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How Do Electricity Pricing Programs Impact the Selection of Energy Efficiency Measures? - A Case Study with U.S. Medium Office Buildings

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Abstract

Building owners usually select energy efficiency measures (EEMs) by referring to return on investment (ROI). Current studies tend to apply static energy price to estimate ROI. However, more and more buildings are adopting dynamic electricity pricing programs. To understand how electricity pricing programs impact the selection of EEMs, this paper presents an analysis of the ROIs of EEMs under different pricing programs using U.S. medium office buildings as an example. Eight EEMs in four typical cities are selected as case studies. Considering five electricity pricing programs scenarios (one static program and four dynamic programs), EEMs are selected based on their ROIs. The main findings are: (1) The ROIs of EEMs change under different pricing programs. (2) In Honolulu, Buffalo, and Denver, replacing interior fixtures with higher-efficiency fixtures has a significantly higher ROI than the rest EEMs under all five pricing programs. However, the ROI of this EEM in Honolulu ranges from 28% to 47% for different pricing programs. (3) Similarly, in Fairbanks, replace heating coil with higher-efficiency coil produce higher ROI than the rest under all five pricing programs. (4) For other EEMs, their ROI rankings vary according to electricity pricing programs.

Key words: Electricity Price; Energy Efficiency Measure; Retrofit; Modeling and Simulation; Demand Response

1. Introduction

Building energy retrofit has great potential to save energy (Hasan 1999; Verbeeck and Hens 2005; Glazer 2017; Griffith et al. 2007; Thornton et al. 2011). For example, Glazer (2017) analyzed 272 buildings and climate combinations, and stated that the energy retrofit of commercial buildings in the U.S. had the potential to achieve approximately 50% site energy saving compared to ASHRAE Standard 90.1-2013 (ASHRAE 2013). Furthermore, the study by Chen et al. (2017) shows that replacing lighting with LED in office and retail buildings in San Francisco will save more than 300 GWh energy consumption annually. According to simulations conducted by Friess et al. (2012), an appropriate wall insulation strategy is able to save up to 30% of energy consumption. Moreover, energy saving with improved lighting systems was found to be 8.3% in the research conducted by Houri and El Khoury (2010). However, energy saving is only one of the considerations for building owners. They also consider cost saving when selecting energy efficiency measures (EEMs). To optimize energy and cost savings, it is crucial to select appropriate EEMs during building energy retrofits.

Currently, a lot of research has studied how to select appropriate EEMs for buildings by considering various factors, such as energy and cost savings (Ferreira et al. 2013; Jensen and Maslesa 2015; Juan et al. 2010; Kumbaroğlu and Madlener 2012; Nielsen et al. 2016). Taking into account energy consumption and net present value (NPV), Liu et al. (2010) introduced a framework to optimize the design of building energy systems. Moreover, using energy saving or cost saving as the main objective, Tan et al. (2016) studied how to select the right EEMs for existing buildings. Mahlia et al. (2011) analyzed the life cycle cost and the payback period of lighting retrofit at the University of Malaya.

The studies mentioned above mainly applies static energy price (or a fixed energy price) to evaluate the cost performance of building retrofits. However, more and more commercial buildings adopt dynamic electricity pricing programs instead of static pricing programs (AEI&P 2019; Hawaiian Electric 2019; UnisourceEnergy 2019; XcelEnergy 2019a; Yoon et al. 2014). For example, commercial buildings in Colorado, U.S. adopt various dynamic electricity pricing programs, such as critical peak pricing and time of use pricing (XcelEnergy 2019b). In this case, electricity prices are different for individual buildings according to the peak power load demanded by each building. Electricity prices vary during different time periods. Generally, electricity price for commercial buildings is higher during the daytime than at night. Another example is that real time electricity pricing programs are being adopted in Texas, U.S. (ercot 2019). Electricity prices fluctuate over short intervals (typically an hour), and building users are charged at a specific price for each interval. Dynamic pricing programs can generate savings if building users respond to the fluctuations in electricity prices and adjust their usage accordingly.

Apparently, for buildings adopting dynamic electricity pricing programs, the conventional approach of selecting EEMs based on static pricing programs may not be valid anymore. For instance, the static pricing program may underestimate the return on investment (ROI) of EEMs that can shift the electricity consumption from peak hour to non-peak hour. This will lead to additional cost savings under the time of use pricing program. However, the additional cost savings for peak-demand reduction is not available under the conventional static pricing program.

To understand how electricity pricing programs impact the selection of EEMs, this paper studies the ROIs of EEMs under different pricing programs using U.S. medium office buildings as an example. In this research, we select four typical cities with different climate features and designed five electricity pricing programs. To simplify the research process, the electricity pricing programs in different cities are similar, which are designed based on a review about existing electricity pricing programs used in the U.S. This paper is organized as follows: Section 2 introduces the methodology to select EEMs; Section 3 designs five electricity pricing programs, and selects four cities as case study to select EEMs for U.S. medium office buildings; finally, findings are concluded in Section 4.

2. Methodology

2.1. General Description

Figure 1 presents a general description of selecting EEMs for an existing building based on the ROIs for different pricing programs. Although this paper focuses on the U.S. medium office buildings, the methodology presented in this section can be applied for other building types. We first establish a baseline model and calculate its energy consumption. Secondly, we upgrade the baseline models with EEM i. Then, energy costs are calculated based on energy predictions and different pricing programs. After that, annual cost saving by applying EEM i can be determined. Finally, ROI for EEM i can be calculated by using initial investment and annual cost saving. The EEMs can be selected based on a threshold defined by users. A detailed introduction is shown in Sections 2.2, 2.3, and 2.4.

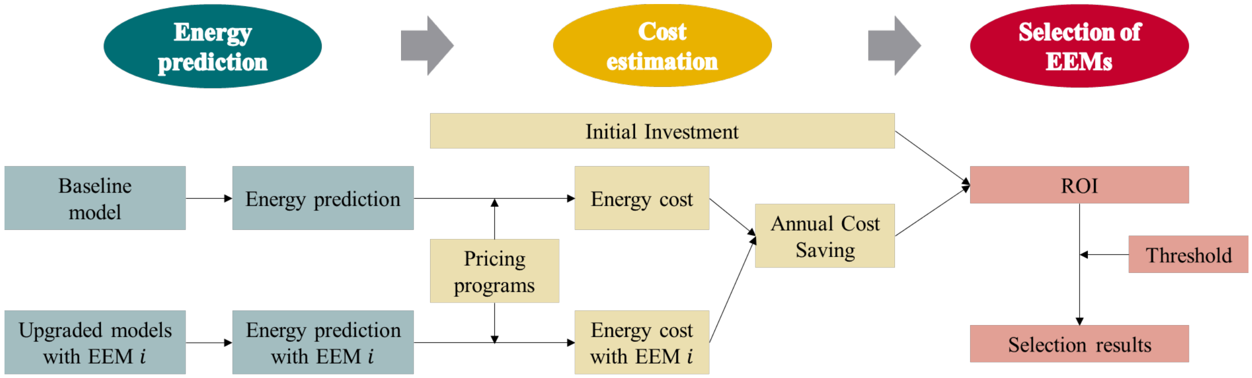


Figure 1. General description of calculating ROI of EEM for an existing building

2.2. Energy Prediction

As mentioned in Section 2.1, we predict energy consumption based on (1) baseline models and (2) upgraded models by adopting individual EEMs. The baseline model can be the model of the actual building if users are only interested in a single building. For large-scale analysis, the baseline models can be prototypical building models, such as Commercial Reference Building Models (Deru et al. 2011; DOE 2019b), Commercial Prototype Building Models (DOE 2019a; Thornton et al. 2011), other prototypical models for religious worship (Ye, Hinkelman, et al. 2019), mechanical shop (Ye, Wang, et al. 2018), and college and university buildings (Ye, Zuo, et al. 2018).

