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Long-term carbon emission reduction potential of building retrofits with dynamically changing electricity emission factors

Yingli Lou[a], Yunyang Ye[b], Yizhi Yang[a], Wangda Zuo[a,c,*]

[a] Department of Civil, Environmental and Architectural Engineering, University of Colorado Boulder, Boulder, CO 80309, U.S.A.

[b] Pacific Northwest National Laboratory, Richland, WA 99354, U.S.A.

[c] National Renewable Energy Laboratory, Golden, CO 80401, U.S.A

* Corresponding author. Email address: Wangda.Zuo@colorado.edu (Wangda Zuo)

Abstract

Buildings account for approximately 36% of the United States' total carbon emissions and building retrofits have great potential to reduce carbon emissions. Current research adopts a constant electricity emission factor although it changes over time due to the increase of renewable energy generation. To accurately predict emission reduction potential of building retrofits, this study develops a novel method by using dynamically changing electricity emission factors. Using medium office buildings as an example, we predicted emission reduction of eight building retrofit measures from 2020 to 2050 in five locations in the U.S. with distinct climates and renewable adoption rates. To evaluate emission reduction potential sensitivity to the compositions of electricity generation, five scenarios for renewable energy adoptions are investigated. The results reveal several new phenomena on emission reduction potential of building retrofits for medium offices in the U.S.: (1) it decreases from 2026 to 2050; (2) it has the same trend with coal usage; and (3) it reaches the maximum under the high renewable cost scenario. Based on the results, it is recommended that building retrofits should focus on 1) improving lighting and equipment efficiency; 2) locations with higher coal usage rate, and 3) buildings under the high renewable cost scenario. The new method can also be used for predicting emission reduction potential of the building sector in the U.S. by applying to other building types and regions.

Keywords: Carbon emission reduction; Building retrofits; Building energy model; Simulation; Electricity emission factors.

1. Introduction

To mitigate climate change, the United States (U.S.) has outlined a pathway to reduce carbon emissions 50% by 2030 [1] and 80% by 2050 [2]. As a major contributor to carbon emissions, buildings play an important role to achieve carbon emission reduction targets in the U.S. According to the U.S. Energy Information Administration (EIA)'s Annual Energy Outlook 2019, buildings account for approximately 36% of energy-related carbon emissions in 2018 [3]. Furthermore, current building energy use is projected to increase by 1.7% annually until 2025 [4]. According to the prediction by Huo et al. [5,6], carbon emissions of building sector in will keep increase until 2037. Current research shows that many existing buildings have poor energy performance and will still be used until 2050 [7–9]. Thus, there is a great potential to reduce carbon emissions by retrofitting existing buildings. Langevin et al. [10] estimated that this potential can be as large as 80% reduction relative to 2005 levels by 2050.

Carbon emission reduction of building retrofits has been studied from different perspectives. First, the emission reduction of a specific building retrofit measure is examined, such as the emission reduction potential by improving insulation [11–14], improving air conditioner efficiency [15,16], and adding external overhang [17]. Second, the strategy of optimal carbon retrofit is investigated. Murray et al. [18] investigated the optimal transformation strategies for buildings to reach carbon emission reduction targets for the Swiss building stock. Garriga et al. [19] investigated the optimal carbon-neutral retrofit of residential communities in Barcelona, Spain. And Niemelä et al. [20] determined the cost-optimal renovation from the carbon emission reduction potential perspectives for apartment buildings in Finland, Sustain. Third, life-cycle carbon emission of building retrofit measures has been studied. Using new commercial buildings as a research object, Kneifel [21] studied the life-cycle carbon emission reduction of various retrofit measures in the U.S. Shirazi and Ashuri B [22] conducted an embodied life-cycle assessment on various single-family residential retrofit measures in Atlanta, U.S. Considering both embodied and operational emissions, Rabani et al. [23] conducted a life-cycle assessment of different building retrofitting scenarios for a typical office building in Norway. The above research generally predicts carbon emissions of buildings by multiplying electricity consumption with emission factors of electricity. A constant electricity emission factor are adopted by current research for the prediction.

