THESIS PROJECT PORTFOLIO

Developing a Dynamic Control Algorithm to Improve Ventilation Efficiency in a University Conference Room

(Technical Report)

A Review of Barriers to Implementation and Investigation into Suboptimal Adoption of Energy Efficient HVAC Technologies

(STS Research Paper)

An Undergraduate Thesis

Presented to the Faculty of the School of Engineering and Applied Science

University of Virginia • Charlottesville, Virginia

In Fulfillment of the Requirements for the Degree

Bachelor of Science, School of Engineering

Caleb A. Neale

Spring, 2022

Department of Engineering Systems and Environment

TABLE OF CONTENTS

With 30% of commercial energy usage being attributed to heating, ventilation, and cooling (HVAC) operation and a rise in public perception of air quality and cleanliness due to the SARS-CoV-2 pandemic, there exists a dual sided need to produce cleaner air and reduce the cost at which clean air is produced. This portfolio seeks to address this problem by answering firstly whether it is possible to reduce energy demands from HVAC systems through an intelligent, occupancy-based control algorithm, and secondly what barriers to adoption does such a control algorithm or other produced technological solutions face once developed.

An occupancy-based control algorithm was chosen as the technical portion of this portfolio as it offered an opportunity to leverage in-pace hardware for significant energy usage reductions while maintaining indoor air quality (IAQ) during the times in which occupants were present. Other considered solutions required significant hardware upgrades or leveraged complex software interactions between models and HVAC equipment frequently not supported natively; a model which determines simply whether or not HVAC equipment should operate at a given time is simple to implement and easily testable, making it a good first step in addressing the dual-sided IAQ and energy problem of HVAC systems. Such an algorithm was developed using a literature review on best practices for IAQ and tested using data from UVA's LinkLab. Results showed a monthly energy savings of $424/month when tested on a single conference room in UVA's LinkLab, though calculated loss in productivity due to degraded IAQ was $522/month. Future work is needed to further refine notions of lost productivity to IAQ and develop an accurate enough occupancy model to maintain energy reductions while maintaining IAQ.

To understand how such a developed control algorithm might see use in the real world, the STS thesis in this portfolio seeks to understand the factors which influence suboptimal adoption of energy efficient technologies generally, with specific effort made to discover factors specific to HVAC technologies and contextualize their adoption with an exploration into electric vehicles and the adoption of LED lighting. The paper determines that both market-based (public good, principal agent) and non-market based (decision making under uncertainty, information dissemination, qualitative factors, optimality definitions) failures contribute to suboptimal adoption rates of energy efficient technologies generally and HVAC technologies. The literature review also discovered geographic dissemination factors specifically applicable to HVAC and residential energy efficiency technologies. The paper determines that further research is needed to quantify the relative effects of each of these barriers and determine which should be addressed with highest priority, though it is immediately apparent that the removal or mitigation of any of the addressed barriers would significantly increase adoption rates of an efficient HVAC technology.

The work of this portfolio shows the path forward for an efficient HVAC future. Short-term technical implementation is achievable, reasonable, and effective given the proposed control algorithm in its current state, and with further research into occupancy prediction models and IAQ-productivity models significant additional gains and mitigations of negative side-effects is imminently achievable. By identifying barriers to adoption, developers of such a technology have a well mapped battlefield on which they will be attempting to win the attention and dollars of residential, commercial, and other users. Leveraging the effectiveness of the solution with an understanding of non-technical factors inhibiting adoption allows for near-term action on this pressing problem.

Developing a Dynamic Control Algorithm to

Improve Ventilation Efficiency in a University

A Technical Report submitted to the Department of Engineering Systems and Environment

Presented to the Faculty of the School of Engineering and Applied Science

University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Science, School of Engineering

Caleb A. Neale

Spring, 2022

Technical Project Team Members
Matthew Caruso
Jason Jabbour
Alden Summerville
Avery Walters

On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Arsalan Heydarian, Engineering Systems and Environment

Arthur Small, Engineering Systems and Environment

Developing a Dynamic Control Algorithm to Improve Ventilation Efficiency in a University Conference Room

Matthew Caruso
Systems Engineering
University of Virginia
Charlottesville, Virginia
mmc2nh@virginia.edu

Jason Jabbour
Systems Engineering
University of Virginia
Charlottesville, Virginia
jjj4se@virginia.edu

Caleb Neale
Systems Engineering
University of Virginia
Charlottesville, Virginia
can4ku@virginia.edu

Alden Summerville
Civil Engineering
University of Virginia
Charlottesville, Virginia
ads3pu@virginia.edu

Avery Walters
Civil Engineering
University of Virginia
Charlottesville, Virginia
acw4mhp@virginia.edu

Arsalan Heydarian
Engineering Systems and Environment
University of Virginia
Charlottesville, Virginia
ah6rx@virginia.edu

Arthur Small
Engineering Systems and Environment
University of Virginia
Charlottesville, Virginia
asmall@virginia.edu

Mahsa Pahlavikhah Varnosfaderani
Engineering Systems and Environment
University of Virginia
Charlottesville, Virginia
mp3wp@virginia.edu

***Abstract*—A robust heating, ventilation, and air conditioning (HVAC) system is needed to maintain a healthy and comfortable indoor environment. However, HVAC systems are responsible for significant energy usage in the United States, and enhancing current systems and implementing additional HVAC sensing are primary strategies for reducing energy consumption. This research developed an HVAC control algorithm (CA) that optimized ventilation operations within a conference room in the University of Virginia Link Lab. Using indoor air quality (IAQ), occupancy, weather, and HVAC operation data streams, the CA recommended a decision to ventilate or not ventilate the conference room every 15 minutes by comparing the cost of lost occupant productivity due to poor IAQ to the energy cost of ventilating the space. The ventilation decision with lower total cost was recommended. This project addressed scheduling inefficiencies of the current HVAC control system, which operates at full power throughout the day regardless of occupancy status. The CA reduced ventilation during unoccupied periods. The CA was tested over two months of historical data from October to December 2021 and recommended ventilating the conference room 15.13 percent of the time. During the same period, the standard system ventilated the conference room 49 percent of the time. Energy savings due to decreased operation were considerable and averaged 424 dollars per month, although these energy savings came at the cost of lost occupant productivity totaling 522 dollars per month. Future work on lost occupant performance will more accurately model the effects of reduced ventilation. However, annual energy savings of 5,000 dollars from a single conference room is encouraging, and scaling a similar CA to consider a set of rooms or an entire floor of a building could result in substantial energy conservation.**

***Index Terms*—Indoor Air Quality, HVAC Ventilation, Control Algorithm, Energy Efficiency, Optimization, Simulation**

I. Introduction

The SARS-CoV-2 pandemic has demonstrated the need for robust ventilation systems, yet implementing these systems often incurs a significant energy cost: 30% of commercial energy usage is due to HVAC operation. However, a 2017 report from the U.S. Department of Energy cites “Technology Enhancements for Current Systems” as one of four high priority interventions for reducing energy usage, with the top-ranked technology, “Advanced HVAC Sensors”, projected to cut current annual commercial energy use by 3.5 percent [1]. Given that Americans spend 90 percent of their time indoors, increasing HVAC efficiency while providing high indoor air quality (IAQ) is paramount [2]. Intensive HVAC operation maintains high IAQ, but at a significant energy cost. This research investigates reducing HVAC operation through automation while maintaining high IAQ.

A. Guidelines for Indoor Air Quality

Carbon dioxide (CO_2), volatile organic compounds (VOCs), and fine particulate matter ($PM_{2.5}$) are the primary effluents that adversely affect productivity and health. Carbon dioxide is a byproduct of metabolic activity and is released into the air through exhalation. In enclosed spaces, CO_2 concentrations can approach levels that cause decreases in productivity [3]–[5]. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) recommends indoor CO_2 concentrations not exceed 1,300 parts per million (ppm), yet some offices fail to meet this guidance [6]. VOCs are emitted from solvents in paint, cosmetics, dry-erase markers, and cleaning products and are often present indoors at levels as high as ten times that of outdoor air. High levels of VOCs can cause short-term irritation to the eyes, nose, and throat, or more serious long-term effects like liver damage or cancer [7]. The World Health Organization notes that VOC levels become marginal around 200 parts per billion (ppb) and should not exceed 600ppb [8]. Particulate matter less than 2.5 microns in width is classified as $PM_{2.5}$, which is generated from vehicle exhaust, burning fossil fuels, cooking, and chemical reactions in the atmosphere [9]. $PM_{2.5}$ can be filtered from building air streams using HEPA (high-efficiency particulate air) or high MERV (Minimum Efficiency Reporting Value) filters, yet buildings that lack these technologies can have elevated indoor $PM_{2.5}$ levels, leading to negative health effects [2]. The EPA maintains a 24-hour maximum $PM_{2.5}$ exposure standard of 12 μg/m^3 [10]. Table 1 summarizes acceptable IAQ levels and their impact on productivity:

TABLE I
IAQ Guidelines and Productivity Impact

Species	Baseline	Moderate	High	Productivity Effect
CO2 (ppm)	600 [3]	1000 [3], [4]	2500 [4]	-21% for every 400 past 600 [3], -44-94% at 2500 [4]
VOCs (ppb)	50 [3], [8]	200 [11]	500 [3]	-13% at 100 [3]
PM2.5 (μg/m^3)	2 [2]	6	12 [10]	Health effects at 24hr exposure of 12 [10]

B. Energy Considerations

Although increased levels of CO_2, VOCs, and $PM_{2.5}$ negatively impact health and performance, the operational cost of continuous ventilation is high. HVAC systems account for 30% of commercial energy consumption, and commercial buildings consume 35% of the electricity use in the United States [1], [12]. Eliminating unnecessary ventilation saves energy, aiding the environment and cutting energy costs. Maintaining high IAQ while reducing energy costs is challenging but feasible. The EPA claims "protecting indoor environmental quality in energy efficiency projects need not hamper the achievement of energy reduction goals" and the CA developed in this research is a strong step forward [13].

