Multi-Objective Optimization Techniques for HVAC Systems: From Classical Methods to Hybrid AI Approaches

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Abstract — HVAC systems account for a substantial share of building energy use and are central to maintaining indoor comfort and sustainability, making their optimization a critical research focus. However, improving HVAC performance involves balancing conflicting objectives such as reducing energy consumption and operational cost while ensuring thermal comfort and acceptable indoor air quality. To address this complexity, this study conducts a systematic review using structured methodologies, including PRISMA-based screening, bibliometric evaluation, and taxonomy-driven classification of existing approaches. The analysis reveals a clear progression in optimization techniques, moving from traditional deterministic methods to advanced artificial intelligence and hybrid models that combine learning and optimization capabilities. These developments have significantly enhanced the ability to manage dynamic and multi-objective HVAC systems. The study further provides a comprehensive comparative framework to evaluate different techniques and highlights key research gaps. Finally, it outlines future directions aimed at developing more adaptive, efficient, and intelligent HVAC optimization solutions.

Keywords: HVAC System Optimization; Energy Efficiency in Buildings; Thermal Comfort; Indoor Air Quality; Artificial Intelligence In HVAC; Multi-Objective Optimization;

I. INTRODUCTION

A. Background

Heating, Ventilation, and Air Conditioning (HVAC) systems play a vital role in maintaining indoor environmental quality in residential, commercial, and industrial buildings. In modern infrastructure, HVAC systems are recognized as one of the largest consumers of energy, accounting for approximately 40–60% of total building energy consumption. This significant energy demand highlights the necessity for efficient control and optimization strategies to reduce operational costs and environmental impact. Recent studies emphasize that inefficient HVAC operation leads not only to excessive energy usage but also to increased carbon emissions, thereby affecting sustainability goals [2], [5].

With the advancement of smart building technologies, the integration of sensors, automation systems, and data-driven approaches has opened new avenues for improving HVAC performance. Smart buildings aim to dynamically adjust HVAC operations based on occupancy patterns, environmental conditions, and user preferences. This transition from conventional control systems to intelligent systems necessitates robust optimization techniques capable of handling complex, dynamic, and uncertain environments [30]. Furthermore, the incorporation of predictive models and digital twin technologies has enabled real-time monitoring and optimization, making HVAC systems more adaptive and efficient [1], [30].

B. Problem Statement

The optimization of HVAC systems is inherently a multi-objective problem, where multiple conflicting objectives must be addressed simultaneously. The key trade-offs involved in HVAC optimization include:

- Energy Consumption: Minimizing energy usage to reduce operational costs and environmental impact
- Thermal Comfort: Maintaining occupant comfort using indices such as Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) [26], [27]
- Indoor Air Quality (IAQ): Ensuring adequate ventilation and maintaining acceptable CO_2 levels
- Cost and Emissions: Reducing lifecycle costs and greenhouse gas emissions

These objectives often conflict with each other. For instance, improving thermal comfort may require increased energy consumption, while reducing energy usage may compromise indoor comfort levels. Similarly, enhancing indoor air quality through increased ventilation can lead to higher energy demand. Therefore, achieving an optimal balance among these parameters remains a critical challenge in HVAC system design and operation [3], [28].

C. Motivation

Traditionally, HVAC optimization has been approached using single-objective optimization techniques, which focus primarily on minimizing energy consumption or cost. However, such approaches are limited in their ability to address the complex and interdependent nature of HVAC performance parameters. Single-objective methods often fail to capture the trade-offs between competing objectives, leading to suboptimal system performance [4], [16].

The growing demand for sustainable and energy-efficient buildings has led to the emergence of multi-objective optimization frameworks, which aim to simultaneously optimize multiple performance criteria. Evolutionary algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Non-dominated Sorting Genetic Algorithm II (NSGA-II) have been widely adopted due to their ability to generate Pareto-optimal solutions [13], [11]. In recent years, the integration of Artificial Intelligence (AI), Machine Learning (ML), and Reinforcement Learning (RL) has further enhanced the capability of HVAC optimization systems, enabling real-time decision-making and adaptive control [17], [18].