However, electricity emission factors change over time due to the increase of clean energy generation. The annual growth rate of electricity generation by clean energy is approximately 7% from 2010 to 2020 in the U.S. [24]. The penetration of clean energy for electricity generation will continue increasing in the U.S. as a result of technological improvements, increased scale of economies, and strong policy support [25].

Emission reduction of building retrofit measures is highly influenced by electricity emission factors because electricity is the major energy source of most existing buildings. Different building retrofit measures can save electricity consumption at different times of the day and on different days of the year. If the emission factor varies with time, their actual emission reduction effects will be different even if they save the same amount of energy [26]. In addition, the emission reduction effects of current building retrofits will last for the next few decades. The long-term impact of emission reduction due to building retrofits highly depends on future electricity emission factors, which are likely change over time. Furthermore, the rate of change depends on the clean energy adoption rate.

Based on our literature review, the long-term carbon emission reduction potential of building retrofits due to the changing electricity emission factors has not been considered yet. To fill the gap, this study examines emission reduction potential of building retrofit measures from 2020 to 2050 based on the predicted dynamic electricity composition under five renewable energy adoption scenarios. The objective of this study is to create a systematic approach to investigate the long-term carbon emission reduction potential of building retrofits considering the changing of electricity emission factors in the era of increased renewable energy adoption. This paper is organized as follows: Section 2 introduces the methodology of predicting long-term carbon emission reduction potential of building retrofit measures using dynamic emission factors; Section 3 describes the design of case study including building energy model preparation, location selection, and building retrofit measures selection; Section 4 presents the results of emission reduction; Section 5 discusses the long-term carbon emission reduction potential from four perspectives: the impact of measures, the impact of locations, the impact of scenarios, and implication to building retrofit policy. Finally, Section 6 makes a conclusion.

2. Methodology

This study investigates the emission reduction potential of building retrofit measures from 2020 to 2050 under five scenarios for renewable energy adoption introduced in 2020 Standard Scenarios Report [27]: (1) high renewable energy cost (HighReCost), (2) mid case (Mid), (3) low battery cost (LowBatCost), (4) low wind cost (LowWinCost), and (5) low renewable energy cost (LowReCost). Fig. 1 summarizes the relationship of the five scenarios.

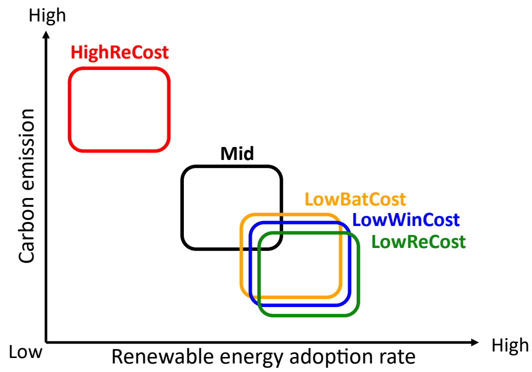


Fig. 1. Renewable energy adoption rate and impact on carbon emission under five scenarios

The HighReCost scenario has the highest cost for renewable energy generation, which leads to the lowest renewable adoption rate among the five scenarios. The Mid scenario is a reference scenario that uses median assumptions for renewable energy adoption, including existing policies. In general, the renewable energy adoption rates under the LowBatCost, LowWinCost, and LowReCost scenarios are higher than the Mid. However, there are exceptions in some cases that they may slow down renewable energy adoption. For example, by reducing the cost of wind power, the LowWinCost scenario is supposed to speed up renewable energy adoption. However, if a location has too much unstable wind power, a large amount of nonrenewable energy (e.g., coal, natural gas) generation capacity is required to meet power demand under the LowWinCost scenario. As a result, the adoption rate of renewable energy becomes lower than the Mid scenario. In addition, the exact adoption rate of renewable energy under the LowBatCost, LowWinCost, and LowReCost scenarios depends on locations. For instance, the LowWinCost scenario tends to have stronger impact in the location with rich wind sources.