II. Methods

A. Testbed

The study was conducted within a conference room in the Link Lab at the University of Virginia. The Link Lab is equipped with over 300 sensors for IAQ, room occupancy, and Bluetooth connectivity to be used in various research projects. The room is 490 ft^2 with an approximate volume of 4575 ft^3 and can accommodate up to 20 occupants at a central table. The Trane HVAC system that serves the conference room is robust, with efficient components and a MERV-13 filtering system. The primary users of the conference room are graduate students and faculty who conduct research in the Link Lab, and during the period of study (October to December 2021), University of Virginia COVID-19 guidelines required that occupants wore masks. IAQ metrics were pulled from the room using an Awair© brand air quality monitor which provided CO_2, TVOC, $PM_{2.5}$, and temperature readings. Historical data from the Link Lab's Building Automation System was pulled to determine energy usage of the HVAC during the study.

B. System Overview

The CA recommends behavior of the Variable Air Volume (VAV) box that ventilates the conference room using a series of three connected models: a statistical model that forecasts binary occupancy status (occupied/not-occupied) within the room, a mathematical model that computes future IAQ values over the next hour for each ventilation state (on/off), and calculations to compute the energy use of each ventilation state. Using findings from [3]-[5], [8], and [10]-[11], the CA then assigns a cost of lost occupant productivity given the modeled IAQ values (see section II-D). The total cost of lost occupant productivity is added to the energy cost of ventilation over the next hour to determine the total cost of a decision to ventilate or not ventilate the room. The output of the CA is a binary decision to ventilate or not ventilate the room for the next hour based on which state has a predicted lower cost and is computed at 15-minute intervals. Fig. 1 provides an overview of the algorithm:

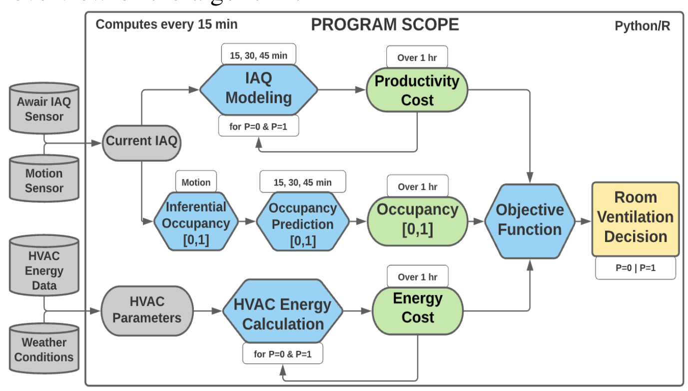

Fig. 1. System Diagram

C. Indoor Air Quality Modeling

Determining future values of IAQ given a decision to ventilate or not ventilate is a key step towards understanding the future impact of a current decision on HVAC operation. Future modeling of each IAQ metric over 15-minute timesteps was handled separately under the decision of ventilation or non-ventilation, and in the cases of the conference room being occupied and unoccupied. Ambient values of CO_2 and total VOCs (TVOCs) were set at 420 ppm and 50 ppb, respectively. The equations in Table 2 return the future value of each IAQ metric in 15 minutes (one timestep) given the current value. Equations for modeling CO_2 and TVOCs were based on information from [14], for $PM_{2.5}$, [15] was used. In modeling CO_2 and TVOCs, the room air change rate of 2.62 ACH (air changes per hour) was used. Temperature was modeled without strict equations.

Modeling accuracy, as displayed in Table 3, was usually within 5% of the actual IAQ readings.

D. Indoor Air Quality Cost Calculation

To determine the cost of poor IAQ, a method for converting IAQ levels to a dollar cost of human productivity was developed. Optimal productivity was valued at $40 per hour per person, with each IAQ metric of CO_2, TVOCs, $PM_{2.5}$, and temperature contributing $10 worth of value. Research from [3]-[5] defined the loss of productivity due to CO2

TABLE II
IAQ MODELING EQUATIONS

State	CO_2	TVOCs	$PM_{2.5}$	Temp
Ventilation, Occupied	1.648x - 272.463	1.648x - 32.436	1.05x	1.02x
Ventilation, Unoccupied	0.519x + 201.834	0.519x + 24.028	0.519x	0.95x
No Ventilation, Occupied	1.40x	1.40x	1.15x	1.10x
No Ventilation, Unoccupied	0.95x	0.95x	0.95x	x

TABLE III
IAQ MODELING COMPARISON TO ACTUAL IAQ

IAQ Modeling Comparison to Actual IAQ				
Timestep	CO_2	TVOC	$PM_{2.5}$ [a]	Temp
15 min	1.41%	-4.46%	-0.34	-0.91%
30 min	-1.41%	-9.03%	-0.54	-2.41%
45 min	-3.44%	-9.72%	-0.66	-3.84%
Net	-1.15%	-7.74%	-0.51	-2.39%

[a]Note: % not calculated for $PM_{2.5}$ as the median value is 1ppm

concentrations, which was built on a baseline of 600 ppm, with 20% loss at 1000 ppm, 50% loss at 1500 ppm, and 100% loss at 3000 ppm. These data were trend-fitted in Microsoft Excel to develop the following loss function for CO_2:

$$y = -1.02 \times 10^{-8} x^3 + 4.27 \times 10^{-5} x^2 + 1.67 \times 10^{-3} x - 14.17 \tag{1}$$

The effect of TVOCs on productivity was defined using [3], [8], and [11], and a curve was built on a baseline of 200 ppb, 50% loss at 600 ppb, 75% loss at 1000 ppb, and 100% loss at 2000 ppb. These data were similarly trend-fitted and produced the following loss function for TVOCs:

$$y = 2.85 \times 10^{-8} x^3 - 1.29 \times 10^{-4} x^2 + 0.213x - 37.798 \tag{2}$$

$PM_{2.5}$ influences health more than it influences productivity. However, due to significant health effects influenced by high $PM_{2.5}$ concentrations, $PM_{2.5}$ was included in the objective function. Using data from [10] and [16], the loss curve was built with 0% loss at 2 µg/m^3, 25% loss at 6 µg/m^3, 50% loss at 12 µg/m^3, and 100% loss at 35 µg/m^3. This curve had the equation:

$$y = -8.68 \times 10^{-2} x^2 + 6.21x + 0.213x - 11.06 \tag{3}$$

Temperature was included in the model due to its effect on occupant comfort. The loss function for temperature was based on a "goal zone" between 20 and 22.5 degrees C, with significant losses mounting below 15.5 degrees C and above 26.8 degrees C. The curve had the following equation:

$$y = -9.21 \times 10^{-3} x^4 + 7.79 \times 10^{-1} x^3 - 22.69x^2 + 264.32x - 960 \tag{4}$$

In each loss function, the current value of the IAQ metric of consideration is passed in as the independent variable. The function returns a "loss factor" at that value of the metric. Multiplying the value of productivity allotted to that metric over the next 15-minute timestep by the loss factor returns the cost of productivity due to the specific metric over the next 15 minutes. Given that optimal productivity is valued at \$40 per hour, or \$10 per 15 minutes, each IAQ metric can affect a maximum of \$2.50 of loss per 15 minutes, given that value is distributed equally across each metric. Modeled future IAQ values from section II-C are passed to the productivity cost generator to predict future costs of lost productivity. Productivity cost over each timestep is summed to determine the total cost of productivity across the next hour.

E. HVAC Energy Cost Calculation

To determine the cost of energy for operating the HVAC system without direct energy metering, the energy cost of ventilating was divided into four components, with equations for each component defining the relationship between system dynamics and energy cost in dollars. The components calculated are fan energy, heating/cooling energy, dehumidifying energy, and zone reheat energy.

The general process of conditioning air takes two main states: cooling and heating. The system enters a cooling state when outside air is warmer than the desired internal temperature. When in a cooling state, a mix of outdoor and indoor resupply air is passed to the chilled water cooler in the main AHU at the building level. The energy used in cooling is as follows [17]:

$$h_s = 1.08qdt \tag{5}$$

where h_s is the sensible heat energy used by cooling in BTU/hr (then converted to kW/hr), q is the volume (cfm) of air being treated, and dt is the temperature differential (°F) before and after cooling. The air is cooled to 55°F in order to dehumidify the air using latent heat reduction; however, because the cooling process also removes moisture from the air, an additional equation is needed to account for energy used in dehumidification [18]-[21]:

$$h_l = \rho h_{we} q dw_{kg} \tag{6}$$

where h_l is the latent heat energy (kW) used for dehumidification, ρ an assumed constant density of air (kg/m^3), q is the volume (cms) of air being treated, h_{we} is the latent heat of vaporization water (kJ/kg), and dw_{kg} is the humidity ratio difference (kg/kg) before and after dehumidification. Once the air has been cooled and dehumidified, it is ducted to zones within the building which can reheat air if necessary. Zone reheating energy is calculated with (5).

When outside air is cooler than the desired internal temperature setpoint, the system enters a heating state. In this state, a mix of outdoor and resupply air is heated to approximately 55 °F at the AHU heating coil. Dehumidification is not a concern in the heating state as cold air holds less moisture than warm air. Air then moves to VAV boxes within the building for reheating if necessary. AHU heating energy is calculated with (5).

During operation, return and supply air fans are used to move air through the HVAC system. The return fan pulls "used" air from the building to be exhausted or reconditioned, while the supply air fan pushes newly conditioned air from the AHU into the building. For each fan, energy consumption is calculated as follows [22]:

$$E_{\text{fan}} = 0.746 P_{\text{hp}} VFD^3 \quad (7)$$

where E_{fan} is the current fan energy consumption (kW), P_{hp} is the horsepower rating of the fan in question, and VFD is the percentage activation of the variable frequency drive controlling the fan.

For the specific case study of the conference room, consideration was only given to AHU-level energy consumption and VAV-level reheating of the conference room. In a fully developed CA, multiple occupancy forecasts and multiple zone level energy calculations must be made to fully understand IAQ and energy costs across the entire building, yet this was out of the scope of this paper.

In order to estimate the energy impact of a decision to ventilate or not ventilate the conference room, two costs are calculated, depending on if the CA makes a decision that matches historical data.

Cost of ventilating: If the historical data used for simulation was ventilating at a timestep that the CA also determined it was optimal to ventilate, the cost of ventilation was the actual operating cost based on equations (5)-(7) using the historical data of operating parameters.

