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OPTIMIZING HVAC OPERATION IN COMMERCIAL BUILDINGS: A GENETIC ALGORITHM MULTI-OBJECTIVE OPTIMIZATION FRAMEWORK

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ABSTRACT

Heating, Ventilation, and Air Conditioning (HVAC) systems account for a large share of the energy consumed in commercial buildings. Simple strategies such as adjusting HVAC set point temperatures can lead to significant energy savings at no additional financial costs. Despite their promising results, it is currently unclear if such operation strategies can have unintended consequences on other building performance metrics, such as occupants' thermal comfort and productivity. In this paper, a genetic algorithm multi-objective optimization framework is proposed to optimize the HVAC temperature set point settings in commercial buildings. Three objectives are considered, namely energy consumption, thermal comfort, and productivity. A reference medium-sized office building located in Baltimore, MD, is used as a case study to illustrate the framework's capabilities. Results highlight important tradeoffs between the considered metrics, which can guide the design of effective and comprehensive HVAC operation strategies.

1 INTRODUCTION

Global warming and the decay of natural resources are leading developed countries to reduce their energy demands and carbon footprint. In the United States (U.S.), the commercial building stock is oftentimes the focus of energy conservation efforts, as it accounts for approximately 20% of the national energy consumption (Laustsen 2008). Over the life-cycle of commercial buildings, more than 80% of the energy consumed occurs during the operation phase, where systems such as the HVAC system contribute to more than 40% of that energy demand (Laustsen 2008; Bissett 2007). There are several efficiency measures that can be implemented in order to reduce the primary energy consumption in buildings. Such measures can be divided in two main categories: technical retrofits and human retrofits.

Technical retrofits represent improvement in the building's physical components (e.g., wall or roof insulation, high performance windows or HVAC units with higher efficiency). The potential of the aforementioned technical retrofits has been studied extensively in the past and is still an active field of research (Ma et al. 2012; Kaklauskas et al. 2005; Rey 2004). Examples can be found in literature where the effect of individual retrofits on building performance was assessed (Afshari et al. 2014), or a comprehensive retrofit strategy was studied as part of an optimization process (Ascione et al. 2015; Karmellos et al.; Asadi et al. 2012; Diakaki et al. 2008).

The term human retrofits on the other hand refers to actions that the occupants of a building take towards more efficient operation (Pisello et al. 2015). Such actions include the adjustment of HVAC system set points, window opening, lighting and equipment usage, to name a few. Occupants' actions and their impact on building performance is a field that has drawn significant attention in the scientific community recently and demonstrates great potential for energy savings (Azar and Menassa 2014; Pisello and Asdrubali 2014; Azar and Menassa 2012). Adjusting thermostat set points has particularly shown a high impact on building consumption, and has been the focus of several studies (Ghahramani et al. 2015; Lakeridou et al. 2014; Mui et al. 2010).

Despite the growing interest in literature, research on human actions in general, and thermostat set point settings in particular, is mostly limited to problems with pre-defined and pre-evaluated sets of solutions (Hoyt et al. 2015; Ghahramani et al. 2015; Lakeridou et al. 2012). As a result, current solutions do not examine a wide search space and are not able to capture the potential tradeoffs that can exist between various performance metrics, such as energy conservation and thermal comfort. Additionally, other metrics such as the productivity of occupants are rarely accounted for and need to be considered for a more comprehensive evaluation of building performance (Kosonen and Tan 2004).

The goal of this work is to propose a human retrofit multi-objective optimization scheme that integrates key performance metrics in the decision–making process, including energy consumption, thermal comfort, and productivity. This will help guide decision-makers to devise the right human retrofit strategies that will reduce the energy footprint, while minimizing tradeoffs with the other performance metrics.

2 LITERATURE REVIEW

There is a growing interest in literature on the understanding and control of human actions in the built environment (Ucci et al. 2012; Ueno et al. 2006). It has been shown that human actions are major determinants of energy use, potentially hindering the optimal operation of buildings and diminishing the effect of technical interventions (Augenbroe et al. 2009; Levine et al. 2007). Additionally, occupancy interventions come with no direct financial cost, compared to technical retrofits that are often extremely costly to implement. As a result, operation-focused solutions and their integration in energy policy making have gained significant attention (Lopes et al. 2012; Ucci et al. 2012).

