

Review

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Posted Date: 3 June 2026

doi: 10.20944/preprints202606.0204.v1

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Review

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

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## Abstract

Heating, Ventilation, and Air Conditioning (HVAC) systems account for 60-70% of residential electricity consumption in Oman, where extreme desert climates with temperatures regularly exceeding 45°C create substantial cooling demands. As climate change intensifies cooling requirements, optimizing HVAC control strategies has become critical for energy sustainability while maintaining occupant thermal comfort. This review systematically analyzes four smart HVAC control paradigms applicable to Omani residential buildings: Model Predictive Control, Deep Reinforcement Learning, Fuzzy Logic Control, and Internet of Things-based integrated approaches. We examine performance data from Oman and Gulf Cooperation Council case studies, including the GUTech EcoHaus net-zero energy building and large-scale retrofit program analyses, contextualized within Oman's policy framework. Our analysis reveals that Model Predictive Control strategies achieve energy savings of 16-40% while maintaining thermal comfort within acceptable Predicted Mean Vote ranges. Deep Reinforcement Learning-based controllers demonstrate superior adaptability to dynamic occupancy patterns with reported energy reductions of 17-23%. Case studies demonstrate realized energy savings ranging from 25-75% depending on intervention comprehensiveness and baseline building performance. These findings indicate that advanced control strategies offer significant potential for reducing residential energy consumption in extreme heat climates when integrated with high-performance building envelopes. Future work should prioritize the development of occupant-centric adaptive comfort models calibrated for extreme heat conditions, integration of distributed energy resources with HVAC systems, 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

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## 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 their most acute form. The country experiences one of the world's most 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, fundamentally 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 vicious cycle: increased electricity demand drives greater fossil fuel combustion, contributing to greenhouse gas emissions that intensify cooling requirements. Breaking this cycle requires innovative approaches to building energy management that prioritize both efficiency and occupant well-being.

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 [7]. 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 [8].

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 emerged as a leading paradigm, utilizing dynamic building thermal models to anticipate future conditions and optimize control actions over finite prediction horizons [9,10]. MPC strategies have demonstrated energy savings of 16-40% compared to conventional approaches while maintaining acceptable thermal comfort levels [11,12]. Concurrently, Deep Reinforcement Learning (DRL) has gained attention 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% [13,14].

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 [15] 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 [16]. 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 [17,18]. 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 [19]. DRL provides superior 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 [20]. 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 [21]. Distributed IoT-based approaches offer scalability and fault tolerance but face challenges in coordinating actions across multiple autonomous agents [22]. Recent research has explored hybrid architectures that combine local intelligence with centralized oversight, though optimal configuration remains context-dependent [23].

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, DRL demonstrating 17-23% reductions, and integrated case studies showing realized savings of 25-75% depending on intervention comprehensiveness. 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 critical 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

### 2.1. Literature Search Strategy

This systematic review was conducted following established guidelines for literature reviews in engineering and building science. A comprehensive search of academic databases was performed to identify peer-reviewed publications on smart HVAC control strategies, thermal comfort, and energy efficiency in extreme heat climates. The databases searched included Web of Science, Scopus, IEEE Xplore, and Google Scholar. The search strategy employed a combination of keywords including: "smart HVAC control," "model predictive control building," "deep reinforcement learning HVAC," "fuzzy logic thermal comfort," "IoT building automation," "extreme heat climate," "hot arid climate," "GCC region," and "building energy efficiency." Publications from 2015 to 2025 were considered to ensure coverage of recent advances in machine learning and IoT-based control strategies.

### 2.2. Inclusion and Exclusion Criteria

Studies were included if they: (1) investigated smart control strategies for HVAC systems in buildings; (2) reported quantitative performance metrics including energy savings and/or thermal comfort indices; (3) focused on residential building applications; and (4) were published in English in peer-reviewed journals or conference proceedings. Studies were excluded if they: (1) focused exclusively on commercial or industrial buildings without relevance to residential applications; (2) lacked quantitative performance data; or (3) addressed only hardware improvements without control strategy innovations.