In the case the CA decided to ventilate at a time without historical operating parameters, an energy cost must be determined using estimated operating parameters. The parameters across all timesteps in which the actual system was ventilating were averaged and used as parameters in the energy calculation equations for an estimated cost of operation. In both of the above cases, actual historical weather data was used.

Cost of not ventilating: Ventilating a room incurs costs at the VAV and AHU level. In the case the CA determines it is optimal not to ventilate, the VAV supply air flow is set to zero. However, the AHU also has a reduced burden in this case, and as such, the AHU supply air flow is adjusted by subtracting the historical VAV supply air flow from the AHU supply. This accounts for costs at both the VAV and AHU level, allowing the approximation of the effects and energy savings of ventilation of just the room under consideration.

Total energy cost under ventilation and nonventilation decisions is calculated by summing equations (5)-(7) to calculate total kilowatt usage, and multiplied by an energy cost of $0.094 per kilowatt-hour to determine the dollar cost of the decision.

F. Occupancy Inferential Model and Forecasting

The final component of the CA is occupancy. Provided IAQ is only a concern in occupied spaces, understanding occupancy patterns in the room could minimize wasted ventilation. An existing low-cost motion sensor was used to collect motion data within the conference room. That data was sampled at 15-minute intervals to collect binary motion data over the study period. Day-of-week, hour-of-week, and 15-minute period features were created and used to train a statistical model in order to approximate the weekly occupancy patterns of the space. A random forest classifier was trained and tested to be a suitable model, achieving 85% accuracy. It should be noted that the False Negative Rate—the model classifying an unoccupied period when the space is actually occupied—is 12.4%, which should be minimized to achieve optimal IAQ. The performance of this model as shown in Fig. 2 appears reasonable: the model learned the conference room was always vacant during weekends and early/late hours of the day.

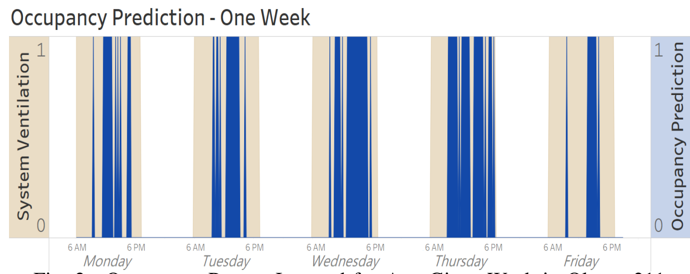

Fig. 2. Occupancy Pattern Learned for Any Given Week in Olsson 211

G. Objective Function Optimization

The CA was backtested on two months of historical data. The data consists of IAQ and motion readings pulled from sensors in the conference room, HVAC operation readings pulled from a UVA Facilities Management database, and weather data pulled from a weather station within 0.15 miles of the building. These fields were cleaned, merged, and filtered for 15 minute intervals using mean resampling and filling any NA values using forward filling. Historical data for each 15 minute timestep was used to calculate the productivity and energy costs of each ventilation state. The lower total cost (productivity + energy) of ventilating or not ventilating serves as the recommendation for each timestep.

There is one case the algorithm handles differently that occurs when the actual system is ventilating, but the algorithm decides to not ventilate: The IAQ values read from the sensors can no longer be used to model the future IAQ as those readings are influenced by the actual system ventilating. To account for this "build up" of the IAQ metrics caused by the algorithm not ventilating, the modeled IAQ values from the last timestep are pushed through and used for the future IAQ modeling. A cascading effect occurs until the productivity cost exceeds the cost of turning the system on, at which the algorithm will recommend to ventilate. The actual form of the optimization equation is as follows:

Objective Function:

$$Min\{P * C_{\text{En}} + \sum_{t \epsilon T} [C_{\text{IAQ}}(CO2_{\text{t}}, VOC_{\text{t}}, PM2.5_{\text{t}}, T_{\text{t}}) * O_{\text{t}}]\} \quad (8)$$

Where P is the HVAC ventilation state $\{0, 1\}$, C_{En} is the calculated cost of HVAC energy usage over the next hour, $C_{\text{IAQ}}(CO2_{\text{t}}, VOC_{\text{t}}, PM2.5_{\text{t}}, T_{\text{t}})$ is the cost of lost productivity due to IAQ values at timestep, and O_{t} is the occupancy at timestep $T = \{0, 15, 30, 45\}$

III. Results

The energy and productivity costs of HVAC operation under the CA decisions versus actual operation were calculated and compared. Over the two-month period, the total energy saving using the CA was $848.14, an average of **$424.07/month**. This value reflects the dollars saved from decreasing the ventilation of the conference room. The algorithm recommended ventilation **15.13%** of the time, compared to the 49% scheduled operation of the actual system. As seen in Fig. 3, which details one week of the CA decision-making, this decrease in operation is mostly on the weekends when occupancy is low.

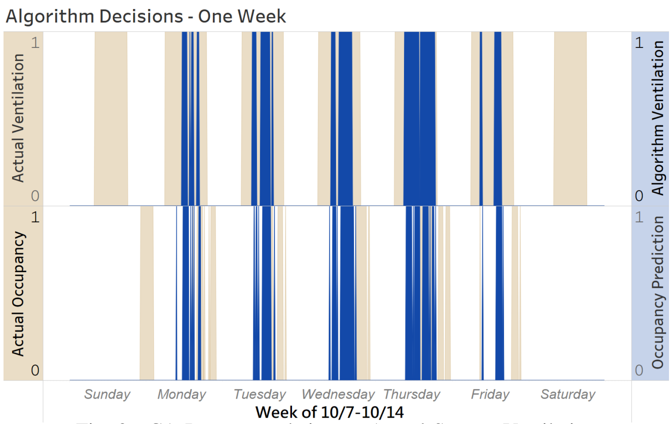

Fig. 3. CA Recommendation vs Actual System Ventilation

While the energy saving is impressive, it came at an estimated cost of $1,043.98 productivity dollars over the two-month period, for an average loss of **$522/month**. Therefore, the CA incurred a net cost of $97.93/month. However, the CA achieves energy savings of $5,089/year, and productivity losses are limited: the average productivity loss under the CA is only $0.29/hour with a maximum of $8.69/hr, compared to actual average loss of $0.11/hour with a maximum of $3.20/hour.

IV. Discussion

A. Results Discussion

A primary concern of these results is the high productivity cost. Maintaining high IAQ is important for health and performance, but the CA was not able to simultaneously improve IAQ and reduce energy consumption. However, “productivity cost” is a calculated parameter with less concrete significance than energy savings. Additionally, HVAC operation is already adept at maintaining healthy indoor air: IAQ metrics rarely reach unhealthy levels, and the average hourly productivity cost is below $1. Under the CA’s ventilation decisions, occupants lose less than 2.5% of their performance due to decreased IAQ compared to standard ventilation. Due to the marginal decrease in IAQ, energy savings are a prime object of optimization, and the energy savings of the control algorithm are justified. A comparison of IAQ values under standard HVAC operation and projected IAQ values under operation of the CA is shown below in Table 4: the standard HVAC system, as well as the CA, both maintain healthy IAQ according to benchmarks defined in Table 1. An important limitation of the CA that explains the high maximum IAQ values is the limited IAQ “build up” methodology. As explained in section II-G, the IAQ modeling equations lead to artificially high readings because there is no ceiling to the adjustment equation. In reality, IAQ would approach a steady state during unoccupied periods. However, the CA offers a valuable foundation that could be made more accurate with additional occupancy detail.

TABLE IV
Average and Maximum IAQ Parameters During Study Period Under Actual and CA Operation

	Actual Operation		CA Operation[a]	
Species	**Average**	**Maximum**	**Average**	**Maximum**
CO2 (ppm)	464.1	1053.0	577.8	21,594.0
TVOC (ppb)	180.0	4388.9[b]	211.0	6926.6
PM2.5 (µg/m^3)	1.5	9.0	1.3	12.9
Temperature (°C)	22.4	24.5	23.47	72.49

a. Note limitations of IAQ buildup. b. Likely result of sensor malfunction.

With additional time and funding, the assumptions and limitations of this research could be more fully developed. Core assumptions and significant limitations should be duly noted, and present exciting opportunities for future research.

B. Assumptions

The energy calculations conflate the cost of ventilating the VAV box that serves the conference room with the cost of operation of the AHU, which serves half of the entire building floor. This simplification causes calculated energy costs to be much larger than the actual cost to ventilate just the conference room of study. Assumptions were also made in computing energy savings. As stated in section II-E, the energy savings are calculated as the energy saved by only altering VAV operation. This is accomplished by subtracting the VAV supply airflow from total supply airflow at the AHU. However, the HVAC system parameters are complexly linked, and additional parameters such as VFD setpoints would be affected. These changes were not accounted for in the energy calculations. Attaining a direct energy meter reading would simplify this matter. Assumptions of occupancy must also be addressed. The “actual room occupancy” was determined using a single infrared motion sensor: a dedicated occupancy count sensor would provide a stronger occupancy determination. Finally, optimal productivity was valued at $40/hour to reflect the general salaries of the most probable room occupants (undergraduates, graduates, faculty). Changing this value directly affects the calculated IAQ costs, and more research could provide a more accurate estimate.

C. Limitations

The main identified limitations of this project are as follows: the short time period of testing (2 months) cannot account for seasonal changes present in the system; IAQ is modeled using generalized mathematical equations rather than a model specifically trained for this use case and under the given system dynamics; due to the occupancy prediction method, this algorithm will only work during the academic school year as it was not trained on data for winter, spring, and summer breaks, and is not currently set up to learn new patterns online; productivity cost is only for a single occupant due to a binary occupancy forecasting, where a room could have *n* occupants and therefore should charge \$40*n per hour instead of the assumed \$40 per hour; and, the algorithm can currently only be run on historical data.