Focusing on the operation of HVAC systems, significant amount of studies examine the impact of set points adjustment and deadband widening (i.e., thermostat set point range) on energy use (Ghahramani et al. 2016; Fernandez et al. 2015; Hoyt et al. 2015). Despite the interesting findings of the works discussed earlier, there is scarcity of research studying the simultaneous effect of HVAC operation of both energy, occupant thermal comfort, and productivity (Lakeridou et al. 2012; Kosonen and Tan 2004).

Multi-objective optimization (MOO) is a method that can be used to tackle optimization problems with more than one, usually opposing, objective functions. Typically, since all objectives cannot simultaneously get their optimal values, the MOO algorithm identifies and minimizes the tradeoffs between them. Thus, there is no unique solution in a MOO problem, but a set of non-dominated ("Pareto" optimal) solutions that support the decision making process. MOO has recently been applied in the context of building energy studies, specifically retrofit decision-making applications. Diakaki et al. (2008) for instance were among the first to introduce MOO in building retrofit process. Their work involved a simplistic representation of the building's components. The goal was to identify the tradeoffs between energy consumption and retrofit cost applying three different MOO techniques. Their findings set the ground for in-depth research in the field, such as the work by Asadi et al. (2014), who proposed a retrofit optimization model based on artificial neural network and genetic algorithm. They used a school building to demonstrate the practicality of their model, and studied the interaction between energy consumption, retrofit cost, and thermal discomfort hours, aiding the decision-making process.

Despite their importance, these studies have two main limitations, which motivate the need for this work. First, they focused on technical retrofits and ignored the human-related ones, which can in turn yield significant energy savings at minimal costs. Second, although some retrofit studies account for occupants' satisfaction in the built environment (thermal comfort objective), they overlook other significant factors, such as occupants' productivity.

The following section presents the proposed methodology, which is then illustrated in a case study where HVAC temperature set point settings are optimized for a reference medium-sized office building in

Baltimore, MD. It is important to highlight that the methodology is general and can be applied on any building.

3 METHODOLOGY

3.1 Overview

Figure 1 illustrates the methodology proposed in the present work. First, a Building Performance Simulation Model (BPS) is developed for the building under study using the EnergyPlus software (US DOE 2015). In parallel, a MOO algorithm is implemented in MATLAB, which evaluates the optimization objectives considered in this study until a stopping criterion is met. The algorithm then produces a Pareto front that includes the non-dominated solutions for all three objectives. The connection between the BPS software and the MOO algorithm is achieved through a coupling scheme also developed in MATLAB. Such connection facilitates a simulation-based evaluation of the objective functions, as well as the alteration in the decision variables until the set of non-dominated solutions is reached.