Fig. 2. shows the proposed systematic approach to predict long-term carbon emission reduction of building retrofit measures using dynamic emission factors: (1) energy prediction; (2) emission prediction, and (3) emission reduction potential. Following the three steps in Fig. 2, the emission reduction potential of building retrofit measures in a certain year under a specific scenario can be predicted. The following subsections will provide detailed explanation with equations used in the three steps. Then the application of the proposed method is demonstrated using an example of medium offices in Section 4.

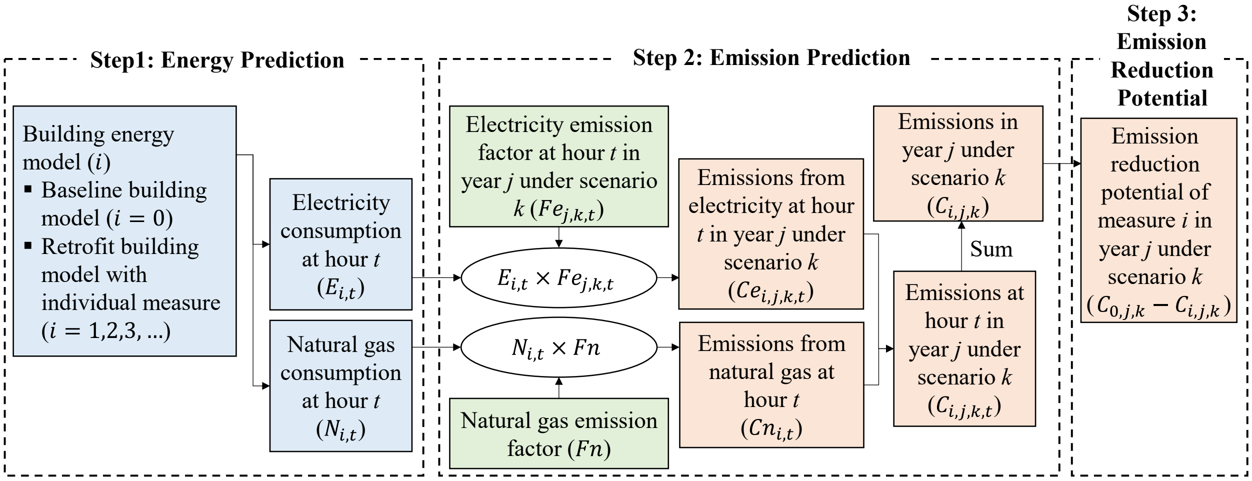


Fig. 2. General steps of predicting long-term carbon emission reduction.

2.1. Step 1: Energy prediction

This study predicts energy consumption for baseline buildings and retrofit buildings by adopting individual measures. Two types of data are extracted after building model simulation for one year: (1) hourly electricity consumption ($E_{i,t}$) in that year and (2) hourly natural gas consumption ($N_{i,t}$) in that year. We assume that energy use behavior in the building will not change over time. In addition, the weather file used for building energy modeling is the actual meteorological year (AMY) data in 2012. This is because the weather file used for predicting electricity emission factors is the AMY data in 2012, which will be introduced in subsection 2.2. The prediction of electricity and natural gas consumption based on the AMY data in 2012 will be applied for emission reduction analysis in the studied period 2020-2050.

2.2. Step 2: Emission prediction

The carbon emissions of a building in one year are the sum of emissions during each hour. Therefore, carbon emissions of the building with an individual measure i in the year j under scenario k can be obtained using the following equation:

$$C_{i,j,k} = \sum_{t=1}^{n} C_{i,j,k,t}, \tag{1}$$

where the C represents carbon emission; the t represents time with a unit of one hour; and the $n = 8784$ is the total number of hours in a year. This study only considers electricity and natural gas for the energy consumption of buildings because these two are the most common energy sources used in commercial buildings in the U.S., which accounts for 93% [28]. Therefore, emissions during each hour are the sum of emissions from electricity and natural gas. The $C_{i,j,k,t}$ can be obtained using the following equation:

$$C_{i,j,k,t} = Ce_{i,j,k,t} + Cn_{i,t}, \tag{2}$$

where, the Ce represents carbon emissions from electricity; and the Cn represents carbon emissions from natural gas.