V. Conclusion

Optimizing HVAC control is a thorny problem, but given the limited timeframe of this research, the results are promising. Producing energy savings of almost \$5,000/year for the optimization of a single conference room is remarkable, although that saving comes at the expense of decreased productivity due to marginally worse IAQ. Primary takeaways include the confirmed difficulty of optimizing HVAC, calculating the energy cost of ventilating a single room solely using energy equations, and predicting room occupancy. Nevertheless, this project is a strong proof of concept. Along with addressing the assumptions and limitations above, other areas of improvement include: implementing a more robust set of energy cost calculations (i.e. specific cost for each room), extending the occupancy classification and prediction from a binary value to an occupancy level (low, medium, high, or specific values), backtesting on a wider timeframe, developing a real-time system and addressing security concerns, and generalizing the algorithm to any room or building.

Acknowledgment

The authors thank Alan Wang and Nabeel Nasir for technical assistance, the members of the UVA Link Lab for maintaining the indoor sensor networks and Doug Livingston from the University of Virginia Facility Management office for providing data and mentorship.

References

[1] W. Goetzler, R. Shandross, J. Young, O. Petrichenko, D. Ringo, and S. McClive, "Energy savings potential and RDD opportunities for commercial building HVAC systems," U.S. Department of Energy, Washington D.C., USA, 2017. https://www.energy.gov/sites/prod/files/2017/12/f46/bto-DOE-Comm-HVAC-Report-12-21-17.pdf. [Accessed: Mar. 12, 2022].

[2] J. G. Allen and J. D. Macomber, *Healthy Buildings: How Indoor Spaces Drive Performance and Productivity*. Boston, MA: Harvard University Press, 2020. [E-book]. http://www.jstor.org/stable/j.ctvz0h97h.6

[3] J. G. Allen, P. MacNaughton, U. Satish, S. Santanam, J. Vallarino, J., and J. D. Spengler, "Associations of cognitive function scores with carbon dioxide, ventilation, and volatile organic compound exposures in office workers: A controlled exposure study of green and conventional office environments," *Environmental Health Perspectives*, vol. 124, no. 6, pp. 805-812, 2016. 10.1289/ehp.1510037. [Accessed: Oct. 16, 2021].

[4] U. Satish, M. J. Mendell, K. Shekhar, T. Hotchi, D. Sullivan, S. Streufert, and W. J. Fisk, "Is CO2 an indoor pollutant? Direct effects of low-to-moderate CO2 concentrations on human decision-making performance," *Environmental Health Perspectives*, vol. 120, no. 12, pp. 1671-1677, 2012. https://doi.org/10.1289/ehp.1104789. [Accessed: Oct. 9, 2021].

[5] J. G. Cedeño Laurent, P. MacNaughton, E. Jones, A. S. Young, M. Bliss, S. Flanigan, J. Vallarino, L. J. Chen, X. Cao, and J. G. Allen, "Associations between acute exposures to PM2.5 and carbon dioxide indoors and cognitive function in office workers: A multicountry longitudinal prospective observational study," *Environmental Research Letters*, vol. 16, no. 9, article 094047, 2021. 10.1088/1748-9326/ac1bd8. [Accessed: Nov. 1, 2021].

[6] American Society of Heating, Refrigerating and Air-Conditioning Engineers, "Ventilation for acceptable indoor air quality," ANSI/ASHRAE Addendum d to NSI/ASHRAE Standard 62.1-2016, 21 Feb. 2018. https://www.ashrae.org/File\%20Library/Technical\%20Resources/Standards\%20and\%20Guidelines/Standards\%20Addenda/62.1-2016/62_1_2016_d_20180302.pdf. [Accessed: Mar. 29, 2022].

[7] Environmental Protection Agency, "Volatile organic compounds' impact on indoor air quality," *United States Environmental Protection Agency*, 2021. https://www.epa.gov/indoor-air-quality-iaq/volatile-organic-compounds-impact-indoor-air-quality. [Accessed: Nov. 23, 2021].

[8] World Health Organization Occupational and Environmental Health Team, "Guidelines for air quality," *World Health Organization*, 2000. https://apps.who.int/iris/handle/10665/66537. [Accessed: Nov. 7, 2021].

[9] New York State Department of Health, "Fine particles (PM2.5) questions and answers," *New York State*, 2018. https://www.health.ny.gov/environmental/indoors/air/pmq_a.htm. [Accessed: Nov. 23, 2021].

[10] United States Environmental Protection Agency, "National ambient air quality standards (NAAQS) for PM," *United States Environmental Protection Agency*, 2020. https://www.epa.gov/pm-pollution/national-ambient-air-quality-standards-naaqs-pm. [Accessed: Mar. 29, 2022].

[11] D. P. Wyon, "The effects of indoor air quality on performance and productivity," *Indoor Air*, vol 14, no. 7, pp. 92-101, 2004. 10.1111/j.1600-0668.2004.00278.x. [Accessed: Oct. 8, 2021].

[12] Office of Energy Efficiency and Renewable Energy, "About the commercial buildings integration program," *U.S. Department of Energy*, 2020. https://www.energy.gov/eere/buildings/about-commercial-buildings-integration-program#:~:text=Commercial\%20Building\%20Basics&text=Commercial\%20buildings\%20consume\%2013.6\%20quads,all\%20U.S.\%20carbon\%20dioxide\%20emissions. [Accessed: Apr. 6, 2022].

[13] United States Environmental Protection Agency, "Energy cost and IAQ performance of ventilation systems and controls – Executive summary," EPA Office of Air and Radiation, EPA-4-2-S-01-001, 2000. https://www.epa.gov/sites/default/files/2015-01/documents/energy_executive_summary.pdf. [Accessed: Apr. 3, 2022].

[14] J. Allen, J. Spengler, E. Jones, and J. Cedeño-Laurent, "5-step guide to checking ventilation rates in classrooms," Harvard T.H. Chan School of Public Health, 2020. https://schools.forhealth.org/ventilation-guide/. [Accessed: Mar. 3, 2022].

[15] N. S. Panji, and M. P. Varnosfaderani, "Indoor airborne transmission of COVID-19: Studying the impact of building ventilation and portable air purifying systems using low-cost PM2.5 sensors," 2021, unpublished. [Accessed: Apr. 3, 2022].

[16] United States Environmental Protection Agency, "EPA to reexamine health standards for harmful soot that previous administration left unchanged," *United States Environmental Protection Agency*, 2021. https://www.epa.gov/newsreleases/epa-reexamine-health-standards-harmful-soot-previous-administration-left-unchanged. [Accessed: Mar. 29, 2022].

[17] Engineering ToolBox, "Cooling and heating equations," Engineering ToolBox, 2004. https://www.engineeringtoolbox.com/cooling-heating-equations-d_747.html. [Accessed: Mar. 20, 2022].

[18] Engineering ToolBox, "Moist air – Enthalpy," Engineering ToolBox, 2004. https://www.engineeringtoolbox.com/enthalpy-moist-air-d_683.html. [Accessed: Mar. 20, 2022].

[19] Engineering ToolBox, "Air-humidity ratio," Engineering ToolBox, 2004. https://www.engineeringtoolbox.com/humidity-ratio-air-d_686.html. [Accessed: Mar. 20, 2022].

[20] Engineering ToolBox, "Mixing of humid air," Engineering ToolBox, 2004. https://www.engineeringtoolbox.com/mixing-humid-air-d_694.html. [Accessed: Mar. 20, 2022].

[21] Engineering ToolBox, "Moist air – Cooling and dehumidifying," Engineering ToolBox, 2004. https://www.engineeringtoolbox.com/cooling-dehumidifying-air-d_695.html. [Accessed: Mar. 20, 2022].

[22] Engineering ToolBox, "Fan affinity laws," Engineering ToolBox, 2003. https://www.engineeringtoolbox.com/fan-affinity-laws-d_196.html. [Accessed: Mar. 20, 2022].

A Review of Barriers to Implementation and Investigation into Suboptimal Adoption of Energy Efficient HVAC Technologies

A Research Paper submitted to the Department of Engineering and Society

Presented to the Faculty of the School of Engineering and Applied Science
University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree
Bachelor of Science, School of Engineering

Caleb A. Neale

Spring 2022

On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Advisor

Kent Wayland, Assistant Professor, Department of Engineering and Society

Problem Frame

With the advent of the COVID-19 pandemic causing the world to both think about the cleanliness of the air we breathe more, and spend more time inside (even before the pandemic, Americans spent, on average, less than two hours outside a day) (Diffey, 2011), technologies like HEPA filters, and “Hospital Grade Filtration” have rapidly entered the public consciousness as a method by which society can make indoor air safer in a post-pandemic world. When prioritizing public health in the short-term, long-term considerations of environmental -- and subsequent health -- effects can fall by the wayside. These indoor air quality (IAQ) public health measures which aim to make our air cleaner can have the long-term effect of significantly increased air pollution due to the increased energy cost associated with constantly filtering, conditioning, heating, cooling, and dehumidifying our shared spaces; this healthier air isn’t free. In fact, pre-pandemic, commercial HVAC operation accounted for a full 30% of US commercial energy usage (Goetzler et al., 2017), a percentage only likely to increase as we face an increasingly hostile outdoor climate and increasingly stringent filtration demands.

This dual-sided set of threats amounts to something of a paradox; how can we ensure comfortable, livable, and safe indoor spaces when the conditioning of these spaces leads to a less livable environment? The key to solving this problem lies in the adoption of HVAC technologies which can meet our comfort and public health needs more intelligently and more efficiently. Though proposals for, prototypes of, and fully developed systems of smart HVAC systems exist, adoption has been anything less than rapid, as shown by an estimated yet-to-be-achieved Technical Energy Savings Potential (Quadrillion BTU/yr.) of 0.63 (in commercial applications alone), a full 3% of commercial energy consumption (Goetzler et al., 2017). The question then becomes not about the technologies which will enable the achievement of this energy savings potential but the incentives, design principles, societal pressures, and circumstances which will actually bring about the implementation of said technologies.

In order to answer this question, this paper will investigate a broad understanding of suboptimal adoption of energy efficient technologies, with specific background research given the adoption of LED lights and electric vehicles, in an effort to understand the socio-technical forces which govern adoption of technologies in the energy efficiency space.