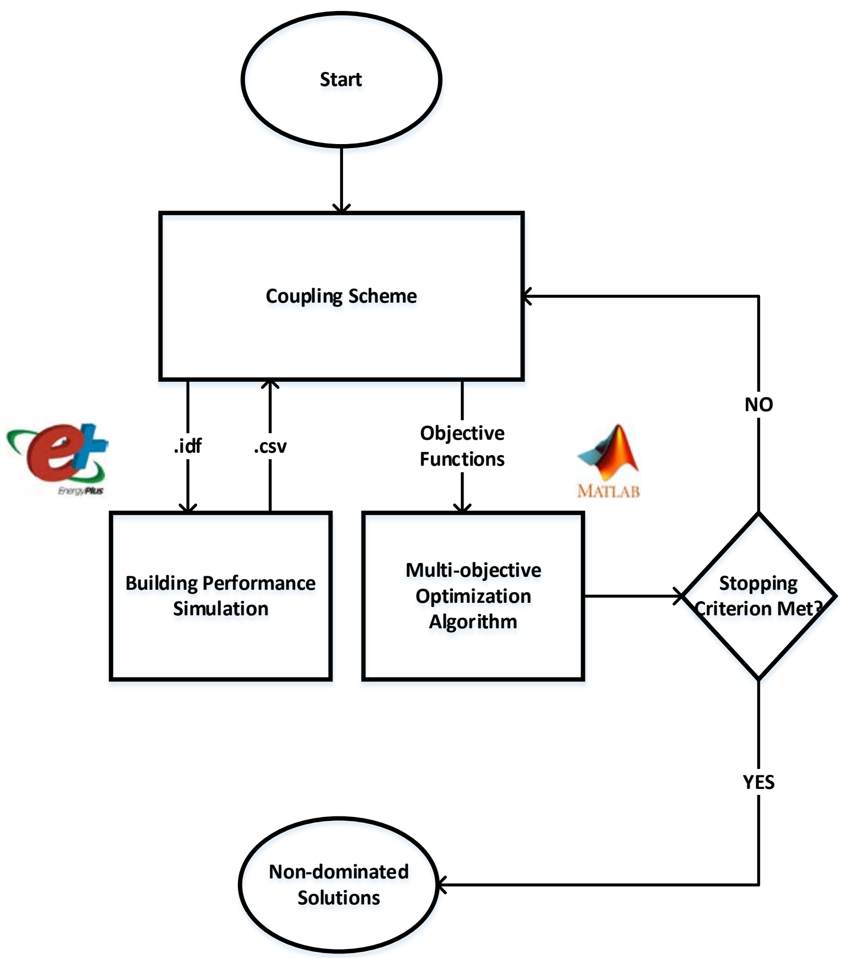

Figure 1: Methodology framework.

3.2 Building Description and BPS Model

The building used in this study, and its corresponding EnergyPlus BPS model, are chosen from the list of commercial prototype building developed by the US Department of Energy (Deru et al. 2011). A medium-size office building located in Baltimore, MD was selected for this specific case study. Baltimore weather characteristics require significant cooling and heating loads in buildings (during summer and winter periods respectively), making decision variables such as heating and cooling thermostat set point temperatures relevant in the optimization process. The major building characteristics used in the development of the model are summarized in Table 1.

Table 1: Reference building BPS model parameters.

Parameter		Value
Location		Baltimore, MD, USA
Building Type		Medium-size office, constructed after 1980
Dimensions & Height	Area	4982 m^2
	Floors	3
	Total Height	11.89 m
	Window-to-wall Ratio	33 %
Building Envelope	Wall U-value	0.51 W/m^2-K
	Roof U-value	0.33 W/m^2-K
	Glazing	U-value: 3.35 W/m^2-K SHGC: 0.36
Lights & Equipment	Lights Intensity	16.89 W/m^2
	Equipment Intensity	10.76 W/m^2
HVAC System	Heating	Furnace
	Cooling	Packaged Air-Conditioning Unit
	Air Distribution	Multi-zone Variable Air Volume

3.3 Coupling Scheme

The goal of the coupling scheme is to integrate BPS (i.e., EnergyPlus) in a software that supports optimization algorithms (i.e., MATLAB). EnergyPlus models use text-based input (.idf file) and output the variables of interest in a comprehensive comma delimited workbook (.csv file). In the first stage of the coupling scheme, the .idf file is transformed into a data structure, where each class refers to a simulation parameter and each field refers to the hyper-parameters associated with the class. For example, if the class is “Construction material”, its fields would include information such as the material name and its properties. Then, the simulation is triggered in MATLAB environment. Following the simulation’s output, the objectives of the problem are evaluated by the optimization algorithm. If the stopping criterion is not met, the algorithm returns a new set of decision variables to be evaluated. The coupling scheme creates a new .idf file with the aforementioned variables (i.e. HVAC set points), converted to EnergyPlus inputs, and the process is repeated until the algorithm converges to the non-dominated solutions.

3.4 MOO Algorithm

A controlled elitist genetic algorithm (GA) (variant of NSGA-II (Deb 2001)) is used for the MOO, implemented in MATLAB’s optimization toolbox. The simulation-based nature of the human retrofit optimization problem is nonlinear, discontinuous and non-differentiable, hence GA is a common tool in

BPS literature to address such problem (Ngyuen et. al 2014). GAs are based on a natural selection process that mimics biological evolution. The algorithm starts with a random population of individual solutions, which repeatedly modifies over generations. At each step, the GA selects the "fittest" individuals from the current population and uses them as parents to produce the children of the next generation. The algorithm evolves towards the optimal solution over successive generations, until the stopping criterion is met (Goldberg and Holland 1998). For this particular case, the chosen stopping criterion is the function tolerance, i.e. the algorithm runs until the average relative change in the fitness function for 50 generations is less than the default tolerance value of 1e-6.

