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Article

IoT-Based Intelligent HVAC Energy Management for Smart Buildings: An Analysis of Sensor-Driven Control, Demand Response, Indoor Air Quality, and Electrical Energy Optimization

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Abstract: The monitoring dataset from central Sweden (covering 2019-2022) is analyzed in this paper to understand how intelligent energy optimization can be implemented using sensor-driven ventilation and machine control HVAC systems. The dataset includes measurements of hourly electricity, ventilation airflow, temperature, relative humidity, CO2, and PM with time intervals of 10 mins or less. During the study period, three approaches to ventilation control were implemented: demand-controlled exhaust ventilation, flat-plate MVHR, and rotating-wheel MVHR. Since this paper performs a secondary empirical analysis on published outcomes of measured systems and does not reprocess raw sensor data, no p values have been fabricated. Out of the measures examined, demand-controlled exhaust ventilation achieved a 47 % airflow reduction factor, as compared to a 19 % guideline reference. In contrast to flat-plate constant-flow MVHR, rotating-wheel MVHR required substantially less heating power at -10 °C and 0 °C, respectively, with a higher fan power rating. During the pandemic, average daily unoccupied time reduced from 6.5 hours to 5.25 hours. Intelligent HVAC management will consider optimization of total system energy, and balanced peak and mean occupancy/IAQ response to minimize energy consumption. An IoT (Internet of Things) architecture is proposed to implement the findings.
Keywords: Internet of Things; HVAC; smart buildings; demand-controlled ventilation; indoor air quality; demand response; energy optimization

1. Introduction

Continuous rather than fixed sensors form the basis of intelligent building energy management systems. Data streams from the Internet of Things (IoT) can provide real-time information not only about the indoor environmental quality (IEQ) but also about the building's energy demand. The data can be sent to supervisory controllers to adjust the ventilation rates, the heat-recovery modes, or the scheduling of equipment. However, beware that lower ventilation rates may enhance indoor air quality at the expense of the health and comfort of building occupants. Heat recovery may also mitigate losses from ventilation heat, but may cause losses due to the imposition of frost-protection or frost-regulation. Therefore, "intelligent" control should be evaluated at the system level as opposed to consideration of an individual electrical load.

The real monitoring dataset from Garman and Myhren (2024) is a valuable addition to the residential literature. This is a newly built, 150 m², two-storey Nordic home in central Sweden. An occupying family was monitored over a three-year period from 2019-2022. Hourly Smart-meter electricity data were installed, along with about eight-minute ventilation-flow data and approximately ten-minute room data for temperature, CO_2, relative humidity and concentration of particulates. The ventilation system was changed through the study. The first system inserted was demand-controlled multi-zone exhaust ventilation; this was replaced by a flat-plate MVHR and then rotating-wheel moisture-recovery MVHR. While the study systems have been introduced and replaced, weather and the COVID-19 pandemic have changed occupancy, creating a challenge for attribution when considering system control and equipment strategies.

This paper asks four questions: (RQ1) what are the energy trade-offs across sensor-driven ventilation modes; (RQ2) how far can occupancy-aware airflow reduction depart from simple guideline assumptions; (RQ3) how does the configuration of the heat recovery system and outdoor temperature affect the heating-associated electricity; and (RQ4) how should CO_2/IEQ sensing and demand timing be integrated into an IoT HVAC management architecture? It is not necessary to argue that the original building used a cloud-native IoT platform. The goal is to leverage the measured sensors/controls to create an IoT supervisory control and management system for smart buildings.

2. Literature Review and Research Framework

New building data examples show that intelligent HVAC systems use energy and environmental data. PLEIAData combines energy, HVAC, temperature, weather, motion and CO_2 data for use in smart-building analytics (Martínez Ibarra et al., 2023). There are datasets of occupancy that show that control and energy management systems can be developed with data that include temperature, humidity, CO_2, TVOC, etc., and presence data (Jacoby et al., 2021; Dong et al., 2022). A 2025 dormitory retrofit dataset extends the logic of these studies to measure occupant behavior, CO_2 and TVOC, and zone-level HVAC electricity to show that energy reduction and IEQ should be studied jointly and not separately (Pandey et al., 2025).