The emissions from one type of fuel can be obtained by multiplying the consumption of that fuel with its emission factor. Various fuels are utilized to generate electricity and the shares of various fuels for electricity generation are dynamically changing. Therefore, the emission factors of electricity are dynamically changing. Emissions from electricity ($Ce_{i,j,k,t}$) can be obtained using following equation:

$$Ce_{i,j,k,t} = E_{i,t} \times Fe_{j,k,t}, \tag{3}$$

where, the E represents the electricity consumption; the Fe represents the electricity emission factor, which is dynamically changing and assumed to be constant during the hour *t*.

Natural gas is one type of fuel, and the burning of natural gas releases a constant amount of carbon emissions. Therefore, emissions from natural gas ($Cn_{i,t}$) be obtained using following equation:

$$Cn_{i,t} = N_{i,t} \times Fn, \tag{4}$$

where, the N represents the natural gas consumption; and the Fn represents the natural gas emission factor, which is a constant value.

The data sources used for emission prediction are explained as follows. (1) Hourly electricity consumption ($E_{i,t}$) and hourly natural gas consumption ($N_{i,t}$) are predicted from subsection 2.1. (2) Electricity carbon emission factors ($Fe_{j,k,t}$) are obtained from the National Renewable Energy Laboratory (NREL)'s Cambium data [29]. Because the available electricity carbon emission factors are on even years, we only investigate emissions on even years. (3) Natural gas emission factor (Fn) is a constant value, which is 50.15 kg/GJ [30].

2.3. Step 3: Emission reduction potential

The emission reduction of building retrofit measures is the emission difference between baseline buildings ($i = 0$) and retrofit buildings ($i = 1,2,3, \ldots$). The emission reduction potential of the building with an individual measure i in the year j under scenario k which can be expressed as following equation:

$$R_{i,j,k} = C_{0,j,k} - C_{i,j,k}, \tag{5}$$

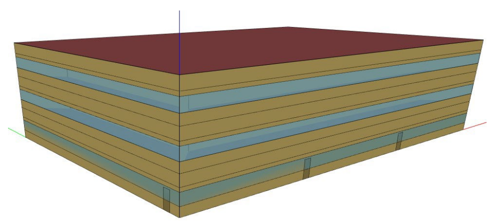
where, the R represents the emission reduction potential; and the C represents carbon emissions, which is calculated by equations (1)-(4).

3. Study Design

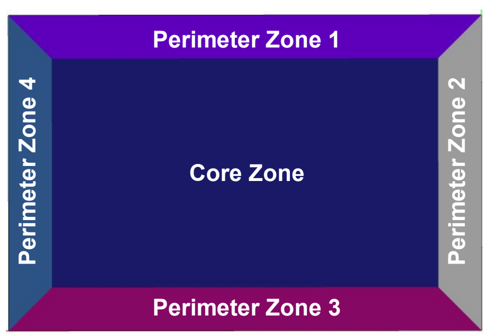
3.1. Building energy models

The U.S. Department of Energy (DOE) has been dedicating to the development of prototype building models to support commercial and residential building energy codes and standards [31,32]. The prototype models include 16 commercial building types in 19 climate locations for different editions of ASHRAE Standard 90.1 and IECC. Those models are widely used to investigate energy saving [33–36], power consumption [37,38], and emission reduction [21,26].