3.4.1 Decision Variables

The decision variables of the problem correspond to the total set of alternative measures considered for the human retrofitting problem. All variables are related to the operation of the HVAC system. More specifically, four variables were considered in the optimization problem setup, and are summarized in Table 2:

Table 2: Decision variables.

x_{cool_occ}	cooling temperature set point for occupied hours	[22-27 ºC]
x_{heat_occ}	heating temperature set point for occupied hours	[17-22 ºC]
x_{cool_unocc}	cooling temperature set point for unoccupied hours	[27-30 ºC]
x_{heat_unocc}	heating temperature set point for unoccupied hours	[14-17 ºC]

All four decision variables are continuous and their corresponding ranges are denoted in the brackets above.

3.4.2 Objective Functions

For this study the tradeoffs between three different objectives are evaluated as mentioned earlier. Those are: (a) energy consumption, (b) thermal comfort, and (c) productivity.

3.4.2.1 Energy Consumption

The building's energy consumption is assessed directly by EnergyPlus. A yearly simulation accounts for both heating and cooling requirements and aggregates them to estimate the annual total energy consumption, expressed in megawatt-hours (MWh). The energy required for lighting, equipment and hot water is not considered, since it is not affected by the decision variables used in this study.

3.4.2.2 Thermal Comfort

There are two main metrics to assess occupants' thermal comfort in the built environment, (a) the Predicted Mean Vote (PMV), and (b) the Predicted Percentage of Dissatisfied people (PPD), both based on Fanger's model (Fanger 1970) and detailed in ISO 7730:2005 (ISO 2005). PMV ranges from -3 (too cold) to +3 (too hot), thus in order to include it in the optimization framework, its absolute value (|PMV|) should be minimized. However, this simplification could lead to the exclusion of potential non-dominated solutions, since it would not be possible to identify whether the solution has a positive or negative PMV value. Therefore, the minimization of the average PPD for all building zones, which is directly associated with the PMV, is considered as the second objective of the problem. PPD values are always positive, ranging from 0% to 100%.

3.4.2.3 Productivity Loss

Although it has not been studied in built environment optimization research, occupants' productivity level is an important metric, especially in the context of commercial buildings. Kosonen and Tan (2004) studied the productivity loss in air-conditioned spaces as a function of PPD. The equation used to model productivity loss in the present work was obtained by fitting a curve to the data found in the work of Kosonen and Tan (2004):

$$ProdLoss\ (\%) = 13.366 * \log(x) - 14.895. \tag{1}$$

where x is the average yearly PPD index of the building. The abovementioned formula accounts for productivity in both thinking and typing tasks, assigning equal weights to both of them (Kosonen and Tan 2004).

3.4.3 Problem Formulation

Having the BPS model configured and coupled with MATLAB, the MOO problem is formulated to simultaneously optimize the building's energy consumption, occupants' thermal comfort and occupants' productivity loss. A multi-objective GA is implemented in MATLAB to identify the set of non-dominated solutions. The MOO problem is summarized as follows:

$$\begin{gathered} minZ_1(X) = EnergyConsumption(X) \\ minZ_2(X) = PPD(X) \\ minZ_3(X) = ProdLoss(X) \\ subject\ to, \\ 22 \leq x_{cool\_occ} \leq 27\ ^oC \\ 17 \leq x_{heat\_occ} < 22\ ^oC \\ 27 < x_{cool\_unocc} \leq 30\ ^oC \\ 14 \leq x_{heat\_unocc} < 17\ ^oC \\ X = \{x_{cool\_occ}, x_{heat\_occ}, x_{cool\_unocc}, x_{heat\_unocc}\}. \end{gathered} \tag{2}$$

where Z_1 corresponds to the annual energy consumption of the building in MWh, Z_2 is the average annual PPD (%), and Z_3 is the occupants' productivity loss (%). The vector X contains the decision variables to be evaluated by the GA.

4 RESULTS

The following section discusses the results of the case study. Figure 2 presents a 3D visualization of the non-dominated solutions after the MOO process was completed. Two main trends can be observed from the results. First, there is a positive correlation between thermal comfort and productivity, which are both negatively affected by energy conservation measures. In other words, efforts that reduce energy consumption (i.e., reducing cooling or heating loads) negatively affect PPD and productivity levels. Second, as also shown in Figure 2, the positive correlation between thermal comfort and productivity follows a non-linear pattern. This can be explained by the logarithmic factor in Equation 1, defining the relationship between PPD and productivity loss.