Moreover, hybrid approaches that combine classical optimization techniques with AI-based models have shown significant potential in improving system efficiency and robustness. These advancements motivate the need for a comprehensive review of existing techniques and their evolution toward hybrid intelligent systems.

D. Objectives of the Review

The primary aim of this review paper is to provide a comprehensive and critical analysis of multi-objective optimization techniques applied to HVAC systems. The specific objectives are as follows:

- To classify optimization techniques:
  Categorizing existing approaches into classical, metaheuristic, AI-based, and hybrid methods
- To critically compare methods:
  Evaluating the performance, advantages, and limitations of different optimization techniques
- To identify research gaps:
  Highlighting the limitations in current studies, such as lack of real-time adaptability, data dependency, and integration challenges
- To propose future hybrid frameworks:
  Suggesting advanced frameworks that integrate AI, IoT, and digital twin technologies for next-generation HVAC systems

These objectives aim to bridge the gap between theoretical developments and practical implementation of optimization strategies in modern smart buildings.

E. Paper Organization

This paper is organized into several sections to provide a systematic and comprehensive understanding of HVAC optimization techniques:

- Chapter 1 (Introduction):
  Presents the background, problem statement, motivation, objectives, and structure of the paper
- Chapter 2:
  Discusses the fundamentals of HVAC systems and key performance indicators
- Chapter 3:
  Reviews classical optimization techniques used in HVAC systems
- Chapter 4:
  Explores metaheuristic and evolutionary algorithms for multi-objective optimization
- Chapter 5:
  Examines AI and machine learning-based optimization approaches
- Chapter 6:
  Focuses on hybrid AI-based optimization frameworks and digital twin integration
- Chapter 7:
  Provides comparative analysis and taxonomy of optimization techniques
- Chapter 8:
  Identifies research gaps and challenges
- Chapter 9:
  Discusses future research directions
- Chapter 10 (Conclusion):
  Summarizes key findings and contributions of the review

II. FUNDAMENTALS OF HVAC SYSTEMS AND PERFORMANCE METRICS

A. HVAC System Types

Heating, Ventilation, and Air Conditioning (HVAC) systems are designed to regulate indoor environmental conditions to ensure thermal comfort and air quality. Depending on the application, scale, and operational requirements, HVAC systems can be categorized into several types.

1) Centralized HVAC Systems:

These systems use a central unit to condition air, which is then distributed throughout the building via ducts or pipes. Centralized systems are commonly used in large commercial and industrial buildings due to their efficiency in handling high cooling or heating loads. They enable better control and monitoring but require significant infrastructure and maintenance [20].

2) Decentralized HVAC Systems:

In decentralized systems, individual units are installed in different zones or rooms. These systems offer flexibility and ease of installation, making them suitable for small buildings or retrofitting applications. However, they may lead to inefficiencies due to lack of coordinated control [16].

3) Variable Refrigerant Flow (VRF) Systems:

VRF systems regulate the flow of refrigerant based on the demand of different zones. They are energy-efficient and provide precise temperature control, making them ideal for modern smart buildings. VRF systems also support simultaneous heating and cooling operations in different zones [5].

4) Chilled Water Systems:

These systems use chilled water as a cooling medium and are widely used in large-scale applications. They are known for their high efficiency and ability to serve multiple zones. However, they involve complex piping networks and require advanced control strategies for optimal performance [3].

The selection of HVAC system type significantly influences energy consumption and optimization strategies, necessitating tailored approaches for different configurations.

B. Key Performance Indicators

The performance of HVAC systems is evaluated using multiple indicators that reflect energy efficiency, occupant comfort, environmental impact, and economic feasibility.

1) Energy Consumption (kWh):

Energy consumption is a primary performance metric, as HVAC systems account for a significant portion of building energy usage. Reducing energy consumption is essential for improving sustainability and lowering operational costs [2].

2) Thermal Comfort (PMV and PPD):

Thermal comfort is typically quantified using the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) indices. These metrics evaluate occupants' thermal sensation and satisfaction levels, ensuring that indoor conditions meet acceptable comfort standards [26], [27].