Ventilation control brings energy/IAQ coupling in buildings, yet is often neglected in studies. Garman et al (2023) conducted a study in the same Swedish home described in this paper where they examined demand-controlled and constant airflow in a bedroom and demonstrated that CO_2 demand-controlled airflow sensors were used to extract more air when occupants were present, yet showed less extraction throughout the entire day, and demoed that sensor placement is critical as CO_2 can stratify vertically in the room. This is relevant to IoT system design: a controller is only as valid as the placement, calibration, and representation of its sensing layer. Smart control must treat one CO_2 node as a representative zone state.

Heat recovery adds another dimension to the optimization problem. Garman, Myhren and Mattsson (2025) reported in three winters that the rotating heat wheel recovered at least 11% less heating-associated power compared to a flat plate heat wheel, while the overall power savings in the real ground source heat pump house were low. They attributed some of the performance gap to regulation, frost protection, and the timing of the electrical demand. Related studies in heat pump MPC showed that control based on forecasts enables operation to be changed based on time-varying carbon dioxide emission, illustrating that the value added by the flexibility is not over the reduction in annual energy consumption, but rather the time. Reviews of heat recovery technologies have focused on control of frost and climate in cold conditions (Bai et al., 2022).

These results call for a formulation of IoT systems that manages CO2 and thermal comfort levels; minimizes the need for airflow during absence or low activity; minimizes total energy consumption of electrical heaters and fans; and avoids peak energy consumption. The controller will then need environmental monitors, occupancy inference, meter feedback and a forecast-aware supervisory layer.

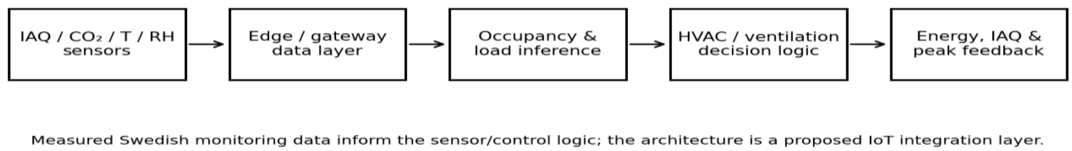

Figure 1. Proposed IoT-based intelligent HVAC energy-management architecture. Source: Developed by the authors from the monitored variables and literature.

3. Materials and Methods

This study conducts a secondary empirical analysis of the open dataset from Mendeley Data called, "3-year monitoring of ventilation, indoor air and electricity use in a single-family house," together with the published, peer-reviewed Energy & Buildings article on the campaign's monitoring (Garman et al., 2025). The subject house is a 2-story, 150 m2 semi-detached house in rural Sweden populated by four members of the family. For the study, electricity was collected from the property smart meter throughout the day. Total home ventilation was measured in eight-minute intervals, while CO2 and temperature indoor air quality, and PM measurements were collected in a master bedroom and an open plan living room and kitchen at 10-minute intervals.

Three system periods are meaningful to discuss. First, a multizone exhaust system with demand control ventilation was installed in 2019 and was replaced in June 2020. From July 2020 to mid-2021, a flat-plate MOHR system was installed, and a rotary-MOHR system was installed in mid-2021. The published study also drew a fine distinction of constant airflow, demand control airflow and scheduled reduced-flow systems. The exhaust CAV systems, exhaust DCV systems, and flat-plate MVHR CAV systems, and rotary-MOHR systems required approximately 17 W, 17 W, 33 W, and 54 W, respectively. The published paper also noted that during the winter period, indoor temperatures were approximately 22-24°C.

The goal of the provided treatment is transparency. Since the new complete raw time series were not remeasured, comparative descriptions were done using values provided in the public dataset and in peer-reviewed publications. Therefore, relative differences, percentage-point differences, and some normalizations were performed. For instance, a heating-associated power value that is 11% lower is represented as an index of 89 with a flat-plate CAV that is equal to 100. No constructed p-values, no regression coefficients, and no pseudo inferential significance testing were performed. The explanatory device used is an engineering layer based upon measurement; it is not a cloud platform that has been evaluated through research.