The EEMs can be selected by engineering experience or referring to literature. A rich set of research identified possible sensitive EEMs, which may have great impacts on energy consumption in buildings (Glazer 2017; Kneifel 2010; Wang et al. 2013; Wang et al. 2018; Wang et al. 2015; Ye, Zuo, et al. 2019).

Depending on the pricing programs, different data will be extracted from the building energy simulations of baseline models and upgraded models with EEM i. In this study, we extract three types of data: (1) hourly electricity consumption; (2) monthly peak power load; (3) annual natural gas consumption.

2.3. Cost Estimation

Cost estimation consists of two types of cost: initial investment and energy cost. Initial investment is the total cost during the retrofit period, including material cost, installation cost, and transport cost. Energy cost includes electricity cost and natural gas cost.

2.3.1 Initial Investment

The investment estimation of EEMs is an important area of research for building energy retrofit (DeCanio and Watkins 1998; Nair et al. 2010). Some existing reports provide the estimated values of the initial investment (I_i) for EEMs. For example, the Advanced Energy Retrofit Guide provides strategies and costs to retrofit existing office buildings (Liu et al. 2011). The RSMeans also provides cost estimations for the initial investment of EEMs (Gordian 2019). This study referred the retrofit guides and used RSMeans as a tool to estimate initial investment.

2.3.2 Energy Cost

Energy cost consists of two types of cost: electricity cost and natural gas cost. In order to analyze the impact of electricity pricing programs on the selection of EEM, electricity cost is calculated under different pricing programs, while natural gas cost is calculated under one static pricing program.

There are different ways to define electricity pricing programs (Albadi and El-Saadany 2007; Doostizadeh and Ghasemi 2012; Joskow and Wolfram 2012). Electricity pricing programs are very complicated in reality, and they are diverse in different electricity companies. In this study, we simplified electricity pricing programs consist of three types of charge: basic charge, demand charge, and energy charge. Basic charge is a monthly fixed charge. Demand charge is the charge for each month's peak power load. Energy charge is the charge for electricity consumption. Therefore, annual electricity cost ($C_{electricity}$) under a typical electricity pricing program is:

$$C_{electricity} = P_B \times 12 + \sum_{j=1}^{12} P_{D,j} \times E_{D,j} + \sum_{k=1}^{n} P_{E,k} \times E_{E,k}, \tag{1}$$

where P_B is the basic price for every month; $P_{D,j}$ is the unit price of the peak power and $E_{D,j}$ is the peak power load in every month; $P_{E,k}$ is the unit price of electricity consumption for time period k. $E_{E,k}$ is electricity consumption during time period k. The P_B, $P_{D,j}$, $P_{E,k}$, and k are different under different electricity pricing programs. For instance, in a static electricity pricing program, $P_B = 0$, $P_D = 0$, and $n = 1$ so that $C_{electicity} = P_E \times E_E$.

To examine the impact of electricity pricing programs, this study applied static natural gas pricing program. Annual natural gas cost (C_{gas}) is:

$$C_{gas} = P_G \times E_G, \tag{2}$$

where P_G is the unit price of natural gas; E_G is the annual natural gas consumption.

Therefore, annual energy cost (C_{energy}) is:

$$C_{energy} = C_{electricity} + C_{gas}. \tag{3}$$

2.3.3 Annual Cost Saving

Energy cost saving (R_i) by applying EEM i is:

$$R_i = C_{energy,base} - C_{energy,upgr,i}, \tag{4}$$

where $C_{energy,base}$ is the annual energy cost before the retrofit; $C_{energy,upgr,i}$ is the annual energy cost after applying EEM i.

2.4. Selection of EEMs

The initial investment of an EEM is returned by annual cost saving. The ratio of annual cost saving and initial investment is termed as ROI, which reflects the economic efficiency of EEMs. The ROI of EEM i (ROI_i) is:

$$ROI_i = \frac{R_i}{I_i}, \tag{5}$$

where R_i is annual energy cost saving by adopting EEM i, which can be calculated by using formula (1), (2), (3), and (4); I_i is initial investment of EEM i, which can be calculated by using the method introduced in 2.3.1.

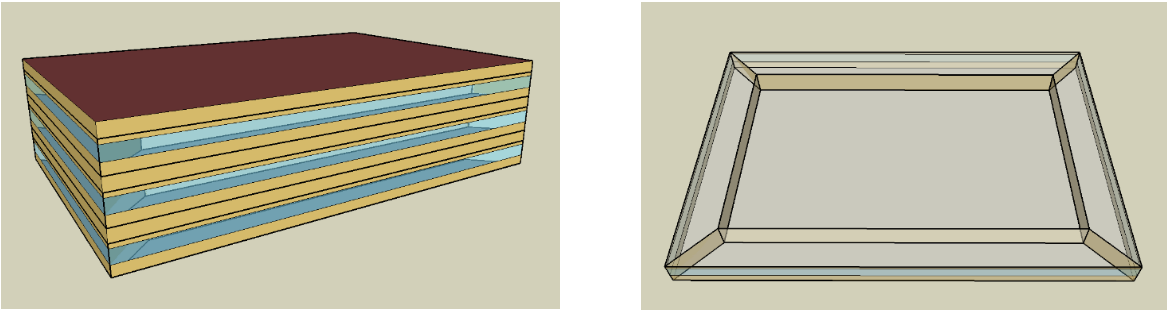
The higher ROI means the shorter payback period, which building owners tend to select for existing building retrofit projects (Fan and Xia 2017; Ma et al. 2012; Tadeu et al. 2016). In this study, the higher the EEM's ROI is, the higher priority it will be selected. The goal of this selection approach is not to maximize energy saving or cost saving, but to value more profitable EEMs.

3. Case Study: U.S. Medium Office Buildings

To evaluate the impact of pricing programs on ROIs, a case study is performed using the U.S. medium office buildings in four typical cities (Honolulu, Buffalo, Denver, and Fairbanks) under the five pricing programs (static, general, critical peak, time of use, and high renewable penetration). The study is conducted in three steps as introduced in Section 2: *energy prediction, cost estimation,* and *selection of EEMs*.

3.1. Energy Prediction

The DOE Commercial Prototype Building Models (DOE 2019a) for medium office buildings are selected as baseline models. Figure 2 shows the geometry and thermal zones of the models, which have a rectangle shape and three stories. Each story contains five thermal zones (one core zone and four perimeter zones).



(a) Geometry (b) Thermal Zones

Figure 2. Geometry and thermal zones of the baseline medium office building models (DOE 2019a)

Table 1 summarizes key model parameters. Four typical cities in different climates were selected. Honolulu in the Climate Zone 1A is hot and humid while Fairbanks in the Climate Zone 8 is extremely cold. Buffalo (5A) and Denver (5B) are in cold climates, which is relatively warmer compared with Fairbanks, but cooler than Honolulu. Buffalo is relatively humid while Denver is dry. Thus, these four studied cities can represent the major climate features in the U.S.

Table 1. Key parameters of the baseline medium office building models (DOE 2019a)

Parameter Name	**Value**			
Location (Climate Zone: Typical City)	1A: Honolulu	5A: Buffalo	5B: Denver	8: Fairbanks
Total Floor Area	4,980 m^2 (50 m ×33.2 m)			
Aspect Ratio	1.5			
Number of Floors	3			
Window-to-Wall Ratio	33%			
Floor-to-Floor Height	3.96 m			
Envelope Type	Exterior Walls: Steel-Frame Walls Roof: Built-up Roof			
HVAC System Type	Heating: Packaged Air Conditioning Unit, Gas Furnace Cooling: Packaged Air Conditioning Unit, DX Cooling Terminal Units: VAV Terminal Box with Electric Reheat			
Service Water Heating Type	Tank-type, Natural Gas Water Heater			

Existing research provides a rich set of EEMs for U.S. commercial buildings (Glazer 2017; Griffith et al. 2007; Wang et al. 2018). For example, Glazer (2017) assembled 30 EEMs for commercial buildings. Based on these literatures, Table 2 selects eight EEMs for U.S. medium office buildings in this study. To make it convenient, we provide the abbreviation for each EEM.