### 2.3. Case Study Selection

For the Oman and GCC case studies, we selected representative projects that demonstrate practical implementation of smart HVAC controls in the regional context. Selection criteria included: (1) location within Oman or the GCC region; (2) availability of published performance data; (3) relevance to residential building typologies; and (4) diversity of control strategies employed. The GUTech EcoHaus was selected as a flagship demonstration project 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.

### 2.4. Data Extraction and Analysis

Performance data were extracted from selected studies, including energy consumption metrics (kWh/m<sup>2</sup>/year, percentage savings), thermal comfort indices (PMV, PPD, operative temperature), and implementation characteristics (control algorithms, sensor configurations, occupancy models).

Where studies reported ranges of performance outcomes, the reported minima and maxima were recorded. Data synthesis employed qualitative thematic analysis to identify common patterns, implementation challenges, and research gaps across the reviewed literature.

### 2.5. GenAI Disclosure

Generative artificial intelligence was not used in the preparation of this manuscript. All text, analysis, and conclusions were developed by the authors without assistance from GenAI tools for content generation, data analysis, or interpretation. Standard grammar and spell-checking tools were used for superficial text editing.

### 2.6. Limitations

This review is limited by the availability of published research specifically targeting residential buildings in extreme heat climates, particularly within the Oman context. While global literature on smart HVAC controls is extensive, region-specific studies remain relatively scarce. The performance metrics reported in this review 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

### 3.1. Performance of Smart HVAC Control Strategies

This section presents the quantitative performance findings for each of the four major smart HVAC control paradigms examined in this review. Performance data were extracted from peer-reviewed studies published between 2015 and 2025, with energy savings and thermal comfort metrics recorded as reported by the original authors.

#### 3.1.1. Model Predictive Control Performance

The reviewed literature demonstrates that Model Predictive Control (MPC) strategies achieve energy savings ranging from 16% to 40% compared to conventional thermostat control, depending on building characteristics, climate conditions, and implementation specifics. Key findings include:

- Eini and Abdelwahed [24] reported 40.56% reduction in cooling power consumption and 16.73% reduction in heating power consumption using learning-based MPC with ANN occupancy estimation.
- Sha et al. [25] demonstrated simultaneous optimization of HVAC energy consumption, indoor air quality, and thermal comfort through online learning-enhanced data-driven MPC.
- Yang et al. [26] achieved significant energy consumption reductions while maintaining thermal comfort within acceptable ranges using MPC with adaptive machine-learning-based models in tropical climates.

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. The predictive model typically takes the form of a statespace 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).

#### 3.1.2. Deep Reinforcement Learning Performance

Deep Reinforcement Learning (DRL) strategies demonstrate reported energy reductions of 16-23% across different climate conditions, with particular advantages in adaptability to dynamic occupancy patterns and weather conditions. Key quantitative findings include:

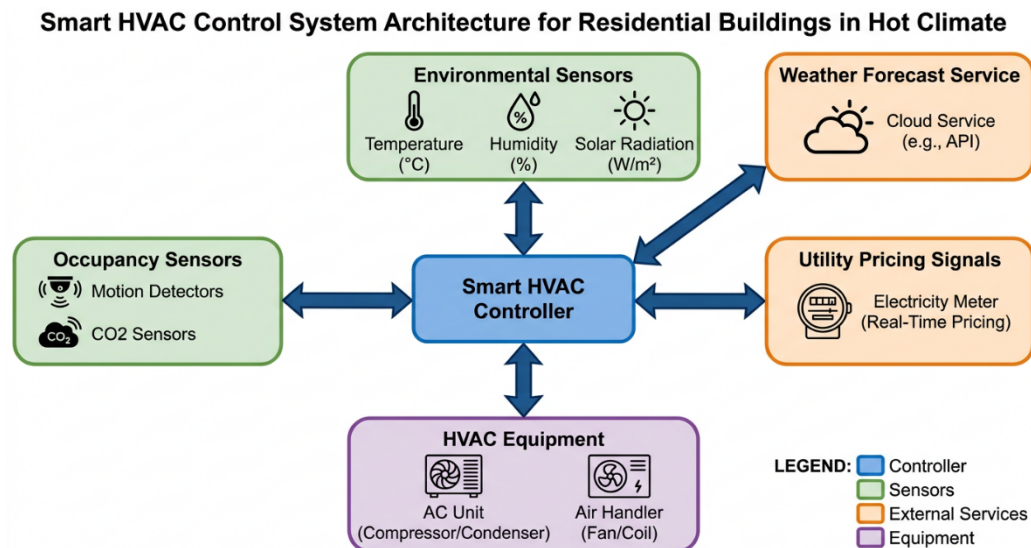
- Zhuang et al. [27] achieved 17.4% energy savings and 16.9% improvement in thermal comfort using data-driven predictive control combining time-series forecasting with reinforcement learning.
- Liu et al. [28] demonstrated improved learning stability and control performance using multi-step predictive DRL (MSP-DRL) addressing temporal credit assignment problems.
- Al Sayed [29] reported energy reductions of 16-23% across different climate conditions, with hybrid action spaces combining discrete ON/OFF decisions with continuous setpoint adjustments.