This study adopted the DOE commercial prototype building models [39] for medium office buildings as a starting point to predict long-term carbon emission reduction potential of building retrofit measures. The medium office building is selected an example in this study because it is more representative in commercial buildings. According to 2012 Commercial Buildings Energy Consumption Survey (CBECS) [40] conducted by the U.S. Energy Information Administration (EIA), office buildings have the largest area share of all building types (22.5%), and the average floor area of office building is 12,878 m^2, which represents the medium-sized office building. Fig. 3 shows the geometry and thermal zones of the medium office model, which has a rectangular shape with three stories. Each story contains five thermal zones (one core zone and four perimeter zones).



(a) Geometry



(b) Thermal zone (each floor)

Fig. 3. Geometry and thermal zones of the U.S. medium office prototype building models.

The total floor area of the medium office prototype building is 4,980 m^2 with a 33% window-to-wall ratio. It has steel-frame exterior walls and insulation entirely above deck roofs. Furthermore, it uses packaged air conditioning units and VAV terminal boxes. There are two types of energy sources in the building energy model: electricity and natural gas. Natural gas is used for air conditioning system heating and service water heating. Electricity is used for others, such as, air conditioning system cooling and heating, lighting, and equipment.

3.2. Locations

The location selection considers the impact of different climates and clean energy adoption rates. As a result, five locations in the U.S. are selected: (1) Tampa, Florida; (2) San Diego, California; (3) Denver, Colorado; (4) Great Falls, Montana; and (5) International Falls, Minnesota. As shown in Fig. 4, they represent different climates (from hot humid to very cold) and have distinct predictions for clean energy adoption rates from 2020 to 2050. For instance, Tampa has a significant increase on solar power generation; the penetration of solar power is always high in San Diego; the penetration of coal power is always higher in Denver than other locations; Great Falls has a significant increase on coal power generation; and International Falls has a significant reduction on coal power and natural gas power.