3) Indoor Air Quality (IAQ):

IAQ is commonly assessed through parameters such as CO_2 concentration, humidity levels, and pollutant levels. Maintaining adequate IAQ is critical for occupant health and productivity, and it often requires balancing ventilation rates with energy consumption [28].

4) *Cost and Carbon Emissions:*

Economic and environmental considerations are increasingly important in HVAC system design. Operational costs include energy expenses and maintenance, while carbon emissions are associated with energy consumption and environmental impact. Optimization strategies aim to minimize both parameters simultaneously [5].

These performance indicators are often interdependent, making it necessary to adopt multi-objective optimization techniques to achieve balanced system performance.

C. *Mathematical Formulation of Multi-Objective Problem*

The optimization of HVAC systems can be formulated as a multi-objective problem, where multiple conflicting objectives are optimized simultaneously under a set of constraints.

1) *Objective Functions*

The primary objective functions typically include:

- Minimization of energy consumption
- Maximization of thermal comfort (or minimization of discomfort indices such as PPD)
- Minimization of operational cost and carbon emissions

These objectives are mathematically represented as functions of system variables such as temperature setpoints, airflow rates, and equipment operation schedules. Multi-objective optimization aims to generate a set of Pareto-optimal solutions that represent trade-offs among these objectives [13].

2) *Constraints*

The optimization process is subject to several constraints, including:

- Temperature constraints: Maintaining indoor temperature within acceptable limits
- Humidity constraints: Ensuring relative humidity remains within comfort range
- Airflow constraints: Maintaining adequate ventilation rates
- System capacity constraints: Equipment limitations and operational bounds

These constraints ensure that the optimized solutions are feasible and comply with comfort and safety standards. Advanced optimization techniques incorporate these constraints to provide realistic and implementable solutions [3], [4].

III. CLASSICAL OPTIMIZATION TECHNIQUES IN HVAC

A. *Deterministic Methods*

Deterministic optimization methods are among the earliest approaches used in HVAC system optimization. These methods rely on mathematical models with known parameters and relationships.

1) *Linear Programming (LP):*

LP techniques are used when the objective function and constraints are linear. They are computationally efficient and suitable for simplified HVAC models. However, real-world HVAC systems often exhibit nonlinear behavior, limiting the applicability of LP methods [4].

2) *Non-linear Programming (NLP):*

NLP methods are used to handle nonlinear relationships between variables. HVAC systems involve nonlinear dynamics due to heat transfer, fluid flow, and equipment characteristics, making NLP more suitable than LP. However, NLP problems are computationally intensive and may require iterative solution techniques [22].

B. *Gradient-Based Methods*

Gradient-based optimization methods utilize derivatives of objective functions to guide the search for optimal solutions.

1) *Advantages*

- Fast convergence toward optimal solutions
- Efficient for problems with smooth and differentiable objective functions
- Suitable for real-time control in simplified systems

2) *Limitations*

- Susceptible to getting trapped in local minima
- Require accurate mathematical models and differentiability
- Not suitable for highly nonlinear or discontinuous problems

Due to these limitations, gradient-based methods are often inadequate for complex HVAC systems with multiple conflicting objectives and uncertainties [24].

C. *Rule-Based and Heuristic Control*

Rule-based and heuristic approaches are widely used in practical HVAC systems due to their simplicity and ease of implementation.

1) *PID Control:*

Proportional-Integral-Derivative (PID) controllers are commonly used for temperature and airflow regulation. They provide stable control but lack adaptability to changing environmental conditions.

2) *Fuzzy Logic Control:*

Fuzzy logic controllers use linguistic rules and expert knowledge to handle uncertainties and nonlinearities. They offer improved flexibility compared to traditional controllers but depend heavily on rule design and tuning [16].

These approaches are suitable for basic control tasks but are limited in their ability to achieve global optimization.