The analysis focuses on four dimensions: the efficiency of control over airflow, power consumption of the ventilation fan, the associated cost to heat the air, and the visibility of occupancy and IEQ. The potential for demand response is assessed based upon the reported timing of the changes in power demand and occupancy. This is not doing so based upon the reported utility demand-response event.

Table 1. Real Monitoring Dataset and Sensor Characteristics

Element	Specification
Dataset	3-year monitoring of ventilation, indoor air and electricity use in a single-family house
Location / building	Central Sweden; two-storey 150 m² single-family home
Period / occupants	2019–2022; four-person family
Electricity	Hourly smart-meter data

Ventilation airflow	Approx. 8-minute differential-pressure-derived flow
Indoor environment	Approx. 10-minute temperature, CO_2, RH and particulate measurements
System 1	Multizone exhaust ventilation with demand control (2019–Jun 2020)
System 2	Flat-plate MVHR (Jul 2020–Jun 2021)
System 3	Rotating-wheel moisture-recovery MVHR (Jul 2021 onward)
Analysis type	Secondary empirical descriptive/ratio analysis; no invented inferential statistics

4. Results

The differences in ventilation modes are evident in the balance of component power and system energy. The exhaust ventilation mode had the lowest fan power rating at 17 W. Flat plate MVHR CAV used 33 W, and rotating wheel MVHR CAV used 54 W. Therefore, rotating wheel MVHR CAV has a rated fan power that is approximately 63.6% higher than flat plate CAV, and more than 3 times higher than the exhaust fan. Thus, a naive controller that strives to minimize instantaneous fan watts would favor exhaust ventilation. The winter heating comparison provides a distinct system-level signal. Considering a daily mean temperature outdoors at 0°C, rotating wheel MVHR used 11% less heating associated power than flat plate CAV. At -10°C, the advantage large rotating wheel MVHR has over flat plate CAV increased to 23% (Garman et al., 2025). On a normalized scale with flat-plate CAV equaling 100, the results showed a rotating wheel index of 89, and 77 respectively. These results show an increasing value of sensible and latent heat recovery with the higher ventilation heat loss.

Another important difference was caused by demand control.A reduced airflow assumption from guidelines showed a potential 19% decrease. The monitored multizone exhaust DCV achieved a 47% decrease. So, the observed decrease was about 2.47 times the guideline's estimate, and about 27% larger. This result shows demand control is justified over a fixed decrease schedule. This is because a fixed decrease schedule may greatly underestimate the potential level of flexibility in airflow. Occupancy patterns were not constant, however. Before the COVID disruption, the mean duration of unoccupied periods was 6.5 hours and decreased to 5.25 hours (roughly a 19% decrease), during the early stage of the COVID pandemic. Therefore, any IoT controller would need to be adjusted, based on new post-disruption occupancy schedules.

The IEQ sensing layer provides flexibility. The dataset included room temperature, CO_2, relative humidity, and particulates. The related bedroom study showed that CO_2 responsive DCV increased extraction during occupancy and decreased total airflow (Garman et al., 2023). This shows that occupancy inference should not turn off ventilation during unoccupied periods. Occupancy inference should control ventilation based on CO_2 levels, as well as humidity. Sensor placement is equally important since the related field work observed vertical CO_2 stratification.

Finally, the Energy & Buildings analysis showed that in heat recovery systems, peaks in demand for power tended to align with drops in outdoor temperature. Although no utility demand response event was tested, this finding is still relevant to demand response. Smart controls should be able to predict changes in outdoor temperature and peak demand to shift heating when thermal storage allows it to be done without drawing too much power at the same time as peak demand for cooling and heating is drawn by fans and heat pumps. Overall, the analysis supports the project's readiness for demand response rather than any savings that can be reasonably quantified from such a response.

