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Optimizing Energy Conservation Measures in a Grocery Store using Present and Future Weather Files

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Abstract

Grocery stores are one of the most energy intensive building types, which makes targets for zero net energy (ZNE) particularly challenging. This study builds on a prior computational optimization study to identify combinations of energy conservation measures (ECMs) for an existing grocery store in San Francisco. As the climate changes, also the retrofit recommendations based on simulation results from historical-based weather files may vary. In this paper, we looked at how the optimization results change when accounting for climate changes over the building's service life by using future weather files. We found that the expected changes in future weather are sufficient to alter retrofit recommendations. This type of analysis is thus important to ensure that buildings designed now can continue to meet performance objectives into the future.

Introduction

As illustrated by the Intergovernmental Panel on Climate Change's (IPCC) special report SR 15, the building industry is critical for mitigating climate change. All pathways that maintain a global temperature increase of 1.5 °C require (a) building emissions to be reduced by 80-90% by 2050, (b) new construction to be fossil free and near-zero energy by 2020, and (c) energy refurbishment of the existing building stock by at least 5% per annum in developed countries (de Coninck, et al., 2018). To meet this challenge, the State of California requires that all new and 50% of existing commercial buildings be Zero Net Energy (ZNE) by 2030 (CARB, 2017; CEC, 2007).

ZNE can be challenging to achieve cost effectively in existing buildings because many design elements, like geometry, are already locked-in, thus limiting the scope of potential energy conservation measures (ECM). Achieving ZNE is also challenging for grocery stores because of the high energy use intensity (EUI) inherent to this building type. Prior studies demonstrate that it is possible to achieve ZNE for new grocery stores where manipulation of the building form is possible (Hachem-Vermette, Cubi, and Bergerson, 2016; Arup, 2012; Acha et al., 2013). Further, the EUI must be offset by large areas of on-site renewable energy generation, such as on roofs, facades, and covered parking lots or off-site renewables (Pless and Torcellini, 2010). This can be especially challenging for buildings in dense urban areas.

The building at the heart of this project is the existing Whole Foods Market in the Noe Valley neighborhood of San Francisco, CA. The building exemplifies all the above challenges in that it is an existing grocery store in an urban area. The overall project goal to demonstrate the feasibility of ZNE despite these issues. The interdisciplinary project team consists of Prospect Silicon Valley, Whole Foods Market, Arup with funding from the California Energy Commission.

As part of the design phase, Arup developed a calibrated building energy model of the existing grocery store and applied computational optimization techniques to select from thousands of possible ECM combinations that met the project budget constraint of $2,000,000 USD (Best and Levine, 2018). The single best design achieved an energy savings of 65% from the existing building but was unable to meet ZNE due to area limitations for on-site renewable energy generation.

One of the most important inputs for building energy models is the weather file, which impacts calculation of heating and cooling loads, and lighting energy requirements. Because of the high variability of measured weather data, conventional practice is to use synthetic weather files, such as Typical Meteorological Year (TMY), which are based on the historical weather record. However, observed global warming trends undermine the validity of this practice. Buildings designed and constructed today will experience climate-related changes over the course of their service life. This suggests that proper assessment of building performance should include simulations using projections of future weather. Especially for buildings evaluating retrofit strategies to meet climate goals, assessment using future weather files is important to understand impacts to ECM impact, feasibility, and cost-effectiveness as the climate changes.

The underlying question of this paper is how do anticipated changes in future weather impact our recommendations today on optimal ECMs? If we find significant changes, then the current standard practice of using only TMY weather files may be setting up buildings for suboptimal performance in the future.

Methods

To test these questions, we evaluated the calibrated model of the Whole Foods store with current and future weather. As part of our process, we applied an

optimization routine to identify high performing combinations of ECMs.