D. *Limitations of Classical Techniques*

Despite their widespread use, classical optimization techniques exhibit several limitations when applied to modern HVAC systems:

1) *Poor Scalability:*

These methods struggle to handle large-scale systems with multiple variables and constraints

2) *Inability to Handle Dynamic Environments:*

HVAC systems operate under varying conditions such as occupancy changes and weather variations, which classical methods cannot effectively address

3) *Limited Capability for Multi-Objective Optimization:*

Traditional methods are primarily designed for single-objective problems and cannot efficiently manage trade-offs among multiple objectives

4) *Dependence on Accurate Mathematical Models:*

Classical methods require precise system models, which may not always be available or feasible

These limitations have driven the development of advanced optimization techniques, including metaheuristic algorithms and AI-based approaches, which are better suited for complex and dynamic HVAC systems [4], [21].

IV. EVOLUTION TO METAHEURISTIC OPTIMIZATION TECHNIQUES

The limitations of classical optimization techniques in handling nonlinear, multi-objective, and dynamic HVAC problems have led to the adoption of metaheuristic algorithms. These algorithms are inspired by natural processes and are capable of exploring large search spaces efficiently to obtain near-optimal solutions. Metaheuristic approaches are particularly suitable for HVAC systems due to their ability to handle conflicting objectives such as energy consumption, thermal comfort, and cost [4], [5].

A. Genetic Algorithm (GA)

Genetic Algorithms (GA) are evolutionary optimization techniques inspired by the process of natural selection. They operate through mechanisms such as selection, crossover, and mutation to evolve a population of candidate solutions over successive generations.

In HVAC systems, GA is widely used for optimizing control parameters, scheduling, and system configurations. It is particularly effective in multi-objective optimization problems where trade-offs between energy efficiency and comfort must be addressed [6], [7].

Key Features:

- Population-based search mechanism
- Ability to avoid local minima
- Suitable for nonlinear and multi-objective problems

However, GA may require significant computational time and careful parameter tuning to achieve optimal performance.

B. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is inspired by the social behavior of birds flocking or fish schooling. Each particle represents a potential solution and moves through the search space by updating its velocity and position based on individual and collective experiences.

PSO has been successfully applied in HVAC optimization for parameter tuning and energy management. It is known for its simplicity and fast convergence compared to other evolutionary algorithms [11], [3].

Key Features:

- Simple implementation
- Fast convergence rate
- Efficient in continuous optimization problems

Despite its advantages, PSO may suffer from premature convergence, especially in complex multi-objective problems.

C. Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is based on the foraging behavior of ants, where they find optimal paths by depositing pheromones. In HVAC applications, ACO is used for solving discrete optimization problems such as system scheduling and routing.

ACO is effective in handling combinatorial problems and can adapt to changing system conditions. However, its application in HVAC systems is relatively limited compared to GA and PSO due to higher computational complexity [4].

D. Simulated Annealing (SA)

Simulated Annealing (SA) is inspired by the annealing process in metallurgy, where materials are heated and gradually cooled to reach a stable state. SA explores the solution space by probabilistically accepting worse solutions to escape local minima.

In HVAC optimization, SA is used for parameter tuning and energy minimization problems. It is particularly useful in avoiding local optima but may require longer computational time due to its stochastic nature [4].

E. Multi-objective Algorithms

To address the trade-offs among multiple conflicting objectives, specialized multi-objective metaheuristic algorithms have been developed.

1) NSGA-II (Non-dominated Sorting Genetic Algorithm II): NSGA-II is one of the most widely used multi-objective optimization algorithms. It uses non-dominated sorting and crowding distance mechanisms to generate a diverse set of Pareto-optimal solutions. It has been extensively applied in HVAC optimization to balance energy consumption and thermal comfort [13].

2) MOPSO (Multi-objective Particle Swarm Optimization): MOPSO extends PSO to handle multiple objectives by maintaining an archive of non-dominated solutions. It combines the advantages of PSO with Pareto-based optimization, making it suitable for HVAC systems with dynamic operating conditions [15].

These algorithms provide a set of optimal solutions rather than a single solution, allowing decision-makers to choose the most appropriate trade-off.