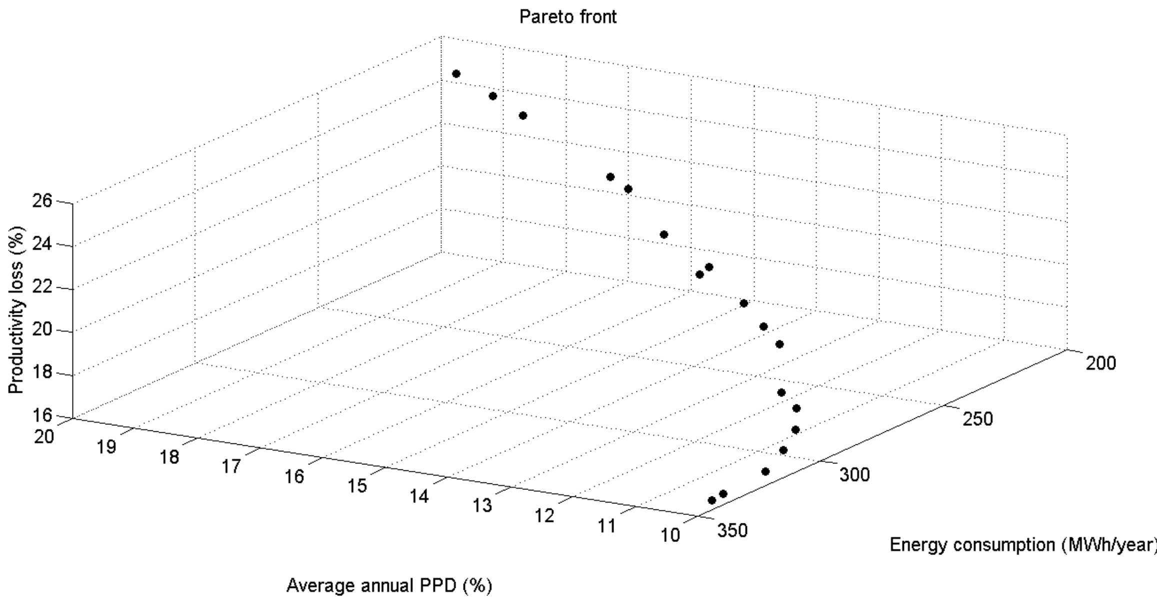

Figure 2: Non-dominated solutions (3D visualization).

In order to further discuss particular solutions, Figure 3 illustrates the results in a 2D plot, with the x-axis representing PPD and the y-axis energy consumption. The third objective of productivity loss, is included in the graph as a color map, with darker colors representing lower levels of productivity loss.

First, Point 1 depicts one extreme solution where thermal discomfort and productivity loss are at their minimum, while energy consumption is at its highest level. For this point, occupied cooling and heating set points are 25.6 ºC and 21.9 ºC, both in the acceptable temperature ranges proposed by Olesen (2000). An interesting finding is that the unoccupied cooling and heating set point hours (29.1 ºC and 16.8 ºC respectively) do not reach the bounds of decision variable ranges. Such findings suggest that even during the unoccupied periods of an office building, extreme set points could impact thermal comfort and productivity in the early working hours, since it might require time for the building to reach acceptable operation conditions. On the other hand, Point 4 demonstrates the solution where energy consumption is minimized. PPD levels reach 18.5% and productivity losses approach 25%. All decision variables reach their extreme bounds in this case, showing the dominance of energy consumption over the other two objectives in this solution.

The ability of MOO to generate a set of non-dominated solutions can be of high aid in the decision making process. For instance, Point 2 can be considered an alternative solution to Point 1 as it shows an important drop in energy consumption from around 340 MWh/year to 280 MWh/year, with minimal penalties in PPD and productivity. Another benefit of the Pareto front is the ability to set targeted thresholds to obtain the solutions of interest. For instance, assuming that an acceptable level of PPD in working spaces should be below 15%, it is easy to identify that solution 3 is the optimal one given this constraint. Additionally, thresholds can be set to the annual energy consumption of the building. Several building codes and certifications (e.g., LEED and BREEAM) require certain levels of energy consumption in existing buildings, where an optimal operation of the HVAC could be a cost-effective approach to reduce energy consumption, while ensuring minimal tradeoffs with the other building performance metrics.

