Sensitivity Analysis of Occupant Preferences on Energy Usage in Residential Buildings

Preprint

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SENSITIVITY ANALYSIS OF OCCUPANT PREFERENCES ON ENERGY USAGE IN RESIDENTIAL BUILDINGS

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ABSTRACT

Residential buildings, accounting for 37% of the total electricity consumption in the United States, are suitable for demand-side management (DSM) programs to support effective and economical operation of the power system. A home energy management system (HEMS) enables residential buildings to participate in such programs. It is important to account for occupant preferences in HEMS to ensure occupant satisfaction while participating in DSM programs. For example, people who prefer a higher thermal comfort level are likely to consume more energy. In this study, we used foresee™, a HEMS developed by the National Renewable Energy Lab (NREL), to perform a sensitivity analysis of occupant preferences with the following objectives: minimize utility cost, minimize carbon footprint, and maximize thermal comfort. To incorporate the preferences into the HEMS, the SMARTER method was used to derive a set of weighting factors for each objective. We performed week-long building energy simulations using a model of a home in Fort Collins, Colorado, where there is mandatory time-of-use electricity rate structure. The foresee™ HEMS was used to control the home with six different sets of occupant preferences. The study shows that occupant preferences can have a significant impact and is important to consider when modeling residential buildings. Results show that the HEMS could achieve energy reduction **ranging** from 3% to 21%, cost savings **ranging** from 5% to 24%, and carbon emission reduction **ranging** from 3% to 21%, while maintaining a low thermal discomfort level ranging from 0.78 K-hour to 6.47 K-hour in a one-week period during winter. These outcomes quantify the impact of varying occupant preferences and will be useful for controlling the electrical grid and developing HEMS solutions.

Keywords: Occupant preferences; HEMS; energy efficiency; residential buildings; cost savings; carbon footprint; thermal comfort; optimization; sensitivity analysis, demand response, transactive energy

1. INTRODUCTION

The U.S. Federal Energy Regulatory Commission defines demand response as changes in normal energy consumption patterns to respond to changes in the price of electricity over time, or “to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” [1]. Demand response (DR) can shift energy use from high to low which can reduce the cost of generation and it can improve the reliability of the grid by maintaining system frequency and supply-demand balance. Power systems have become more complicated since demand response programs were implemented. For example, global variable renewable energy deployment has increased rapidly, with double-digit annual growth rates over the last few decades [2]. Smart devices are also being implemented in homes to control the home equipment to save energy [3]. To accommodate for these advancements, a new framework is needed to operate the grid more efficiently: transactive energy.

The GridWise® Architecture Council defines transactive energy as, “a system of economic and control mechanisms that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter” [4]. Transactive energy extends the concept of demand response to both the supply side and demand side, and aims to balance supply and demand in a real-time, autonomous, and decentralized manner. Transactive energy has been described as the “eBay of electricity” [5]. There have been many approaches towards integrating transactive energy in the real world such as proposing a coalitional game-based model [6], an energy trading framework [7], and a multi agent based framework [8]. An important step in testing these approaches is being able to control home equipment and participate in DR/transactive energy.

Home energy management systems (HEMS) allow users to more effectively control the equipment in their homes by participating in demand response programs. For example, simple rule-based HEMS [9] are often used but lack the ability of predictive controls. Other HEMS can take information from the electrical grid in the form of demand response or incentive [10,11]. These more advanced systems use optimization techniques that sometimes require substantial computing power that would usually not be available in the typical house, thus making the HEMS impractical. While more advanced HEMS can be effective, there are more issues that need to be addressed. Many DR programs require full control of building equipment, which could lead to discomfort for the user. But, on the other hand, some users are very tolerant of discomfort and would prefer to increase the financial benefits by reducing loads more aggressively [10]. In [12] a HEMS that is aimed at low-cost residential buildings for low-income occupants. In [13] electricity cost savings and comfort are maximized while minimizing curtailed energy.