Base Building Energy Model

Arup developed the baseline building energy model in EnergyPlus v8.6. The model incorporates the existing building geometry and a detailed end-use build-up of all internal electrical loads, HVAC system distribution, and observed operating parameters from in-store monitoring. Arup tuned uncertain model parameters including schedules, refrigeration system operation, and additional unreported plug loads using 15-minute electricity and monthly gas utility data (Best and Levine, 2018). Arup calibrated the model in accordance to tolerances suggested by ASHRAE Guideline 14-2014: *Measurement of Energy, Demand and Water Saving*s, resulting in a final calibrated model with a normalized mean bias error (NMBE) of less than 4% and a coefficient of variation of the root mean square error CV[RMSE] less than 11% for electricity and natural gas.

ECM Selection

The project team determined potential ECMs based on: 1) a design charrette with industry experts including a "blue sky" brainstorming session, 2) a site visit and kitchen equipment audit, 3) analyzed energy consumption data, and 4) a technology discovery competition. Together, these approaches generated a list of over 350 ECMs that the team reduced to 107 unique measures based on feasibility that were carried forward for modeling and cost analysis. Arup implemented these 107 ECMs within EnergyPlus by identifying mutually exclusive options and systems with parametric possibilities (i.e., insulation thickness) to create 58 unique pieces of equipment and systems, each with 1 to 19 parametric possibilities. These 58 ECM categories with their variants form the design space of possible retrofit options for this study. A full list of ECMs and descriptions can be found in (Best and Levine, 2018).

Computational Optimization

Identifying deep energy savings within a fixed capital budget, especially with interacting systems, requires assessing packages of measures rather than individual ECMs (Pless and Torcellini, 2010; O'Brien, Athienitis, and Kesik, 2011). However, with a large number of ECMs, enumeration of all combinations is computationally infeasible. We employed a genetic algorithm (GA) to efficiently evaluate different combinations of ECMs and identify the best opportunities for energy savings within the capital budget. This approach has been used previously for net-zero and energy efficient building design due to its ability to operate on problems with nonlinear relationships between variables and objectives (Wang, Zmeureanu, and Rivard, 2005; Tuhus-Dubrow and Krarti, 2010; Evins, 2013).

We defined the objective of the GA to minimize operational energy cost as well as three constraints. First,

the capital cost of all ECMs could not exceed the $2,000,000 USD construction budget. Second, we prevented mutually exclusive ECMs (e.g. HVAC system types) from inclusion in the same model. Third, we required any ECMs built on a DC (direct current) microgrid for the store to be implemented together to maximize the value of the microgrid.

We encoded the optimization in a Python script in which we selected ECMs for each major equipment or system from a discrete set of options using integer variables, and direct edits were made to the EnergyPlus file. Each combined test file was run for a four-month period (February, May, September, and November). We allowed the GA to run for 51 generations of 50 ECM packages per generation for a total of 2,448 successful packages of ECMs. We repeated this process for each weather file. Best and Levine describe the building energy model and optimization process in more detail elsewhere (Best and Levine, 2018).

Future Weather

We obtained future weather files from WeatherShift, an online tool developed by Arup and Argos Analytics to morph present TMY weather files to account for climate change (Dickinson and Brannon, 2016). Modeling future weather requires consideration of uncertainty in future GHG emissions. In the Fifth Assessment Report (AR5), the IPCC defines a set of four emissions scenarios, called Representative Concentration Pathways (RCP): RCP 2.5, RCP 4.5, RCP 6.0, and RCP 8.5. Emissions scenarios capture the range of possible human impact on future GHG emissions given factors such as population growth, economic development, technological innovation, and policy interventions. The RCP numbers refer to radiative forcing values, i.e. the difference between incoming insolation absorbed by the Earth and energy radiated back to space, in 2100 relative to pre-industrial levels in W/m^2. Lower levels of radiative forcing correspond to lower GHG emissions and concentrations. The four RCP pathways span the range of radiative forcing levels found in the literature.

This study compares results from two future emissions scenarios, RCP 4.5, which roughly corresponds to the objectives of the Paris Climate Agreement signed in 2014, and RCP 8.5, which is often dubbed "business as usual". Together, the two pathways represent realistic lower and upper bounds on future GHG emissions.