F. Comparative Analysis Table

Algorithm	Strength	Limitation	HVAC Application
GA	Handles nonlinear multi-objective problems, avoids local minima	High computational cost, parameter tuning required	Energy optimization, scheduling, control tuning [6], [7]
PSO	Fast convergence, simple implementation	Premature convergence risk	Real-time HVAC parameter optimization [3], [11]
ACO	Suitable for discrete and combinatorial problems	Computational complexity	HVAC scheduling and routing [4]
SA	Escapes local minima effectively	Slow convergence	Energy minimization and system tuning [4]
NSGA-II	Provides Pareto-optimal solutions,	Computational overhead	Multi-objective HVAC

	maintains diversity		optimization [13]
MOPSO	Combines PSO efficiency with multi-objective capability	Archive management complexity	Dynamic HVAC optimization [15]
Algorithm	Strength	Limitation	HVAC Application
GA	Handles nonlinear multi-objective problems, avoids local minima	High computational cost, parameter tuning required	Energy optimization, scheduling, control tuning [6], [7]

V. AI AND MACHINE LEARNING-BASED OPTIMIZATION

With the advancement of computational intelligence, Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as powerful tools for HVAC optimization. These methods enable data-driven decision-making and adaptive control, making them highly suitable for modern smart building environments [16], [20].

A. Supervised Learning Models

Supervised learning techniques are widely used for predicting HVAC system behavior and optimizing performance.

1) Artificial Neural Networks (ANN):
ANN models are capable of capturing complex nonlinear relationships between input variables (e.g., temperature, occupancy) and output parameters (e.g., energy consumption). They are commonly used for energy prediction and system modeling [19].

2) Support Vector Machines (SVM):
SVM models are effective for regression and classification tasks in HVAC systems, particularly for predicting energy demand and detecting anomalies.

3) Regression Models:
Regression techniques provide simple and interpretable models for estimating HVAC performance metrics. They are often used as baseline models for comparison.

B. Deep Learning

Deep learning techniques have gained significant attention due to their ability to process large datasets and extract complex patterns.

1) Long Short-Term Memory (LSTM):
LSTM networks are used for time-series prediction, such as forecasting HVAC load and energy demand. They are particularly effective in capturing temporal dependencies in building data.

2) Convolutional Neural Networks (CNN):
CNN models are used for pattern recognition and feature extraction from sensor data. They can identify spatial and temporal patterns in HVAC system performance.

These techniques enhance predictive accuracy and enable proactive optimization strategies [18].

C. Reinforcement Learning (RL)

Reinforcement Learning (RL) is a powerful approach for sequential decision-making in dynamic environments. In HVAC systems, RL algorithms learn optimal control policies through interaction with the environment.

1) Q-learning:
A model-free RL algorithm that learns optimal actions based on reward feedback.

2) Deep Reinforcement Learning (Deep RL):
Combines RL with deep neural networks to handle complex and high-dimensional HVAC control problems.

RL-based approaches are particularly effective for real-time adaptive control, where system conditions continuously change [17], [18].

D. Advantages of AI-Based Optimization

AI and ML-based approaches offer several advantages over traditional methods:

- Adaptive and real-time optimization:
  Ability to adjust system operation based on real-time data
- Handling nonlinear and complex systems:
  Effective in modeling complex HVAC dynamics
- Reduced reliance on explicit mathematical models:
  Data-driven approaches eliminate the need for precise system modeling
- Improved prediction accuracy:
  Enables proactive control strategies

E. Challenges of AI-Based Optimization

Despite their advantages, AI-based methods face several challenges:

- Data dependency:
  Requires large and high-quality datasets for training
- Computational cost:
  High processing requirements for training and deployment
- Model interpretability:
  Difficulty in understanding decision-making processes
- Integration complexity:
  Challenges in integrating AI models with existing HVAC systems

These challenges highlight the need for hybrid approaches that combine the strengths of AI and traditional optimization techniques [21], [22].

VI. HYBRID AI-BASED OPTIMIZATION APPROACHES

The increasing complexity of HVAC systems and the limitations of standalone optimization techniques have led to the development of hybrid approaches that combine the strengths of metaheuristic algorithms and artificial intelligence. Hybrid AI-based optimization integrates data-driven models with search-based algorithms to achieve improved accuracy, adaptability, and computational efficiency. These approaches are particularly effective in addressing multi-objective problems involving energy efficiency, thermal comfort, and operational cost [21], [25].

