

**Investigation of multiple indoor air quality and energy use tradeoffs to
inform the development of next-generation ventilation strategies for office buildings**

A Thesis

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Adams Edwin Rackes

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DEDICATIONS

For Barbara, Mike, and Elizabeth.

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ABSTRACT

Investigation of multiple indoor air quality and energy use tradeoffs to inform the development of next-generation ventilation strategies for office buildings

Adams Edwin Rackes
Michael S. Waring, Ph.D.

In commercial buildings, ventilation, or air exchange between an indoor environment and the outdoors, is necessary for controlling contaminants emitted by indoor sources such as occupants, cleaning and personal care products, and building materials. In offices, increased ventilation has also been shown to significantly increase worker productivity and reduce sick leave. At the same time, increasing ventilation introduces more outdoor air pollutants, including ones with known public health consequences like particulate matter and ozone. Furthermore, ventilation accounts for about one-fourth of U.S. commercial heating, ventilation, and air-conditioning (HVAC) energy use and changes can have significant effects on building energy consumption. This research project aims to quantify, compare, and optimally or nearly optimally balance these multiple impacts for office buildings, while remaining alert to the fact that outcomes differ significantly by building, operating conditions, and user preference.

The project had three objectives. The first was to use Monte Carlo analysis over a wide range of climates and office building characteristics to evaluate combinations of mature existing technologies including demand-controlled ventilation (DCV), economizing, supply air temperature reset, and increased ventilation rate (VR). Some combinations were ‘win-win,’ reducing HVAC energy consumption by 12–27% while increasing work performance by 0.5% and eliminating 5 hours of absenteeism per year. Annually, such strategies could save U.S. \$1.25 billion in energy costs and generate \$28–55 billion in total net benefits.

The second objective was to develop an outcome-based ventilation (OBV) decision-making framework, using a loss function to combine scientific knowledge, uncertainty, and parameters to

express user preferences. The OBV framework confirmed that human-related outcomes are much more valuable than energy use. For example, we evaluated an intervention that increased the VR by ~ 10 L/s/occ on a dataset representing the office sector. With “best estimate” user parameters, the average loss impact of every other outcome was greater than the one related to HVAC energy costs—by a factor of 47 for work performance, 25 for excess absence, 3.9 for particle exposure, and 1.1 for ozone exposure. Even the most ventilation-adverse user preferences still produced VRs that were very often as high as 30 L/s/occ and only rarely lower than 15 L/s/occ.

The third objective was to use optimization with the OBV framework to minimize loss over a daylong horizon and take advantage of weather, pollution, occupancy, and other transient dynamics. An optimal control problem was formulated, then translated to a nonlinear optimization problem, and solved by interior point methods. Results showed that, contrary to our hypothesis, numerically optimizing ventilation control for a single day did not provide substantial Pareto improvements over existing control methods. In fact, a strategy with economizer and DCV was very close to Pareto optimal on most days. Neither time-of-use pricing nor any factor in a sensitivity analysis revealed opportunities in which optimizing ventilation within each day of the year saved more than 5% of annual HVAC energy costs.

In concluding, we used the insights of this research to outline a procedure for next-generation ventilation that takes advantage of opportunities to optimize over an annual horizon and adjust for the influential climate and building parameters identified by sensitivity analysis. For daily control, it would employ existing successful technology components, like DCV and economizer controls, that we have shown to be capable of significant energy savings and, on a daily timescale, nearly optimal. These methods would be embedded in and guided by a more conscious annual strategy that includes an initial preference elicitation step and an offline annual optimization to intelligently allocate ventilation resources across the year. Such an approach could help make ventilation more effective and reliable, and allow users to make informed decisions about ventilation tradeoffs and understand their consequences.

CHAPTER 1: INTRODUCTION

1.1 Odors and the historical case for ventilation

Most residents of the United States and other developed countries spend the large majority of their lives indoors, where they experience the greatest fraction of their exposure to many airborne pollutants (Klepeis et al., 2001; Ott & Roberts, 1998; Wallace, 1995). For example, volatile organic compounds (VOC) often have higher concentrations indoors than outdoors (Bennett et al., 2011; Brown, Sim, Abramson, & Gray, 1994; Daisey, Hodgson, Fisk, Mendell, & Tenbrinke, 1994; Ekberg, 1994). Ventilation, along with source control and air cleaning/filtration, is a critical part of controlling the concentration of pollutants emitted indoors and maintaining acceptable indoor air quality (IAQ). In U.S. commercial buildings, where Americans spend about 18% of their time (Klepeis et al., 2001), minimum levels ventilation levels are generally required by building code.

Historically, ventilation requirements developed to promote the hygiene of indoor spaces and combat “bad air,” which by the middle of the 19th century was recognized to mean limiting the accumulation of human bioeffluents (Persily, 2015). In 1858, Pettenkofer, correlating odor perception by subjects with carbon dioxide (CO₂) levels, proposed a CO₂ concentration limit of 1000 ppm. This “Pettenkofer number” established the use of CO₂ level as an indicator, or “a benchmark from which we can then also estimate a higher or lower content of other (pollutant) substances” (Zhang, Wargocki, Lian, & Thyregod, 2017). The indicator is useful because of the proportionality of human bioeffluent and human CO₂ emissions.

In terms of the ventilation rate (VR), or the outdoor air flow per occupant, Pettenkofer’s CO₂ limit translates to 9–10 L/s/occ (Gids & Wouters, 2010). Additional calculations and experiments in the first few decades of the 20th century, also based on controlling organic odors exhaled by occupants, established minimum VRs ranging from 5 to 15 L/s/occ (Persily, 2015). Chamber

studies conducted by Yaglou and colleagues in the 1930s concluded that a VR of 7.5–9 L/s/occ produced an odor level that 80% of people entering from a clean air environment rated acceptable; the roughly 8 L/s/occ value, later backed up by multiple studies in the 1980s and 1990s, has had an enduring influence on ventilation standards (Persily, 2015).

Today, such standards are often incorporated by reference into building codes for commercial buildings. The most widely adopted in the U.S. is ASHRAE Standard 62.1 (ASHRAE, 2013b), which sets minimum VR in its ventilation rate procedure (VRP). For office spaces, the minimum VR specified by Standard 62.1 and its precursor Standard 62 has varied over time, from 7.5 L/s/occ in the first version in 1973, to 2.5 L/s/occ (for non-smoking spaces) in 1981, to 10 L/s/occ in 1989, to 8.5 L/s/occ (at default occupant density) from 2004 to the present (Persily, 2015). That historical range matches 3 to 10 L/s/occ required in offices by various contemporary ventilation standard around the world. The 10 L/s/occ adopted in the 1989 version of the standard was apparently based on beginning with the 7.5 L/s/occ derived from the Yaglou and similar studies, and adding 2.5 L/s/occ to control non-human contaminants. Persily found no specific justification for this increase, nor for the significant decrease from 1981–1989.

According to Persily, based on his own experience on the Standard 62.1 committee, setting minimum VRs “has always been challenging based on limited research results to support specific values, pressures by some to lower rates based on energy considerations, and pressures by others to raise them based on IAQ benefits” (Persily, 2015). ASHRAE and the Standard 62 committee struggled with the question of whether an engineering society should even consider health impacts when writing standards. After contentious debate and a member survey, the ASHRAE Board ultimately decided that while the Society would make no claims or guarantees about health, its standards would “consider health impacts where appropriate” (Persily, 2015). The 2013 version of the standard states its goal as maintaining IAQ that “is acceptable to human occupants and that minimizes adverse health effects” (ASHRAE, 2013b). The net effect of these competing pressures seems to have been to maintain the minimum VR values near the ~8 L/s/occ mark

established nearly a century ago as sufficient for diluting bioeffluents to achieve 80% occupant acceptability.

It should be noted that, for the purposes of this project, ventilation includes two components. Infiltration, or natural ventilation, occurs when outdoor air enters leakage pathways in the building envelope due to wind- and temperature-driven pressure differences. Mechanical ventilation refers to outdoor air introduced intentionally by a building heating, ventilation, and air conditioning (HVAC) system. In most commercial buildings, the mechanical portion dominates, though that is not always the case because infiltration varies significantly with building proportions, envelope quality, and weather conditions (ref). Nonetheless, the VR minimum requirements in ASHRAE 62.1 and similar standards are most frequently interpreted as design rates of mechanical ventilation, and any infiltration would be additional. When the VR minimum is used to determine a CO₂ setpoint to which to control a space, however, the contribution from infiltration would be naturally included.

1.2 Benefits of ventilation on comfort, acute health, task performance, and illness risk

Though aimed primarily at reducing occupant perception of odors associated with bioeffluents, ventilation also has significant impacts on a range of comfort, acute health, and performance outcomes, as demonstrated by numerous empirical findings in the lab and the field (Carrer et al., 2015; Clausen et al., 2011; Sundell et al., 2011). At the more innocuous end, it affects perceived freshness of the air, sensations of dryness in mouth or throat, and self-assessments of mental performance or overall satisfaction. More serious acute health reactions like dry or irritated eyes, respiratory irritation or difficulty, drowsiness, fatigue, and headaches are regarded as symptoms of sick building syndrome (SBS).

A 1999 review of literature on human responses to ventilation and CO₂ levels, including more than forty studies and 60,000 subjects, indicated that nearly every investigation had found that

one or more health or perceived air quality outcomes were statistically significantly worse at VR below 10 L/s/occ (Seppänen, Fisk, & Mendell, 1999). Many studies found additional reductions in SBS symptoms at VR up to about 20 L/s/occ. A statistical analysis of CO₂ measurements and SBS symptom reports in 41 buildings found that odds of wheezing, chest tightness, or a sore throat, nose, or sinuses increases by 1.2–1.5 for each 100 ppm increase in indoor-outdoor CO₂ differential (Apte, Fisk, & Daisey, 2000). A quantitative meta-analysis of eight studies, including together a few thousand respondents, found that increased VRs in offices up to about 25 L/s/person are associated with reduced SBS symptom incidence (Fisk, Mirer, & Mendell, 2009). According to the central estimate of the model fit in that investigation, an increase in VR from 10 to 25 L/s/occ would, on average, reduce SBS symptom incidence by 29%.

Controlled experiments have found similar results. Evaluating 30 subjects at 3, 10, and 30 L/s/occ, Wargocki et al. found that increasing ventilation monotonically and statistically significantly decreased the percentage of occupants dissatisfied with the air quality and odor intensity and increased perceived air freshness (Wargocki, Wyon, Sundell, Clausen, & Fanger, 2000). It also consistently decreased average sensations of dryness in the mouth and nose, reduced reported difficulty thinking clearly, and made respondents feel better. Similarly, workers in a call center reported significant improvements in many SBS symptoms including air quality acceptability, aching eyes, dry skin, overall well-being, and fatigue (but not for eye irritation) in interventions involving changing VR and replacing particle filters (Wargocki, Wyon, & Fanger, 2004). Although there remains uncertainty about specific causal pathways for many of these effects, many believe that exposure to VOCs from bioeffluents, building materials, personal care, or cleaning products play a substantial role in SBS symptom prevalence (Sundell et al., 2011; Zhang et al., 2017). It has been demonstrated that reduced VOC source strength and increased VRs have similar impacts on perceived air quality (Wargocki, Bako-Biro, Clausen, & Fanger, 2002).

A number of studies have established significant relations between ventilation levels and various measures of cognitive and task performance. In a study of one hundred fifth-grade school classrooms, each 1 L/s/occ increase in VR between 1 and 7 L/s/occ was associated with a nearly 3% increase in students passing standardized tests in both math and reading (Haverinen-Shaughnessy, Moschandreas, & Shaughnessy, 2011). Similarly, better performance on computerized testing of cognitive ability in English primary schools was observed at 8 L/s/occ compared to a very low rate of 1 L/s/occ (Bakó-Biró, Clements-Croome, Kochhar, Awbi, & Williams, 2011).

The relation of ventilation to performance has been studied even more frequently in offices, where it has also been observed well beyond the ~8 L/s/occ level. Wargocki et al. also tested four simulated office tasks like typing, proofreading, and addition at VR of 3, 10, and 30 L/s/occ (Wargocki et al., 2000). Only typing was significantly affected by ventilation at a 5% significance level, but performance on all tasks improved monotonically with increasing ventilation, and all associations were significant at a 10% significance level. For each doubling of the VR, typing performance increased by 1.7% on average. In the call center experiment, talk time was a key metric, with shorter calls indicating efficiency and better performance (Wargocki et al., 2004). When outdoor airflow was increased considerably, talk time decreased by 6% if the building had a new particle filter (but increased if a dirty filter was in place).

Compiling nine studies, covering nearly a thousand subjects, Seppänen and colleagues developed a quantitative relationship between the VR and work performance (Seppänen, Fisk, & Lei, 2006). The included studies used performance measures like talk time, typing speed, addition speed, and reaction time. The authors' model indicated a 1–3% improvement in performance per 10 L/s/occ VR increase, on average. The association was greatest when the VR was low, particularly below about 20 L/s/occ, but continued up to over 45 L/s/occ. It was significant up to 15 L/s/occ with a 95% confidence interval (CI) and 17 L/s/occ with a 90% CI.

Some recent research has indicated that CO₂ levels, in addition to indicating the VR, can themselves affect performance on multiple cognitive assessments. One chamber study on 22 participants found that, with the VR held constant, there were large and significant declines on seven of nine decision-making performance tests at a CO₂ concentration of 2500 ppm compared to 1000 ppm (Satish et al., 2012). There were also moderate, though still statistically significant, improvements at 600 ppm compared to 1000 ppm. A second chamber study with 24 participants found that VOC concentration and CO₂ concentration were independently associated with nine tests of cognitive performance (J. G. Allen et al., 2015). Cognitive scores were lower when VOC sources were present, when the VR was 20 L/s/occ versus 40 L/s/occ, and when purified CO₂ was artificially injected and other variables were held constant. However, other recent, high-quality chamber experiments have found no direct relation of task performance to CO₂ concentration (Zhang et al., 2017). One possible reason for the discrepancy is that the Satish and Allen studies measured performance with a battery of tests that required greater mental concentration and acuity, while the tasks in the Zhang study were more repetitive and manual. In any case, all studies found that ventilation—which reduces bioeffluents and other VOCs as well as CO₂, after all—has a positive effect on cognitive and task performance.

Finally, a number of studies have shown that increasing ventilation can reduce the rate of sick leave. For example, examination of illness absence and VRs over two years in 162 elementary school classrooms in 28 California schools showed a statistically significant impact (Mendell et al., 2013). Over the range of 1–20 L/s/occ, each added 1 L/s/occ reduced illness absence by 1.6%. The most comprehensive investigation in offices was conducted at Polaroid in 1994 (Milton, Glencross, & Walters, 2000), based on sick leave rates over a year for nearly 4000 workers in 40 buildings with more than a hundred ventilated spaces. The authors divided spaces into two bins based on VR, with moderate ventilation estimated at ~12 L/s/occ and high ventilation at 24 L/s/occ. For the 705 office workers in the study, the relative risk (RR) of absence at the lower ventilation level, compared to the higher one, was 1.52 (95% CI: 1.18–1.97). In the same terms as

the Mendell study of classrooms, this would be a 3.5% decrease in sick leave absence per 1 L/s/occ of added ventilation.

As Milton et al. noted, there are two potential causal mechanisms for the relation between sick leave absence and ventilation: reactions to irritants and allergens, or impacts on respiratory illness due to either airborne transmission of infections or altered human susceptibility. The irritation explanation would be similar to the presumed mechanism for comfort, SBS, and performance impacts. After considering variations of both explanations, Milton et al. essentially ruled irritation explanation, because controlling for air quality complaints did not reduce the association between ventilation and sick leave. In addition, the airborne transmission pathway is consistent with the three studies on ventilation and respiratory illness collected in a review (Seppänen, Fisk, and Mendell 1999), which all had relative risk of 1.5–2 for respiratory illness at a low ventilation condition versus a high ventilation condition. Other corroboratory evidence comes from a field study in offices that modulated outdoor air supply for periods of a week and measured rhinovirus RNA and CO₂ levels as a proxy for ventilation (Myatt et al., 2004). Data analysis indicated that the probability of detecting airborne rhinovirus was elevated whenever the indoor CO₂ was more than 100 ppm greater than outdoors. A panel including experts in building science, microbiology, epidemiology, and ventilation reviewed 40 studies about airborne transmission of infectious diseases (Li et al., 2007). They concluded that ten studies were conclusive, and that there “is strong and sufficient evidence to demonstrate the association between ventilation, air movements in buildings and the transmission/spread of infectious diseases such as measles, tuberculosis, chickenpox, influenza, smallpox and SARS.”

1.3 Ventilation impacts on chronic exposures

Ventilation could also have long-term health impacts, including on outcomes such as cancer, pulmonary disease, myocardial infarction, or endocrine disruption. However, unlike the short-

term associations with perceived air quality, environmental comfort, acute SBS symptoms, work performance, and sick leave absence, long-term ventilation impacts are speculative, and may well remain uncertain for the foreseeable future (Sundell et al., 2011). As a general rule, chronic impacts cannot be linked to occupant perceptions or sensitivities (Seppänen & Fisk, 2004). The typical method for assessing chronic impacts is to use the average indoor concentration as a proxy for occupant exposure—a reasonable assumption, for most VOCs (Sexton et al., 2004)—and compare it to any established chronic exposure thresholds (Logue, McKone, Sherman, & Singer, 2011; Parthasarathy, McKone, & Apte, 2011) or use it in concentration-response functions (Chan, Parthasarathy, Fisk, & McKone, 2016; Logue, Price, Sherman, & Singer, 2012). However, for most contaminants, exposure thresholds are only available for industrial occupational settings, and often exceed typical concentrations in non-industrial settings, sometimes by orders of magnitude (Persily, 2015). The threshold approach is also not appropriate for long-term, low concentration exposures, in which mixtures of chemicals may have non-additive effects (Sundell et al., 2011). Furthermore, while ventilation is effective at diluting bioeffluents, ventilation's removal efficacy varies widely for pollutants with indoor sources, like VOCs from personal care products, cleaning supplies, and building material emissions (Chan et al., 2016; Rackes & Waring, 2016).

Two exposures affected by ventilation that almost certainly do have long-term chronic effects are to outdoor fine particulate matter ($PM_{2.5}$ = particles with aerodynamic diameter $< 2.5 \mu m$) and ozone (O_3), both of which ventilation introduces from the outdoors. Both also have well-established, no-threshold associations with multiple adverse short- and long-term health endpoints, although the precise causal mechanisms by which PM exposure affects human health remain uncertain (Phalen & Wolff, 2000). In the public health and epidemiology literature, increases in outdoor $PM_{2.5}$ have been correlated with increased cardiovascular and respiratory diseases (Hoek et al., 1998; Peters et al., 2000; Dominici et al., 2006; Pope et al., 2009), chronic

bronchitis (Abbey et al., 1995), and increased mortality (Dockery et al., 1992; Dockery & Pope, 1993; Pope et al., 1995; Pope et al., 2002; Schwartz et al., 1996).

Increasing ventilation introduces more outdoor air pollutants to the indoor environment (Bekö, Clausen, & Weschler, 2008; Ben-David & Waring, 2016; Quang, He, Morawska, & Knibbs, 2013; Rakes & Waring, 2013; Stephens, Gall, & Siegel, 2012; Weschler, 2000). Indeed, most exposure to outdoor PM_{2.5} occurs indoors (Klepeis et al., 2001; Jenkins et al., 1992; Liroy et al., 1988; Wallace, 1993), though the bulk of that is in residences. Some studies have associated urban-level exposure impacts to predicted changes in exposure inside buildings (Hänninen, 2005; Bekö et al., 2008), but others maintain that there is a lack of understanding regarding the health effects of outdoor PM once indoors (Clausen et al., 2011). There is suggestive evidence both that impacts are valid for indoor exposures and of endpoint mechanisms. For example, employing high-efficiency particulate air (HEPA) filters in residential buildings reduces markers used to predict future adverse coronary events (Allen et al., 2011; Brauner et al., 2008). In any case, it has become common in the indoor air literature to apply outdoor air correlations for PM_{2.5} and ozone exposure to the fraction of exposure that occurs indoors (Chan et al., 2016; Logue et al., 2012), and that approach is followed here.

1.4 Ventilation energy impacts

In addition to these many IAQ implications, current ventilation practice accounts for ~1/4 of HVAC energy consumed by commercial buildings (Fisk, Black, & Brunner, 2012; U.S. Energy Information Administration (EIA), 2006b). This is quite substantial when one considers that buildings consume about two-fifths of primary energy in the U.S., which is essentially evenly split between residential and commercial uses (U.S. DOE, Energy Efficiency and Renewable Energy, 2012a). Heating, ventilation, and air-conditioning (HVAC) accounts for 30–40% (U.S. DOE, Energy Efficiency and Renewable Energy, 2012b; U.S. Energy Information Administration

(EIA), 2006c) of U.S. commercial buildings' energy consumption, or 5–6% of all U.S. primary energy. Even the substantial one-fourth fraction likely underestimates ventilation's potential to impact heating, cooling, and fan energy consumption. Ventilation and infiltration are routinely identified as the most important variables in sensitivity analyses of total building energy use (Eisenhower, O'Neill, Narayanan, Fonoberov, & Mezić, 2012; Hopfe & Hensen, 2011; Rodríguez, Andrés, Muñoz, López, & Zhang, 2013; Sanchez, Lacarrière, Musy, & Bourges, 2014), and a next-generation optimized ventilation strategy could potentially reduce HVAC energy use by as much as half in some situations (Rackes & Waring, 2014). Increasing VRs generally increases energy use, though in some settings can also save energy when free cooling is available. Some practitioners' desires to save energy provides significant pressure on technical committees setting minimum ventilation rates to select lower values, or avoid increases (Persily, 2015).

1.5 Considering multiple criteria and ventilation tradeoffs

There are, therefore, numerous and competing impacts of ventilation. This research proposes sorting the impacts into three categories. Short-term impacts on occupant comfort, environmental satisfaction, SBS symptoms, performance, and illness absence are grouped as “profitable IAQ impacts.” Here “profitable” means that these short-term impacts can benefit occupants directly, and that in a market-based economic system these benefits can be monetized to demonstrate profit to an actor like a business owner or a building owner. Long-term impacts are classified as “IAQ public health impacts” or “IAQ health impacts,” considered as risk adjustments in a public health framework. Energy consumption costs, including associated social costs if desired, make up the third category.

Previous studies have investigated elements of two of the three impact categories. Fisk et al. showed that the economic benefits of increasing the minimum VR in U.S. offices from 8 to 15

L/s/occ, due to improved work performance and reduced absence, were about 200 times the added energy costs (Fisk et al., 2012). Similarly, under four hypothetical office sector scenarios, the economic benefits of ventilation's profitable IAQ outcomes were estimated to exceed the costs of increased energy consumption by two orders of magnitude (Fisk, Black, & Brunner, 2011). Dutton et al. found that natural ventilation could expose office workers to outdoor pollutants whose public health impacts overwhelmed the benefits of reduced SBS symptoms, in economic terms (Dutton, Banks, Brunswick, & Fisk, 2013). Dutton and Fisk compared multiple interventions across the California office stock in terms of both formaldehyde exposure and HVAC energy consumption (Dutton & Fisk, 2014).

No study appears to have considered profitable IAQ impacts, IAQ public health impacts, and energy consumption all together. Doing so is one goal of this research. More broadly, the existence of multiple outcomes introduces the overarching need for better analysis and consideration of tradeoffs.

1.6 Dynamic strategies and Pareto improvements

When there are multiple criteria to consider when making a decision, at some point there will be tradeoffs. However, it is also often possible to achieve Pareto improvements, or better outcomes for one objective without sacrificing results for others. A central part of this research is investigating the hypothesis that Pareto improvements are possible for ventilation strategies. The first part of that investigation takes the form of examining existing approaches for dynamically modulating ventilation. These alternative ventilation strategies have been designed to save energy, but can also be combined or adjusted to, for example, save energy without harming profitable IAQ, or improve profitable IAQ outcomes without using more energy.

One mature dynamic ventilation technology is *demand-controlled ventilation* (DCV), which modifies the OA flow based on current occupancy or a proxy for it. Studies have estimated DCV

to save from about 10% of HVAC energy for offices in a variety of climates (Hart, Callahan, Anderson, & Johanning, 2011), to 20% for restaurants and retail even in mild climates (Lawrence & Braun, 2007). Most of the savings come from heating, with 5–40% heating use reductions in offices (Brandemuehl & Braun, 1999; Fisk & De Almeida, 1998), and minimal cooling savings opportunity in most offices (Fisk & De Almeida, 1998). In general, savings may depend more on rightsizing ventilation for actual occupancy that is lower than design, rather than on dynamic control (Brandemuehl & Braun, 1999; Hart et al., 2011). To our knowledge, DCV has only been considered as an energy-saving technology; in this context, it is likely to degrade IAQ related to indoor-emitted contaminants (Rackes & Waring, 2013). However, by modifying DCV characteristics, like target VR or CO₂ setpoint, we hypothesize that it can be deployed to achieve Pareto improvements.

A second mature technology is *airside economizing*, which is a control sequence that introduces more OA when it can provide free cooling. Multiple simulated assessments in offices have found that 5–15% HVAC electricity savings are possible from economizing (Brandemuehl & Braun, 1999; Fisk, Seppanen, Faulkner, & Huang, 2005; Yao & Wang, 2010). Installing economizers in the approximately half of U.S. offices that do not have them could save an estimated \$320 million in aggregate energy costs annually (Fisk et al., 2012). Furthermore, economizing naturally provides Pareto improvements, at least in terms of profitable IAQ impacts and energy savings. In the study that considered adding economizers to the half of U.S. where they are absent, for example, the annual economic benefits were \$220 million from decreased SBS symptoms, \$8.6 billion from reduced sick leave, and \$24.2 billion from increased work performance (Fisk et al., 2012). Another simulation study showed that implementing economizers in California office buildings would on average lower indoor formaldehyde exposure by 38% while savings 20% of HVAC energy (Dutton & Fisk, 2014).

Despite the maturity of DCV, economizing, and other mature ventilation-affecting technologies like supply air temperature reset, these technologies appear to have low-to-medium

market penetration (Hamilton, Rackes, Gurian, & Waring, 2016). Furthermore, there has been little research on how best to combine these technologies or set parameters or targets like minimum VRs or CO₂ setpoints. One goal of this research is to analyze which among, and in what situations, these technologies should be adopted, and to provide guidance to both decision-makers and policymakers. We also conduct optimizations to determine if meaningful Pareto improvements over existing strategies like DCV and economizing are possible.

1.7 The importance of setting: parameter sensitivity

All of these potential impacts can look very different depending on the building, and achieving the same desired tradeoff point (however defined) in two buildings, or in the same building on two days, can require different strategies. Therefore, another broad goal of this research was to expand the parameter space of investigation and incorporate significant sensitivity analysis of ventilation impacts. The only previous study to have thoroughly examined more than a single ventilation technology on more than a case study or prototype basis is now nearly two decades old. It tested combinations of DCV and economizer use in single zone, for constant-air-volume mechanical systems in 20 locations (Brandemuehl & Braun, 1999), and concluded that the largest benefits of the two technologies are mostly mutually exclusive, especially in offices.

By and large, variations among building, mechanical system, and climate parameters, despite their strong influences on ventilation strategy energy and indoor air quality impacts, have not previously been studied or quantified. This research repeatedly adopts a Monte Carlo approach to construct datasets that climatologically represented of U.S. offices, with broadly but realistically varied building parameters, allowing the sensitivity of energy impacts to building and climate predictors to be evaluated. These methods were broadly in line with model-based sensitivity analysis of building performance (Tian, 2013), which has recently been applied to evaluate

uncertainties in design inputs (Hopfe & Hensen, 2011; Rodríguez et al., 2013; Sanchez et al., 2014), prune non-influential model parameters (Eisenhower et al., 2012), assess design impacts (Rackes, Melo, & Lamberts, 2016) and operational strategies (Rackes & Waring, 2013), and identify favorable equipment implementation scenarios (Burhenne, Tsvetkova, Jacob, Henze, & Wagner, 2013). The goals of this research were some of the central ones of sensitivity analysis: relating output to input variables, identifying important regions of the input space, and, ultimately, using models and analysis to improve recommendations to decision-makers (Saltelli et al., 2008).

1.8 Research objectives: informing next-generation ventilation

This research investigates advanced commercial building ventilation strategies and develops next-generation control approaches. The focus is on office buildings, which are the largest category of commercial buildings in the U.S. in terms of floorspace (U.S. EIA, 2015a), and also the most-studied commercial building type, providing reasonably reliable building parameter distributions and ventilation impact estimates. Through successive iterations of this research, we developed three ways in which next-generation ventilation approaches can improve on deficiencies in current approaches, and that we believe should guide development: ventilation strategies should be *outcome-based*, *setting-sensitive*, and *dynamic*.

Outcome-based ventilation strategies are guided by their expected impact on outcomes. They are based on models of performance, rather than prescriptive requirements. Determining what outcomes to include and their relation to ventilation required significant literature research and synthesis, to select and adapt appropriate models and establish reasonable ranges of input parameters. Defining outcome-based ventilation also ultimately required developing an approach for combining multiple outcomes into a single objective by which a ventilation decision can be evaluated and made.

Setting-sensitive ventilation strategies adjust depending on important climate, building, and mechanical system characteristics. For example, a building with high infiltration might require less mechanical ventilation, or a mild day might call for more outdoor air than a very cold day would. Identifying important parameters required varying many parameters in Monte Carlo samples, to study ventilation impacts in a wide variety of settings and conduct sensitivity analyses.

Dynamic ventilation strategies adjust flows over time to take advantage of the transient patterns of exogenous variables like outdoor temperature, outdoor pollution, occupancy, and electricity prices. Whether the time scope is annual and the resolution daily, or the scope is a day and the resolution is a few minutes, dynamic modulation can provide Pareto improvements, that is, increase performance for some outcomes without decreasing it for any others.

To develop next-generation ventilation with these characteristics, research is needed to explore multiple outcomes affected by ventilation, systematically assess the influence of building and climate characteristics on outcomes, and explores dynamic ventilation strategies that may provide Pareto improvements. We divided these needs into three research objectives:

- **Objective 1:** Evaluate existing alternative ventilation strategies over a wide range of climates and office building characteristics, in terms of multiple outcomes including economically profitable IAQ impacts, IAQ public health impacts, and energy use costs. Include combinations and variations of existing dynamic strategies in offices, and using Monte Carlo sampling to investigate the influence of numerous parameters. Chapter 2 addresses this objective for energy use, and Chapter 3 addresses it for both energy and IAQ outcomes.
- **Objective 2:** Develop a general outcome-based ventilation (OBV) decision-making framework for evaluating ventilation decisions. Using the idea of a loss function, combine multiple outcomes, and integrate scientific knowledge, uncertainty, and user preferences. This framework must be sensitive to setting- and user-specific tradeoffs

among IAQ and energy impacts, including social costs of energy consumption. Chapter 4 addresses this objective.

- **Objective 3:** Use the OBV framework to optimize ventilation over a daylong horizon to determine if there are significant opportunities for novel control schemes to improve multiple outcome objectives. Convert the loss function into an optimal control problem, then translate that to a nonlinear optimization problem and solve by interior point methods. Use the results to assess whether there are significant opportunities for Pareto improvement by altering control over a daylong timescale. Chapter 5 addresses this objective.

Chapter 6 briefly pulls together the insights from the completion of the three research objectives described in Chapters 2–5. It provides an outline of a path forward to next-generation ventilation that is outcome-based, setting-specific, and dynamic in ways that this research indicates would be most useful. The proposed procedure would make use of existing successful technology components, like DCV and economizer controls, for real-time control. Rather than allow those feedback mechanisms to implicitly make important decisions about ventilation impacts, though, it would employ an explicit preference elicitation step and an offline annual optimization to intelligently allocate ventilation resources across the year. Essentially, the procedure would impose an outcome-based, climate- and user-specific supervisory control while allowing effective local control methods to achieve control targets. Such an approach could help make ventilation more effective and reliable, and allow users to make informed decisions about ventilation tradeoffs and understand their consequences.

CHAPTER 2: COMPREHENSIVE ASSESSEMENT AND SENSITIVITY ANALYSIS OF ENERGY SAVINGS OF MATURE ALTERNATIVE VENTILATION STRATEGIES

Chapter abstract: Mature technologies exist to reduce the heating, ventilation, and air-conditioning (HVAC) energy associated with ventilation and use ventilation proactively to save energy. This study investigated the energy use impacts in U.S. office buildings of multiple alternative ventilation strategies that combined: economizing, demand controlled ventilation (DCV), supply air temperature reset (SR), and/or a doubled ventilation rate. We used energy simulations in a Monte Carlo analysis, sampling 17 building inputs and varying locations to match the climate zone distribution of the U.S. office stock. Results indicated the possibility for significant savings compared to a baseline that ventilated constantly at a minimum rate in both a small office type with a constant air volume (CAV) HVAC system and a medium office type with a variable air volume (VAV) system. In 95% of instances, HVAC source energy savings were 5–25% in the small-CAV office (median: 11%) and 6–42% in the medium-VAV office (median: 27%). In the small-CAV office, DCV typically saved the most energy, usually from heating, and heating degree days and occupant density were decisive influences. In the medium-VAV office, economizing and SR were most important, DCV usually only had minor impacts, and zone temperature setpoints, along with climate indicators, were the critical influences. Other than infiltration, envelope characteristics did not strongly influence energy impacts. The untapped primary energy savings of alternative ventilation strategies over the 74% of U.S. office floorspace reasonably represented by our modeling was estimated at 36 TWh per year, with an annual value of U.S. \$1.25 billion.

2.1 Chapter introduction

Buildings consume about two-fifths of primary energy in the U.S., which is essentially evenly split between residential and commercial uses (U.S. DOE, Energy Efficiency and Renewable Energy, 2012a). Heating, ventilation, and air-conditioning (HVAC) accounts for 30–40% (U.S. DOE, Energy Efficiency and Renewable Energy, 2012b; U.S. Energy Information Administration (EIA), 2006c) of U.S. commercial buildings' energy consumption, or 5–6% of all U.S. primary energy. Ventilation is the provision of outdoor air (OA) to an interior space to control contaminant levels, odors, humidity, or temperature (ASHRAE, 2013b; Sundell et al., 2011), and it alone accounts for about one-fourth of U.S. commercial HVAC energy use (Fisk et al., 2012; U.S. Energy Information Administration (EIA), 2006c). Even that substantial fraction likely underestimates ventilation's potential to impact heating, cooling, and fan energy consumption. Ventilation and infiltration are routinely identified as the most important variables in sensitivity analyses of total building energy use (Eisenhower et al., 2012; Hopfe & Hensen, 2011; Rodríguez et al., 2013; Sanchez et al., 2014), and a next-generation optimized ventilation strategy could potentially reduce HVAC energy use by as much as half in some situations (Rackes & Waring, 2014).

Currently, in most mechanically conditioned commercial buildings, the ventilation strategy is simply to supply a constant minimum ventilation rate prescribed by a standard (ASHRAE, 2013b). However, a number of mature technologies that can save HVAC energy relative to a fixed minimum-rate baseline already exist. One of these is *demand controlled ventilation* (DCV), which dynamically modifies the OA flow based on current occupancy or a proxy for it. Studies have estimated DCV to save from about 10% of HVAC energy for offices in a variety of climates (Hart et al., 2011), to 20% for restaurants and retail even in mild climates (Lawrence & Braun, 2007). Most of the savings come from heating, with 5–40% heating use reductions in offices (Brandemuehl & Braun, 1999; Fisk & De Almeida, 1998), depending on location, occupant density, and control logic. One review concluded cooling savings were minimal in offices (Fisk &

De Almeida, 1998), but savings are available in other building types (Brandemuehl & Braun, 1999; Chao & Hu, 2004; Nassif, 2012). In general, savings may depend more on rightsizing ventilation for actual occupancy that is lower than design, rather than on dynamic control (Brandemuehl & Braun, 1999; Hart et al., 2011).

A second mature technology is *airside economizing*, which is a control sequence that introduces more OA when it can provide free cooling. Multiple simulated assessments in offices have found that 5–15% HVAC electricity savings are possible from economizing (Brandemuehl & Braun, 1999; Fisk et al., 2005; Yao & Wang, 2010). Installing economizers in the approximately half of U.S. offices that do not have them could save an estimated \$320 million in aggregate energy costs annually (Fisk et al., 2012). A third technology is *supply air temperature reset* (SR), or increasing the supply air temperature setpoint at part-load conditions to save compressor and reheat energy (California Energy Commission, 2003). Though it does not manipulate OA flow explicitly, it interacts significantly with the economizer cycle; when both are installed, SR alters OA control and enhances energy savings (Gang Wang & Song, 2012). A final possible way to modify a ventilation strategy is simply *changing the minimum or target ventilation rate*, which can have potentially large energy impacts (Fisk et al., 2012), whose magnitude and even direction of change can vary greatly among buildings and locations (Hamilton et al., 2016).

Despite their maturity, these technologies appear to have low-to-medium market penetration (Hamilton et al., 2016). The goal of this study, therefore, was to analyze which among, and in what situations, these technologies should be adopted, and to provide guidance to both decision-makers and policymakers. With U.S. offices as the focus, this investigation is comprehensive in terms of considering, in most cases for the first time, (i) multiple component technologies and their combined effects, (ii) a wide array of building and climate parameters for more detailed impact understanding and prediction, and (iii) multiple building and system types, including variable air volume (VAV) systems. Furthermore, while this chapter focuses on energy impacts,

Chapter 3 expands to a fourth dimension of comprehensiveness: consideration of energy along with a number of important indoor air quality impacts, including worker productivity (Seppänen et al., 2006), volatile organic compound concentrations (Rackes & Waring, 2016), and pollutants introduced from outdoors (Ben-David & Waring, 2016; Johnson, Waring, & DeCarlo, 2017).

To do so, we defined eight ‘alternative ventilation strategies’ that were combinations of economizing, DCV, SR, and doubled ventilation. We used Monte Carlo analysis and building performance simulation to evaluate energy impacts relative to a fixed minimum-rate baseline, for both a small office type with a constant air volume (CAV) HVAC system and in a medium office type with a VAV system. The only previous study to have thoroughly examined more than a single ventilation technology tested combinations of DCV and economizer use in single zone, for CAV mechanical systems in 20 locations (Brandemuehl & Braun, 1999), and concluded that the largest benefits of the two technologies are mostly mutually exclusive, especially in offices. Here, we re-examined that conclusion in light of interactions with additional technologies like SR, and in buildings with VAV systems.

Even more importantly, this work assessed variations among building, mechanical system, and climate parameters, whose strong influences on ventilation strategy energy impacts have not previously been studied or quantified. A Monte Carlo approach was used to construct datasets that climatologically represented of U.S. offices, with broadly but realistically varied building parameters, allowing the sensitivity of energy impacts to building and climate predictors to be evaluated. These methods were broadly in line with model-based sensitivity analysis of building performance (Tian, 2013), which has recently been applied to evaluate uncertainties in design inputs (Hopfe & Hensen, 2011; Rodríguez et al., 2013; Sanchez et al., 2014), prune non-influential model parameters (Eisenhower et al., 2012), assess design impacts (Rackes et al., 2016) and operational strategies (Rackes & Waring, 2013), and identify favorable equipment implementation scenarios (Burhenne et al., 2013). Though our application was somewhat different—i.e., understanding real variability among instances, not uncertainty in a single

model—our goals were those of sensitivity analysis: relating output to input variables, identifying important regions of the input space, and, ultimately, using models and analysis to improve recommendations to decision-makers (Saltelli et al., 2008).

2.2 Methods

2.2.1 Building typologies and modeling

This study focused on offices, which are the largest users of U.S. commercial building floorspace (U.S. Energy Information Administration (EIA), 2015c), and for which building parameters are relatively well characterized and mechanical systems typically capable of using the strategies investigated. We conducted assessments in two office building types. The ‘small-CAV’ office was single story and small (325 m²), with a single zone served by a packaged CAV HVAC system with a single-speed direct expansion (DX) cooling coil and a gas-fired heating coil. The ‘medium-VAV’ office was medium-sized (4,982 m²) with three stories, each with one core and four perimeter zones. Each floor had a VAV system that distributed air to modulable terminal units with hot water reheat coils in each zone. A central boiler supplied the building’s 15 reheat coils, as well as three central heating coils. Each VAV air handler cooled air with a two-speed DX cooling coil.

The goal in evaluating energy impacts in these two particular office buildings was to explore the range of size- and system-related effects likely to be observed in typical offices. The ratio of exterior surface area to building volume was much greater in the small building, driving infiltration and envelope thermal transfer. Internal gains, on the other hand, were expected to be more dominant in the medium building. At the same time, the two buildings’ HVAC systems differed in two key ways. First, the medium-VAV office’s HVAC system served multiple thermal zones with distinct loads, while the system in the small-CAV office only had a single zone. Second, the medium-VAV air handler could vary the supply airflow rate but not the supply air

temperature, unless using a strategy that employed SR. The small-CAV system, by contrast, provided constant supply flow at variable temperature.

The office building models were implemented in the whole-building energy simulation program EnergyPlus (U.S. DOE, 2015). We selected EnergyPlus because it is physics-based, is validated (e.g., to ASHRAE Standard 140-2011 (ASHRAE, 2011)), allows modification of a wide array of parameters, has an active research and development community, and is in general the most mature research-grade whole-building energy simulation engine available. The office types were derived from existing EnergyPlus reference models (Deru et al., 2011) but underwent slight modifications, including adjustment of mechanical systems, elimination of the attic in favor of a flat roof in the small-CAV office, and slight alteration of schedules for consistency.

The most significant change we made in the reference models was implementing our own infiltration calculation routine, since infiltration can have a strong influence on ventilation control and its impacts. The original reference buildings' infiltration was constant during the day and unaffected by outdoor conditions. It also assumed infiltration would be drastically and uniformly reduced during HVAC system operation, to an extent unlikely to be achievable in small buildings. Instead, our routine was based on first sampling the building envelope's air-leakage coefficient C from a statistical model of commercial buildings (Chan, 2006), and then using a whole-building form of the LBL infiltration model (ASHRAE, 2013a) at runtime to determine infiltration airflows given time-varying temperatures and wind speeds. Infiltration reductions during system operation were based on the building pressurization achieved by returning less air (by a quantity that was either 10% of the supply flow, or the OA intake flow, whichever was smaller) from the building zones than the system supplied (Ng, Musser, Persily, & Emmerich, 2012).

2.2.2 Ventilation strategies

We assessed a single Baseline and multiple alternative ventilation strategies in each office building (Table 1). The Baseline ventilation strategy used a fixed mechanical ventilation rate (VR) of 9.4 L/s per occupant (20 ft³/min/occ), the minimum rate specified by ASHRAE Standard 62-2001 (ASHRAE, 2001). The alternative strategies used combinations of economizer controls, DCV, SR, and a doubled constant mechanical VR (= 18.9 L/s/occ). Economizing could either be lockout, meaning it operated only when OA could meet the cooling load completely without any mechanical cooling, or integrated economizing that was based on the differential enthalpy (DE) difference between return and outdoor air. When DCV was used, it adjusted OA to not exceed a CO₂ setpoint in the critical (highest CO₂ concentration) zone. The setpoint was based on the steady state CO₂ concentration achieved with a VR of 9.4 L/s/occ (i.e., 950 ppm) for all strategies with D950 in their name, or of 18.9 L/s/occ (i.e., 675 ppm) for strategies with D675 in their name. In the medium-VAV office, all strategies with SR in their name allowed the supply air temperature to rise to the highest temperature capable of meeting the cooling load in all zones when VAV flows were at minimum, up to a maximum of 18 °C (64.4 °F). In all other strategies, including the Baseline, the supply air temperature was fixed at 12.8 °C (55 °F). (SR is not an applicable technology in the small-CAV office, where the HVAC system modulates the supply air temperature to meet the load by definition.)

Table 1 Evaluated Baseline and alternative ventilation strategies.

Strategy	Office type	Minimum VR (L/s/occ [cfm/occ])	Economizing	DCV CO ₂ setpoint (ppm)	Supply air temperature reset
Baseline	Both	9.4 (20)	No	-	No
EconLock	Both	9.4 (20)	Yes - Lockout	-	No
Econ	Both	9.4 (20)	Yes - DE	-	No
Econ+SR	Med-VAV	9.4 (20)	Yes - DE	-	Yes
D950	Both	-	No	950	No
Econ+D950	Both	-	Yes - DE	950	No
Econ+SR+D950	Med-VAV	-	Yes - DE	950	Yes
2×VR	Both	18.9 (40)	No	-	No
Econ+D675	Sm-CAV	-	Yes - DE	675	No
Econ+SR+D675	Med-VAV	-	Yes - DE	675	Yes

VR = ventilation rate; DCV = demand controlled ventilation; Lockout = no economizing when cooling coil is active; DE = (integrated) differential enthalpy controls

2.2.3 Varied building parameters

To assess these strategies' impacts over a wide range of situations, we conducted building energy simulations within a comprehensive Monte Carlo analysis, both by varying climates (described in the following section) and sampling 17 building parameters to determine each unique modeled instance. Table 2 lists the parameters, related details, and their sampling distributions. Every effort was made to match probability distributions to realistic values for U.S. offices, while at the same time to sample a broad enough parameter space to capture all effects of interest.

Table 2 Varied building parameters and their units, short names, and sampling distributions.

Parameter	Units	Short name	Distribution			Truncation	
			Type	<i>a</i>	<i>b</i>	Lower	Upper
Envelope air-leakage coefficient, small-CAV	m ³ /s/m ² /Pa ^{0.65}	-	<i>LN</i>	3.52E-04	2.3	-	-
Envelope air-leakage coefficient, medium-VAV	m ³ /s/m ² /Pa ^{0.65}	-	<i>LN</i>	2.81E-04	2.3	-	-
Wall insulation <i>U</i> -value	W/m ² ·K	wallU	<i>LN</i>	0.70	3.0	0.10	6.00
Roof insulation <i>U</i> -value	W/m ² ·K	roofU	<i>LN</i>	0.50	3.0	0.10	6.00
Wall thermal mass	kJ/K·m ²	wallCT	<i>LN</i>	100	3.0	5	600
Window <i>U</i> -value	W/m ² ·K	winU	<i>U</i>	1.00	5.80	-	-
Window solar heat gain coefficient	-	SHGC	<i>U</i>	0.20	0.80	-	-
Day start	hour of day	dayStart	<i>U</i>	5.00	9.00	-	-
Day end	hour of day	dayEnd	<i>U</i>	18.00	24.00	-	-
Lighting power density	W/m ²	LPD	<i>N</i>	10.5	10.0	0.0	-
Equipment power density	W/m ²	EPD	<i>N</i>	2.7	5.0	0.0	-
Occupant density	occ per 100 m ²	occDens	<i>LN</i>	5.2	1.7	1.9	14.6
Zone heating setpoint	°C	heatStpt	<i>N</i>	21.5	1.5	-	-
Zone cooling setpoint	°C	coolStpt	<i>N</i>	24.5	1.5	-	-
Unoccupied period zone setpoint setback	°C	stptSetback	<i>U</i>	0.0	5.0	-	-
Heating efficiency	-	heatEff	<i>N</i>	0.80	0.20	0.60	1.00
Cooling coefficient of performance	-	coolCOP	<i>N</i>	3.00	1.00	1.50	4.50
Fan efficiency	-	fanEff	<i>N</i>	0.70	0.20	0.40	1.00

LN = lognormal distribution, *a* = geometric mean, *b* = geometric standard deviation

U = uniform distribution, *a* = min, *b* = max

N = normal distribution, *a* = mean, *b* = standard deviation

The distribution for the building envelope air-leakage coefficient *C* was derived from an analysis of empirical air leakage data, which developed a regression model for the relation between leakage and a building's height and floor area (Chan, 2006). Applying that model yielded a separate lognormal air-leakage coefficient distribution for each office type. For all other parameters, the two office types had the same distributions. For occupant density, we used a published distribution (Rackes & Waring, 2013). For heating and cooling temperature setpoints, we fit our own distributions to indoor temperatures reported by the U.S. EPA's Building Assessment Survey and Evaluation (U.S. EPA, n.d.; Womble et al., 1995). To do so, we assumed that the indoor temperature reflected an effective heating setpoint when it was higher than the outdoor temperature, and an effective cooling setpoint when it was lower than the outdoor temperature. There are no sources for statistical distributions in existing offices for envelope parameters, lighting and equipment power densities, and equipment efficiencies. For these, we relied on values used in previous sensitivity analyses (Eisenhower et al., 2012; Rackes et al.,

2016), sector-wide assessments (Brandemuehl & Braun, 1999; Deru et al., 2011), and industry references (ASHRAE, 2013a). For day occupied start and end times and the unoccupied temperature setpoint setback, uniform ranges were selected to explore a reasonable space of interest.

Translating these scalar parameter values to EnergyPlus model descriptions required some additional implementation steps, a few of which are worth mentioning:

- Changing the start and end of the day required adjusting a number of other schedules, including occupancy, lights, equipment, and the operation of the HVAC system. A preprocessing routine left the fractional schedule values in middle of the day as in the default schedule, and applied appropriate stretching and truncation to the profiles at the beginning and end of the day to make all schedules consistent. The HVAC system always turned on one hour before the occupied day start.
- When the sampled value for heating setpoint exceeded that for the cooling setpoint, the average of the two was applied to both. In these instances, which were about 9% of the total, there was no zone setpoint deadband.
- The unoccupied period temperature setpoint setback was applied to both heating and cooling zone temperature setpoints when the HVAC system was off. It was added to the cooling setpoint and subtracted from heating setpoint.
- In the small-CAV office, heating efficiency corresponded to the gas burner efficiency for the furnace coil, while in the medium-VAV office it was the boiler thermal efficiency.
- For the two stage DX coils in the medium-VAV office, the cooling coefficient of performance (COP) was applied to the high-speed stage, and the low-speed COP was adjusted to always be 50% higher.

2.2.4 Locations and climate zones

Probably the most important dimension varied in the Monte Carlo analysis was climate. We conducted simulations in 18 locations spanning the IECC/ASHRAE 90.1 U.S. climate zones. Sampling from these locations was weighted so that the final datasets matched the geographic/climate distributions of U.S. offices. Fractional representation was first set for five broad climate categories defined by the Building America program (Baechler et al., 2010), illustrated in Figure 1. According to the 2012 Commercial Building Energy Consumption Survey (CBECS) (U.S. Energy Information Administration (EIA), 2015a), the best available statistical model of the existing U.S. building stock, 13% of U.S. offices are in hot-humid areas, 14% are in mixed-dry or hot-dry ones, 31% are in mixed-humid climates, 3% are in marine zones, and 39% are in cold or very cold climates.

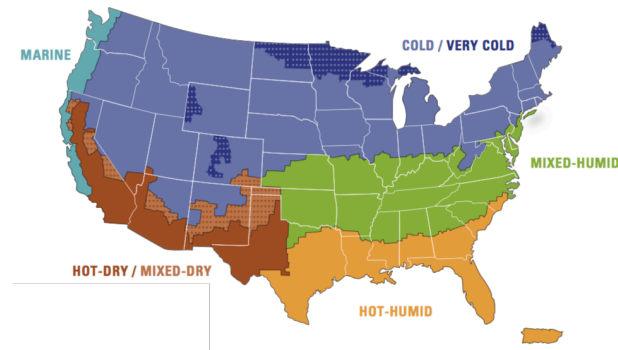


Figure 1 Building America climate zones. (Image courtesy of the U.S. Department of Energy's Building America Solution Center.)

The fractional makeup of IECC climate zones within each Building America climate zone category was based on weights derived in a previous analysis of the office stock (Jarnagin & Bandyopadhyay, 2010). These fractions, which were very slightly different for the two building

sizes, can be seen in Table 3 along with the cities used to represent each IECC zone and selected climate indicators for them.

Table 3 Fractions of simulations in each Building America climate zone category, and fractional makeup of those categories by representative IECC climate zone locations, along with selected climate indicators for the locations. Cooling degree days (CDD) and heating degree days (HDD) used a base of 18 °C. The CDD and summer enthalpy residuals are explained in Section 2.2.7.

Building America (BA) climate zone	Fraction of offices in BA zone	Location	IECC climate zone	Fraction of BA zone represented		HDD base 18 °C (K-days)	CDD base 18 °C (K-days)	Average summer enthalpy (kJ/kg)	CDD residual (K-days)	Summer enthalpy residual (kJ/kg)	Direct normal solar irradiance (W/m ²)
				Small offices	Medium offices						
Hot-Humid	12.7%	Miami	1A	7.3%	13.7%	73	2,476	73.0	743	4.0	200
		Houston	2A	92.7%	86.3%	786	1,667	72.4	212	9.7	186
Hot-Dry / Mixed-Dry	14.2%	Phoenix	2B	35.6%	28.0%	525	2,532	57.1	975	-11.2	239
		Los Angeles	3B	29.3%	34.3%	714	344	47.0	-1139	-8.2	208
		Las Vegas	3B	29.3%	34.3%	1,169	1,859	47.0	554	-16.0	232
		Albuquerque	4B	5.8%	3.5%	2,261	749	43.0	-129	-11.1	226
Mixed-Humid	31.2%	Atlanta	3A	50.7%	39.2%	1,497	1,024	62.0	-153	4.6	192
		Baltimore	4A	24.6%	30.4%	2,538	683	56.6	-86	3.6	170
		New York	4A	24.6%	30.4%	2,684	544	57.8	-168	5.8	163
Marine	3.0%	San Francisco	3C	38.8%	41.0%	1,504	80	36.4	-1094	-15.5	196
		Seattle	4C	61.2%	59.0%	2,626	99	37.7	-636	-11.8	141
Cold / Very cold	38.8%	Chicago	5A	29.7%	29.9%	3,506	470	52.7	79	3.0	160
		Boston	5A	29.7%	29.9%	3,122	417	49.4	-124	-0.8	160
		Denver	5B	20.8%	19.3%	3,302	431	40.6	-40	-9.4	190
		Minneapolis	6A	15.6%	16.8%	4,202	417	49.0	298	1.2	159
		Missoula	6B	1.9%	2.0%	4,157	162	35.3	26	-11.1	157
		Duluth	7	2.1%	1.9%	5,236	116	41.0	402	-2.7	153
		Fairbanks	8	0.3%	0.4%	7,516	40	33.2	1218	-5.0	108

2.2.5 Sampling, simulation, and data processing

The Monte Carlo analysis simultaneously varied all 18 inputs—i.e., the 17 varied building parameters plus the location. Such a multidimensional analysis produces more reliable and robust measures of impacts and sensitivity than investigations based on perturbing parameters one at a time (Saltelli et al., 2008). For sampling, we used quasi-random low-discrepancy sequences, whose good space-filling properties become particularly important in high dimensional spaces. In addition, the Sobol sequences (Bratley & Fox, 1988; Joe & Kuo, 2003; The MathWorks, Inc, n.d.) that we used are conceptually simpler and perform slightly better than Latin hypercube

sampling, another quasi-random approach, both in general (Homma & Saltelli, 1996) and in particular for building simulation applications (Burhenne, Jacob, & Henze, 2011).