From GHG emissions estimates, climate scientists use numerical models to simulate interactions between atmospheric and oceanic processes at a global scale, called general circulation models (GCM). There can be lot of variation across climate models because they involve stochastic processes and are highly dependent on initial conditions. WeatherShift uses an ensemble of 14 GCM and ranks them based on projected changes in weather outputs to obtain a percentile distribution, called

warming percentile. For this study, we used the median (50th percentile) changes in weather outputs.

Results and Discussion

The results below compare outcomes from repeating the computational optimization procedure wherein the only change was the weather file for the building energy simulations.

Future Weather

Before analyzing optimization results, we reviewed differences between the present TMY3 weather file and both future scenarios. Figure 1 compares the mean monthly dry bulb temperature (DBT). In the future the mean monthly DBT increases by between 1.5 – 3 °C.
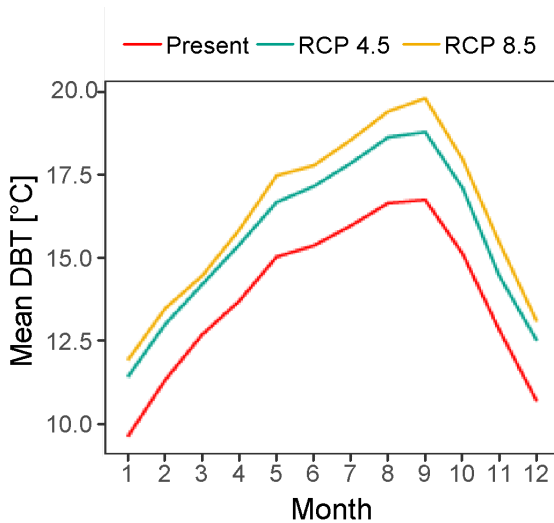
Figure 1: Mean monthly dry-bulb temper in present and future weather scenarios for San Francisco

To begin to understand the impact of this temperature change on building energy consumption, we calculated the heating and cooling degrees, HDD and CDD respectively, for the present and future, with a base temperature of 18.5 °C. The results, plotted in Figure 2, show that San Francisco is currently a heating dominated climate with very few CDD. Under the RCP 4.5 emissions scenario, HDDs decrease by around 1/3 but CDD increase 4-fold. Under RCP 8.5 HDD decrease by around 1/2 but CDD increase 9-fold. The optimization results will show how significant these weather changes are for decisions on cost-effective energy conservation measures.
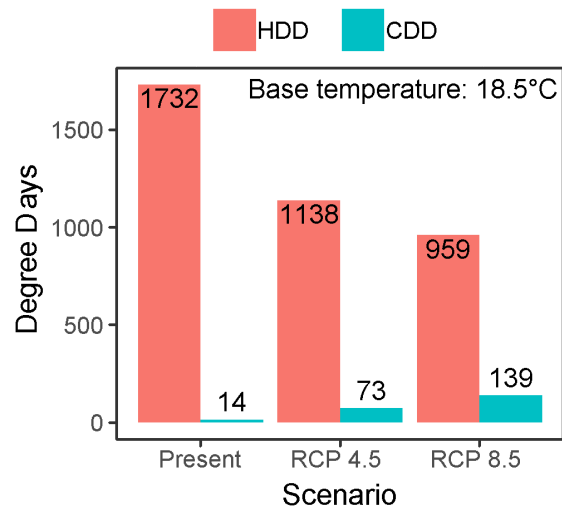
Figure 2: Heating and cooling degree days in present and future weather scenarios for San Francisco