A. Hybrid Models

Hybrid models leverage the complementary advantages of different optimization and learning techniques.

1) GA + ANN:
Genetic Algorithms are used to optimize the structure and parameters of Artificial Neural Networks, enhancing prediction accuracy and optimization performance. In HVAC

systems, GA–ANN models are widely applied for energy consumption prediction and control parameter tuning, resulting in improved system efficiency [6], [25].

2) PSO + Fuzzy Logic:

Particle Swarm Optimization is combined with fuzzy logic controllers to optimize rule sets and membership functions. This hybrid approach improves the adaptability of fuzzy systems in handling uncertainties and nonlinear HVAC dynamics, leading to better control performance compared to conventional methods [4].

3) RL + Digital Twin:

Reinforcement Learning integrated with digital twin technology enables real-time decision-making based on simulated environments. The digital twin acts as a virtual replica of the HVAC system, allowing RL algorithms to learn optimal control policies without affecting actual operations. This approach enhances system reliability and reduces operational risks [30].

These hybrid models significantly outperform standalone techniques by combining predictive capabilities with optimization efficiency.

B. *Digital Twin Integration*

Digital twin technology has emerged as a transformative tool in HVAC optimization. It involves creating a virtual model of the physical system that continuously receives real-time data from sensors and simulates system behavior.

- Enables real-time monitoring and predictive analysis
- Facilitates optimization of system performance under varying conditions
- Supports fault detection and preventive maintenance

By integrating optimization algorithms with digital twins, HVAC systems can achieve dynamic and adaptive control. This integration allows continuous improvement of system performance by evaluating multiple scenarios in a virtual environment before implementation [30].

C. *IoT-enabled Smart HVAC Systems*

The Internet of Things (IoT) plays a crucial role in modern HVAC optimization by enabling seamless communication between sensors, controllers, and optimization algorithms.

Key features of IoT-enabled HVAC systems include:

- Real-time data acquisition: Temperature, humidity, occupancy, and air quality data
- Remote monitoring and control: Cloud-based platforms for system management
- Adaptive control strategies: Dynamic adjustment of system parameters
- Energy-efficient operation: Optimization based on real-time demand

IoT integration enhances the effectiveness of AI-based optimization techniques by providing continuous data streams required for learning and decision-making. It also enables the implementation of smart building concepts, where HVAC systems operate autonomously to achieve optimal performance [16], [20].

D. *Case Studies*

1) Smart Buildings

In smart buildings, hybrid optimization techniques are used to balance energy consumption and occupant comfort. AI-driven control systems combined with metaheuristic algorithms enable efficient energy management and adaptive control. Digital twin integration further enhances system performance by enabling real-time optimization and predictive maintenance [1], [30].

2) Commercial HVAC Systems

Commercial buildings often have complex HVAC requirements due to varying occupancy patterns and operational conditions. Hybrid approaches such as GA–ANN and RL-based control have demonstrated significant improvements in energy efficiency and cost reduction. These methods provide scalable solutions capable of handling large and dynamic systems [7], [18].

VII. COMPARATIVE ANALYSIS AND TAXONOMY

A. *Classification Framework*

HVAC optimization techniques can be broadly classified into four categories:

- Classical Methods:
  Deterministic and rule-based approaches with limited adaptability
- Metaheuristic Methods:
  Evolutionary algorithms such as GA, PSO, and NSGA-II capable of handling complex optimization problems
- AI-Based Methods:
  Machine learning and reinforcement learning approaches that enable data-driven optimization
- Hybrid Methods:
  Integration of AI and metaheuristic techniques for enhanced performance

This classification framework provides a structured understanding of the evolution of HVAC optimization techniques and highlights the transition toward intelligent and adaptive systems [4], [16].

B. *Performance Comparison*

The performance of different optimization techniques can be compared based on key criteria such as accuracy, complexity, real-time capability, and scalability.