Table 2. Description of EEMs

EEM	**EEM Abbreviation**	**Variable**
Add wall insulation	WALL	Wall insulation R-value
Add roof insulation	ROOF	Roof insulation R-value
Replace windows	WINDOW	Window U-factor, Window SHGC
Replace interior fixtures with higher-efficiency fixtures	LPD	Lighting Power Density
Replace office equipment with higher-efficiency equipment	EQUIP	Plug Load Density
Replace cooling coil with higher-efficiency coil	COOLING	COP
Replace heating coil with higher-efficiency coil	HEATING	Heating Efficiency
Replace service hot water system with higher-efficiency system	DHW	Hot Water Efficiency

The baseline values of the selected EEMs are the values in the baseline models, which is DOE Commercial Prototype Building Models for ASHRAE Standard 90.1-2007. The upgraded values are the values of the EEMs after the retrofits based on the Advanced Energy Retrofit Guide (Liu et al. 2011). Table 3 lists the baseline and upgraded values of the EEMs in the four studied cities. The baseline values refer to ASHRAE Standard 90.1-2007 (ASHRAE 2007), and the upgraded values refer to Advanced Energy Design Guide (Bonnema et al. 2012).

Table 3.Values of variables

Variable	**Unit**	**1A: Honolulu**		**5A: Buffalo**		**5B: Denver**		**8: Fairbanks**	
		Base[1]	**Upgr**[2]	**Base**[1]	**Upgr**[2]	**Base**[1]	**Upgr**[2]	**Base**[1]	**Upgr**[2]
Wall insulation R-value	m^2-K/W	1.04	4.38	2.37	5.71	2.37	5.71	2.37	5.71
Roof insulation R-value	m^2-K/W	2.60	3.95	3.47	5.50	3.47	5.50	3.47	6.18
Window U-factor	W/m^2-K	5.78	3.69	2.65	2.21	2.65	2.21	2.49	1.93
Window SHGC	-	0.31	0.25	0.43	0.25	0.43	0.25	0.43	0.25
Lighting Power Density	W/m^2	10.76	8.07	10.76	8.07	10.76	8.07	10.76	8.07
Plug Load Density	W/m^2	8.07	5.92	8.07	5.92	8.07	5.92	8.07	5.92
COP	-	3.23	3.37	3.23	3.37	3.23	3.37	3.23	3.37
Heating Efficiency	-	0.80	0.90	0.80	0.90	0.80	0.90	0.79	0.90
Hot Water Efficiency	-	0.81	0.90	0.81	0.90	0.81	0.90	0.81	0.90

[1] Base: Baseline model (Source: ASHRAE Standard 90.1-2007 (ASHRAE 2007; DOE 2019a)).

[2] Upgr: Upgraded model (Source: AEDG 50% Energy Savings (Bonnema et al. 2012)).

The EEMs impact building's monthly maximum power and annual energy consumption. In this analysis, the main contributors of electricity are cooling, reheating, fans, lighting, electric equipment, and pumps for hot water while the main contributors of natural gas are heating and water heater. Figure 3 shows the impact of varying a single EEM on average monthly peak power for buildings. The first six EEMs reduce the average monthly peak power. Since the heating coil and hot water system consume natural gas, HEATING and DHW do not change the average monthly peak power. Because the efficiency of the cooling coil is not significantly improved, the COOLING only has a low impact on the changes of average monthly peak power. Furthermore, EEM's impacts on reducing average monthly peak power varies depending on the climates. For example, improving insulation of envelopes (WALL and ROOF) can reduce more peak power in the extremely cold/cold climate (Denver, Buffalo, and Fairbanks) than the hot climate (Honolulu). Another example shows that LPD and EQUIP reduce more peak power in the hot climate (Honolulu).

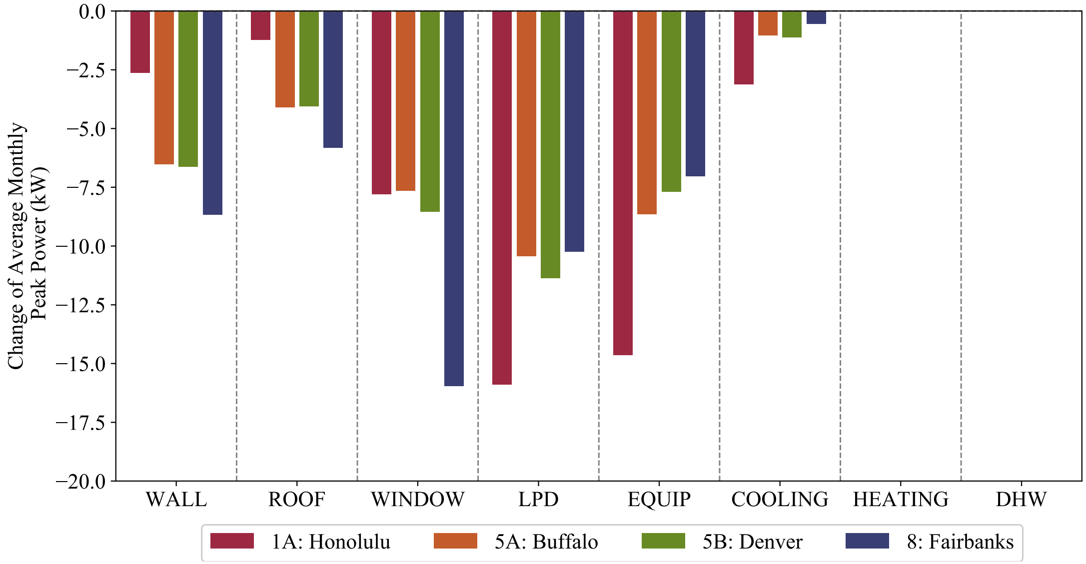


Figure 3. Changes in average monthly peak power by applying EEMs for buildings

Figure 4 shows the changes in annual electricity consumption and natural gas consumption by applying individual EEMs. By using WALL or ROOF, the annual electricity consumption is reduced whereas there is only a minor change for the annual natural gas consumption. The COOLING only impacts the annual electricity use while the HEATING and DHW only change the annual natural gas consumption. Furthermore, the rest three EEMs (WINDOW, LPD, and EQUIP) reduce the annual electricity use while they increase the annual natural gas use. For example, the EQUIP reduces the annual electricity use in all four cities while it increases the annual natural gas use in cold and extremely cold climates (Buffalo, Denver, and Fairbanks). The high-efficiency office equipment consumes less electricity for internal load. Furthermore, these models use electricity for cooling and natural gas for heating. By using the EQUIP, the cooling load is decreased and heating load is increased. In hot climate (Honolulu), the heating load is almost zero. The EQUIP reduces the annual electricity use for both internal load and cooling, and only has a small impact on the annual natural gas use. In the cold and extremely cold climates (Buffalo, Denver, and

Fairbanks), the high-efficiency office equipment reduces both internal load and cooling load, but increases energy consumption for heating. Thus, the electricity consumption is reduced and natural gas consumption is increased. It is noticed that although the EQUIP EEM reduction (2.15 W/m^2) is lower than LPD EEM reduction (2.69 W/m^2), EQUIP EEM has a small higher reduction for electricity consumption than the LPD EEM. It is because plug load has higher contribution to generate cooling load than lighting.