Each instance of an office type was defined by a unique set of sampled building parameters and a location. For each instance, the Baseline strategy and the six or eight alternative strategies (for the small-CAV and medium-VAV offices, respectively; see Table 1) were instantiated from templates, written to EnergyPlus input format, and simulated. Mechanical system capacities for all strategies were determined automatically by EnergyPlus' auto-sizing procedure applied to the Baseline strategy. Therefore, while coil and fan capacities varied among instances, each given instance had a single mechanical system that was used consistently to evaluate all ventilation strategies. In post-processing, each simulated strategy's annual cooling electricity, fan electricity, and heating natural gas consumption were normalized by the office's floor area to obtain annual energy use intensities in kWh/m². Then the change from the Baseline was calculated for each alternative strategy. These changes show the impact of an alternative ventilation strategy in terms of a single piece of information. Moreover, the study so-designed provides good observational power, with each instance representing a set of consistent experimental conditions under which the multiple ventilation strategies were tested and compared.

Tests indicated that sensitivity indicators had very good convergence properties for above approximately 500 unique simulations. We exceeded that significantly, conducting simulations for 3000 instances (with seven or nine ventilation strategies per instance) in each office type. These 3000 instances were sampled equally among the eighteen cities. In order to match the climate distribution of U.S. offices, the original simulations for each office type were bootstrap re-sampled 10,000 times with each location's selection probability determined by the climate zone fractions listed in Table 3. The result was one 10,000-element, climate-weighted dataset for each office type. The weighted datasets were based on 2459 unique instances in the small-CAV office and 1650 in the medium-VAV office (where there were fewer usable instances because of the VAV control limitations discussed in the following section). The number 10,000 was selected

as a round number that was a reasonable compromise between avoiding excessive duplication of unique instances and ensuring that climate zones with smaller fractional representation would have more than a handful of data points. All analysis was conducted on the two climate-weighted datasets.

2.2.6 Outdoor air limitation under VAV control

In a substantial fraction of medium-VAV office instances, some alternative strategies did not operate as intended because they were, at times, limited by the total supply airflow determined by the VAV HVAC system. Deviation from design intent was clearest for 2×VR, and we classified instances as ‘VAV-limited’ if the annual geometric mean of the actual mechanical VR supplied by 2×VR was less than the specified mechanical VR of 18.9 L/s/occ. Compliance with design intent was harder to evaluate for dynamic strategies that included economizing and SR, but ability to meet the 2×VR strategy appeared to be a good surrogate for ability to provide higher flow rates generally. For example, implementing Econ+SR in San Francisco increased the VR by a median of 23.6 L/s/occ among instances that were not VAV-limited, but only by 3.7 L/s/occ among instances that were.

Just under 40% of medium-VAV instances were VAV-limited. As identified by logistic regression (Table 4), these were instances with high occupancy and frequently low cooling loads, due to some combination of relaxed cooling setpoints, lower internal gains, lower window solar gains, and milder outdoor temperatures. In other words, the systems that most frequently limited occupant-normalized OA flow rates (i.e., VRs) were those likely to have low occupant-normalized supply air flow rates. In these instances, standard methods for design and control of VAV systems usually permitted the minimum VR of the Baseline strategy to be met, but limited higher VRs. Further research is needed to determine the best ways to integrate control of OA flow, system supply air flow and temperature, and zone-level discharge air flows and

temperatures to permit increased ventilation in such situations, without undesired energy or comfort consequences.

Table 4 Logistic regression model of the probability that ventilation changes in the medium-VAV office will be VAV-limited. $ELPD = EPD + LPD$.

$\text{logit}(\text{VAV-limited}) \sim 1 + \text{occDens} + \text{coolStpt} + ELPD + SHGC + CDD$				
	Coefficient (raw)	Coefficient (standardized)	Standard error (standardized)	<i>p</i> -value
(Intercept)	-39.42	-2.93	0.07	0.0000
occDens	153.2	3.58	0.09	0.0000
coolStpt	1.631	2.35	0.06	0.0000
ELPD	-0.2215	-1.99	0.06	0.0000
SHGC	-9.694	-1.66	0.05	0.0000
CDD	-0.002077	-1.34	0.05	0.0000

Percent correct: 87% for VAV-limited, 94% for as-intended, 91% overall

The scope of this investigation, however, was alternative ventilation strategies, so we only included the 60% of instances where OA control and VAV supply air control did not come into conflict, and in which all ventilation strategies performed substantially as intended. Removal of VAV-limited instances was done before resampling to construct the medium-VAV office's weighted dataset, and as such ultimate parameter distributions were barely affected. The only meaningful exception was occupant density, for which removing VAV-limited observations reduced the mean from 5.8 to 4.5 occupants per 100 m², and nearly eliminated instances with more than 10 people per 100 m².

2.2.7 Defining sensitivity analysis predictors

We analyzed the sensitivity of alternative strategy energy impacts to predictors that in some cases differed from the directly sampled inputs listed in Table 2. Additional predictors were defined in order to represent climate attributes, improve model fits, and normalize inputs (usually by building volume) to make results more intuitive and generalizable. We also defined several

lumped predictors, which enabled holistic recognition of some influences that appeared minor when spread among multiple inputs.

For climate, for which many annual measures are highly correlated, principal components analysis indicated three predictors were necessary; more would simply confound the analysis. We found heating and cooling degree-days (HDD and CDD), both calculated with a base balance temperature of 18 °C, and the average outdoor air enthalpy during the summer the best three metrics for capturing heating and sensible and latent cooling demands, respectively. In order to reduce confounding in sensitivity analysis, we allowed HDD to be the primary climate indicator, then successively defined linearly independent ‘residual’ CDD and summer enthalpy predictors. Thus the CDD residual (CDD_{res}) was the portion of CDD not explained by a linear regression of CDD against HDD, namely

$$CDD_{res} = CDD - (1762 - 0.3911 \cdot HDD) \quad (1)$$

and the average summer enthalpy residual (sumEnthpyRes) was the portion of average summer enthalpy not explained by HDD and CDD, or

$$sumEnthpy_{res} = sumEnthpy - (52.82 - 2.240 \cdot HDD/1000 + 5.792 \cdot CDD/1000) \quad (2)$$

The values of the CDD and average summer enthalpy residuals for the 18 locations are listed in Table 3. In general, CDD_{res} was negative in mild climates and positive in both hot and cold ones, while sumEnthpyRes was negative in dry climates and positive in humid ones.

Infiltration rate was used as a predictor, rather than the sampled envelope air-leakage coefficient C . It was calculated during post-processing of EnergyPlus results by averaging the time-varying infiltration air exchange rate (h^{-1}) over all hours of the year. Infiltration was a stronger explanatory predictor than C because it encapsulated not merely a building’s envelope leakiness, but also the environmental and operating conditions to which the envelope was subject. Infiltration rate is also intuitive, and generalizes well because it is the air flow normalized by the building volume.

For envelope heat transfer, a lumped parameter K_{cond}/V (short name: KcondPerV; units: W/K/m^3) was defined as the building conductive heat transmission coefficient K_{cond} (W/K) (Kreider, Curtiss, & Rabl, 2009) normalized by building volume, or

$$\frac{K_{\text{cond}}}{V} = \frac{U_{\text{roof}}A_{\text{roof}} + U_{\text{wall}}A_{\text{wall}} + U_{\text{window}}A_{\text{window}}}{V} \quad (3)$$

where U and A refer, respectively, to individual component U -values ($\text{W/K}\cdot\text{m}^2$) and areas (m^2).

The use of KcondPerV, in addition to normalizing for component areas, made more apparent the influence of envelope conduction, which appeared trivial when split between individual components.

The window solar heat gain coefficient was replaced with a simple lumped parameter $Q_{\text{sol,window}}/V$ (short name: winSolarPerV; units W/m^3), defined as the product of the solar heat gain coefficient (SHGC), the window area, and the annual average direct normal solar irradiance \bar{I}_n (W/m^2) available in weather files, normalized by the building volume, or

$$\frac{Q_{\text{sol,window}}}{V} = \frac{\text{SHGC} \cdot A_{\text{window}} \bar{I}_n}{V} \quad (4)$$

Finally, a summed equipment and lighting power density (ELPD) replaced separate equipment and lighting values, and a day length predictor replaced separate day start and end times. Both substitutions increased model simplicity and explanatory clarity, without meaningfully reducing predictive power.

Table 5 lists and summarizes the final 16 predictors used in the sensitivity analysis. The statistics are based on observations in both buildings, i.e., the merged 20,000 points of each building type's climate-weighted dataset. Only the four predictors included in Table 6 were meaningfully different in the two offices. That is, the infiltration rate, the building conductive heat transfer coefficient per volume, and the window solar gain per volume were all higher in the small-CAV office, because of its much greater envelope-to-volume ratio. Occupant density, on

the other hand, was somewhat lower in the medium-VAV office because more densely occupied offices were more likely to be classified as VAV-limited and therefore removed.

Table 5 Building and climate parameters used as predictors in sensitivity analysis, with their units and short names. The mean, standard deviation (SD), and selected percentiles (prefix “p”) are shown for the combined dataset for both offices.

Parameter	Units	Short name	Mean	SD	p5	p25	Median	p75	p95
Heating degree days, base 18 °C.	K·days	HDD	2,308	1,221	530	1,156	2,566	3,267	4,147
Cooling degree days (base 18 °C) residual	K·days	CDDres	0	431	-1,024	-180	-14	203	797
Summer enthalpy residual	kJ/kg	sumEnthpyRes	0.0	7.6	-14.4	-6.0	2.1	5.3	10.1
Infiltration air exchange rate	h ⁻¹	infAER	0.38	0.38	0.04	0.12	0.25	0.50	1.16
Conductive heat transfer coefficient per volume	W/K/m ³	KcondPerV	0.45	0.33	0.14	0.23	0.35	0.57	1.13
Wall thermal mass	kJ/K·m ²	wallCT	136	125	16	45	93	186	414
Window solar gain per volume	W/m ³	winSolarPerV	3.8	1.5	1.6	2.6	3.6	4.7	6.5
Day length	hours per day	dayLen	13.9	2.1	10.4	12.4	13.9	15.5	17.4
Combined LPD and EPD	W/m ²	ELPD	19.3	9.0	6.1	12.6	18.5	25.1	35.1
Occupant density	occ per 100 m ²	occDens	5.1	2.3	2.3	3.4	4.6	6.3	9.9
Zone heating setpoint	°C	heatStpt	21.5	1.4	19.1	20.6	21.5	22.4	23.8
Zone cooling setpoint	°C	coolStpt	24.3	1.4	22.1	23.3	24.3	25.3	26.8
Unoccupied period zone setpoint setback	°C	stptSetback	2.5	1.4	0.3	1.3	2.6	3.8	4.8
Heating efficiency	-	heatEff	0.80	0.11	0.63	0.71	0.80	0.89	0.97
Cooling coefficient of performance	-	coolCOP	3.02	0.74	1.79	2.45	3.02	3.60	4.24
Fan efficiency	-	fanEff	0.70	0.15	0.46	0.59	0.70	0.81	0.95

Table 6 Statistics for each office type for the only four predictors that varied meaningfully between the two office types. These mean and standard deviation (SD) values were *not* used for standardization in regression models.

Parameter	Units	Short name	Office type	Mean	SD	p5	p25	Median	p75	p95
Infiltration air exchange rate	h ⁻¹	infAER	Small-CAV	0.53	0.46	0.06	0.18	0.39	0.72	1.51
			Medium-VAV	0.23	0.19	0.03	0.09	0.17	0.31	0.64
Conductive heat transfer coefficient per volume	W/K/m ³	KcondPerV	Small-CAV	0.64	0.36	0.25	0.39	0.55	0.80	1.36
			Medium-VAV	0.26	0.12	0.11	0.18	0.24	0.32	0.50
Window solar gain per volume	W/m ³	winSolarPerV	Small-CAV	4.4	1.6	1.9	3.0	4.3	5.6	7.1
			Medium-VAV	3.2	1.1	1.4	2.3	3.2	4.0	4.9
Occupant density	occ per 100 m ²	occDens	Small-CAV	5.8	2.6	2.5	3.7	5.2	7.3	11.1
			Medium-VAV	4.5	1.8	2.3	3.2	4.2	5.5	7.9

2.3 Results and discussion

The results are organized from general to specific, as follows. Section 2.3.1 briefly summarizes the Baseline strategy’s energy use intensity results for context. Section 2.3.2 provides an overview of the alternative ventilation strategies’ energy impacts, and Section 2.3.3 estimates the aggregate energy saving potential in a large segment of the U.S. office stock. Section 2.3.4

examines selected results by climate zone category. Sections 2.3.5–2.3.7 turn to detailed sensitivity analysis of climate and building parameters. Section 2.3.8 applies sensitivity analysis results to answer some specific ventilation strategy questions, and 2.3.9 discusses implications for high performance buildings. Finally, Section 2.3.10 describes the spreadsheet implementation of accurate models to estimate energy impacts provided as Supplementary Information with the published article version of the chapter.

Most discussion focuses on the principal strategies designed to save energy: Econ, D950, and Econ+D950 in the small-CAV office, and those three plus Econ+SR and Econ+SR+D950 in the medium-VAV office. Overview and sensitivity analysis results are given for EconLock, 2×VR, Econ+D675, and Econ+SR+D675, but they are discussed less. Economizing with lockout (EconLock) nearly always saved less than differential enthalpy economizing (Econ), and 2×VR would generally be implemented for work performance and absenteeism benefits (Fisk et al., 2012), not energy savings. Both EconLock and 2×VR are discussed in in depth strategy analysis in Section 2.3.8. In terms of energy savings, Econ+D675 and Econ+SR+D675 never performed better than Econ+D950 or Econ+SR+D950, respectively, but provided a substantial fraction of the maximum savings, and are discussed in detail in a Chapter 3.

For much of the treatment, HVAC natural gas and electricity energy use were combined into a single value for HVAC source (or primary) energy use. To do so, we used the national average site-to-source energy conversion factors used by the U.S. EPA, which are 3.14 and 1.05 source kWh per site kWh for electricity and natural gas, respectively (U.S. EPA, 2013). Because in the U.S. the ratio of average site-to-source conversion factors for electricity and natural gas is nearly identical to the ratio of average electricity and natural gas prices—\$0.1086 per kWh for electricity and \$0.0375 per kWh natural gas, based on average consumption-weighted U.S. prices in all states from 2005–2014 (U.S. Energy Information Administration (EIA), n.d.-e, n.d.-g, n.d.-f, n.d.-a))—changes in source energy use are a very good proxy for changes in energy operating

costs. To estimate cost impacts from source energy impacts, one can multiply by \$0.035 per kWh, or estimate \$1 saved for every approximately 30 kWh of source energy reduction.

2.3.1 Baseline energy consumption

Table 7 summarizes the annual energy consumption of the Baseline strategy to provide context for the remainder of the paper. In general, the medium-VAV office consumed somewhat less energy. The largest and most consistent reason for this was less heating gas use, which accounted for 45% of HVAC source energy consumption in the small-CAV office type but only 25% in the medium-VAV office. In the hottest areas, the small-CAV office type also consumed more electricity for cooling. In both offices, total HVAC electricity consumption was about evenly split between cooling and fans.

Figure 2 illustrates the Baseline strategy natural gas and electricity annual use intensities in individual cities. For comparison, the background indicates the median (dark green line) and 25–75th percentile interval (green shading) of the use intensities derived from real consumption data in the 2003 CBECS, the most recent year for which energy consumption was available (U.S. Energy Information Administration (EIA), 2006a). The CBECS data were restricted to offices and divided into the five broad climate classifications used in 2003, but not differentiated by size (since that resulted in too few data points in some bins). Lack of size resolution probably helps explain why natural gas consumption was sometimes on the higher side of the CBECS reference range for the small-CAV office, and on the lower side of it for the medium-VAV one. There are many other good reasons to expect some differences between 2003 CBECS end-use intensities and our modeled results, such as independent variation of all parameters in our study, significant changes in lighting and equipment power density in the past thirteen years, and the uncertain assumptions in the CBECS end-use estimates themselves. Overall, though, the modeled baselines matched the reported office sector estimates quite well.

Table 7 Baseline ventilation strategy annual energy use intensity statistics for the two model typologies, for weighted datasets over the U.S. The prefix “p” indicates percentile.

	Baseline annual energy use intensity, kWh/m ²						
	Mean	SD	p5	p25	Median	p75	p95
<i>Small-CAV</i>							
HVAC natural gas	111	100	5	34	87	158	305
HVAC electricity	51	30	17	30	45	64	111
Cooling electricity	27	21	5	13	21	35	69
Fan electricity	24	13	9	16	22	30	48
HVAC site energy	162	103	43	89	140	210	353
HVAC source energy	278	137	96	185	254	349	523
<i>Medium-VAV</i>							
HVAC natural gas	45	38	1	15	37	65	115
HVAC electricity	48	20	23	34	44	59	87
Cooling electricity	26	14	11	17	23	32	52
Fan electricity	22	10	10	15	20	27	42
HVAC site energy	93	44	35	60	86	118	173
HVAC source energy	199	78	93	145	185	244	342

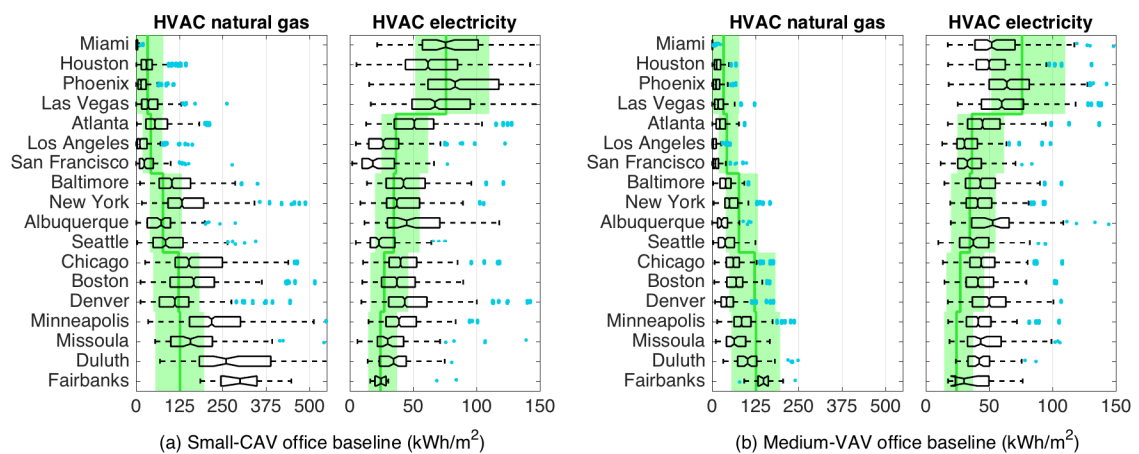


Figure 2 Boxplots of HVAC natural gas and electricity usage in the two offices by city. The green shaded area in the background shows CBECS 25–75th percentile span, and the line in the middle of it is the CBECS median. These references are the same in (a) and (b), and based on only offices and divided into the five broad climate bins used in 2003 CBECS.

2.3.2 Overview of alternative strategy energy impacts

Table 8 shows median and 95% data intervals for the changes in energy consumption intensity under the six strategy HVAC alternatives in the small-CAV office. Herein, the ‘95% data

interval' or 95% DI is the interval bounded by the 2.5th and 97.5th percentiles of a set of data. The D950 strategy saved the most natural gas but typically little electricity, while Econ saved some electricity but no natural gas. The combined Econ+D950 had the maximum source energy savings of any strategy 98% of the time. At the median, it saved 28 kWh/m² of source energy, and at the top of the 95% DI, it saved up to 72 kWh/m². In percent terms, Econ+D950 reduced HVAC source use intensity by 11% at the median (95% DI: 5–25% savings). The final row of Table 8 shows the fraction of maximum savings each strategy provided. On average, D950 alone achieved about two-thirds, and Econ alone about one-third, of the source energy consumption reductions of Econ+D950.

Table 8 For the small-CAV office, median and 95% data intervals (DI) for each strategy's change from the baseline for natural gas, electricity, and source energy in annual kWh/m², as well as in percent of baseline for source energy. Negative changes indicate energy saved. Also shown are the frequency that each strategy yielded maximum savings in source energy and the average fraction of the maximum possible savings each strategy achieved.

	EconLock	Econ	D950	Econ+D950	2×VR	Econ+D675
Median (95% DI) natural gas change, kWh/m ²	1 (0, 2)	1 (0, 2)	-12 (-53, -1)	-12 (-53, 0)	16 (1, 72)	-5 (-37, 7)
Median (95% DI) electricity change, kWh/m ²	-2 (-8, 0)	-3 (-10, 0)	0 (-5, 1)	-4 (-13, -1)	1 (-2, 6)	-3 (-11, 0)
Median (95% DI) source energy change, kWh/m ²	-5 (-23, 0)	-7 (-32, 0)	-16 (-57, 0)	-28 (-72, -8)	21 (1, 75)	-18 (-54, 3)
Median (95% DI) source energy % change, %	-2 (-10, 0)	-3 (-16, 0)	-6 (-20, 0)	-11 (-25, -5)	9 (1, 29)	-7 (-18, 1)
Frequency strategy had maximum source savings	0%	0%	1%	98%	0%	0%
Average fraction of maximum savings	0.22	0.31	0.62	1.00	0.00	0.66

Table 9 lists analogous impacts in the medium-VAV office. As with the small-CAV office, the greatest energy savings nearly always came from the strategy with the most ventilation technology components. For the medium-VAV office, this was Econ+SR+D950, which substantially reduced both natural gas and electricity use, for a median total source use intensity reduction of 50 kWh/m² and reductions up to 124 kWh/m² within the 95% DI. In percent terms, Econ+SR+D950 saved 27% of HVAC source energy at the median (95% DI: 6–42% savings). Most savings could be realized without the use of the DCV component, however, with Econ+SR

having a median and 95% DI only marginally lower than those of Econ+SR+D950, and capturing 84% of the savings of the more complex strategy on average.

Table 9 For the medium-VAV office, median and 95% data intervals (DI) for each strategy's change from the baseline for natural gas, electricity, and source energy in annual kWh/m², as well as in percent of baseline for source energy. Negative changes indicate energy saved. Also shown are the frequency that each strategy yielded maximum savings in source energy and the average fraction of the maximum possible savings each strategy achieved.

	EconLock	Econ	Econ+SR	D950	Econ+D950	Econ+SR+D950	2×VR	Econ+SR+D675
Median (95% DI) natural gas change, kWh/m ²	-1 (-4, 0)	-1 (-4, 0)	-13 (-36, 0)	0 (-5, 1)	-2 (-9, 0)	-18 (-42, 0)	4 (0, 24)	-13 (-38, 0)
Median (95% DI) electricity change, kWh/m ²	-5 (-15, 0)	-6 (-18, -1)	-9 (-27, -1)	1 (-3, 5)	-7 (-19, -2)	-9 (-28, -2)	0 (-3, 9)	-8 (-26, 1)
Median (95% DI) source energy change, kWh/m ²	-17 (-49, 0)	-22 (-61, -4)	-43 (-117, -4)	3 (-11, 14)	-26 (-65, -7)	-50 (-124, -9)	8 (-6, 31)	-41 (-115, 2)
Median (95% DI) source energy % change, %	-9 (-19, 0)	-11 (-23, -3)	-24 (-41, -3)	2 (-5, 6)	-14 (-24, -7)	-27 (-42, -6)	4 (-4, 15)	-23 (-40, 1)
Frequency strategy had maximum source savings	0%	0%	0%	0%	4%	95%	0%	0%
Average fraction of maximum savings	0.32	0.44	0.84	0.04	0.56	0.99	0.01	0.77

There were three important differences between the two offices types. First, economizing saved much more energy in the medium-VAV office, on the order of 2–3 times the savings observed in the small-CAV office. This greater savings potential was partially due to envelope-to-volume ratio differences, but mostly to the fact that supply air temperature is maintained consistently low in multizone air distribution systems, increasing opportunities for economizing. Second, SR was available as a strategy, and SR nearly always saved significant energy in both heating and cooling. Comparing Econ+SR to Econ, the addition of SR approximately doubled the source energy savings generated by an economizer alone. Third, DCV was not typically a useful strategy in the medium-VAV office. By itself, it was about as likely to increase source energy consumption as decrease it. Even with other components, DCV did not provide large additional energy savings, at least in terms of the median or average. In sum, the much greater savings from economizing, additional large savings from SR, and sharply reduced savings potential of DCV in the medium-VAV office combined to yield source energy savings opportunities that were about twice the magnitude of those available in the small-CAV office.

2.3.3 Aggregate office sector energy and expenditure savings

Before investigating the sensitivity of the energy savings to variations in the input parameters, we demonstrate the large potential of alternative ventilation strategies to save energy across the U.S. office sector. To do so, we used the small-CAV office results to represent the 296 million m² of floorspace in offices less than 930 m² (10,000 ft²), and the medium-VAV office to represent the 800 million m² of floorspace in offices between 930 m² and 18,590 m² (200,000 ft²) (U.S. Energy Information Administration (EIA), 2015c). These two estimates cover 74% (or 1,095 million m²) of U.S. office floorspace in small to medium-large offices, but exclude possible benefits in the 26% of floorspace in high-rise and extremely large offices beyond the scope of our modeling domain. Under the Baseline strategy, this segment of the office sector was estimated to use 241 TWh of primary energy annually, at a total cost of \$8.4 billion (using average consumption-weighted electricity and natural prices in all U.S. states from 2005–2014 (U.S. Energy Information Administration (EIA), n.d.-e, n.d.-g, n.d.-f, n.d.-a)). If all represented offices started from the Baseline and moved to the alternative with the greatest energy savings, the aggregate annual source energy savings would be 53 TWh, or a 22% reduction of all primary energy consumed by HVAC end-uses. Energy costs would be reduced by the same percent, at a value of \$1.84 billion.

Table 10 Aggregate impacts over all small to medium-large U.S. offices, which represent about three-quarters of office floorspace. Untapped savings account for the technologies' estimated current market penetration.

Aggregate U.S. small to medium-large office sector:	Sector total, under Baseline	Savings, starting from Baseline	Untapped savings
HVAC source energy consumed (TWh)	241	53	36
HVAC energy cost (billion \$)	8.43	1.84	1.25

Of course, not all offices currently operate with the Baseline strategy, so we also estimated the untapped market potential, only counting the portion of floorspace not yet penetrated by component technologies. Current economizer adoption rates, from CBECS 2012, were 9% for small offices and 44% for medium to medium-large offices (U.S. Energy Information Administration (EIA), 2015c, 2015b). For DCV and SR penetration, which CBECS does not ask about, we relied on survey information from building industry professionals, limited only those referring to offices ($N = 67$) (Hamilton et al., 2016). These indicated 33% adoption for DCV and 37% for SR, among recent projects. There is more uncertainty in these adoption rate estimates for DCV and SR, given the small sample and the self-reported nature of the survey. Results indicated that most (68%) of the total theoretical savings potential judged against the Baseline strategy appeared to be untapped, with 36 TWh of annual primary energy savings still available across the sector even after accounting for current technology adoption rates. Such savings would represent 16% of all primary energy consumed by HVAC end-uses.

The small-CAV segment represented 27% of the small to medium-large stock's floorspace, and even more (34%) of baseline energy use. However, in terms of savings from alternative ventilation strategies, it was a significantly less attractive target, accounting for only 17% of theoretical savings (from the Baseline strategy) and 20% of untapped potential. Therefore, at the coarsest level, medium and larger offices with multizone distribution systems should be more immediate targets for market actors and policymakers interested in realizing energy savings from these alternative ventilation strategies.

2.3.4 Energy impacts by climate zone

Our Monte Carlo investigation also enabled much finer analysis, providing insights to target the most promising savings opportunities in both office types. We first examine the principal energy-saving strategies' results in each of the five broad Building America climate zone

categories. For the small-CAV office, Figure 3 shows the ranges of annual HVAC source energy, natural gas, and electricity changes observed for Econ, D950, and Econ+D950. Economizer electricity savings were similar in hot-humid, mixed-humid, and cold climates, and substantially higher in hot-dry/mixed-dry and marine climates. Savings from DCV were almost entirely from natural gas for heating, and much greater in cold climates. Only in hot-humid locations did DCV consistently save electricity, and in all other climates it frequently increased electricity use by reducing free cooling.

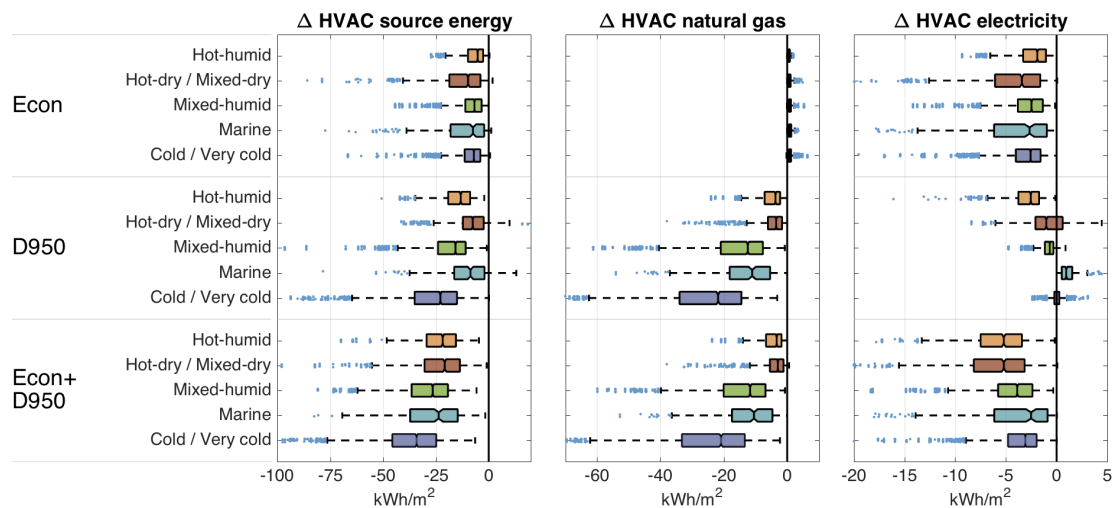


Figure 3 Ranges of HVAC source energy, natural gas, and electricity from implementing three alternative ventilation strategies in the small-CAV office, divided by five broad Building America climate zones. (See Table 3 for cities in each zone.)

Combining economizer with DCV eliminated this unintended consequence, so Econ+D950 never increased energy use. The two components' source energy savings were largely additive. In hot-humid, mixed-humid, and especially cold climates, DCV made up the larger part of combined Econ+D950 source energy savings, and could potentially be more cost-effective to implement on its own. On the other hand, in hot-dry/mixed-dry and marine climates, D950 alone was less

attractive, both because economizer was more beneficial and because DCV without economizer control override could increase energy use there.

For the medium-VAV office, Figure 4 shows the impacts of Econ, D950, Econ+D950, Econ+SR, and Econ+SR+D950. Comparison to small-CAV results in Figure 3 again confirms that alternative strategies in the medium-VAV office typically saved significantly greater source energy. (Note that source energy and electricity have larger scales in Figure 4 than in Figure 3.) This source energy difference was the combined effect of slightly smaller natural gas reductions and much larger electricity savings, due to the three important broad differences already identified between the two office types: in the medium-VAV office economizer saved much more energy, SR was applicable and saved significant energy, and DCV savings were minor (and, to an even greater extent than in the small-CAV office, D950 alone often increased electricity use by reducing free cooling.) Thus, for example, the combined Econ+D950 strategy happened to have similar source energy savings in both office types, but economizing and not DCV accounted for nearly all of them in the medium-VAV office—for which, in any case, the strategies Econ+SR and Econ+SR+950 saved far more energy.

Within these broad conclusions, medium-VAV office impacts did vary by climate. Economizer and SR savings, both independently and together, rose consistently as the climate zones' cooling demands decreased. This was true for both natural gas and electricity savings from SR, reflecting significant potential for reducing both primary cooling and zone reheat energy in all but a small minority of instances in the very hottest climates. The potential benefits of moving from Econ+SR to Econ+SR+D950 were subtler, with small increases in electricity savings in hotter climates, and small increases in natural gas savings in colder ones. (More specific detail on the latter two questions can be found in Section 2.3.8.)

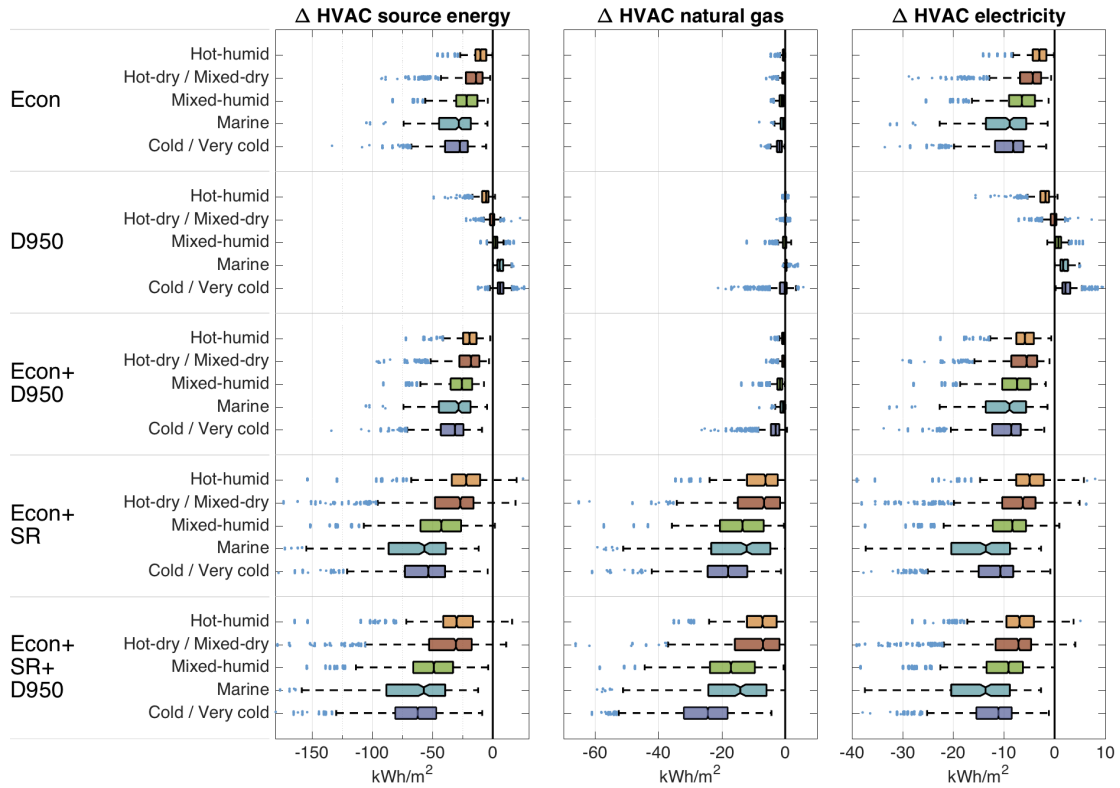


Figure 4 Ranges of HVAC source energy, natural gas, and electricity from implementing five alternative ventilation strategies in the medium-VAV office, divided by five broad Building America climate zones. (See Table 3 for cities in each zone.)

2.3.5 Sensitivity analysis tools

To quantitatively assess the influence of building and climate parameters on the alternative ventilation strategies' energy impacts, we turn to sensitivity analysis based on linear regression, which captures first-order effects well and is clear and intuitive. (More precise models that include nonlinear and interaction effects are available in the Supplementary Information to the published article version of this chapter, as described in Section 2.3.10). The linear regression model with standardized predictors for response y is

$$y = \beta_0 + \sum_i \beta_i z_i + \varepsilon = \beta_0 + \sum_i \beta_i \frac{x_i - \mu_i}{\sigma_i} + \varepsilon \quad (5)$$

where ε is an error term, z_i is the standardized value of predictor x_i obtained by subtracting the mean μ_i and dividing by the SD σ_i . Sensitivity was assessed by the coefficient β_i , herein called the

standardized effect. The constant term β_0 is the response when all predictors are at their means. Though separate regression analyses were conducted for each office, the same μ_i and σ_i values were used for both offices to allow consistent comparisons. These μ_i and σ_i values are in Table 5, but are also provided in the result tables in this section for easy reference.

Here, the response y was the change from the Baseline in source energy use intensity owing to alternative strategy adoption, with positive changes indicating increased energy use compared to the Baseline strategy, and negative changes representing energy savings. Therefore, a negative constant term β_0 indicates the strategy saved energy when all predictors were at the standardizing mean values. A negative standardized effect for a predictor means that on average more energy was saved when that predictor had higher values. Further, as Equation (5) shows, β_i is the average change that a change of σ_i in predictor i has on source energy changes in real units of kWh/m² (Lattin, Carroll, & Green, 2002).

To make it clearer when parameters had truly negligible impact, a pruning routine tested the impact of removing each parameter from a regression model and did so if it increased the model's root mean square error (RMSE) by less than 1%. To rank the influence of predictors, we used a sensitivity index (SI) based on the square of the standardized regression coefficient, which gives an estimate of the fraction of variance accounted for by variation in that parameter (Saltelli et al., 2008). (For this statistic only, we used separate predictor standard deviations for each office type, rather than the ones for the combined dataset.) A 'weighted SI' combined results for the six or eight alternative strategies by averaging their SI values, with each strategy weighted by the variance of the energy changes it produced. These variance-based weights preserve the interpretation that the weighted SI indicates the fraction of variance, across all strategies, for which a predictor accounted. With coefficients of determination (R^2) between 0.6 and 0.8, the regression models accounted for 60–80% of the variance in source energy use intensity, depending on the strategy.

2.3.6 Small-CAV office sensitivity analysis

Table 11 shows the results of the regression sensitivity analysis for the small-CAV office. Seven building predictors—occupant density, the infiltration rate, the day length, ELPD, and heating and cooling setpoints and efficiencies—plus HDD explained 68% of the variance in ventilation strategy impacts. Occupant density and HDD alone accounted for nearly 40% of variance, because of their decisive influence on heating energy savings, which is illustrated in Figure 5a. Similarly, as Figure 5b shows, whether economizer saved significant energy could largely be predicted by internal gains and the cooling setpoint.

Table 11 Small-CAV office sensitivity analysis results. Values are coefficients of linear regressions against standardized predictors, and indicate the average change in a strategy's impact in kWh/m² produced by a change of σ in the predictor. Negative changes represent energy savings. The constant is the change in the outcome produced by the strategy when all predictors are at the values in the μ column.

Predictor	μ	σ	Weighted SI	Standardized effect size (kWh/m ²)					
				EconLock	Econ	D950	Econ+ D950	2×VR	Econ+ D675
Constant	-	-	-	-6.0	-8.3	-16.6	-26.9	22.8	-16.0
occDens	5.1	2.3	26%	-	-	-6.8	-7.6	12.0	-
HDD	2,308	1,221	13%	-	-	-6.2	-6.4	8.3	-3.2
infAER	0.38	0.38	8%	0.5	0.7	-3.7	-2.8	0.8	-6.7
dayLen	13.9	2.1	5%	-1.1	-1.2	-3.2	-4.7	4.2	-3.3
coolStpt	24.3	1.4	4%	2.6	3.4	-	4.2	-	3.6
ELPD	19.3	9.0	4%	-2.9	-4.0	1.8	-3.0	-1.7	-3.5
heatStpt	21.5	1.4	4%	-0.7	-1.1	-2.8	-4.1	3.7	-2.4
coolCOP	3.02	0.74	3%	2.2	2.8	-	3.9	-0.9	2.8
heatEff	0.80	0.11	2%	-	-	2.4	2.2	-3.1	1.2
KcondPerV	0.45	0.33	2%	-1.7	-2.2	-	-2.2	-	-2.2
sumEnthpyRes	0.0	7.6	1%	0.6	1.2	-2.6	-	2.9	-
CDDres	0	431	1%	1.0	1.7	-2.2	-	2.5	1.3
winSolarPerV	3.8	1.5	1%	-1.3	-1.9	1.2	-1.0	-1.4	-1.9
RMSE (R^2)	-	-	-	3.6 (0.68)	4.7 (0.70)	7.5 (0.74)	8.7 (0.74)	8.9 (0.80)	9.2 (0.62)
Weight	-	-	-	3%	6%	18%	23%	32%	18%

Note: the pruning routine eliminated wallCT, fanEff, and stptSetback from all strategies' models.

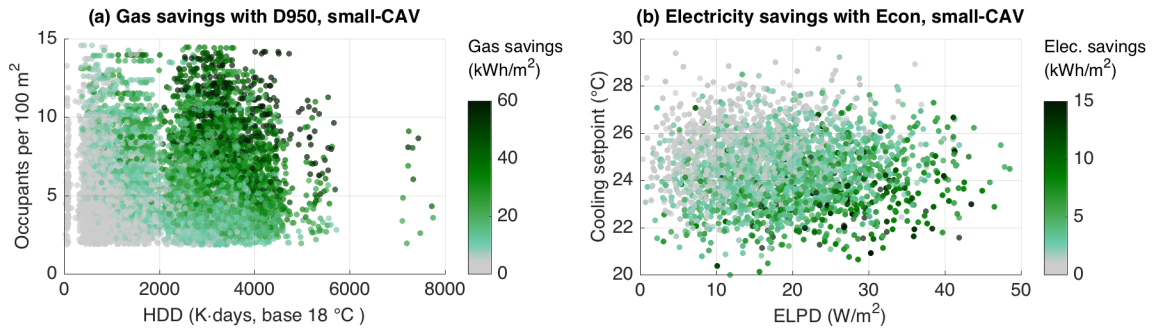


Figure 5 In the small-CAV office, (a) gas savings from D950, as a function of HDD and occupant density, and (b) electricity savings, as a function of the cooling setpoint and ELPD. Note the color scales are for site energy intensity units.

Detailed results, organized by predictor category, included:

- Climate variables:* The number of HDD was so important because of its strong influence on heating energy, particularly on reductions from DCV and increases from doubling ventilation. In climates that were also hotter than average given HDD, and more humid than average given HDD and CDD, there were also fewer savings from economizing, more savings from DCV, and greater energy use increases from doubling ventilation. The residual climate effects not explained by HDD, however, were a small fraction of the effects associated with HDD.
- Envelope:* Infiltration was an important influence on strategies with DCV, since, along with occupant density, it determined by how much mechanical ventilation could be reduced without exceeding the CO₂ setpoint. Other envelope characteristics, however, played a small role, with the lumped building conductive heat transfer coefficient and the window solar gain parameter (mostly based on the SHGC) ranked as the two least influential predictors that were not pruned, and the thermal mass of exterior walls pruned from all models.
- Occupancy:* Along with HDD, occupant density decisively influenced heating energy changes, particularly for 2×VR and for strategies with DCV. (Occupant density also influenced increases in electricity use from doubling ventilation, but very weakly.) The

length of the day was also quite important, with each ~2 hours of additional operating time increasing a given energy impact by about 20%, on average, for all strategies.

- *Gains*: The equipment and lighting power density was the most important single predictor of economizer savings, which increased as ELPD increased. Solar gains, via the lumped window solar gain, were also associated with economizer savings, but much less strongly. (Increases in both types of gains reduced DCV savings, too, but the effects were modest.)
- *Setpoints*: A tight control range for indoor temperatures increased the impact of alternative strategies on energy use. Lower cooling setpoints significantly increased savings of strategies with economizers, while higher heating setpoints enhanced energy-saving potential of strategies with DCV (and the energy impacts of doubling ventilation). As an example, an office with a zone temperature control range of 22–23 °C would save about 12 kWh/m² per year more on average from Econ+D950 than one with a more relaxed 20–25 °C allowable range. However, the unoccupied temperature setback had no meaningful influence on ventilation strategy impacts.
- *Efficiencies*: As would be expected, impacts were smaller on average for more efficient mechanical systems. Interestingly, cooling COP was most important, and heating efficiency much less so. Fan efficiency, in this CAV system, had negligible influence.

2.3.7 Medium-VAV office sensitivity analysis

Table 12 shows the results of the regression sensitivity analysis for the medium-VAV office. Because of the multizone distribution and VAV control of the building, and the fact that SR was a dominant energy-saving technology component, results were most sensitive to zone temperature setpoints and climate. Just five building predictors—the three setpoints, the cooling coil COP, and the infiltration rate—plus HDD accounted for 64% of alternative strategy impacts' variance.

Table 12 Medium-VAV office sensitivity analysis results. Values are coefficients of linear regressions against standardized predictors, and indicate the average change in a strategy's impact in kWh/m² produced by a change of σ in the predictor. Negative changes represent energy savings. The constant is the change in the outcome produced by the strategy when all predictors are at the values in the μ column.

Predictor	μ	σ	Weighted SI	Standardized effect size, kWh/m ²							
				EconLock	Econ	Econ+SR	D950	Econ+D950	Econ+SR+D950	2×VR	Econ+SR+D675
Constant			-	-21.6	-27.6	-61.0	2.2	-33.4	-68.9	10.7	-59.6
heatStpt	21.5	1.4	17%	-5.0	-5.8	-14.2	0.9	-5.6	-14.0	-	-13.7
HDD	2,308	1,221	14%	-7.5	-7.4	-10.9	4.1	-6.1	-11.8	-	-10.9
stptSetback	2.5	1.4	13%	4.3	4.9	12.0	-	4.8	12.1	-	11.8
coolCOP	3.02	0.74	9%	4.3	5.8	9.2	-0.7	6.7	9.9	-	8.5
coolStpt	24.3	1.4	7%	4.0	4.7	8.6	-	5.2	9.0	-	8.0
infAER	0.38	0.38	3%	-	-	-8.5	-	-3.0	-11.9	-	-17.1
winSolarPerV	3.8	1.5	3%	-3.3	-4.6	-7.7	-	-4.4	-7.2	-1.4	-6.4
KcondPerV	0.5	0.3	2%	-4.9	-5.4	-15.5	-	-4.8	-15.0	-	-14.2
ELPD	19.3	9.0	2%	-2.3	-3.9	-3.2	-	-4.1	-2.8	-1.2	-3.7
CDDres	0	431	2%	-	1.0	4.0	-1.7	-	2.5	3.8	4.8
occDens	5.1	2.3	1%	1.5	2.0	2.8	-0.9	-	-	7.3	4.9
sumEnthpyRes	0.0	7.6	1%	-	2.0	2.0	-1.3	-	-	3.8	2.8
fanEff	0.70	0.15	1%	1.2	1.6	2.5	-	1.6	2.2	-	2.3
heatEff	0.80	0.11	0%	-	-	1.7	-	-	2.1	-0.8	1.5
dayLen	13.9	2.1	0%	1.3	-	-	-	-	-	1.3	-
RMSE (R^2)			-	6.5 (0.76)	7.0 (0.78)	14.5 (0.76)	3.5 (0.66)	7.0 (0.78)	14.3 (0.78)	5.9 (0.63)	14.6 (0.77)
Weight				5%	7%	25%	1%	6%	26%	3%	27%

Note: the pruning routine eliminated wallCT from all strategies' models.

Results for all predictors, by category, included:

- Climate variables:* HDD was again a critical influence on potential heating and cooling savings, with greater savings from economizing and SR in colder climates. Furthermore, the CDD and average summer enthalpy residuals indicated that economizing and SR were even less effective (and doubling ventilation more energy intensive) in the hottest and most humid locations.
- Envelope:* Infiltration was less influential overall than in the small-CAV office, but strategies with SR and DCV saved more heating energy in leakier buildings. The lumped building conductive heat transfer coefficient was more important in the medium-VAV office than in the small-CAV one, because less insulated envelopes (leading to greater load diversity among zones) were associated with greater SR savings.

- *Occupancy*: In a stark contrast to the small-CAV office, neither occupant density nor the length of the occupied day strongly influenced the medium-VAV alternative ventilation strategy energy impacts. The only exception was occupant density's influence on the energy impact of $2 \times VR$.
- *Gains*: Higher solar gains were associated in particular with larger energy savings from SR, leading them to be more important than internal gains in the medium-VAV office (unlike in the small-CAV office). Solar gains only affect perimeter zones, and SR can typically save more energy in situations where there is greater zone load diversity. Furthermore, although ELPD had almost the same standardized effect for Econ in both offices, it was much less relatively influential in the medium-VAV office because economizing did not require high internal gains to be beneficial.
- *Setpoints*: Higher heating setpoints, lower cooling setpoints, and smaller unoccupied period setbacks all led to larger alternative strategy impacts on energy use; together the three indoor air temperature control variables accounted for 38% of strategies' variance. Unlike in the small-CAV office, the zone temperature setpoint setback for unoccupied periods was influential, because the setback determined how frequently the HVAC system had to operate on weekends and holidays. (Unoccupied period control mattered little in the small-CAV office, where strategies' energy savings depended on occupants being present or high internal gains.)
- *Efficiencies*: Impacts were again smaller on average for more efficient mechanical systems, with cooling COP emerging as extremely important for both economizer and SR impacts. At least in this linear analysis, neither fan efficiency (despite the variable speed fan) nor heating efficiency (even though SR saved significant heating energy) registered as meaningful.

Figure 6 illustrates some of the most important influences for Econ+SR, which captured the bulk of the significant savings frequently available in the medium-VAV office. Figure 6a shows the influence of the heating setpoint and HDD on gas savings, which were greatest for buildings with heating setpoints greater than 20 °C in climates colder than about 1000 K·days. Figure 6b shows the role of CDD and COP on electricity savings, which were quite limited in the very hottest climates and also reduced with highly efficient cooling coils.

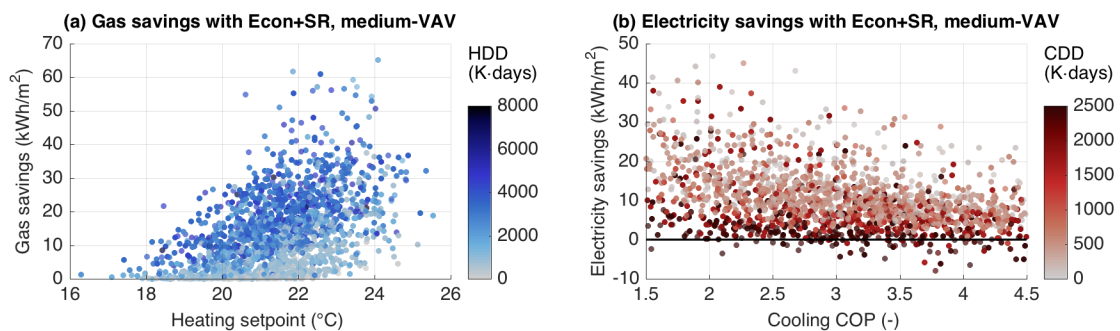


Figure 6 (a) Econ+SR gas savings vs. heating setpoint, colored by HDD; and (b) Econ+SR electricity savings vs. cooling COP, colored by CDD.

2.3.8 Specific strategy questions

2.3.8.1 Small-CAV office: When to use Econ vs. D950 vs. Econ+D950?

According to the sensitivity analysis, in the small-CAV office, characteristics most likely to lead to significant economizing benefit were higher ELPD, lower cooling setpoint, lower COP, and more transmissive envelope both in terms of higher heat transfer coefficients and higher window solar gains. Savings were also greater when all climate indicators were lower (but no one indicator was decisive). Savings from DCV were greater when HDD, occupant density, infiltration, and summer enthalpy were higher, and window solar gains were lower. Thus, economizer and DCV savings were to some extent in conflict, with economizer more beneficial for buildings with high gains located in mild climates, and DCV more apt for buildings with low gains and in climates with cold winters and/or hot and humid summers.

Figure 7 illustrates that economizing and DCV were, indeed, most attractive in different regions of the parameter space, an observation in line with previous analyses for offices (Brandemuehl & Braun, 1999) and in a school (Lawrence & Braun, 2007). The reference lines in red are at 12.5 kWh/m², which is 5% of the median baseline HVAC source energy intensity. A quarter of the time neither strategy saved above the threshold, while 51% of the time only D950 exceeded it and another 11% only Econ did so. Only 13% percent of offices were in the upper right quadrant, where Econ and D950 each saved more than 12.5 kWh/m².

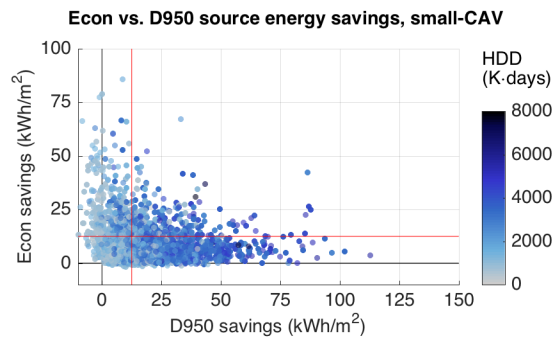


Figure 7 Source energy savings of D950 vs. those of Econ. The red lines are at 12.5 kWh/m², or about 5% of the median baseline HVAC source energy use intensity. Savings from D950 were closely associated with heating degree days (HDD), but economizer savings were not.