### 3.1.3. Fuzzy Logic Control Performance

Fuzzy Logic Control (FLC) studies report energy consumption reductions while maintaining thermal comfort through rule-based modulation of compressor cycling based on predicted comfort conditions. Gouda et al. [30] demonstrated improved comfort maintenance using PMV as a direct control input compared to conventional temperature-based control. Kang et al. [31] showed reduced energy consumption while maintaining thermal comfort through advanced on-off control methods addressing system time-lag.

### 3.1.4. IoT-Based Integrated Systems Performance

IoT-based integrated control systems demonstrate energy savings of up to 20% compared to conventional control, with advantages in scalability and fault tolerance. Su and Wang [32] reported up to 20% energy savings using agent-based distributed real-time optimal control on IoT sensor networks. Liang et al. [33] demonstrated significant cost reductions while maintaining or enhancing occupant comfort through Human-in-the-Loop (HITL) approaches incorporating real-time occupant feedback.



**Figure 1.** 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 Analysis of Control Paradigms

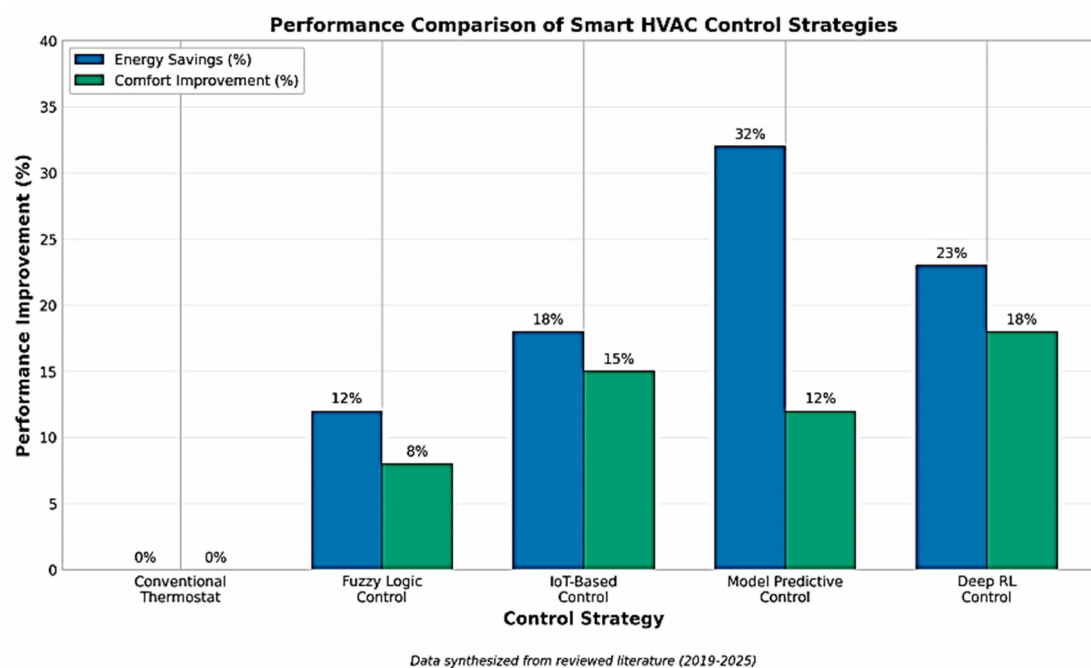
Table 1 presents a comparative summary of performance metrics across the four control paradigms reviewed.