Base Building Energy Consumption

To understand the optimization results, we also reviewed the base building energy consumption and how it changes due to the weather changes illustrated in Figures 1 and 2. Figure 3 breaks down the energy consumption by end use for the existing Whole Foods Store.
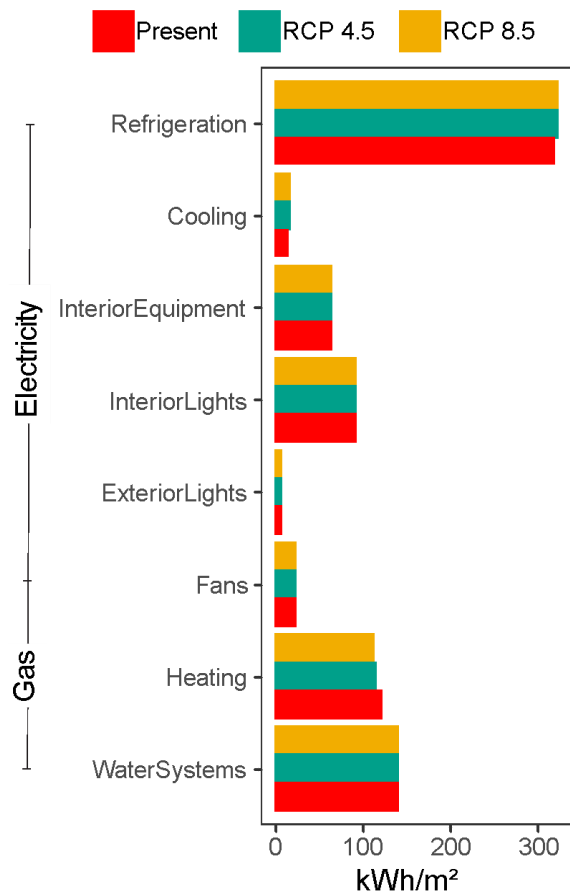
Figure 3: Energy consumption by end use for the existing Whole Foods grocery store in the present and two future weather scenarios

From Figure 3, we see that the store's energy consumption is dominated by refrigeration. It is also interesting to note that while most commercial buildings are cooling dominated due to high internal heat gains, grocery stores are generally heating dominated due to the cooling lost from refrigeration cases, as is also the case here. Due to the warming climate, we see an increase in energy consumption by refrigeration and cooling and a decrease in energy consumption by heating. Other end uses like interior equipment and interior lights are not affected by future weather. Nevertheless, reducing end uses seemingly independent of future weather indirectly impact space heating and cooling loads, and thus could affect the cost effectiveness of individual ECMs during computational optimization.

Computational Optimization

The GA is a stochastic process, so rather than review the results of a single optimal design, we reviewed the distribution of ECMs in the 250 best performing designs, which represents approximately 10% of simulated ECM combinations. We can then look for patterns in how frequently ECMs are selected or not selected to form an overall design recommendation.

Figure 4, at the end of this paper, compares the probability of the optimization selecting an individual ECM in the present and both future weather scenarios. While ECMs differ on the number of parametric variants, we considered an ECM as "selected" if the optimization included any variant. As a result, our results do not explore potential changes to the optimal ECM variant across weather scenarios. For visualization, we ordered ECMs by the probability of selection in the present.

From Figure 4, we can identify that there are many ECMs that the GA selected in the present and the future such as upgrade computers, replace rotisserie, heat pump water heater, and ensure plug loads off at night. These strategies often relate to directly reducing plug loads and are largely independent of weather, so it makes sense that they should be cost effective in both the present and future.

There are also many ECMs that the GA did not select in the present nor in either future weather scenario, such as installing windows on the 2nd floor, insulate medium temperature piping, insulate roof, and solar air preheating. These strategies are associated with high capital costs relative to the savings in operational energy cost. In particular, installing new windows, insulation, and solar air preheating all benefit store heating, which is a decreasing portion of energy use in the future.

From Figure 4, we can also start to see that the likelihood of selecting some ECMs may also change between the present and either future scenarios, such as refrigeration heat recovery, which is nearly always selected in the present, but almost never selected by either future scenario.

