EVALUATING THE EFFICIENCY OF HVAC SYSTEMS CONSIDERING OCCUPANCY AND CO_2 CONCENTRATION

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Abstract

This study examines the effectiveness of HVAC (Heating, Ventilation, and Air Conditioning) systems that integrate occupancy and CO_2 sensing technologies. These smart systems enable real-time, demand-controlled ventilation (DCV), dynamically adjusting airflow to maintain indoor air quality while reducing energy use. The article presents a comprehensive analysis of modern sensor technologies, mathematical models, and AI-based control methods such as Model Predictive Control (MPC) and Reinforcement Learning (RL). It also compares international ventilation standards and outlines key implementation challenges. Findings show that integrating occupancy and CO_2 data into HVAC control can yield energy savings of 10–30% while improving indoor air quality and cognitive performance. The results support the transition toward intelligent, energy-efficient, and health-conscious building environments.

Keywords

HVAC systems; CO_2 concentration; occupancy detection; demand-controlled ventilation (DCV); energy efficiency; indoor air quality (IAQ); model predictive control (MPC); reinforcement learning (RL); smart buildings; sustainable technologies.

Introduction

Heating, Ventilation, and Air Conditioning (HVAC) systems are fundamental to maintaining thermal comfort and indoor air quality (IAQ) in residential, commercial, and industrial buildings. However, they also represent one of the largest sources of energy consumption worldwide. According to the International Energy Agency (IEA), space heating, cooling, and ventilation collectively account for approximately **40–50%** of total energy use in buildings [1], and up to **60%** in certain commercial facilities such as schools, hospitals, and office towers [2].

Conventional HVAC systems typically operate based on **predefined schedules, static temperature set points,** or **manual user input,** without adapting to real-time occupancy levels or actual air quality. This often results in **over-ventilation during unoccupied periods,** leading to unnecessary energy waste, or **under-ventilation during high occupancy,** compromising comfort and productivity [3].

Carbon dioxide (CO_2) has emerged as a reliable and cost-effective proxy for both **human presence** and **ventilation adequacy.** Since CO_2 is a direct byproduct of human respiration, its indoor concentration correlates strongly with occupancy levels and the effectiveness of air exchange. Research has consistently shown that elevated CO_2 levels (above **1000 ppm**) can impair cognitive function, cause drowsiness, and reduce decision-making ability [4,5].

To address these inefficiencies and health risks, modern buildings are increasingly adopting **Demand-Controlled Ventilation (DCV)** strategies. DCV dynamically adjusts ventilation rates based on **real-time CO_2 measurements** and **occupancy detection,** using a combination of **smart sensors, machine learning algorithms,** and **IoT-based control platforms** [6–8].

The integration of CO_2 and occupancy sensors into HVAC control systems represents a critical advancement toward **energy-efficient, health-oriented,** and **data-driven** building management. These technologies are aligned with global sustainability goals such as **net-zero energy buildings, LEED certification,** and **smart city development** [9-10].

This paper aims to evaluate the effectiveness of HVAC systems enhanced with CO_2 and occupancy sensors. It presents:

- a review of current sensing and control technologies,
- mathematical models for air quality and energy optimization,
- real-world case studies showing economic and environmental benefits,
- and an analysis of implementation challenges and future trends.

This comprehensive approach highlights the transformative potential of sensor-driven HVAC systems in achieving sustainable and healthy indoor environments.

1. Significance of CO_2 Monitoring in Indoor Environments

Indoor CO_2 concentration is a well-established indicator of ventilation adequacy. Poor ventilation can lead to CO_2 accumulation, causing drowsiness, reduced concentration, and health issues. Studies show that:

- 600–800 ppm — ideal for high productivity;

• 1000 ppm — ASHRAE's upper comfort threshold;

• >1400 ppm — associated with up to 50% drop in decision-making ability [4-5].

Furthermore, CO_2 accumulation often correlates with increased concentrations of volatile organic compounds (VOCs) and humidity, which can lead to mold and sick building syndrome (SBS).

2. Advanced Occupancy Detection Techniques

Traditional presence sensors (e.g., PIR, ultrasonic) are often binary and inaccurate. Modern systems use:

• Vision-based analytics (e.g., thermal or optical cameras with AI)

• Wi-Fi or Bluetooth signal tracking (anonymous, privacy-safe)

• Pressure sensors on furniture

• Infrared depth sensors (e.g., Microsoft Kinect for room-level tracking)

Machine learning algorithms are increasingly used to predict occupancy patterns and ventilation needs [3,11].

Table 1

№	Component	Function
1	Sensors	Measure CO_2, humidity, temperature, presence
2	Controller	Processes sensor data and runs control logic
3	Actuators	Adjust airflows, damper positions, and fan speeds
4	AI/ML Engine	Predicts occupancy, optimizes scheduling and load
5	Interface	Visualizes data, allows manual override

Table 1. An optimal HVAC control system using CO_2 and occupancy data includes the components

Recent research shows that hybrid systems combining real-time data and predictive modeling outperform rule-based controls by up to 20% [6].