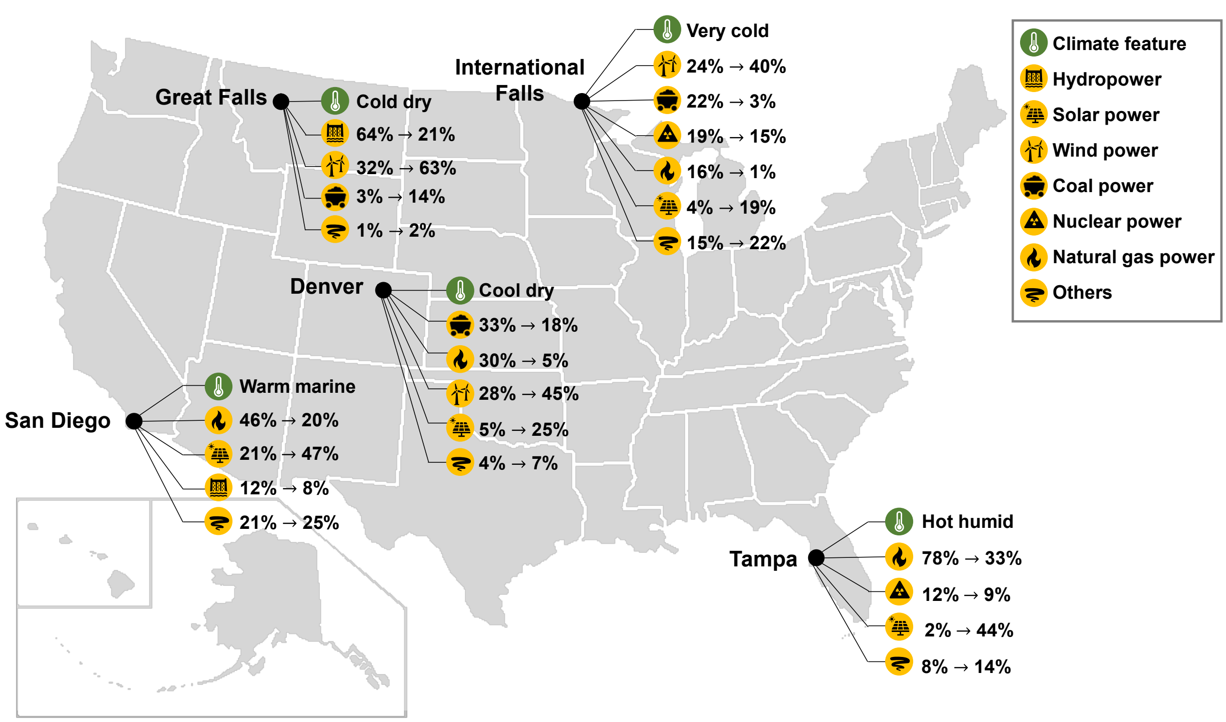


Fig. 4. Locations investigated in this study and the change of their electricity composition under the Mid scenario from 2020 to 2050.

In these studied locations, the composition of electricity generation by energy source is different under various renewable energy adoption scenarios. Fig. 5 shows the composition of electricity generation in the studied locations under five scenarios. According to the definition stated by the DOE [41], clean energy includes solar, wind, water, geothermal, bioenergy, and nuclear. The clean energy adaptation rate increases over time for all locations, except for Great Falls. In Great Falls, coal fired power plants are expected to provide additional electricity to meet the quickly increased demand from 2020. With the new clean energy generation capacity (such as wind) become available 2034, the percentage of clean energy increases from 2034 to 2050. In addition, the clean energy adaptation rate has a significant difference under five scenarios in Great Falls. The clean energy adaptation rate is highest under the LowReCost scenario, followed by LowWinCost, LowBatCost, Mid, and HighReCost.