Table 2. Ventilation Configuration and Reported Operating Values

Mode	Airflow / control	Fan power	Analytical interpretation
Ex-CAV	0.5 ACH constant	17 W	Low fan power; no occupancy modulation
Ex-DCV	0.15–0.5 ACH demand-controlled	≤17 W	Occupancy/IAQ-responsive airflow
fMVHR-CAV	0.5 ACH constant	33 W	Heat recovery with higher fan demand
fMVHR-Scheduled	0.37 or 0.5 ACH	29–33 W	Scheduled reduced-flow strategy
rMVHR-CAV	0.5 ACH constant	54 W	Highest fan power; stronger cold-weather heat recovery

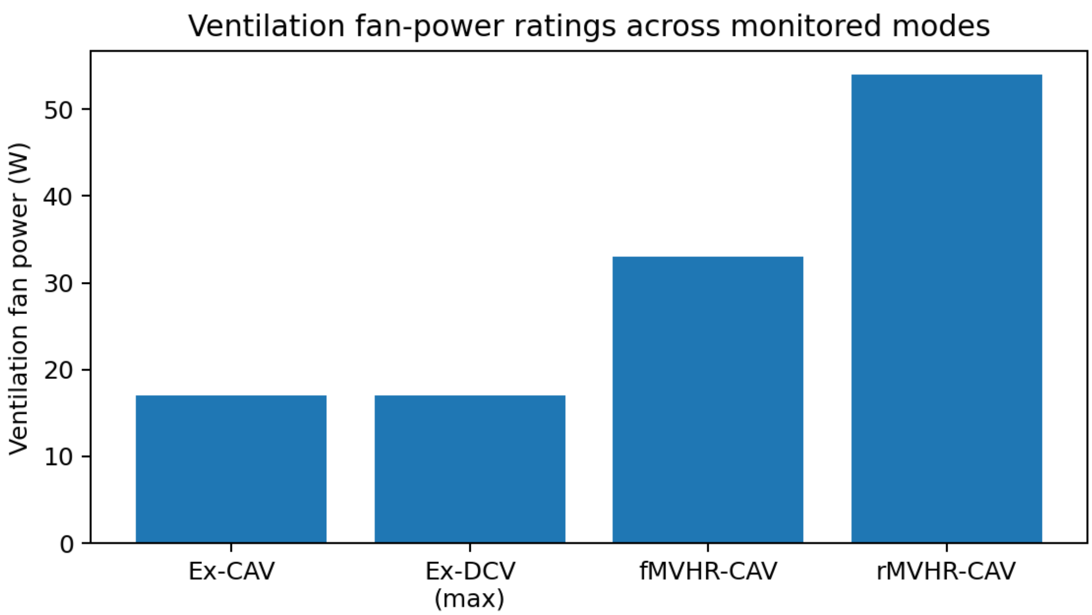

Figure 2. Fan-power ratings for the principal monitored ventilation modes. Source: Replotted from reported system values in Garman et al. (2025).

Table 3. Descriptive Energy and Control Comparisons

Indicator	Reference	Observed / derived result	Interpretation
Airflow reduction factor	Guideline-style reference: 19%	Ex-DCV: 47%	+28 percentage points; 2.47× reference factor
Heating-associated power at 0°C	fMVHR-CAV index = 100	rMVHR-CAV index = 89	11% lower
Heating-associated power at -10°C	fMVHR-CAV index = 100	rMVHR-CAV index = 77	23% lower

Daily unoccupied time	Pre-COVID: 6.5 h/day	Early pandemic: 5.25 h/day	19.2% reduction in setback opportunity
Fan power trade-off	fMVHR-CAV: 33 W	rMVHR-CAV: 54 W	63.6% higher fan rating despite heating-demand advantage