However, the rationale for combining the two components into one strategy (i.e., Econ+D950) was stronger than Figure 7 suggests, since economizing also eliminated DCV's unintended reduction of free cooling. Thus, about one-fourth of instances benefitted meaningfully from Econ+D950, meaning they saved at least 12.5 kWh/m² more with the combined strategy than they did with either Econ or D950 alone. The instances where Econ+D950 was most attractive were defined by the characteristics whose influence on economizing and DCV were not in conflict: low cooling setpoints, low COP, high ELPD, high occupant density, and high building heat transfer coefficients. This combination characterizes buildings that use cooling energy

intensely because of internal and solar gains, an exacting comfort zone, and inefficient equipment—regardless of the climate dimension that is so highly influential on DCV savings.

2.3.8.2 Medium-VAV office: When to add DCV to Econ+SR?

In the medium-VAV office, Econ+SR was a dominant ventilation strategy with highly significant energy savings, particularly in colder climates and with narrower indoor temperature setpoint ranges. But adding DCV could potentially save even more energy. On average, the additional source energy savings were modest, about 6 kWh/m². Figure 8 was constructed to be directly comparable to Figure 5a, and it shows just how much less impactful DCV was in the medium-VAV office than in the small-CAV office. But it also shows that added savings from DCV were sometimes substantial, and in exactly the same types of situations small-CAV office savings were also greatest: buildings with high occupant density in the most extreme climates.

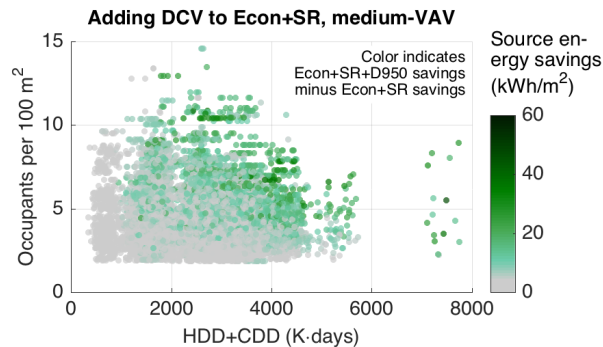


Figure 8 Source energy use intensity savings from adding DCV to the Econ+SR strategy, vs. the sum of heating degree days (HDD) and cooling degree days (CDD).

2.3.8.3 Medium-VAV office: When is SR inadvisable?

Supply air temperature reset generally saved significant energy in the medium-VAV office, but in about 4% of instances (per Table 9) a strategy without SR performed better, because SR increased fan energy more than it reduced cooling coil energy. Using logistic regression to

explore when Econ saved more energy than Econ+SR indicated that CDD was the most important influence. Figure 9a shows the adding SR to Econ only reduced savings a significant fraction of the time in the hottest locations, like Miami, Houston, Phoenix, and Las Vegas.

Even in those locations, though, large majorities of buildings saved additional energy with SR. According to the logistic regression, however, SR proved inadvisable for buildings that had high internal gains, relatively tight envelopes in terms of both conduction and infiltration, and low setpoints for both heating and cooling. We can combine these features with a single parameter, an annual average heating balance point temperature based only on internal (not solar) gains:

$$T_{\text{bal,heat,int}} = T_{\text{stpt,heat}} - (\text{ELPD}/h) / (K_{\text{cond}}/V + \rho c_p \lambda_{\text{inf}})$$

where h is the ceiling height, ρ and c_p are the density and specific heat of air, and λ_{inf} is the infiltration rate (Kreider et al., 2009).

Figure 9b illustrates that so long as this balance temperature is above about 15 °C, SR will nearly always save source energy everywhere, except in a climate like Miami's where SR still must be considered carefully.



Figure 9 The HVAC source energy savings difference between Econ+SR and Econ in the medium-VAV office for (a) all instances and (b) instances where the heating balance point temperature (based only internal gains) exceeded 15 °C.

2.3.8.4 Medium-VAV office: When to use lockout vs. differential enthalpy economizing?

Finally, did differential enthalpy (DE) economizing (Econ) provide significant benefit over non-integrated economizing (EconLock) in which the economizer was locked out when it could not meet the full cooling load? Figure 10 summarizes the HVAC source energy savings of DE economizing in excess of those of lockout economizing, by climate zone category. On the right of the plots, text indicates how the median energy savings would change if all office moved from EconLock to Econ. For the small-CAV office, the relative benefits of DE economizing were small in the median, 1–2 kWh/m², though they were somewhat greater in hot-dry and mixed-dry climates. For the medium-VAV office, added savings were a little larger, 4–7 kWh/m², and much greater in marine climates, where in the median savings of DE economizing was nearly double the median savings of lockout economizing. Thus, integrated controls are of only modestly beneficial in hot-humid, mixed-humid, and cold climates, but save substantially more energy than lockout economizing in dry and especially marine climates.

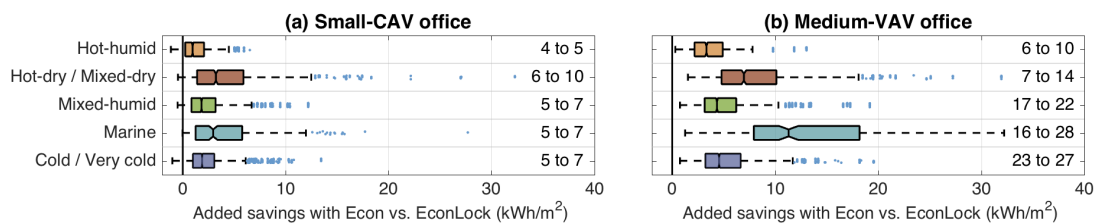


Figure 10 HVAC source energy savings from Econ minus savings from EconLock in the (a) small-CAV and (b) medium-VAV offices. The text on the right indicates the median savings with EconLock “to” the median savings with Econ.

2.3.8.5 How much added energy does 2×VR require?

Increasing ventilation with 2×VR is not motivated by a desire for energy savings, but may have significant positive work performance and absenteeism benefits (Fisk et al., 2012).

Knowledge of how much doubling mechanical ventilation affects energy use may be useful for informing decision-makers about ventilation choices (Hamilton et al., 2016). Table 13 shows

median percent changes in HVAC source energy consumption and median absolute added annual cost per occupant for doubling ventilation in all locations and Building America climate zones. Percent changes generally did not exceed about 10%, and were often much lower, and even negative, in the medium-VAV office. In real costs, the utility bill cost of doubling ventilation was typically quite low. For reference, according to the U.S. Bureau of Labor Statistics, the average cost to an employer of 15 minutes of an office worker's time is about \$12.

Table 13 Median energy percent changes and absolute annual cost changes for doubling ventilation in all locations and Building America climate zone categories.

Building America (BA) climate zone	Location	Small-CAV office		Medium-VAV office	
		HVAC source energy change (%)	Added cost per occupant (\$/year)	HVAC source energy change (%)	Added cost per occupant (\$/year)
Hot-Humid	Miami	7%	\$10.74	15%	\$19.06
	Houston	8%	\$11.67	9%	\$11.51
	<i>Zone median</i>	8%	<i>\$11.67</i>	10%	<i>\$12.29</i>
Hot-Dry / Mixed-Dry	Phoenix	5%	\$8.91	5%	\$7.78
	Los Angeles	1%	\$0.63	-1%	-\$1.21
	Las Vegas	6%	\$9.02	2%	\$3.24
	Albuquerque	6%	\$8.59	0%	-\$0.04
	<i>Zone median</i>	4%	<i>\$7.45</i>	1%	<i>\$2.75</i>
Mixed-Humid	Atlanta	8%	\$11.72	5%	\$6.19
	Baltimore	11%	\$16.57	5%	\$5.98
	New York	11%	\$19.02	4%	\$6.46
	<i>Zone median</i>	9%	<i>\$14.56</i>	5%	<i>\$6.21</i>
Marine	San Francisco	5%	\$3.67	-7%	-\$5.49
	Seattle	12%	\$13.45	-3%	-\$4.28
	<i>Zone median</i>	10%	<i>\$9.47</i>	-4%	<i>-\$5.04</i>
Cold / Very cold	Chicago	11%	\$21.40	5%	\$9.97
	Boston	10%	\$19.60	4%	\$6.11
	Denver	7%	\$12.98	1%	\$1.32
	Minneapolis	12%	\$25.64	8%	\$12.42
	Missoula	11%	\$21.73	3%	\$4.37
	Duluth	12%	\$30.05	7%	\$13.97
	Fairbanks	13%	\$36.14	15%	\$30.18
	<i>Zone median</i>	10%	<i>\$19.92</i>	4%	<i>\$7.11</i>
<i>National median</i>		9%	<i>\$14.65</i>	4%	<i>\$6.49</i>

2.3.9 Implications for energy savings in high performance buildings

One interesting interpretation in both offices is that buildings likely to use the most energy were the ones that could save more energy from alternative strategies. The strategies with the most energy reductions in both office types saved more energy in colder climates, in buildings with leakier and less insulated envelopes, more occupants, longer operating hours, greater internal and solar gains, a tighter range of indoor air temperature acceptability, and less efficient heating and cooling equipment. One might wonder, then: are alternative ventilation strategies only effective in inefficient buildings?

In Figure 11, we have plotted probability density estimates for the Baseline strategy's HVAC source energy use intensity, an alternative strategy's savings, and its savings as a percent of the Baseline strategy usage. There are curves both for all instances and for a subset representing the top 10% most energy efficient buildings in each city. Clearly the savings available in the subset of high performance buildings were significantly less on an absolute basis. However, the Baseline strategy consumption was also significantly less in the subset, so that on a percent basis the savings achieved in high performance buildings were practically indistinguishable from those in the general building stock.

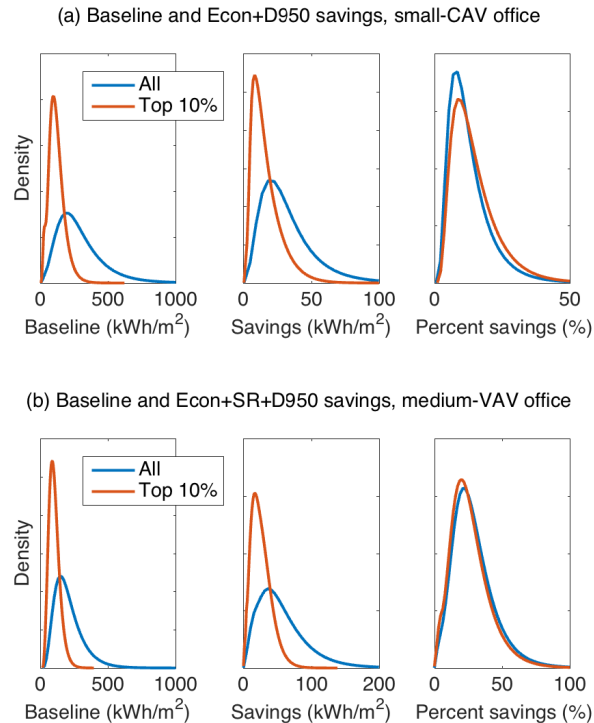


Figure 11 Probability density estimates of Baseline energy use intensity, alternative strategy absolute savings, and percent savings for (a) Econ+D950 in the small-CAV office and (b) Econ+SR+D950 in the medium-VAV office. Estimates are shown for all instances and for only the top 10% of high performance buildings.

2.3.10 Detailed models and analysis as Supplementary Information

In addition to the linear regression models employed for the explanatory sensitivity analysis above, we also fit more detailed regression models, with interaction and quadratic terms, for changes in natural gas and electricity use separately. There are versions that include baseline consumption as a predictor, appropriate for retrofit evaluations when utility bills are available, and versions fit without baseline energy use, for use with new construction or other applications without existing energy histories. For both full versions, the fits were quite good, with every strategy and outcome having either $R^2 > 0.85$ or root mean square error (RMSE) $< 3 \text{ kWh/m}^2$, and often significantly better, as indicated in Table 14.

Table 14 Fit statistics for detailed prediction models available as a spreadsheet implementation in the SI.

Office	Outcome	Number of terms	RMSE in kWh/m ² (R ²)							
			EconLock	Econ	Econ+SR	D950	Econ+D950	Econ+SR+D950	2×VR	Econ(+SR)+D675
Small-CAV	Natural gas	32	0.5 (0.39)	0.5 (0.39)	-	4.1 (0.92)	4.2 (0.92)	-	4.6 (0.95)	4.1 (0.87)
Small-CAV	Natural gas, with BL	43	0.5 (0.47)	0.5 (0.47)	-	3.2 (0.95)	3.2 (0.95)	-	3.8 (0.96)	3.7 (0.89)
Small-CAV	Electricity	66	0.6 (0.90)	0.8 (0.91)	-	0.5 (0.89)	0.9 (0.93)	-	0.6 (0.91)	1.0 (0.89)
Small-CAV	Electricity, with BL	60	0.6 (0.93)	0.7 (0.93)	-	0.5 (0.90)	0.8 (0.95)	-	0.6 (0.92)	0.9 (0.91)
Medium-VAV	Natural gas	64	0.6 (0.72)	0.6 (0.73)	2.9 (0.92)	1.1 (0.63)	1.3 (0.73)	3.1 (0.93)	2.6 (0.85)	3.2 (0.91)
Medium-VAV	Natural gas, with BL	60	0.5 (0.74)	0.5 (0.75)	2.2 (0.95)	1.1 (0.64)	1.2 (0.76)	1.9 (0.97)	2.3 (0.88)	2.7 (0.94)
Medium-VAV	Electricity	70	1.2 (0.91)	1.3 (0.92)	2.1 (0.90)	0.6 (0.90)	1.3 (0.92)	2.1 (0.90)	0.7 (0.94)	2.2 (0.90)
Medium-VAV	Electricity, with BL	51	1.0 (0.94)	1.0 (0.95)	1.6 (0.95)	0.6 (0.89)	1.1 (0.94)	1.5 (0.95)	0.8 (0.93)	1.7 (0.95)

These detailed models were provided in spreadsheet form as Supplementary Information to the article version of this chapter. There, in a simple interface, in a matter of minutes, a user can enter specific building and climate information and see estimates of all the alternatives' energy use impacts, with estimate uncertainties.

2.4 Conclusions

Comprehensive simulations and sensitivity analyses were used to explore the energy saving potential of multiple alternative ventilation strategies relative to a Baseline strategy dictated by the ASHRAE minimum standard in a small office with a CAV HVAC system and in a medium office with a VAV system. Some of the most important results included:

- In the small-CAV office, DCV was usually the single component with the most energy savings, and most of its savings came from natural gas used for heating. However, combining economizer and DCV approximately doubled the median HVAC source energy savings of DCV alone, in part because an economizer prevented DCV from inadvertently reducing free cooling.
- In the medium-VAV office, economizer and SR were the dominant ventilation technologies recommended, and both heating (including reheat) and cooling savings were substantial. Adding DCV by itself usually saved little energy and was often counterproductive, but adding it to Econ+SR was often beneficial in colder climates.

- If the 74% of U.S. office floorspace reasonably represented by our modeling replaced the Baseline strategy with the best alternative, 53 TWh of primary energy annually would be saved, of which 36 TWh—with an annual value of U.S. \$1.25 billion—was estimated as still untapped given current technology adoption rates.
- In the small-CAV office, the most decisive factors influencing the alternative strategy energy impacts were HDD and occupant density. Those two predictors plus infiltration, the day length, ELPD, and heating and cooling setpoints and coil efficiencies explained about two-thirds of impact variance.
- In the medium-VAV office, zone temperature setpoints and HDD were the decisive influences. Along with the cooling coil COP and the infiltration rate, the heating setpoint, cooling setpoint, setpoint setback during unoccupied periods, and HDD explained about two thirds of impact variance.
- Other than the infiltration's influence on DCV savings in the small-CAV office, envelope parameters were not important predictors of alternative strategy impacts. However, the building conductive heat transfer coefficient did play a role in adjudicating some specific questions, like when both economizer and DCV were advisable in the small-CAV office, and when SR should be used in the medium-VAV office (in both cases, when the envelope was less insulated).
- Detailed models are supplied in the Supplementary Information to the article version of this chapter in a user-friendly spreadsheet that allows fast estimation of energy impacts of alternative ventilation strategies for specific office buildings.

CHAPTER 3: EVALUATION OF WORK PERFORMANCE, ABSENTEEISM, POLLUTANT EXPOSURE, AND ENERGY USE TRADEOFFS OF MATURE ALTERNATIVE VENTILATION STRATEGIES

Chapter abstract: Mechanical ventilation can improve occupant productivity, use or save energy, and increase outdoor-to-indoor pollutant transport. This work explores those impacts for eight ventilation strategies, relative to a baseline constant mechanical ventilation rate (VR) of 9.4 L/s/occ, in two representative offices. Strategies were unique combinations of airside economizing, demand-controlled ventilation, and supply air temperature reset, along with doubling the baseline VR. These were evaluated within a Monte Carlo analysis that varied climate and outdoor pollution, along with 19 building parameters. Energy modeling, empirical correlations, and indoor air quality (IAQ) modeling were used to quantify outcomes of: (i) energy use; (ii) profitable IAQ impacts, e.g. work performance; and (iii) negative IAQ health impacts due to indoor particle and ozone exposure. ‘Win-win’ strategies were defined as those that saved energy and increased work performance, and these always included an economizer. Relative to the baseline, the win-win strategies: increased annual geometric mean VRs by 5–10 L/s/occ; reduced mechanical system energy consumption by 12–27% (saving \$1–1.75/m²/year); increased work performance by 0.5%; eliminated 5 hours of absenteeism per year; and increased indoor PM_{2.5} by 0.5 µg/m³ and ozone by 3 ppb. A sensitivity analysis identified infiltration and climate as the largest outcome drivers. Median annual benefits for small-to-medium-large offices in the U.S. (~75% of office floorspace) were \$28 billion for implementing the win-win strategy with the greatest energy savings, and \$55 billion for implementing the win-win strategy with the greatest work performance increase. Particle exposure tradeoffs were mitigated by use of efficient filters.

3.1 Chapter introduction

Mechanical ventilation is the intentional supply of outdoor air (OA) inside buildings by heating, ventilation, and air conditioning (HVAC) systems. Minimum mechanical ventilation rates are prescribed throughout the developed world by standard-setting organizations like ASHRAE, as a crucial part of providing “acceptable indoor air quality (IAQ)” (ASHRAE, 2013b). Ventilation dilutes indoor-emitted pollutants, reducing potentially unhealthy or irritating exposures and advancing occupant olfactory comfort and perceived IAQ satisfaction (Persily, 2015). Low ventilation rates (VR) have been correlated with increased illness absence and sick building syndrome (SBS) symptoms, negative odor perceptions, and reduced task performance (Bakó-Biró, Kochhar, Clements-Croome, Awbi, & Williams, 2007; Carrer et al., 2015; Fisk et al., 2009; Haverinen-Shaughnessy et al., 2011; Mendell et al., 2013; Wargocki et al., 2004). Conversely, significant cognitive and task performance increases and sick leave reductions have been associated with VRs that well exceed ASHRAE Standard 62.1 recommendations (J. G. Allen et al., 2015; Milton et al., 2000; Satish et al., 2012; Seppänen et al., 2006). From an energy perspective, however, current ventilation practice is costly, accounting for ~1/4 of HVAC energy consumed by commercial buildings (Fisk et al., 2012; U.S. Energy Information Administration (EIA), 2006b). Increasing VRs could further increase energy use, but *alternative ventilation strategies*, particularly with dynamic control sequences, can also save energy (Brandemuehl & Braun, 1999; Fisk et al., 2012; Lawrence & Braun, 2007; Rackes & Waring, 2014). Finally, in addition to these multiple ramifications for decision-makers to consider, ventilation control also affects broader public health risks. That is because increasing ventilation increases occupant indoor exposure to outdoor air pollutants like fine particulate matter ($PM_{2.5}$ = particles with aerodynamic diameter $< 2.5 \mu m$) and ozone (O_3) (Bekö et al., 2008; Ben-David & Waring, 2016; Quang et al., 2013; Rackes & Waring, 2013; Stephens et al., 2012; Weschler, 2000), both of which have well-established, no-threshold associations with multiple adverse short- and long-term health endpoints (Burnett, Smith-Doiron, Stieb, Cakmak, & Brook, 1999; Dominici, Peng,

& Bell, 2006; Dutton et al., 2013; Fann et al., 2012; Pope, Burnett RT, Thun MJ, & et al, 2002), including mortality (Dockery, Schwartz, & Spengler, 1992; Dutton et al., 2013; Hänninen et al., 2005; Pope et al., 2009, 2002).

This study models the interplay among these three groups of ventilation impacts: (i) energy consumption costs; (ii) profitable IAQ impacts (like work performance and reduced absenteeism); and (iii) IAQ health impacts (from indoor exposure to outdoor pollutants). The scope is restricted to U.S. offices, which have well-characterized parameters and occupy the largest fraction of U.S. commercial floorspace, at 18% (U.S. EIA, 2015a). Previous studies have investigated two of the three impact categories. For example, the economic benefits of profitable IAQ outcomes correlated to ventilation were estimated to exceed the costs of increased energy consumption by roughly two orders of magnitude, under four hypothetical office sector scenarios (Fisk et al., 2011, 2012). Other studies have compared energy consumption and IAQ health impacts of indoor exposures to outdoor pollutants when using natural ventilation (Dutton et al., 2013), increasing or decreasing minimum VRs (Chan et al., 2016), or reducing OA with additional recirculated air (Montgomery, Reynolds, Rogak, & Green, 2015). No study appears to have considered energy consumption, profitable IAQ impacts, and IAQ public health impacts all together.

This simulation study explores dynamic *alternative ventilation strategies* that may provide better outcomes over multiple impact categories. The eight studied strategies included unique combinations of three available technologies: (i) demand controlled ventilation (DCV), which dynamically modifies OA flow based on actual occupancy-driven requirements, rather than design ones; (ii) airside economizing, a control sequence that introduces more OA when it provides free cooling; and (iii) supply air temperature reset (SR), or increasing the supply air temperature setpoint at part-load conditions to save compressor and reheat energy. All of these have been shown capable of reducing energy consumption (Ben-David & Waring, 2016; Brandemuehl & Braun, 1999; Fisk et al., 2012; Fisk, Seppanen, Faulkner, & Huang, 2004; Fisk & De Almeida, 1998; Xu, Wang, Sun, & Xiao, 2009; Yao & Wang, 2010), but few if any have been

assessed in terms of profitable or health-based IAQ impacts, as done here. In addition, we modeled multiple building typologies and Monte Carlo methods to thoroughly explore a wider parameter space than previously studied—varying climates, outdoor PM_{2.5} and ozone profiles, envelope parameters, mechanical system efficiencies, internal loads, and schedules.

This chapter expands the analysis in Chapter 2 to include profitable IAQ impacts and IAQ health impacts. Many IAQ impacts are expected to have significantly more economic value than energy expenditures (Ben-David & Waring, 2016; Fisk et al., 2011), and good IAQ is of significant interest to a majority of tenants occupying office space (Hamilton et al., 2016). After summarizing impacts for all considered strategies, most attention is given to strategies that were ‘win-win’ from a business perspective, meaning that they both saved energy *and* had positive profitable IAQ impacts—the two categories likely to be of greatest interest to most decision-makers. After identifying the win-win strategies, a sensitivity analysis was used on the output dataset to craft targeted design guidance indicating what types of buildings are likely to benefit from each strategy. Then, we assessed the IAQ exposure impacts for PM_{2.5} and ozone for each strategy, and provided some parametric guidance on situations in which win-win strategies may have negative exposure tradeoffs, including possible ways to modify building operation to reduce those tradeoffs. Finally, aggregate economic outcomes of implementing win-win strategies for all three of the impact categories were estimated for the small-to-medium-large U.S. office sector.

3.2 Methods

At the core of this work were geographically representative simulation datasets of energy consumption and IAQ outcomes in two types of U.S. office buildings, for multiple considered ventilation strategies (a Baseline strategy along with 6 or 8 alternative strategies). The flowchart in Figure 12 presents an overview of the construction of these datasets, with descending levels indicating (*i*) the definition of energy model templates, statistical distributions, and outdoor

pollution trajectories; (ii) energy simulations in EnergyPlus, followed by day-resolved IAQ calculations; (iii) computation of annual metrics and comparison to baseline values; and (iv) weighting the dataset to match the geographic/climate distribution of U.S. offices. The following sections provide details.

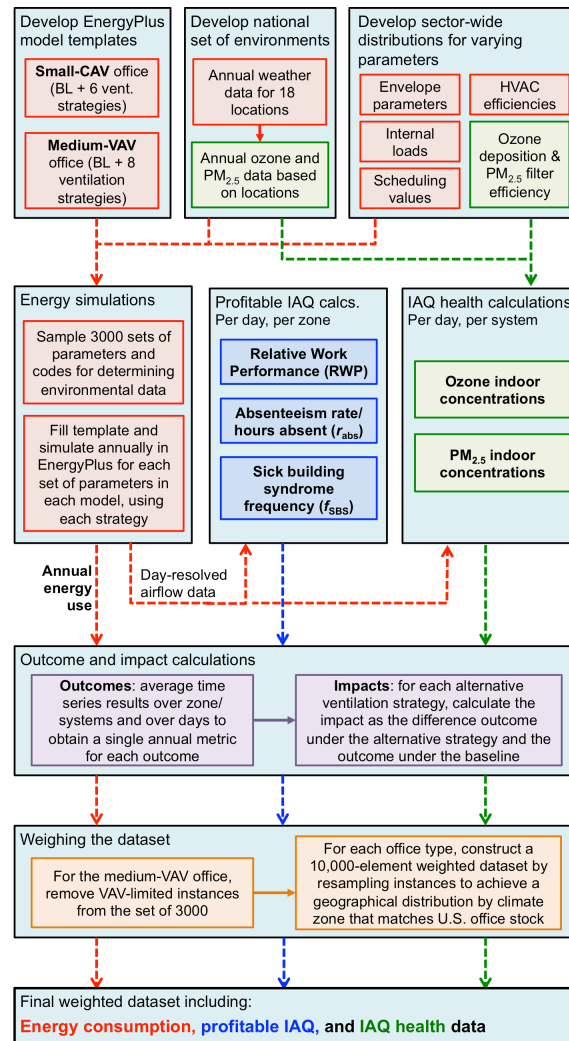


Figure 12 Flowchart of the methodology used to produce the dataset of office building outcomes and impacts for energy consumption, profitable IAQ, and health IAQ.

3.2.1 Added modeling inputs and outputs

The office types, energy modeling, Monte Carlo approach, and ventilation strategies are the same as those described in Chapter 2. In addition, carbon dioxide (CO₂) concentration was also modeled in EnergyPlus, based on the transient solution of a well-mixed mass balance applied to each building zone, assuming a constant outdoor concentration of 400 ppm and human CO₂ exhalation at a rate of 0.31 L/min per occupant (ASHRAE, 2013b). All non-energy outputs from EnergyPlus, such as airflow rates and CO₂ concentrations, were recorded as 8 a.m. to 6 p.m. day-resolved time-averages. This ‘prime occupancy’ period was used to avoid biasing the results, particularly occupancy-sensitive ones like the per-occupant ventilation rate, toward periods when few occupants were present. All subsequent calculations were day-average, with the profitable IAQ impacts (work performance, absenteeism, and SBS symptoms) computed for each zone and the IAQ pollutant exposure impacts computed for each HVAC system. Thus, day-average CO₂ concentration (ppm), number of occupants P_z (occ), mechanical ventilation airflow Q_{mv} (m³/h), and infiltration airflow Q_i (m³/h) were outputted for each zone, and recirculation airflow Q_r (m³/h) was output for each HVAC system.

The effective ventilation rate (VR, in L/s/occ), or per-person outdoor airflow, was calculated for each day and zone according to

$$VR = \frac{(Q_{mv} + Q_i)/3.6}{P_z} \quad (6)$$

where 3.6 is the conversion from m³/h to L/s. Note that the effective VR includes the contributions of intentional mechanical ventilation supplied by the HVAC system *and* leakage due to envelope infiltration. This VR would be the value estimated by a tracer-gas air-exchange measurement, and is appropriate given the equal dilution capability of mechanical and infiltration air exchange. When we need to refer to only the mechanical contribution to per-person ventilation, we call it the ‘mechanical VR’ or VR_{mv}.

Chapter 2 described the Monte Carlo sampling process, climate weighting (see Table 3), and 18 sampled inputs, including 17 varied building parameters and one location code. For the analysis in this chapter, there were two additional codes for indexing outdoor PM_{2.5} and ozone concentration data, and two additional scalar building parameters. As before, predictors were defined for sensitivity analysis. These are summarized in Table 15. It differs from Table 5 in Chapter 2 only in the inclusion of four additional predictors. Two of these are average annual outdoor PM_{2.5} and ozone averages (PMout and O3out), while the other two are the additional scalar building parameters, the PM_{2.5} single-pass filter efficiency and the ozone deposition rate. Outdoor pollution modeling is described in more detail in Section 3.2.6, while the filter efficiency and deposition rate are described in Section 3.2.4.

Table 15 Varied building parameters, short names, units, and sampling distributions. The final columns give descriptive statistics of all data, i.e., merging the final weighted datasets of the two office types.

Parameter	Units	Short name	Mean	SD	p5	p25	Median	p75	p95
Heating degree days, base 18 °C.	K-days	HDD	2,308	1,221	530	1,156	2,566	3,267	4,147
Cooling degree days (base 18 °C) residual	K-days	CDDres	0	431	-1,024	-180	-14	203	797
Summer enthalpy residual	kJ/kg	sumEnthpyRes	0.0	7.6	-14.4	-6.0	2.1	5.3	10.1
PM _{2.5} annual average outdoor concentration	µg/m ³	PMout	8.6	2.7	4.4	7.0	8.4	10.0	12.8
O ₃ annual average outdoor concentration	ppb	O3out	36.6	5.8	29.0	33.0	35.3	39.2	47.4
Infiltration air exchange rate	h ⁻¹	infAER	0.38	0.38	0.04	0.12	0.25	0.50	1.16
Conductive heat transfer coefficient per volume	W/K/m ³	KcondPerV	0.45	0.33	0.14	0.23	0.35	0.57	1.13
Wall thermal mass	kJ/K·m ²	wallCT	136	125	16	45	93	186	414
Window solar gain per volume	W/m ³	winSolarPerV	3.8	1.5	1.6	2.6	3.6	4.7	6.5
Day length	hours per day	dayLen	13.9	2.1	10.4	12.4	13.9	15.5	17.4
Combined LPD and EPD	W/m ²	ELPD	19.3	9.0	6.1	12.6	18.5	25.1	35.1
Occupant density	occ per 100 m ²	occDens	5.1	2.3	2.3	3.4	4.6	6.3	9.9
Zone heating setpoint	°C	heatStpt	21.5	1.4	19.1	20.6	21.5	22.4	23.8
Zone cooling setpoint	°C	coolStpt	24.3	1.4	22.1	23.3	24.3	25.3	26.8
Unoccupied period zone setpoint setback	°C	stptSetback	2.5	1.4	0.3	1.3	2.6	3.8	4.8
Heating efficiency	-	heatEff	0.80	0.11	0.63	0.71	0.80	0.89	0.97
Cooling coefficient of performance	-	coolCOP	3.02	0.74	1.79	2.45	3.02	3.60	4.24
Fan efficiency	-	fanEff	0.70	0.15	0.46	0.59	0.70	0.81	0.95
PM _{2.5} filter efficiency on mechanical ventilation air	-	PMeta_mv	0.25	0.20	0.04	0.11	0.19	0.33	0.69
O ₃ deposition rate	h ⁻¹	O3beta	2.72	1.13	1.28	1.90	2.50	3.30	4.87

3.2.2 Modeling profitable IAQ impacts

Profitable IAQ outcomes (outcome category 2) are herein defined as benefits that will increase the revenues or reduce the costs of the business occupying the office. Three effects were identified as sufficiently well-established to include: (i) work performance, or the labor productivity of employees; (ii) sick-leave absenteeism, or employees missing work due to illness; and (iii) sick building syndrome (SBS) symptom prevalence, or nonspecific adverse health or discomfort effects related to time spent indoors—including eye, nose or throat irritation, coughing, difficulty breathing, or other lower respiratory distress, and headache, drowsiness, and fatigue (Apte et al., 2000; Fisk et al., 2009; Joshi, 2008)—whose treatment costs may impact employer-based health care plans. Mechanisms for all three remain scientifically uncertain, and likely based on highly variable or difficult-to-measure quantities, so existing empirical formulas that directly link each outcome to the VR were employed.

Work performance has been positively associated with ventilation (or surrogates) in a number of studies (J. G. Allen et al., 2015; Carrer et al., 2015; Fisk et al., 2011, 2012; Maddalena et al., 2014; Satish et al., 2012; Seppänen et al., 2006; Wargocki et al., 2004). The association is likely in part related to ventilation's dilution of volatile organic compounds (J. G. Allen et al., 2015; Wargocki et al., 2004), possibly in part due to dilution of CO₂ (J. G. Allen et al., 2015; Carrer et al., 2015; Satish et al., 2012) though there is contradictory evidence (Zhang, Wargocki, & Lian, 2016), and possibly in part due to ventilation's role in improving perceived IAQ (Kosonen & Tan, 2004) though performance benefits are also observed when perceived IAQ is unchanged (Maddalena et al., 2014). The effect may be related to cognitive performance (J. G. Allen et al., 2015; Bakó-Biró et al., 2007; Haverinen-Shaughnessy et al., 2011; Satish et al., 2012), which could have large impacts in high-compensation sectors (MacNaughton et al., 2015). This study used a more conservative relation, based on a meta-analysis of studies primarily focused on task performance (Seppänen et al., 2006). That relation holds that relative work performance (RWP), compared to a reference ventilation rate, VR_{ref} , can be determined by

$$RWP_{VR_{ref}} = \exp(f(VR') - f(VR_{ref})) \quad (7)$$

where

$$f(x) = (-76.38x^{-1} - 0.78x \cdot \ln x + 3.87x)/1000 \quad (8)$$

and $VR' = \min(\max(VR, 6.5), 47)$ L/s/occ limits the domain of the function f to a valid range. We report baseline values for VR_{ref} of 10 L/s/occ (RWP_{10}), a commonly used reference (Fisk et al., 2011), and also for 47 L/s/occ (RWP_{47}) which indicates performance relative to the maximum achievable by altering the VR. The choice of reference does not matter, however, for the most important results, since it cancels when comparing an alternative strategy to the Baseline ventilation rate.

Sick-leave absenteeism has also been linked to lower ventilation (Milton et al., 2000). The presumed mechanism is that infectious diseases spread more easily in environments with lower ventilation (Carrer et al., 2015; Li et al., 2007; Myatt et al., 2004). This study used the exponential risk model formulated by Fisk et al. (Fisk et al., 2012), which was based on a study that determined that the relative risk of absence at a lower VR (~12 L/s/occ) compared to a higher VR (~24 L/s/occ) was 1.53 (Milton et al., 2000). Inserting the base absence rate of 2% at 12 L/s/occ (Milton et al., 2000), as Fisk et al. (Fisk et al., 2012) did, the absence rate in hours absent per hour worked is

$$r_{abs} = 0.02 \cdot 1.53^{(1-VR''/12)} \quad (9)$$

where $VR'' = \min(\max(VR, 5), 30)$ L/s/occ limits estimation of outcomes to a domain reasonably similar to the VRs in the original study. Fisk et al. (Fisk et al., 2012) did not propose formal limits for the relation, but multiple studies have failed to find sick leave or illness absence relations at higher VRs (Mendell et al., 2013, 2015; Myatt et al., 2002). In order to make

absenteeism rates more intuitive, later results additionally report ‘hours absent’ per standard 2000-hour work year (i.e. $r_{\text{abs}} \times 2000$ h/year).

SBS symptoms have been linked with lower ventilation in a number of studies (Apte et al., 2000; Carrer et al., 2015; Fisk et al., 2009; Sundell et al., 2011). The relation is assumed to be related to ventilation’s role in diluting indoor-generated air pollutants whose presence chemically or physically stresses some occupants, but exact mechanisms, pathways, sensory irritant species, and contributing factors are not well understood (Apte et al., 2000; Fisk et al., 2009; Wolkoff, Wilkins, Clausen, & Nielsen, 2006). This work employed the quantitative empirical relation between relative SBS symptom prevalence and the VR developed by Fisk et al. (2009). Combining that expression with the base fraction of SBS sufferers (16.8% at a VR of 18.3 L/s/occ) used in a previous study (Fisk et al., 2012), the fraction of occupants that experience SBS symptoms is given by

$$f_{\text{SBS}} = 0.2137 \cdot \exp(0.00089 \cdot (\text{VR}'')^2 - 0.0542 \cdot \text{VR}'' + 0.453) \quad (10)$$

where VR'' remains as defined in Equation (9) above. (The original upper limit for the SBS function was 35 L/s/occ, but the curve is practically flat above 30 L/s/occ.)

All calculations were performed at a day-averaged resolution for each zone, and then subsequently aggregated to whole-building annual values for each instance, by means of occupant-weighted averages. For sector-wide benefit estimates, we calculated not only the central estimates of each relation but also the uncertainties in the impacts, which are presented in terms of 95% confidence intervals (CIs).

3.2.3 Deriving profitable IAQ uncertainties

3.2.3.1 Work performance

The original fit in (Seppänen et al., 2006) was for the change in work performance per change in VR. Comparing two ventilation rates is therefore accomplished by integrating and evaluating at the VR of interest and the reference to which it is relative. Seppänen et al. also provided the 95% CI of the estimate in graphical form, and by fitting a curve to the difference between the 95% CI bounds and the central estimate and assuming a normal error distribution, one can establish an uncertainty distribution, $f_{\text{unc}}(x)$, by letting

$$f_{\text{unc}}(x) = f(x) + z \cdot h(x) \quad (11)$$

where $f(x)$ given by Equation (8), and z is a standard normal random variate. That is, the probabilistic function f_{unc} can be decomposed into a deterministic function f , and the product of a random variable z with another deterministic function h . The function h was determined from the curve-fit, standardized (divided by 1.96), and integrated yielding

$$h = (-11.617x^{-1.276} + 0.607x)/1000 \quad (12)$$

Given these definitions, one can replace the deterministic formula for $\text{RWP}_{\text{VRref}}$ (Equation (7)) with the uncertainty distribution, so that

$$\begin{aligned} \text{RWP}_{\text{VRref,unc}} &= \exp(f_{\text{unc}}(\text{VR}') - f_{\text{unc}}(\text{VR}_{\text{ref}})) \\ &= \exp\left((f(\text{VR}') + z \cdot h(\text{VR}')) - (f(\text{VR}_{\text{ref}}) + z \cdot h(\text{VR}_{\text{ref}}))\right) \\ &= \exp(f(\text{VR}') - f(\text{VR}_{\text{ref}})) \cdot \exp(z \cdot h(\text{VR}') - z \cdot h(\text{VR}_{\text{ref}})) \\ &= \text{RWP}_{\text{VRref}} \cdot \exp\left(z \cdot (h(\text{VR}') - h(\text{VR}_{\text{ref}}))\right) \end{aligned} \quad (13)$$

3.2.3.2 Absenteeism

Assuming $\log(\text{RR})$ is normally distributed, the central estimate and 95% CI given by (Milton et al., 2000) imply that $\log(\text{RR})$ has a mean of $\ln(1.53) = 0.425$ and standard deviation of $\ln(1.12) = 0.116$. Therefore, with z again as a standard normal random variate, one can express the relative risk uncertainty distribution as

$$\text{RR}_{\text{unc}} = \exp(0.116z) \cdot 1.53 \quad (14)$$

which means that

$$r_{\text{abs,unc}} = 0.02 \cdot (\exp(0.116z) \cdot 1.53)^{(1-\text{VR}''/12)} = r_{\text{abs}} \cdot (\exp(0.116z))^{(1-\text{VR}''/12)} \quad (15)$$

where r_{abs} is given by the deterministic formula in Equation (9).

3.2.3.3 Sick building syndrome

If one defines the function

$$g(x) = 0.00089x^2 - 0.0542x \quad (16)$$

then one can rewrite the equation for fraction of occupants with SBS (Equation (10)) as

$$f_{\text{SBS}} = 0.2137 \exp(g(\text{VR}'') - g(10)) \quad (17)$$

As with work performance, $g(x)$ arises in (Fisk et al., 2009) as the indefinite integral of a relation between VR and the change in f_{SBS} . It is only a slight simplification to approximate the error bands in that relation as constant (i.e., independent of VR), corresponding to a standard deviation of about 0.007. Recognizing that a stronger relation corresponds to a negative deviation from the central estimate, one can express the uncertain fraction of SBS sufferers as

$$\begin{aligned}
 f_{\text{SBS,unc}} &= 0.2137 \exp(g(\text{VR}'') - z \cdot 0.007 \cdot \text{VR}'' - (g(10) - z \cdot 0.007 \cdot 10)) \\
 &= f_{\text{SBS}} \cdot \exp(z \cdot 0.007 \cdot (10 - \text{VR}''))
 \end{aligned}
 \tag{18}$$

where f_{SBS} is the deterministic version given by either Equation (10) or Equation (17). The formula in Equation (18) produces a 95% CI nearly identical to the one plotted in Figure 2 of (Fisk et al., 2009).

3.2.4 Modeling indoor exposure to PM_{2.5} and ozone

IAQ public health impacts (outcome category 3) are defined herein as society-wide risks whose costs are unlikely to be perceptible by a building-related decision-maker. There are many potential health risks related to indoor air, but few are certain and well-characterized enough to evaluate in the context of ventilation decisions (Sundell et al., 2011). For example, volatile organic compounds (VOC) are too variable in strength and composition and too uncertain in health impact (Andersson et al., 1997; Logue et al., 2012; Rackes & Waring, 2013, 2016) (although some of their shorter-term effects may be at least partially captured by the empirical relations for profitable impacts). Two pollutants with enough information on sources, fate and transport mechanisms, and health impacts are PM_{2.5} and ozone originating outdoors, which have been studied extensively (Burnett et al., 2014, 1999; Fann et al., 2012; Laden, Schwartz, Speizer, & Dockery, 2006; Pope et al., 2009, 2002).

Indoor PM_{2.5} and ozone concentrations were modeled with day-averaged mass balances, over the prime 8 a.m. to 6 p.m. working period. Unlike the VR-correlated impacts, these calculations were performed for each HVAC system (the medium VAV building had three separate HVAC systems each serving five thermal zones, which meant three daily calculations, rather than 15 calculations). All systems were assumed to have a single filter located in the mixed air stream, acting on both mechanical ventilation and recirculation air. Indoor sources of PM_{2.5} and ozone

were neglected because their emission rates are variable and poorly characterized (Girman, Apte, Traynor, Allen, & Hollowell, 1982; Lee, Lam, & Kin Fai, 2001; Weschler, 2000), and for PM_{2.5} the composition may be quite different than the outdoor PM_{2.5} for which health impacts have been ascertained.

The daily time-averaged indoor PM_{2.5} concentration $C_{PM,in}$ ($\mu\text{g}/\text{m}^3$), where the subscript “PM” is used for brevity and always refers to PM_{2.5}, was calculated as

$$C_{PM,in} = \frac{((1 - \eta_{PM,mv})Q_{mv} + p_{PM}Q_i)C_{PM,out}}{Q_{mv} + Q_i + \eta_{PM,r}Q_r + \beta_{PM}V} = \frac{(1 - \eta_{PM,mv})\lambda_{mv} + p_{PM}\lambda_i}{\lambda_{mv} + \lambda_i + \eta_{PM,r}\lambda_r + \beta_{PM}}C_{PM,out} \quad (19)$$

where Q_{mv} , Q_i , and Q_r (m^3/h) are the flow rates for mechanical ventilation, infiltration, and recirculation, respectively. In the second expression, λ_{mv} , λ_i , and λ_r (h^{-1}) are the corresponding air exchange rates (AER). The remaining terms are the dimensionless filter efficiencies for mechanical ventilation air $\eta_{PM,mv}$ and for recirculating air $\eta_{PM,r}$, the dimensionless envelope penetration factor p_{PM} , the deposition rate β_{PM} (h^{-1}), the volume V (m^3) served by the HVAC system, and the outdoor concentration $C_{PM,out}$ ($\mu\text{g}/\text{m}^3$). Equation (19) neglects that some components of outdoor aerosol can transform upon entry indoors due to outdoor-to-indoor gradients of temperature and relative humidity (Johnson et al., 2017).

For the PM_{2.5} filter efficiency for mechanical ventilation air, $\eta_{PM,mv}$, this study developed a lognormal distribution (GM = 20%, GSD = 2.4) based on combining information about what filters are employed in commercial buildings with data on removal efficiencies for multiple individual filters (Azimi, Zhao, & Stephens, 2014); see the following section for details. The recirculating air filter efficiency, $\eta_{PM,r}$, was related to $\eta_{PM,mv}$ by

$$\eta_{PM,r} = 0.5923\eta_{PM,mv}^2 + 0.3604\eta_{PM,mv} \quad (20)$$

which was an empirical fit ($R^2 = 0.98$) based on integrating size-resolved removal efficiencies for the two air streams for multiple conditions including urban and rural size distributions (Jaenicke,

1993; Riley, McKone, Lai, & Nazaroff, 2002) and various typical ventilation, infiltration, and recirculation rates. Another empirical fit, previously developed by similar means (Rackes & Waring, 2013), gave the integrated PM_{2.5} deposition rate as

$$\beta_{PM} = 0.1710\eta_{PM,mv}^2 - 0.1378\eta_{PM,mv} + 0.0918 \quad (21)$$

The integrated PM_{2.5} envelope penetration factor, p_{PM} , was constant at 0.73 (Zhao & Stephens, 2016).

The daily time-averaged indoor ozone concentration, $C_{O_3,in}$ (ppb), was similarly calculated as

$$C_{O_3,in} = \frac{((1 - \eta_{O_3})Q_{mv} + p_{O_3}Q_i)C_{O_3,out}}{Q_{mv} + Q_i + \eta_{O_3,r}Q_r + \beta_{O_3}V} = \frac{(1 - \eta_{O_3})\lambda_{mv} + p_{O_3}\lambda_i}{\lambda_{mv} + \lambda_i + \eta_{O_3,r}\lambda_r + \beta_{O_3}} C_{O_3,out} \quad (22)$$

where η_{O_3} is the dimensionless ozone filter removal efficiency, p_{O_3} the dimensionless envelope penetration factor, β_{O_3} (h^{-1}) the deposition rate, and $C_{O_3,out}$ (ppb) the outdoor concentration.

Equation (22) is nearly identical to Equation (19), except that the HVAC filter removed ozone in the mechanical ventilation and recirculation air streams with equal efficiency, at a fixed value of 5% (Bekö, Clausen, & Weschler, 2007). The penetration factor p_{O_3} was fixed at 0.80 (Stephens et al., 2012). The deposition rate β_{O_3} was sampled from a lognormal distribution ($GM = 2.5 h^{-1}$, $GSD = 1.5$) used in previous analyses (Morrison, Shaughnessy, & Shu, 2011; Rackes & Waring, 2013). Though this work calls β_{O_3} a deposition rate, it can be conceived as a total decay parameter for ozone that also includes any occurring gas phase reactions.

3.2.5 Filter efficiency distribution

For the integrated PM_{2.5} filter efficiency for outdoor air in the mechanical ventilation stream, $\eta_{PM,mv}$, a sector-wide filter efficiency distribution was fit to a set of removal efficiencies generated in a two-step process. We first sampled a Minimum Efficiency Reporting Value (MERV) based on MERV prevalence in the U.S. office sector, as determined principally by sales numbers

provided by a friendly industry representative. Then, given the MERV value, we sampled the single-pass efficiency for $PM_{2.5}$ of outdoor origin from the distributions (over multiple outdoor particle distribution shapes) for ten filters developed by Azimi et al. (2014). After adjusting MERV use frequencies among offices for the MERV ratings available in Azimi et al. (2014), they were 5% for MERV 5, 15% for MERV 6, 10% for MERV 7, 35% for MERV 8, 25% for MERV 10, 6% for MERV 12, 3% for MERV 14, and 1% for MERV 16.

The best-fit lognormal distribution for the set of sampled filter efficiencies had a GM of 20% and a GSD of 2.4. Despite the clustered nature of the sampled efficiencies, a unimodal distribution was used because of its simplicity, and because the real distribution of filter efficiencies across offices is expected to be less punctuated. In other words, combining MERV occurrence frequencies with Azimi et al. (2014) $PM_{2.5}$ removal efficiencies is likely to provide a good estimate of the central tendency and spread of sector-wide filter efficiencies, but attempting to capture higher moments of that distribution would risk overfitting. Hundreds of filter products are in use in real offices, and the Azimi et al. (2014) results themselves show that even filters with the same MERV rating can vary in efficiency by a factor of 2–3.

3.2.6 Outdoor $PM_{2.5}$ and ozone data

Outdoor concentrations were taken directly from U.S. EPA data, from hour-resolved monitoring sites over the years of 2011 to 2014 (U.S. EPA, 2015b). In order to produce 8 a.m. to 6 p.m. daily averages, hourly data was averaged over that time period each day. The result was 1814 $PM_{2.5}$ and 2460 ozone site/year records of yearlong, day-resolved, 8 a.m. to 6 p.m. outdoor concentration trajectories.

For each instance, two sampled inputs were used to assign records for annual $PM_{2.5}$ and ozone trajectories. Only trajectories from EPA monitoring sites within a certain radius—generally 300 km, but 500 km for a few areas with sparse EPA sites—of the location were allowed. The

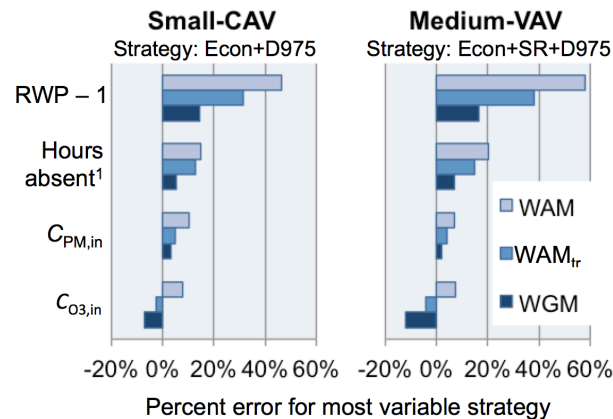
goal was to sample broadly enough geographically to capture pollution levels in the climate zone represented by the regional location, not just in the city. On average, each location had associated with it records for 75 $PM_{2.5}$ trajectories and 106 ozone trajectories. The annual averages were also used as explanatory variables for data analysis and are summarized for the total weighted dataset in Table 15.

3.2.7 Annual averaging, best annual VR metric, and impacts

IAQ calculations were performed for each day of the year and (in the multizone medium-VAV office) for each zone or HVAC system. For CO_2 , RWP, r_{abs} , f_{SBS} , $PM_{2.5}$, and ozone results, occupant-weighted averages were used to first average zones and then average days of the year. (The offices had partial occupancy on Saturdays, and were unoccupied on Sundays and holidays.) For this study, time-varying trends within the office building or during the year were not analyzed.

It was not obvious that arithmetic averaging over zone and the year was the best way to define a representative annual VR metric, so we tested three possibilities: an occupant-weighted arithmetic mean (WAM), an occupant-weighted arithmetic mean where VRs were truncated to 50 L/s/occ before averaging (WAM_{tr}), and an occupant-weighted geometric mean (WGM). We assessed the three possibilities by plugging the annual VR metric into the RWP, r_{abs} , $C_{PM,in}$, and $C_{O_3,in}$ relations (i.e., Equations 2, 4, 6, and 9), and comparing the simplified estimates to the respective true values (based on applying the relations for each zone and day and then averaging). Figure 13 shows comparisons for the most challenging strategies—i.e., those with the most variable VR were Econ+D975 in the small-CAV office and Econ+SR+D975 in the medium-VAV office. The important implications are that: the principal challenge is seasonal, not zonal, averaging (since errors were only slightly greater in the multizone medium-VAV office); (when the VR is dynamic, all annual VR metrics tend to overestimate the effect of ventilation on most

outcomes; and (the weighted geometric mean is the best of the three options for capturing annual performance. Therefore, the WGM was used to calculate the annual metric, VR_{year} , for this analysis.



1. Negated to illustrate trend consistently.

Figure 13 Median percent error from using the weighted annual mean (WAM), truncated WAM (WAM_{tr}), and weighted geometric mean (WGM) as single annual VR metrics, compared to the true outcome values aggregated from daily calculations performed in each zone.

Thus far we have described the calculation of annual outcome values—HVAC natural gas and electricity consumption, VR_{year} , RWP , r_{abs} , f_{SBS} , and concentrations of CO_2 , $C_{PM,in}$, and $C_{O3,in}$ —for all seven or nine simulated ventilation strategies for each instance. However, what we analyze primarily are the ‘impacts’ of alternative ventilation strategies, by which we mean the *changes* (using the symbol Δ) in energy and IAQ outcomes compared to the Baseline strategy. As an experimental design, evaluating the Baseline and alternatives on the same building and then analyzing the impacts provides greater statistical power since all building and climate parameters are held constant for each instance.

3.2.8 Monetizing impacts and calculating sector-wide benefits

The final section of this chapter computes aggregate costs and benefits across much of the U.S. office sector. For natural gas and electricity consumption valuation, mean prices were used from distributions developed from all U.S. states' average commercial retail prices from 2005–2014, as derived in Chapter 2, which were 3.75 and 10.86 U.S. cents per kWh for natural gas and electricity, respectively. For profitable IAQ outcomes, changes in work performance and absenteeism were monetized by multiplying by the average annual compensation per office worker, or \$91,500/person/year according to the U.S. Bureau of Labor Statistics (U.S. DOL, 2016a, 2016b). This value was the employment-weighted mean of the total wage and benefit compensation for management, business and financial operations, office and administrative support, legal, architecture and engineering, computer and mathematics, building cleaning, and other occupational groups that work in offices. SBS symptom treatment costs were estimated at \$213 per person with SBS per year (U.S. EPA, 2007). Calculation of public health risk distributions associated with PM_{2.5} and ozone exposures and monetization of those risks required applying concentration-response (C-R) functions along with relative risk (RR) uncertainty distributions and population data. These calculations represented a significant modeling effort, and one that was also necessary to develop the loss function in the following chapter. To avoid redundancy, this work is described only once in detail, in Section 4.2.4.