Figure 5, at the end of this paper, highlights changes in the likelihood of selecting an individual ECM by subtracting the probability of selecting an ECM in the present from the probability of selecting that ECM in either future scenario. A positive value means that the probability of selecting that ECM increases in the future, while a negative value means the probability decreases.

Where some ECMs were almost never selected in the present, like upgrade RTUs, natural ventilation, and improving loading doors, these strategies are now almost always selected by both future weather scenarios. The performance of these strategies is directly tied to the exterior climate and their cost effectiveness improves as the weather warms.

It is particularly interesting that the energy model found natural ventilation to be cost effective. For cooling dominated building types, the efficiency of natural ventilation as a passive cooling strategy in many climates will likely decrease as the climate warms. However, as observed in Figure 3, grocery stores are generally heating dominated due to the large number of refrigeration cases. additionally, the location of this store in San Francisco provides a relatively cool starting point from which warming may increase the number of comfortable hours in parts of the city.

Another interesting result was a decrease in the frequency of solutions with refrigeration heat recovery via a desuperheater under both future climate scenarios. Reduced dependence on a desuperheater may indicate in a warmer climate there would be more extra heat than the one that is needed for heating or hot water. The finding highlights the need to evaluate interacting systems to determine the impact of future climate rather than isolating subsystems or individual building technology or ECM decisions.

Procurement Approach

An additional observation from the finding is that while there is overlap in many of the selected ECMs, designing optimally for the future requires either planning for the future today or planning to retrofit systems over time. Which approach is taken will vary by system depending on the expected life of each piece of equipment. Though not the focus of this study, each ECM can be ranked by expected life to prioritize when investments should be made.

For instance, rooftop HVAC unit replacement should occur every 15 years according to expected ASHRAE replacement schedules. This is also a case where choice of RTU upgrade varied between the present and future. Given the short life span of units, RTUs could be replaced today and optimally selected for near-term climate with the intent of re-evaluating the selection when the next purchase is required. By contrast, changes to the refrigeration system architecture or envelope improvements to facilitate natural ventilation are significant investments which are unlikely to be

replicated until the next major renovation. Given that the choice of including these ECMs varied between present and future, a more detailed risk study may be required to ensure the correct investment is made initially to prepare the building changes in climate.

Conclusion

Our study finds that changes in future weather can tip the scales of decision making during the design process. Overall, we found that of the 57 ECMS we evaluated for energy and cost effectiveness, roughly 24 were effective at the present and 14 were ineffective in the present. Of those that were effective, 15 remained effective in the future, such as LED lights, while 9 became less effective in the future, such as refrigeration heat recovery. Of those that were ineffective, 4 remain ineffective, such as insulating walls, while 10 became more effective, such as upgrading rooftop units.

This shows that we should be careful with recommending ECMs that represent significant capital investments and whose payoff may decrease due to future weather changes, such refrigeration system architecture or envelope improvements. For ECMs with shorter service lives, likes mechanical equipment, it may be suitable to optimize for the present and reevaluate system performance at the time of future upgrades. Our study demonstrates the importance of evaluating performance with future weather projections. This will help ensure that buildings designed to be ZNE in the present can continue to achieve their performance goals throughout their service life, even with uncertainty in future weather