Introduction

Despite the potential effectiveness of proposed technologies or those under development, without the combination of positive and normative arguments and incentives for the implementation of the technologies the practical effects on energy consumption will be limited. Different potential use cases require different understanding and presentations of the benefits of smart HVAC technologies; for instance, decreased energy costs could appeal to private and corporate clients, while a definitive understanding of carbon emission reduction from implementation could contribute to governmental management of incentives and policy. Contextualization of this problem will explore historical examples of efficient energy technologies through an economic lens and seek to enumerate the ways in which government and economic incentives align, or don't, to incentivize adoption of said technologies.

The past century contains multiple examples of extant technologies with the potential to significantly improve on performance of existing solutions being delayed by forces, often economic or social, delaying their adoption. LED lights pose a particularly interesting example, showing quite clearly the effects of market regulated price incentives on the adoption rate of the technology. The first LED to emit light in the visible spectrum was produced by Nick Holonyak in 1962, yet LEDs weren't widely available until approximately 2002, and even then, at prices easily an order of magnitude higher than traditional halogen or fluorescent bulbs. It was not until 2019, almost a full 60 years after the invention of the technology, that we saw LEDs begin to take over other sources of lighting (Di Maria et al., 2009).

LED lighting simply didn't see widespread adoption until it became economically advantageous for the individual consumer, despite societal and long-term benefits to consuming less energy. This can be described as a failure of the market to price in the externality of pollution related to energy consumption and the related decision to purchase a lightbulb which may reduce the cost of that externality. Considering the relative complexity of HVAC systems and a lightbulb, it becomes apparent that a similar market failure is not only likely but is currently occurring. Though users of HVAC systems pay for their energy consumption, the pricing system for paying for the externality of pollution may not be effectively nor progressively priced in. Consider the US income tax system; our system does not tax all earners at an equal rate, but instead uses marginal brackets to tax higher earners at a higher rate than lower earners. In short, we believe that people who have outsized income and outsized effects on the economy should have associated outsized costs, and thus have adopted a progressive taxation system. In the case of energy consumption, we've adopted the opposite model. Economies of scale have dictated that the largest consumers (polluters) of energy pay a *lower* rate for their consumption than even household uses necessary for survival.

Historically, the US government has taken action against these inconsistencies between market dynamics and values not by taxation or price floors, but by funding and incentivizing the adoption of technologies which are advantageous to the country as a whole. In recent years and in the energy sector, a prevalent example of this has been electric vehicle (EV) incentives and tax breaks. Since 2010, the US federal government has added an incentive of $7,500 to the purchase of EVs and plug-in hybrids to combat the relative expense of this emerging technology (www.fueleconomy.gov, 2022), showing a recognition of the need to speed up an otherwise market driven adoption in order to continue working for the greater good.

The relevance of this policy and history to HVAC systems lies in the cost associated with implementing even software changes to HVAC systems, much like the high upfront costs of purchasing an EV. Frequently not connected to the internet and governed by complicated, specialized, and/or out of date proprietary software, HVAC management is often a practice which requires specialized technicians, engineers, and developers to implement, much less design. HVAC hardware upgrades are similarly expensive, with an HVAC system for a 20,000 square foot office building easily running over $450,000. That is to say, to break even on a 5-year time horizon, a new system would need to save $90,000 a year in energy costs, an unlikely sum given current energy costs.

The above factors of adoption all contribute to a phenomenon known as the *efficiency gap*, which generally defines the slower than optimal adoption of energy efficient technologies, even in cases where net present value (at a market acceptable discount rate) calculation shows said adoption to be cost effective (Jaffe and Stavins, 1994). Despite these financial incentives, it is understood that adoption of more economical technologies is most commonly a gradual process (Jaffe and Stavins, 1994). So, at what rate should we expect these technologies to be adopted? What reasons might cause LED lights to be adopted faster or slower than HVAC technologies, and how do the rates of adoption for both technologies compare to the optimal or expected rate of diffusion? These questions will guide the literature review of this paper.

Literature Review

Before continuing further into the literature, it may first be useful to establish a definition of energy efficiency as it relates to HVAC systems, and how that definition may translate to other technologies which will be subsequently compared. Generally, energy efficiency can be defined as "using less energy to provide an energy service." (Cleary and Palmer, 2020) Specifically for HVAC systems, the energy service in question is not as simple as that of other more familiar use cases such as lighting. Consumers are generally familiar with LED light bulbs which are able to produce the same amount of light as incandescent light bulbs by using 75 to 80 percent less electricity (Di Maria et al., 2009); the service provided here is simply light. However, in the case of HVAC systems, consider the metric(s) by which the successful execution of the service can be defined. Do we consider consistent achievement of a temperature setpoint to be success? How about achievement of a setpoint in 100% of occupied instances, as opposed to without regard to occupancy? When we expand setpoints to include CO2, CO, Particulate Matter (PM), and other pollutants, what standards do we set, how do we set them, and what should we be willing to pay to achieve them? Energy efficiency in the HVAC context can pursue any one of these objectives with lower energy cost in order to increase the general energy efficiency of the system, or even, as is the case of modified control models, create more specific objectives for the system based around better understandings of the occupancy of a space or redefined understandings of the effects of environmental conditions on occupants.

When comparing energy efficiency goals and frameworks, this comparative simplicity and complexity must be accounted for. To say that problem definition or solving strategies which worked for a simple, light producing service could be adapted without modification to the more complex case is a likely path to oversimplification and failure to account for important factors. In the same manner, the details of other complex energy efficiency cases can lead to difficulties in generalization due to specific assumptions or goals set in one case that are simply not relevant to another.

This literature review will thus seek to generally understand the state of knowledge around the adoption rates of efficient energy technologies, then understand which factors in the HVAC case may be understood through contextualization with other technologies, leveraging HVAC specific research where available and appropriate.

Generally understanding the factors which influence the sub-optimal adoption of energy efficient technologies requires an investigation into market failure and non-market-failure based explanations. As a foundation to further analysis, both will be explored briefly here.

Market failure explanations of suboptimal adoption

Adoption of energy efficient technologies faces both public good and principal/agent market failures.

In the case of principal/agent market failures, a classic example is that of new construction. A home builder will likely be able to cut costs in construction by using less energy efficient or cheaper building materials, and since the future cost of energy savings will not be seen by the builder, little inherent incentive exists to build with more energy efficient designs. Only in the case that some of the future energy saving value can be priced into building *and* sale costs are the incentives of principal and agent aligned, contrary to the current pricing structure of new construction. In any case, currently, the builder (principal) faces a different set of incentives than the agent, leading to slower than optimal adoption.

In the case of public good market failures, information is of key concern. Information acts like a public good in that once created it can be used by others at little additional cost, it is difficult to prevent its use by others once created, and, in this case, adoption of a technology is itself a source of information for others on the effectiveness of this technology. Public goods with these characteristics are frequently underprovided for in market-based systems due to a lack of compensation of the positive externalities generated. This under provision of information on efficient technologies is one explanation for suboptimal adoption rates.

Non-market failure explanations of suboptimal adoption

To understand suboptimal adoption outside of the scope of market failures, the literature suggests that an investigation into why the observed "suboptimal" adoption may appear optimal from the perspective of the decision maker. One explanation is that consumers of energy efficient technologies may simply act on the uncertain future return of an irreversible efficiency investment with much higher discount rates than the one used to determine optimal adoption rates (Hassett and Metcalf, 1993). That is to say, there is no one right answer as to how to deal with the uncertainty around future energy savings; it is entirely reasonable to assume that a rational, risk averse attitude could devalue uncertain future returns and thus favor other, more certain investments. Additional non-market failure factors include the difficulty of pricing in adoption costs, such as research, understanding of one's specific circumstances, and determination of reliable suppliers also increase costs of adoption in difficult to quantify ways, further contributing to behavior which appears suboptimal to an economic analyst but in reality accounts for additional information (Stern, 1987). Qualitative aspects of a technology, outside its energy efficiency may also play a role (e.g., not wanting to purchase an electric vehicle so as to avoid characterizations about people who drive them). Finally, optimality calculations often use the mean user to understand adoption rates; however, technologies with positive NPV for the mean consumer will likely be suboptimal for at least a portion of the population under consideration (Jaffe and Stavins, 1991).

Influences Specific to of HVAC Adoption

With an established understanding on the state of knowledge around general suboptimal adoption of energy efficient technologies, we can now turn to establishing a specific understanding of the state of the literature around HVAC adoption.

Spatial contagion is of particular interest in the residential adoption of efficient HVAC technologies; a study published in 2013 showed that if over 85% of one neighborhood adopted a new efficient HVAC technology, adoption rates in adjacent neighborhoods doubled from baseline adoption rates (Noonan et al., 2013). Related to the aforementioned information-cost explanation, it is hypothesized that communication and education via actor networks reduces cost of adoption by making information more readily available in the community (Noonan et al., 2013); however, the aforementioned 2013 study makes a distinction between spatial contagion and cost to adoption. This is likely from a perspective which considers cost of adoption to only contain explicit costs, or from a less economically minded scholarly approach.

Outside of cost reduction, spatial contagion may also play a role in adoption of HVAC technologies through social means. Shared information, spatial competition, and mimicking play a role in incentivizing potential consumers to take the time to investigate options for reducing energy consumption, and these forces also show strong spatial diffusion (Abrahamse et al., 2005). The level of social pressure or information available to you is heavily influenced by the actions of surrounding actors.

It is likely that the above effects can be seen for other efficient technologies, but the current state of the literature appears to only have evaluated these effects for HVAC specifically (Noonan et al., 2013).

Findings and Discussion

HVAC and General Suboptimal Adoption

Having established some understanding of the general theory of suboptimal adoption, a discussion of how these factors may affect HVAC adoption is worthwhile.

Firstly, principal/agent problems apply strongly in HVAC investments. Consider the case of a landlord, commercial or otherwise, deciding to invest in a new HVAC system which has the potential to, without loss of generalization, reduce energy consumption by 35% compared to the current system. Given the tenant pays the energy bill, what incentive does the landlord have to make this investment upgrade? Unless part of the reduced energy costs can be recouped through increased rent, there is little to no incentive for a landlord to make such an upgrade. Pricing in energy savings to rent may be a difficult task as when a renter makes a decision to occupy a space, comparative information on prospective energy costs may be unreliable and difficult to obtain for properties under consideration.