Monetary costs and benefits were calculated in what amounted to a second Monte Carlo simulation, with uncertainty in profitable IAQ outcomes and IAQ public health outcomes as sampled parameters. In addition, presence or absence of the alternative ventilation technology components was sampled to calculate the sector-wide untapped benefit, only counting the portion of office-sector floorspace not yet penetrated by a ventilation strategy's technologies. Technology adoption rates and weighting by building size were described in the previous chapter, in Section 2.3.3.

3.3 Results and discussion

3.3.1 Outcomes under the baseline strategy

Table 16 summarizes the simulated outcomes resulting from the application of the Baseline constant ventilation strategy. The annual average mechanical-only $VR_{mv,year}$ was consistent and similar in both offices, exceeding the design 9.4 L/s/occ because the average occupant density from 8 a.m. to 6 p.m. was typically ~85% of design. The total VR_{year} , which includes the contribution of infiltration, was much higher, particularly in the small-CAV office. As a result, CO_2 concentrations were lower than one would expect at the design mechanical VR (~950 ppm), but consistent with the low levels observed in many real U.S. offices, both with and without economizers. For example, in a study of 100 U.S. offices the mean CO_2 concentration was 617 ppm and rarely exceeded 900 ppm (Persily & Gorfain, 2008), and in a more recent investigation of 16 office spaces mean CO_2 levels were generally in the 500–700 ppm range, and all means were in 432–873 ppm (Mendell et al., 2015). Energy outcomes were highly consistent with reported sector-wide consumption and costs, as detailed in Chapter 2.

Work performance was always improved relative to a reference of 10 L/s/occ, and often significantly so, thanks to infiltration (which also gave the small-CAV office greater RWP). However, significant work productivity gains were generally still available compared to the reference of 47 L/s/occ. For absenteeism and SBS, which cannot be driven to zero by ventilation, Table 16 lists excess values, which are amounts by which they exceeded their theoretical minima (21.4 hours absent per year, and 14.1% of occupants with SBS symptoms). The excess values reveal that additional gains are available in terms of reducing absent hours, but there is low excess SBS prevalence under the Baseline in the large majority of instances. Finally, the modeled indoor $PM_{2.5}$ and ozone concentrations were similar to measured values in offices (Weschler, 2000; Weschler, Shields, & Naik, 1989).

Table 16 Percentiles of selected outcomes under the Baseline constant ventilation strategy in the two offices.

	Small-CAV baseline percentiles					Medium-VAV baseline percentiles				
	5	25	50	75	95	5	25	50	75	95
Ventilation indicators										
VR _{year} (L/s/occ)	11.5	14.1	18.9	27.4	50.6	10.2	12.3	15.7	21.2	34.6
VR _{mv,year} (L/s/occ)	11.0	11.3	11.3	12.2	12.5	11.0	11.3	11.3	12.2	12.5
CO ₂ (ppm)	498	569	640	712	802	566	646	715	779	860
Energy outcomes										
HVAC natural gas (kWh/m ²)	5	34	87	158	305	1	15	37	65	115
HVAC electricity (kWh/m ²)	17	30	45	64	111	23	34	44	59	87
HVAC energy cost (\$/m ²)	\$3.34	\$6.46	\$8.92	\$12.22	\$18.44	\$3.22	\$5.02	\$6.48	\$8.52	\$11.97
Profitable IAQ outcomes										
RWP ₄₇ - 1	-2.3%	-1.9%	-1.3%	-0.7%	-0.1%	-2.5%	-2.2%	-1.7%	-1.2%	-0.4%
RWP ₁₀ - 1	0.3%	0.7%	1.3%	1.9%	2.6%	0.1%	0.4%	0.9%	1.5%	2.2%
Hours absent (per 2000 hours)	21.5	24.8	31.5	37.1	40.6	22.7	29.6	35.0	38.9	41.5
Excess hours absent	0.1	3.4	10.1	15.7	19.2	1.3	8.2	13.6	17.5	20.1
SBS symptom prevalence	14.1%	14.5%	16.1%	18.1%	19.6%	14.2%	15.8%	17.7%	19.2%	20.7%
Excess SBS symptom prevalence	0.0%	0.4%	2.0%	4.0%	5.6%	0.2%	1.7%	3.6%	5.2%	6.6%
IAQ health outcomes										
PM _{2.5} concentration (µg/m ³)	0.8	2.3	3.9	5.5	8.0	1.5	3.4	4.8	6.2	8.3
O ₃ concentration (ppb)	4.0	6.3	8.7	11.6	15.7	2.5	4.1	5.8	8.0	11.4

3.3.2 Alternative ventilation strategy impacts

Figure 14 shows the ranges of alternative ventilation strategy impacts, demonstrated as changes of the value of outcomes relative to the Baseline strategy. On average, all alternative strategies except D950 increased VR_{year}, with economizing strategies predictably producing VR increases of greater variability than 2×VR did. Differential enthalpy economizing (Econ) increased VRs much more than lockout economizing (EconLock) did, especially in the medium-VAV office. When both an economizer and DCV were included, the economizer usually dominated, so that Econ+D950 experienced a net increase on the annual average VR > 75% of the time.

All strategies *saved energy* except for 2×VR in both offices and D950 in the medium-VAV office, as explained in detail Chapter 2. In the small-CAV office, DCV often drove the majority of energy savings. The three ventilation strategies with greatest energy savings were D950, Econ+D950, and Econ+D675, and the median best-strategy energy cost (and primary energy consumption) reduction was 12%, equivalent to annual cost savings of ~\$1.00 per m². In the

medium-VAV office, economizing and SR were the most important technologies. Econ+SR, Econ+SR+D950, and Econ+SR+D675 provided the most energy savings, and the median best-strategy reduction was 27%, equivalent to ~\$1.75 per m².

Changes in *profitable IAQ outcomes* predictably followed changes in VR_{year} and indicators like CO₂. (Indeed, a regression over all strategies in both models indicated that a 100 ppm decrease in CO₂ concentration predicts a 0.76% increase in productivity with $R^2 = 0.91$.) That is, in the majority of cases all ventilation strategies except D950 (and Econ+D950 in the small-CAV office) increased work performance and decreased absenteeism and SBS prevalence. Work performance generally changed less than 1%, and absent hours rarely decreased by more than 10 h/year/occ. However, small changes in both metrics have large monetary values. SBS symptom prevalence reductions rarely exceeded a few percentage points.

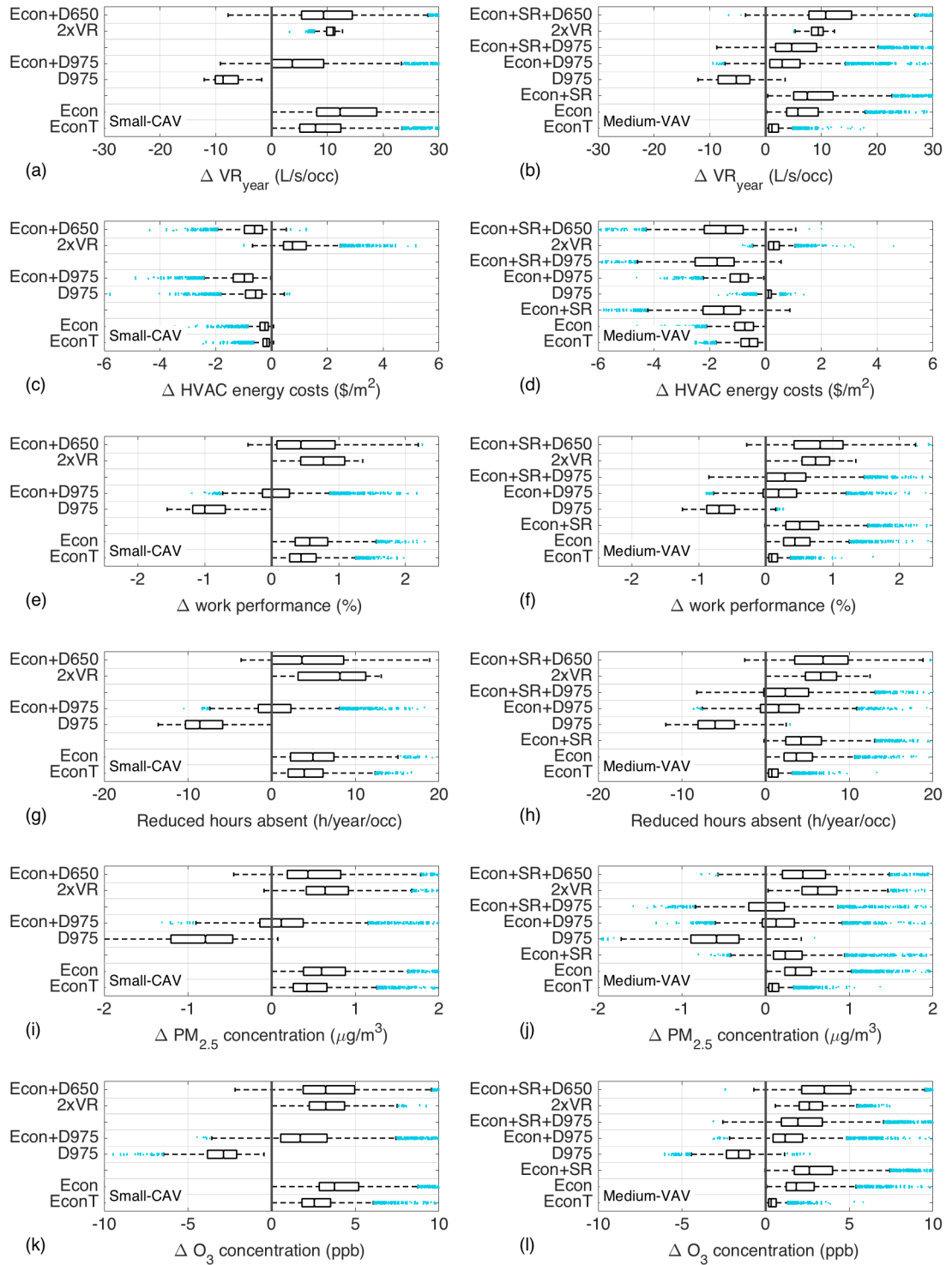


Figure 14 Ranges of impacts, defined as changes from the baseline values, for six selected outcomes, for six alternative ventilation strategies in the small-CAV office and eight alternatives in the medium-VAV office.

In terms of *IAQ public health impacts*, all strategies except D950 increased indoor PM_{2.5} and ozone concentrations on average. In at least 75% of instances, the changes were no more than 1.2 µg/m² PM_{2.5} and 5.2 ppb for ozone. Grouping all strategies that included economizers, median increases were 0.24–0.40 µg/m³ for PM_{2.5} and 2.0–3.0 ppb for ozone. While small in magnitude, these changes represented substantial fractional increases of ~8% for PM_{2.5} and ~40% for ozone above baseline exposures.

Economic values are discussed in much more detail in Chapter 4, but for quickly comparing magnitudes, consider the following approximate values for typical occupant density, salaries, and demographic characteristics. A \$1 per m² change in energy costs is worth \$20 per person; a 0.5% change in annual work performance is worth \$450 per person; five fewer hours absent per person is worth about \$230 per person; a 2% reduction in SBS prevalence is worth \$4 per person; a yearlong 0.5 µg/m³ increase in workplace PM_{2.5} concentration increases health risks valued at \$40 per person; a 3 ppb annual increase in workplace ozone adds risk valued at \$10 per person.

3.3.3 Win-win strategies for owners

Figure 14 and the preceding section make clear one of the central findings: that strategies with economizing—and only those with economizing, in the large majority of cases—can on average both save energy and provide profitable IAQ benefits (but also increase PM_{2.5} and ozone concentrations). To move beyond averages and examine specific strategies with economizers and their tradeoffs in particular instances, we defined ‘*win-win*’ strategies as those that both saved energy costs and increased work performance, the most valuable profitable IAQ impact. Such strategies can be attractive and mutually beneficial to multiple stakeholders like business owners, building owners (or utility rate payers), facilities managers, and tenants. This and the following two sections examine win-win strategies, and Sections 3.3.6 and 3.3.7 examine the win-win strategies in the context of pollution exposure consequences and mitigation.

For any instance, depending on building and climate characteristics, multiple ventilation strategies were likely to be win-win. The ‘*best*’ among winners was selected for two categories, each with its own evaluation criterion. The best ‘*energy-leaning*’ strategy was the win-win strategy with the most energy cost savings that also had at least minimal improvements in the secondary benefit of work performance. The best ‘*productivity-leaning*’ strategy was the win-win strategy that most increased work performance and at least minimally saved energy as a secondary benefit. If the best strategy was less than 10% better than a win-win alternative with fewer technology components, however, the simpler one was selected, in order to avoid selecting more complicated strategies when they had little practical benefit.

The principal win-win alternative ventilation strategies were Econ, Econ+D950, and Econ+D675 in the small-CAV office, and Econ+SR, Econ+SR+D950, and Econ+SR+D675 in the medium-VAV office. These strategies all included economizing, and in the medium-VAV office, they always included SR. D950 was not a win-win strategy, though as noted in Chapter 2 the energy savings of Econ+D950 were sometimes nearly all achieved by D950 alone in small-CAV offices. Similarly, while energy savings alone never suggested using a D675 strategy in either office, strategies with that technology included with economizing and SR if applicable were often best from a holistic win-win perspective, because they saved somewhat less energy but improved IAQ significantly more in terms of work performance, as compared to their D950 counterparts.

Figure 15 includes area plots that show the fraction of instances for which each strategy was best; win-win strategies are *those at or to the left of the vertical centerline*, for either category (energy- or productivity-leaning). The vertical centerlines are strictly win-win according to the category definitions. For example, the areas at the centerlines of the productivity-leaning plots demonstrate the strategies with maximum productivity gains achievable for no additional use of energy (\$0 cost). Moving along the *x*-axis of each plot in Figure 15 either strengthens (to the left) or relaxes (to the right) the win-win definition. The left-hand side of the centerline represents ‘*win-win-plus*’ strategies that also provide additional secondary benefits (i.e., the best

productivity leaning strategy also saves energy, and vice versa). The grey areas labeled ‘None’ represent cases for which those secondary enhancements cannot be met by any strategy, illustrating the limits at which tradeoffs cannot be avoided. The right-hand side represents ‘win-win minus’ strategies that allow some decrease in secondary benefits, with the negative requirement value indicating the tolerance. Thus, when some additional energy costs are tolerated, 2×VR becomes the strategy with the greatest labor productivity enhancements in some offices. Similarly, when some work performance decreases are tolerated, strategies with DCV and higher CO₂ setpoints of 950 ppm often provide the greatest energy savings (but are only win-win if they also have economizers). The following section explores the factors that determined which strategy was best for a given requirement or tolerance.

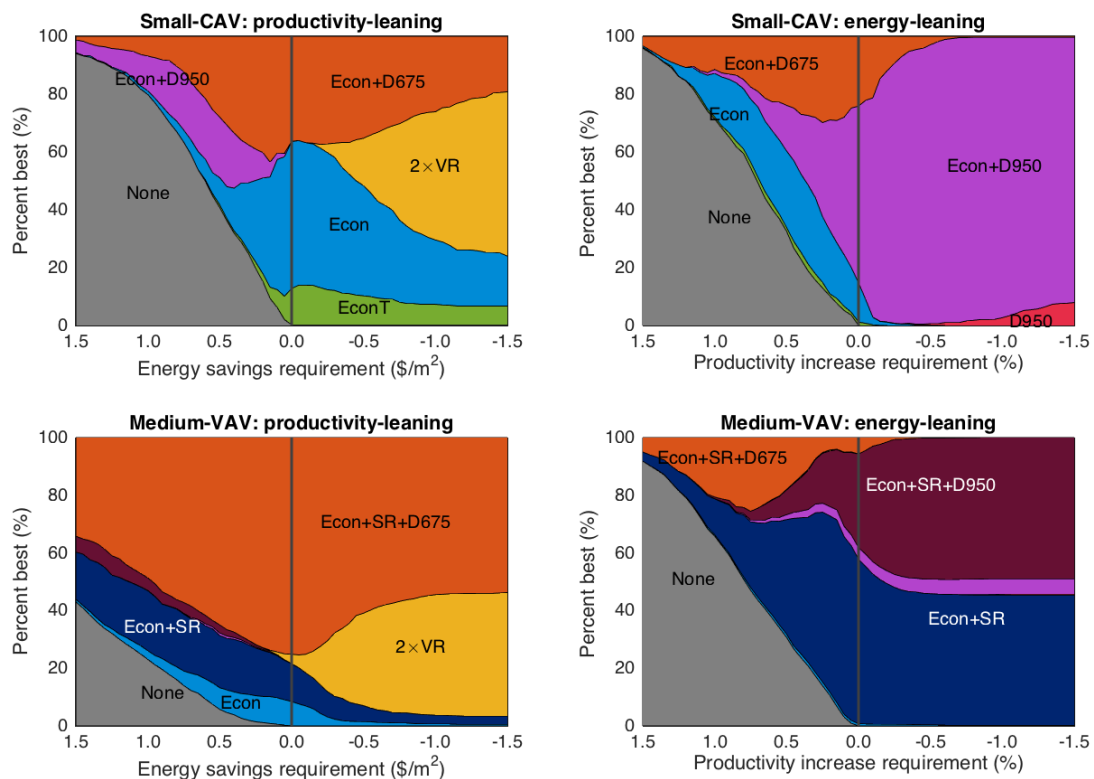


Figure 15 Percent of instances that were best under productivity-leaning and energy-leaning criteria, subject to energy savings and productivity increase requirements, respectively. The vertical centerlines, where there are no requirements, are strictly win-win. The left half of each plot, with additional positive requirements, is the win-win plus region. The right half is win-win minus, where a tradeoff up to a tolerance (negative requirement) is allowed.

3.3.4 Sensitivity analysis for VR, energy, and profitable IAQ impacts

A sensitivity analysis (SA) was conducted to better understand how building and climate parameters influenced the impacts of each strategy. We used linear regression to fit both explanatory and predictive models. Here, we present only the explanatory ones, which were restricted to linear terms, and limited results to the top eight predictors. Ranking was based on the sensitivity indices (SIs) of the different predictors over all strategies, but only frequent win-win strategies are listed in Table 17. The inputs were standardized, using the means (μ) and standard deviations (σ) listed in Table 15, so each coefficient is interpretable as the average change in impact in real units caused by a one standard deviation increase in the predictor. Furthermore, the constant is the change in the impact produced by the strategy when all predictors are at their mean values. Predictive or ‘full’ models included quadratic and interaction terms, and were included as a spreadsheet implementation as supplementary material to the journal article on which this chapter is based. A more detailed treatment of SA methods is included in Chapter 2.

According to Table 17, occupant density was the most important influence on VR_{year} , primarily because of its role as the normalizing factor for the OA flow rate. That is, the same Q_{mv} provided by economizing will yield a higher VR if the occupant density is low, rather than if it is high. Internal gains (ELPD) and solar gains (winSolarPerV) were important in both offices, though especially in the medium-VAV office with its lower envelope-to-volume ratio. The lumped envelope heat conductivity parameter (KcondPerV) was important in the small-CAV office, where more transmissive envelopes led to greater VR increases from economizing. This somewhat surprising result was due to the fact that solar gains through an opaque roof can make economizing favorable. In both offices, more humid conditions (high sumEnthpyRes) and more extreme conditions (high CDDres) were associated with lower VR increases, but the fundamental hotness or coldness of the climate (HDD) was not particularly influential.

Table 17 Results of linear sensitivity analysis of impacts of model inputs on outcomes of ventilation rate (VR_{year}), HVAC energy cost, and work performance, for frequent win-win alternative ventilation strategies from a business owner's perspective. Values are the change in the impact per one standard deviation change in the predictor (input). The constant is the change in the impact produced by the strategy when all predictors are at their mean values. For predictor definitions and units see Table 15.

Small-CAV							Medium-VAV							
SI	Predictor	μ	σ	Standardized effect size			SI	Predictor	μ	σ	Standardized effect size			
				Econ	Econ+D950	Econ+D675					Econ+SR	Econ+SR+D950	Econ+SR+D675	
ΔVR_{year} (L/s/occ)							ΔVR_{year} (L/s/occ)							
	Constant				13.6	5.3	10.5					8.9	5.1	9.9
21%	occDens	5.1	2.3	-4.7	-3.7	-2.5	18%	occDens	5.1	2.3	-5.5	-4.8	-4.6	
10%	KcondPerV	0.45	0.33	2.9	2.7	2.7	18%	ELPD	19.3	9.0	4.3	3.9	4.0	
6%	ELPD	19.3	9.0	2.4	2.7	2.6	12%	sumEnthpyRes	0.0	7.6	-3.2	-3.6	-2.8	
5%	sumEnthpyRes	0.0	7.6	-2.2	-2.4	-2.1	6%	CDDres	0	431	-2.5	-2.9	-2.1	
4%	winSolarPerV	3.8	1.5	1.9	2.0	1.9	6%	winSolarPerV	3.8	1.5	3.0	3.1	3.4	
3%	infAER	0.38	0.38	1.3	-	-1.4	6%	coolStpt	24.3	1.4	-2.4	-2.1	-2.6	
3%	coolStpt	24.3	1.4	-1.4	-1.6	-1.9	4%	infAER	0.38	0.38	-	-2.2	-4.9	
1%	CDDres	0	431	-1.2	-1.5	-1.0	1%	HDD	2308	1221	-	-	-	
	$RMSE (R^2)$				6.6 (0.58)	6.7 (0.53)	6.6 (0.49)		$RMSE (R^2)$			4.4 (0.70)	4.5 (0.71)	4.2 (0.73)
	$RMSE (R^2), full model$				4.4 (0.81)	4.6 (0.78)	4.6 (0.75)		$RMSE (R^2), full model$			3.0 (0.86)	3.1 (0.86)	2.9 (0.87)
$\Delta HVAC$ energy cost ($\\$/m^2$)							$\Delta HVAC$ energy cost ($\\$/m^2$)							
	Constant				-0.35	-1.00	-0.63		Constant			-1.75	-2.02	-1.77
26%	occDens	5.1	2.3	-	-0.27	-	-	18%	heatStpt	21.5	1.4	-0.49	-0.48	-0.47
14%	HDD	2308	1221	-	-0.22	-0.10	-0.10	15%	stptSetback	2.5	1.4	0.43	0.43	0.42
8%	infAER	0.38	0.38	-	-0.10	-0.24	-0.24	13%	HDD	2308	1221	-0.34	-0.37	-0.36
5%	dayLen	13.9	2.1	-0.04	-0.17	-0.12	-0.12	10%	coolCOP	3.02	0.74	0.32	0.34	0.30
4%	heatStpt	21.5	1.4	-0.03	-0.14	-0.08	-0.08	5%	coolStpt	24.3	1.4	0.25	0.29	0.22
4%	coolStpt	24.3	1.4	0.12	0.14	0.13	0.13	3%	infAER	0.38	0.38	-0.27	-0.40	-0.58
4%	ELPD	19.3	9.0	-0.14	-0.10	-0.12	-0.12	2%	CDDres	0	431	0.14	0.09	0.18
3%	coolCOP	3.02	0.74	0.09	0.13	0.09	0.09	1%	occDens	5.1	2.3	-	-	-
	$RMSE (R^2)$				0.21 (0.49)	0.33 (0.70)	0.35 (0.56)		$RMSE (R^2)$			0.59 (0.68)	0.57 (0.71)	0.59 (0.70)
	$RMSE (R^2), full model$				0.16 (0.71)	0.24 (0.84)	0.24 (0.79)		$RMSE (R^2), full model$			0.31 (0.91)	0.31 (0.91)	0.32 (0.91)
Δ work performance (%)							Δ work performance (%)							
	Constant				0.65	0.08	0.58		Constant			0.41	0.19	0.55
43%	infAER	0.38	0.38	-0.22	-0.10	-0.29	-0.29	35%	infAER	0.38	0.38	-0.44	-0.46	-0.73
6%	occDens	5.1	2.3	-	-0.06	0.10	0.10	11%	sumEnthpyRes	0.0	7.6	-0.15	-0.19	-0.10
3%	KcondPerV	0.45	0.33	0.06	0.09	0.06	0.06	10%	ELPD	19.3	9.0	0.15	0.15	0.12
3%	sumEnthpyRes	0.0	7.6	-0.07	-0.11	-0.06	-0.06	4%	CDDres	0	431	-0.10	-0.15	-0.06
2%	ELPD	19.3	9.0	0.05	0.11	0.07	0.07	3%	winSolarPerV	3.76	1.50	0.08	0.14	0.10
2%	winSolarPerV	3.8	1.5	0.05	0.09	0.05	0.05	2%	coolStpt	24.3	1.4	-0.07	-0.06	-0.07
1%	coolStpt	24.3	1.4	-	-0.06	-0.05	-0.05	2%	HDD	2308	1221	-	0.06	-
1%	CDDres	0	431	-0.03	-0.06	-	-	2%	occDens	5.1	2.3	-0.04	-0.06	0.05
	$RMSE (R^2)$				0.22 (0.64)	0.29 (0.46)	0.30 (0.63)		$RMSE (R^2)$			0.19 (0.76)	0.23 (0.74)	0.23 (0.79)
	$RMSE (R^2), full model$				0.14 (0.85)	0.21 (0.71)	0.18 (0.88)		$RMSE (R^2), full model$			0.13 (0.89)	0.15 (0.89)	0.12 (0.94)

For HVAC energy costs, much of the savings in the small-CAV office were driven by DCV, for which occupant density, HDD, and infiltration were decisive parameters. Higher values of all three were associated with greater energy savings (i.e., more negative changes in consumption) with Econ+D950. For the medium-VAV office, SR was quite sensitive to zone temperature

setpoints and the temperature setback, and all strategies with Econ and SR saved more energy in colder climates. While these predictors affected energy savings, they generally had little effect on profitable IAQ impacts.

For work performance, most of the influences were those that affected VR_{year} , i.e., the characteristics relevant to how mechanical ventilation is controlled. But the largest influence by far was one unrelated to the provision of mechanical ventilation: the infiltration rate. This fact was because infiltration played a fundamental role in determining the baseline values of outcomes, especially strongly nonlinear ones like RWP (and r_{abs}), for which changes in VR have very different efficacies depending on the baseline operating point. Thus, for every one standard deviation increase in infiltration (0.38 h^{-1}), the improvement in work performance expected from implementing an economizer decreased by about 0.25% in the small-CAV office, and nearly 0.5% in the medium-VAV office. A leakier office has more air exchange to start, and therefore less to gain from economizing, at least in terms of work performance.

3.3.5 Selecting owner win-win strategies

The insights from the sensitivity analysis, which showed infiltration and climate variables as the largest influences on energy and work performance outcomes, were used to construct Figure 16, which is a simple graphic to help individual building owners decide among the three common win-win alternative ventilation strategies for each office type. For both offices, it shows the binned infiltration rates on the x -axis, with HDD (for the small-CAV office) or average summer enthalpy (for the medium-VAV office) values on the y -axis. Within those grids of binned input variables, median magnitudes of the outcomes are shown by the size of the circle for energy savings and the color of the circle for work performance.

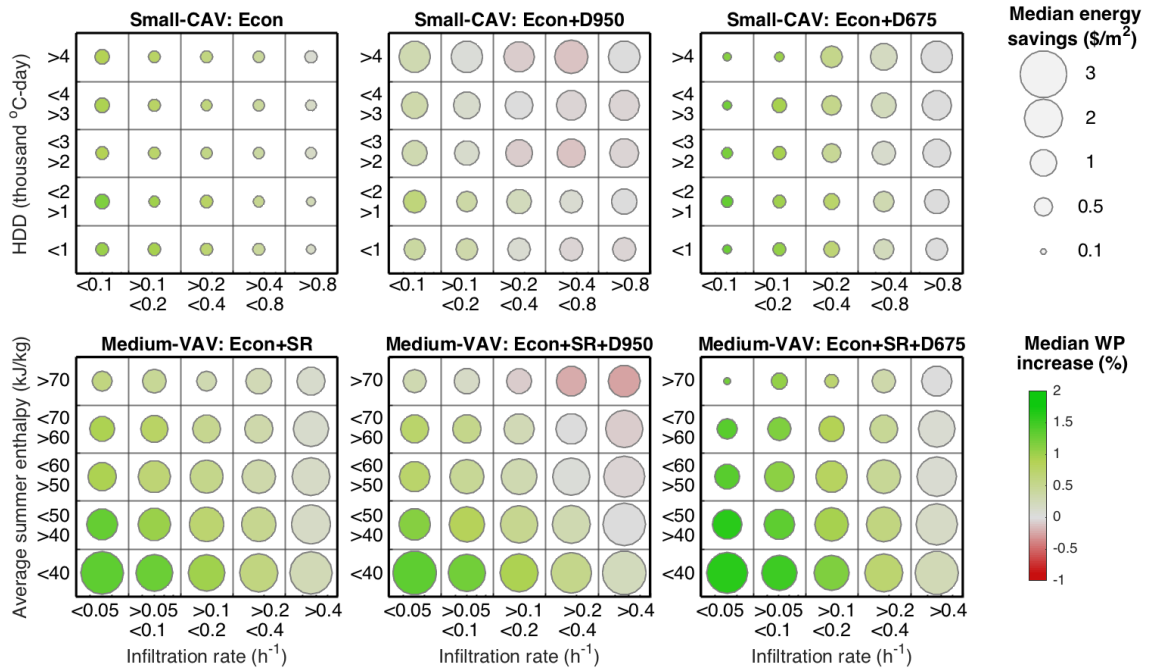


Figure 16 Median energy (cost) savings and work performance (WP) changes for three win-win strategies, based on infiltration and outdoor conditions.

Thus, with estimates of the infiltration rate and the value of the outdoor climatic variable for the building, a decision-maker can use Figure 16 as a tool to evaluate the median magnitude of impacts of the three strategies on energy savings and work performance. For example, for a very tight (infiltration $< 0.1 \text{ h}^{-1}$) small-CAV office in any climate, approximate median energy cost savings and work performance increases would be, respectively: $\$0.25/\text{m}^2$ and 1% with Econ; $\$0.85/\text{m}^2$ and 0.4% with Econ+D950; and $\$0.20/\text{m}^2$ and 1.3% with Econ+D675. All three strategies are win-win (something that would not be true in a leakier building in a climate with meaningful heating needs), so decision-makers would have to weigh the balance of impacts and consider implementation cost differences to make a choice.

Figure 16 also illustrates some broad trends at a glance. In the small-CAV office type, Econ+D950 can save the most energy, but in all but the tightest offices it usually comes with work performance decreases. However, both Econ and Econ+D675 save less energy but usually also enhance (or at least do not reduce) work performance. The medium-VAV office has much

greater potential energy savings and performance enhancements than the small office, and they are possible at the same time, especially in climates without excessively high summer enthalpy. Furthermore, most benefits come from Econ+SR, the simplest win-win strategy. Adding DCV with a higher setpoint to Econ+SR rarely saves substantial additional energy (and sometimes hurts work performance), but adding DCV with a low CO₂ setpoint can further enhance the work performance benefits of Econ+SR, particularly at low infiltration rates, without substantially reducing energy savings. Of course, Figure 16 only shows medians given two parameters. Many other parameters are influential. Occupant density, in particular, is critical in determining whether adding DCV to Econ or Econ+SR is warranted. The role of multiple parameters can be assessed for a given circumstance with the detailed predictive strategy impact models in the spreadsheet that accompanied with the published article version of this chapter.

3.3.6 Quantifying outdoor pollutant exposure tradeoffs

Positive profitable IAQ impacts and negative IAQ public health impacts from exposure to outdoor pollutants both increase with VR and are in direct conflict. To understand the tradeoffs, Figure 17 plots PM_{2.5} and ozone impacts versus work performance for Econ in the small-CAV office and for Econ+SR in the medium-VAV office. With these ventilation strategies, each 1% increase in work performance corresponded to an average increase in indoor concentrations of 0.5–1 µg/m³ for PM_{2.5} and 5–6 ppb for ozone, with the steeper tradeoffs in the small-CAV office.

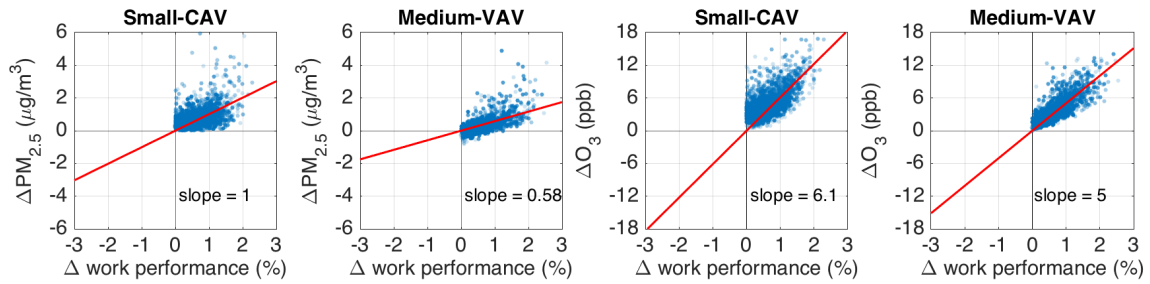


Figure 17 Change in $PM_{2.5}$ and ozone concentrations versus change in work performance for Econ in the small-CAV office and for Econ+SR in the medium-VAV office, with zero-intercept best-fit lines in red.

Table 18 includes similar tradeoffs for most other strategies in both offices, in terms of both medians and interquartile ranges of impact ratios. The positive values confirm that no strategy could avoid increasing outdoor pollutant exposure indoors as a tradeoff of increasing work performance. Most had similar tradeoffs. Somewhat lower tradeoff slopes were found for $PM_{2.5}$ under economizing strategies in the medium-VAV office, and for ozone under non-economizing strategies (D950 and $2\times VR$) in both offices. These results are due principally to the interplay between slopes of the governing impact relations at different VR operating points, since there are diminishing returns to work performance benefits as the VR increases.

Table 18 Indoor $PM_{2.5}$ and ozone concentration changes divided by work performance (WP) change, with $\Delta PM_{2.5}$ in $\mu g/m^3$, ΔO_3 in ppb, and ΔWP in %. In the medium office, strategies with SR were assessed where applicable. The median values of these impact-tradeoffs are shown with their respective interquartile ranges in parentheses.

Tradeoff	Office	Econ(+SR)	D975	Econ(+SR)+D950	$2\times VR$	Econ(+SR)+D675
$\Delta PM_{2.5}/\Delta WP$	Small-CAV	1.1 (0.72, 1.7)	0.96 (0.61, 1.3)	1.0 (0.24, 2.0)	0.96 (0.65, 1.4)	0.90 (0.54, 1.5)
	Medium-VAV	0.46 (0.21, 0.76)	0.93 (0.69, 1.2)	0.34 (-0.13, 1.2)	0.90 (0.68, 1.2)	0.57 (0.36, 0.83)
$\Delta O_3/\Delta WP$	Small-CAV	6.4 (5.0, 10)	3.4 (2.5, 4.5)	5.4 (-2.3, 13)	4.7 (3.7, 6.3)	5.6 (4.1, 9.6)
	Medium-VAV	5.4 (4.2, 7.0)	2.5 (1.7, 3.4)	5.4 (3.3, 8.6)	3.8 (2.8, 5.0)	4.8 (3.6, 6.4)

3.3.7 Predicting and mitigating outdoor pollutant exposure impacts

Sensitivity analysis for $PM_{2.5}$ and ozone concentration changes can help identify and perhaps protect against collateral exposure from win-win strategies. Eight-term regression model results in Table 19 show that, in both office types, buildings with high outdoor $PM_{2.5}$ concentrations, low

infiltration, low efficiency filters, and low occupant density experienced the largest increases in indoor PM_{2.5} concentration. In addition, more humid climates (high sumEnthpyRes) and more extreme ones (high CDDres) were associated with lower PM_{2.5} exposure increases, especially in the medium-VAV office, both because economizer was used less frequently and because they had greater total filtration losses because of higher recirculation rates (which are a function of thermal-load-driven supply air flows). For ozone, the influences were similar for predictors influencing VR_{year}, with the outdoor ozone concentration and infiltration rate also highly influential. Compared to PM_{2.5}, climate was a weaker influence on ozone, which changed little with changes in recirculation because there was no intentional gas-phase filtration (Bekö et al., 2007).

Table 19 Results of linear sensitivity analysis of IAQ health impacts for strategies that were frequently win-win from a business owner's perspective. Values are the change in the response per one standard deviation change in the predictor. The constant is the change in the outcome produced by the strategy when all predictors are at their mean values. For predictor definitions, units, and means and standard deviations, see Table 15.

Small-CAV							Medium-VAV						
SI	Predictor	μ	σ	Standardized effect size			SI	Predictor	μ	σ	Standardized effect size		
				Econ	Econ+D950	Econ+D675					Econ+SR	Econ+SR+D950	Econ+SR+D675
Δ PM_{2.5} concentration ($\mu\text{g}/\text{m}^3$)							Δ PM_{2.5} concentration ($\mu\text{g}/\text{m}^3$)						
	Constant			0.72	0.14	0.59		Constant			0.17	-0.11	0.27
20%	PMout	8.6	2.7	0.26	0.13	0.22	14%	sumEnthpyRes	0.0	7.6	-0.20	-0.25	-0.15
10%	PMeta_mv	0.25	0.20	-0.10	0.06	-0.05	14%	PMout	8.6	2.7	0.15	0.09	0.19
8%	infAER	0.38	0.38	-0.10	-	-0.20	12%	infAER	0.38	0.38	-0.21	-0.27	-0.51
5%	occDens	5.1	2.3	-0.12	-0.15	-	6%	occDens	5.1	2.3	-0.17	-0.16	-0.10
4%	KcondPerV	0.45	0.33	0.11	0.13	0.11	6%	CDDres	0	431	-0.13	-0.18	-0.10
4%	sumEnthpyRes	0.0	7.6	-0.12	-0.18	-0.11	5%	PMeta_mv	0.25	0.20	-0.10	-	-0.11
2%	ELPD	19.3	9.0	0.09	0.14	0.10	4%	ELPD	19.3	9.0	0.11	0.11	0.07
2%	HDD	2308	1221	-0.08	-0.12	-0.08	1%	HDD	2308	1221	-	0.05	-
	RMSE (R^2)			0.32 (0.59)	0.42 (0.42)	0.39 (0.51)		RMSE (R^2)			0.25 (0.66)	0.31 (0.60)	0.27 (0.68)
	RMSE (R^2), full model			0.20 (0.83)	0.27 (0.75)	0.24 (0.81)		RMSE (R^2), full model			0.16 (0.86)	0.19 (0.84)	0.16 (0.89)
Δ O₃ concentration (ppb)							Δ O₃ concentration (ppb)						
	Constant			4.10	2.01	3.62		Constant			2.87	1.99	3.34
18%	O3out	36.6	5.8	1.10	0.87	0.98	15%	ELPD	19.3	9.0	0.86	0.88	0.70
11%	occDens	5.1	2.3	-0.37	-0.78	-	13%	infAER	0.38	0.38	-0.98	-1.33	-1.97
10%	KcondPerV	0.45	0.33	0.66	0.77	0.66	12%	sumEnthpyRes	0.0	7.6	-0.68	-0.79	-0.58
10%	infAER	0.38	0.38	-0.40	-0.39	-0.93	9%	O3out	36.6	5.8	0.62	0.50	0.70
6%	ELPD	19.3	9.0	0.52	0.73	0.60	8%	CDDres	0	431	-0.65	-0.78	-0.51
5%	O3beta	2.72	1.13	-0.42	-	-0.34	8%	O3beta	2.72	1.13	-0.48	-0.31	-0.63
3%	coolStpt	24.3	1.4	-0.31	-0.52	-0.48	7%	winSolarPerV	3.8	1.5	0.72	0.79	0.83
3%	winSolarPerV	3.8	1.5	0.36	0.48	0.39	5%	occDens	5.1	2.3	-0.41	-0.58	-
	RMSE (R^2)			1.23 (0.67)	1.55 (0.61)	1.43 (0.66)		RMSE (R^2)			0.95 (0.79)	1.05 (0.77)	0.99 (0.81)
	RMSE (R^2), full model			0.76 (0.87)	0.96 (0.85)	0.85 (0.88)		RMSE (R^2), full model			0.55 (0.93)	0.61 (0.92)	0.53 (0.95)

Both the $PM_{2.5}$ filter efficiency and the ozone deposition rate were less influential than expected. For example, each standard deviation increase in filter efficiency (0.20) only reduced the $PM_{2.5}$ concentration increases expected from adding an economizer by $0.1 \mu\text{g}/\text{m}^3$. Figure 18 illustrates why this is true for $PM_{2.5}$, using the indoor/ outdoor (I/O) concentration ratio. While filter efficiency played a large role in determining the I/O ratio and was highly correlated with it, as shown in Figure 18a for the Baseline strategy, filter efficiency was weakly related to the *change* in I/O between the Baseline and Econ strategy, which was typically relatively modest in any case, as shown in Figure 18b.

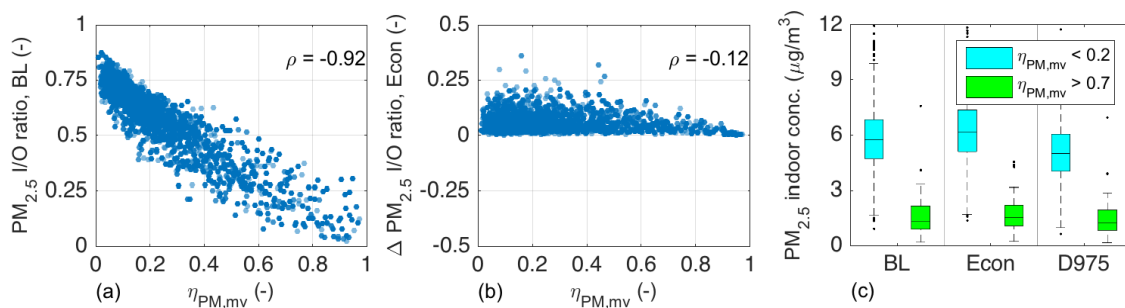


Figure 18 (a) Indoor/outdoor (I/O) ratio of $PM_{2.5}$ under the Baseline (BL), versus $PM_{2.5}$ filter efficiency; (b) change in $PM_{2.5}$ I/O ratio from implementing Econ, versus $PM_{2.5}$ filter efficiency; and (c) indoor $PM_{2.5}$ concentrations using BL, Econ, and D975 for two filter efficiency bins in the small-CAV office; ρ is a correlation coefficient measuring the linear dependence between $PM_{2.5}$ I/O ratio and filter efficiency.

Figure 18c shows box plots of the indoor $PM_{2.5}$ concentration for the Baseline, Econ, and D975 strategies, binned into instances with average-or-lesser ($\eta_{PM,mv} < 0.2$) or superior ($\eta_{PM,mv} > 0.7$) filter efficiency. (Figure 18c used data from the small-CAV office, but the medium-VAV office had similar trends.) These binned results illustrate that the small regression coefficients for filter efficiency in Table 19 indicate not that filtration has little ability to alleviate increased $PM_{2.5}$ with win-win strategies, but exactly the opposite. That is, filter efficiency is a much stronger determinant of indoor $PM_{2.5}$ than the ventilation strategy. Indeed, indoor $PM_{2.5}$ concentrations were similar across strategies (especially with superior filters), but very different across filter

efficiency bins, indicating that filter enhancement is a more effective method to influence $PM_{2.5}$ concentration than any alteration in ventilation strategy. A similar result held for the ozone deposition rate, implying that for buildings with high ozone outdoors, air-cleaning with filtration or passive removal of ozone could be an effective mitigation approach, no matter the ventilation strategy.

3.3.8 Sector-wide benefits of win-win strategies

The aggregate benefits of implementing win-win strategies in the U.S. small-to-medium-large office sector (~1.1 billion m^2 or ~75% of total U.S. office floorspace (U.S. EIA, 2015b)) are presented in Table 8. These are the annual benefits associated with selecting (independently for each instance) the best energy-leaning or productivity-leaning win-win ventilation strategy, which in the small-CAV office were nearly always Econ, Econ+D950, or Econ+D675, and in the medium-VAV office were Econ+SR, Econ+SR+D950, or Econ+SR+D675. Estimates are given for the theoretical total benefit based on simply scaling up modeled impacts to the sector floorspace, and for the untapped market potential, which accounts for estimated current adoption rates of economizers, DCV, and SR in offices (Hamilton et al., 2016). An important caveat is that, to maintain the consistent yardstick used throughout this chapter, the benefits in Table 20 are relative to the Baseline determined by ASHRAE Standard 62-2001.

Table 20 Aggregate annual benefits in the small-to-medium-large office sector for both energy-leaning and productivity-leaning win-win ventilation strategies. The theoretical total estimate assumes all offices currently use the baseline strategy, while the untapped estimate attempts to account for current adoption levels of component technologies. For IAQ impacts subject to uncertainty, medians are given, with 95% confidence intervals in parentheses.

Aggregate annual benefit (billion US \$)	Theoretical total		Untapped potential	
	Energy-leaning	Productivity-leaning	Energy-leaning	Productivity-leaning
Energy impacts	1.7	1.2	1.1	0.7
Profitable IAQ impacts	28.1 (5.4, 51.4)	51.4 (3.7, 100.6)	24.9 (10.5, 39.9)	46.9 (8.7, 86.4)
Work performance gain	19.7 (-5.1, 45.6)	37.7 (-14.0, 91.9)	17.3 (1.7, 33.7)	32.5 (-7.0, 73.9)
Reduced absenteeism	8.4 (4.4, 11.9)	16.3 (8.9, 22.5)	7.4 (6.4, 8.2)	14.1 (9.1, 18.0)
Reduced SBS symptoms	0.1 (0.0, 0.2)	0.2 (0.1, 0.4)	0.1 (0.1, 0.1)	0.2 (0.1, 0.3)
IAQ public health impacts	-1.9 (-2.8, -0.9)	-4.1 (-5.8, -2.5)	-1.7 (-1.9, -1.5)	-3.7 (-4.8, -2.5)
Increased PM _{2.5} exposure	-1.0 (-1.8, -0.1)	-2.8 (-4.5, -1.2)	-1.0 (-1.2, -0.9)	-2.6 (-3.6, -1.5)
Increased O ₃ exposure	-0.9 (-1.2, -0.6)	-1.3 (-1.8, -0.9)	-0.7 (-0.9, -0.5)	-1.1 (-1.4, -0.7)
Total	28.3 (5.6, 51.5)	54.5 (6.8, 103.4)	23.1 (8.8, 38.1)	43.2 (5.1, 82.8)

Importantly, the sector-wide benefit of implementing win-win strategies was *always positive* for the entire 95% CI, for both selection categories, for both the theoretical total and untapped potential. Profitable IAQ impacts dominated the benefits, with work performance accounting for about two-thirds of the benefits and absenteeism the remainder, while SBS symptom treatment costs were two orders of magnitude lower. Energy benefits were generally 5% of profitable IAQ impacts for selected energy-leaning strategies, and only 2% for productivity-leaning strategies. For this reason, the productivity-leaning criterion had nearly double the benefit of the energy-leaning one, but retained 65–70% of the energy savings. Energy benefits under the energy-leaning selection rule were in line with those calculated in Chapter 2 on pure energy economics terms, except very slightly lower because of the exclusion here of energy-saving strategies that decreased work performance, like D950 in the small-CAV office.

The IAQ public health costs of added indoor exposure to outdoor-originating PM_{2.5} and ozone were mostly due to mortality, which made up 87% of the median value for PM_{2.5} and 83% (19% respiratory, 64% short-term) for ozone. Coronary revascularization contributed 7% and chronic bronchitis 5% to PM_{2.5} costs, and chronic asthma contributed 15% to ozone costs, but all other endpoints accounted for less than 2% of each pollutant's total. Like energy costs, health

impact costs were also overwhelmed by the work performance and absenteeism benefits, with the magnitude of median IAQ health costs only ~7% of the median profitable IAQ impacts benefits. Nonetheless, any additional deaths should clearly be prevented by use of more efficient particle (and eventually ozone) filtration and possibly curtailment of higher ventilation when outdoor concentrations are high.

Estimates of untapped potential in the office sector market were nearly as high as the theoretical total estimates that did not account for current technology adoption rates. This similarity in estimates appeared to be because buildings that already had only DCV (according to the current market adoption fractions) experienced significantly greater benefits from switching to a win-win strategy, a fact that mostly balanced the much lower realized benefits for buildings that already had economizers installed. In short, selecting win-win ventilation strategies can tap into a largely unexplored portion of the office sector market that bears significant potential financial gain for building owners and businesses.

3.4 Conclusions

This work examined the impacts of *alternative ventilation strategies* that combined economizing, DCV, and SR on three outcome categories: (i) energy savings, (ii) profitable IAQ impacts (work performance, absenteeism, and SBS symptoms), and (iii) negative IAQ public health impacts (due to indoor exposure to outdoor PM_{2.5} and ozone). A combination of energy modeling, empirical outcome correlations, and mass-balance modeling was employed. Outcome datasets were constructed by varying 19 building parameters and outdoor climate and pollution data in a large Monte Carlo analysis, weighted to be representative of ~75% of the U.S. office sector floorspace in small-to-medium-large buildings. Impacts of alternative ventilation strategies in a small-CAV and medium-VAV office were evaluated with respect to a baseline fixed VR

based on U.S. minimum standards. Baseline results for all outcomes were in good agreement with available energy use data and air quality measurements for offices.

There was a large amount of variability in the outcomes, among both strategies and building instances. Overall trends though, were clear, as the following approximate median impacts illustrate. Most strategies except doubling the VR saved energy, with annual HVAC energy costs and primary energy consumption reductions of 12–27%, equivalent to \$1–1.75 per m² in energy costs, for the most successful strategies. Strategies with economizer increased VRs by 5–10 L/s/occ, which resulted in increased work performance of 0.5% and five fewer hours absent per year, accompanied by indoor concentration increases of about 0.5 µg/m³ for PM_{2.5} and 3 ppb for ozone.

‘Win-win’ strategies were defined as ones that saved energy and achieved profitable IAQ benefits, as indicated by the change in the most valuable one, work performance. Most importantly, *all win-win strategies included an economizer*, and in the multizone medium-VAV office they also included SR. An economizer was particularly beneficial because it increased the amount of ventilation air introduced indoors, while also saving energy. Two variants added DCV with a CO₂ setpoint of 950 ppm or 675 ppm, which performed better than an economizer alone under certain conditions. Sensitivity analysis showed that infiltration, climate indicators, and occupant density were strong determinants on both energy and profitable IAQ impacts. This insight was used to develop a simple graphical tool that allows users to compare median energy and work performance impacts of the three win-win strategies for bins of specific infiltration and HDD or outdoor air enthalpy values.

Increases in VR also increased indoor exposure to outdoor pollutants, with a 1% increase in work performance associated with 0.8 µg/m³ and 5 ppb increases in PM_{2.5} and ozone concentrations, respectively. Sensitivity analysis revealed that outdoor concentrations were the largest influence on the changes in indoor concentrations. Further analysis indicated that, for PM_{2.5}, filter efficiency is a far more important determinant of the indoor concentration than

ventilation strategy, and mitigating health effects due to PM_{2.5} indoors can be done effectively by improving filtration, even at high ventilation rates.

An office sector-wide analysis of win-win strategies indicated theoretical total benefits of \$28 billion U.S. (95% CI: \$6–52 billion) when the win-win strategy with the greatest energy savings was selected, and \$55 billion U.S. (95% CI: \$7–103 billion) when the win-win strategy with the greatest work performance increase was selected. Profitable IAQ impacts dominated the benefits of alternative strategies, with work performance increases accounting for ~2/3 of the profitable IAQ benefits, reduced absenteeism ~1/3, and SBS symptom reduction comparatively negligible. Energy savings were substantial but were only 2–5% as valuable as profitable IAQ impacts. Likewise, while IAQ health risk economic valuations represented substantial aggregate public health costs, largely due to added mortality for both PM_{2.5} and ozone, their magnitude was about an order lower than the profitable benefits (again filtration can mitigate many mortality impacts). Importantly, the total benefit of implementing win-win strategies was *always positive* over the 95% CI interval. Estimates of benefit that took into account portions of the strategies already adopted by offices indicated that most benefits remain untapped.

CHAPTER 4: OUTCOME-BASED VENTILATION: A FRAMEWORK FOR INTEGRATED ASSESSMENT OF INDOOR AIR QUALITY AND ENERGY IMPACTS OF COMMERCIAL BUILDING VENTILATION

Chapter abstract: *This chapter presents a framework called outcome-based ventilation (OBV) for evaluating ventilation rates (VR) in commercial buildings and making informed decisions based on the resultant indoor air quality (IAQ) and energy consumption outcomes. A loss function combines outcomes, using scientific knowledge to establish the form of ventilation-outcome relations, and user-selected parameters to adjusted for preferences; therefore, minimizing loss optimizes ventilation for a given decision-maker. The approach was developed for U.S. offices, and included six outcomes: occupant work performance and sick leave absenteeism (profitable IAQ outcomes), health risks from exposure to fine particles and ozone from outdoors (IAQ public health outcomes), and electricity and natural gas consumption (energy outcomes). Literature research was used to develop low, medium (central estimate), and high reference values for user parameters. Applying medium parameters to a dataset representing the U.S. office stock, median loss changes in \$/occ/h from an intervention that increased VRs by ~10 L/s/occ were: -0.36 (work performance), -0.21 (excess absence), 0.02 (PM_{2.5} exposure), 0.01 (ozone exposure), 0.00 (electricity use), and 0.00 (natural gas use). Work performance and absenteeism nearly always remained dominant unless a user selected low parameters for profitable IAQ outcomes and high values for public health and energy outcomes. With medium parameters, profitable IAQ outcomes were determinative, leading to outcome-based VRs that were 45–50 L/s/occ—approximately five times current minimum office VRs—regardless of time of year of building characteristics. The most ventilation-adverse user preferences, with low parameters for profitable IAQ impacts and high values for public health and energy impacts, still produced VRs that were very often as high as 30 L/s/occ and only rarely lower than 15 L/s/occ. With the latter user parameters, optimal VRs*

varied over the year and depended on weather, pollution, and building specifics in ways that no existing non-outcome-based ventilation strategy captures.