3. Mathematical Modeling and Control Algorithms (Expanded)

Demand-Controlled Ventilation (DCV) systems rely heavily on mathematical models to predict indoor air conditions and adjust airflow accordingly. These models enable the system to respond dynamically to variations in occupancy and air quality, optimizing both **energy use** and **indoor environmental quality.**

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•Dynamic Mass Balance Equation for CO_2 Concentration

The most widely used mathematical framework for CO_2-based ventilation control is the **dynamic mass balance equation,** which describes the rate of change of indoor CO_2 concentration over time:

$$\frac{dC(t)}{dt} = \frac{G(t)}{V} - \frac{Q(t)}{V}(C(t) - C_{out}) \quad (1)$$

Where:

- $C(t)$: indoor CO_2 concentration at time ttt (ppm)
- $G(t)$: CO_2 generation rate (e.g., from occupants, mg/h)
- $Q(t)$: ventilation airflow rate (m^3/h)
- V: room volume (m^3)
- C_{out}: outdoor CO_2 concentration, typically 400–450 ppm

This equation assumes well-mixed air and can be solved numerically to anticipate CO_2 build up and control ventilation dynamically [12].

•Modeling Occupancy and CO_2 Generation Rate

The CO_2 generation rate G(t) depends on:

- Number of occupants at time ttt
- Metabolic activity (e.g., resting, walking)
- Additional factors like age or gender

Typical value for an adult at rest is ~18 L/h of CO_2 (~0.005 m^3/h) [2].

Advanced estimation methods combine:

- Motion sensors (PIR, ultrasonic)
- Computer vision and AI occupancy models
- Wi-Fi/Bluetooth signal-based detection
- Inverse modeling from CO_2 trends [3]

•Ventilation Control Strategies

1. *Rule-Based Control*

If CO_2 > threshold → increase airflow; If CO_2 < threshold → reduce airflow. Easy to implement but inflexible in dynamic environments [8].

2. *Proportional-Integral (PI) Control*

PI control uses the error between actual and target CO_2:

$$Q(t) = K_p(C(t) - C_{target}) + K_i \int (C(t) - C_{target})dt \quad (2)$$

PI controllers are widely used in building automation [8].

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•Model Predictive Control (MPC)

MPC optimizes HVAC operation by forecasting future CO_2 concentrations and solving a constrained optimization problem:

$$\min_{Q(t)} \sum_{t=0}^{T} [\omega_1 (C(t) - C_{target})^2 + \omega_2 E(Q(t))] \quad (3)$$

This approach balances indoor air quality with energy savings [6,14]. MPC has shown better stability and responsiveness compared to traditional feedback methods, especially in spaces with irregular occupancy patterns [13].

•Reinforcement Learning (RL)

RL uses agents that learn optimal HVAC policies through experience. Each "episode" teaches the controller how to:

- Minimize energy consumption
- Avoid high CO_2 concentrations

Modern RL techniques such as DQN or PPO can adapt to diverse environments without explicit models [15]. RL is especially valuable when building conditions are highly dynamic and uncertain [7].

•Hybrid Approaches and Digital Twins

Emerging HVAC control systems now integrate:

- Physics-based models (mass balance)
- Machine learning for prediction
- Real-time digital twins for simulation and optimization

This fusion enhances system robustness, fault detection, and control precision [10].

4. Comparison with International Standards

Table 2

№	Standard	Max CO_2 (ppm)	Basis of Ventilation	Regio
1	ASHRAE 62.1 (2022)	1000	People and area	U.S.
2	EN 16798-1 (2019)	800	Air quality level	EU
3	WELL v2 (IWBI)	600-800	Health-focused	Global
4	SNIP 41-01-2003	900-1000	Fixed rates	Russia

Table 2. Comparison with International Standards

Most modern systems go beyond these thresholds by dynamically controlling air supply based on occupancy and measured CO_2.

5. Challenges and Barriers

Despite the promise, DCV systems face certain limitations:

- **Sensor drift** and calibration needs
- **Privacy concerns** with camera-based tracking
- **Complex integration** into legacy HVAC systems
- **Initial cost** of implementation, especially for retrofits
- **False positives** in occupancy detection due to pets, fans, etc.

Hybrid sensing and robust AI algorithms are addressing these challenges [8].

Conclusion

The integration of CO_2 concentration monitoring and occupancy detection into HVAC systems represents a significant advancement in energy-efficient building management. Demand-Controlled Ventilation (DCV), supported by predictive models and intelligent algorithms, enables adaptive control of ventilation that responds to real-time indoor environmental conditions. The use of mathematical modeling, such as dynamic mass balance equations, along with advanced strategies like Model Predictive Control and Reinforcement Learning, allows for more precise and energy-conscious HVAC operations. Real-world data and international benchmarks indicate that such systems can reduce energy consumption by 10–30% while ensuring compliance with health-oriented air quality standards. Despite challenges such as sensor calibration, system complexity, and privacy concerns, ongoing innovations in hybrid sensing, AI, and digital twin integration continue to improve reliability and performance. Overall, CO_2- and occupancy-aware HVAC control systems offer a robust solution for achieving sustainable, healthy, and smart building environments.

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