Information as a public good also affects HVAC adoption. In both commercial and residential settings, HVAC maintenance, operation, and installment is generally considered well outside the understanding of most users of the technology. As such, acquiring the necessary information to even make a financial investment in a new HVAC system is fraught with uncompensated externalities and opportunity costs. Even understanding enough about the state of technologies to know that such a journey into information gathering is necessary can be difficult to achieve, possibly shedding light into another reason spatial contagion may be particularly effective and disseminating HVAC technology.

When considering how uncertainty of returns may affect HVAC adoption, commercial and residential decision making, while in economic theory may be quite similar, in actuality, likely face very different incentives. If it was assumed that the modal homeowner would, in fact, select an appropriate discount rate and calculate the NPV of an investment in an HVAC system after researching precisely the expected cash flows of such an investment in order to make an investment decision then the decision would likely be the same. However, it could be reasonably supposed that this would not be the decision-making process of the modal homeowner, leading to a decision made under much more uncertainty: uncertainty of cash flow, of true investment cost, of discount rate, and of the optimal manner in which such an investment should be made. In a commercial setting, where there is often more knowledge and more of an existing framework with which these types of decisions are made, the described NPV approach may be more reasonable, though given the prevalence of small business run by proprietors without formalized business nor analytic knowledge, even this assumption may not hold. As such, using an understanding of NPV of various HVAC investments may simply be a method of approaching the problem that, while logical and founded in a history of optimal economic decision making, is simply disconnected from the reality of the way actual actors make their decision, leading to “suboptimal” behavior.

Qualitative Factors

It is also worth discussing a gap in the current literature on the subject of adoption of HVAC technologies; economic incentive may be easy to logically optimize, but what is it that actors actually care about in the HVAC investment decisions? Here we return to the idea of what the goal of the system is. Much like EVs, it may be easy to show via NPV calculation that purchasing an EV is ideal; however, this entirely misses what the product actually does. If NPV states buying an EV is optimal, but said EV only has 90 miles of range and does not perform to the specification of an internal combustion vehicle, such a comparison is moot. Do similar "apples and oranges" comparisons exist in the HVAC space? Are more efficient systems larger, louder, less effective, or carry unaccounted for societal implications? It can be assumed that the largest factor in making an HVAC investment decision is simply the ability of the system to provide comfort for occupants; it is easy to see how, especially in the United States, many would find it absolutely unacceptable if the system did not provide the exact required comfort near to 100% of the time, and any system which offers energy savings at even a small cost of comfort would simply never be adopted.

Furthermore, in a residential context specifically, housing and decisions about it are often much more about sentiment than economics. People view their homes and indicative of their lives, from both an internal and external signaling perspective. A decision to make a change to an integral part of the functioning of one's home is often as much a factor of the disruption that change will cause to the lives of the residents and other modifications which may be needed to support the installation of an HVAC system into a home. As an anecdote from my own experience, the roof of my childhood home needed to be removed in order to replace an HVAC unit when it failed. It will be left to the reader's imagination to consider the effects of this on a family with three children under the age of 5 and further consider the lack of an economist's ability to account for this in determining optimal adoption rates.

Conclusion

HVAC adoption, like much of the process for understanding and incentivizing energy efficient technologies, is complex, suffering from market failures, non-market failure-based barriers, difficult to quantify qualitative factors, and complex technological underpinnings. In order to properly incentivize adoption of HVAC technologies, an understanding of which of these factors might be most cost-effectively addressed should be pursued as a manner of triaging obstacles and moving towards faster adoption on the nearest time horizon. This paper has shown that many of the obstacles faced by HVAC adoption are not unique and are faced by emergent technologies seeking improved energy efficiency generally; specific HVAC challenges revolve around qualitative factors in the home and around baseline necessary comfort. Adoption of energy efficient HVAC systems will be a necessary part of reducing our impact on the climate over the coming year and future research may address the removal or addressing of the defined barriers as a starting methodology for taking that necessary step.

References

2022 HVAC System Costs | *Installation & Replacement Cost Estimator*. HomeGuide. Retrieved March 4, 2022, from https://homeguide.com/costs/hvac-cost

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2005). *A review of intervention studies aimed at household energy conservation*. Journal of Environmental Psychology, 25(3), 273–291. https://doi.org/10.1016/j.jenvp.2005.08.002

B.L. Diffey. *An overview analysis of the time people spend outdoors*. British Journal of Dermatology—Wiley Online Library. (2010). Retrieved April 11, 2022, from https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2133.2010.10165.x

Andrews, C. J., & Krogmann, U. (2009). *Explaining the adoption of energy-efficient technologies in U.S. commercial buildings*. Energy and Buildings, 41(3), 287–294. https://doi.org/10.1016/j.enbuild.2008.09.009

Christie, L., Donn, M., & Walton, D. (2011). *The 'apparent disconnect' towards the adoption of energy-efficient technologies*. Building Research & Information, 39(5), 450–458. https://doi.org/10.1080/09613218.2011.592485

Cleary, K., & Palmer, K. (2020, June 17*). Energy Efficiency 101*. Resources for the Future. https://www.rff.org/publications/explainers/energy-efficiency-101/

Di Maria, C., Ferreira, S., & Lazarova, E. (2010). *Shedding Light on the Light Bulb Puzzle: The Role of Attitudes and Perceptions in the Adoption of Energy Efficient Light Bulbs*. Scottish Journal of Political Economy, 57(1), 48–67. https://doi.org/10.1111/j.1467-9485.2009.00506.x

Federal Tax Credits for Electric and Plug-in Hybrid Cars. (n.d.). Retrieved March 4, 2022, from https://www.fueleconomy.gov/feg/taxevb.shtml

Goetzler, W., Shandross, R., Young, J., Petritchenko, O., Ringo, D., McClive, S. (2017). *Energy Savings Potential and RD&D Opportunities for Commercial Building HVAC Systems* (DOE/EE--1703, 1419622; p. DOE/EE--1703, 1419622). https://doi.org/10.2172/1419622

Hassett, K., & Metcalf, G. (1992). *Energy Tax Credits and Residential Conservation Investment* (NBER Working Paper No. 4020). National Bureau of Economic Research, Inc. https://econpapers.repec.org/paper/nbrnberwo/4020.htm

Hesselink, L. X. W., & Chappin, E. J. L. (2019). *Adoption of energy efficient technologies by households – Barriers, policies and agent-based modelling studies*. Renewable and Sustainable Energy Reviews, 99, 29–41. https://doi.org/10.1016/j.rser.2018.09.031

Jaffe, A. B., & Stavins, R. N. (1994a). *The energy paradox and the diffusion of conservation technology*. Resource and Energy Economics, 16(2), 91–122. https://doi.org/10.1016/0928-7655(94)90001-9

Jaffe, A. B., & Stavins, R. N. (1994b). *The energy-efficiency gap What does it mean?* Energy Policy, 22(10), 804–810. https://doi.org/10.1016/0301-4215(94)90138-4

Letnik, T., Marksel, M., Luppino, G., Bardi, A., & Božičnik, S. (2018). *Review of policies and measures for sustainable and energy efficient urban transport*. Energy, 163, 245–257. https://doi.org/10.1016/j.energy.2018.08.096

Mohamed, M., Ferguson, M., & Kanaroglou, P. (2018). *What hinders adoption of the electric bus in Canadian transit? Perspectives of transit providers*. Transportation Research Part D: Transport and Environment, 64, 134–149. https://doi.org/10.1016/j.trd.2017.09.019

Nair, G., Gustavsson, L., & Mahapatra, K. (2010*). Factors influencing energy efficiency investments in existing Swedish residential buildings*. Energy Policy, 38(6), 2956–2963. https://doi.org/10.1016/j.enpol.2010.01.033

Noonan, D. S., Hsieh, L.-H. C., & Matisoff, D. (2013). *Spatial Effects in Energy-Efficient Residential HVAC Technology Adoption*. Environment and Behavior, 45(4), 476–503. https://doi.org/10.1177/0013916511421664

Quarles, N., Kockelman, K. M., & Mohamed, M. (2020*). Costs and Benefits of Electrifying and Automating Bus Transit Fleets*. Sustainability, 12(10), 3977. https://doi.org/10.3390/su12103977

Shi, J., Yu, N., & Yao, W. (2017*). Energy Efficient Building HVAC Control Algorithm with Real-time Occupancy Prediction*. Energy Procedia, 111, 267–276. https://doi.org/10.1016/j.egypro.2017.03.028

Stern, P. C. (1986*). Blind spots in policy analysis: What economics doesn't say about energy use.* Journal of Policy Analysis and Management, 5(2), 200–227.

The history of LED lighting -. (2019, November 19). https://www.energysavinglighting.org/the-history-of-led-lighting/

Jaffe, A. B., & Stavins, R. N. (1991). *Evaluating the relative effectiveness of economic incentives and direct regulation for environmental protection: impacts on the diffusion of technology.* Center for Science & International Affairs, John F. Kennedy School of Government, Harvard University.

Developing a Dynamic Control Algorithm to Improve Ventilation Efficiency in a University Conference Room

A Review of Barriers to Implementation and Investigation into Suboptimal Adoption of Energy Efficient HVAC Technologies

A Thesis Prospectus
In STS 4500
Presented to
The Faculty of the
School of Engineering and Applied Science
University of Virginia
In Partial Fulfillment of the Requirements for the Degree
Bachelor of Science in Systems Engineering

By
Caleb A Neale

Fall 2021

Technical Project Team Members
Matthew Caruso
Jason Jabbour
Alden Summerville
Avery Walters

On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

ADVISORS

Adarsh Ramakrishnan, Department of Engineering and Society
Arsalan Heydarian, Engineering Systems and Environment
Arthur Small, Engineering Systems and Environment

Introduction

In UVA's LinkLab, as a part of the Living Link Lab Program, there is a significant amount of environmental, occupancy, and HVAC system operational data available for analysis. This presents an opportunity for a detailed case study of the performance of an HVAC system among multiple metrics outside of just temperature and humidity with the intention of improving HVAC control systems' ability to maintain occupant comfort and health with reduced energy consumption. Investigation of multiple metrics of occupant comfort, whether a given room even has occupants which require comfort, various metrics of system operation, and energy consumption consumption (actual and calculated) has the potential to produce an environmental model which may aid in the development of an improved policy for the HVAC system control problem.