4.1 Chapter introduction

How should one make deliberate decisions about setting building ventilation rates, which can have many implications? Ventilation's principal purpose is diluting indoor-emitted pollutants, reducing odors as well as potentially unhealthy or irritating chemical exposures (ASHRAE, 2013b; Persily, 2015; Sundell et al., 2011). Low ventilation rates (VR) are associated with increased illness, greater prevalence of sick building syndrome (SBS) symptoms, and reduced task performance (Bakó-Biró et al., 2007; Carrer et al., 2015; Fisk et al., 2009; Haverinen-Shaughnessy et al., 2011; Mendell et al., 2013; Wargoeki et al., 2004). VRs that significantly exceed current minimum standards have also been associated with significant cognitive and task performance increases and sick leave reductions (J. G. Allen et al., 2015; Milton et al., 2000; Satish et al., 2012; Seppänen et al., 2006). Ventilation control also affects broader public health risks, for example by introducing outdoor air pollutants like fine particulate matter (PM_{2.5} = particles with aerodynamic diameter < 2.5 μm) and ozone (O₃) (Bekö et al., 2008; Ben-David & Waring, 2016; Quang et al., 2013; Rackes & Waring, 2013; Stephens et al., 2012; Weschler, 2000) both of which have well-established, no-threshold associations with multiple adverse short- and long-term health endpoints (Burnett et al., 1999; Dominici et al., 2006; Dutton et al., 2013; Fann et al., 2012; Pope et al., 2002), including mortality (Dockery et al., 1992; Dutton et al., 2013; Hänninen et al., 2005; Pope et al., 2009, 2002). In addition to these many indoor air quality (IAQ) implications, current ventilation practice accounts for ~1/4 of HVAC energy consumed by commercial buildings (Fisk et al., 2012; U.S. Energy Information Administration (EIA), 2006b). Though increasing VRs generally increases energy use, in some settings it can also save energy by economizing under certain weather conditions, as shown in the previous two chapters.

The most influential decisions about ventilation rely on minimum VRs set by regulatory standards. Persily (2015) recounted the historical twists and turns in the development of ASHRAE Standard 62.1, the most well-known ventilation standard for commercial buildings (ASHRAE, 2013b). The minimum VR for office spaces specified by Standard 62.1 (and its precursor Standard 62) has fluctuated significantly, from 7.5 L/s/occ in the first version in 1973, to 2.5 L/s/occ (for non-smoking spaces) in 1981, to 10 L/s/occ in 1989, to 8.5 L/s/occ (at default occupant density) from 2004 to the present. Persily (2015) reports that VR standards worldwide similarly require between 3 and 10 L/s/occ in offices. These values persist despite the 2011 conclusion of more than a dozen experts that “increasing ventilation rates above currently adopted standards and guidelines should result in reduced prevalence of negative health outcomes” (Sundell et al., 2011). According to Persily, based on his own experience on the Standard 62.1 committee, setting minimum VRs “has always been challenging based on limited research results to support specific values, pressures by some to lower rates based on energy considerations, and pressures by others to raise them based on IAQ benefits” (Persily, 2015).

Meanwhile, a number of research efforts have attempted to compare the multiple costs and benefits that create those pressures. Fisk (2012) showed that the economic benefits of increasing the minimum VR in U.S. offices from 8 to 15 L/s/occ, owing to improved work performance and reduced absence at the higher VR, were about 200 times the additional energy costs. Dutton et al. (2013) found that natural ventilation could expose office workers to outdoor pollutants whose public health impacts overwhelmed the benefits of reduced SBS symptoms, in economic terms. Chapters 2 and 3 of this thesis and two associated journal papers (Ben-David, Rackes, & Waring, 2017; Rackes & Waring, 2017) examined specific alternative ventilation strategies like demand-controlled ventilation and economizer control in offices, in terms of (i) *profitable IAQ* outcomes (work performance and reduced absenteeism), (ii) *IAQ public health* outcomes (from indoor exposure to outdoor PM_{2.5} and ozone); (iii) and *energy* consumption outcomes. In that work, we

also varied about two-dozen building, weather, and pollution parameters and showed that building and location specifics can influence ventilation impacts substantially.

Here we take the insights of the whole-sector analysis from the preceding two chapters and apply it to developing an evaluation framework that can be applied to a specific building by a unique decision-maker with distinct beliefs and preferences. We call this approach ‘outcome-based ventilation’ (OBV) because it leads to making a ventilation decision based on consideration of its outcomes, rather than on a prescriptive formula. The outcome categories remain *profitable IAQ*, *IAQ public health*, and *energy consumption*, although the latter category has been expanded to make it possible to include values for ‘externalities’ associated with energy use. To incorporate scientific uncertainty and decision-maker preference, each outcome is associated with a *loss*, representing lost utility for the user.

The framework is developed here for offices because their parameters are relatively well characterized and they represent the largest U.S. commercial building activity at 18% of floorspace (U.S. Energy Information Administration (EIA), 2015c). (With some modifications, the basic ideas could be extended to other commercial building types.) After formulating the loss function, we use the existing dataset from described in Chapters 2 and 3 to examine to examine the implications of OBV in the context of day-averaged ventilation rates and outcomes. Then, a series of case studies illustrate how loss and loss-minimal VRs might change over the year. In Chapter 5, we will turn to the possibility of using the loss formulation for OBV to optimize ventilation dynamically, similar to Rackes and Waring (2014), but based on more detailed information about outcomes and their values.

4.2 Methods

4.2.1 Minimizing loss

The basic principle of this outcome-based ventilation (OBV) decision-making framework is that well-characterized positive and negative consequences of ventilating commercial buildings can be organized into a governing equation centered on a unit of avoidable loss, called the *loss function*. However, doing so is not necessarily straightforward. The benefits and costs of ventilation fall upon different stakeholders, some of whom may be far from the building. At the same time, many of the impacts associated with indoor air exposures and environmental externalities are subject to substantial epistemic uncertainty. The approach taken, therefore, was to establish scientific ranges or distributions of impact strengths, and then allow an *end user*—i.e., a building owner, utility bill payer, property manager, business executive, institution, or other decision-making stakeholder—to select parameters to reflect her own preferences. This leaves discretion to the user, and avoids conferring certainty not indicated by the science. The user's preferences transform an outcome into a loss, reflecting what a decision-maker would pay to avoid an outcome. Less loss is better, and the ventilation strategy or rate that minimizes loss is therefore optimal for a given user. These are (optimal) *outcome-based* ventilation strategies and ventilation rates.

Many potential ventilation outcomes were considered for inclusion. The rationale for the IAQ-related components included remains that described in Chapter 3: for an outcome to be included, it needed to have sound and practical methods to calculate its magnitude, assign it a value, and measure or estimate necessary physical quantities in a real building. For example, we did not include impacts of exposure to volatile organic compound concentrations, for which there is insufficient information to assign a loss value, and no reliable or cost-effective building-grade option for measuring. Additional outcomes can be added in the future as scientific knowledge evolves, without altering the general approach.

The *loss function* L , over a given time horizon with a constant electricity price, is

$$\begin{aligned} L &= L_{WP} + L_{EA} + L_{PM} + L_{O_3} + L_e + L_g \\ &= P_{WP} \cdot LWP + P_{EA}r_{EA} + P_{PM}C_{exp,PM} + P_{O_3}C_{exp,O_3} + P_eE_e/\Sigma_h + P_gE_g/\Sigma_h \end{aligned} \quad (23)$$

The loss terms, which all have units of \$/occ/h, associated with the six included outcomes are:

1. $L_{WP} = P_{WP} \cdot LWP$ is loss due to reduced work performance (WP). Lost work performance (LWP, dimensionless) is a function of VR, expressing the performance at a VR relative to the maximum possible performance. Because the strength of the empirically derived VR-WP correlation is uncertain, the function depends on a user-supplied estimate percentile (EP), as explained in Section 4.2.2. A unit change in LWP is valued at P_{WP} , a user-supplied price (\$/occ/h), most reasonably taken as an employer's cost of compensation for an hour of employee work.
2. $L_{EA} = P_{EA}r_{EA}$ is loss due to employee excess absence (EA) due to sick leave. The excess absenteeism rate (r_{EA} , dimensionless), or the fraction of time workers are absent over and above the minimum possible fraction, is a function of the VR. The function also depends on a user-supplied estimate percentile at which the empirical VR-absenteeism correlation is evaluated. A unit change in r_{EA} is valued at P_{EA} , a user-supplied price (\$/occ/h), again likely an employer's cost of compensation for an hour of employee work.
3. $L_{PM} = P_{PM}C_{exp,PM}$ is loss due to costs of public health risks associated with exposure to $PM_{2.5}$ at an average concentration of $C_{exp,PM}$ ($\mu\text{g}/\text{m}^3$). A unit change in $C_{exp,PM}$ is valued at P_{PM} (\$/occ/h per $\mu\text{g}/\text{m}^3$), which is set by a user based on tabulated results derived from evaluating epidemiological risk functions for different estimate percentiles and population characteristics.
4. $L_{O_3} = P_{O_3}C_{exp,O_3}$ is loss due to costs of public health risks associated with exposure to ozone at an average concentration of C_{exp,O_3} (ppb). A unit change in C_{exp,O_3} is valued at

P_{O_3} (\$/occ/h per ppb), which is set based by a user based on tabulated results of evaluating epidemiological risk functions for different estimate percentiles and population characteristics.

5. $L_e = P_e E_e / \Sigma_h$ is loss due to electricity consumption E_e (kWh), normalized by the total number of occupant-hours in the time horizon Σ_h (occ·h) to be on a comparable per-occupant, per-hour basis. The value of a kWh of consumed electricity, P_e (\$/kWh), can reflect both electricity utility rates and social costs of externalities associated with electricity generation and transmission. A time-varying version for dynamic electricity pricing or demand response is also possible, and is formulated in Section 4.2.5.
6. $L_g = P_g E_g / \Sigma_h$ is loss due to natural gas consumption E_g (kWh), also normalized by Σ_h . The value of a kWh of consumed natural gas, P_g (\$/kWh), can reflect both natural utility rates and social costs of externalities associated with natural gas extraction, delivery, and combustion.

Together L_{WP} and L_{EA} are the *profitable IAQ* impacts, or IAQ_{profit} , for which a business case can be made directly to revenue-maximizing actors. Together L_{PM} and L_{O_3} are the *IAQ public health* impacts, or IAQ_{health} , which will affect workers breathing the indoor air. Together L_e and L_g are the **energy** consumption costs, both direct and social. (We neglected ventilation's impact on sick building syndrome (SBS) symptoms, even though there is an existing relation that has been monetized, because, as Chapter 3 showed, work performance and sick-leave absenteeism have similar associations with ventilation but with values two orders of magnitude greater.)

The loss function depends on the values of five physical variables over the time horizon: the average VR, the average concentrations of $PM_{2.5}$ and ozone to which occupants are exposed ($C_{exp,PM}$ and C_{exp,O_3}), and the electric and natural gas energy consumed (E_e and E_g). Well-developed techniques are available for measuring or modeling all five quantities. As for the definition of "average" for the VR and exposed concentrations, some type of occupant-weighted

mean is intended. Here, where outcomes are primarily drawn from strategies that produce constant or relatively smooth ventilation over time, we use simple averages during the middle of the workday, but more sophisticated metrics may be appropriate for strategies under which ventilation can vary more sharply.

In addition to the five physical variables (VR , $C_{exp,PM}$, $C_{exp,O3}$, E_e , E_g), a value is also required for the occupant-hours sum Σ_h , which is formally the integral of the number of occupants, N_{occ} (occ), present in the control volume (building or zone) evaluated over the time horizon (t_0 to t_f):

$$\Sigma_h = \int_{t_0}^{t_f} N_{occ}(t) dt \quad (24)$$

For example, if ten occupants each worked 8 hours during the time horizon, Σ_h would be 80 occ·h.

The following subsections describe the rationale behind the individual outcomes included in the loss function in Equation (23), as well as guidance to set values of the user parameters.

4.2.2 L_{WP} : Loss due to reduced work performance

The first outcome is lost work performance (LWP), which varies with VR based on the relation for relative work performance, or the proportional difference in worker productivity achieved at two VRs, developed by Seppänen et al. (2006). The change in work performance per each L/s/occ change in the VR, which is valid from 6.5 to 47 L/s/occ, is shown in Figure 19a. The dark blue line is the central estimate, and the grey shaded area is the 95% confidence band of the fit by Seppänen et al. As developed in Chapter 3, this relation can be expressed as the sum of a deterministic function for the central estimate and another function indicating uncertainty. Seppänen et al. gave the former directly, and we fit the latter to the 95% confidence limits under an assumption of normal uncertainty distribution.

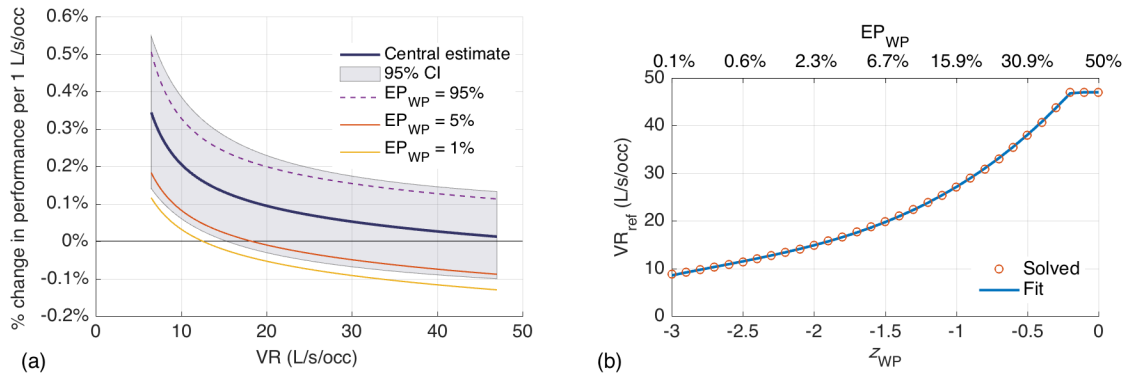


Figure 19 (a) Relative change in work performance (WP) per each 1 L/s/occ change in ventilation rate (VR), at central estimate, 95% confidence interval (CI), and selected estimate percentiles (EP); (b) reference value VR_{ref} , or the VR at which the change in WP is zero, as a function of the EP and the corresponding z_{WP} value.

This approach yields a family of relations parameterized by what we call the *estimate percentile* (EP), in this case for work performance (EP_{WP}). The user can set his or her estimate percentile, with a low EP indicating a weak relation (i.e., there is a small chance that the true relation is weaker, given the studies compiled by Seppänen et al.) and a high EP indicating a strong relation (i.e., a good chance of being stronger than the true relation). Figure 19a shows the curves for $EP_{WP} = 1\%$, $EP_{WP} = 5\%$, and $EP_{WP} = 95\%$, in addition to the central estimate, or $EP_{WP} = 50\%$. An EP value is associated with a standard normal variate, z_{WP} , by means of the quantile function (inverse cumulative distribution function or CDF) of the standard normal distribution (Φ^{-1}),

$$z_{WP} = \Phi^{-1}(EP_{WP}) \quad (25)$$

Cumulative lost performance is judged relative to a reference ventilation rate, VR_{ref} , at which work performance is maximized. If $EP_{WP} > 50\%$, then the $VR_{ref} = 47$ L/s/occ, which is the upper limit for the fit from Seppänen et al. (2006). For $EP_{WP} < 50\%$, the maximum possible work performance is obtained where the resulting curve equals zero. Figure 19b shows the value of VR_{ref} obtained by solving to find the zeros for multiple z_{WP} values. A fit to those results ($R^2 = 1.00$) allows VR_{ref} to be calculated directly as:

$$VR_{ref} = \min(53.60 + 36.41z_{WP} + 11.30z_{WP}^2 + 1.39z_{WP}^3, 47) \quad (26)$$

The work performance at a given VR relative to that at VR_{ref} is determined by integrating the curves for change per L/s/occ from Figure 19a from VR to VR_{ref} (Seppänen et al., 2006). Calling that indefinite integral $g(\cdot)$ and recognizing that lost work performance is unity minus that relative difference,

$$LWP = 1 - \exp(g(VR') - g(VR_{ref})) \quad (27)$$

where $VR' = \min(\max(VR, 6.5), VR_{ref})$ L/s/occ limits VR to a valid range. The function $g(\cdot)$ can be written as the sum of a deterministic central tendency and uncertainty offset determined by z_{WP} ,

$$g(x) = f(x) + z_{WP} \cdot h(x) \quad (28)$$

where

$$f(x) = (-76.38x^{-1} - 0.78x \cdot \ln x + 3.87x)/1000 \quad (29)$$

which was provided in (Fisk et al., 2012) based on the relation in (Seppänen et al., 2006) and

$$h(x) = (-11.617x^{-1.276} + 0.607x)/1000 \quad (30)$$

was developed in Chapter 3.

The final relation between VR and LWP, the result of applying Equations (25) through (30), is shown in Figure 20 for selected EP_{WP} values. For VR above VR_{ref} or below 6.5 L/s/occ, LWP is held at the limit value. To determine the loss for the work performance outcome, the dimensionless LWP is multiplied by P_{WP} (\$/occ/h). This is most likely an employer's cost for an hour of productive employee time. Some guidance about compensation rates for office workers is given in Section 4.2.6.

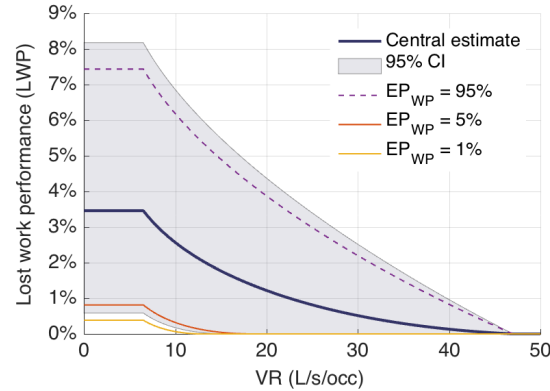


Figure 20 Lost work performance as a function of total ventilation rate (VR), at central estimate, 95% confidence interval (CI), and selected estimate percentiles (EP).

4.2.3 L_{EA} : Loss due to excess employee absence

A second outcome is excess absence (EA) due to illness, based on the work of Milton et al. (2000). That study estimated the relative risk (RR) of sick leave absence at a low VR (estimated as 12 L/s/occ) compared to a higher VR (~24 L/s/occ). The study's central and 95% CI estimates for RR were used to generate an uncertainty distribution. As with LWP, a user can set the relationship strength within this distribution by selecting an estimate percentile, in this case EP_{EA} . By using the inverse CDF, as in Equation (25), EP_{EA} can be associated with a standard normal variate z_{EA} , and then the relative risk can be calculated as:

$$RR_{abs} = \exp(0.116z_{EA}) \cdot 1.53 \quad (31)$$

To extrapolate to a continuous function, we adopted the exponential relative risk model formulated by Fisk et al. (2012), and took as fixed the 2% base absence rate that Milton et al. (2000) reported at 12 L/s/occ. Fisk et al. did not propose formal limits for the relation, but the original study only included VRs at 12 and 24 L/s/occ, and multiple studies have failed to find sick leave or illness absence relations at higher VRs (Mendell et al., 2013; Myatt et al., 2002).

Therefore, we limited the domain to 5–30 L/s/occ, defining $VR'' = \min(\max(VR, 5), 30)$ L/s/occ.

The excess absence rate r_{EA} (dimensionless, or hours absent per hour worked) is then:

$$r_{EA} = 0.02 \cdot \left(RR_{abs}^{(1-VR''/12)} - RR_{abs}^{-1.5} \right) \quad (32)$$

where the first term is the actual absence rate and the second is the minimum possible absence rate at 30 L/s/occ. Figure 21 illustrates Equation (32) for the central estimate ($EP_{EA} = 50\%$) and the 95% confidence band about it, as well as for the relation with $EP_{EA} = 1\%$, $EP_{EA} = 5\%$, and $EP_{EA} = 95\%$. The loss per hour due to an absent employee is the outcome r_{EA} multiplied by P_{EA} (\$/occ/h), likely total hourly employee compensation.

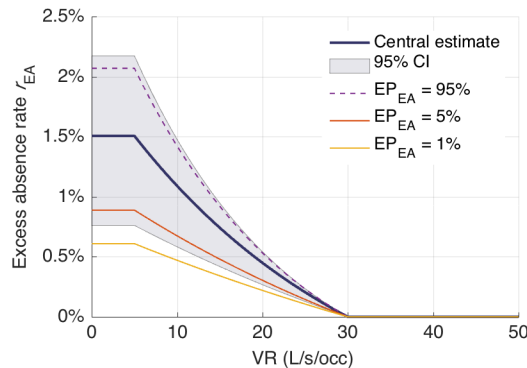


Figure 21 Excess absence rate r_{EA} as a function of total ventilation rate (VR), at central estimate, 95% confidence interval (CI), and selected estimate percentiles (EP).

4.2.4 L_{PM} and L_{O_3} : Losses due public health risks of $PM_{2.5}$ and ozone exposure

Indoor air quality also impacts occupant health in ways that do not figure into the business interests of a decision-maker like a business owner or office manager. Because these impacts are incremental, or modify a small base risk, it makes sense to think of them in the aggregate as public health costs. Many such risks with indoor pollutant exposure have been identified (Chan et

al., 2016; Logue et al., 2012), but nearly all present insurmountable challenges in terms of real-time estimation or of impact quantification.

However, two species introduced from outdoors pass both tests: particulate matter with aerodynamic diameter $< 2.5 \mu\text{g}$ ($\text{PM}_{2.5}$) and ozone (O_3). Multiple large-population studies have established health impacts associated with outdoor concentrations, and a significant amount of exposure to outdoor pollutants occurs indoors (Clausen et al., 2011; Riley et al., 2002). Though uncertainty remains about applying this information to indoor exposures (Brook et al., 2010), we follow the lead of multiple other indoor air studies that have done so (Bekö et al., 2008; Dutton et al., 2013; Logue et al., 2012). For an individual, the change in annual incidence risk Δy_{ij} of a health endpoint j due to a change in average concentration ΔC_i of pollutant i ($\text{PM}_{2.5}$ or ozone) can be modeled with a concentration-response (C-R) function (Fann et al., 2012) as:

$$\Delta y_{ij} = y_{0,j}(e^{\beta_{ij}\Delta C_i f_i} - 1) \quad (33)$$

where β_{ij} is the response coefficient for endpoint j to pollutant i , and $y_{0,j}$ is the population baseline incidence of the endpoint ($\text{occ}^{-1} \text{year}^{-1}$). The variable f_i is the duration of the exposure expressed as a fraction of a year. The coefficient β_{ij} has units of $(\mu\text{g}/\text{m}^3)^{-1}$ for $\text{PM}_{2.5}$ and $(\text{ppb})^{-1}$ for O_3 , and can be derived from RR exposure estimates from epidemiological studies, while the baseline incidences can be determined from broader population health statistics (e.g., from the U.S. Centers for Disease Control). Each endpoint can be assigned a monetary value M_j , allowing calculation of the expected costs of risk changes.

There were eight health endpoints for $\text{PM}_{2.5}$ and seven for ozone. Table 21 lists RR values for the endpoints and baseline prevalence $y_{0,j}$ for non-mortality endpoints. Table 22 gives baseline mortality prevalence for selected populations.

Table 23 lists endpoints' monetary values M_j . The starting point for most of this information was Dutton et al. (2013), itself largely based on standard U.S. Environmental Protection Agency procedures (U.S. EPA, 1999). We then made a number of modifications and additions. For $\text{PM}_{2.5}$

mortality, we included not only the American Cancer Society cohort follow-up (Pope et al., 2002) but also the higher RR estimates of the Harvard six cities study follow-up (Laden et al., 2006). For mortality linked to long-term O₃ exposure, endpoints were altered to match the conclusions of Jerrett et al. (2009), who did not find a significant link to all-cause mortality, but did find one to respiratory mortality. Because respiratory mortality has a much lower baseline incidence, this correction substantially lowered O₃-related mortality and monetary benefits. That reduction was partially reversed by inclusion of a short-term ozone mortality C-R function (Smith, Xu, & Switzer, 2009; Zanobetti & Schwartz, 2008). There were other minor changes, such as for coronary revascularization and non-fatal stroke relations to PM_{2.5} (K. A. Miller et al., 2007; Mozaffarian et al., 2015; U.S. CDC, 2010) and for hospital admissions (Burnett, Cakmak, Brook, & Krewski, 1997). Though presented here for the first time, these are the same parameters used to characterize the health endpoints of indoor PM_{2.5} and ozone exposure in Chapter 3.

Table 21 Concentration-response (C-R) function parameters and baseline incidence for health endpoints associated with PM_{2.5} and ozone. Relative risk (RR) values are per concentration change of 10 µg/m³ for PM_{2.5} or 10 ppb for ozone.

Endpoint	Effect estimates		RR lognormal distribution		Beta normal distribution		Baseline incidence, y ₀	
	RR (95% CI)	Source	GM	GSD	Mean	SD	per 100,000	Source
PM_{2.5} endpoints (RR per 10 µg/m³)								
Mortality, all-cause	1.06 (1.02–1.11)	Pope et al., 2002	1.0600	1.0218	5.83E-03	2.16E-03	----- See Table 22 -----	
Mortality, all-cause	1.16 (1.07–1.26)	Laden et al., 2006	1.1600	1.0426	1.48E-02	4.17E-03	----- See Table 22 -----	
Chronic bronchitis	2.48 (2.18–3.00)	Dutton et al., 2013 ¹	2.4843	1.0851	9.10E-02	8.16E-03	40	Dutton et al., 2013 ¹
Coronary revascularization	1.20 (1.00–1.43)	Miller et al., 2007 ²	1.2000	1.0955	1.82E-02	9.12E-03	1268	U.S. CDC, 2010
Non-fatal stroke	1.28 (1.02–1.62)	Miller et al., 2007 ²	1.2840	1.1245	2.50E-02	1.17E-02	1244	Mozaffarian et al. 2015 ³
Hospital admission, respiratory	1.04 (1.02–1.05)	Burnett et al., 1997	1.0363	1.0080	3.57E-03	7.99E-04	367	Burnett et al., 1997 ⁴
Hospital admission, cardiac	1.02 (1.00–1.05)	Burnett et al., 1997	1.0227	1.0131	2.24E-03	1.31E-03	659	Burnett et al., 1997 ⁴
Minor restricted activity days	1.08 (1.06–1.09)	Dutton et al., 2013 ¹	1.0768	1.0072	7.40E-03	7.14E-04	2140	Dutton et al., 2013 ¹
Asthma attack	1.01 (1.00–1.03)	Dutton et al., 2013 ¹	1.0141	1.0056	1.40E-03	5.59E-04	2700	Dutton et al., 2013 ¹
Ozone endpoints (RR per 10 ppb)								
Mortality, short-term	1.00 (1.00–1.01)	Smith et al., 2009; Zanobetti & Schwartz, 2008	1.0049	1.0012	4.89E-04	1.20E-04	----- See Table 22 -----	
Mortality, respiratory	1.03 (1.01–1.05)	Jerrett et al., 2009	1.0290	1.0095	2.86E-03	9.42E-04	----- See Table 22 -----	
Chronic asthma	1.32 (1.01–1.72)	Dutton et al., 2013 ¹	1.3231	1.1442	2.80E-02	1.35E-02	219	Dutton et al., 2013 ¹
Hospital admission, respiratory	1.06 (1.04–1.08)	Burnett et al., 1997	1.0589	1.0093	5.72E-03	9.24E-04	367	Burnett et al., 1997 ⁴
Hospital admission, cardiac	1.05 (1.02–1.08)	Burnett et al., 1997	1.0494	1.0138	4.82E-03	1.37E-03	659	Burnett et al., 1997 ⁴
Minor restricted activity days	1.02 (1.01–1.04)	Dutton et al., 2013 ¹	1.0222	1.0066	2.20E-03	6.61E-04	2140	Dutton et al., 2013 ¹
Asthma attack	1.02 (1.00–1.03)	Dutton et al., 2013 ¹	1.0182	1.0071	1.80E-03	7.04E-04	2700	Dutton et al., 2013 ¹

1. All values cited from Dutton et al. (2013) were used without modification; see that reference for the original study sources.

2. The Women's Health Initiative (Miller et al., 2007) estimated hazard ratios for 58,610 women, used here as relative risk estimates regardless of sex.

3. Average prevalence for all sexes and races, for ages 20 to 59.

4. Hospital admission baseline incidence estimated from total prevalence in study population (metropolitan Toronto) divided by the study population, unadjusted.

Some of the most important changes were to the baseline incidence of mortality, by far the highest-valued endpoint. Using total population mortality rates, as some previous studies have done, is appropriate for residential assessments but overstates impacts in offices, because non-working populations have higher death rates. Therefore, we adjusted all baseline mortality rates to reflect averages for ages 25–64. In addition, death rates differ substantially by educational attainment and finer age gradations (Table 22). Costs were calculated for some of these subgroups to enable more targeted loss valuation.

Table 22 Death rates per 100,000 for U.S. residents and selected groups.

	Deaths rate, per 100,000				
	Age 25-34	Age 35-44	Age 45-54	Age 55-64	Average ³
All-cause mortality ¹					
All education levels	107	172	408	862	332
High school or less	190	286	638	1271	518
Some college or greater	57	99	228	541	196
Respiratory mortality ²	1	3	14	51	17

All data from U.S. CDC National Vital Statistics Reports, Vol. 64 No. 2, February 2016.

1. For total mortality, the values from two sets of states were averaged, weighted by the sets' populations. Death rates for high school and less than high school, which were very similar, were also averaged, weighted by each group's proportion of total deaths.

2. Not including deaths from influenza and pneumonia, pneumoconiosis and chemical effects, or pneumonitis due to solids and liquids.

3. For ages 25-64. For total mortality, the age-adjusted figure provided by CDC was used. For respiratory causes, it is the population-weighted average of the four age bins.

Table 23 Monetary values of public health IAQ endpoints.

Endpoint	M_j (2016 \$)	Source
Mortality	\$8,920,800	(Dutton et al., 2013)
Chronic bronchitis	\$479,058	(Dutton et al., 2013)
Coronary revascularization	\$101,847	(Stroupe et al., 2006)
Chronic asthma	\$54,798	(Dutton et al., 2013)
Non-fatal stroke	\$21,416	(Guijing Wang et al., 2014)
Hospital admission ¹	\$9,050	(AHRQ, 2016)
Minor restricted activity days	\$71	(Dutton et al., 2013)
Asthma attack	\$45	(Dutton et al., 2013)

General note: All values cited from (Dutton et al., 2013) were used without modification; see that reference for the original sources.

1. Hospital admission for general medical treatment, excluding mental health, childbirth and neonatal treatment, and admissions for surgery.

Combining the costs of all endpoints associated with a concentration change ΔC_i of a pollutant, sustained over a fraction of the year f_t , we have:

$$(\Delta \text{ risk costs})_i = \sum_j M_j y_{0,j} (e^{\beta_{ij} \Delta C_i f_t} - 1) \approx \sum_j M_j y_{0,j} \beta_{ij} \Delta C_i f_t \quad (34)$$

where the simplification holds because $e^a - 1 \approx a$ for very small a . Testing with sampling from the distributions of β_{ij} indicated that the error introduced by linearization was negligible when f_t represented a day, and almost never greater than 5% even when f_t represented a full work year of consistently very large concentration changes.

Hourly risk costs are evaluated by setting f_t to 1/8760. We define a price as:

$$P_i = \sum_j M_j y_{0,j} \beta_{ij} / 8760 \quad (35)$$

that indicates the value (in \$, often expressed ϕ) of a one unit change in indoor concentration ($\mu\text{g}/\text{m}^3$ or ppb) for one occupant for one hour. We calculated distributions of P_i values using a Monte Carlo sample from the β_{ij} distributions listed in Table 21, and other parameters in Table 22 and

Table 23. For $\text{PM}_{2.5}$ mortality, we selected with equal probability from the American Cancer Society (Pope et al., 2002) and Harvard six cities (Laden et al., 2006) studies' RR estimate distributions. Results indicated that, for both $\text{PM}_{2.5}$ and ozone, total mortality was by far the largest contributor due to its high monetary value. There were additional moderate contributions from chronic bronchitis and coronary revascularization for $\text{PM}_{2.5}$ (4–21%, depending on the subgroup's death rate) and chronic asthma for ozone (11–41%, depending on subgroup). No other endpoint contributed more than 6% in any group.

Figure 22 shows inverted CDF plots of the P_{PM} and P_{O_3} results against the estimate percentiles (EP), and Table 24 gives some specific numerical results. For the 'All' group, death rates for all people aged 25–64 were used, while 'HS or less' and 'College' divided the working

age population by education level (where HS stands for high school), and ‘College, young’ used death rates for college-educated 25–44 year-olds. Because of the dominant influence of mortality risk, the prices for the young college-educated population were extremely low, while those for the general non-college-educated population were 3 to 5 times greater. For $PM_{2.5}$, the two distinct regions results represent RR based on (Pope et al., 2002) below the 50th percentile, and on (Laden et al., 2006) above the 50th percentile.

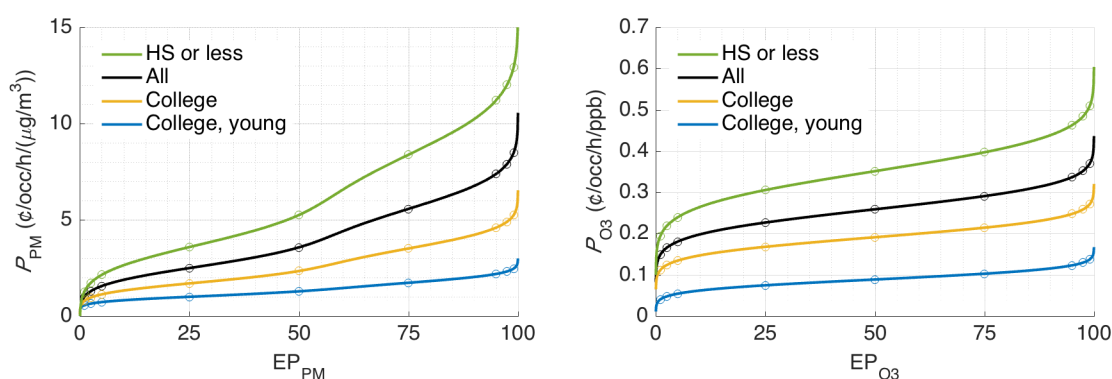


Figure 22 Unit prices for $PM_{2.5}$ and ozone exposure expressed in cents (¢), derived from sampling public health concentration-response functions and endpoint monetary values, versus the estimate percentile (EP) of the Monte Carlo results.

Table 24 Prices P_{PM} and P_{O_3} for unit, hour-long, per-occupant changes in concentration. Prices are shown in cents. $PM_{2.5}$ prices are for the blended sample including both American Cancer Society and Harvard Six Cities relative risk distributions.

	PM _{2.5} and ozone prices for selected estimate percentiles (EP)								
	1	2.5	5	25	50	75	95	97.5	99
P_{PM} (¢/occ/h/(µg/m ³))									
All	1.0	1.3	1.6	2.5	3.6	5.6	7.4	7.9	8.5
High school or less	1.3	1.7	2.1	3.6	5.2	8.4	11.2	12.0	12.9
Some college or more	0.8	1.0	1.1	1.7	2.3	3.5	4.6	4.9	5.2
College, and young	0.6	0.6	0.7	1.0	1.3	1.7	2.2	2.3	2.5
P_{O_3} (¢/occ/h/ppb)									
All	0.1	0.2	0.2	0.2	0.3	0.3	0.3	0.4	0.4
High school or less	0.2	0.2	0.2	0.3	0.4	0.4	0.5	0.5	0.5
Some college or more	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3
College, and young	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Subpopulation variations based only on differences in mortality rates. 'All' includes ages 25-64 and 'young' includes ages 25-44.

To assess loss in comparison to a complete absence of the pollutant, the relevant concentration change ΔC_i is just the concentration C_i . Therefore, the instantaneous risk cost is $P_i C_i(t)$, and loss is determined by multiplying this expression by the number of occupants present, integrating over the time horizon, and then normalizing on a per-occupant, per-hour basis, as in:

$$L_i = \frac{\int_{t_o}^{t_f} N_{\text{occ}}(t) P_i C_i(t) dt}{\Sigma_h} = P_i \frac{\int_{t_o}^{t_f} N_{\text{occ}}(t) C_i(t) dt}{\Sigma_h} = P_i C_{\text{exp},i} \quad (36)$$

where the implicitly defined quantity $C_{\text{exp},i}$ is simply the occupant-weighted average concentration of pollutant i to which occupants are exposed during time horizon, expressed in the units of pollutant i .

4.2.5 L_e and L_g : Losses due to electricity and natural gas consumption

The final two outcomes are electricity and natural gas consumption, respectively denoted E_e and E_g (kWh) and valued at prices P_e and P_g (\$/kWh, often expressed in ϕ /kWh). The prices can include standard utility rates as well as social costs, if desired. For a static electricity price, the losses are simply the price times the usage, normalized by the number of occupant hours Σ_h :

$$L_e = P_e E_e / \Sigma_h \quad (\text{for constant } P_e) \quad (37a)$$

$$L_g = P_g E_g / \Sigma_h \quad (37b)$$

Dynamic electricity pricing can also be incorporated—a possibility we explore in Chapter 5. Dynamic pricing structures are relevant in smart-grid settings, for time-of-use (TOU) pricing and demand-response applications. They might also be needed if social costs change as a supply mix changes, for example, with intermittent use of on-site solar. In either case, the loss is then the integration over time of the product of instantaneous price and the consumption rate $E'_e(t)$ (kW),

$$L_e = \frac{1}{\Sigma_h} \int_{t_o}^{t_f} P_e(t) E'_e(t) dt \quad (38)$$

The energy consumption prices P_e and P_g can have two contributors: utility rates and social costs. The first two columns of Table 25 show the median of annual average commercial utility rates for grid electricity and for purchased natural gas from 2005 to 2015, broken down by U.S. state (U.S. Energy Information Administration (EIA), n.d.-a). A majority of states had median commercial electricity prices of 8.4–11.7 ¢/kWh, and all states except Hawaii were 6.9–17.3 ¢/kWh. For natural gas, the majority of states' commercial prices were 2.9–3.8 ¢/kWh, and all except Hawaii were \$2.5–5.4 ¢/kWh. (For both sources, prices were also relatively stable over time during 2005 to 2015, only very rarely deviating from the medians by more than 2 ¢/kWh.)

The second contributor to energy prices is a judgment related to the “social costs” of energy production, generation, and distribution that are not reflected in current market prices. What to include among externalized costs and how to calculate them are subjects of substantial debate and uncertainty. For electricity, the largest social cost is often due to public health impacts of exposure to regional air pollution generated from coal-fired (and to a lesser extent, oil and natural gas) power plants. Machol and Rizk (2013), building on the work of Fann (Fann, Fulcher, & Hubbell, 2009), calculated the public health impacts of existing U.S. power generation. Their work only considers PM_{2.5}, but includes both primary or directly-emitted particles and secondary particles resulting from precursors SO₂ and NO_x generated by fossil fuel combustion. Their calculation is based on pollution inventories for all U.S. power plants, used as inputs to a model that includes atmospheric chemistry, weather, and the geographic distribution of U.S. population.

Table 25 Reference prices by U.S. state for components of P_e and P_g . Utility rates are medians of annual averages from 2005 to 2015. The health costs are for combustion-related public health impacts for grid electricity (Machol & Rizk, 2013).

	Natural Gas utility rate (¢/kWh)	Electric grid utility rate (¢/kWh)	Electric grid, combustion health costs (¢/kWh)
<i>U.S.</i>	3.3	10.9	24.5
Alabama	4.6	10.8	32
Alaska	2.8	15.3	-
Arizona	3.7	9.9	10
Arkansas	3.4	8.0	17
California	2.9	14.5	7
Colorado	2.8	9.6	12
Connecticut	3.6	16.5	4
Delaware	5.0	11.6	42
District of Columbia	4.4	13.4	-
Florida	3.8	10.5	20
Georgia	4.0	9.9	33
Hawaii	13.3	30.4	-
Idaho	2.9	6.9	-
Illinois	3.4	9.4	25
Indiana	3.0	9.1	36
Iowa	2.8	8.4	27
Kansas	3.7	8.8	17
Kentucky	3.5	8.5	28
Louisiana	3.4	9.2	14
Maine	4.4	13.3	3
Maryland	3.7	12.2	71
Massachusetts	4.1	15.4	15
Michigan	3.3	10.4	31
Minnesota	2.7	8.9	13
Mississippi	2.9	10.3	14
Missouri	3.9	7.9	26
Montana	3.2	9.3	15
Nebraska	2.5	8.2	26
Nevada	3.3	10.9	5
New Hampshire	4.8	15.1	42
New Jersey	3.4	13.9	19
New Mexico	2.7	9.5	12
New York	3.5	17.3	11
North Carolina	3.6	8.7	23
North Dakota	2.6	7.7	41
Ohio	3.3	9.9	48
Oklahoma	4.4	8.1	13
Oregon	3.5	8.3	6
Pennsylvania	3.8	10.4	50
Rhode Island	5.4	14.4	-
South Carolina	3.5	9.7	30
South Dakota	2.6	8.0	34
Tennessee	3.4	10.3	27
Texas	2.8	10.3	15
Utah	2.6	7.7	11
Vermont	4.4	14.4	-
Virginia	3.4	8.1	31
Washington	3.8	7.8	10
West Virginia	3.7	7.7	20
Wisconsin	2.9	10.7	29
Wyoming	2.7	8.1	21

Note: The California $PM_{2.5}$ combustion-related health social cost reflects externalities incurred in other states due to imported electricity.

The third column of Table 25 shows Machol and Rizk's average results for each U.S. state for these combustion-related PM_{2.5} health impacts of U.S. electricity generation. Even the states with the lowest estimates—Connecticut, Maine, Nevada, and Oregon—have combustion-related externalities \$0.03–0.06 per kWh, or 25–70% as much as those states' respective median commercial retail utility rates. The most affected states are those like Maryland (\$0.71 /kWh), Pennsylvania (\$0.51 /kWh), and Ohio (\$0.48 /kWh), with continued reliance on coal-fired generation and significant population centers, and where PM_{2.5} exposure externalities are 5 to 6 times as great as the direct cost of electricity. (Other researchers have arrived at much lower estimates, discussed below.)

Perhaps the most well-known energy externality is the social cost of carbon (SC-CO₂), which attempts to capture the impacts of a marginal unit of energy on future climate change damages. The US Government Interagency Working Group on Social Cost of Greenhouse Gases and U.S. EPA (Interagency Working Group on Social Cost of Greenhouse Gases, 2016; U.S. EPA, 2015c) have estimated SC-CO₂ values ranging from \$13–130 per ton of CO₂ emitted (updated to 2016 US\$). The low estimate is for a high discount rate (5%), indicating low present valuation of future impacts, and the highest value is for a close to worst-case (95th percentile) future damage scenario. More conservatively, Nordhaus (2014) has estimated the 2015 SC-CO₂ at \$23 per ton of CO₂. Recently, Moore and Diaz (2015) incorporated feedbacks between climate change economic impacts and the discount rate, and determined the optimal SC-CO₂ trajectory to limit global temperature rise to 1.5 °C; the value of that trajectory in 2015 was \$220 per ton of CO₂.

For electricity generation, one can use SC-CO₂ values with source emission factors—i.e., ton of CO₂ emitted per kWh delivered (U.S. Energy Information Administration (EIA), n.d.-b, n.d.-c; U.S. EPA, 2015a)—to determine the climate change social cost of electricity consumption. Table 26 shows resulting figures for fossil fuel generation sources. For the total U.S. electric grid, the marginal value of climate impacts ranges from 0.9–15.5 ¢/kWh. The costs may go even higher in

areas with significant dependence on coal for electricity generation, and might be lower in some areas of the country with significant hydroelectric or wind generation.

Table 26 Climate change components of P_e , in U.S. cents per kWh, for fossil fuel generation sources and the marginal value for the U.S. electric grid, at multiple social costs of carbon dioxide (SC-CO₂) emission estimates. Note for natural gas, the estimates are only for CO₂ from combustion, not warming due to methane leakage.

Generation source	Emission factor (ton CO ₂ per kWh)	SC-CO ₂ = \$13 / ton	SC-CO = \$23 / ton	SC-CO ₂ = \$45 / ton	SC-CO ₂ = \$67 / ton	SC-CO ₂ = \$130 / ton	SC-CO ₂ = \$220 / ton
Coal	9.93E-04	1.3	2.2	4.4	6.7	12.9	21.8
Natural gas	3.93E-04	0.5	0.9	1.8	2.7	5.1	8.7
Oil	8.37E-04	1.1	1.9	3.7	5.6	10.9	18.4
Marginal (non-baseload) national grid	7.03E-04	0.9	1.6	3.1	4.7	9.2	15.5

Emission factors for electricity generation from US EPA (2016) GHG inventory figures and US EIA (2014) net generation figures. Non-baseload factor from US EPA (2015) eGRID.

From left to right, SC-CO₂ values are from US EPA (2014) average scenario and 5% discount rate; Nordhaus (2014); US EPA (2014) average scenario and 3% discount rate; US EPA (2014) average scenario and 2.5% discount rate; US EPA (2014) 95th percentile scenario and 3% discount rate; and Moore and Diaz (2015). EPA values are for costs in mid-2017, and others are for costs in 2015. All figures adjusted to 2016 US\$.

Table 27 summarizes the range of impact estimates for multiple types of externalities, including climate-related and combustion-related costs as well other externalities like environmental damages due to fuel extraction and reduced agricultural yields as a function of pollution. The estimate range is large. For example, Machol and Rizk's national PM_{2.5} exposure cost estimate is \$0.14–0.35 /kWh, but Muller et al. (Muller, Mendelsohn, & Nordhaus, 2011) only estimated it at \$0.02 /kWh. According to Machol and Rizk, Muller et al. arrived at such a low estimate because they did not “examine the variation at the state or plant level” and also use “a source-receptor (SR) model which does not account for nonlinearities resulting from photo-chemical reactions.” Other estimates have fallen in between (Epstein et al., 2011; Shindell, 2015). Summing the literature estimates of the various social costs yields a range 4.8–53.6 ¢/kWh, for the U.S. average. Excluding combustion-related public health impacts, which can be added for a particular state from Table 25, U.S. average social cost totals are 3.2–18.6 ¢/kWh.

Table 27 Summary of social cost estimate ranges for electricity generation for the U.S. grid, in U.S. cents (¢) per kWh.

	Climate impacts	Combustion-related health impacts	Other impacts, e.g. crops, extraction	Social costs, U.S. electric grid (¢/kWh)	Source
Social cost of carbon	✓			0.9–15.5	Various, see Table 26
Combustion PM _{2.5} impacts on public health		✓		14.0–35.0	Machol & Rizk (2013)
"Gross external damages"		✓	✓	1.6	Muller et al. (2011)
"Social cost of atmospheric release"	✓	✓	✓	6.5–20.1	Shindell (2015)
Total coal lifecycle	✓	✓	✓	3.9–11.6	Epstein (2011)
Coal lifecycle (excluding climate and combustion)			✓	2.3–3.1	Epstein (2011)
<i>SUM of non-overlapping social costs</i>	✓	✓	✓	4.8–53.6	
<i>SUM of costs, excluding combustion-related health</i>	✓		✓	3.2–18.6	

Although most social cost research has focused on the externalities of electricity generation, natural gas delivered for consumption on site for space or water heating also has significant social costs. Unfortunately, it is difficult to assign costs to many local impacts of natural gas use, transportation, and extraction. While we discuss some of these briefly at the end of this section, only the climate impact of natural gas use has been included at present. Table 28 summarizes climate change impacts per kWh of delivered heat content of natural gas. The cost depends on three principal factors: the SC-CO₂ value, the system-wide methane leakage rate, and the global warming potential time horizon.

Table 28 Social costs of purchased natural gas for on-site combustion, per kWh of delivered heat content, at six possible social cost of carbon dioxide (SC-CO₂) values. The first line assumes no methane leakage. The remainder of the table uses hypothetical leakage rate at two different time horizons to calculate prices including climate impacts of methane leakage.

Leakage rate	Time horizon ¹ (years)	Emission factor (ton CO ₂ e per kWh)	SC-CO ₂ = \$13 / ton	SC-CO = \$23 / ton	SC-CO ₂ = \$45 / ton	SC-CO ₂ = \$67 / ton	SC-CO ₂ = \$130 / ton	SC-CO ₂ = \$220 / ton
0%	-	1.81E-04	0.2	0.4	0.8	1.2	2.4	4.0
1%	100	2.03E-04	0.3	0.5	0.9	1.4	2.6	4.5
3%	100	2.49E-04	0.3	0.6	1.1	1.7	3.2	5.5
5%	100	2.97E-04	0.4	0.7	1.3	2.0	3.9	6.5
10%	100	4.26E-04	0.6	1.0	1.9	2.9	5.5	9.4
1%	20	2.37E-04	0.3	0.5	1.1	1.6	3.1	5.2
3%	20	3.54E-04	0.5	0.8	1.6	2.4	4.6	7.8
5%	20	4.75E-04	0.6	1.1	2.1	3.2	6.2	10.4
10%	20	8.01E-04	1.0	1.8	3.6	5.4	10.4	17.6

¹The global warming potential (GWP) of methane is 34 times that of CO₂ over a 100 year time horizon, and 86 times as great over a 20 year horizon (Myhre et al., 2013).

Assuming no methane leakage, the climate-related externality price is 0.2–4.0 ¢/kWh. These prices are much lower than those associated with using natural gas for electricity generation, where about two-thirds of heat content is not converted to electricity. However, if methane leakage during extraction and transportation is taken into account, the climate change social costs associated with natural gas use could be much larger.

The U.S. EPA estimates a leakage rate of 2.5% for conventional gas and 4.0% for hydraulically fractured shale gas (Cathles, Brown, Taam, & Hunter, 2012; U.S. EPA, 2016). This would imply a 3.5% overall leakage rate, since in 2015 about two-thirds of U.S. natural gas was produced by hydraulic fracturing (U.S. Energy Information Administration (EIA), n.d.-d). Some researchers have endorsed this rough magnitude (Cathles et al., 2012), but lower estimates also exist (D. T. Allen et al., 2013). Other research has suggested that methane emissions associated with natural gas production may be significantly greater (Karion et al., 2013; S. M. Miller et al., 2013), and that wells may leak substantially more methane than expected (Ingraffea, Wells, Santoro, & Shonkoff, 2014), potentially for a very long time after production has ceased (Kang et al., 2014), and that methane emissions from shale gas production systems can rise even as drilling activity declines (Goetz et al., 2017). In addition, recent studies suggest urban distribution infrastructure could be a significant loss pathway, leaking an estimated 2.7% in the local system in Boston, for example (McKain et al., 2015). One synthesis of the research compiled leakage rate estimates of 1.7–6.0% for conventional gas and 3.6–7.9% for shale gas (Howarth, Santoro, & Ingraffea, 2011), while another surveyed the research and reported a range of 0.2–10%, globally (Balcombe, Anderson, Speirs, Brandon, & Hawkes, 2017).

The other significant influence on the climate impact of methane is the time horizon, since methane does not persist in the atmosphere as long as does CO₂. Some have argued that a 100-year horizon is appropriate under an assumption of gradual change (Cathles et al., 2012), while others hold that a 20-year frame is also important to avoid sudden climate system tipping points that could create feedback effects (Howarth, Santoro, & Ingraffea, 2012). Table 28 includes

estimates for both, at four hypothetical natural gas system leakage rates, for both time horizons' methane global warming potential (Myhre et al., 2013).

Social cost estimates were only made for the climate change externalities of natural gas use, but there are many other impacts that have costs, even if they are complex and difficult to quantify. In particular, Sovacool and Finkel & Law have summarized many of the negative consequences of shale gas development and transportation, including: use and pollution of fresh water, local air pollution from diesel pumps and trucks, leakage and accidents at sites and pipelines, toxic and radioactive wastewater and hazardous waste, local health impacts ranging from increased asthma incidence to potential miscarriages and cancers, earthquakes, reduced property values, and significant public expense for infrastructure and environmental remediation (Finkel & Law, 2011; Sovacool, 2014). Also not priced in this work, but worth noting, are any possible negative impacts from natural gas at the combustion site, i.e., near the building heated with natural gas. Though a recent study found few impacts from small boilers and furnaces on local levels of ozone or $PM_{2.5}$ (Penn et al., 2016), there could potentially be other combustion products with health impacts.

4.2.6 Reference values for user parameters in the loss equation

To explore the influence of user preferences, we developed reference values for all parameters used in the OBV loss function. For P_{WP} and P_{EA} , we compiled data on employment numbers, hourly wages, and hourly compensations for office workers in various fields from the U.S. Bureau of Labor Statistics (U.S. DOL, 2016a, 2016b). Table 29 lists this information. The employment-weighted average hourly wage was \$31, while the average total compensation including benefits was \$46 per hour.