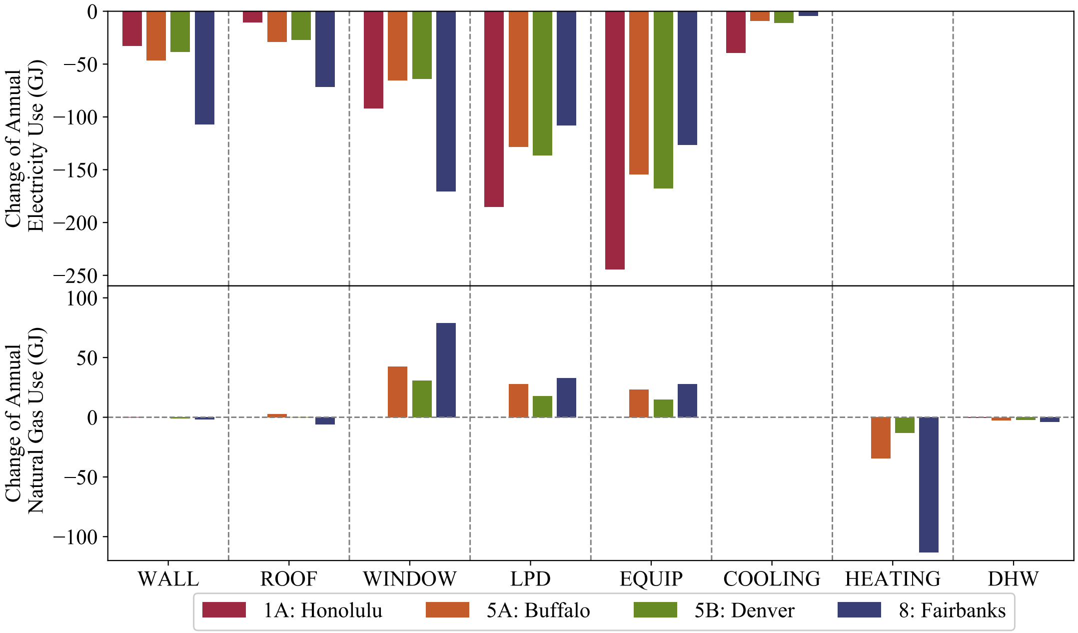


Figure 4. Changes in annual electricity and natural gas consumption by applying EEMs

3.2. Cost Estimation Under Different Electricity Pricing Programs

This section considers five types of electricity pricing programs: static, general, critical peak, time of use, and high renewable penetration. First, the initial investments of eight EEMs introduced in Table 2 will be estimated in this section. Secondly, energy costing saving contributed by individual EEMs will be calculated under the five types of pricing programs.

3.2.1 Initial Investment Estimation

Using the methodology described in 2.3.1, the initial investment of each individual EEM (I_i) in the four studied cities was estimated, as shown in Table 4. The initial cost for WALL, ROOF, and WINDOW can be estimated by using the RSMeans online portal. The initial cost for the other five EEMs can be estimated by starting with the Advanced Energy Retrofit Guide Office Buildings and then adjusting to regional pricing based on RSMeans. Initial investment estimated in this research is the total cost for retrofit based on 2011 pricing level. For specific building retrofit project, building users can use the actual estimated cost data for their projects.

Table 4. Initial investment (I_i) for the EEMs in building retrofits

EEM	1A: Honolulu	5A: Buffalo	5B: Denver	8: Fairbanks
WALL	\$49,632 (\$38/m^2)	\$45,639 (\$34/m^2)	\$34,800 (\$26/m^2)	\$51,344 (\$39/m^2)
ROOF	\$28,735 (\$17/m^2)	\$32,483 (\$20/m^2)	\$28,235 (\$17/m^2)	\$50,223 (\$30/m^2)
WINDOW	\$155,202 (\$238/m^2)	\$131,678 (\$202/m^2)	\$143,634 (\$220/m^2)	\$166,441 (\$255/m^2)
LPD	\$33,496	\$27,658	\$25,942	\$35,868
EQUIP	\$64,725	\$58,640	\$57,352	\$66,302
COOLING	\$11,063	\$10,516	\$9,776	\$11,008
HEATING	\$2,968	\$2,780	\$2,678	\$2,961
DHW	\$1,910	\$1,864	\$1,824	\$1,908

It can be seen from Table 4 that the initial investment of WINDOW is significantly higher than the other EEMs in all four studied cities. It is costly to replace all exterior windows into the new windows with lower U-factor and SHGC. Then WALL and EQUIP are the second or third expensive EEMs for the initial investment. By compared with these EEMs, it is relatively cheaper to replace systems (COOLING, HEATING, and DHW).

Generally, the initial investments of EEMs are similar among four cities, while they are a little higher in Fairbanks than in the other three cities. But, the initial investment of ROOF in Fairbanks is significantly higher than that in the other three cities. One reason is that the difference of roof insulation R-value between baseline and upgraded in Fairbanks is larger than that in other cities. As shown in Table 3, the difference of roof insulation R-value between baseline and upgraded in Fairbanks is 2.71 m^2-K/W, while the difference value in Honolulu, Buffalo, and Denver are 1.36 m^2-K/W, 2.03 m^2-K/W, and 2.03 m^2-K/W, respectively.

3.2.2 Energy Cost Saving Estimation

In reference to existing electricity pricing programs (XcelEnergy 2017; Dütschke and Paetz 2013; Dutta and Mitra 2017; ercot 2019; Joskow and Wolfram 2012), this study designed five electricity pricing programs using the equation (1). The parameters of each program are given in Table 5. In this research, same electricity pricing scheme is applied for four case cities, but unit price is different among four cities. The unit price is designed by referring city price level.

Table 5. Electricity pricing programs designed to case cities

Electricity Pricing Programs	City	Basic ($/Mon) P_B	Demand ($/kW Peak Power Every Month) P_D	Energy ($/kWh) P_E		
				Peak		Off-Peak
				Critical-Peak	On-Peak	
Static	Honolulu	0	0	0.2917		
	Buffalo	0	0	0.1527		
	Denver	0	0	0.1080		
	Fairbanks	0	0	0.2007		
General	Honolulu	144.0	79.60	0.01245		
	Buffalo	75.4	41.67	0.00652		
	Denver	53.0	29.47	0.00461		
	Fairbanks	99.0	54.77	0.00857		
Critical Peak[1]	Honolulu	92.9	53.07	4.1	-	0.01245
	Buffalo	48.6	27.78	2.1		0.00652
	Denver	34.4	19.65	1.5		0.00461
	Fairbanks	63.9	36.52	2.8		0.00857
Time of Use[2]	Honolulu	92.9	15.21	-	0.24441	0.06047
	Buffalo	48.6	7.96		0.12794	0.03166
	Denver	34.4	5.63		0.09049	0.02239
	Fairbanks	63.9	10.46		0.16816	0.04161
High Renewable Penetration[3]	Honolulu	92.9	15.21	4.1	0.24441	0.06047
	Buffalo	48.6	7.96	2.1	0.12794	0.03166
	Denver	34.4	5.63	1.5	0.09049	0.02239
	Fairbanks	63.9	10.46	2.8	0.16816	0.04161

[1] We select 15 days, which are assumed to appear critical-peak for the power grid. The critical-peak time period is from 12:00 pm to 17:00 pm in these 15 days.

[2] The on-peak time appears on workdays in Jun, Jul, Aug and Sept. The on-peak time period is from 12:00 pm to 20:00 pm. The other time period is off-peak.

[3] The days are divided into three categories based on the one day's radiation level: low, moderate, high radiation days. In the low radiation day, the critical-peak time period is from 13:00 pm to 17:00 pm, the on-peak time period is from 12:00 pm to 13:00 pm and from 17:00 pm to 20:00 pm, and the other time period is off-peak. In the moderate radiation day, the on-peak time period is from 12:00 pm to 20:00 pm, and the other time period is off-peak. In the high radiation day, the on-peak time period is from 17:00 pm to 20:00 pm, and the other time period is the off-peak.

Static: There is no basic charge or demand charge in this program. The unit price of electricity consumption (P_E) is same during the year. The electricity cost ($C_{electricity}$) is the product of P_E and electricity consumption. Static pricing program provides building users price signal to reduce energy consumption (Dütschke and Paetz 2013; Dutta and Mitra 2017). In this study, P_E is designed by referring the average price of electricity in the studied cities (EIA 2019).