One important factor to consider when modelling residential buildings is the variability in energy consumption because it has a significant impact that will affect the demand/supply of energy between homes. For example, it is important for the grid to know that a house with more efficient HVAC and solar panels has a surplus of PV generation while another house needs more electricity to keep the space cool. In this case, some of the surplus can be given to the other house, in turn reducing the stress on the grid. While it is important to consider the different types of houses and home equipment, it is also important to consider the occupant preferences. For example, people who prefer a higher thermal comfort level are likely to consume more energy and have less utility bill savings. Many efforts to develop advanced HEMS in residential buildings have been made, but many fail to account for occupant preferences. [14] performs a sensitivity analysis of thermal comfort in commercial buildings. Even though some existing work includes occupant preferences as an element in their HEMS, few have a systematic approach to "determine the relative weights of different objectives, such as cost savings, thermal comfort, user inconvenience, and so on" [10].

At the National Renewable Energy Laboratory (NREL), foresee™, a HEMS that incorporates occupant preferences by assigning weights to different objectives using the SMARTER (Simple Multi-Attribute Rating Technique Exploiting Risks) [15] method has been developed. While there are other objectives and capabilities that can be implemented with foresee™, this paper considers occupant preferences to determine weights for the following objectives: economic savings, thermal comfort (for both air and water temperature), and carbon emission reduction. Many case studies have already been performed showing that foresee™ is effective [10]. For example, energy efficiency mode can increase energy savings significantly when compared to traditional "dead-band" controllers [10]. This paper performs a *sensitivity analysis* of different occupant preferences by ranking economic savings, thermal comfort, and carbon emission reduction by importance. When the rankings are changed, the weights of each objective are also changed. By analyzing the cost savings, thermal comfort, and carbon emissions, we will gain a better understanding of how the occupant preferences affect energy consumption in residential buildings. It is important to show that occupant preferences have a significant impact and should be considered when modelling residential homes. Accurate modeling of occupant preference would ensure the continued participation of the residents in DR/transactive programs to provide the necessary grid services. The main contributions of this work are presented below:

1. Systematic approach of determining the relative weights of different objectives.
2. Senstivity analysis with different user preference to demonstrate the impact of variation of user preference.
3. Detailed case study demonstrating impact of user preference on utility bill savings, user discomfort, and carbon emission.

2. MATERIALS AND METHODS

A more detailed explanation of the objectives in foresee™ helps explain how to account for occupant preferences. To find an optimized schedule, foresee™ creates an *overall* objective function which is the sum of all the *individual* objective functions (in this study: economic savings, thermal comfort (for air and water temperature), and carbon emission reduction). Equation (1) shows the overall objective function, J, where H is the number of time steps in the horizon, β is a vector of occupant preference weightings, and Φ is a vector of normalized individual objective functions. The details on the constraints of the optimization can be found in previous work [10] and the individual objective functions are discussed later in TABLE 1.

$$J = \sum_{t=0}^{H-1} \beta\Phi \tag{1}$$

To create the overall objective function, foresee™ loads the information required for each individual objective function over the horizon (4hrs ahead in this study). For example, foresee™ loads the next 4hrs of utility rates to predict the economic cost and the next 4hrs of MOER (Marginal Operating Emissions Rate) data to predict carbon emissions.

Thermal comfort is more difficult to measure, a survey has shown that as the temperature increases/decreases from the desired temperature, the user discomfort varies similarly to the square of the difference from the desired temperature [10]. To create an individual objective function for thermal comfort, instead foresee™ creates a penalty for thermal *discomfort*, which is calculated as the square of the difference between the heating/cooling setpoint (depending on if the system is heating or cooling) and the indoor temperature. Rather than using one temperature value as the desired temperature, foresee™ adds a "comfort band" around the heating/cooling setpoint that does not increase the penalty (for the sensitivity analysis this comfort band was ±1°C). Finally, foresee™ minimizes this overall objective function using a convex optimizer to create the optimal schedule over the horizon.

2.1 Normalization of individual objective functions

One of the most important steps needed to make sure foresee™ can equally compare economic savings, carbon emission reduction, and thermal comfort is normalization of the objective functions. There are many methods of normalization but the intention for this study is to normalize the objective functions so that they vary between 0 and 1. By accomplishing this, the optimization will consider economic savings, carbon emission reduction, and thermal comfort with equal importance. The method of normalization that this study implemented into foresee™ is shown in equation 2. $\bar{X}$ is the normalized value, $X_{current}$ is the current value, $X_{minimum}$ is the minimum values, and $X_{maximum}$ is the maximum value.

$$\bar{X} = \frac{X_{current} - X_{minimum}}{X_{maximum} - X_{minimum}} \quad (2)$$