Table 29 Summary of occupation categories, base wages, and total compensation per hour for U.S. office workers

U.S. Bureau of Labor Statistic (BLS) category	BLS code	Employment (millions)	Fraction of office workers (%)	Average wage (\$/h)	Average compensation (\$/h)
Management Occupations	11-0000	6.9	14%	\$58	\$86
Business and Financial Operations Occupations	13-0000	7.0	14%	\$37	\$55
Office and Administrative Support Occupations	43-0000	21.8	44%	\$18	\$27
Computer and Mathematical Occupations	15-0000	4.0	8%	\$44	\$64
Building Cleaning Workers	37-2010	3.1	6%	\$13	\$19
Supervisors of Building, Grounds, and Maintenance Workers	37-1000	0.3	1%	\$22	\$32
Architecture and Engineering Occupations	17-0000	2.5	5%	\$42	\$62
Legal Occupations	23-0000	1.1	2%	\$52	\$77
Art and Design Workers	27-1000	0.6	1%	\$26	\$39
Media and Communication Workers	27-3000	0.6	1%	\$31	\$46
Media and Communication Equipment Workers	27-4000	0.2	0%	\$27	\$40
Sales Representatives, Services	41-3000	1.8	4%	\$35	\$51
<i>Weighted average</i>	-	<i>49.9</i>	<i>100%</i>	<i>\$31</i>	<i>\$46</i>

For all user parameters, we selected low, medium, and high “reference values” to use to evaluate to OBV framework (Table 30). For parameters with distributions, the low, medium, and high reference values corresponded to the 5th, 50th, and 95th percentiles. That applied to the EP_{WP} and EP_{EA} settings that determine the strength of work performance and excess absenteeism relations to the VR. It also applied to the EP_{PM} and EP_{O_3} settings that determine the strength of public health impacts to changes in $PM_{2.5}$ and ozone concentrations, respectively; for public health relations, the values based on ‘All’ (ages 25–64) death rates were used. The reference values for P_{WP} and P_{EA} were based on total compensation (i.e., including benefits) per hour, with the low value corresponding to office and administrative support occupants, the medium value to the \$46/hour weighted average for all office workers, and the high value to management occupations.

Table 30 Low, medium, and high reference values for user-defined parameters in the loss function. The P_{PM} and P_{O_3} values correspond to respective EP_{PM} and EP_{O_3} values for all office occupants ages 25-64.

User parameter	Unit	Low value	Medium value	High value
$EP_{WP}, EP_{EA}, EP_{PM}, EP_{O_3}$	%	5	50	95
P_{WP}, P_{EA}	\$/occ/h	27	46	86
P_{PM}	¢/($\mu\text{g}/\text{m}^3$)/occ/h	1.56	3.57	7.38
P_{O_3}	¢/ppb/occ/h	0.18	0.26	0.34
P_e	¢/kWh	6.9	14.7	79.0
P_g	¢/kWh	2.5	3.7	15.8

For P_e the low value is the lowest state utility rate (Idaho) from Table 25. The medium value is the median state utility rate (9.9 ¢/kWh) plus a modest social cost estimate: 4.8 ¢/kWh, which was the lowest possible “Sum of non-overlapping social costs” for U.S. electricity generation from Table 27. The high value is the utility rate (10.4 ¢/kWh) plus public health cost of combustion for electricity generation (50.0 ¢/kWh) for the state with the second highest sum of those values (Pennsylvania), plus the highest estimate (18.6 ¢/kWh) for the “Sum of costs, excluding combustion-relation health” from Table 27.

For P_g the low value is the lowest state utility rate (Nebraska). The medium value is the median state utility rate (3.4 ¢/kWh) plus a small climate change externality (0.3 ¢/kWh) based on the lowest possible SC-CO₂ value with 1% methane leakage and a 100-year time-horizon. The high value is the utility rate (5.4 ¢/kWh) in the second most expensive state (Rhode Island) plus a climate change externality (10.4 ¢/kWh) based on the highest possible SC-CO₂ value with 5% methane leakage and a 20-year time-horizon.

4.2.7 Office sector dataset

We explored the magnitude of the loss function over the same dataset of energy simulation results that has been described in Chapter 2 and Chapter 3. For the present work, we sampled to achieve a dataset that was 75.9% small offices and 24.1% medium ones, matching the distribution

for number of office types in the U.S. (U.S. Energy Information Administration (EIA), 2015a). In addition, whereas in previous chapters the dataset was examined at an annual timescale, here individual days' results are examined. The final sampled datasets, believed to be good statistical representations of the U.S. small-to-medium-large office stock, had 5000 instances for annual results, with 1,260,000 instances for day-resolved values. Of the simulated ventilation strategies, four are included here: the baseline, doubled mechanical ventilation, or $2\times VR$; differential enthalpy economizing with the baseline VR as the minimum, or Econ; and demand-controlled ventilation (DCV), in which enough outdoor air was provided to avoid exceeding 950 ppm of CO_2 in the critical (highest CO_2 concentration) zone.

Figure 23 includes histograms of results of five key simulation outputs over the dataset, for the four ventilation strategies used in this work. These are day-resolved values, and are averages during primary occupied hours of 8 a.m. to 6 p.m. The VR, here and in all that follows, refers to the total outdoor air rate, including the sum of mechanical ventilation and infiltration divided by average number of occupants. That is why even ventilation strategies like ASHRAE 62-2001 and $2\times VR$, in which the mechanically-provided OA was fixed, had substantial variability. At a glance, Figure 23 gives a sense of typical results and of the extent to which ventilation strategy changes affected outcomes.

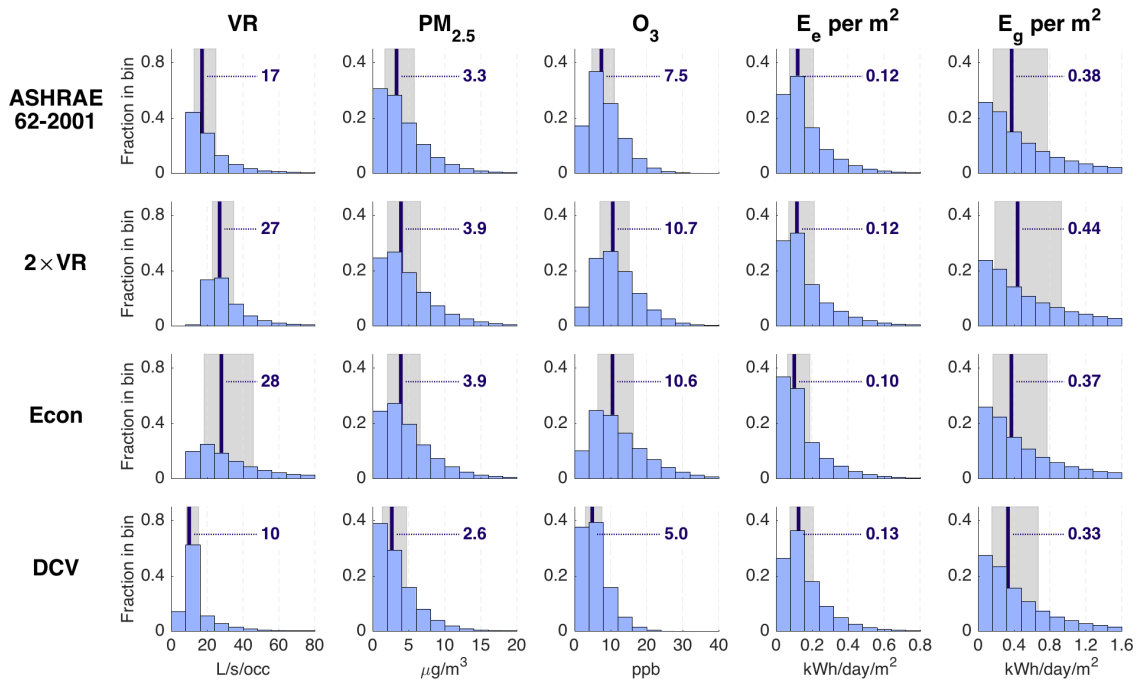


Figure 23 Day-resolved histograms for five outcomes—total (mechanical + natural) ventilation rate (VR), PM_{2.5} and O₃ indoor concentrations, and electricity and natural gas daily use intensities—for four ventilation strategies. In the background, the dark line with the numerical label indicates the median and the gray box extends from the 25th to 75th percentile of instances.

4.3 Results and discussion

4.3.1 Outcome loss magnitudes

Figure 24a shows the range of magnitude of losses for each outcome for the low, medium, and high reference values from Table 30, for the baseline ASHRAE 62-2001 ventilation strategy. It is immediately clear that the profitable IAQ outcomes generated much greater losses than did IAQ public health or energy ones. With medium parameter values, median ASHRAE 62-2001 losses for work performance and excess absence were 0.69 and 0.28 \$/occ/h, respectively, while PM_{2.5} and ozone losses were 0.12 and 0.02 \$/occ/h, respectively, and electricity and natural gas losses were 0.04 and 0.00 \$/occ/h, respectively. With high reference parameters, the contrast was even starker, with performance and absence losses rising to 3.81 and 0.63 \$/occ/h, respectively, while no other component exceeded 0.24 \$/occ/h.

The much greater value of profitable IAQ impacts compared to energy ones is not a surprise, given the 1.5–2 order of magnitude difference already observed for the office sector (Ben-David et al., 2017; Fisk et al., 2012). The relative magnitude of public health impacts was smaller than has previously been suggested (Dutton et al., 2013). That difference is because of our focus on the working-age population that occupies offices, which have a lower mortality rate; the relative magnitude was similar to that observed in Chapter 3.

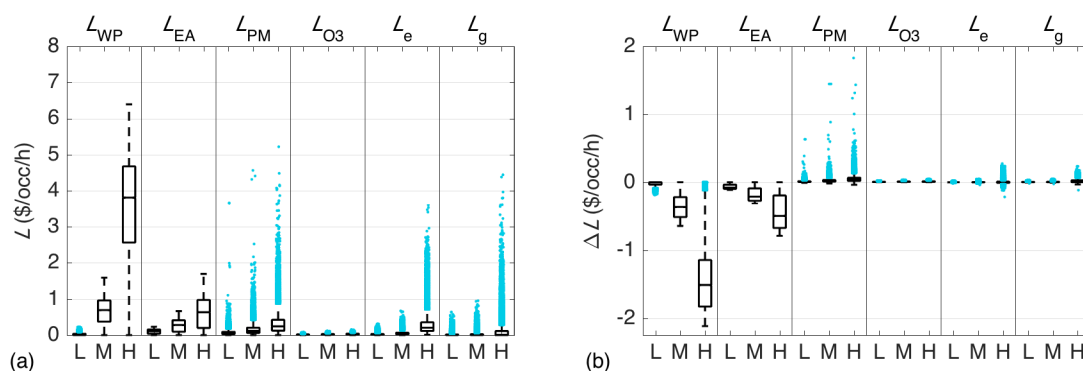


Figure 24 (a) Magnitude of loss components for ASHRAE 62-2001 and (b) loss component changes when switching from ASHRAE 62-2001 to $2 \times VR$. Magnitudes and changes are shown at low (L), medium (M), and high (H) parameter reference values.

Ultimately, the difference in losses produced by available strategies, not the absolute magnitude of losses themselves, drives outcome-based ventilation. Figure 24b shows the outcome loss changes when switching from the ASHRAE 62-2001 minimum rate to $2 \times VR$, which equates to adding ~ 10 L/s/occ to the VR. The median loss changes, with medium-valued parameters, were -0.36 (L_{WP}), -0.21 (L_{EA}), 0.02 (L_{PM}), 0.01 (L_{O3}), 0.00 (L_e), and 0.00 (L_g) $\$/occ/h$. As expected, increasing ventilation always reduced losses related to productivity and sick leave, nearly always increased public health and natural gas consumption losses, and usually increased electricity consumption loss. Given this fact and the difference of component magnitudes, almost every set of user parameters would nearly always lead to a decision to increase ventilation.

In fact, the *only* possible set of parameters under which the profitable benefits of increasing ventilation would be meaningfully opposed by the deleterious impacts on public health and energy is one in which IAQ_{profit} parameters are quite low while IAQ_{health} or energy parameters, or both, are quite high. Figure 25 illustrates this fact with an enlargement of the 0–0.50 \$/occ/h range, and IAQ_{profit} differences negated for graphical comparison. With low-level parameters, the median IAQ_{profit} was -0.09 \$/occ/h. With *high*-level parameters, the medians were 0.05, 0.01, 0.07 \$/occ/h for IAQ_{health} , Energy, and their sum, respectively.

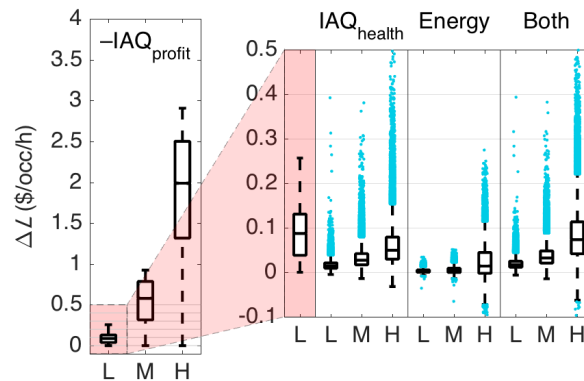


Figure 25 Change in loss moving from ASHRAE 62-2001 to $2\times VR$, shown on the left for the negation of IAQ_{profit} at three levels, and then enlarged on the right to include low-valued IAQ_{profit} and all three levels for IAQ_{health} , energy, and their sum.

To further illustrate the dominance of IAQ_{profit} outcomes, consider the ratio of loss changes in IAQ_{profit} to loss changes in the other two categories, again when adding ~ 10 L/s/occ to the ASHRAE 62-2001 minimum VR. IAQ_{profit} and IAQ_{health} were always in conflict, and IAQ_{profit} and Energy were in conflict (i.e., no free cooling) 72% of the time. In these tradeoff situations, when the initial VR was 15 L/s/occ or less and using all medium parameters, the reduced IAQ_{profit} loss was, at the median, 22 times as large as the added IAQ_{health} loss, and 150 times as large as the added Energy loss. Even with the most ventilation-adverse settings—with low IAQ_{profit}

parameters and high IAQ_{health} and energy parameters—the median reduction in IAQ_{profit} loss was twice the added IAQ_{health} loss and five times the added energy loss.

4.3.2 Decisive outcomes and categories

So far we have examined outcome losses for ASHRAE 62-2001 and $2\times VR$, and the differences between them, and seen the dominant role of profitable IAQ impacts. Here and in the following two sections, we expand analysis to the implications for decision-making when considering all four ventilation strategies: ASHRAE 62-2001, $2\times VR$, Econ, and DCV. Two sets of user preferences are employed for illustration. ‘Medium Parameters’ simply uses the medium reference values from Table 30 for all user parameters. ‘Public & Planet’ is the ventilation-adverse parameter set just described: low reference values for profitable IAQ parameters (EP_{WP} , EP_{WP} , P_{WP} , P_{EA}), and high reference values for parameters related to IAQ public health (P_{PM} , P_{O3}) and energy (P_e , P_g). Since the influence of IAQ_{profit} is so decisive, any parameter set other than ‘Public & Planet’ would lead to nearly the same decisions as ‘Medium Parameters.’

First, we examine which components were most influential on outcome-based ventilation. Figure 26 shows the percentage of occurrences where removing a particular outcome or category changed the outcome-based VR (among the options produced by the four existing strategies) by at least 1 L/s/occ. With Medium Parameters, the IAQ_{profit} category was truly decisive. As long as either L_{WP} or L_{EA} was present, the decision usually remained the same: use the strategy with the highest VR. If both L_{WP} and L_{EA} were removed, the outcome-based VR nearly always changed. For Public & Planet, the tradeoffs were more complex. All outcomes were sometimes influential on their own at least 10% of the time, and L_{WP} , L_{EA} , and L_{PM} changed the decision at least 25% of the time. Removing any of the three categories changed the decision at least one-third of the time.

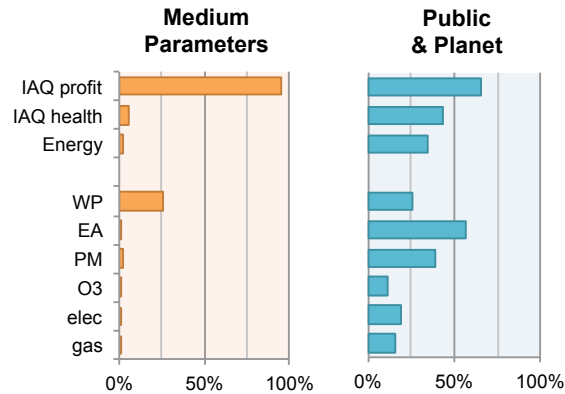


Figure 26 Impact of loss function elements on ventilation strategy decision-making. Percentage of day instances where removing an outcome changed the outcome-based VR (among the options available by at least 1 L/s/occ).

4.3.3 Outcome-based VRs and parameter sensitivity

To examine outcome-based VRs, we compiled daily VRs resulting from the four strategies, screening the set to only include the 580,013 days where there was at least one VR less than 15 L/s/occ, one between 15 and 25 L/s/occ, and one above 25 L/s/occ. For each day, the VR that produced the lowest loss was recorded. Summary statistics and bin membership (Table 31) broadly indicate the magnitude of outcome-based VRs, even if they are not quite *optimal* outcome-based VRs (since the strategies did not intentionally minimize loss). The results indicated much greater ventilation than the 8.5 L/s/occ minimum prescribed by ASHRAE 62.1-2016 for a typical office space, with medians near 30 L/s/occ for both illustrative user profiles. With Medium Parameters, there were literally no conditions or building features that drove the outcome-based VR lower than 25 L/s/occ. Even for Public & Planet, 57% of days had a VR > 25 L/s/occ, and only 17% had a VR < 15 L/s/occ.

Table 31 Summary statistics and membership in one of three bins for outcome-based VRs over the office dataset.

	VR (L/s/occ)		Percent of instances in VR bin		
	Median	Mean	< 15 L/s/occ	15 – 25 L/s/occ	> 25 L/s/occ
Medium Parameters	32.5	43.1	0%	0%	100%
Public & Planet	26.4	29.0	17%	25%	57%

While all days ended up in the highest VR bin with Medium Parameters, building characteristics and weather conditions did affect the outcome-based VR with the Public & Planet profile. Using a multinomial regression to rank these factors revealed three as critical: outdoor $PM_{2.5}$ concentration, $PM_{2.5}$ filter efficiency, and outdoor temperature. Figure 27 illustrates the influence of these parameters on Public & Planet decisions. Figure 27a shows the influence of the outdoor $PM_{2.5}$ concentration and $PM_{2.5}$ filter efficiency $\eta_{PM,mv}$ (single pass in the mechanical ventilation airstream). When the outdoor $PM_{2.5}$ concentration was below $8 \mu\text{g}/\text{m}^3$, regardless of filter efficiency, the lowest-loss VR was usually $> 25 \text{ L/s/occ}$ (76% of the time). But when outdoor $PM_{2.5}$ was above $15 \mu\text{g}/\text{m}^3$ and filter efficiency was less than 40%, the lowest-loss VR was nearly always $< 15 \text{ L/s/occ}$ (82% of the time). Figure 27b shows bin membership by outdoor $PM_{2.5}$ concentration and outdoor temperature T_{out} . When T_{out} was between about 10 and 30 °C and outdoor $PM_{2.5}$ less than about $10 \mu\text{g}/\text{m}^3$, even the Public & Planet decision-maker nearly always selected strategies with $VR > 25 \text{ L/s/occ}$ (84% of the time). Only when outdoor temperatures were more extreme or outdoor PM concentration elevated were lower VRs selected.

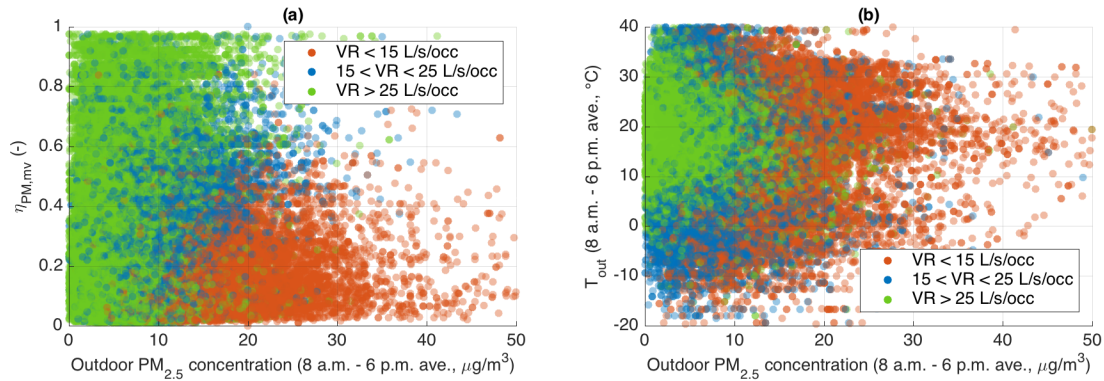


Figure 27 For the Public & Planet user profile, lowest-loss VR bin membership as a function of (a) outdoor PM_{2.5} concentration and PM_{2.5} filter efficiency, and (b) outdoor PM_{2.5} concentration and outdoor temperature.

4.3.4 Deciding among existing strategies

Consider using outcomes to select the best long-term strategy—over the entire year, rather than for a single day—from the options of ASHRAE 62-2001, 2×VR, Econ, and DCV. We examined this question for the two office types in each of the five climate categories defined by the Building America program (Baechler et al., 2010). (According to the 2012 Commercial Building Energy Consumption Survey (CBECS) (U.S. Energy Information Administration (EIA), 2015a), 13% of U.S. offices are in hot-humid areas, 14% are in mixed-dry or hot-dry ones, 31% are in mixed-humid climates, 3% are in marine zones, and 39% are in cold or very cold climates.) First, Figure 28a shows the percentage of instances for which each strategy yielded the highest annual geometric mean VR. In most climate zones, the highest annual VR resulted from 2×VR, but it often came from economizing in Hot Dry and Mixed Dry climates (with high solar envelope gains compared to outdoor air enthalpy) and the mild Marine zone.

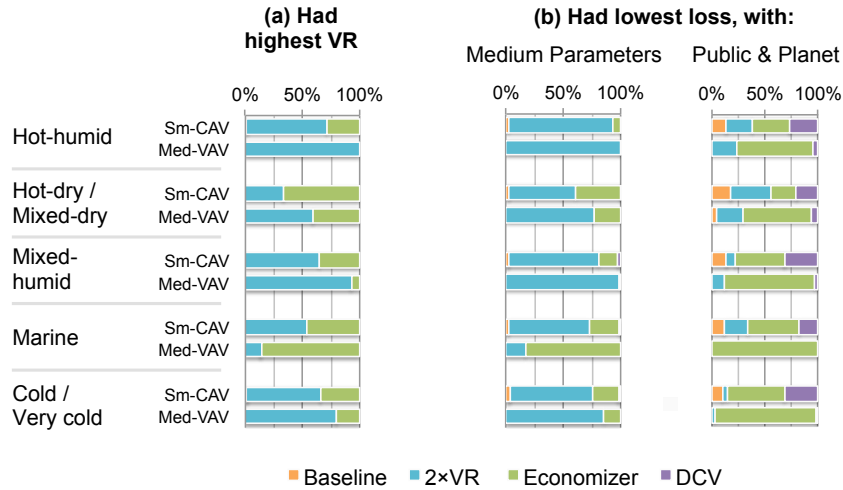


Figure 28 (a) frequency that each ventilation strategy achieved the highest annual VR, by climate category and office type; (b) frequency that each ventilation strategy had the lowest loss of the four options, for Medium Parameters and Public & Planet user profiles.

Figure 28b shows the percentage of instances that each ventilation strategy led to the lowest loss. With Medium Parameters, the percentages were very similar to those depicted in Figure 28a, meaning that most of the time the strategy that provided the most ventilation was the one that minimized loss—a result consistent with everything we have noted so far about the dominance of IAQ_{profit} components. For Public & Planet, on the other hand, the lowest-loss strategies were much more varied. Simply doubling mechanical ventilation at all times ($2 \times VR$) was much less often favorable, and economizing was more often most favorable. In addition, both ASHRAE 62-2001 and DCV sometimes minimized loss in the small-CAV building, despite never producing the highest VR. With Public & Planet, the tradeoffs between categories became apparent, and the outcome-based strategy selection depended on specific building characteristics and outdoor conditions, like outdoor pollution and filter efficiency.

4.3.5 Case studies

This section applies the loss framework to two variants of a small-CAV office building located in New York City. The office type is the same as already described, with building physical and efficiency parameters set at median, typical values. The only distinction between the two variants is that one has a typical particle filter ($\eta_{PM,mv} = 0.2$) and the other has a superior one ($\eta_{PM,mv} = 0.7$). For both case studies, natural infiltration was set at zero. The cases were simulated with constant design ventilation rates, or VR_{des} , from 5 to 50 L/s/occ in 5 L/s/occ intervals. In the absence of infiltration, the VR as already defined—the average outdoor air flow divided by the average occupancy—would be about 18% greater than VR_{des} , based on average occupancy. For example, a VR_{des} of 10 L/s/occ would yield a VR of 11.8 L/s/occ.

4.3.5.1 Loss as a function of VR, on selected days

Figure 29 illustrates the losses associated with the six outcomes as a function of VR_{des} , with Medium Parameters in blue and Public & Planet in orange. For L_{WP} and L_{EA} , the relations depend only on VR and do not vary by day of year, building, or other conditions. For L_{PM} , results are shown both for a low scenario (the superior filter case, with median outdoor $PM_{2.5}$ pollution) and a high scenario (the typical filter case, with high outdoor $PM_{2.5}$ concentration). L_{O_3} is shown for a day with relatively high outdoor ozone levels. L_e is shown for a typical summer day (August 14), L_g for a cold winter day (January 19), and the total energy, $L_g + L_e$, is shown for a spring day (April 15).

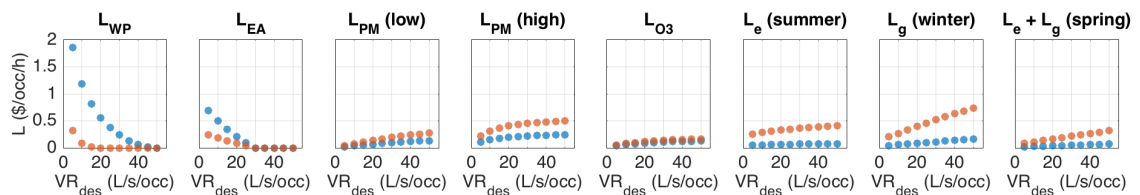


Figure 29 Loss component values as a function of VR_{des} with Medium Parameters (blue) or Public & Planet (orange) user profiles. Each panel is for a single day; see the text for more detail.

In terms of the VR_{des} selected by an outcome-based approach, what matters in Figure 29 is not the value of loss components but their slopes as a function of VR_{des} . With Medium Parameters, it is clear on the strength of work performance impacts alone that the outcome-based VR_{des} would be about 45 L/s/occ, above which there is no lost work performance. No other outcome's loss would ever be sufficient to counteract L_{WP} fully, although L_{PM} on a polluted day with a typical filter, or L_g on a cold winter day, could potentially lower the best VR_{des} a little. For the Public & Planet profile, on the other hand, L_{WP} is zero above about 17 L/s/occ, and the influence of L_{EA} is diminished (and, as always, zero above 30 L/s/occ). At the same time, the slopes of L_{PM} , L_e , L_g , and $L_e + L_g$ are all much greater. Therefore, the outcome-based VR_{des} would never exceed 30 L/s/occ except in free cooling situations, and could often be significantly lower.

4.3.5.2 Loss as a function of VR over the year

Figure 30 shows the loss associated with the six outcomes over the year, for both user profiles, and at 5, 10, 20, 30, and 50 L/s/occ. For both profiles, it is clear that increasing ventilation above 5 L/s/occ generally reduced total loss. With Medium Parameters, every increase in VR_{des} reduced loss, and did so for every day of the year. For Public & Planet, VR_{des} increases up to between 20 and 30 L/s/occ reduced loss at most times. Increasing VR_{des} shifted the loss makeup from approximately equal parts energy, work performance, excess absenteeism, and $PM_{2.5}$, to loss made up of energy and $PM_{2.5}$. With the greater value accorded electricity and $PM_{2.5}$, VR_{des} above about 10 L/s/occ increased total loss in the early summer, around June 1. This fact makes it clear that the ideal VR_{des} would not be constant for the year.

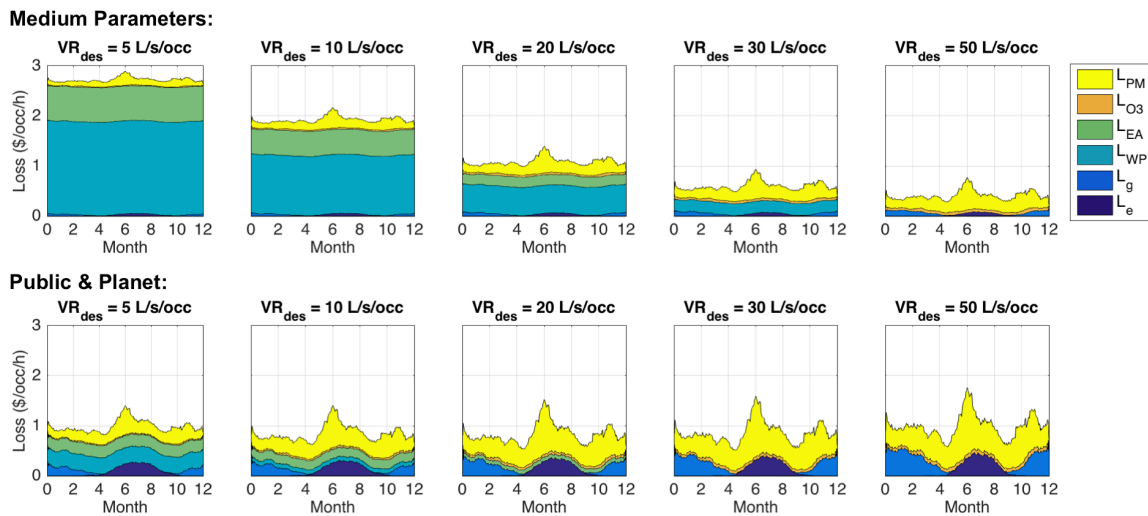


Figure 30 Loss magnitudes for six components over a year, for Medium Parameters and Public & Planet user profiles, each at five ventilation rates, for the case study building with a typical filter ($\eta_{PM,mv} = 0.2$).

Figure 31 is similar but for the variant with a superior PM filter that captures 70% of outdoor $PM_{2.5}$ on a single pass. Compared to the office with a typical filter with an efficiency of 20%, the contribution of L_{PM} to the total loss was much smaller. Indeed, even with the Public & Planet profile where P_{PM} is based on the 95th percentile scientific estimate, the superior filter succeeds in nearly eliminating loss associated with $PM_{2.5}$ exposure. This example illustrates a key point, which is that if high VR strategies are used in buildings to realize positive performance and absentee benefits, high efficiency filtration should accompany those strategies to mitigate indoor associated $PM_{2.5}$ exposure.

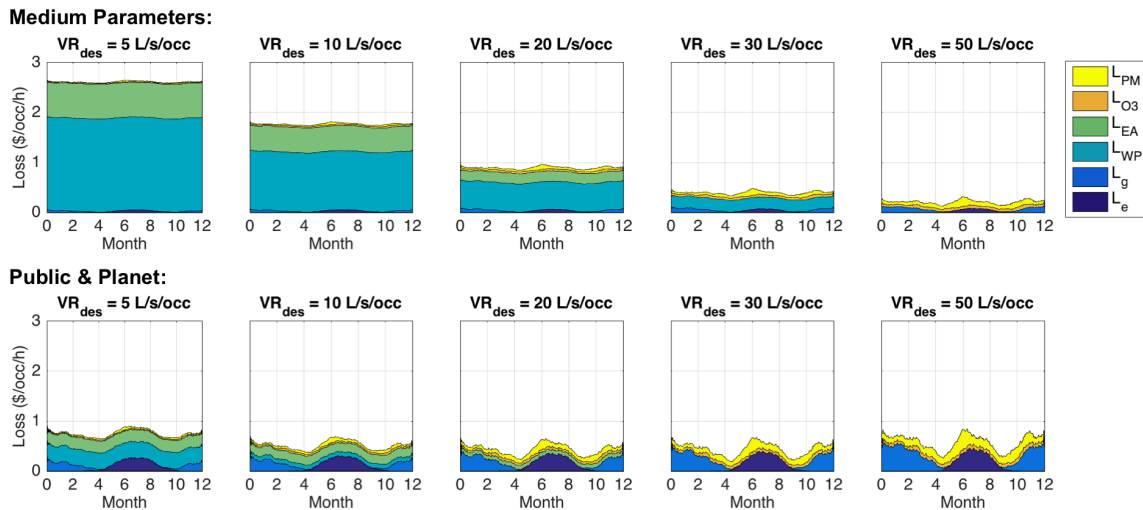


Figure 31 Loss magnitudes for six components over a year, for Medium Parameters and Public & Planet user profiles, each at five ventilation rates, for the case study building with a superior filter ($\eta_{PM,mv} = 0.7$).

4.3.5.3 Outcome-based VRs over the year

Figure 32 illustrates the total loss (indicated by color) over the year as a function of VR_{des} , for both user profiles and both case study variants. With Medium Parameters (top row), for both filter conditions, loss decreased consistently from low to high VR_{des} . For the typical filter, the relationship between VR_{des} and L varied somewhat over the year, because of the greater loss associated with $PM_{2.5}$ during a few high outdoor air pollution weeks; for the superior filter, it was remarkably consistent because, with $PM_{2.5}$ effectively filtered, all impacts other than productivity and sick leave were comparatively marginal. For Public & Planet (bottom row), the relation between VR_{des} and L was both less strong and less one-directional, and ventilation was generally less able to produce large changes in the total loss magnitude. In particular, with the typical filter, there were times of the year with high loss that could not be fully reduced by changing VR_{des} .

The outcome-based VR_{des} —i.e., the VR_{des} that produced the lowest loss—is indicated by the black dots in Figure 32. With Medium Parameters, regardless of filter quality, it was either 45 or 50 L/s/occ all year. With Public & Planet values, the outcome-based VR_{des} was 30 L/s/occ for large portions of summer, fall, and especially spring (for both filter conditions, but somewhat

more in the summer and fall with the superior filter). In the winter, the outcome-based VR_{des} was much lower, very rarely exceeding 15 L/s/occ with the typical filter or 20 L/s/occ with the superior filter. In all seasons, when the outcome-based VR_{des} was not 30 L/s/occ, it was most often 10 or 15 L/s/occ with a typical filter (although values as low as 5 L/s/occ were observed) and 15 or 20 L/s/occ with a superior filter (and almost never lower). For both filter conditions, the middle ground of 25 L/s/occ was almost never loss-minimal.

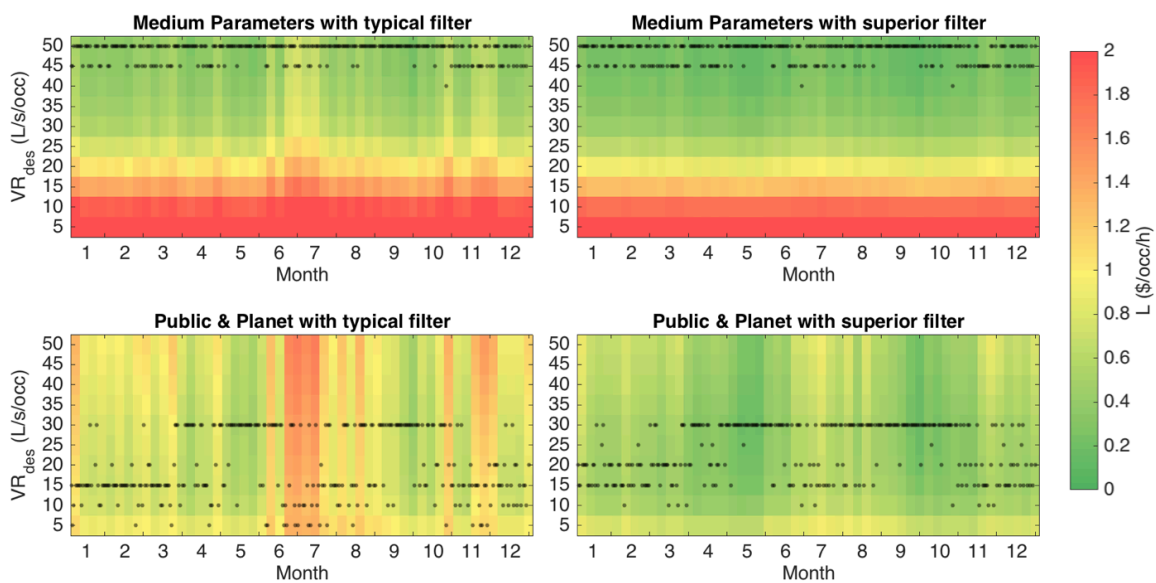


Figure 32 Heat maps showing the total loss throughout the year for different design ventilation rates (VR_{des}) for two user profiles, each with a typical or a superior filter. Black dots indicate the outcome-based VR_{des} , i.e. the one that had lowest loss.

With Medium Parameters, simply setting the design VR to 50 L/s/occ and employing fixed ventilation all year would practically achieve minimal loss. However, for a profile similar to Public & Planet, there is no existing ventilation strategy that would have a similar annual profile to the one produced by intentionally minimizing loss in an outcome-based approach.

4.4 Conclusions

This chapter presented an outcome-based ventilation (OBV) framework for making decisions about ventilation strategies and rates in commercial buildings by combining IAQ and energy outcomes into a loss function. Minimizing loss is a way to optimize ventilation rates for a given decision-maker based on ventilation outcomes. A loss function was developed for U.S. offices, including six outcomes: occupant work performance and sick leave absenteeism (*profitable IAQ* outcomes), health risks from exposure to PM_{2.5} and ozone from outdoors (*IAQ public health* outcomes), and electricity and natural gas consumption, including climate change and air pollution externalities as desired (*energy* outcomes). For each outcome there were one or two user-defined parameters. Reasonable ranges were developed for all parameters based on scientific information, the research literature, and new analysis and Monte Carlo simulation. Low, medium, and high reference values for user parameters were supplied.

The outcome-based ventilation framework was illustrated and explored with an existing dataset that statistically represented the U.S. office stock, as well as new case study simulations in a small office. For both, and through multiple types of analysis, profitable IAQ impacts of ventilation changes were shown to be much more valuable than public health or energy consumption impacts. For an intervention that added ~10 L/s/occ to the VR, with all medium parameter values, median changes in profitable IAQ losses were 20 times those associated with public health IAQ impacts and 200 times energy-related losses.

For medium user parameter values, and most other combinations, profitable IAQ impacts were so dominant that the outcome-based strategy was always the one that provided the most ventilation, up to 45–50 L/s/occ, regardless of the building, the time of year, or other conditions. The *only* exception was a user profile (Public & Planet) comprising very low (5th percentile) values for parameters related to profitable IAQ impacts and very high (95th percentile) values for

public health and energy impact parameters. Even so, case studies with a Public & Planet user profile resulted in outcome-based VRs that, at 30 L/s/occ for much of the year, far exceeded current standard minimum VRs. However, with the Public & Planet profile, outcome-based VRs varied during the year, sometimes as low as 5 L/s/occ, depending chiefly on outdoor pollution and temperature, and filter efficiency. No existing ventilation strategy captures these influences.

CHAPTER 5: VENTILATION AS OPTIMAL CONTROL PROBLEM: MINIMIZING DAILY LOSS AND ASSESSING THE POTENTIAL FOR PARETO IMPROVEMENTS

Chapter abstract: This chapter applies the outcome-based ventilation (OBV) framework developed in Chapter 4 to real-time ventilation control to assess whether numerically optimizing ventilation can provide Pareto improvements over existing control methods. Optimizing outdoor airflow during a single day, it was hypothesized, could take advantage of weather, pollution, occupancy, and other transient dynamics. An effective ventilation rate, VR_{eff} , was defined based on the aggregate exposure of occupants to three types of contaminants. An optimal control problem was formulated, then transformed into a nonlinear optimization problem, which was solved by interior point methods. Results showed that, contrary to our hypothesis, modulating how ventilation is provided during a single day typically did not change energy use substantially compared to other control trajectories that had the same VR_{eff} . Optimization showed that a strategy with economizer and demand-controlled ventilation (EDCV) was very close to Pareto optimal at most times of the year, and annually saved 3–5% of HVAC energy costs compared to fixed ventilation. Optimized OBV only saved energy when the average outdoor temperature was between 20 and 30 °C and met particular conditions, like a morning that was significantly cooler than afternoon. The annual savings from switching from EDCV to optimized OBV were 2–3%. In terms of loss, the negative public health impact of bringing in so much OA was often greater than the energy savings. Neither time-of-use pricing nor any of the factors in a sensitivity analysis revealed opportunities in which optimizing ventilation within each day of the year saved more than 5% of annual HVAC energy costs.

5.1 Chapter introduction

This chapter applies the loss function framework developed in Chapter 4 to ventilation control. For a given set of building and user parameters, the loss function provides an objective that can be used to optimize ventilation. The following hypothesis was tested: numerically optimizing ventilation control to minimize loss can provide Pareto improvements over existing ventilation control methods, including not just a fixed ventilation rate (VR) but also already-existing feedback-based ventilation control methods like economizing and demand-controlled ventilation (DCV). While the preceding chapter explored tradeoffs among indoor air quality, energy, and public health impacts and the implications for how ventilation rates should be determined, this chapter asks if there are ways that are more effective than current methods to deliver a given VR. In particular, the focus is on optimizing outdoor airflow during a single day, with the hypothesized benefits resulting from adjusting to take advantage of weather, pollution, occupancy, and other transient dynamics. Related work, outside the scope of this dissertation, takes up the question of optimally allocating a fixed ventilation energy budget over a yearlong time horizon, in light of longer-term seasonal energy and pollution dynamics.

In order to test whether dynamically modulating ventilation to minimize loss can provide significant benefits over a single day, a number of steps were required. Since the traditional definition of the ventilation rate is only appropriate for steady or near-steady outdoor air flows, a robust day-average VR metric needed to be defined. We formulated a concentration-based measure called the effective ventilation rate, VR_{eff} , to meet this need. The work performance and excess absenteeism relations were simplified with fits to closed form, single-equation expressions that can be used in an optimization problem without requiring mixed-integer programming. The optimal control problem was then formulated, with the dynamics of indoor air and energy processes acting as constraints on the system.

To solve the control problem, a method was employed to approximate energy demands as a function of outdoor airflow rate at the current and preceding timesteps. The indoor air process

system dynamics were discretized. Then the optimal control problem was recast as a constrained nonlinear optimization problem, of moderate to moderately-large size depending on the discretization timestep chosen. This problem was solved efficiently, within a few seconds, with interior point (IP) optimization algorithms.

Although we formulated the optimal control problem to include $PM_{2.5}$ and ozone, the prices for them were set to zero for the optimizations presented here. This was principally to simplify analysis, because it is very difficult to keep track of multi-objective optimization problems with three objectives—and particularly difficult to use insightful graphical methods like Pareto curves. Throughout this chapter, when we refer to tradeoffs or Pareto improvements, we mean the tradeoffs between energy use and increasing ventilation to improve work performance and decrease absenteeism.

5.2 Methods

5.2.1 Terminology

Subscripts

bcd – generic building-emitted contaminant with ventilation-dependent emission rate
 bci – generic building-emitted contaminant with ventilation-independent emission rate
 e – electricity
 ea – excess absence
 exp – exposed concentration, an occupant-weighted average over the time horizon
 g – natural gas
 hc – generic human-emitted contaminant
 inf – infiltration or uncontrolled ventilation
 k – timestep index
 mv – mechanical ventilation
 nt – nighttime, indicating the period when the HVAC system is scheduled to be off
 o3 – ozone (O_3 , in ppb)
 oa – outdoor air, including mechanical ventilation and infiltration
 out – for $PM_{2.5}$ and ozone, outdoor concentrations
 pm – particulate matter with aerodynamic diameter $< 2.5 \mu g$ ($PM_{2.5}$, in $\mu g/m^3$)
 rec – recirculated supply air
 s – IAQ contaminant species index
 sa – supply air

wp – work performance

Superscripts

u – upper bound

l – lower bound

Building parameters and variables

Θ – set of building and setting parameters

λ – air exchange rate, or volume-normalized airflow (h^{-1})

ϕ – volumetric airflow (m^3/h)

A – floor area served by mechanical system (m^2)

$\dot{E}_{g,\text{heat}}$ – rate of natural gas consumed by the heating coil (kW)

$\dot{E}_{e,\text{cool}}$ – rate electricity consumed by the cooling coil (kW)

N_{occ} – number of occupants in control volume (occ)

V – control volume served by mechanical system (m^3)

VR_{eff} – effective day-average ventilation rate metric (L/s/occ)

Indoor air quality

β_{O_3} – lumped ozone loss rate due to surface and air reactions (h^{-1})

β_{pm} – deposition rate for $\text{PM}_{2.5}$ (h^{-1})

η – filter removal efficiency (-)

C – a concentration ($\mu\text{g}/\text{m}^3/\text{h}$ or ppb/h)

C_{eq} – equilibrium concentration for ventilation-dependent building-emitted contaminant ($\mu\text{g}/\text{m}^3$)

D – a contaminant loss term (h^{-1})

G_{hc} – generation rate of human-emitted contaminant ($\mu\text{g}/\text{h/occ}$)

G_{bci} – generation rate of ventilation-independent building-emitted contaminant ($\mu\text{g}/\text{m}^2/\text{occ}$)

kL – time constant for ventilation-dependent building-emitted contaminant (h^{-1})

p – penetration factor (-)

S – a contaminant source term ($\mu\text{g}/\text{m}^3/\text{h}$ or ppb/h)

Loss function and optimization problem

Ω – set of user preference parameters

L – loss ($\$/\text{occ}/\text{h}$)

P – a price ($\$/\text{unit}$, where unit depends on the valued quantity)

t_0 – start of time horizon, when HVAC system turns on (h)

t_f – end of time horizon, when HVAC system turns off (h)

Δt – control timestep, also used for discretization (h)

N_{ts} – number of timesteps in discretized problem (-)

τ – a time duration since an arbitrary initial time t_{init} (h)

x – state variables

u – control variables

w – exogenous variables

5.2.2 From loss formulation to optimal control problem

To test using the loss function to optimize ventilation, a single day's operation was examined. Although an entire 24-hour period is implicated, since cyclical conditions are imposed to account for indoor air process overnight, the optimization time horizon is the period of HVAC system operation. This period starts at an initial time t_0 and ends at final time t_f , and this operation period is fixed.

5.2.2.1 Assumptions and single-zone IAQ modeling

This investigation regards the space conditioned and ventilated by an HVAC system as a single zone. This avoids the need to model distribution systems and helps limit the dimensionality of the problem, which are useful simplifications in order to assess feasibility and benefits. Of course, even a large multizone building can be treated like a single zone by lumping together the zones served by a single HVAC system. We have not formally assessed performance in multizone buildings (not even in simulation), but would hypothesize that these methods would be reasonably applicable to ones with stable occupancy and spatially similar loads, but will probably require modification to be applied to multizone systems with diversity of conditioning loads and particularly with diversity and time-variability of ventilation loads.

For the single zone, the flow of outdoor air (oa) is the sum of mechanical ventilation (mv) and infiltration (inf) flows, all denoted by ϕ and expressed in m^3/h :

$$\phi_{\text{oa}} = \phi_{\text{mv}} + \phi_{\text{inf}} \quad (39)$$

The flows are modeled as balanced, meaning exfiltration equals infiltration, and also that exhaust flows equal mechanical ventilation flows, so that the flow of air recirculated through the HVAC system (rec) is the supply air (sa) flow minus the mechanical ventilation flow, or

$$\phi_{\text{rec}} = \phi_{\text{sa}} - \phi_{\text{mv}} \quad (40)$$

The air exchange rate, defined for all subscripts (λ_{oa} , λ_{mv} , λ_{inf} , λ_{sa} , and λ_{rec}), is the flow divided by the space volume V (m^3)

$$\lambda = \phi/V \quad (41)$$

Indoor air pollutants are modeled with the differential equation

$$\frac{dC}{dt} = S - DC \quad (42)$$

where C ($\mu\text{g}/\text{m}^3$) is a concentration, S ($\mu\text{g}/\text{m}^3/\text{h}$) a volume-normalized source strength, and D a decay rate (h^{-1}). (In reactor modeling the decay rate is usually called a loss rate, but here D is used because “loss” already has another meaning in this work.)

For periods in which sources and decays are constant or can be time-averaged, the concentration at time t after some initial time t_{init} is given by the analytical solution to Equation (42)

$$C(t) = C(t_{\text{init}})e^{-D\tau} + \frac{S}{D}(1 - e^{-D\tau}) \quad (43)$$

where $\tau = t - t_{\text{init}}$. This fact is used to calculate concentration trajectories during nighttime when the HVAC system is not operating.

Five indoor air pollutants are modeled. Although we do not preclude the possibility that some of these, or related species, could one day be measured in real-time and the measurements integrated with data fusion techniques, the models are expected in most cases to be the only information about these pollutants. Indeed, three of the pollutants are fictitious, and intended to represent three types of volatile organic compound (VOC) pollutants with indoor sources. These are a human-emitted compound (hc), emitted at a constant rate by each occupant present, and representing a bioeffluent; a building-emitted compound with emissions independent of the

indoor-outdoor air exchange rate (bci); and a building-emitted compound for which effective emissions are dependent on the air exchange rate (bcd). The final two pollutants are PM_{2.5} (pm) and ozone (o3), exposure to which is directly included in the loss function. Source and decay terms for all five are listed in Table 32.

Table 32 Modeled contaminant species and source and decay terms. Time-varying quantities are explicitly indicated.

Species	S	D	Eq.
C_{hc}	$\frac{G_{hc}}{V} N_{occ}(t)$	$\lambda_{oa}(t)$	(44)
C_{bci}	$\frac{G_{bci}}{V} A$	$\lambda_{oa}(t)$	(45)
C_{bcd}	kLC_{eq}	$\lambda_{oa}(t) + kL$	(46)
C_{pm}	$\left((1 - \eta_{pm,mv}) \lambda_{mv}(t) + p_{pm} \lambda_{inf}(t) \right) C_{pm,out}(t)$	$\lambda_{oa}(t) + \eta_{pm,rec} \lambda_{rec}(t) + \beta_{pm}$	(47)
C_{o3}	$\left((1 - \eta_{o3}) \lambda_{mv}(t) + p_{o3} \lambda_{inf}(t) \right) C_{o3,out}(t)$	$\lambda_{oa}(t) + \eta_{o3} \lambda_{rec}(t) + \beta_{o3}$	(48)

For each species s , the occupant-weighted “exposed concentration” is defined by the weighted integration from t_0 to t_f

$$C_{s,exp} = \frac{\int_{t_0}^{t_f} N_{occ}(t) C_s(t) dt}{\int_{t_0}^{t_f} N_{occ}(t) dt} = \frac{\int_{t_0}^{t_f} N_{occ}(t) C_s(t) dt}{\Sigma_{oh}} \quad (49)$$

where N_{occ} is the number of occupants present and Σ_{oh} is the number of occupant hours (occ·h) during the time horizon. (For example, 10 occupants each working 8 hours would be $\Sigma_{oh} = 80$ occ·h.) For PM_{2.5} and ozone, the occupant-weighted exposed concentration values are used directly in the loss function, while for the three fictional VOCs they are used to calculate the day-average effective ventilation rate VR_{eff} .

5.2.2.2 The effective ventilation rate, VR_{eff}

The ventilation rate is the outdoor airflow per person. It has traditionally been defined for steady conditions, for example in the sense that ASHRAE 62.1 provides tables of minimum VR to be provided constantly. For relatively smooth ventilation adjustments, like DCV and economizing, the VR can be calculated using time averages. However, adapting the VR to entirely arbitrary dynamic outdoor air modulation presents problems. To see why, consider the two possible definitions. One could define the VR instantaneously as the current outdoor flow divided by the current number of occupants, and then average that value over the day. In that case, the instantaneous VR would be very high when few occupants were present, and infinite when the space was unoccupied. Any *ad hoc* method for addressing this problem would need to determine how to weight outdoor airflow during unoccupied periods, a question to which there does not seem to be a single appropriate answer. The other option is to take the average outdoor airflow over the day and divide it by the average number of occupants over the day. While this method would be more robust than the first, it completely disregards the timing of ventilation. For example, increasing ventilation in the fully occupied middle of the day would have an equal effect on the metric as increasing it in the evening after most occupants had left, although obviously the latter would provide almost no practical benefit.

These types of flaws would be exploited immediately by optimization routines, and so a metric more robust to numerical tricks was needed. Our answer was the effective ventilation rate VR_{eff} , based the occupant-weighted time-averaged concentration of indoor VOCs. The more effective the strategy at reducing these concentrations experienced by occupants, the higher VR_{eff} . To represent “indoor VOCs” three fictional contaminants were defined: a human-emitted compound (hc, for human contaminant) representing a bioeffluent, a building-emitted compound with air-exchange-independent emissions (bci, for building contaminant independent), and the building-emitted compound with air-exchange-dependent emissions (bcd, for building contaminant dependent). The idea is simple: for each contaminant, calculate the steady state (or

time-averaged) VR that would produce the same exposed concentration, or occupant-weighted time-averaged concentration. For example, for the human-emitted contaminant alone, the equivalent effective VR is

$$VR_{hc} = \frac{G_{hc}}{3.6 \cdot C_{hc,exp}} \quad (50)$$

where G_{hc} is a per-occupant emission rate in $\mu\text{g}/\text{h}/\text{occ}$. Similarly, for the building-emitted contaminant with independent emissions, the equivalent effective VR is

$$VR_{bci} = \frac{G_{bci}A}{3.6 \cdot C_{bci,exp} \cdot N_{occ,ave}} \quad (51)$$

where A is the area of the space (m^2) and $N_{occ,ave} = \frac{1}{\Sigma_{oh}} \int_{t_0}^{t_f} N_{occ}(t) dt$ is the occupant-weighted average occupancy. For the building-emitted contaminant with dependent emissions, the equivalent effective VR is

$$VR_{bcd} = \frac{kL(C_{eq} - C_{bcd,exp})V}{3.6 \cdot C_{bcd,exp} \cdot N_{occ,ave}} \quad (52)$$

The effective ventilation rate, VR_{eff} , was a simple average of the metric determined by the human- and building-emitted species, with the latter, VR_{build} , being a simple average of the independent and dependent emission rate contaminants, so that

$$VR_{eff} = 0.50 \cdot VR_{hc} + 0.25 \cdot VR_{bci} + 0.25 \cdot VR_{bcd} \quad (53)$$

As a rule, the contribution from VR_{hc} tends to increase VR_{eff} somewhat, since the lag time for bioeffluents to reach steady state increases the apparent ventilation rate. The contributions from VR_{bci} acts to decrease VR_{eff} , since buildup of independent emissions overnight take some time to be diluted in the morning, decreasing the apparent ventilation rate. The value of VR_{bcd} is typically quite close to the final value of VR_{eff} .

