.; Yang, L. Review of adaptive thermal comfort models in built environmental regulatory documents. *Build. Environ.* **2018**, *137*, 73–89. <https://doi.org/10.1016/j.buildenv.2018.03.053>.
52. Oman Vision 2040 Implementation Follow-up Unit. *Vision Document*; Sultanate of Oman: Muscat, Oman, 2020. Available online: <https://www.oman2040.om/oman2040?lang=en> (accessed on 9 March 2026).
53. Ministry of Housing and Urban Planning (MoHUP), Oman. *Oman Building Code (OBC)*; MoHUP: Muscat, Oman, 2025. Available online: <https://studylib.net/doc/28622767/oman-building-code-2025> (accessed on 9 March 2026).

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.