More specifically, this method had to be properly applied to all the objectives in foresee™ so that the optimization was possible. Previously, there were cases where the normalized objective functions would not range between 0 and 1 and cause problems when the net energy consumption was negative. The normalization method in Equation 2 solved this issue. Table 1 shows the normalization for each individual objective function. ‘P’ represents power, ‘rate’ represents utility rate, ‘MOER’ represents carbon emission data, ‘T’ represents temperature, ‘horizon’ represents number of hours foresee™ is optimizing for, and ‘timestep’ represents the number of timesteps in an hour. Finally, to optimize the controls, foresee™ takes the sum of each time step in the horizon for each individual objective function (Φ), adds the appropriate weighting factors (B), and finally minimizes the sum of the individual objective functions (J) (refer back to Equation 1). Because the individual objectives are summed over the horizon, the normalizations also need to be summed. For air and water temperature maximum values of 4 and 36 $℃^2$ were chosen to normalize the objectives.

TABLE 1: SUMMARY OF NORMALIZATION FOR EACH INDIVIDUAL OBJECTIVE FUNCTION.

Objective Function	Normalization
Utility Cost	$\frac{\sum[(\mathrm{P} - \mathrm{P_{min}}) \text{ x rate}]}{\sum[(\mathrm{P_{max}} - \mathrm{P_{min}}) \text{ x rate}]}$
Carbon Emissions	$\frac{\sum[(\mathrm{P} - \mathrm{P_{min}}) \text{ x MOER}]}{\sum[(\mathrm{P_{max}} - \mathrm{P_{min}}) \text{ x MOER}]}$
Air Temperature	$\frac{\sum[[\max((\mathrm{T} - \mathrm{T_{max}}), 0)]^2 + [\min((\mathrm{T} - \mathrm{T_{min}}), 0)]^2]}{4 \text{ x horizon x } 60 \div \text{timestep}}$
Water Temperature	$\frac{\sum[[\max((\mathrm{T} - \mathrm{T_{max}}), 0)]^2 + [\min((\mathrm{T} - \mathrm{T_{min}}), 0)]^2]}{36 \text{ x horizon x } 60 \div \text{timestep}}$

2.2 Occupant preference cases and house model

Now that each objective is properly normalized between 0 and 1, appropriate weighting factors can be added to each individual objectives to account for occupant preferences. To determine the proper weighting values for each objective, foresee™ uses the SMARTER (Simple Multi-Attribute Rating Technique Exploiting Risks) method which requires users to rank the different objectives in order of importance (economic savings, carbon emission reduction, thermal comfort (air), and thermal comfort (water)). The values in table 2 show the weighting values when there are four different objectives. [15]

TABLE 2: OCCUPANT PREFERENCE WEIGHTING (β) VALUES BASED ON SMARTER METHOD.

Ranking	Occupant Preference Weighting Value (β)
1	0.4180
2	0.2986
3	0.1912
4	0.0922

Finally, this study considered 6 different cases where economic cost, carbon emission reduction, and thermal comfort are ranked differently (see TABLE **3**). Each case represents a different user. For example, a low-income user who prioritizes comfort over environmental awareness might fall under Cost Savings Priority Case 1. Another example that falls under the Thermal Comfort Priority Case 4 is a user who has a high income and is willing to spend more to be comfortable but also reduce their carbon footprint.

TABLE 3: RANK OF SIX DIFFERENT USER PREFERENCES ON ECONOMIC SAVINGS, THERMAL COMFORT, AND CARBON EMISSION REDUCTION FOR THE SENSITIVITY ANALYSIS.

Objective	Cost Savings Priority Case 1	Cost Savings Priority Case 2	Thermal Comfort Priority Case 3	Thermal Comfort Priority Case 4	Carbon Emission Priority Case 5	Carbon Emission Priority Case 6
Utility Cost	1	1	3	4	4	2
Air Temp	2	3	1	1	2	3
Water Temp	3	4	2	2	3	4
Carbon Emission	4	2	4	3	1	1

NREL’s Object-oriented Controllable High-resolution Residential Energy (COHRE) model was used to run the simulations in this study [16]. OCHRE is a residential building model that incorporates controllable devices such as HVAC equipment, water heaters, electric vehicles, photovoltaic systems, and batteries. The simulations used a building model for an all-electric new construction single family home located in Fort Collins, CO where there is mandatory time-of-use electricity rate structure. The building includes an air source heat pump, a heat pump water heater, a 15 kW PV system, a 6kWh/3kW battery, and other typical energy consuming equipment.