5.2.2.3 Simplified fits for lost work performance and excess absence rate

Chapter 4 presented models for calculating lost work performance (LWP) and the excess absence rate (EAR), both as a function of ventilation. However, both models required conditional switching depending on the VR value, and the LWP model required multiple calculation steps. In order to facilitate optimization, simplified models with a single, universally valid were fit for both outcomes. In both cases, it was decided to fit the models over a VR domain with a lower limit of 5 L/s/occ (the lower limit for EAR) and no upper limit. In optimizations, the VR is constrained to be above 5 L/s/occ to avoid applying the model outside the domain.

After significant trial and error and formal experimentation, it was determined that LWP can be estimated as

$$\text{LWP} = \exp(b_0 + b_1 \cdot \text{VR} + b_2 \cdot \text{VR}^2 + b_4 \cdot \text{VR}^4) \quad (54)$$

where

$$b_i = a_{i0} + a_{i1}z_{\text{WP}} + a_{i2}z_{\text{WP}}^2 + a_{i3}z_{\text{WP}}^3 \quad (55)$$

where z_{WP} is the standard normal variate corresponding to the work performance estimate percentile EP_{WP} , as in Chapter 4, and the a coefficients are listed in Table 33.

Table 33 Coefficients for lost work performance (LWP) simplified model

i	a_{i0}	a_{i1}	a_{i2}	a_{i3}
0	-2.7104E+00	2.9882E-01	5.7120E-02	-2.2533E-02
1	-1.0934E-01	5.7993E-02	-3.2264E-02	6.2251E-03
2	1.3686E-03	-4.2509E-04	3.7571E-04	-9.3105E-05
4	-7.0671E-07	6.7187E-08	-6.4313E-08	1.6321E-08

Similarly, the excess absence rate can be estimated as follows

$$r_{\text{ea}} = \exp(b_0 + b_1 \cdot \text{VR} + b_2 \cdot \text{VR}^2 + b_4 \cdot \text{VR}^4) \quad (56)$$

where

$$b_i = a_{i0} + a_{i1}z_{ea} + a_{i2}z_{ea}^2 + a_{i3}z_{ea}^3 \quad (57)$$

where z_{ea} is the standard normal variate corresponding to the absence rate estimate percentile EP_{EA} , as in Chapter 4, and the a coefficients are listed in Table 34. Note that while the forms of the equations for LWP and r_{ea} are the same, and the coefficient names are reused, the coefficient values in Table 33 and Table 34 should not be confused.

Table 34 Coefficients for excess absence rate r_{ea} simplified model

i	a_{i0}	a_{i1}	a_{i2}	a_{i3}
0	-3.7671E+00	2.6210E-01	-4.5102E-02	7.8335E-03
1	-9.0902E-02	-4.0111E-03	-2.9685E-04	2.4554E-05
2	1.9395E-03	-1.3030E-04	3.4550E-06	1.9576E-06
4	-3.6894E-06	1.1644E-07	1.3104E-09	-1.5154E-09

For both LWP and r_{ea} , the R^2 of all fits for all z values between -2 and 2 were 0.9996 or greater. Figure 33 illustrates fits for LWP for five z_{WP} values.

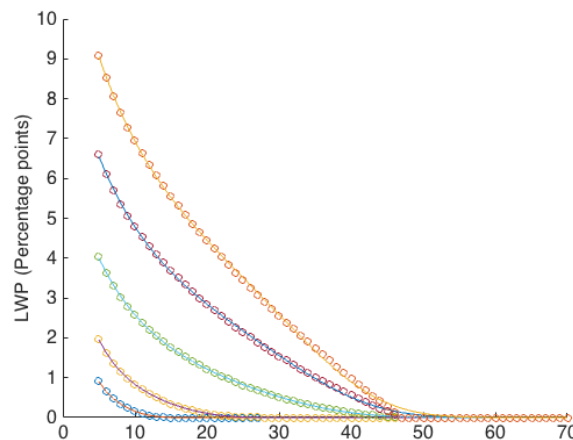


Figure 33 Fits for the simplified model for LWP for five z_{WP} values, from the top down: 2, 1, 0, -1 , and -2 . The o's result from the original expressions developed in Chapter 4, while the lines show the simplified fits introduced here.

It is also worth noting that, while Equations (54) and (55) or (56) and (57) look complicated and multivariate, the values of z_{wp} and z_{ea} are not adjusted within the optimization problem. Their values are set by a user decision at the outset, and once fixed, Equations (54) and (56) are functions only of the VR.

5.2.2.4 Loss function formulation

The loss function remains as introduced in Chapter 4, except that the prices associated with LWP and excess absenteeism are fixed at the same value of an hour of labor, called P_{wage} , and gas and electricity usage are expressed in their transient forms. Total loss is

$$\begin{aligned}
 L &= L_{wp} + L_{ea} + L_{pm} + L_{o3} + L_{g,heat} + L_{e,cool} \\
 &= P_{wage} \cdot LWP + P_{wage} \cdot r_{ea} + P_{pm} C_{pm,exp} + P_{o3} C_{o3,exp} + \frac{1}{\Sigma_{oh}} \int_{t_0}^{t_f} P_g \dot{E}_{g,heat}(t) dt \\
 &\quad + \frac{1}{\Sigma_{oh}} \int_{t_0}^{t_f} P_e(t) \dot{E}_{e,cool}(t) dt
 \end{aligned} \tag{58}$$

5.2.2.5 Optimal control problem

For the single zone problem, we work with a single control variable u , which is the total outdoor airflow. The state variables x in this case are the indoor concentrations as well as the energy consumed by the heating and cooling system; supply air is constant in the current formulation, and therefore fan energy is not affected by ventilation control. All the state variables depend on the control variable as well as exogenous variables w that include occupancy, supply air and infiltration flows, and outdoor pollutant concentrations. Outdoor weather variables are not included in the exogenous variables because, in the current approach, they are embedded in the equations for building thermal dynamics that relate energy consumption to outdoor airflow. In summary, these definitions are

$$\begin{aligned}
u(t) &= \phi_{\text{oa}}(t) \\
x &= [C_{\text{hc}}, C_{\text{bci}}, C_{\text{bcd}}, C_{\text{pm}}, C_{\text{o3}}, \dot{E}_{\text{g,heat}}, \dot{E}_{\text{e,cool}}] \\
w &= [N_{\text{occ}}, \phi_{\text{sa}}, \phi_{\text{inf}}, C_{\text{pm,out}}, C_{\text{o3,out}}]
\end{aligned} \tag{59}$$

The optimal control problem can then be formulated as

$$\begin{aligned}
&\underset{u(t), t \in [t_0, t_f]}{\text{minimize}} && L \\
&\text{subject to} && F(x(t), \dot{x}(t), u(t), w(t), \Omega, \Theta) = 0, t \in [t_0, t_f] \\
&&& F_0(x(t_0), x(t_f)) = 0 \\
&&& \phi_{\text{oa}}^l \leq \phi_{\text{oa}}(t) \leq \phi_{\text{oa}}^u, t \in [t_0, t_f] \\
&&& 0 \leq \dot{E}_{\text{g,heat}}(t) \leq \dot{E}_{\text{g,heat}}^u, t \in [t_0, t_f] \\
&&& 0 \leq \dot{E}_{\text{e,cool}}(t) \leq \dot{E}_{\text{e,cool}}^u, t \in [t_0, t_f]
\end{aligned} \tag{60}$$

where the first condition subjects the solution to the dynamics of the problem expressed by some set of functions F . These functions include the dynamics expressed for the five indoor air pollutants in Equations (42) and (44)–(48), as well as the dynamics of the building, mechanical system, and weather that relate ϕ_{oa} to $\dot{E}_{\text{g,heat}}$ and $\dot{E}_{\text{e,cool}}$. F is also conditioned on the two parameter sets Ω, Θ . Ω includes user parameters such as the EPs for work performance and excess absence, $P_{\text{wage}}, P_{\text{pm}}, P_{\text{o3}}, P_{\text{e}}$, and P_{g} . Θ includes building parameters like the space volume and area, and emission rates and other IAQ constants.

The second condition in Equation (60) expresses initial conditions and final conditions. As part of these conditions, we also impose cyclical conditions on indoor air pollutants. Without setting constraints on the contaminant concentrations at t_{on} , an optimization would set all of them at zero. However, concentrations of all species (possibly excepting the purely human-emitted

contaminant) are unlikely to be zero at the beginning of system operation, and for building emitted contaminants nighttime emissions can be a serious source of exposure. We therefore impose the constraint that the concentration when the system turns on must be consistent with the solution of the governing differential equation, the concentration when the system turned off, and the time-averaged sources and losses during the night. Thus, for each species $s \in \{hc, bci, bcd, pm, o3\}$

$$C_s(t_0) = C_s(t_f)e^{-D_{s,nt}\tau_{nt}} + \frac{S_{s,nt}}{D_{s,nt}}(1 - e^{-D_{s,nt}\tau_{nt}}) \quad (61)$$

where “nt” indicates nighttime, the nighttime duration is $\tau_{nt} = t_0 + 24 - t_f$, and $S_{s,nt}$ and $D_{s,nt}$ are the time-averaged sources and decays of species s during the nighttime period, which can be seen in detail in the Appendix to this chapter. The third condition in Equation (60) establishes bounds at each timestep on the control variable ϕ_{oa} cannot be less than a lower bound or greater than an upper bound at each timestep. These are established by, on the low end, infiltration, and, on the high end, the HVAC system’s supply airflow plus infiltration. The fourth and fifth conditions place limits on the heating and cooling energy consumption that are imposed by the system capacity, which can vary by timestep depending on loads and outdoor air conditions.

Additional constraints could be imposed to limit indoor concentrations or energy use. We conducted some exploration of these ideas, in order to require solutions to provide better air quality or use less energy than some reference strategy, for example. However, the principal purpose of this investigation is to establish Pareto curves for tradeoffs, and so there is at present no need to establish artificial cutoffs of the solution space. It is sufficient to modulate prices and then view where the imposition of a cutoff would dictate that a ventilation strategy would operate, i.e., where the Pareto curve crosses the cutoff boundary.

5.2.3 From optimal control problem to nonlinear optimization problem and solution

There are numerous options for solving optimal control problems (Biegler & Zavala, 2009; Dong & Lam, 2014; Ma, Qin, Salsbury, & Xu, 2012; Mayne, 2014; Wetter, Bonvini, & Nouidui, 2016). Here we adopt perhaps the most straightforward, discretizing system dynamics and other governing equations, and transforming these into a constrained nonlinear optimization problem. In this approach, both the control variables and the state variables become decision variables, which is necessary to allow system dynamics to be expressed as constraints. For example, a pollutant's concentration is not a control variable in the original optimal control problem, but the species' concentration at timestep k becomes a decision variable in the nonlinear optimization problem, which is constrained by discrete dynamic relations to the control and exogenous variables and the concentrations at timesteps $k - 1$ and $k + 1$.

Only timesteps within the period when the HVAC system is on are included. The only nighttime information is coded in the nighttime source and decay term parameters for contaminants. These timesteps are indexed from $k = 1 \dots N_{ts}$, where $N_{ts} = \frac{t_f - t_0}{\Delta t}$, where Δt is the timestep length in hours. A slightly different convention is used for flows and energy than is used for concentrations. For ϕ_{oa} , $\dot{E}_{g,heat}$, and $\dot{E}_{e,cool}$, there are N_{ts} values, each representing the held or average value for the duration of a timestep. Thus, for example, $\phi_{oa,1}$ represents the constant value of outdoor airflow from time t_0 to time $t_0 + \Delta t$. For indoor air concentrations, however, there are $N_{ts} + 1$ instantaneous timeslice values. Timeslices are indexed from $0 \dots N_{ts}$, so that, for example, timestep 1 is the duration between times t_0 and t_1 , and in general timestep k is the duration between times t_{k-1} and t_k , where $t_k = t_0 + k\Delta t$, and $t_{N_{ts}} = t_0 + N_{ts}\Delta t = t_f$. In this work, a constant-length timestep Δt (h) has been used for simplicity; a variable-length option could potentially improve performance in a practical implementation.

5.2.3.1 Polynomial fits for energy use as a function of outdoor airflow

Independent of the formulation of the optimal control problem, or the decision of how to approach solving it, is the question of modeling building and HVAC system dynamics. For this work, an approach was developed that executed a detailed building simulation with several possible ϕ_{oa} at each timestep, then fit response curves for each timestep for the resulting values of $\dot{E}_{g,heat}$ and $\dot{E}_{e,cool}$. In this case, the detailed simulation tool was EnergyPlus and the case study model was essentially the same as the small-CAV model described in Chapters 2, 3, and 4. In this section, we describe the basic approach. In fact, the final equations were slightly different, because of a correction to account for highly dynamic ventilation, which is described in the next section.

Using an initial EnergyPlus simulation, we fit polynomial curves for electricity and natural gas use rates at each timestep k (i.e., the average consumption rate from time t_{k-1} to time t_k),

$$\dot{E}_{g,heat,k} = \frac{a_{g,0,k} + a_{g,1,k}\lambda_{oa,k} + a_{g,2,k}(\lambda_{oa,k})^2}{1 + \exp(-k_{s,g,k}(\lambda_{oa,k} - \lambda_{c,g,k}))} \quad (62)$$

and

$$\dot{E}_{e,cool,k} = \frac{a_{e,0,k} + a_{e,1,k}\lambda_{oa,k} + a_{e,2,k}(\lambda_{oa,k})^2}{1 + \exp(-k_{s,e,k}(\lambda_{oa,k} - \lambda_{c,e,k}))} \quad (63)$$

For better scaling, these models were fit with the air exchange rate λ_{oa} as the independent variable. The a values, k_s , and λ_c are parameters fit at each timestep. The a 's are polynomial coefficients. The denominator is a logistic function that splits the domain into an "active region" and zero-valued "inactive region" while maintaining the function twice-continuously differentiable everywhere. The parameter k_s controls the sharpness of the transition between the two regions, and its sign also determines whether the active region is below the cutoff λ_c or above it. The equations are flexible enough to fit any type of relation of energy use to ventilation. If

energy use increases with ventilation, k_s is positive, so that if λ_{oa} is less than λ_c the denominator will be large and the estimate will be effectively zero, while if λ_{oa} is greater than λ_c the denominator will approach unity and the estimate will follow the polynomial equation in the numerator. If energy use decreases with ventilation, as in free cooling, k_s is negative, so that if λ_{oa} is less than λ_c the denominator approaches unity and the polynomial equation in the numerator will provide the estimate, while if λ_{oa} is greater than λ_c the denominator will become large and the estimate will indicate that increased ventilation cannot save more energy.

The routine that fit the models also determined upper and lower limits for λ_{oa} . Generally, lower limits were established by infiltration in the absence of mechanical ventilation, below which the total outdoor air delivery cannot fall. The upper limit was a system limit, the lesser of the physical capacity of the HVAC system's fan or a maximum flow determined to safely keep the heating or cooling coil within its maximum capacity for a given timestep. These limits were translated to the box constraints $\phi_{oa,k}^l$ and $\phi_{oa,k}^u$ for the optimization problem at each timestep.

Figure 34 illustrates heating natural gas consumption fits for four hourly timesteps on a cold day. The infeasible regions below the lower λ_{oa} limit and above the upper λ_{oa} limit are shown in grey. In the morning, the slope of energy use rate per outdoor air flow was steep, and the domain constrained below about 2 h^{-1} . By midday, the slope was gentler as the energy required to heat outdoor air decreased, and much higher air exchanges could be achieved without exceeding the coil's heating capacity. By the evening, as outdoor temperature dropped, that process had begun to reverse.

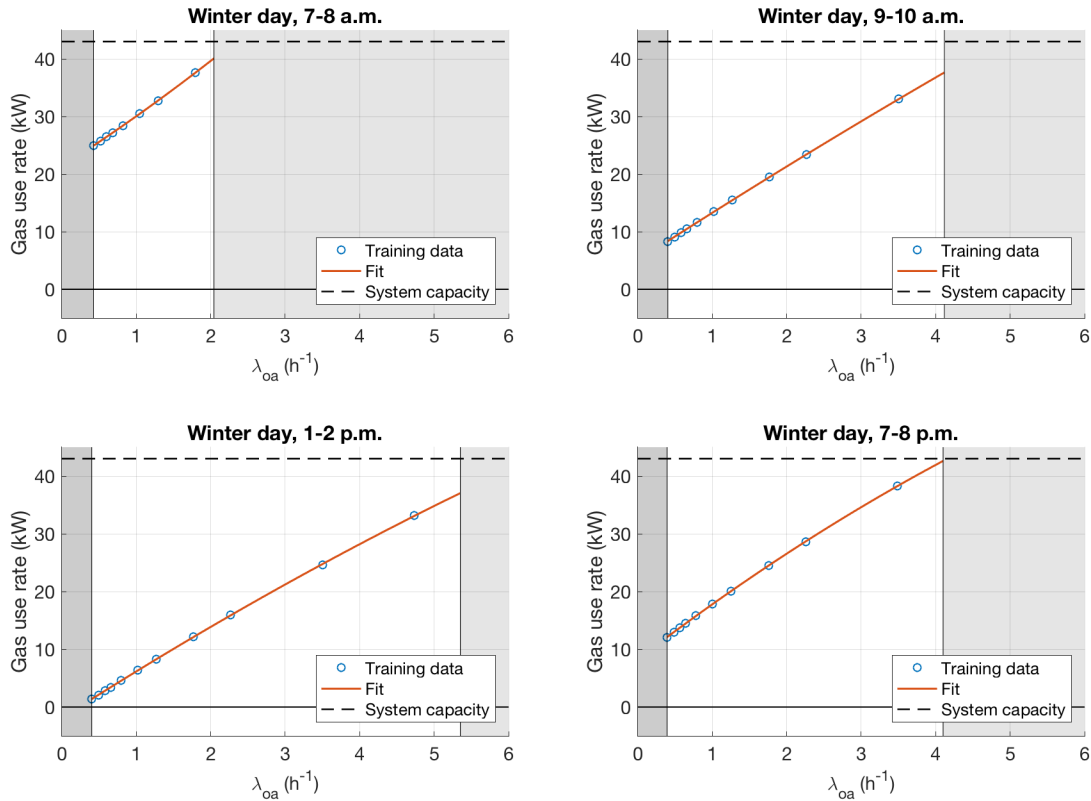


Figure 34 Heating energy fits for four hourly timesteps on a cold day. The setup routine generates the fit and also determines the lower limit of infiltration and upper limit of system capacity, indicated here by infeasible grey regions.

Similarly, Figure 35 illustrates cooling coil electricity consumption fits for four hourly timesteps on a hot summer day. The trajectory of slope and domain changes over the day are the opposite of winter. In the morning, ventilation requires less energy, meaning a flatter slope and wider feasible domain. By early afternoon, the maximum air exchange barely exceeds $1 h^{-1}$ and the electricity use slope is steeper. The process reverses by the evening, when more ventilation again becomes feasible and less costly.

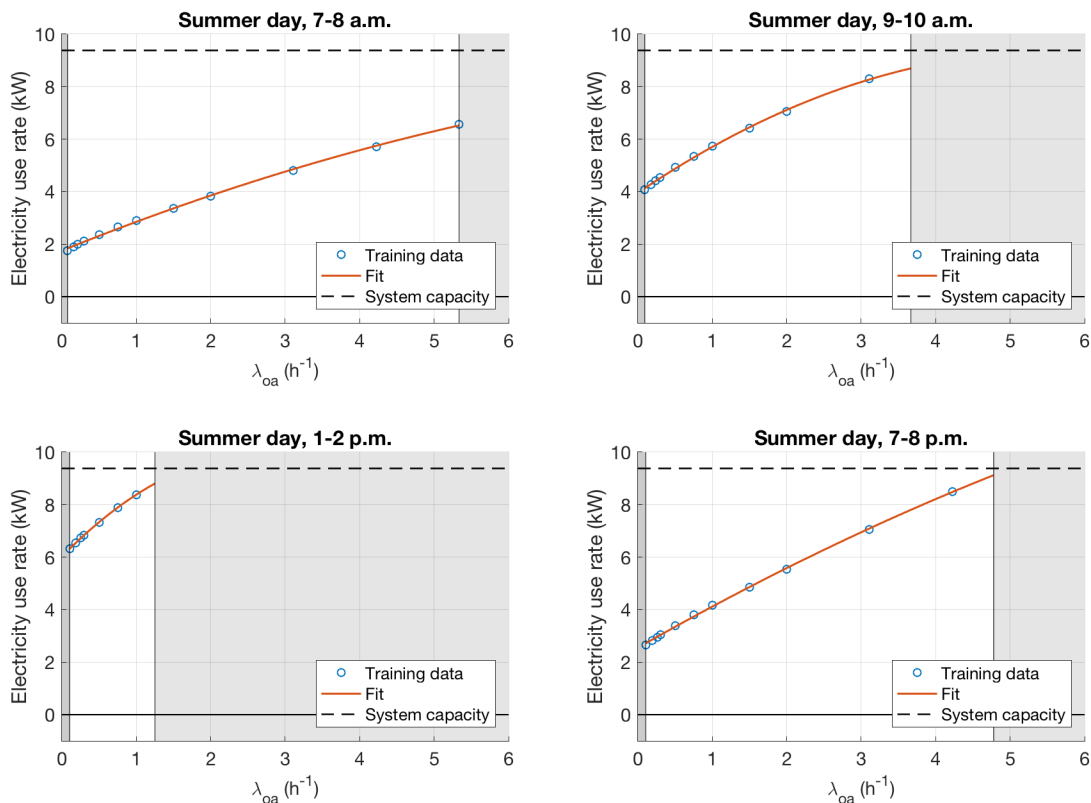


Figure 35 Cooling energy consumption fits on a hot day for four hourly timesteps, with infeasible gray regions indicating limits on outdoor air that can be delivered.

Figure 36 and Figure 37 illustrate for a spring day where, depending on the outdoor air flows, either heating or cooling, or potentially both, might be required. Figure 36 shows heating natural gas consumption as a function of λ_{oa} . Earlier in the morning, any air exchange above about $1 h^{-1}$ would call for heating, but lower ventilation could avoid it. By late morning, the cutoff point between the active and inactive heating regions moved to nearly $4 h^{-1}$. By midday, no air exchange would require heating. On the other hand, there are no cooling implications in the morning or evening, but Figure 37 shows that in mid-afternoon, cooling would be required if ventilation is too low. For example, from 1–2 p.m., the domain was divided into the active region below $1 h^{-1}$ where mechanical cooling was required, and the inactive region above $1 h^{-1}$ where free cooling met the full conditioning load and therefore had not impact on electricity consumption. By 4–5 p.m., the cutoff point between the regions had moved up to about $1.5 h^{-1}$.

Figure 36 and Figure 37 illustrate how the fits of the form given in Equations (62) and (63) flexibly account for multiple energy impact scenarios. In the morning, there was no energy required below an air exchange cutoff; above the cutoff, heating energy was consumed. In the afternoon, there was no energy required above an air exchange cutoff; below the cutoff free cooling was wasted and mechanical cooling energy was consumed.

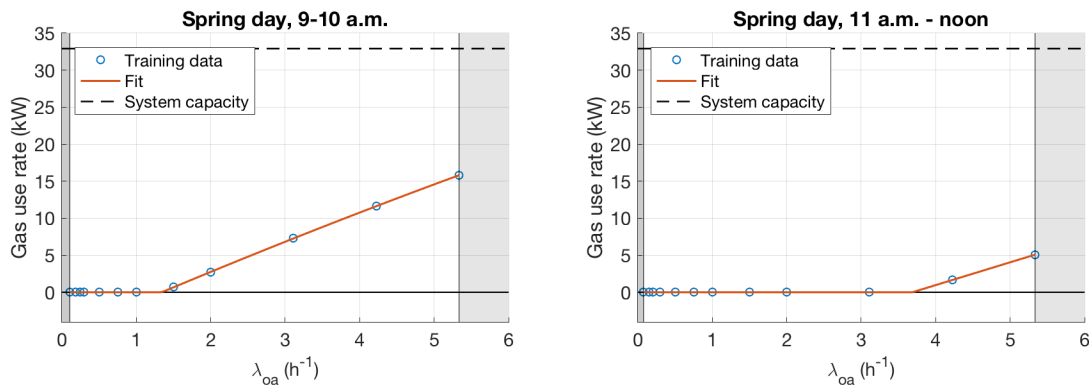


Figure 36 Heating natural gas use fits for two hourly timesteps on a mild spring day.

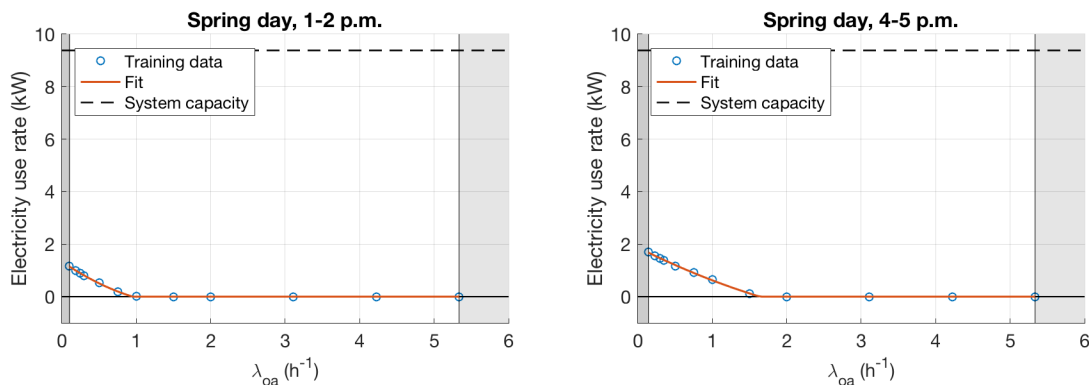


Figure 37 Cooling electricity fits for two hourly timesteps on the same mild day as the previous figure.

5.2.3.2 Energy polynomial fit corrector for dynamics

The form of Equations (62) and (63) is sound, and as the figures in the preceding section show, it can fit constant-flow ventilation very well. That is, all of the preceding illustrations are based on each λ_{0a} having also been applied at the previous timestep. But, in a dynamic

optimization problem, flows may change substantially between two consecutive timesteps, and these changes can introduce significant modeling errors. This was especially true at times when some values of λ_{oa} at the preceding timestep allowed the indoor temperature to float in the setpoint deadband but other values caused the indoor temperature to reach one of the setpoints. In such cases, the value of $\lambda_{oa,k-1}$ affected both the thermal energy stored in the air and structure during timestep $k-1$ and the temperature at the beginning of timestep k , and therefore affected the relation between $\lambda_{oa,k}$ and energy consumption.

To address this problem, we introduced the trajectory-corrected flow $\psi_{oa,k}$ to replace the actual timesteps outdoor flow $\phi_{oa,k}$. “Corrected” is with respect to the energy model, i.e., it means adjusted based on previous timesteps to maximize the accuracy of the energy model. The corrected flow is a weighted average of flows at all other timesteps:

$$\psi_{oa,k} = \sum_{j=1}^{N_{ts}} \zeta_{kj} \phi_{oa,j} \quad (64)$$

where ζ_{kj} is a coefficient that expresses the specific influence of the flow $\phi_{oa,j}$ at timestep j on the corrected flow $\psi_{oa,k}$. The ζ coefficients were calculated for each timestep in a second step after initial models were fit. In this step, a series of sinusoidal and highly intermittent outdoor airflow trajectories (e.g., alternating every hour or two hours between maximum and minimum possible flows) were simulated in EnergyPlus and used as training data to determine the ζ coefficients.

The final equations for energy use were simply a matter of substituting $\psi_{oa,k}$ for $\phi_{oa,j}$. Since the energy equations were formulated in terms λ_{oa} rather than ϕ_{oa} , we included the inverse volume Λ (m^{-3}),

$$\Lambda = 1/V \Rightarrow \lambda = \Lambda\phi \quad (65)$$

to help avoid nested fractions when converting between air exchange and airflows. With the corrector in place, the energy equations can be written as

$$\dot{E}_{g,heat,k} = \frac{a_{g,0,k} + a_{g,1,k}\Lambda\psi_{oa,k} + a_{g,2,k}(\Lambda\psi_{oa,k})^2}{1 + \exp(-k_{s,g,k}(\Lambda\psi_{oa,k} - \lambda_{c,g,k}))} \quad (66)$$

and

$$\dot{E}_{e,cool,k} = \frac{a_{e,0,k} + a_{e,1,k}\Lambda\psi_{oa,k} + a_{e,2,k}(\Lambda\psi_{oa,k})^2}{1 + \exp(-k_{s,e,k}(\Lambda\psi_{oa,k} - \lambda_{c,e,k}))} \quad (67)$$

With the corrected airflows, the R^2 value of the fits to the highly intermittent EnergyPlus training data was nearly always greater than 0.95, and typically was 0.99 or 1.

5.2.3.3 Discretizing IAQ equations

Driving forces for indoor air process are timestep averages, collectively denoted S_k for sources and D_k for decay terms during the k -th timestep. Concentrations, however, are tracked as instantaneous timeslices, with the notation $C(t_k)$ indicating the concentration at time t_k , that is, at the end of the k -th timestep. Given this, Equation (42) can be discretized as

$$\frac{C(t_k) - C(t_{k-1})}{\Delta t} \approx S_k - D_k \cdot \frac{C(t_k) + C(t_{k-1})}{2} \quad (68)$$

where the left-hand side is an incremental approximation of the derivative and $\frac{C(t_k)+C(t_{k-1})}{2}$ approximates the average concentration during timestep k .

After some rearranging, this relation yields a formula for calculating instantaneous concentration values forward in time,

$$C(t_k) = \frac{2S_k\Delta t + (2 - D_k\Delta t)C(t_{k-1})}{2 + D_k\Delta t} \quad (69)$$

For each species, there are $N_{ts} + 1$ variables $C(t_0), C(t_1), \dots, C(t_f)$. There are an equal number of constraints, with Equation (69) providing N_{ts} constraints, and Equation (61), relating the concentration at t_0 and t_f based on nighttime source and decay terms, providing the final constraint. All that remains is to substitute in the particular source and decay terms particular to each compound, per Table 32 and Equations (44) – (48).

The discrete version of Equation (49) is used to calculate exposed concentration,

$$C_{\text{exp}} = \frac{\sum_{k=1}^{N_{ts}} \frac{C(t_{k-1}) + C(t_k)}{2} N_{\text{occ},k} \Delta t}{\Sigma_{\text{oh}}} \quad (70)$$

where the discrete version of Σ_{oh} is

$$\Sigma_{\text{oh}} = \sum_{k=1}^{N_{ts}} N_{\text{occ},k} \Delta t \quad (71)$$

Similarly, the discrete version of the occupant-weighted average occupancy, used in the VR metric calculations, is

$$N_{\text{occ,ave}} = \frac{\sum_{k=1}^{N_{ts}} N_{\text{occ},k} \cdot N_{\text{occ},k}}{\sum_{k=1}^{N_{ts}} N_{\text{occ},k}} \quad (72)$$

5.2.3.4 Forward versions of equality constraint equations

Table 35 lists forward versions of all process dynamics equations. It combines the polynomial fits for energy use, the discretized indoor air equations with appropriate source and decay terms substituted, and the nighttime relation for the cyclical requirement from Equation (61). Table 36 lists the specific source and decay terms to be used for nighttime (nt) calculations.

Table 35 Forward versions of equations that define equality constraints in the nonlinear optimization problem.

Equation	Description	#
$\dot{E}_{g,heat,k} = \frac{a_{g,0,k} + a_{g,1,k}\Lambda\phi_{oa,k} + a_{g,2,k}(\Lambda\phi_{oa,k})^2}{1 + \exp(-k_{s,g,k}(\Lambda\phi_{oa,k} - \lambda_{c,g,k}))}$	Natural gas use as function of OA flow	N_{ts}
$\dot{E}_{e,cool,k} = \frac{a_{e,0,k} + a_{e,1,k}\Lambda\phi_{oa,k} + a_{e,2,k}(\Lambda\phi_{oa,k})^2}{1 + \exp(-k_{s,e,k}(\Lambda\phi_{oa,k} - \lambda_{c,e,k}))}$	Electricity use as function of OA flow	N_{ts}
$C_{hc}(t_k) = \frac{2\Lambda G_{hc} N_{occ,k} \Delta t + (2 - \Lambda\phi_{oa,k} \Delta t) C_{hc}(t_{k-1})}{2 + \Lambda\phi_{oa,k} \Delta t}$	C_{hc} dynamics during each timestep	N_{ts}
$C_{hc}(t_0) = C_{hc}(t_{N_{ts}}) e^{-D_{hc,nt} \tau_{nt}} + \frac{S_{hc,nt}}{D_{hc,nt}} (1 - e^{-D_{hc,nt} \tau_{nt}})$	Cyclical requirement	1
$C_{bci}(t_k) = \frac{2\Lambda G_{bci} A \Delta t + (2 - \Lambda\phi_{oa,k} \Delta t) C_{bci}(t_{k-1})}{2 + \Lambda\phi_{oa,k} \Delta t}$	C_{bci} dynamics during each timestep	N_{ts}
$C_{bci}(t_0) = C_{bci}(t_{N_{ts}}) e^{-D_{bci,nt} \tau_{nt}} + \frac{S_{bci,nt}}{D_{bci,nt}} (1 - e^{-D_{bci,nt} \tau_{nt}})$	Cyclical requirement	1
$C_{bcd}(t_k) = \frac{2kL C_{eq} \Delta t + (2 - (\Lambda\phi_{oa,k} + kL) \Delta t) C_{bcd}(t_{k-1})}{2 + (\Lambda\phi_{oa,k} + kL) \Delta t}$	C_{bcd} dynamics during each timestep	N_{ts}
$C_{bcd}(t_0) = C_{bcd}(t_{N_{ts}}) e^{-D_{bcd,nt} \tau_{nt}} + \frac{S_{bcd,nt}}{D_{bcd,nt}} (1 - e^{-D_{bcd,nt} \tau_{nt}})$	Cyclical requirement	1
$C_{pm}(t_k) = \frac{2 \left((1 - \eta_{pm,mv}) \Lambda (\phi_{oa,k} - \phi_{inf,k}) + p_{pm} \Lambda \phi_{inf,k} \right) C_{pm,out,k} \Delta t + (2 - (\Lambda\phi_{oa,k} + \eta_{pm,rec} \Lambda (\phi_{sa,k} - (\phi_{oa,k} - \phi_{inf,k})) + \beta_{pm}) \Delta t) C_{pm}(t_{k-1})}{2 + (\Lambda\phi_{oa,k} + \eta_{pm,rec} \Lambda (\phi_{sa,k} - (\phi_{oa,k} - \phi_{inf,k})) + \beta_{pm}) \Delta t}$	C_{pm} dynamics during each timestep	N_{ts}

$C_{pm}(t_0) = C_{pm}(t_{N_{ts}})e^{-D_{pm,nt}\tau_{nt}} + \frac{S_{pm,nt}}{D_{pm,nt}}(1 - e^{-D_{pm,nt}\tau_{nt}})$	Cyclical requirement	1
$C_{o3}(t_k) = \frac{2 \left((1 - \eta_{o3})\Lambda(\phi_{oa,k} - \phi_{inf,k}) + p_{o3}\Lambda\phi_{inf,k} \right) C_{o3,out,k}\Delta t + \left(2 - \left(\Lambda\phi_{oa,k} + \eta_{o3}\Lambda(\phi_{sa,k} - (\phi_{oa,k} - \phi_{inf,k})) \right) + \beta_{o3} \right) \Delta t}{2 + \left(\Lambda\phi_{oa,k} + \eta_{o3}\Lambda(\phi_{sa,k} - (\phi_{oa,k} - \phi_{inf,k})) \right) + \beta_{o3}} C_{o3}(t_{k-1})$	C_{o3} dynamics during each timestep	N_{ts}
$C_{o3}(t_0) = C_{o3}(t_{N_{ts}})e^{-D_{o3,nt}\tau_{nt}} + \frac{S_{o3,nt}}{D_{o3,nt}}(1 - e^{-D_{o3,nt}\tau_{nt}})$	Cyclical requirement	1
$C_{hc,exp} = \frac{\sum_{k=1}^{N_{ts}} \frac{C_{hc}(t_{k-1}) + C_{hc}(t_k)}{2} N_{occ,k} \Delta t}{\Sigma_{oh}}$	Occupant-weighted averaging	1
$C_{bci,exp} = \frac{\sum_{k=1}^{N_{ts}} \frac{C_{bci}(t_{k-1}) + C_{bci}(t_k)}{2} N_{occ,k} \Delta t}{\Sigma_{oh}}$	Occupant-weighted averaging	1
$C_{bcd,exp} = \frac{\sum_{k=1}^{N_{ts}} \frac{C_{bcd}(t_{k-1}) + C_{bcd}(t_k)}{2} N_{occ,k} \Delta t}{\Sigma_{oh}}$	Occupant-weighted averaging	1
$C_{pm,exp} = \frac{\sum_{k=1}^{N_{ts}} \frac{C_{pm}(t_{k-1}) + C_{pm}(t_k)}{2} N_{occ,k} \Delta t}{\Sigma_{oh}}$	Occupant-weighted averaging	1
$C_{o3,exp} = \frac{\sum_{k=1}^{N_{ts}} \frac{C_{o3}(t_{k-1}) + C_{o3}(t_k)}{2} N_{occ,k} \Delta t}{\Sigma_{oh}}$	Occupant-weighted averaging	1
$VR_{hc} = \frac{G_{hc}}{3.6 \cdot C_{hc,exp}}$	Definition	1
$VR_{bci} = \frac{G_{bci}A}{3.6 \cdot C_{bci,exp} \cdot N_{occ,ave}}$	Definition	1

$VR_{bcd} = \frac{kL(C_{eq} - C_{bcd,exp})V}{3.6 \cdot C_{bcd,exp} \cdot N_{occ,ave}}$	Definition	1
$VR = 0.50 \cdot VR_{hc} + 0.25 \cdot VR_{bci} + 0.25 \cdot VR_{bcd}$	Definition	1
$\psi_{oa,k} = \sum_{j=1}^{N_{ts}} \zeta_{kj} \phi_{oa,j}$	Definition	N_{ts}

Table 36 Nighttime sources and decay terms for five indoor air pollutants

C	S_{nt}	D_{nt}	Eq.
C_{hc}	0	$\int_{t_f}^{t_0+24} \lambda_{inf}(t \bmod 24) dt$	(73)
C_{bci}	$\frac{G_{bci}}{V} A$	$\int_{t_f}^{t_0+24} \lambda_{inf}(t \bmod 24) dt$	(74)
C_{bcd}	kLC_{eq}	$\int_{t_f}^{t_0+24} \lambda_{inf}(t \bmod 24) dt + kL$	(75)
C_{pm}	$\int_{t_f}^{t_0+24} p_{pm} \lambda_{inf}(t \bmod 24) C_{pm,out}(t \bmod 24) dt$	$\int_{t_f}^{t_0+24} \lambda_{inf}(t \bmod 24) dt + \beta_{pm}$	(76)
C_{o3}	$\int_{t_f}^{t_{on}+24} p_{o3} \lambda_{inf}(t \bmod 24) C_{o3,out}(t \bmod 24) dt$	$\int_{t_f}^{t_0+24} \lambda_{inf}(t \bmod 24) dt + \beta_{o3}$	(77)

5.2.3.5 Final nonlinear optimization problem

The decision variables in the final optimization problem are listed in Table 37. There are a total of $9 \times N_{ts} + 14$ variables. For the given case study, there were 16 hours of HVAC operation per day. Thus, for one-hour timesteps, there were 158 variables.

Table 37 Decision variables in the nonlinear optimization problem

Variable	Units	Number	Lower limit	Upper limit
ϕ_{oa}	m ³ /h	N_{ts}	$\phi_{oa,k}^l$	$\phi_{oa,k}^u$
ψ_{oa}	m ³ /h	N_{ts}	$\phi_{oa,k}^l$	$\phi_{oa,k}^u$
$\dot{E}_{g,heat}$	kW	N_{ts}	0	$\dot{E}_{g,heat}^u$
$\dot{E}_{e,cool}$	kW	N_{ts}	0	$\dot{E}_{e,cool}^u$
C_{hc}	μg/m ³	$N_{ts} + 1$	0	
C_{bci}	μg/m ³	$N_{ts} + 1$	0	
C_{bcd}	μg/m ³	$N_{ts} + 1$	0	
C_{pm}	μg/m ³	$N_{ts} + 1$	0	
C_{o3}	ppb	$N_{ts} + 1$	0	
$C_{hc,exp}$	μg/m ³	1	0	
$C_{bci,exp}$	μg/m ³	1	0	
$C_{bcd,exp}$	μg/m ³	1	0	
$C_{pm,exp}$	μg/m ³	1	0	
$C_{o3,exp}$	ppb	1	0	
VR_{hc}	L/s/occ	1	0	
VR_{bci}	L/s/occ	1	0	
VR_{bcd}	L/s/occ	1	0	
VR	L/s/occ	1	5	

The objective function, in discrete form and with appropriate substitutions, is

$$\begin{aligned}
 L = & P_{wage} \exp(b_{wp,0} + b_{wp,1} \cdot VR + b_{wp,2} \cdot VR^2 + b_{wp,4} \cdot VR^4) \\
 & + P_{wage} \exp(b_{ea,0} + b_{ea,1} \cdot VR + b_{ea,2} \cdot VR^2 + b_{ea,4} \cdot VR^4) \\
 & + P_{pm} C_{pm,exp} + P_{o3} C_{o3,exp} + \frac{1}{\Sigma_{oh}} \sum_{k=1}^{N_{ts}} (P_g \dot{E}_{g,heat,k} + P_{e,k} \dot{E}_{e,cool,k}) \Delta t
 \end{aligned} \tag{78}$$

The remainder of the problem is defined in terms of equality constraints, listed in Table 38,

which derive from the governing equations for process dynamics listed in Table 35.

Table 38 Equality constraints in the nonlinear optimization problem

Equation	Description	Number
$\frac{a_{g,0,k} + a_{g,1,k}\Lambda\psi_{oa,k} + a_{g,2,k}(\Lambda\psi_{oa,k})^2}{1 + \exp(-k_{s,g,k}(\Lambda\psi_{oa,k} - \lambda_{c,g,k}))} - \dot{E}_{g,heat,k} = 0$	Natural gas use as a function of corrected OA flow	N_{ts}
$\frac{a_{e,0,k} + a_{e,1,k}\Lambda\psi_{oa,k} + a_{e,2,k}(\Lambda\psi_{oa,k})^2}{1 + \exp(-k_{s,e,k}(\Lambda\psi_{oa,k} - \lambda_{c,e,k}))} - \dot{E}_{e,cool,k} = 0$	Electricity use as a function of corrected OA flow	N_{ts}
$2\Lambda G_{hc} N_{occ,k} \Delta t + (2 - \Lambda\phi_{oa,k} \Delta t) C_{hc}(t_{k-1}) - (2 + \Lambda\phi_{oa,k} \Delta t) C_{hc}(t_k) = 0$	C_{hc} dynamics during each timestep	N_{ts}
$C_{hc}(t_{N_{ts}}) e^{-D_{hc,nt}\tau_{nt}} + \frac{S_{hc,nt}}{D_{hc,nt}} (1 - e^{-D_{hc,nt}\tau_{nt}}) - C_{hc}(t_0) = 0$	Cyclical requirement	1
$2\Lambda G_{bci} A \Delta t + (2 - \Lambda\phi_{oa,k} \Delta t) C_{bci}(t_{k-1}) - (2 + \Lambda\phi_{oa,k} \Delta t) C_{bci}(t_k) = 0$	C_{bci} dynamics during each timestep	N_{ts}
$C_{bci}(t_{N_{ts}}) e^{-D_{bci,nt}\tau_{nt}} + \frac{S_{bci,nt}}{D_{bci,nt}} (1 - e^{-D_{bci,nt}\tau_{nt}}) - C_{bci}(t_0) = 0$	Cyclical requirement	1
$2kLC_{eq} \Delta t + (2 - (\Lambda\phi_{oa,k} + kL) \Delta t) C_{bcd}(t_{k-1}) - (2 + (\Lambda\phi_{oa,k} + kL) \Delta t) C_{bcd}(t_k) = 0$	C_{bcd} dynamics during each timestep	N_{ts}
$C_{bcd}(t_{N_{ts}}) e^{-D_{bcd,nt}\tau_{nt}} + \frac{S_{bcd,nt}}{D_{bcd,nt}} (1 - e^{-D_{bcd,nt}\tau_{nt}}) - C_{bcd}(t_0) = 0$	Cyclical requirement	1
$2 \left((1 - \eta_{pm,mv}) \Lambda (\phi_{oa,k} - \phi_{inf,k}) + p_{pm} \Lambda \phi_{inf,k} \right) C_{pm,out,k} \Delta t \\ + \left(2 - (\Lambda\phi_{oa,k} + \eta_{pm,rec} \Lambda (\phi_{sa,k} - (\phi_{oa,k} - \phi_{inf,k}))) + \beta_{pm} \right) \Delta t C_{pm}(t_{k-1}) \\ - \left(2 + (\Lambda\phi_{oa,k} + \eta_{pm,rec} \Lambda (\phi_{sa,k} - (\phi_{oa,k} - \phi_{inf,k}))) + \beta_{pm} \right) \Delta t C_{pm}(t_k) = 0$	C_{pm} dynamics during each timestep	N_{ts}
$C_{pm}(t_{N_{ts}}) e^{-D_{pm,nt}\tau_{nt}} + \frac{S_{pm,nt}}{D_{pm,nt}} (1 - e^{-D_{pm,nt}\tau_{nt}}) - C_{pm}(t_0) = 0$	Cyclical requirement	1

$2 \left((1 - \eta_{o3}) \Lambda (\phi_{oa,k} - \phi_{inf,k}) + p_{o3} \Lambda \phi_{inf,k} \right) C_{o3,out,k} \Delta t$ $+ \left(2 - \left(\Lambda \phi_{oa,k} + \eta_{o3} \Lambda (\phi_{sa,k} - (\phi_{oa,k} - \phi_{inf,k})) \right) + \beta_{o3} \right) \Delta t C_{o3}(t_{k-1})$ $- \left(2 + \left(\Lambda \phi_{oa,k} + \eta_{o3} \Lambda (\phi_{sa,k} - (\phi_{oa,k} - \phi_{inf,k})) \right) + \beta_{o3} \right) \Delta t C_{o3}(t_k) = 0$	C_{o3} dynamics during each timestep	N_{ts}
$C_{o3}(t_{N_{ts}}) e^{-D_{o3,nt} \tau_{nt}} + \frac{S_{o3,nt}}{D_{o3,nt}} (1 - e^{-D_{o3,nt} \tau_{nt}}) - C_{o3}(t_0) = 0$	Cyclical requirement	1
$\frac{\sum_{k=1}^{N_{ts}} \frac{C_{hc}(t_{k-1}) + C_{hc}(t_k)}{2} N_{occ,k} \Delta t}{\Sigma_{oh}} - C_{hc,exp} = 0$	Occupant-weighted averaging	1
$\frac{\sum_{k=1}^{N_{ts}} \frac{C_{bci}(t_{k-1}) + C_{bci}(t_k)}{2} N_{occ,k} \Delta t}{\Sigma_{oh}} - C_{bci,exp} = 0$	Occupant-weighted averaging	1
$\frac{\sum_{k=1}^{N_{ts}} \frac{C_{bcd}(t_{k-1}) + C_{bcd}(t_k)}{2} N_{occ,k} \Delta t}{\Sigma_{oh}} - C_{bcd,exp} = 0$	Occupant-weighted averaging	1
$\frac{\sum_{k=1}^{N_{ts}} \frac{C_{pm}(t_{k-1}) + C_{pm}(t_k)}{2} N_{occ,k} \Delta t}{\Sigma_{oh}} - C_{pm,exp} = 0$	Occupant-weighted averaging	1
$\frac{\sum_{k=1}^{N_{ts}} \frac{C_{o3}(t_{k-1}) + C_{o3}(t_k)}{2} N_{occ,k} \Delta t}{\Sigma_{oh}} - C_{o3,exp} = 0$	Occupant-weighted averaging	1
$G_{hc} \Lambda - 3.6 \Lambda \cdot VR_{hc} \cdot C_{hc,exp} = 0$	Definition	1
$G_{bci} \Lambda \Lambda - 3.6 \Lambda \cdot N_{occ,ave} \cdot VR_{bci} \cdot C_{bci,exp} = 0$	Definition	1
$kL C_{eq} - kL C_{bcd,exp} - 3.6 \Lambda \cdot N_{occ,ave} \cdot VR_{bcd} \cdot C_{bcd,exp} = 0$	Definition	1
$0.50 \cdot VR_{hc} + 0.25 \cdot VR_{bci} + 0.25 \cdot VR_{bcd} - VR = 0$	Definition	1
$\sum_{j=1}^{N_{ts}} \zeta_{kj} \phi_{oa,j} - \psi_{oa,k} = 0$	Definition	N_{ts}

The various parameters and exogenous variable trajectories required by the optimization routine, such as occupancy, supply airflows, and infiltration, were extracted from simulations during the problem setup routines, at approximately the same time as the polynomial energy models were fit.

5.2.4 Solution method

After discretizing and translating the optimal control problem, the resulting nonlinear optimization problem can be solved efficiently by interior point methods (Biegler & Zavala, 2009; Byrd, Hribar, & Nocedal, 1999). While there are more powerful open source options, notably IPOPT, the interior point solver in Matlab proved sufficient for the present research, capable of solving each problem in a few seconds. Providing analytical expressions for gradients and the Hessian (second derivatives of the Lagrangian) was critical for achieving the speed and performance of the solver. It was also necessary to use some trial and error with multipliers to change the scaling of the Hessian and improve numerical performance. All of the results explored in this chapter are for timesteps of one hour. Testing did not indicate additional improvements available with optimization using shorter timesteps.

5.2.5 Testbed

The model used for assessment throughout was a small office with the same size, construction, and other physical properties as the office used in Chapter 4. Simulations in this chapter were conducted in Philadelphia. Energy prices were the medium level prices from Chapter 4, i.e. \$0.1586 /kWh for electricity and \$0.0469 /kWh for natural gas. Work performance and absenteeism parameters were also the medium reference values established in Chapter 4. Prices were set to zero for PM_{2.5} and ozone for the present work. The “standard” version of the model refers to a version with median envelope leakiness, a typical office schedule, design

occupant density of 5 occupants per 100 m², and no time-of-use pricing. The standard office model was used for much of the analysis, then expanded to include dynamic time-of-use electricity pricing. Finally, a sensitivity analysis broadened the scope to buildings with tighter envelopes, less typical occupancy profiles, and more occupants.

5.3 Results

5.3.1 The effective ventilation rate

This section illustrates the effective ventilation rate VR_{eff} and the principle of equivalency that will be used throughout the rest of the results. We compare three strategies on a single day, January 11, which had significant wind- and temperature-driven infiltration. The first strategy employed fixed ventilation ('Fixed'), or a constant outdoor airflow rate, determined based on the design occupancy, during mechanical system operation. Though the fixed mechanical ventilation rate VR_{mv} was 10 L/s/occ, all of the VR metrics were much greater because of infiltration. As Table 39 indicates, VR_{build} , an average of the VR metrics for the ventilation-independent (bci) and dependent (bcd) building-emitted contaminants, was 19.8 L/s/occ. VR_{hc} , based on the human-emitted contaminant, was greater, at 21.8 L/s/occ. VR_{hc} was nearly always greater than VR_{build} , regardless of ventilation strategy, because of the morning transients. The transient rise of the human-emitted contaminant in the morning makes $C_{\text{hc,exp}}$ less than what the steady state concentration would be, while the transient dilution of the building-emitted contaminant makes $C_{\text{bcd,exp}}$ and $C_{\text{bci,exp}}$ greater than what the steady state concentration would be.

The time plots in Figure 38 illustrate the phenomenon. C_{hc} rises during the morning and falls during the evening, so that its average is less than the steady state value it approaches in the middle of the day (and thus the computed VR_{hc} greater than one based on the maximum C_{hc}). On the other hand, C_{bci} and C_{bcd} fall during the morning and rise during the evening, so that their averages are greater than the steady state values they respectively approach in the middle of the

day (and thus the computed VR_{bci} or VR_{bcd} less than one based on the maximum C_{bci} or C_{bcd}). We regard these phenomena as beneficial features of the equivalent VR approach. Most importantly, the approach accurately reflects aggregate exposure, which is, in our view, the principal outcome ventilation aims to affect. In addition, the inclusion of both human and building contaminants, which usually have negatively correlated trajectories at the beginning and end of the day, helps make the approach more robust to undesirable optimization solutions.