Considering HVAC usage accounts for 30% of total commercial building energy consumption, there is significant environmental and economic incentive to reduce the energy load of HVAC systems both for regulators and commercial operators. A commissioned report by the US Dept. of Energy (Goetzler et al. - 2017) cites "Technology Enhancements for Current Systems" as one of four groups of high priority technology options, with "Advanced HVAC Sensors" as the top ranked technology within this category at an estimated Technical Energy Savings Potential (Quadrillion BTU/yr.) of 0.63, lending particular credence to the idea that advanced sensing combined with more efficient control could be a significant contributor to reduced HVAC system burden on energy resources.

In order to pursue results in this identified field, the current technical project seeks to compile answers to four primary research questions and leverage their answers to produce a sample control algorithm to be tested in UVA's Link Lab. We seek to answer: what makes high quality indoor air? What control systems are available within the Link Lab (and commercial HVAC systems generally)? How do available control systems affect the quality of indoor air? How can a new control system be implemented?

To extend this technical project, this thesis seeks to investigate further the barriers to widespread implementation of improved HVAC control systems. Taking a sociotechnical lens to this problem and evaluating both technical and economic barriers will provide a comprehensive view of the path to widespread reductions in energy usage and improvements in indoor air quality.

Technical Topic

The optimization of Indoor Air Quality (IAQ) and energy efficiency the Link Lab will combine a literature review on existing optimization methods and an in-depth investigation of the current HVAC system in place. The literature review will be leveraged to answer questions around which metrics of IAQ should be focused on and how HVAC operation affects these metrics. Though an overview of the current HVAC system is provided here, additional investigation is needed to enumerate all the possible control mechanisms which may be manipulated as a part of HVAC control. Finally, using a fully developed state space, an optimization control model can be implemented and tested on the LinkLab HVAC system, comparing actual and forecasted results.

To manipulate the existing system, an understanding of the current state is needed. The current control mechanisms of the Link Lab system do not take into account any information other than a preset “occupied” status indicator which is defined as times in which the building is generally considered to be occupied -- not a measure of actual occupancy -- and temperature. This is despite available data from motion sensors in each HVAC control zone, as well as CO2 data which is a well known proxy for occupancy (Pedersen et al. - 2017).

The current system is known as a Variable Air Volume (VAV) system, which consists of two primary Air Handling Units (AHUs), and VAV boxes per assigned air control zone. AHUs perform the primary heating, cooling, and dehumidification of air to be provided to users, while VAV boxes may perform additional heating but primarily serve to regulate air flow to specific zones within the area served by an AHU in order to meet differing temperature needs within those zones (PNNL, Accessed 2021).

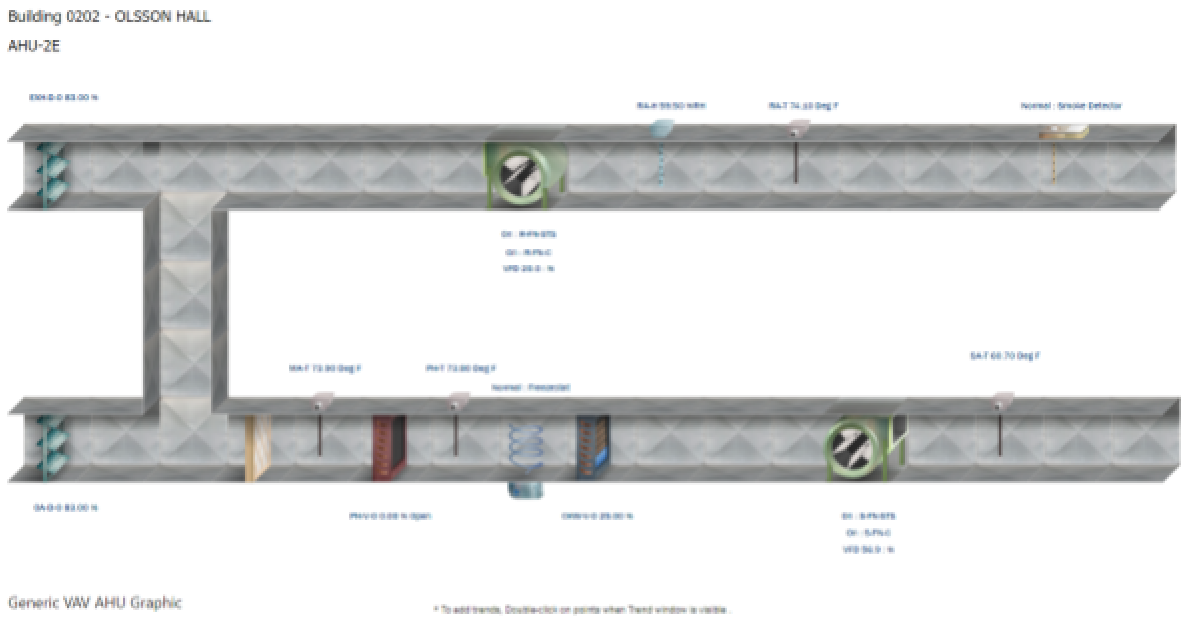

Figure 1: AHU Diagram

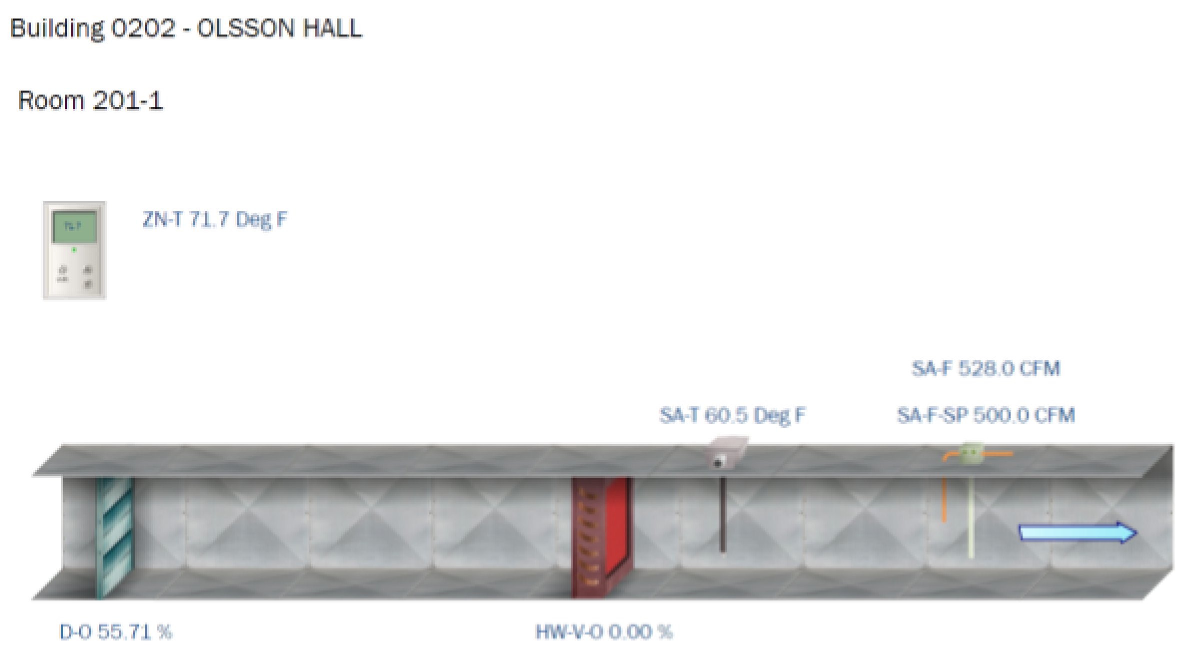

Figure 2: VAV Box

Two major problems have been identified with this system which will be considered when generating and evaluating solutions. Primarily, the blunt method of assignment of occupancy not by zone and actual occupancy, but by building and by daily blocks of time; there is significant potential for over usage of HVAC resources in unoccupied zones and under usage in occupied zones. Secondarily, the consideration of only temperature when deciding air flow can lead to rooms which may have low IAQ and require ventilation to not receive needed ventilation due to the temperature being in an acceptable range. Given ventilation can be provided without temperature treatment by making use of return air from unoccupied zones, there is no system requirement that ventilation only be provided due to temperature needs.

Though occupancy data is not currently available to address the current blunt method, this project will evaluatie multiple approaches to solving this problem. Air quality data could be readily leveraged to produce an occupancy flag, as CO_2 levels spiking in a room is an effective indicator of occupancy. With enough funding and time, occupancy sensors could be installed throughout the building, though this level of additional equipment needed implementation may increase the costs of generalizing the system to other use cases, but provide significantly more precise data for modeling and prediction purposes (Mutis et al. - 2020).

Providing rooms with ventilation when IAQ requires it but temperature does not poses a different problem. A formulation of trade offs and potential solutions to this problem will be needed for the final optimization problem.

HVAC operation is a classic example of the operation of a complex system which impacts users and operators through energy, implementation, upkeep, and health costs. To create a system which truly serves all stakeholders, all of these costs must be considered when creating a control system. This requires advanced data collection and processing not currently implemented in traditional HVAC systems which this project is seeking to develop and implement.

STS Topic

This thesis will examine the larger societal implications of improved efficiency in commercial HVAC systems, considering implications on the larger energy usage patterns in the US as well as health outcomes, both infectious and long term where possible. Specifically, examining the costs and benefits of retrofitting this portion of the US energy grid over short and long time horizons to provide a holistic view of the necessary actions to implement the advanced sensor and efficiency technology found in the LinkLab. The thesis will serve as a complement to the technical research of my capstone by providing a well-rounded understanding of the space in which the tested and designed technology would be implemented.