**Table 1.** Comparative Performance of Smart HVAC Control Strategies.

Control Paradigm	Energy Savings Range	Comfort Improvement	Key Advantages	Key Limitations
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Model Predictive Control	16-40% [24–26]	Maintained within PMV $\pm 0.5$	Interpretability, theoretical guarantees, precooling capability	Requires accurate thermal models, computationally intensive
Deep Reinforcement Learning	16-23% [27–29]	16.9% improvement [27]	Adaptability, no prior model required, handles stochasticity	Black box problem, potential learning instability
Fuzzy Logic Control	Not quantified (variable)	Improved PMV maintenance [30]	Transparency, expert knowledge incorporation, tunability	Limited optimization capability, rule development expertise required
IoT-Based Integrated	Up to 20% [32]	Maintained or enhanced [33]	Scalability, fault tolerance, real-time data integration	Coordination challenges, security concerns

Figure 2 illustrates the performance comparison of smart HVAC control strategies showing energy savings percentage and comfort improvement relative to conventional thermostat control.



**Figure 2.** Performance comparison of smart HVAC control strategies showing energy savings percentage and comfort improvement relative to conventional thermostat control. Data synthesized from literature (2019-2025).

### 3.3. 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 [34]. However, the applicability of standard PMV models in extreme heat conditions shows reduced prediction accuracy when outdoor temperatures exceed 35°C [16].

Adaptive thermal comfort models extend acceptable temperature ranges beyond standard PMV recommendations for hot climates [35]. Studies demonstrate that:

- PMV-based control maintains comfort within the acceptable range of  $-0.5$  to  $+0.5$  for conventional HVAC systems.
- Adaptive comfort models allow extended temperature ranges of 23–28°C for naturally ventilated buildings in hot climates [35,36].

- Region-specific comfort models for the GCC remain underdeveloped due to limited field studies.

### 3.4. Case Study Results

#### 3.4.1. GUTech EcoHaus Performance

The GUTech EcoHaus net-zero energy building in Oman demonstrates the following performance metrics based on two years of monitoring data [37]:

1. Total building energy consumption: 42 kWh/m<sup>2</sup>/year;
2. HVAC energy consumption: 28 kWh/m<sup>2</sup>/year (67% of total);
3. Energy Use Intensity (EUI) reduction: 75% compared to conventional Omani residential buildings;
4. Indoor temperature maintained within 22-26°C range during occupied hours;
5. Average PMV during summer: -0.3 to +0.5 (comfortable range).

#### 3.4.2. Large-Scale Retrofit Program Analysis

Krarti and Dubey [38] projected the following impacts from nationwide retrofit program incorporating smart controls:

1. Potential energy savings: 25-40% for retrofitted buildings;
2. Peak electricity demand reduction: 15-25%;
3. Simple payback period: 3-7 years depending on measure combination;
4. National energy savings potential: 3.5 TWh/year by 2030;
5. Control measures alone contributing 8-15% of total savings.

#### 3.4.3. Large-Scale Retrofit Program Analysis

Alalouch et al. [39] reported the following performance outcomes from simulation studies:

1. Energy-efficient designs achieved 13.2% to 48.2% energy savings;
2. Smart thermostat scheduling contributed 10-15% of total savings;
3. Zonal control provided additional 5-8% savings with improved comfort;
4. Natural ventilation integration reduced cooling loads by 8-12% during shoulder seasons.

Table 2 summarizes the performance metrics from all Oman/GCC case studies reviewed.