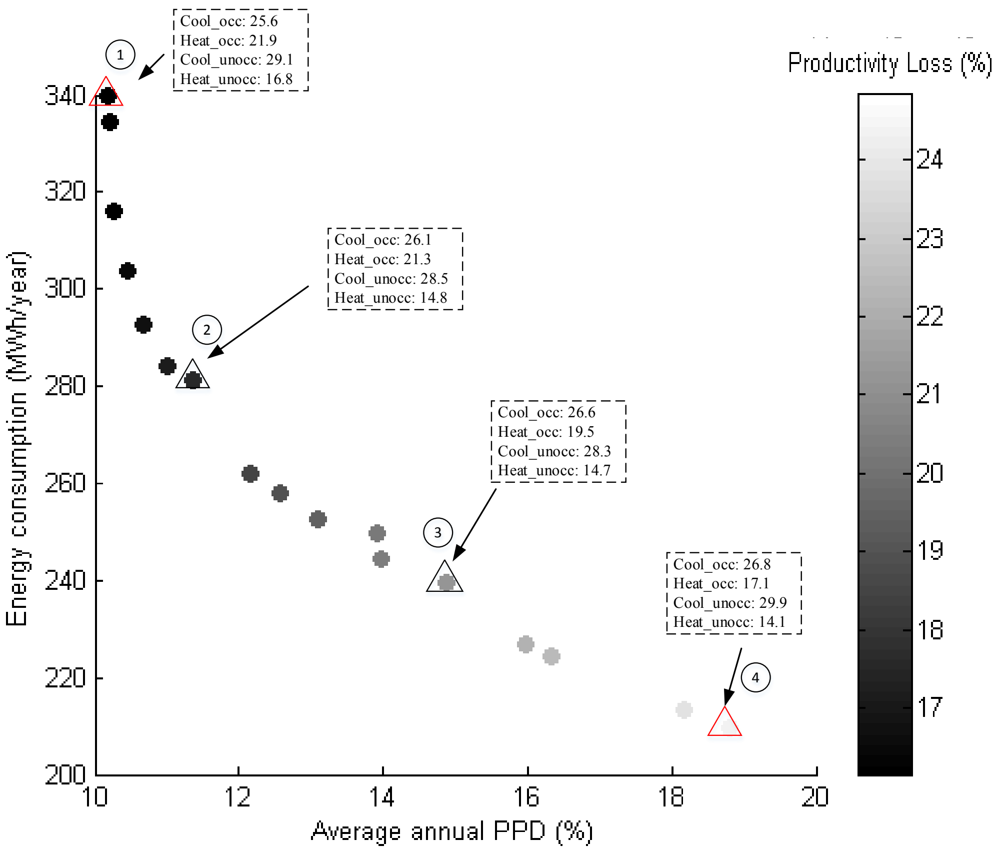

Figure 3: Non-dominated solutions (2D visualization with color map).

5 CONCLUSION

In this work, a simulation-based GA MOO framework is proposed to optimize the operation of HVAC systems in commercial buildings. It simultaneously accounts for energy consumption, thermal comfort and productivity loss, given a range of heating and cooling set points, for both occupied and unoccupied hours.

The framework was then illustrated through a case study on a medium-sized office building in Baltimore, MD. The set of non-dominated solutions was successfully identified, giving valuable insights on the interplay between various building performance metrics. This can help design energy conservation strategies that do not compromise occupants' wellbeing and work efficiency. On the other hand, it is worth mentioning that the proposed framework does not investigate drivers of particular behaviors and HVAC settings, such as the energy awareness of occupants. While such consideration is an important field of study, it does not fall within the scope of this work, which is mostly focused on presenting the generic optimization framework.

Future work could feature increased granularity of decision variables (e.g., hourly set point values), in an effort to identify a holistic building operation profile. Additional objectives, such as building operation costs, can also be incorporated in the optimization scheme. Such a financial-driven objective can help evaluate the feasibility of retrofit options (e.g., chiller replacement). Finally, the framework can be applied on buildings located in regions with more extreme weather conditions, evaluating how optimal HVAC operation strategies could vary for different climates.

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