Method	Accuracy	Complexity	Real-time Capability	Scalability
Classical Methods	Low–Moderate	Low	Limited	Poor
Metaheuristic Methods	High	Moderate–High	Moderate	Good
AI-Based Methods	Very High	High	High	Moderate
Hybrid Methods	Very High	High	Very High	Excellent

Hybrid approaches generally provide superior performance due to their ability to combine predictive accuracy with optimization efficiency.

C. *Visualization*

Visualization techniques play an important role in analyzing and interpreting optimization results.

- Radar Charts:
  Used to compare multiple performance metrics across different optimization methods
- Heat Maps:

Provide visual representation of performance variations across different parameters

These visualization tools help researchers and practitioners understand trade-offs and select appropriate optimization strategies.

VIII. RESEARCH GAPS AND CHALLENGES

Despite significant advancements in HVAC optimization, several research gaps and challenges remain.

- Lack of Real-Time Adaptive Optimization:
  Although AI-based methods offer real-time capabilities, many systems still rely on offline optimization techniques, limiting their adaptability to dynamic environments [17].
- Integration Issues with Legacy Systems:
  Existing HVAC infrastructure often lacks compatibility with advanced optimization technologies, making integration challenging and costly [21].
- Limited Datasets for AI Training:
  AI models require large and high-quality datasets, which are often unavailable or difficult to obtain in real-world scenarios [16].
- Energy–Comfort Trade-off Unresolved:
  Achieving an optimal balance between energy efficiency and thermal comfort remains a complex challenge due to conflicting objectives [26], [28].
- Cybersecurity Issues in IoT-Based HVAC Systems:
  The increasing use of IoT introduces vulnerabilities related to data privacy and system security, which must be addressed to ensure reliable operation [30].

Addressing these challenges requires the development of robust, scalable, and secure optimization frameworks that integrate advanced technologies such as AI, IoT, and digital twins.

A. Future Directions

The rapid evolution of optimization techniques and intelligent control systems has opened new research avenues in HVAC system design and operation. Future developments are expected to focus on integrating advanced computational technologies to enhance system efficiency, adaptability, and sustainability.

B. Digital Twin + AI Integration

The integration of Digital Twin technology with Artificial Intelligence represents a promising direction for next-generation HVAC systems. Digital twins provide a real-time virtual representation of physical systems, enabling continuous monitoring, simulation, and optimization.

When combined with AI algorithms, digital twins can:

- Predict system behavior under varying operating conditions
- Enable self-learning and adaptive control
- Optimize performance in real-time without disrupting actual operations

This integration enhances decision-making capabilities and supports predictive maintenance strategies, thereby improving system reliability and efficiency [30], [21].

C. Edge Computing for HVAC

Edge computing is emerging as a key enabler for real-time HVAC optimization. Unlike cloud-based systems, edge computing processes data closer to the source, reducing latency and improving response time.

Key advantages include:

- Faster decision-making for dynamic environments
- Reduced dependency on centralized servers
- Improved data privacy and security

In HVAC applications, edge computing facilitates real-time control of system parameters based on local sensor data, making it highly suitable for smart building environments [16].

D. Explainable AI (XAI)

As AI-based HVAC optimization systems become more complex, the need for transparency and interpretability has increased. Explainable AI (XAI) aims to provide insights into how AI models make decisions.

- Enhances trust in AI-driven HVAC systems
- Facilitates debugging and model validation
- Supports regulatory compliance and user acceptance

XAI is particularly important in critical applications where understanding system behavior is essential for safe and efficient operation [18].

E. Net-Zero Energy Buildings

The concept of net-zero energy buildings (NZEB) focuses on minimizing energy consumption and balancing it with renewable energy generation. HVAC systems play a crucial role in achieving this goal.

Future HVAC optimization strategies will:

- Minimize energy demand through intelligent control
- Integrate with renewable energy sources
- Optimize energy storage and utilization

Advanced optimization techniques and AI-based control systems are expected to significantly contribute to the realization of NZEB objectives [2], [5].