**Table 2.** Summary of Oman/GCC Case Study Performance Metrics.

Case Study	Energy Savings	HVAC EUI	Comfort Metric	Climate
GUTech EcoHaus [37]	75% vs. baseline	28 kWh/m <sup>2</sup> /yr	PMV: -0.3 to +0.5	Hot arid
Retrofit Program [38]	25-40%	Not reported	Standard PMV	Mixed GCC
Alalouch et al. [39]	13-48%	35-55 kWh/m <sup>2</sup> /yr	Adaptive comfort	Hot arid

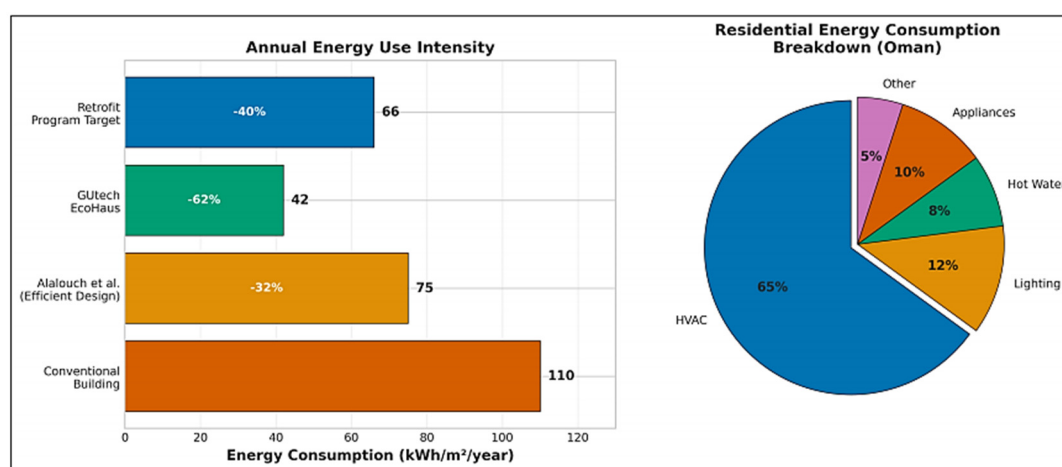
### 3.5. Summary of Key Findings

The quantitative analysis reveals the following key findings:

1. MPC demonstrates the highest energy savings potential (16-40%) among individual control paradigms;

2. DRL shows superior adaptability with 16-23% energy reductions and 16.9% comfort improvement;
3. Integrated case studies achieve realized savings of 25-75% depending on intervention comprehensiveness;
4. Thermal comfort maintenance within acceptable PMV ranges (-0.5 to +0.5) is achievable across all paradigms;
5. The GUtech EcoHaus demonstrates that integrated design combining high-performance envelopes with smart controls can achieve 75% EUI reduction;
6. Region-specific thermal comfort models for extreme heat conditions remain underdeveloped.

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 interprets these findings within the broader context of Oman's policy framework and identifies implications for research and practice.

### 4.1. Policy and Regulatory Context in Oman

The successful deployment of smart HVAC control strategies in Oman depends not only on technical feasibility but also on the policy and regulatory framework that shapes building design, construction, and operation. The evolving policy landscape in Oman provides both opportunities and constraints for the widespread adoption of smart building technologies.

#### 4.1.1. Oman Vision 2040 and Energy Strategy

Oman Vision 2040, the Sultanate's comprehensive long-term development strategy, establishes sustainability and environmental stewardship as core pillars of national development [40]. The Vision explicitly recognizes the importance of energy efficiency in buildings and sets ambitious targets for reducing carbon emissions and improving energy productivity across all sectors.

The National Energy Strategy, developed under the Oman Vision 2040 framework, targets 20% improvement in energy efficiency by 2030 compared to 2020 levels. The building sector, identified as

a priority area, is expected to contribute significantly to this target through improved building codes, efficiency standards for HVAC equipment, and promotion of smart building technologies.