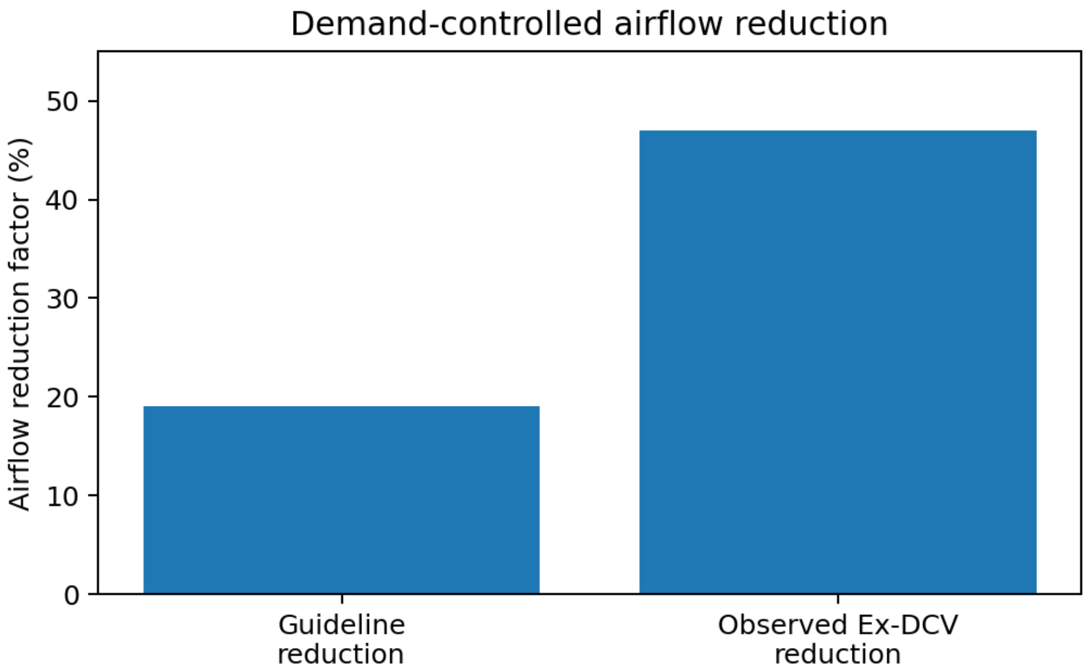

Figure 3. Guideline versus monitored demand-controlled airflow reduction factor. Source: Authors' arithmetic from Garman et al. (2025).

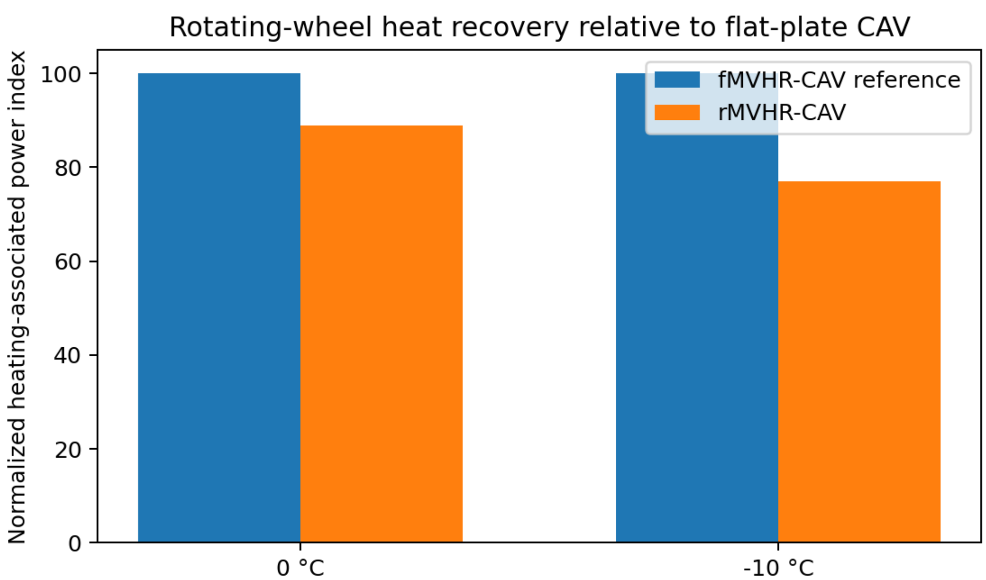

Figure 4. Normalized heating-associated power for rotating-wheel versus flat-plate MVHR. Source: Derived from the reported 11% and 23% reductions in Garman et al. (2025).