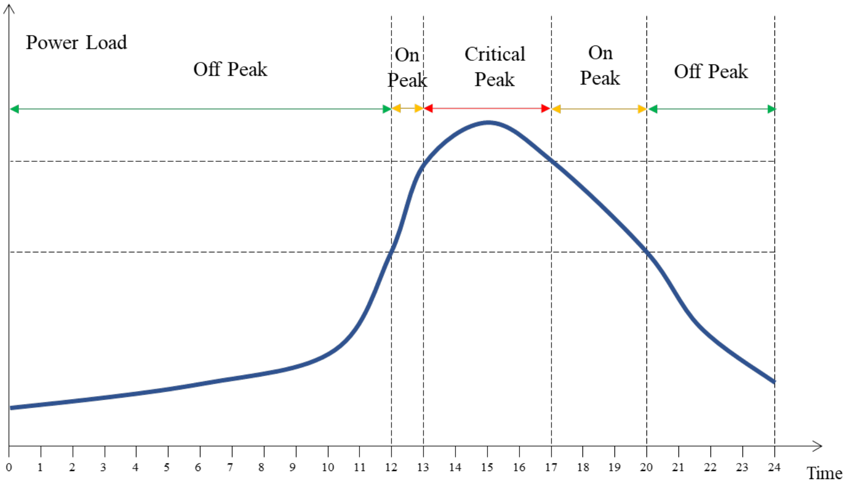
General: The electricity prices (P_B, P_D, and P_E) in this program are same during the year (XcelEnergy 2017). The electricity cost ($C_{electricity}$) is the sum of basic charge, demand charge, and energy charge. Basic charge is fixed. Demand charge is the product of P_D and monthly peak power. Energy charge is the product of P_E and electricity consumption. Therefore, general pricing program provides building users price signals to reduce peak power and electricity consumption.

Critical Peak: P_B and P_D in this program are same during the year. But P_E is different during different time period. P_E is high during a few critical-peak hours of the day and discounted during the rest of the day (Dütschke and Paetz 2013; Dutta and Mitra 2017). The critical-peak hours are only designed for a certain number of days (e.g. 15 days in this study) during a year. Critical peak pricing program gives building users strong price signals and encourages them to reduce their electricity use during critical-peak periods.

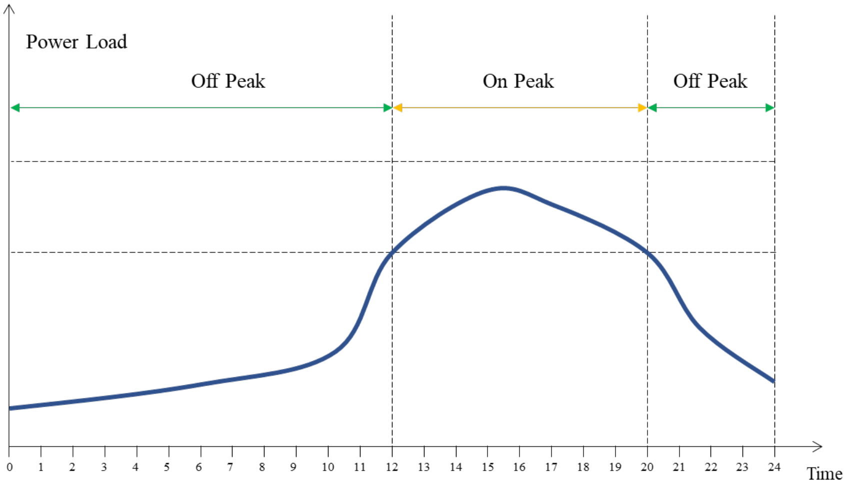
Time of Use: P_B and P_D in this program are same during the year. But P_E in this program varies during different times of the day, that is, high during on-peak hours and low during off-peak hours (Dütschke and Paetz 2013; Dutta and Mitra 2017; Torriti 2012). The on-peak hours are designed in summer (e.g. from 12:00 pm to 20:00 pm in this study). This program provides building users price signals to reduce their electricity consumption during on-peak hours and shift electricity consumption to off-peak hours.

High Renewable Penetration: We design this electricity pricing program for the scenario of future high renewable energy penetration. Many studies show that Photovoltaic (PV) power systems will have an important role in electricity generation in the future (Dincer 2011; Zhang et al. 2013). Most buildings will have PV power systems and thus, the peak power load demanded from the power grid will change in the future. Based on this assumption, we designed a dynamic pricing program named high renewable penetration. The schematic diagram of this future program is shown in Figure 5. Based on the one day's radiation level, the days are divided into three categories: low, moderate, and high radiation days.

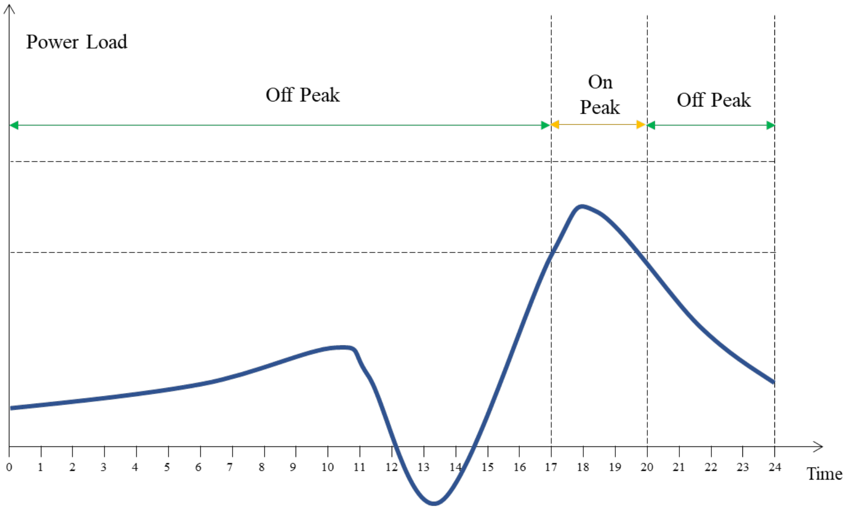
The low radiation days are the 15 days with the lowest radiation levels over a year. In these days, the PV only generates a small amount of electricity due to the low radiation, and the critical-peak time period appears in these days (Figure 5a). To simplify the process of this study, we assume that the critical-peak time period is from 13:00 pm to 17:00 pm, the on-peak time period is from 12:00 pm to 13:00 pm and from 17:00 pm to 20:00 pm, and the other time period is the off-peak. The moderate radiation days (Figure 5b) are the 15 days with the $16^{th} \sim 30^{th}$ lowest radiation levels. The PV generates more electricity on the moderate radiation days than it does during the low radiation days. As a result, the peak powers in moderate radiation days are all lower than the critical-peak threshold. Here, we assume that the on-peak time period is from 12:00 pm to 20:00 pm, and the other time period is the off-peak. The high radiation days are the rest days (Figure 5c). The PV generate a lot of electricity during the daytime, which can significantly reduce the peak power. We assume that the on-peak time period is from 17:00 pm to 20:00 pm, and the other time period is the off-peak.



(a) Low radiation day



(b) Moderate radiation day



(c) High radiation day

Figure 5. Schematic diagram of high renewable penetration

The natural gas price (P_G) is designed by referring the natural gas prices released by U.S. Energy Information Administration (EIA 2019). The natural gas prices in Honolulu, Buffalo, Denver, and Fairbanks are \$27.41/kft^3, \$6.87/kft^3, \$7.17/kft^3, and \$9.79/kft^3, respectively.

Based on the five electricity pricing programs in Table 5, and applying formulas (1), (2), (3), and (4), annual energy cost saving (R_i) resulted by each EEM is calculated, as shown in Figure 6. Generally, EEMs have the highest R_i under static and general pricing program. The LPD, EQUIP, and COOLING have significant higher R_i in Honolulu than in other cities.