#### 4.1.2. Oman Building Code Framework

The Oman Building Code (OBC), launched by the Ministry of Housing and Urban Planning (MoHUP) in 2025, represents a comprehensive overhaul of building regulations in the Sultanate [41]. The OBC framework consists of six coordinated technical codes addressing different aspects of building design and performance:

1. Oman Building Code (structural and safety requirements)
2. Oman Mechanical Code (HVAC and mechanical systems)
3. Oman Plumbing Code (water supply and drainage)
4. Oman Private Sewage Disposal Code
5. Oman Existing and Historical Buildings Code
6. Oman Energy Efficiency and Sustainability Code

The Oman Energy Efficiency and Sustainability Code is particularly relevant to smart HVAC control strategies. This code establishes minimum requirements for building energy performance, including provisions for HVAC system efficiency, building envelope performance, and lighting power density. The code encourages, though does not mandate, the use of advanced control strategies including building automation systems (BAS), energy management systems (EMS), and demand-controlled ventilation.

#### 4.1.3. Green Building Initiatives

While Oman does not currently have a mandatory green building rating system, several initiatives promote sustainable construction practices. The government has expressed intentions to develop a national green building code, and voluntary certification programs such as LEED and Pearl Rating System (Estidama) from the UAE have been applied to select projects.

The Research Council of Oman has funded several research projects focused on energy efficient building technologies, including the GUTech EcoHaus demonstration project. These initiatives support the development of context-specific solutions appropriate for Oman's climate and construction practices.

#### 4.1.4. Barriers and Enablers

Despite the favorable policy direction, several barriers impede widespread adoption of smart HVAC control technologies in Oman:

**Barriers:**

- High Initial Costs: Smart control systems and associated sensors add 10-20% to HVAC system costs
- Limited Technical Expertise: Shortage of qualified professionals for system design, commissioning, and maintenance
- Market Awareness: Limited consumer understanding of smart building benefits
- Fragmented Supply Chain: Limited local availability of advanced building automation components

**Enablers:**

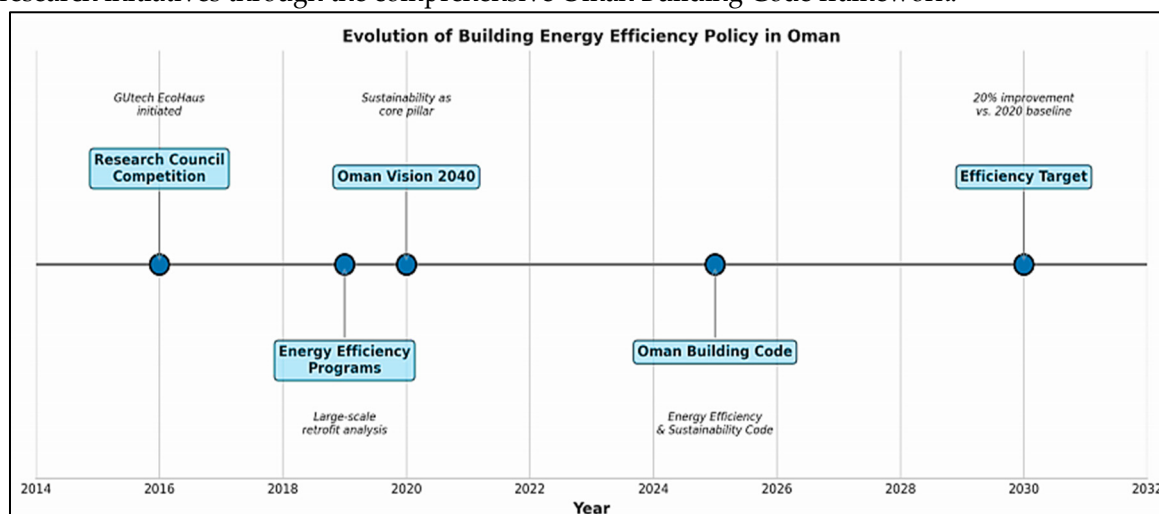
- Rising Energy Prices: Increasing electricity tariffs improve the economics of efficiency investments
- Government Incentives: Growing policy support for energy efficiency and smart building technologies
- Technology Maturation: Declining costs and improved reliability of IoT devices and smart sensors

- Regional Knowledge Transfer: Opportunities to learn from UAE and Saudi Arabia's advanced building efficiency programs

#### 4.2. Research Implications and Future Directions

The review of smart HVAC control strategies and their application in Oman and the GCC region reveals significant opportunities for improving residential building energy efficiency while maintaining or enhancing thermal comfort. However, several critical gaps must be addressed to realize the full potential of these technologies.