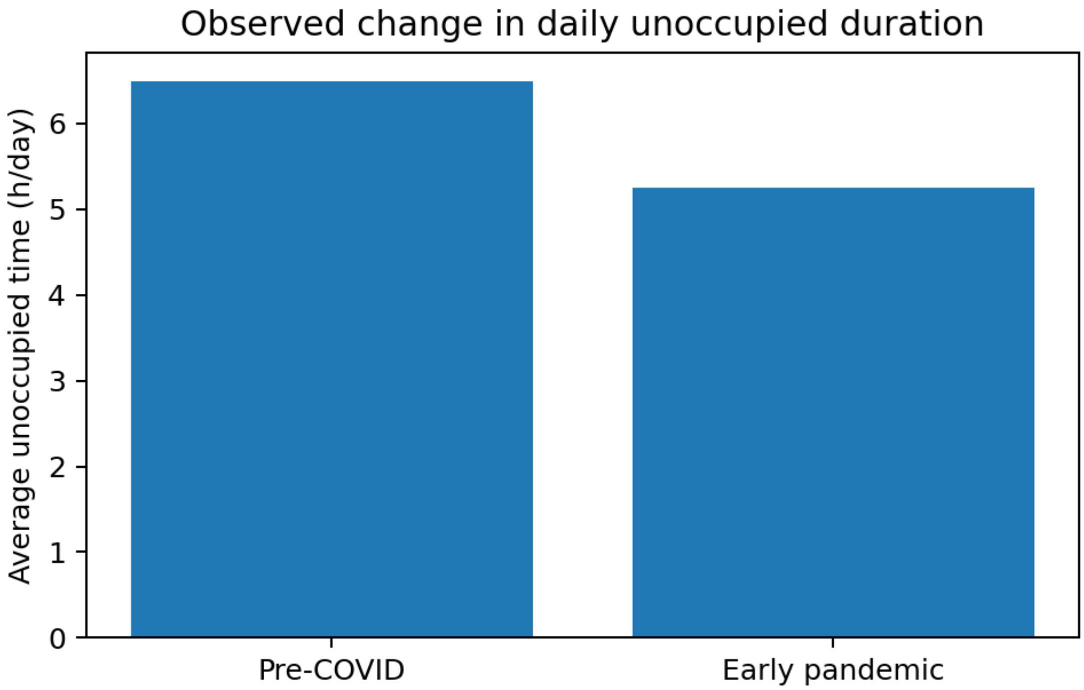

Figure 5. Change in average daily unoccupied duration. Source: Authors' presentation of monitored occupancy-period values reported by Garman et al. (2025).

Table 4. IoT Control Variables, Functions, and Constraints

Sensor / input	Control function	Energy objective	Constraint / risk
CO_2	Occupancy/ventilation demand inference	Reduce unnecessary airflow	Sensor placement; CO_2 is not full IAQ
Temperature	Thermal state and load forecast	Avoid over-heating/cooling	Comfort bounds
Relative humidity	Moisture/ventilation state	Coordinate airflow and recovery	Dryness/condensation risk
Particulates	Pollution safeguard	Avoid energy-only ventilation cuts	Outdoor/indoor source variability
Airflow	Verify commanded ventilation	Fan and heating-load optimization	Calibration and duct effects
Smart-meter power	Whole-system feedback / peak detection	Minimize total electricity and peaks	Disaggregation and time alignment
Weather forecast	Preconditioning / peak timing	Exploit thermal flexibility	Forecast error

5. Discussion

The first big idea is that minimizing cost for the entire IoT HVAC system should be the primary goal, rather than minimizing the highest wattage for visible devices. In this case, for example, rotating-wheel MVHRs had a higher fan-power rating than either flat-plate HRVs or exhaust systems, but in cold conditions, these systems required less heating energy. This sort of energy trade-off illustrates why smart building control systems must have multiple meters and environmental observations. A control system that has only fan current control has the potential to select the incorrect operation mode; however, control systems that consider outdoor conditions, heat pump demand, airflow, and IAQ can positively impact the overall electrical load.