Despite the potential effectiveness of the proposed technology under development, without positive and normative arguments for the implementation of the technology, it's effectiveness will be limited. Different use cases require different understanding of the technology; decreased energy costs could appeal to private and corporate clients, while a definitive understanding of carbon emission reduction from implementation could contribute to governmental management of incentives and policy. This thesis will focus on understanding financial and environmental effects across a range of scenarios to understand and incentivize additional development in technology which benefits user comfort, profit bottom lines, and environmental outcomes.

Additionally, this thesis will investigate previous methods by which this problem may have been addressed in order to improve the developed solution and provide adequate background for the development of both a solution and implementation plan. The primary research questions will address the nature and implementation success of previous solutions for managing IAQ.

In order to answer these questions in a socio-technical context, various STS frameworks can be applied to contextualize the problem. The adoption curve will be leveraged to distinguish the characteristics of early adopters and late adopters. The production possibilities frontier can be used to enumerate and understand tradeoffs between energy usage and IAQ/temperature, useful for presenting a solution which directly acknowledges the costs of improvement to a potential client. Anticipatory Governance could also be leveraged to consider policy and incentives which would help overcome initial costs to adoption and allow for the long term benefits of improved health and reduced energy consumption to be realized.

The economics of technology adoption will be a significant point of consideration. Potential points of research could include EV incentive plans and adoption, clean energy adoption rates, and effects of cap and trade policies on consumer/corporate behavior. All of these policies and technologies are related to HVAC consumption in that a combination of government and market incentives have been and continue to lead to adoption of the technology. By using these (and others) as case studies, and comparing technology implementation costs, an understanding of adoption rates and potential need for government backed incentives can be gained.

Research Question and Methods

This thesis will seek to understand previous technologies which have been developed to address IAQ and/or HVAC efficiency and the barriers to implementation they have faced. Specifically, a literature review would seek to obtain a general understanding and quantification of proposed benefits of previous advanced HVAC technologies, and their related costs. To understand the effects of cost-benefit relationships in this space (which costs and benefits may have an outsized effect on adoption), data on adoption rates and real world success/failure of technologies will be investigated. If sufficient data is obtained, modeling attempts can be made to predict project success based on proposed characteristics; exploratory data analysis and visualization could also be leveraged in the production of a new technology, as well as in the effective argument for the adoption and production of newly developed control system. To understand the backdrop of new technology adoption in the energy efficiency space, consideration will be given to adoption of other green technologies and related government incentives, outside of just HVAC systems. The primary method of research for answering the above questions and background investigation will be literature review.

Conclusion

The result of the technical project associated with this thesis will be an improved control mechanism for the HVAC system in UVA's Link Lab which considers IAQ in addition to temperature, and attempts to do so using less energy than the original system. This improved model will leverage IAQ data and consider the generalizability of the solution in it's design, with the hope that the system can be leveraged to generally improve IAQ and energy usage in commercial HVAC systems.

The STS thesis will seek to understand the factors which influence adoption of technologies similar to the developed one by performing a literature review and data analysis on previously developed technologies, both specifically HVAC and other green/energy efficiency technologies. If data is sufficient, a model of adoption based on proposed costs and benefits would be developed in order to forecast the adoption of the developed technical solution. Consideration will be given to economic and social factors including adoption curves, production possibilities frontiers, NPV, and the sociotechnical triangle in order to understand barriers and effects of the technical solution in a broader context.

Locally at UVA Link Lab, an implemented solution to the IAQ and energy efficiency problems would reduce energy usage and improve occupant comfort, health, and potentially even academic performance. A nationwide implementation and generalization could significantly contribute to the estimated Technical Energy Savings Potential (Quadrillion BTU/yr.) of 0.63 stated by the Department of Energy.

Sources

Anon. n.d. "American Society of Heating, Refrigerating and Air-Conditioning Engineers - IWrapper." Retrieved November 1, 2021a (https://ashrae.iwrapper.com/ASHRAE_PREVIEW_ONLY_STANDARDS/STD_62.1_2019).

Anon. n.d. "Energy_executive_summary.Pdf."

Anon. n.d. "Variable Air Volume (VAV) Systems Operations and Maintenance | PNNL." Retrieved November 1, 2021c (https://www.pnnl.gov/projects/best-practices/variable-air-volume-systems).

Anthes, Emily. 2021. "The Hot New Back-to-School Accessory? An Air Quality Monitor." *The New York Times*, October 10.

Cacciottolo, M., X. Wang, I. Driscoll, N. Woodward, A. Saffari, J. Reyes, M. L. Serre, W. Vizuete, C. Sioutas, T. E. Morgan, M. Gatz, H. C. Chui, S. A. Shumaker, S. M. Resnick, M. A. Espeland, C. E. Finch, and J. C. Chen. 2017. "Particulate Air Pollutants, APOE Alleles and Their Contributions to Cognitive Impairment in Older Women and to

Amyloidogenesis in Experimental Models." *Translational Psychiatry* 7(1):e1022–e1022. doi: 10.1038/tp.2016.280.

EERE Publication and Product Library, Washington, D.C. (United States). 2014. *Energy Savings Potential and RD&D Opportunities for Non-Vapor-Compression HVAC Technologies*. DOE/EE-1021. doi: 10.2172/1220817.

Gao, Xu, Brent Coull, Xihong Lin, Pantel Vokonas, Avron Spiro, Lifang Hou, Joel Schwartz, and Andrea A. Baccarelli. 2021. "Short-Term Air Pollution, Cognitive Performance and Nonsteroidal Anti-Inflammatory Drug Use in the Veterans Affairs Normative Aging Study." *Nature Aging* 1(5):430–37. doi: 10.1038/s43587-021-00060-4.

GmbH, finanzen net. n.d. "Johnson Controls Develops Industry-First AI Driven Digital Solution to Manage Clean Air, Energy, Sustainability, Comfort and Cost in Buildings." *Markets.Businessinsider.Com*. Retrieved November 1, 2021 (https://markets.businessinsider.com/news/stocks/johnson-controls-develops-industry-first-ai-driven-digital-solution-to-manage-clean-air-energy-sustainability-comfort-and-cost-in-buildings-1030894310).

Goetzler, William, Richard Shandross, Jim Young, Oxana Petritchenko, Decker Ringo, and Sam McClive. 2017. *Energy Savings Potential and RD&D Opportunities for Commercial Building HVAC Systems*. DOE/EE-1703. Navigant Consulting, Burlington, MA (United States). doi: 10.2172/1419622.

Kumar, Prashant, Claudio Martani, Lidia Morawska, Leslie Norford, Ruchi Choudhary, Margaret Bell, and Matt Leach. 2016. “Indoor Air Quality and Energy Management through Real-Time Sensing in Commercial Buildings.” *Energy and Buildings* 111:145–53. doi: 10.1016/j.enbuild.2015.11.037.

Künn, Steffen, Juan Palacios, and Nico Pestel. 2019. *Indoor Air Quality and Cognitive Performance*. *SSRN Scholarly Paper*. ID 3460848. Rochester, NY: Social Science Research Network.

Laurent, Jose Guillermo Cedeño, Piers MacNaughton, Emily Jones, Anna S. Young, Maya Bliss, Skye Flanigan, Jose Vallarino, Ling Jyh Chen, Xiaodong Cao, and Joseph G. Allen. 2021. “Associations between Acute Exposures to PM2.5 and Carbon Dioxide Indoors and Cognitive Function in Office Workers: A Multicountry Longitudinal Prospective Observational Study.” 16(9):094047. doi: 10.1088/1748-9326/ac1bd8.

MacDonald, M., D. Goldenberg, and E. Hudgins. 1982. *RD and D Opportunities for Large Air-Conditioning and Heat-Pump Systems. Final Report*. ORNL/Sub-80-13817/1. Oak Ridge National Lab., TN (USA); TRW, Inc., Oak Ridge, TN (USA).

Mutis, Ivan, Abhijeet Ambekar, and Virat Joshi. 2020. “Real-Time Space Occupancy Sensing and Human Motion Analysis Using Deep Learning for Indoor Air Quality Control.” *Automation in Construction* 116:103237. doi: 10.1016/j.autcon.2020.103237.

Pedersen, Theis Heidmann, Kasper Ubbe Nielsen, and Steffen Petersen. 2017. “Method for Room Occupancy Detection Based on Trajectory of Indoor Climate Sensor Data.” *Building and Environment* 115:147–56. doi: 10.1016/j.buildenv.2017.01.023.

Risbeck, Michael J., Martin Z. Bazant, Zhanhong Jiang, Young M. Lee, Kirk H. Drees, and Jonathan D. Douglas. 2021. “Modeling and Multiobjective Optimization of Indoor Airborne Disease Transmission Risk and Associated Energy Consumption for Building HVAC Systems.” *Energy and Buildings* 253:111497. doi: 10.1016/j.enbuild.2021.111497.

Younan, Diana, Andrew J. Petkus, Keith F. Widaman, Xinhui Wang, Ramon Casanova, Mark A. Espeland, Margaret Gatz, Victor W. Henderson, JoAnn E. Manson, Stephen R. Rapp, Bonnie C. Sachs, Marc L. Serre, Sarah A. Gaussoin, Ryan Barnard, Santiago Saldana, William Vizuete, Daniel P. Beavers, Joel A. Salinas, Helena C. Chui, Susan M. Resnick, Sally A. Shumaker, and Jiu-Chiuan Chen. 2020. “Particulate Matter and Episodic Memory Decline Mediated by Early Neuroanatomic Biomarkers of Alzheimer’s Disease.” *Brain* 143(1):289–302. doi: 10.1093/brain/awz348.

Yu, Liang, Di Xie, Chongxin Huang, Tao Jiang, and Yulong Zou. 2019. “Energy Optimization of HVAC Systems in Commercial Buildings Considering Indoor Air Quality Management.” *IEEE Transactions on Smart Grid* 10(5):5103–13. doi: 10.1109/TSG.2018.2875727.

Zhong, Sailin, Denis Lalanne, and Hamed Alavi. 2021. “The Complexity of Indoor Air Quality Forecasting and the Simplicity of Interacting with It – A Case Study of 1007 Office Meetings.” Pp. 1–19 in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. New York, NY, USA: Association for Computing Machinery.