Acknowledgements

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Frequency	ECM	Present	RCP 4.5	RCP 8.5	Key
					0%
					25%
					50%
					75%
					100%
Nearly always selected in Present	Upgrade Computers				
	Insulate Glass				
	Replace Rotisserie				
	Heat Pump Water Heater				
	LED Store Lights				
	Case Occupancy Controls				
	Sales Occupancy Controls				
	Upgrade Walk-Ins				
	Enclose Refrigeration Cases				
	Automatic Door Closers on Walk-Ins				
	Upgrade Compressor Racks				
	Secondary Refrigeration Loop				
	Refrigeration Heat Recovery				
	Efficient Condenser				
	Add Doors to Walk-Ins with Curtains Only				
	Mechanical Subcooler				
	Improve Doors on Walk-Ins with Doors				
	Replace Back of House AC				
	Replace Ice Machines				
	Ensure Plug Loads Off at Night				
	BOH Occupancy Controls				
	Anti-Sweat Heater Controls				
	LED Exterior Lights				
	Enclose Warming Cases				
Sometimes selected in the Present	Widen Store Temperature Setpoints				
	Restroom Occupancy Controls				
	Enclose Refrigerated Bins				
	Consolidate Walk-Ins				
	Medium Temperature Floating Suction Head				
	Destratification Fans				
	Low Temperature Refrigerant Piping				
	HRV on Kitchen Exhaust				
	Upgrade Registers				
	Upgrade Refrigerated Table				
	Dishwasher Heat Recovery				
	Demand-Based Defrost on Walk-Ins				
	Low Flow Spray Valves				
	HRV on Restroom Exhaust				
	Natural Ventilation				
	Upgrade Conveyor Belt Motors				
	Mid-voltage DC Bus				
	Improve Loading Doors				
	Install Skylighting				
Nearly never selected in Present	Upgraded Server Room AC				
	Variable Speed Kitchen Exhaust				
	Replace Once-Through Dipperwell				
	Widen Server Room Temperature Setpoints				
	Install Windows on 2nd Floor				
	Hot Water Recirculation				
	Demand Control Ventilation				
	Shade Front Façade				
	Insulate Medium Temp Refrigerant Piping				
	Upgrade RTUs				
	Insulate Walls				
	Insulate Roofs				
	Solar Air Preheating				
	Low Temperature Floating Suction Head				

Figure 4: Comparison of probability of ECM selection between the present and future weather scenarios

Optimal Time	ECM	RCP 4.5	RCP 8.5	Key
Future but not Present	Upgrade RTUs			1
	Natural Ventilation			0.5
	Improve Loading Doors			0
	HRV on Restroom Exhaust			-0.5
	Mid-voltage DC Bus			-1
	Demand-Based Defrost on Walk-Ins			
	Install Skylighting			
	Hot Water Recirculation			
	Variable Speed Kitchen Exhaust			
	Shade Front Façade			
	Upgraded Server Room AC			
	Insulate Walls			
	Upgrade Refrigerated Table			
	Replace Once-Through Dipperwell			
	Consolidate Walk-Ins			
	Dishwasher Heat Recovery			
	Low Flow Spray Valves			
No change between Present and Future	HRV on Kitchen Exhaust			
	Demand Control Ventilation			
	Widen Server Room Temperature Setpoints			
	Insulate Medium Temp Refrigerant Piping			
	Upgrade Conveyor Belt Motors			
	Widen Store Temperature Setpoints			
	Low Temperature Floating Suction Head			
	BOH Occupancy Controls			
	Insulate Roofs			
	Solar Air Preheating			
	Replace Rotisserie			
	Heat Pump Water Heater			
	LED Store Lights			
	Case Occupancy Controls			
	Sales Occupancy Controls			
	Upgrade Walk-Ins			
	Enclose Refrigeration Cases			
	Upgrade Compressor Racks			
	Secondary Refrigeration Loop			
	Efficient Condenser			
	Medium Temperature Floating Suction Head			
	Upgrade Computers			
Present but not Future	Automatic Door Closers on Walk-Ins			
	Mechanical Subcooler			
	Install Windows on 2nd Floor			
	Ensure Plug Loads Off at Night			
	LED Exterior Lights			
	Enclose Warming Cases			
	Destratification Fans			
	Upgrade Registers			
	Enclose Refrigerated Bins			
	Replace Ice Machines			
	Replace Back of House AC			
	Low Temperature Refrigerant Piping			
	Add Doors to Walk-Ins with Curtains Only			
	Insulate Glass			
	Restroom Occupancy Controls			
	Anti-Sweat Heater Controls			
	Improve Doors on Walk-Ins with Doors			
	Refrigeration Heat Recovery			

Figure 5: Comparison of change in probability of ECM selection between the present and future weather scenarios