The second big idea is that, in occupant-aware control systems, there is a good deal of flexibility. In one case studied, an exhaust DCV was observed to reduce airflow by 47%, while the typical assumed number would be 19%. This is consistent with recent studies that show ventilation control systems respond to the presence of people, rather than controlling a constant flow, by venting air when people are present (Garman et al., 2023). For occupant presence, it would be best to base this control system on multiple inputs that can fail individually, rather than relying on any single input. This is based on studies of occupant behavior globally and how this behavior relates to building systems and controls (Dong et al., 2022).

Third, indoor air quality (IAQ) must not be considered a tertiary outcome. While CO_2 is a useful indicator of ventilation, air quality cannot be reduced to this measurement. TVOCs, humidity, and particulates capture different exposure pathways and are therefore useful proxy measures. The advantage of the Swedish dataset over energy-only smart meter datasets is that it links airflow decisions together with several indoor environmental quality (IEQ) variables. Similarly, the 2025 dormitory dataset shows the importance of maintaining a co-operative measurement of HVAC, CO_2, TVOC and behavior in assessing the efficiency of interventions (Pandey et al., 2025). An intelligent controller should be set to enforce IAQ requirements over energy optimization.

Fourth, the COVID-19 pandemic has caused a shift in occupancy patterns. The loss of occupancy reduced the time available for ventilation by 19%, thus illustrating model drift. The operation of IoT systems requires algorithms which are, at a minimum, sufficiently flexible to protect themselves from rules to be changed as behavioral patterns change. This is equally applicable to demand response, where a schedule learned from peaks of occupancy may become inappropriate when other factors of the demand, such as occupancy, weather, tariffs or grid signals also change. For example, the timing of heat pump control can be used to create flexibility, with similar annual energy use (Leerbeck et al., 2020).

The proposed architecture has five primary functions: validated zone-based sensing, occupancy and load inference, constrained HVAC/ventilation decision making, feedback on energy, air quality, and peak demand. Cloud services can extend the functionality, but remain subservient to local control for ventilation safety priorities. This architecture employs control strategy based on validated measurements to convert the likely evidence in the field into an IoT-based control framework.

Data synchronization is one of the implementation-level challenges that are as important as the choice of sensors. Hourly Electricity, Eight-Minute Airflow, and Ten-Minute IEQ data must be synchronized to a control interval by providing explicit logic for handling gaps and lags. Edge logic keeps the last safe position on ventilation control when the cloud goes down, while longer-horizon services can perform weather forecasting, runtime optimization, and fleet-level analytics. Event logs must record every setpoint change and the sensor state that caused the change to permit post-analysis to verify whether the energy savings were made without compromising IAQ.

6. Conclusion

This paper presented the case for the integration of ventilation, heating demand, occupancy, and indoor air quality in intelligent HVAC energy management, based on a real 2019-2022 Swedish monitoring campaign. Rotating-wheel MVHR systems in combination with CAV systems reduced heating power by 11% and 23% respectively at 0°C and -10°C. The demand-controlled exhaust ventilation system achieved a 47% reduction in airflow (compared to the 19% reference), while reducing the unoccupied household time from 6.5 to 5.25 hours reduced daily household airflow requirements. These demonstrate the shortcomings of fixed schedules and single-component energy metrics.

A supervisory system incorporating IoT technology should include particulate and CO2 sensing along with airflow and electricity meters. They should also include the ability to sense air movement, infer occupancy, forecast potential weather and loads, and control overall energy usage while ensuring IEQ is not compromised. In relation to demand response, peak energy consumption should be prioritized, and flexible usage should be implemented rather than making unsubstantiated claims of achieving savings by measuring utility response. The available evidence points toward the adoption of an adaptive control system using sensors, while also showing that the real-world operation of a system may result in issues with performance that cannot be captured using laboratory efficiency ratings.

7. Limitations and Future Research

This analysis is a secondary empirical study based on publicly available measurement data, and as such is not a complete re-analysis of each individual sensor data file. Therefore, percentage comparisons are descriptive and no inferential p-values are included. The available system data was collected across different years and therefore comparison across years was done considering the differences in weather, occupancy, and the presence of COVID-related changes in human behavior. As a result, direct comparison across years should not be considered as random changes to the treatment being studied. In this analysis, the context is a single-family home and, therefore, the results should not be extrapolated to large commercial HVAC systems.

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