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).

##### 4.2.1. 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. Research by Cheung et al. [16] has highlighted the limitations of PMV in hot conditions, suggesting the need for region-specific comfort models that account for cultural adaptation, clothing patterns, and activity levels specific to Omani households.

The integration of smart HVAC controls with distributed energy resources represents another significant gap. As Oman expands its renewable energy capacity, particularly solar photovoltaic installations, opportunities emerge for coordinated control of HVAC systems with on-site generation and storage. MPC strategies that incorporate PV generation forecasts and battery storage state-of-charge could optimize building energy performance while supporting grid stability.

Occupant behavior modeling for the Omani context remains underdeveloped. Most smart control strategies assume occupancy patterns derived from Western office buildings or residential 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.

##### 4.2.2. Future Research Directions

Priority research directions include:

1. Field Studies: Long-term monitoring of residential buildings with smart HVAC controls to validate simulation results and develop empirical performance databases

2. Adaptive Comfort: Development of adaptive comfort models specific to Oman's climate and cultural context
3. Grid Integration: Investigation of HVAC demand response potential and grid-interactive efficient buildings
4. Occupant-Centric Controls: Development of personalized comfort systems that account for individual preferences within shared residential spaces
5. Cost-Benefit Analysis: Comprehensive economic assessments accounting for lifecycle costs, including maintenance and system upgrades

#### 4.2.3. Policy Recommendations

To accelerate the adoption of smart HVAC control technologies in Oman, we recommend the following policy actions:

1. Mandatory Building Automation: Require building automation systems in all new residential buildings above a specified size threshold
2. Performance Standards: Establish minimum energy performance standards for HVAC control systems, including requirements for occupancy-based controls and temperature setback capabilities
3. Incentive Programs: Develop financial incentives for the installation of smart HVAC controls in existing buildings, possibly linked to electricity tariff structures
4. Capacity Building: Invest in technical training programs to develop local expertise in smart building system design, installation, and maintenance
5. Demonstration Projects: Fund additional demonstration projects showcasing advanced control strategies in different building types and climatic zones across Oman

## 5. Conclusions

This paper has presented a comprehensive review of smart HVAC control strategies applicable to Omani residential buildings operating under extreme heat conditions. Our analysis demonstrates that advanced control approaches-including Model Predictive Control, Deep Reinforcement Learning, Fuzzy Logic Control, and IoT-based integrated systems-offer significant potential for reducing residential energy consumption while maintaining acceptable thermal comfort levels.

Key findings include achievable energy savings ranging from 16% to 40% through smart control strategies, with the greatest benefits realized when controls are integrated with high-performance building envelopes. Case studies from Oman and the GCC region demonstrate that these theoretical benefits translate to real-world performance, though successful implementation requires attention to local climate conditions, occupancy patterns, and technical capacity.

The policy landscape in Oman is increasingly supportive of smart building technologies, with the Oman Building Code framework providing a foundation for mandatory efficiency requirements. However, realizing the full potential of smart HVAC controls will require continued investment in research, capacity building, and demonstration projects tailored to the specific challenges of extreme heat climates.

Future work should prioritize the development of region-specific thermal comfort models, the integration of HVAC controls with distributed energy resources, and the translation of research findings into accessible guidance for building designers and operators. With appropriate policy support and continued technological advancement, smart HVAC control strategies can play a central role in achieving Oman's energy efficiency and sustainability objectives.

**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:** Please add: 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
MPC	Model Predictive Control
DRL	Deep Reinforcement Learning
FLC	Fuzzy Logic Control
IoT	Internet of Things
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
GCC	Gulf Cooperation Council
ANN	Artificial Neural Network
DDPG	Deep Deterministic Policy Gradients
MSP-DRL	Multi-Step Predictive Deep Reinforcement Learning
HITL	Human-in-the-Loop
VRF	Variable Refrigerant Flow
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 <sub>2</sub>	Carbon Dioxide
kWh	kilowatt-hour
m <sup>2</sup>	Square meter
yr	Year

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