The second strategy in Table 39 shows the results of implementing an economizer and demand-controlled ventilation (EDCV), though only the DCV portion was in effect on this cold winter day. The CO_2 setpoint corresponds to a mechanical VR of 10 L/s/occ with a typical office-work CO_2 emission rate. The VR_{eff} that resulted was 11.6 L/s/occ, somewhat greater than 10 L/s/occ because of the morning transients, but much less than the 20.8 L/s/occ VR_{eff} that resulted from the fixed VR_{mv} of 10 L/s/occ. This was because, as the left column of Figure 38 shows, the EDCV strategy (in red) nearly doubled exposed concentrations of the human-emitted and independent building-emitted contaminants. To achieve the same VR_{eff} as fixed ventilation with a VR_{mv} of 10 L/s/occ in a DCV strategy, the CO_2 setpoint would need to be much lower, at 633 ppm. The right column of Figure 38 shows this strategy, and how it produced approximately the same exposure for each of the three contaminants as the fixed VR_{mv} strategy.

Table 39 For three ventilation strategies on January 11, ventilation rate (VR) values in L/s/occ. For the two strategies with economizer and demand-controlled ventilation (EDCV), the CO_2 setpoint in ppm is given.

Strategy	VR_{mv}	CO_2 setpoint	VR_{eff}	VR_{hc}	VR_{build}	VR_{bci}	VR_{bcd}
Fixed	10	-	20.8	21.8	19.8	19.5	20.1
EDCV	-	917	11.6	12.4	10.8	10.8	10.8
EDCV	-	633	20.8	22.8	18.7	17.9	19.5

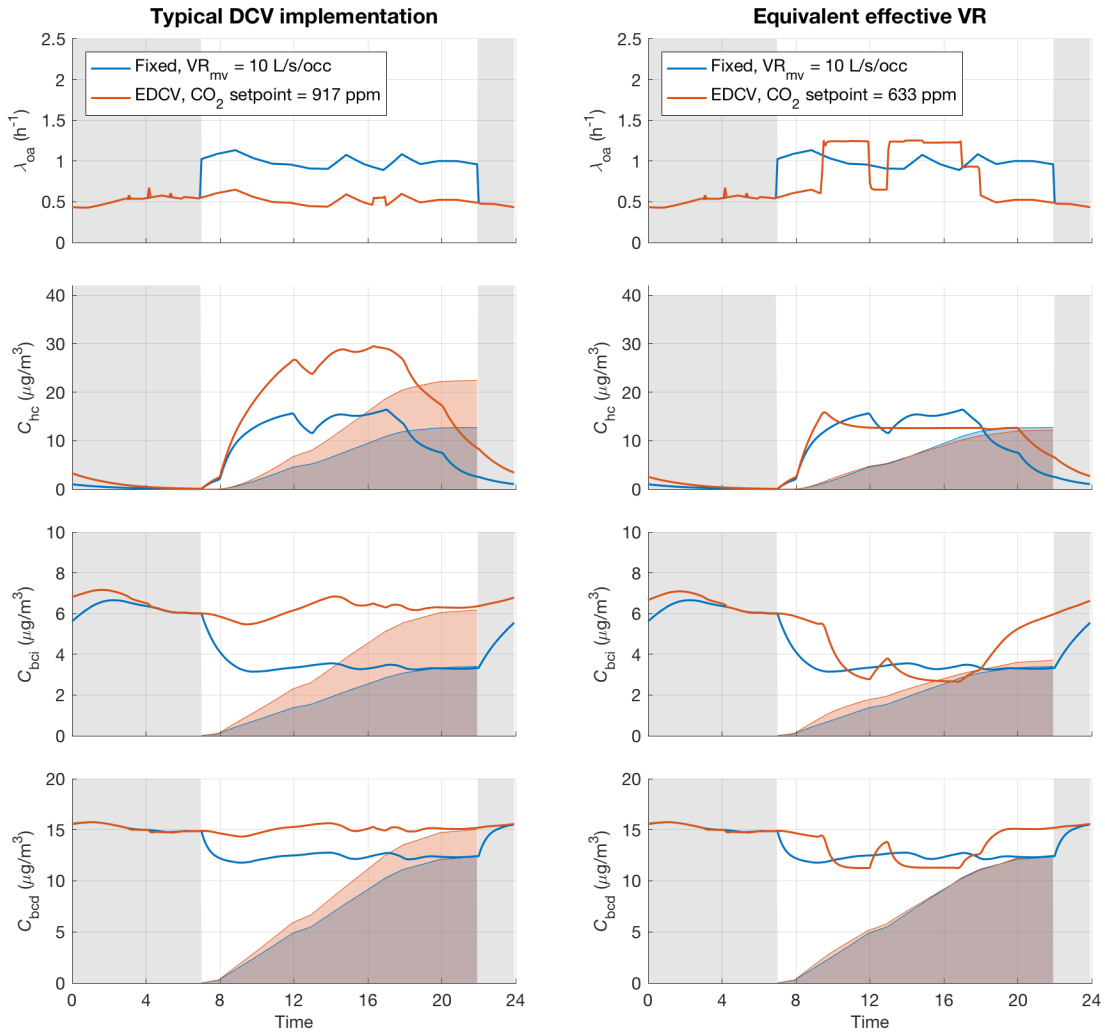


Figure 38 Time plots of the total outdoor air exchange rate λ_{oa} and concentrations of a human-emitted contaminant (hc) and building-emitted independent (bci) and dependent (bcd) contaminants. The columns show two different demand-controlled ventilation implementations (red line); the fixed ventilation strategy (blue line) is the same. The curves with shaded areas underneath show cumulative occupant-weighted exposure; the gray shaded areas are unoccupied periods.

In addition to illustrating the VR metrics, these strategies demonstrate one of the central principles of our analysis in this chapter: equivalency between any two strategies that have the same effective VR. This is an important point that extends beyond the work here. Consider the three dots that illustrate the lost work performance (with VR_{eff} on the upper x -axis) versus daily energy cost for the three strategies just described. In most typical implementations, including as permitted by ASHRAE Standard 62.1-2016, the EDCV strategy with a CO_2 setpoint derived from

10 L/s/occ is considered acceptable to meet a 10 L/s/occ requirement for mechanical ventilation. The fixed strategy cost \$14.68 for the day, while the EDCV version cost \$11.50, representing a \$3.18 or 22% savings. These types of savings are consistent with numerous evaluations of DCV potential, including those in the second chapter. However, as Figure 39 makes clear, the two strategies were not equivalent. The EDCV strategy with a setpoint of 917 ppm saved money *by reducing ventilation*.

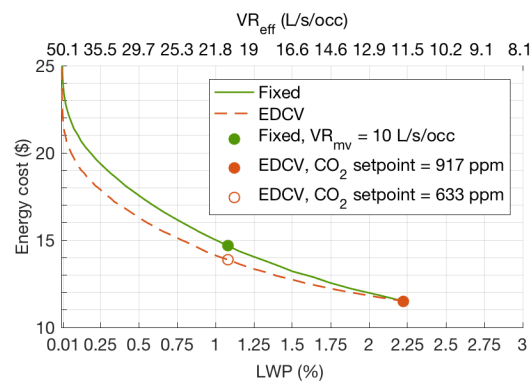


Figure 39 Fixed and economizer and demand-controlled ventilation (EDCV) Pareto curves, with points marked for the three strategies listed in Table 39.

Before considering the cost savings, one must consider whether the desired effective VR is 20.8 L/s/occ or 11.6 L/s/occ. Figure 39 also shows Pareto curves for fixed ventilation and EDCV—that is, plots of the tradeoffs between LWP/ VR_{eff} and energy costs. We can see that EDCV provides Pareto improvements since its curve is below and to the left of that of fixed ventilation. Our equivalent ventilation approach quantifies these improvements by calculating the distance between the curves at a given target VR_{eff} . Graphically, it is like taking a vertical cross-section of the Pareto curves at a VR_{eff} value. In the example at hand, for a target VR_{eff} of 11.6 L/s/occ, fixed ventilation and EDCV achieved it with identical energy costs. For a target VR_{eff} of 20.8 L/s/occ, EDCV saved \$0.81 or 6% compared to fixed ventilation.

While Chapter 4 explored how the VR should be set, this chapter assumes that a VR_{eff} has already been determined, and examines about whether there is any benefit changing the way the given VR_{eff} is achieved on a single day.

5.3.2 Pareto improvements, by day

The next few sections explore the optimized OBV results in the “standard case” of the small office testbed, that is with median envelope leakiness, default occupant density of 5 people per 100 m², a typical schedule, and no time-of-use pricing. A sensitivity analysis in Section 5.3.7 expands on these findings. We illustrate with four days: January 11, June 15, July 3, and July 18, Pareto curves for which are shown in Figure 40.

On January 11, a day with an occupant-weighted average outdoor temperature (T_{oa}) of about 0 °C, the DCV control of EDCV provided equivalent VR_{eff} to fixed ventilation with some energy savings. Optimized OBV, however, did not provide additional savings, yielding a Pareto curve nearly identical to EDCV. On June 15, which had an occupant-weighted average T_{oa} of about 25 °C, EDCV provided relatively few savings, while the OBV provided meaningful benefits even over EDCV. On July 3, though, which also had an occupant-weighted average T_{oa} of about 25 °C, the relation between VR_{eff} and energy consumption was nearly flat. None of the strategies used significantly less energy than the others, though employing fixed ventilation at any rate less than the maximum would be a lose-lose proposition in terms of LWP and energy costs. Finally, on July 18, with an occupant-weighted average T_{oa} of about 30 °C, there was again a tradeoff between VR_{eff} and energy costs, but no Pareto improvements were possible, with all strategies yielding essentially the same tradeoff curve.

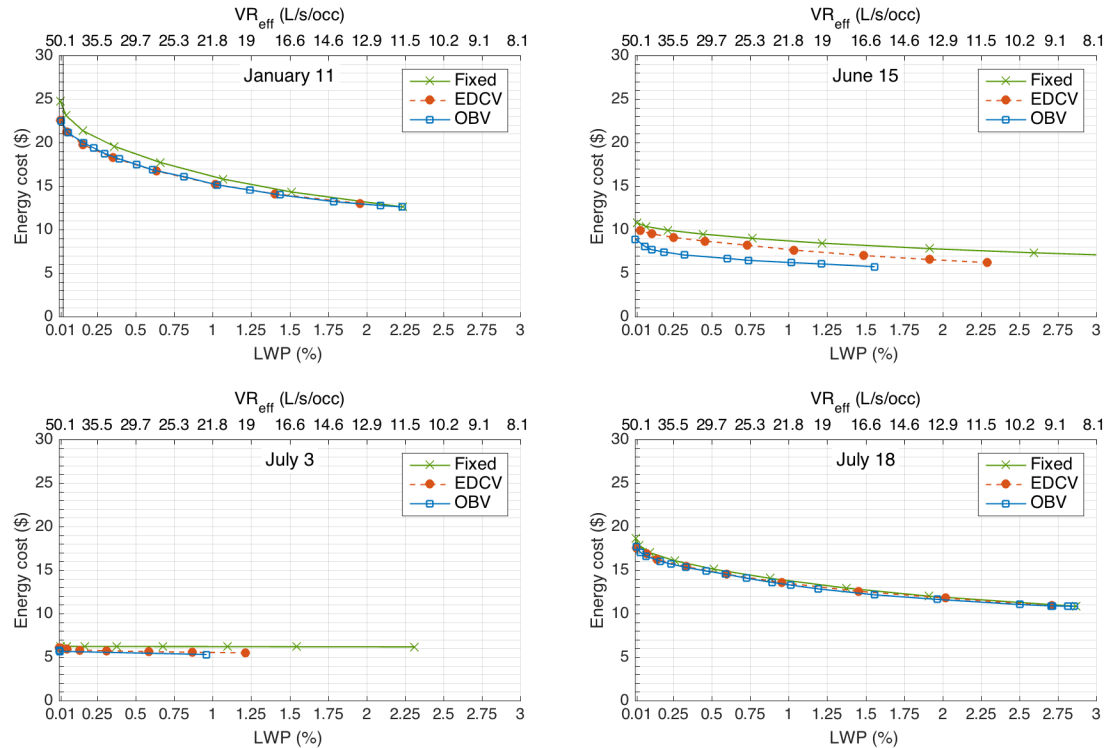


Figure 40 Pareto curves for four illustrative days showing energy costs versus lost work performance (LWP) and effective ventilation rate (VR_{eff}) for fixed ventilation, economizer with demand-controlled ventilation (EDCV), and optimized outcome-based ventilation (OBV).

The days illustrated in Figure 40 were representative of general trends. In the winter, the DCV component of EDCV saved energy compared to fixed ventilation, but optimized OBV presented no additional savings. The same was true on most spring and fall days, though on those days it was the economizer component of EDCV rather than DCV that saved energy. On the hottest summer days, neither EDCV nor OBV used meaningfully less energy than fixed ventilation for equivalent VR_{eff} . Only on days that were warm but not excessively hot did optimized OBV provide energy savings beyond those of EDCV.

These results are illustrated in Figure 41, Figure 42, and Figure 43. In each, the top left panel shows energy costs for fixed ventilation and EDCV, and the bottom left panel the savings of EDCV versus fixed ventilation. Similarly, the top right panel shows energy costs for EDCV and OBV, and the bottom right panel the savings of OBV versus EDCV. In all plots, the x -axis is the

time-weighted average outdoor air temperature. Figure 41 corresponds to $VR_{\text{eff}} = 10 \text{ L/s/occ}$, i.e. shows the points one would get by slicing the Pareto curves at an effective VR of 10 L/s/occ, or an LWP of 2.54%. In this relatively leaky small office, a VR_{eff} of 10 L/s/occ was typically achieved by with or nearly with infiltration alone, and so there was no difference between DCV and fixed ventilation on most days. However, economizing saved energy when the average T_{oa} was between about 15 and 25 °C. OBV saved energy vis-à-vis EDCV on some days when the average T_{oa} was between 20 and 30 °C.

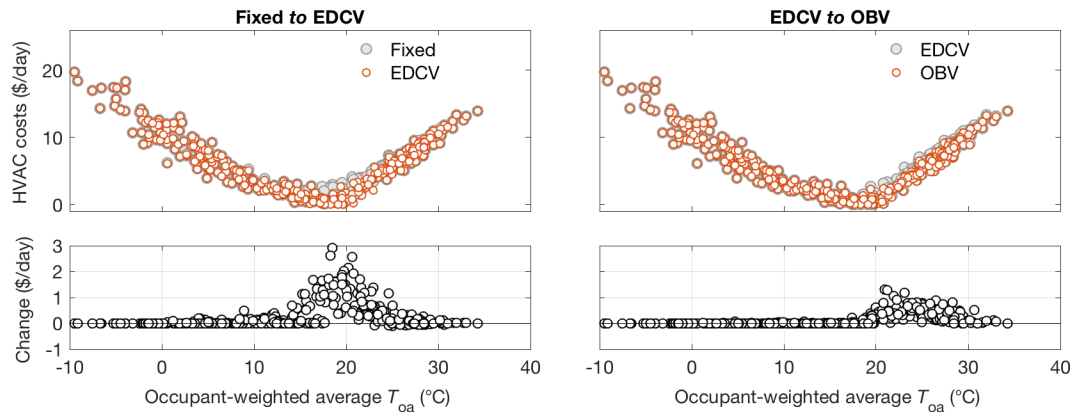


Figure 41 HVAC costs and savings for fixed ventilation, economizer and demand-controlled ventilation (EDCV), and optimized outcome-based ventilation (OBV) for $VR_{\text{eff}} = 10 \text{ L/s/occ}$.

For $VR_{\text{eff}} = 20 \text{ L/s/occ}$ (Figure 42), EDCV continued to save meaningful energy costs on mild days. The DCV component also provided a better tradeoff than fixed ventilation on cold days, but not hot ones. The savings from moving from EDCV to OBV were greater than for $VR_{\text{eff}} = 10 \text{ L/s/occ}$, but remained available only for average T_{oa} between about 20 and 30 °C.

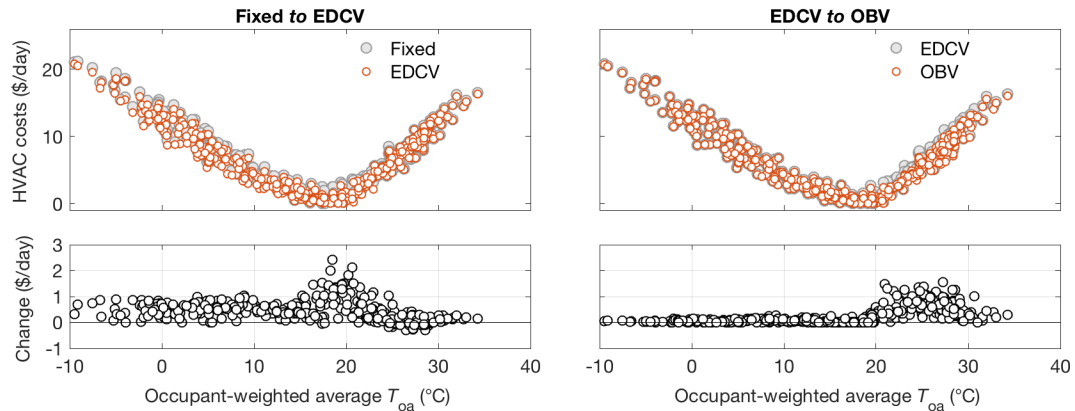


Figure 42 HVAC costs and savings for fixed ventilation, economizer and demand-controlled ventilation (EDCV), and optimized outcome-based ventilation (OBV) for $VR_{\text{eff}} = 20 \text{ L/s/occ}$.

The trends for $VR_{\text{eff}} = 30 \text{ L/s/occ}$ (Figure 43) were similar, with EDCV saving even more on cold days and still none on hot ones, so that the DCV and economizer benefits create savings typically up to \$1/day continuously from low temperatures to just over $20 \text{ }^\circ\text{C}$. The savings from moving from EDCV to OBV were greater but again only observed for average T_{oa} between about 20 and $30 \text{ }^\circ\text{C}$.

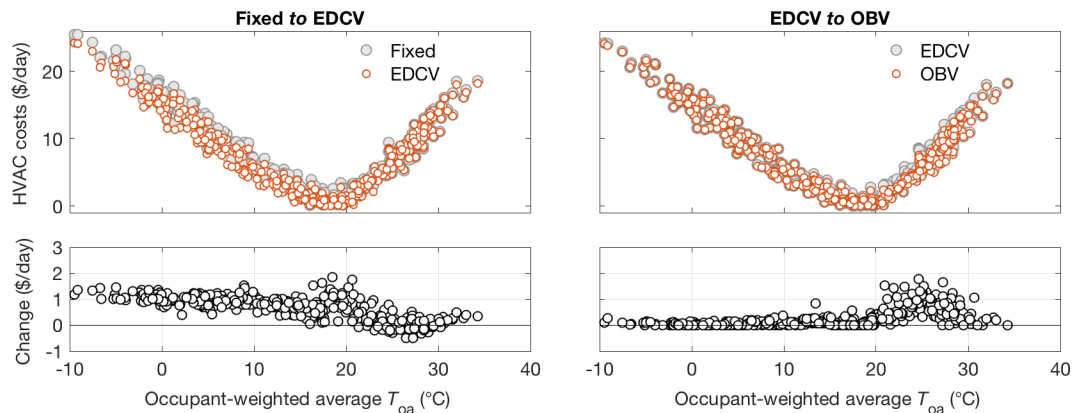


Figure 43 HVAC costs and savings for fixed ventilation, economizer and demand-controlled ventilation (EDCV), and optimized outcome-based ventilation (OBV) for $VR_{\text{eff}} = 30 \text{ L/s/occ}$.

5.3.3 Strategy examination

Figure 44 shows time trajectories of the ventilation strategies behind these results, along with the concentration and electricity use profiles they produced. Plots for economizer with demand-controlled ventilation (EDCV) are in blue and optimized outcome-based ventilation (OBV) in red for three days. Gray areas represent unoccupied times. Filled areas show cumulative occupant-weighted average concentrations or, in the case of E_e , cumulative energy use. The plots for June 15 and July 18 are for a VR_{eff} of 20 L/s/occ. The plots for July 3 are for a VR_{eff} of 22.2 L/s/occ, because economizing was favorable for so much of the day that the Pareto curve for OBV never went lower.

On June 15, traditional economizing was favorable until late morning, and outdoor airflow increased as thermal load increased. The optimized OBV strategy instead began the occupied period immediately with maximum ventilation and continued until noon. Thereafter, it brought in less outdoor air than EDCV, thereby savings energy in the hot afternoon. Compared to EDCV, the OBV strategy produced a somewhat higher $C_{hc,exp}$, but achieved the same VR_{eff} with slightly lower results for $C_{bci,exp}$, and $C_{bcd,exp}$. The bottom plot shows that most energy savings were in the afternoon, when OBV ventilated less because of the additional morning ventilation.

On July 3, the situation was similar in the morning. However, the afternoon outdoor temperature and especially enthalpy were not very high, so much so that economizing again became favorable in the later afternoon. The result was that outcome-based OBV was quite similar to EDCV. Although OBV provided some additional outdoor air in the early morning and late afternoon, it saved no appreciable energy. On July 18, the situation was different: with higher outdoor air temperatures, there was little opportunity for savings. The search for savings led the optimized OBV strategy to oscillate back and forth, which could in theory save some energy, because ventilation is always more effective when concentrations are greater. However, the energy savings were extremely minimal.

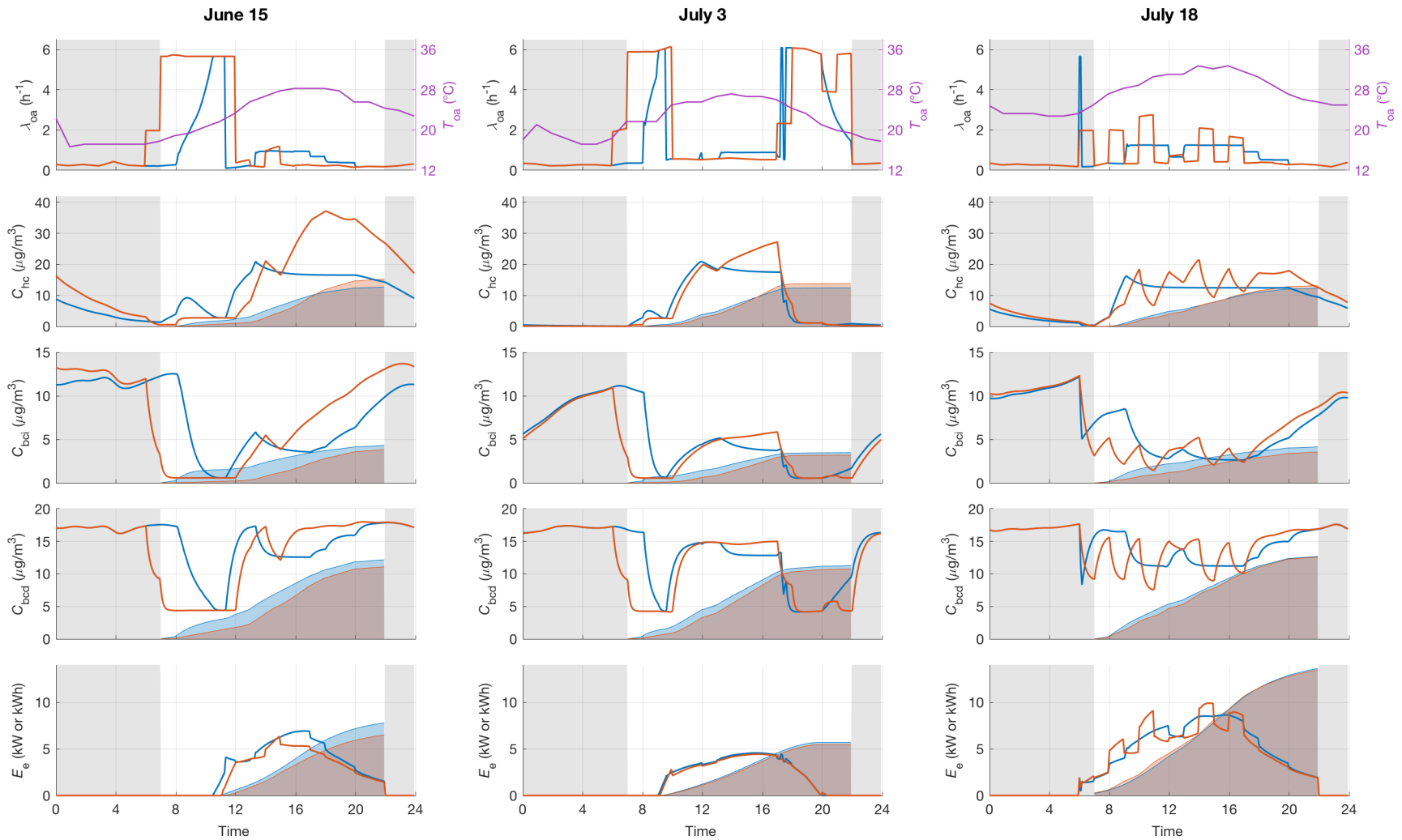


Figure 44 Plots for economizer with demand-controlled ventilation (EDCV) in blue and optimized outcome-based ventilation (OBV) in red for three days. Gray areas represent unoccupied times. Filled areas show cumulative occupant-weighted average concentrations or, in the case of E_e , cumulative energy use.

5.3.4 Outdoor pollution exposure implications

The work in this chapter proceeds from the assumption that high quality filters are likely to be better than ventilation strategy modification for dealing with outdoor air pollution, and therefore does not include PM_{2.5} and ozone exposure in the objective function used by the optimization problem. It is nonetheless instructive to assess the impacts of the optimized OBV strategies on outdoor pollution exposure. For the three strategies at VR_{eff} = 20 L/s/occ (or 22 L/s/occ) shown in Figure 44, Table 40 lists some of the exposed concentration values. In all cases, the mechanical ventilation filter PM_{2.5} removal efficiency was 40% and the recirculation efficiency was 20%. On June 15, while OBV led to substantially lower cooling coil electricity costs, it also increased exposed concentrations of both PM_{2.5} and ozone. The same was true, to a lesser extent on July 3 and July 18.

Table 40 Comparison of impacts on exposure to outdoor pollutants.

Day	Strategy	VR _{eff} (L/s/occ)	Electricity cost (\$)	C _{pm,exp} (µg/m ³)	C _{o3,exp} (ppb)	L _e (\$/occ/h)	L _{pm} (\$/occ/h)	L _{o3} (\$/occ/h)
June 15	EDCV	20.0	7.79	7.3	12.9	0.05	0.26	0.03
June 15	OBV	20.0	6.50	8.6	15.7	0.04	0.31	0.04
June 15	Change	0.0	-1.29	1.30	2.80	-0.01	0.05	0.01
July 3	EDCV	22.2	5.70	8.5	13.1	0.04	0.30	0.03
July 3	OBV	22.2	5.46	9.1	14.5	0.03	0.32	0.04
July 3	Change	0.0	-0.24	0.61	1.39	0.00	0.02	0.00
July 18	EDCV	20.0	13.62	7.1	11.2	0.08	0.25	0.03
July 18	OBV	20.0	13.47	7.4	11.6	0.08	0.26	0.03
July 18	Change	0.0	-0.15	0.31	0.34	0.00	0.01	0.00

The increase in loss due to increased outdoor pollutant exposure was much greater than the loss reduction due to lower energy costs. For example, on even the significant energy savings on June 15 only amounted to an electricity use loss reduction of 0.01 \$/occ/h, while the public health losses increased by 0.06 \$/occ/h. This may be another factor mitigating against the adoption of strategies like those discovered by the optimizations. More study would be needed, on the

influence of filter efficiency and different outdoor air pollution profiles. It is also worth noting that the same issue pertains to the difference between fixed ventilation and EDCV. For example, on June 15, the fixed ventilation strategy that yielded a VR_{eff} of 20 L/s/occ cost significantly more, at \$9.19, than EDCV, but also produced lower exposed concentrations of $PM_{2.5}$, at 6.6 $\mu\text{g}/\text{m}^3$, and ozone, at 11.7 ppb.

5.3.5 Impact summary

Figure 45 shows the annual HVAC energy cost in US \$ per m^2 , for achieving a given target VR_{eff} for each day of the year. While most results in this chapter only include heating and cooling coil energy costs, the values in Figure 45 also include fan energy costs, to enable accurate percent savings comparisons. Recall from Chapters 2 and 3 that annual HVAC costs in the range of 5–7 $\$/\text{m}^2$ are typical for offices. The costs herein are higher because both the electricity and natural gas unit prices are about 50% greater than median prices, reflecting more expensive states or inclusion of minimal social costs.

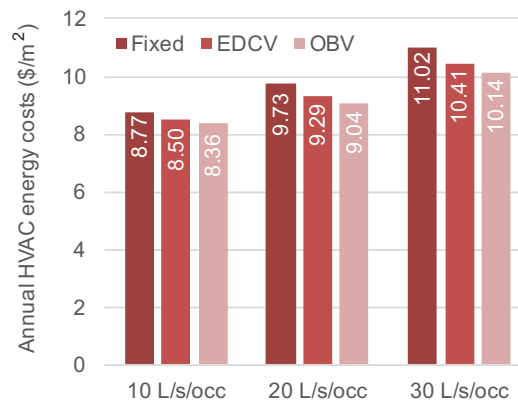


Figure 45 Annual HVAC energy costs for fixed, economizer with demand-controlled ventilation (EDCV), and optimized outcome-based ventilation (OBV) strategies, each at three effective ventilation rates.

The percent savings from switching from fixed ventilation to EDCV, in terms of annual HVAC energy costs, were 3%, 4%, and 5%, respectively, at VR_{eff} of 10, 20, and 30 L/s/occ. The analogous percent savings from switching from EDCV to optimized OBV were 2%, 3%, and 3%. (The combined reductions from going directly from fixed ventilation to optimized OBV were 5%, 7%, and 8% respectively.)

Three conclusions stand out:

1. First, the energy implications of changing the target VR_{eff} were significantly greater than the energy implications of selecting the particular strategy used to achieve a given VR_{eff} . For example, choosing a VR_{eff} of 30 L/s/occ rather than 10 L/s/occ increased costs by 22–25% regardless of the strategy.
2. When the effective VR was held constant, the energy and cost savings of economizing and DCV were much less than are typically reported when the effective VR is also allowed to change. When we speak about the energy savings of typical DCV implementations, we should be clear that most of them do not represent Pareto improvements, but rather result from a *de facto* decision to move the ventilation-energy tradeoff point, with less ventilation for less energy use.
3. Nonetheless, EDCV does provide meaningful Pareto improvements, in addition to providing a practical method for achieving or getting close to a target VR_{eff} . At least for the standard office, the optimized ventilation did not appear to yield sufficient savings above and beyond EDCV to justify the complexity of its implementation.

5.3.6 Time-of-use pricing

One potential use of dynamically optimizing outdoor air delivery in the outcome-based ventilation framework is for energy costs savings in a dynamic time-of-use (TOU) electricity pricing structure. To assess this opportunity, we optimized all the days in June, July, and August

with prices that remained at 0.1586 \$/kWh for most of the day but nearly doubled to 0.3000 \$/kWh from 2 p.m. to 4 p.m. Figure 46 shows Pareto curves for June 15 and July 3, and Table 41 summarizes results for the entire summer.

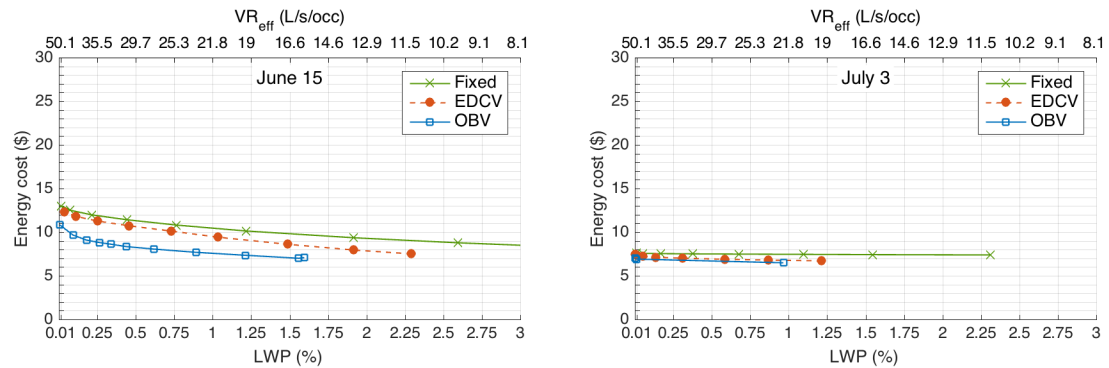


Figure 46 Pareto curves of tradeoff space between lost work performance (LWP) or effective ventilation rate VR_{eff} and energy costs, for two summer days with time-of-use pricing, showing fixed ventilation, economizer with demand-controlled ventilation (EDCV), and optimized outcome-based ventilation (OBV).

Comparing the plots in Figure 46 to their analogues in Figure 40 shows that TOU pricing increased total energy costs on both days. On June 15, the dynamic pricing also increased the difference between EDCV and optimized OBV slightly. On July 3, TOU pricing did not add any meaningful distinctions among the three strategies. Table 41 summarizes HVAC costs per m^2 for the summer. It shows that the absolute cost savings of OBV versus EDCV were slightly greater with TOU pricing, but the relative cost savings were almost identical to cases without TOU pricing. In other words, TOU pricing increased the average unit cost of energy, and the savings from OBV increased by a corresponding proportion. No qualitatively novel or beneficial behavior was enabled by applying optimization in a dynamic pricing context. Table 41, it is worth noting, also confirms that, with or without TOU pricing, the greatest savings from OBV were during the summer.

Table 41 Summer HVAC costs and percent changes for fixed ventilation, economizer with demand-controlled ventilation (EDCV), and optimized outcome-based ventilation (OBV), with and without time-of-use (TOU) electricity pricing.

TOU pricing	VR _{eff} (L/s/occ)	Summer HVAC cost (\$/m ²)			Percent change			Cost change (\$/m ²)
		Fixed	EDCV	OBV	Fixed to EDCV	EDCV to OBV	Fixed to OBV	EDCV to OBV
No	10	2.59	2.52	2.43	3%	3%	6%	-0.09
Yes	10	2.93	2.86	2.76	2%	4%	6%	-0.10
No	20	2.79	2.73	2.59	2%	5%	7%	-0.14
Yes	20	3.17	3.12	2.93	2%	6%	8%	-0.20
No	30	2.96	2.92	2.77	1%	5%	6%	-0.15
Yes	30	3.37	3.34	3.13	1%	6%	7%	-0.22

5.3.7 Sensitivity analysis

So far, results presented have shown that, for the standard office, optimizing ventilation in an outcome-based framework can achieve equivalent VR_{eff} while providing some cost savings over both fixed ventilation and EDCV, but only during a limited number of warm-but-not-hot days—cumulatively providing relatively minor savings over EDCV, which turns out to be reasonably close to optimal. To assess other situations, we conducted a factorial sensitivity analysis (SA), varying five factors:

- the day of the year, among the four days already used for illustration: January 11, June 15, July 3, and July 18;
- the daily schedule of fractional occupancy, among the typical (“Typ”) schedule used in all simulations presented so far, a morning pattern (“Morn”), an afternoon schedule (“Aft”), and a highly intermittent occupancy (“Int”);
- occupant density, between 5 occupants and 20 occupants per 100 m²;
- infiltration, between that produced by a median envelope leakage coefficient and that produced by an extremely low leakage coefficient;
- the absence or presence of time-of-use pricing.

The schedules are shown in Figure 47.

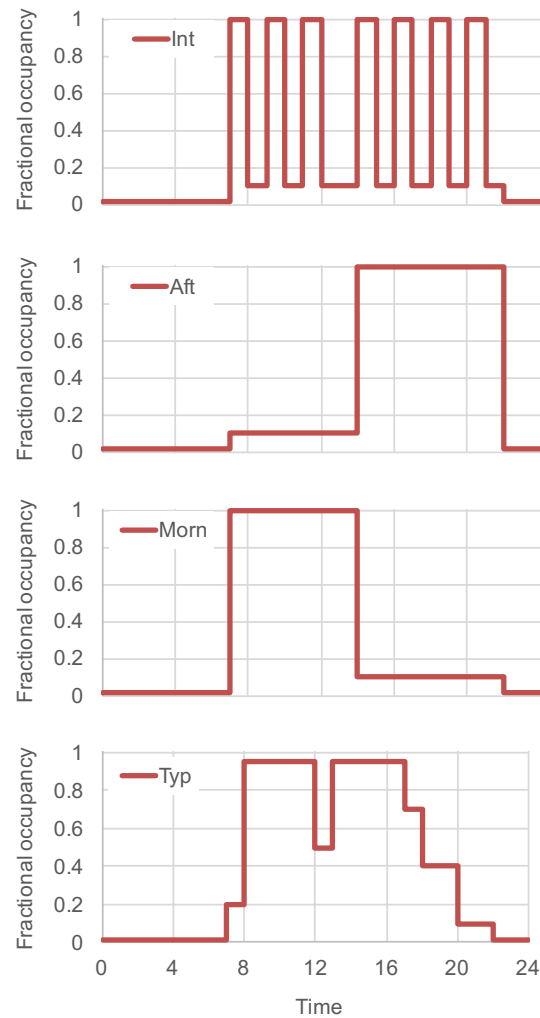


Figure 47 Typical (Typ), morning (Morn), afternoon (Aft), and intermittent (Int) occupancy schedules.

The SA results seemed to confirm that optimizing outcome-based ventilation is unlikely to provide any benefits on heating days. On January 11, regardless of occupancy schedule, occupant density, or infiltration, the optimized OBV strategy saved no energy compared to EDCV. The results for the other three days for $VR_{\text{eff}} = 10 \text{ L/s/occ}$ are shown in Figure 48. The bars span from the low to the high savings of OBV versus EDCV, and the black line in the middle is the mean of the SA cases.

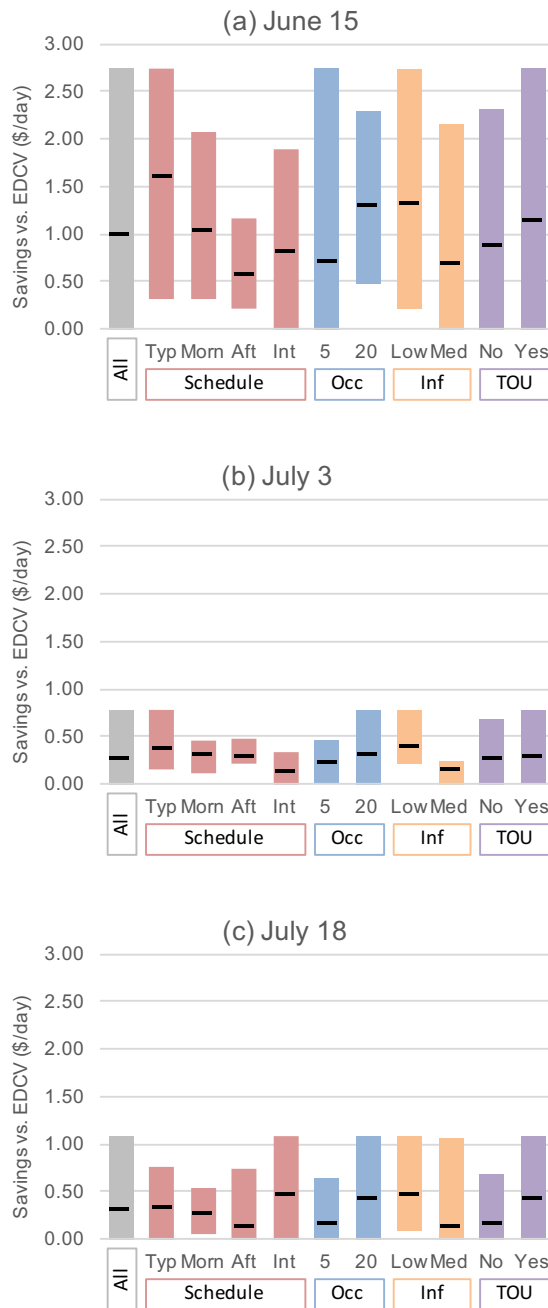


Figure 48 Sensitivity results for three days, for the savings of optimized outcome-based ventilation versus economizer and demand-controlled ventilation (EDCV). For each factor value, the bars span from the minimum to maximum savings and the black lines indicate the mean savings.

Of the three, June 15 remained the day with the most potential for savings, though the varied parameters opened more savings opportunities on the other two days. In general, somewhat surprisingly, the typical schedule offered the greatest potential for savings (except on July 18, where the intermittent schedule had slightly greater mean savings.) On July 18, the lower occupant density had greater savings, since the higher occupant density caused economizing to be used earlier in the morning, thus reducing the difference between the EDCV and OBV trajectories. On the other days, savings were greater with more occupants. In all cases, savings were greater with low infiltration, which creates a nighttime buildup of building-emitted contaminants. DCV often allows these higher levels to linger, but an optimized strategy can capitalize on the value of diluting them early in the morning. On all days, absolute savings were greater with TOU pricing.

Based on these results, we simulated a case in which we expected OBV to have a high impact: the typical schedule with high occupant density and low infiltration (but no TOU pricing). Interestingly, the OBV's savings over EDCV for a VR_{eff} of 10 L/s/occ over the whole year were only very slightly greater proportionally than for the standard office case (3% as opposed to 2%), though they were about twice as great in absolute terms, at \$0.30 per m^2 annually. But for greater VR_{eff} , savings were proportionally *lower* with the "high impact" case, and for VR_{eff} of 30 L/s/occ, they were lower in proportional and even absolute terms. In other words, even the case that sensitivity analysis indicated had greater savings on examined days produced relatively minimal savings over the entire year.

5.4 Conclusions

The central finding of this chapter was the substantial rejection of our hypothesis that when and how ventilation is provided during a single day can make a significant difference in energy consumption. Introducing the concept of the effective ventilation rate VR_{eff} and using it to make

consistent comparisons confirmed that ventilation does have significant energy impacts. Those impacts, however, were essentially determined by outdoor weather conditions, and the tradeoff between VR and energy use was largely unavoidable, regardless of the dynamic trajectory of ventilation. In other words, there is only a small amount of room for single-day Pareto improvements over current ventilation practice, at least in terms of tradeoffs between effective ventilation (or profitable IAQ) and energy consumption.

Some specific conclusions included:

- Effective ventilation was a good way to characterize VR for comparing tradeoffs, in that it facilitated consistent evaluations of ventilation impacts regardless of the control profile of a specific ventilation method.
- Compared to fixed, constant-rate ventilation, a strategy with economizer and demand-controlled ventilation (EDCV) saved energy when the occupant-weighted average outdoor temperature was below about 25 °C. It saved almost no energy at higher outdoor temperatures. Optimization showed that the EDCV strategy was very close to Pareto optimal at most times of the year. The annual HVAC energy cost savings from switching from fixed ventilation to EDCV, while maintaining the same VR_{eff} , were 3–5%.
- Compared to EDCV, optimized OBV saved literally no energy in the winter. Indeed, while it saved some energy on days when the average outdoor temperature was between 20 and 30 °C, it never saved energy outside of this domain. The annual savings from switching from EDCV to optimized OBV were 2–3%.
- Days when OBV saved energy were ones in which the outdoor temperature and enthalpy were lower in the morning than in the afternoon. In particular, the morning had to be cool enough that standard feedback economizing did not call for 100% OA, while the afternoon had to be hot enough to require significant mechanical cooling and not be favorable for economizing.

- However, in terms of loss, the negative health impact of bringing in so much OA was often greater than the energy savings. Thus, even if a rule-based method for capturing the benefits sometimes achieved by optimized OBV was devised, it might not be desirable to implement, depending on outdoor air quality and filter efficiency.
- Time-of-use pricing did not present a qualitatively different opportunity for optimized OBV, which in general saved no more than an additional percentage point with TOU pricing compared to without it.
- Sensitivity analysis of optimized OBV indicated that a typical schedule yielded more savings than highly intermittent occupancy patterns or schedules heavily skewed towards the morning or the afternoon. Savings were also greater with higher occupant density and lower infiltration. Even with all of the most favorable characteristics, however, the total savings never rose above about \$0.30 per m², and were always less than 5% of HVAC energy costs.

On any given day on which economizing is not favorable all day, there is a mostly unavoidable tradeoff between VR_{eff} and energy use, though demand-controlled ventilation and optimized OBV can achieve modest Pareto improvements. Even so, there remain multiple needs—in addition to being as close to Pareto optimal as possible—that next generation ventilation should address. One is to provide guidance and clarity about these tradeoffs and help users select scientifically sound tradeoff points. It is also no trivial matter to implement a ventilation strategy that reliably achieves a target VR_{eff} . Finally, because the energy costs of ventilation depend so much on weather and time of year, there are also significant possibilities for redistributing ventilation seasonally to achieve Pareto improvements over a yearlong timescale.

CHAPTER 6: CONCLUSIONS AND IMPLICATIONS FOR NEXT-GENERATION VENTILATION

In Chapter 5, we applied the loss function framework to optimizing ventilation over a daylong horizon. In terms of profitable IAQ impacts and energy consumption, there were only very modest Pareto improvements available from optimization of ventilation during a day. This was true not only in comparison to a mature dynamic strategy that combined economizing and DCV (EDCV), but also in comparison to fixed ventilation. In other words, there is little slack in the tradeoff between higher VRs and higher energy use on days when free cooling is not available. Yes, as we saw in Chapter 2, ventilation strategies like DCV can save significant energy—but *they do so by reducing the effective VR*. The reason that, on an annual basis, a strategy like economizing with DCV can both save energy and improve profitable IAQ outcomes is that it increases ventilation on some days and decreases it on others. This works on an annual timescale because IAQ on different days, even consecutive ones, is almost entirely decoupled. On the other hand, during a single day, indoor air processes act to tightly couple ventilation control at different moments of the day. As a result, it appears that the daylong timescale may be too short for the type of shifting that works on an annual scale to have meaningful benefit.

Further pursuit of an optimization-based control method does not appear justified given the complexity of the approach and the smallness of the savings. In deciding how to proceed, let us review some of the core insights produced by the research in this project.

- *Mature ventilation strategies have significant benefits and can be nearly optimal; we should build on them.* In Chapters 2 and 3, we saw that there are very significant opportunities across the office sector for improving ventilation by implementing combinations economizing, demand-controlled ventilation, and supply air temperature reset. In Chapter 5, we found that a strategy with both economizing and demand-controlled

ventilation (EDCV) was near-optimal in a small office at most times of the year. To put it in perspective, mature strategy savings were on the order of \$1.00 /m² in the small-CAV office and \$1.75 /m² in the medium-VAV office, while optimizing outcome-based ventilation (OBV) in the highest impact case explored saved an additional \$0.30 /m² over EDCV.

- *Ventilation rates should usually be high.* In Chapters 3 and 4, we saw that bringing in more outdoor air produced profitable IAQ impacts the economic value of which exceeded the added energy costs by two orders of magnitude. Even when the most ventilation-adverse parameters were selected, VRs as high as 30 L/s/occ—approximately three times the current minimum rate—were usually loss-minimizing.
- *High quality is the best protection against outdoor particle pollution—though perhaps outdoor air should be limited (e.g., at 30 or 47 L/s/occ.* In Chapters 3 and 4, we saw that bringing in more outdoor air could have public health risk impacts whose value substantially exceeded the value of energy savings, but remained much lower than the value of increased ventilation on work performance and excess absence. The quality of the particle filter had a much greater impact on health risk costs than ventilation strategy. Nonetheless, since marginal profitable IAQ benefits are substantially lower above 30 L/s/occ, and disappear above 47 L/s/occ, while PM_{2.5} exposure continues to increase, limiting the upper VR may be beneficial.
- *Ventilation strategies need to take into account and deal effectively with infiltration.* All strategies, in Chapters 2 and 3 as well as in Chapter 4 were strongly affected by envelope leakage and infiltration. In Chapter 5, infiltration was handled by means of defining an effective ventilation rate VR_{eff} based on concentrations of indoor-emitted contaminants.
- *Ventilation strategies should also adjust for occupancy.* Occupant density was another of the most important factors affecting ventilation strategy impacts.

- *Outdoor thermal conditions matter tremendously.* Whether comparing annual results by climate, as in Chapters 2 and 3, or individual days across seasons in a single location, as in Chapters 4 and 5, energy impacts were very sensitive to outdoor conditions.

Concretely, a practical near-optimal ventilation strategy should:

- Include supply air temperature reset nearly always (in the United States);
- Include differential enthalpy economizer controls;
- Require the use of a high-quality particle filter;
- Use CO₂ setpoint control, in part because DCV can provide some Pareto improvements on very cold days, but more importantly because it is the only practical way to implement a strategy that reliably achieves desired operating, given variations in infiltration and occupancy.

On the other hand, the results from DCV with different setpoints in Chapter 3 and the OBV framework in Chapter 4 both point to the need to make more conscious and informed decisions about the tradeoffs among ventilation outcomes. There is also a significant opportunity to search for Pareto improvements over the year (rather than within a single day). Thus, vis-à-vis existing ventilation strategy options, there remain three principal benefits and one additional potential benefit to be sought with next-generation, outcome-based multi-objective ventilation control:

1. It can provide clarity to users about tradeoff points, to allow them to make more informed decisions and understand the consequences of them.
2. It should control outdoor air so that selected tradeoff points are achieved in practice, and provide clear information about the state of IAQ.
3. It should take advantage of opportunities for shifting ventilation energy seasonally, beyond what is currently done by economizing (which only considers energy use), to optimally allocate a fixed energy budget over the year.

4. It may potentially be able to provide ancillary benefits on a daylong scale, such as reduction of outdoor pollution exposure (particularly during economizer cycle).

Achieving these benefits is beyond the scope of this thesis, but we believe it can be with a procedure that takes advantage of existing successful technology components, like CO₂ sensing and economizer controls, potentially adds rules-based control logic, and incorporates this control logic into an initial preference elicitation step that will determine user preference for tradeoffs and intelligently allocate ventilation resources across the year.

A central insight behind this chapter and the previous one is that the problem of selecting among tradeoff points is simplified by separating ventilation control into two separate scopes. An annual scope, with day-average resolution, is most appropriate for allocating ventilation resources. The annual scope is also the ideal one for consideration of tradeoffs in ventilation decisions. Once these decisions have been made, they do not need to be reconsidered each day. In essence, the annual scope functions as a supervisory control for setting the high-level objectives of the ventilation system, while the daily control uses mostly off-the-shelf feedback-based strategies to achieve daily targets set by the supervisory control.

Here we outline a proposed method to be taken up, fleshed out, and developed by colleagues building upon this work.

Method – Annual scope for supervisory control

1. Elicit user's energy vs. profitable IAQ tradeoff point (no pollution considered here).
 - a. Get user preferences parameters (EP_{WP} , EP_{EA} , P_{WP} , P_{EA} , P_e , P_g), building descriptors, and weather file.
 - b. Use an annual optimization model to formulate an annual Pareto curve. (This refers to an annual, day-resolved optimization model, not related to any of the models discussed in Chapter 5.) The simplified energy model on which this step would be based has already been developed and published (Ben-David, Rackes, & Waring, 2018). Display

the annual Pareto curve, with annual work performance and excess absence losses on the x -axis and annual energy costs on the y -axis. A number of reference points can also be displayed, to indicate the tradeoffs obtained by fixed ventilation strategies like the ASHRAE 62.1-2016 fixed minimum and doubled ventilation.

- c. Allow the user to select a point on the Pareto curve. The y -value of this point is the energy cost budget. Run the annual optimization forward to determine the optimal day-averaged VR_{DA} for each day of the weather file such that the total annual energy use cost does not exceed the selected energy cost budget.
2. Create a simple method (a fit, interpolation, or a combination) that estimates the optimal day-average VR_{DA} as a function of day-averaged outdoor temperature (during winter) or outdoor enthalpy (during the summer). Note because this is a procedure, that this relation is *not* a metamodel. It is for this particular building only, so no complex fits need to be used and no building parameters need to be inputs.

Method – Daily scope for local feedback control

1. At the outset of each day, use the predictions for the day-average values of the condition variables as inputs to the optimal day-average fit to determine appropriate VR_{DA} for the day.
2. Relate VR_{DA} to a CO_2 -based control strategy in a consistent way. It is likely that simply determining the CO_2 setpoint associated with VR_{DA} would be sufficient.
3. Control based on the CO_2 setpoint or economizer controls, whichever calls for greater outdoor air flow.
4. If desired, assess any modifications to this basic control. These might, for example, enable economizing or partial economizing at some times when it is not strictly thermally favorable, add a rule to shift or limit ventilation in light of pollution trajectories, or add a rule to implement a morning flush for buildings with low infiltration.

It is hoped that these procedures, based on many of the insights developed in this research, can provide the basis for next-generation commercial building ventilation and can capture some benefits that no existing ventilation strategy can. These benefits include setting the appropriate balance between energy, profitable IAQ, and IAQ public health interests; right-sizing ventilation based on infiltration; and shifting ventilation to the times of year when it is most effective per unit of energy consumption.

Together, shifting ventilation approaches so they are based on expected outcomes, targeted to a setting, and dynamically adjusted in response to changing conditions over time can enhance beneficial outcomes, avoid negative outcomes, and lead to more effective strategies. Importantly, this shift in approach can also provide greater certainty about outcomes, and greater clarity to help make decisions when tradeoffs among outcomes are unavoidable.

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VITA

Adams Rackes completed his Ph.D. in Civil Engineering at Drexel University in 2017. His research interests include energy efficiency of buildings, machine learning and automation, indoor air processes and impacts, climate change and resource use, simulation and modeling, building mechanical systems and automation, and optimal estimation and control.

In 2015, Adams received a Fulbright grant to conduct a year of research in Brazil, to study combinations of building parameters that can enable passive, naturally ventilated buildings to remain comfortable in hot climates. Adams was also a 2014 NSF Graduate Research Fellow, and received a 2012 ASHRAE Grant-in-Aid.

Adams earned M.S. and B.S. degrees from Drexel, both in Architectural Engineering, in 2014 and 2012, and is an Engineer-in-Training. He also holds a 2003 B.A. in History and Literature from Harvard University, and formerly worked as a welder. He lives in South Philadelphia with his wife and sons. As co-founder of Kinetic Buildings, he continues to investigate and implement computational tools for improving the design and operation of sustainable buildings.

Journal Publications

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