The annual cost savings are generated by the combined effects of power changes, energy changes, and price (P_B, P_D, P_E and P_G). For example, the annual cost savings for using more efficient office electric equipment (EQUIP) is significantly higher in Honolulu than the other three studied cities. The reason is that the EQUIP in Honolulu has the greatest reductions for average monthly peak power and annual electricity consumption, and Honolulu has the highest energy price among all four cities. The aggregated effect leads to a significant difference in the annual cost saving for the EQUIP between Honolulu and the other three studied cities. Another example is that adding roof insulation (ROOF) in Fairbanks reduces a significantly more annual cost than the other three studied cities. The ROOF in Fairbanks reduces the most average monthly peak power, and annual electricity and natural gas consumption. Furthermore, Fairbanks has the second highest price among the four studied cities. Thus, the highest annual cost saving is the aggregated effect of these two reasons.

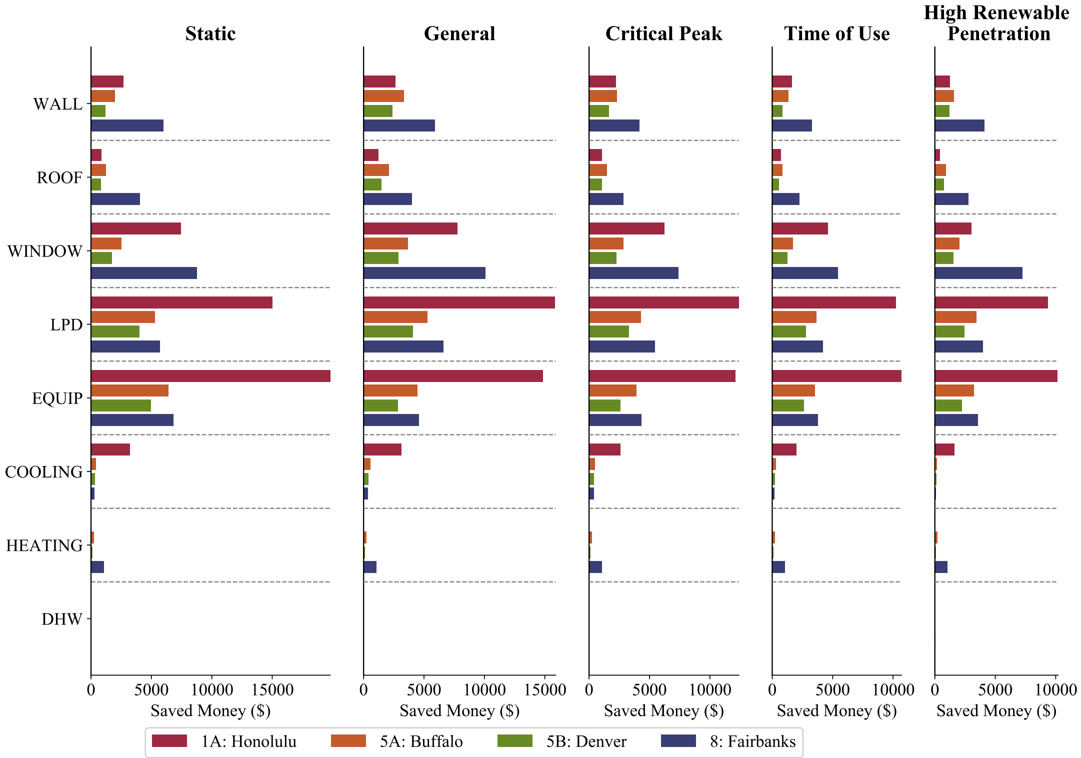


Figure 6. Annual cost saving (R_i) under the five electricity pricing programs

3.3. Selection of EEMs

After obtaining the initial investment of each EEM (I_i) and annual energy cost saving (R_i) in Sections 3.1 and 3.2, and by using the formula (5), the ROI of the each EEM in the four studied cities under five electricity pricing programs can be calculated. The results are shown in Figure 7 ~ Figure 10.

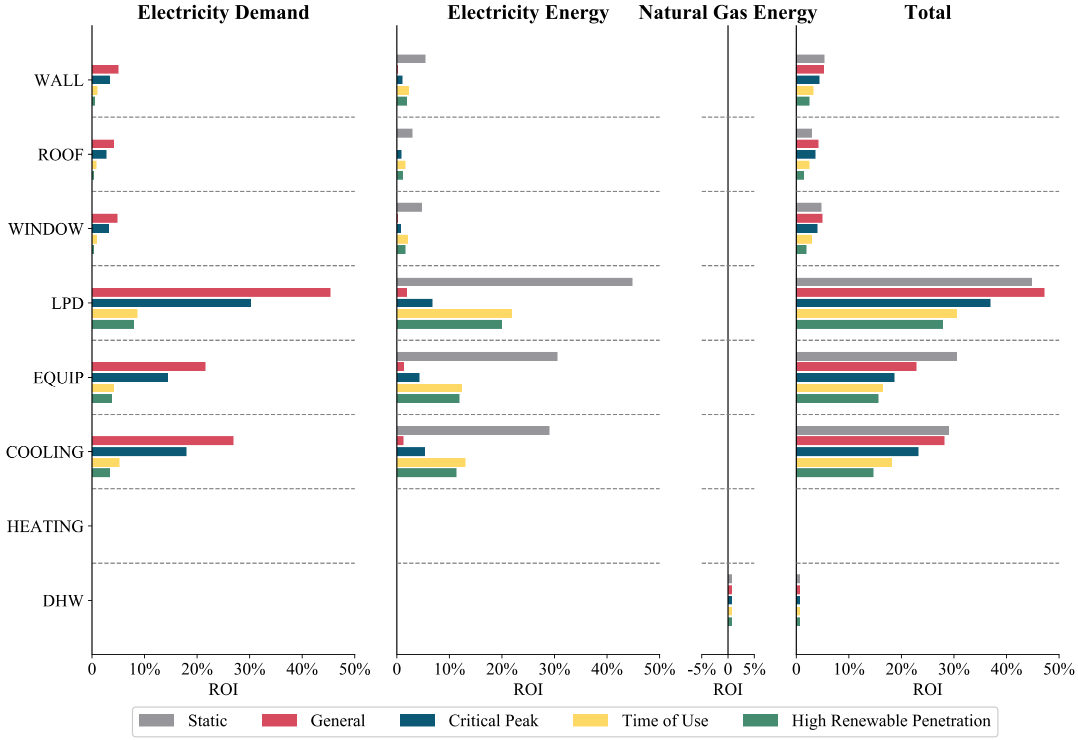


Figure 7. ROIs of EEMs under five electricity pricing programs for Honolulu (1A)

As shown in Figure 7, LPD can result in the highest ROI (~40%) in Honolulu. This is largely due to the factors: On one hand, LPD has higher annual cost saving (R_i) than the other EEMs under all pricing programs as previously shown in Figure 6. On the other hand, the initial investment (I_i) of LPD is not the highest one as shown in Table 4.

The EEM ranking by ROI is the same under five different pricing programs. EEMs with the higher ROI are LPD, EQUIP, and COOLING. But the ROIs of these EEMs has considerable variations. For example, the ROI of COOLING varies from 15% to 29% under different pricing programs. And the ROI of LPD varies from 28% to 47%.

For a specific EEM, the pricing program, which can generate higher ROI, is different because the total ROI is a combined result of electricity demand and electricity energy when the initial investment is the same. The EQUIP and COOLING can generate the highest ROI under the static electricity pricing program. The LPD can generate the highest ROI under the general pricing program. The total ROI under static pricing program is mainly contributed by electricity energy, while the total ROI under general pricing program is mainly contributed by electricity demand.