3. RESULTS AND DISCUSSION

To investigate the sensitivity of different occupant preferences, this study compared the total energy consumption, utility cost, carbon emissions, and thermal comfort of each of the cases. We found that the annual results of a building model with PV generation in Fort Collins, CO using a mandatory time-of-use electricity rate structure and past MOER data was able to follow the correct trends if the averages of the economic savings cases, thermal comfort cases, and carbon emission reduction cases are used for comparison. A qualitative analysis of the annual results in FIGURE 1 shows that cases with economic savings as the priority have the lowest utility cost, cases with thermal comfort priority have the lowest thermal discomfort, and cases with carbon emission reduction as the priority have the lowest carbon emissions. The maximum and minimum refer to the values from the 3 averages (Economic Savings Priority Case 1 & 2, Thermal Comfort Priority Case 3 & 4, and Carbon Emission Priority Cases 5 & 6).

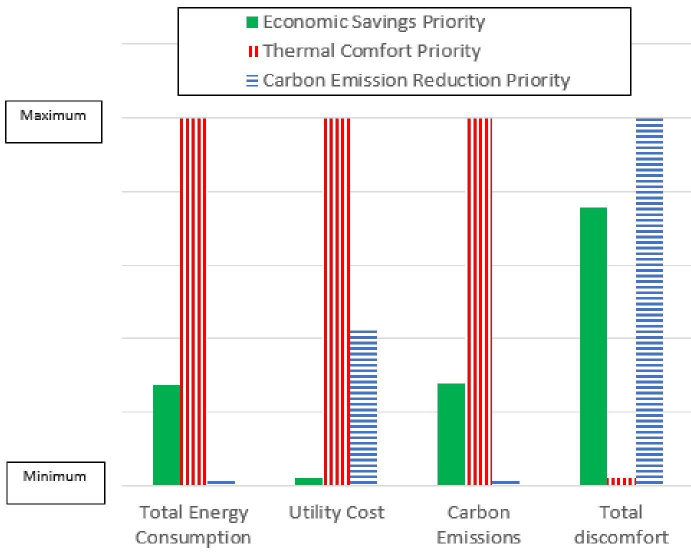

FIGURE 1: QUALITATIVE COMPARISON OF ANNUAL COST, CARBON EMISSION, THERMAL DISCOMFORT, TOTAL ENEGY CONSUMPTION FOR AVERAGE OF CASES 1 & 2 (ECONOMIC SAVINGS PRIORITY), 3 & 4 (THERMAL COMFORT PRIORITY), AND 5 & 6 (CARBON EMISSION REDUCTION PRIORITY)

While the averages are able to follow the correct trends, there are outliers among the individual cases. One of the outliers was carbon emission reduction case 6 which had a lower utility cost than both economic savings cases. Another interesting outcome from the simulations was that some cases using foresee™ to optimize the objectives, worsened the results compared to controlling the house with no HEMS (for example thermal comfort case 3 is worse than the no HEMS case in every category). The no HEMS case just maintains the temperature between the heating and cooling setpoint. A potential issue was that the net energy consumption for all cases was significantly below zero. This is why the utility cost and carbon emissions are negative.

TABLE 4: ANNUAL SIMULATION DATA FOR A HOUSE MODEL WITH PV GENERATION. THE DATA IS GIVEN AS A PERCENTAGE DIFFRERENCE FROM THE "NO HEMS" CASE. THE SYMBOLS IN THE PARENTHESES REPRESENT THE RANKING OF OCCUPANT PREFERENCE. $ = COST SAVINGS, T = THERMAL COMFORT, AND C = CARBON EMISSION.