F. Integration with Renewable Energy Systems

The integration of HVAC systems with renewable energy sources such as solar and wind energy is gaining importance in sustainable building design.

Key considerations include:

- Managing variability of renewable energy supply
- Coordinating HVAC operation with energy generation
- Optimizing energy storage systems

Hybrid optimization approaches can effectively balance energy demand and supply, ensuring efficient utilization of renewable resources [5], [22].

IX. PROPOSED CONCEPTUAL FRAMEWORK

To address the limitations of existing approaches, a hybrid AI-based multi-objective optimization framework is proposed for HVAC systems. This framework integrates advanced computational techniques with real-time data acquisition and control mechanisms.

Key Components of the Framework

- Sensors (IoT):
  Collect real-time data on temperature, humidity, occupancy, and air quality
- Predictive Models:
  Utilize machine learning algorithms such as ANN and LSTM for forecasting system behavior
- Optimization Engine:
  Employ hybrid algorithms (e.g., GA–ANN, PSO–Fuzzy, RL-based methods) to determine optimal control strategies
- Control System:
  Implement optimized parameters in real-time to regulate HVAC operation

This integrated framework enables adaptive, data-driven optimization and enhances system performance in dynamic environments. The use of digital twin technology further supports real-time simulation and decision-making [25], [30].

X. METHODOLOGY FOR REVIEW

A systematic methodology is essential to ensure the quality and reliability of the review.

A. PRISMA Flow Diagram

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework is used to identify, screen, and select relevant studies. It ensures transparency and reproducibility in the review process.

1) Database Sources

The literature review is conducted using reputable databases, including:

- Scopus
- Web of Science
- IEEE Xplore

These databases provide access to high-quality peer-reviewed articles relevant to HVAC optimization.

B. Inclusion and Exclusion Criteria

- Inclusion:
  - Peer-reviewed journal articles
  - Studies focusing on HVAC optimization techniques
  - Publications within the selected time frame
- Exclusion:
  - Non-peer-reviewed sources
  - Irrelevant or duplicate studies
  - Studies lacking sufficient methodological detail

C. Time Span

The review considers publications from 2005 to 2025, capturing the evolution of optimization techniques from classical methods to hybrid AI approaches.

D. Bibliometric Analysis

Bibliometric techniques are used to analyze:

- Publication trends
- Citation patterns
- Research hotspots

This analysis provides insights into the development and impact of HVAC optimization research [4], [16].

XI. DISCUSSION

The comprehensive review of HVAC optimization techniques reveals several critical insights.

A. Critical Insights

- Transition from classical to AI-based methods has significantly improved system performance
- Hybrid approaches offer superior accuracy and adaptability
- Multi-objective optimization is essential for balancing energy, comfort, and cost

B. Practical Implications

- Adoption of AI-based optimization can reduce energy consumption and operational costs
- Smart HVAC systems enhance occupant comfort and productivity
- Integration with IoT and digital twin technologies enables real-time control

C. Industrial Relevance

- Applicable in commercial buildings, smart cities, and industrial facilities
- Supports sustainability goals and regulatory compliance
- Enhances competitiveness through energy-efficient operations

These findings highlight the importance of adopting advanced optimization techniques in modern HVAC systems [7], [18].

XII. CONCLUSION

A. Summary of Findings

This review highlights the evolution of HVAC optimization techniques from classical deterministic methods to advanced hybrid AI-based approaches. Metaheuristic algorithms and machine learning techniques have significantly enhanced the ability to handle complex and multi-objective optimization problems.

B. Key Contributions

- Comprehensive classification of HVAC optimization techniques
- Critical comparison of classical, metaheuristic, AI, and hybrid methods
- Identification of research gaps and future directions
- Proposal of a hybrid AI-based conceptual framework

C. Final Recommendations

- Adoption of hybrid optimization approaches for improved performance
- Integration of AI, IoT, and digital twin technologies
- Development of real-time adaptive control systems
- Focus on sustainability and net-zero energy objectives

The study concludes that hybrid AI-based optimization represents the most promising approach for next-generation HVAC systems, offering enhanced efficiency, adaptability, and sustainability [21], [30].

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