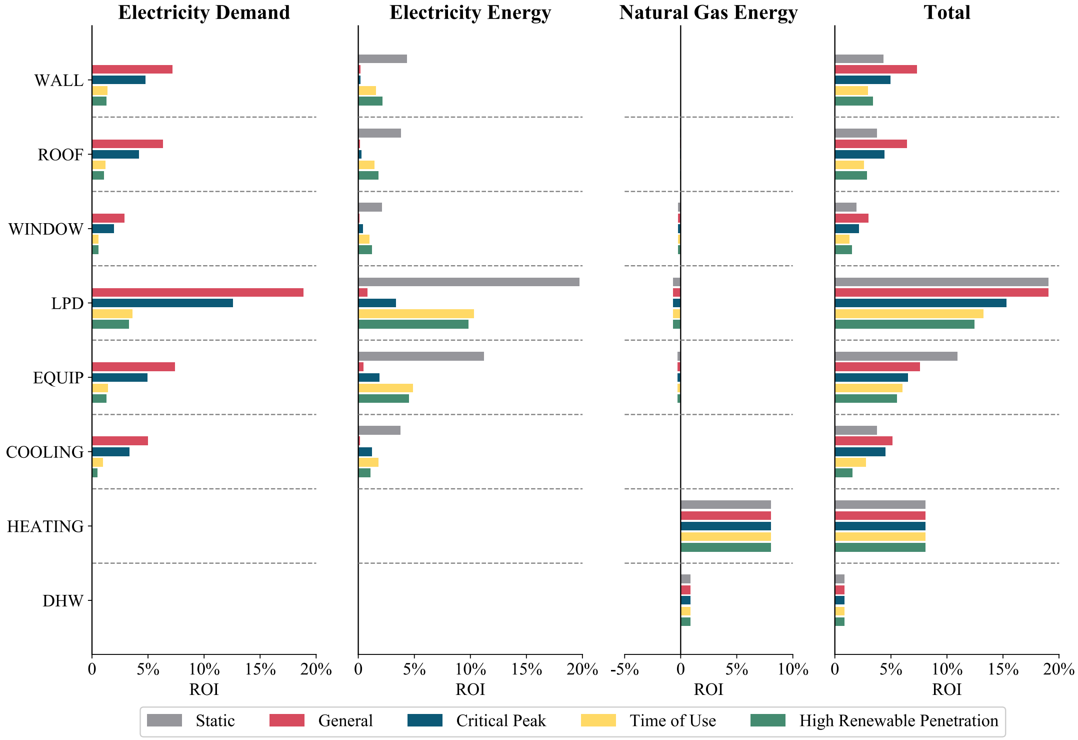


Figure 8. ROIs of EEMs under the five electricity pricing programs for Buffalo (5A)

As shown in Figure 8, LPD has the highest ROIs in Buffalo, which is about 15%. The LPD can achieve high ROI because it can significantly reduce peak power and energy consumption, as shown in Figure 3 and Figure 4. Although EQUIP's impact on reducing power load and energy consumption is similar with LPD, its initial investment is significantly higher than LDP. As a result, EQUIP has a lower ROI than LPD.

The EEM ranking by ROI is different under five pricing programs. Under the static pricing program, LPD, EQUIP, and HEATING have higher ROIs than others. Under the general pricing program, LPD, HEATING, EQUIP, WALL, and ROOF have higher ROIs than others. Under the critical peak, time of use, and high renewable penetration pricing program, LPD, HEATING, and EQUIP have higher ROIs than others. The EEM with the highest ROI is LPD under these five pricing programs. But the ROIs of LPD varies from 13% to 19%

WALL and ROOF only have higher ROIs under general pricing program. It is because the ROIs of WALL and ROOF are mainly contributed by electricity demand. The general pricing program has highest demand price compared with the other four programs. Therefore, the EEM which can reduce peak power significantly has higher ROI under the general pricing program.

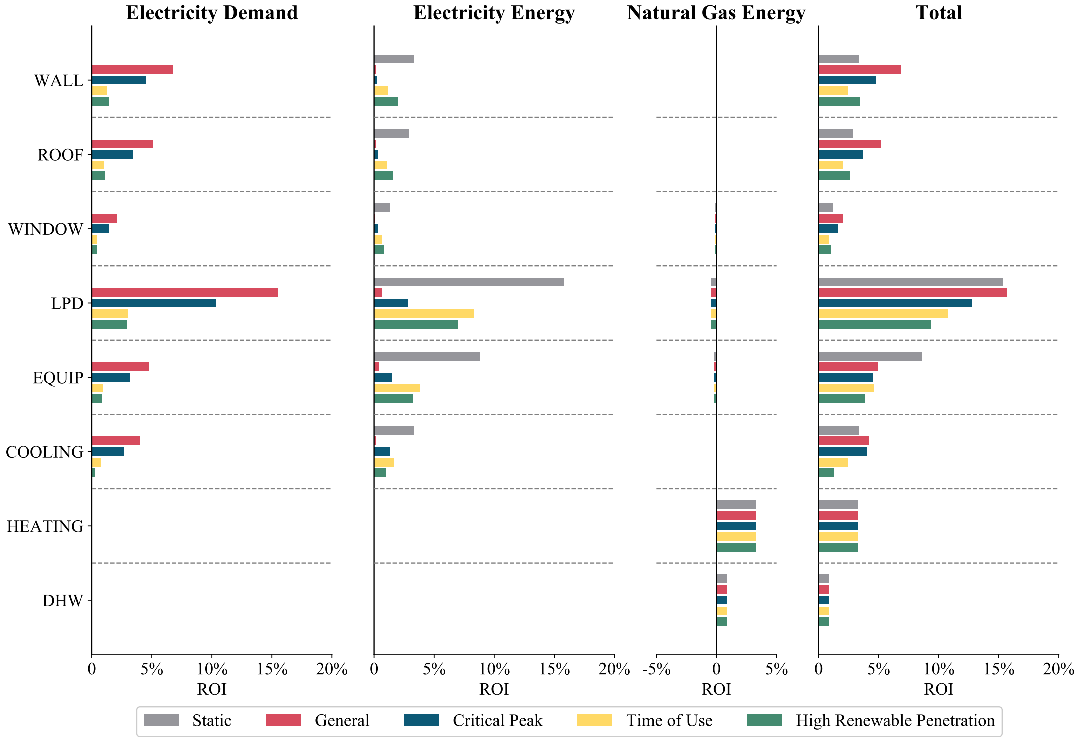


Figure 9. ROIs of EEMs under the five electricity pricing programs for Denver (5B)

As shown in Figure 9, generally, LPD can result in highest ROI in Denver, which is approximately 13%. This result is similar with Buffalo. However, the ROI of HEATING in Denver is lower than that Buffalo.

The EEM ranking by ROI is also different under five different pricing programs. Under static pricing program, LPD and EQUIP have higher ROIs than others. Under general pricing program, LPD and WALL have higher ROIs than others. Under critical peak, time of use, and high renewable penetration pricing, only LPD has higher ROIs than others.