Case #	Total Electric Energy Usage	Utility Price	Carbon Emission	Total Discomfort [K·hr]
Baseline (No HEMS)	-11520 kWh	-$940	-23,594 lbs CO_2	0
1 ($,T,C)	-0.2%	2.7%	-1.4%	24.7
2 ($,C,T)	0.5%	9.7%	5.1%	46.2
3 (T,$,C)	-0.5%	-2.1%	-4.4%	14.9
4 (T,C,$)	-0.3%	-9.3%	-3.3%	16.9
5 (C,$,T)	0.2%	-7.8%	1.8%	33.3
6 (C,T,$)	0.6%	10.2%	6.3%	50.3

The results in TABLE 4 suggest that the PV generation for the house model was too large because the negative energy consumption of the baseline case means that more energy was generated than used. In other words, the house is net positive. To investigate this issue, this study performed a simulation of the same house model without PV generation. To better understand the results, weekly simulations during winter (heating season) and summer (cooling season) were performed and analyzed. There are still small deviations where for example, a carbon emissions reduction priority case may have more cost savings than an economic savings priority case, but now every case has more favorable results than the no HEMS case. Thermal discomfort may be increased but energy consumption, utility cost, and carbon emissions are always reduced (shown in TABLE 5 and TABLE 6).

TABLE 5: WEEK LONG ***WINTER*** SIMULATION DATA FOR A HOUSE MODEL WITH NO PV GENERATION. THE DATA IS GIVEN AS A PERCENTAGE DIFFRERENCE FROM THE "NO HEMS" CASE. THE SYMBOLS IN THE PARENTHESES REPRESENT THE RANKING OF OCCUPANT PREFERENCE. $ = COST SAVINGS, T = THERMAL COMFORT, AND C = CARBON EMISSION.

Case #	Total Electric Energy Usage	Utility Price	Carbon Emission	Total Discomfort [K·hr]
Baseline (No HEMS)	335 kWh	$28.62	679 lbs CO_2	0
1 ($,T,C)	-8%	-13%	-8%	2.33

Case #	Total Electric Energy Usage	Utility Price	Carbon Emission	Total Discomfort [K·hr]
2 ($,C,T)	-20%	-23%	-19%	5.95
3 (T,$,C)	-3%	-6%	-3%	0.78
4 (T,C,$)	-4%	-5%	-4%	0.88
5 (C,$,T)	-10%	-11%	-10%	3.10
6 (C,T,$)	-21%	-24%	-21%	6.47

TABLE 6: WEEK LONG ***SUMMER*** SIMULATION DATA FOR A HOUSE MODEL WITH NO PV GENERATION. THE DATA IS GIVEN AS A PERCENTAGE DIFFRERENCE FROM THE "NO HEMS" CASE. THE SYMBOLS IN THE PARENTHESES REPRESENT THE RANKING OF OCCUPANT PREFERENCE. $ = COST SAVINGS, T = THERMAL COMFORT, AND C = CARBON EMISSION.

Case #	Total Electric Energy Usage	Utility Price	Carbon Emission	Total Discomfort [K·hr]
Baseline (No HEMS)	177 kWh	$17.63	355 lbs CO_2	0
1 ($,T,C)	-9%	-14%	-9%	1.4
2 ($,C,T)	-19%	-25%	-19%	2.9
3 (T,$,C)	-4%	-7%	-4%	0.53
4 (T,C,$)	-5%	-6%	-5%	0.57
5 (C,$,T)	-12%	-14%	-12%	1.83
6 (C,T,$)	-20%	-26%	-20%	3.08

Results from this sensitivity analysis show that occupant preferences have a significant effect on energy consumption in residential buildings. For a single week in winter there is up to an 18% difference in energy consumption for the same house model among the six occupant preferences. Another interesting observation from the results is that utility price and carbon emissions were closely correlated. This happened because the peak time-of-use prices often coincided with the highest rate of carbon emissions and so optimizing carbon emissions and optimizing utility price were practically the same. A potential problem is that each individual objective (thermal comfort, utility cost, and carbon emissions) is in different units (K^2, $, lbs. CO_2).

4. CONCLUSION

This work shows that occupant preferences have a substantial impact on energy consumption and needs to be accounted for in residential buildings. By using appropriate weighting values for individual objectives such as economic savings, thermal comfort, and carbon emission reduction, foresee can optimize the controls of a home to achieve greater energy efficiency while also accommodating occupant preferences. Based on a house simulation in Fort Collins, CO the energy consumption can vary by up to 18% in a single week.

There is still further research that can build on the results of this study. One way is to determine a method to differentiate carbon emissions and utility cost by converting all the objectives into a common unit. This will potentially solve the utility cost and carbon emission correlation issue. Another way to validate this work is to run simulations with different house models in different locations using various pricing strategies and carbon emission data. The results of this study are useful because they not only show that occupant preferences have a significant impact, but they also show that foresee™ is a valid tool that can account for occupant preferences.

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