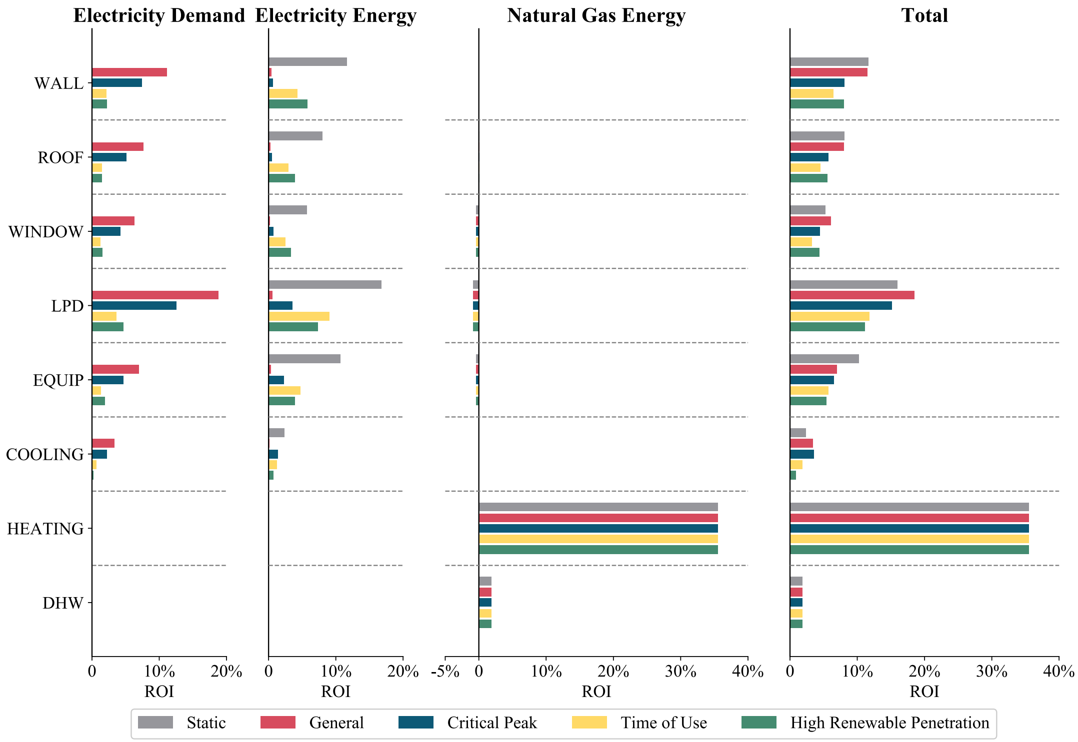


Figure 10. ROIs of EEMs under the five electricity pricing programs for Fairbanks (8)

As shown in Figure 10, generally, HEATING can result in the highest ROIs in Fairbanks, which is approximately 35%. Although the annual saved money (R_i) of HEATING is not high, the initial investments (I_i) of it are lower than the other EEMs. Therefore, it has higher ROIs.

Same as Buffalo and Denver, the EEM ranking by ROI in Fairbanks is also different under five different pricing programs. Under static pricing program, HEATING, LPD, WALL, and EQUIP have higher ROIs than others. Under general pricing program, HEATING, LPD and WALL have higher ROIs than others. Under critical peak, time of use, and high renewable penetration pricing programs, HEATING and LPD have higher ROIs than others. The EEM with the highest ROI is HEATING under these five pricing programs. The ROI of HEATING is not changed. It is because HEATING reduces natural gas consumption, but HEATING has no impact on electricity consumption. So, electricity pricing programs has no impact on the ROI of HEATING.

3.4. Discussion

In order to compare the ROIs among the four studied cities, the total ROIs of EEMs in the four cities are compared in Figure 11.

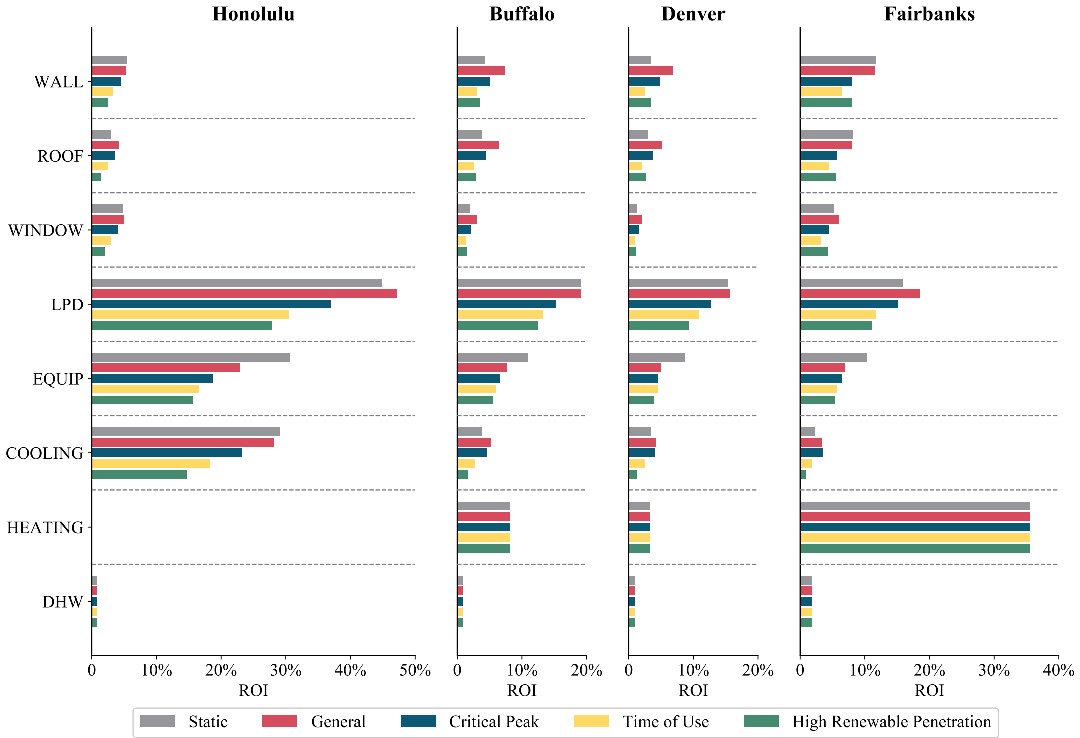


Figure 11. Total ROIs of EEMs in four studied cities

In terms of the EEMs with high ROIs, Honolulu has the highest ROIs (up to 50%) among all four cities due to its high energy price. LPD, EQUIP, COOLING in Honolulu almost have doubled ROIs than the other cities. This is because energy used for internal load (equipment operation and lighting) and cooling plays an important role in total energy consumption in hot areas, such as Honolulu. HEATING and WALL applied in Fairbanks has higher ROI than the other cities since heating and insulation plays an important role in total energy consumption in the extremely cold area, such as Fairbanks. Therefore, retrofitting internal load (e.g. LPD, EQUIP) and cooling is more profitable in hot area, while retrofitting heating system and wall insulation is more profitable in extremely cold area.

In terms of variations of ROIs of an EEM under different pricing program, the ROI of LPD in Honolulu varies most dramatically under different pricing programs. It is because the LPD in Honolulu can generate more energy savings and power reduction. However, the ROI of HEATING and DHW do not vary under different pricing programs. It is because natural gas is used for heating and hot water system. The price of natural gas is stable.

In term of high renewable penetration pricing program, the ROIs of EEM in Buffalo, Denver, and Fairbanks will change slightly while the ROIs of EEM in Honolulu will decrease considerably. This is because the PV panels generate more electricity power in Honolulu than other three studied cities and peak power impact will greatly decrease in Honolulu. However, by using the high renewable penetration pricing programs, the ROI of the LPD still has approximately 30% in Honolulu, which is necessary to conduct building energy retrofits.

4. Conclusion

To understand how electricity pricing programs impact the selection of EEMs, this paper conducts an analysis of the ROIs of EEMs under the five electricity pricing programs: static, general, critical peak, time of use, and high renewable penetration. The results reveal that: (1) The ROIs of EEMs are changed under different pricing programs. (2) The EEM with higher ROI in hot areas are replacing office equipment with higher-efficiency equipment, replacing interior fixtures with higher-efficiency fixtures, and replacing cooling coil with higher-efficiency coil. But the EEM with higher ROI in cold areas is replacing heating coil with higher-efficiency coil. (3) The ROI of LPD in Honolulu is affected by electricity pricing programs most significantly, which varies from 28% to 47%.

The innovation and contribution of this study mainly lie in the following aspects. Firstly, it designs a reasonable electricity pricing program for the scenario of high renewable penetration. Secondly, it reveals the importance of electricity pricing programs on EEMs selection. Finally, it can help building owners to select optimal EEMs under different electricity pricing programs.

This study is intended to show the potential impact of electricity pricing programs on the selection of EEMs. The ROIs of EEMs generated in this study show a relative profit level. Due to the criteria to determine the baseline and upgraded models, EEM values are not aggressive compared to the new ASHRAE Standards. For example, the cooling COP upgrade is small. Furthermore, models selected in this study are DOE Commercial Prototype Building Models instead of models for actual buildings, which have some limitations. For example, models use the same HVAC system type for all climate zones. To apply this research to real world practice, one will need to use their own building model and real pricing data.

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