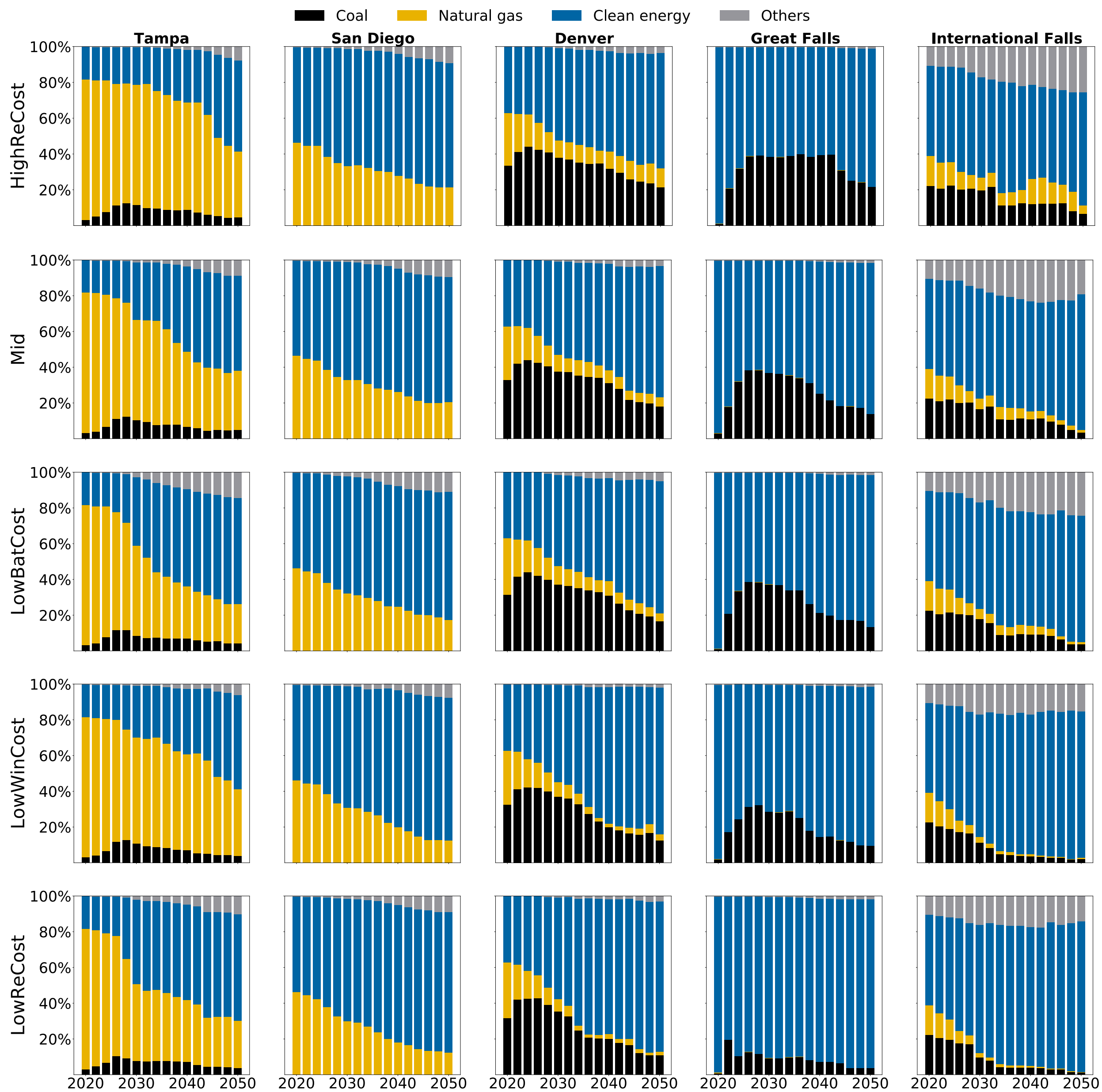


Fig. 5. Composition of electricity generation under five renewable energy adoption scenarios.

3.3. Building retrofit measures

Existing research has provided a rich set of building retrofit measures for commercial buildings [42–46]. Based on the above research, this study examined eight building retrofit measures, which potentially have significant impacts on the carbon emissions of medium office buildings across different climate feature locations [42]. Table 1 shows these eight retrofit measures. Eight building retrofit models are created separately to represent these eight retrofit measures. We also examined the emission reduction potential of the aggregated effect of these eight measures. One building retrofit model which applied these eight measures is created, and the abbreviation ALL is used to represent this building. Thus, there are 50 building energy models (5 locations × (1 baseline model + 9 retrofit models)) in this study. The model input values of baseline models are based on the ASHRAE Standard 90.1-2007 [47]. The model input values of retrofit models are based on the Advanced Energy Design Guide 50% Energy Savings [48].

Table 1. Building retrofit measures and values.

Building Retrofit Measure	Abbreviation	Model Input	Tampa		San Diego		Denver		Great Falls		International Falls	
			Base[1]	Retr[2]	Base[1]	Retr[2]	Base[1]	Retr[2]	Base[1]	Retr[2]	Base[1]	Retr[2]
Add wall insulation	WALL	Wall insulation R-value (m^2-K/W)	1.04	2.75	1.71	2.75	2.37	4.19	2.37	4.76	2.37	4.76
Add roof insulation	ROOF	Roof insulation R-value (m^2-K/W)	3.47	4.52	3.47	4.52	3.47	5.50	3.47	5.50	3.47	6.29
Replace windows	WINDOW	Window U-factor (W/m^2-K)	4.09	2.56	3.52	2.33	2.73	1.99	2.73	1.99	2.38	1.87
		Window SHGC	0.25	0.25	0.25	0.25	0.4	0.26	0.4	0.35	0.45	0.40
Improve lighting efficiency	LIGHT	Lighting power density (W/m^2)	10.76	8.07	10.76	8.07	10.76	8.07	10.76	8.07	10.76	8.07
Improve equipment efficiency	EQUIP	Plug load density (W/m^2)	8.07	5.92	8.07	5.92	8.07	5.92	8.07	5.92	8.07	5.92
Improve cooling coil efficiency	COOLING	Nominal coefficient of performance	3.23	3.37	3.23	3.37	3.23	3.37	3.23	3.37	3.23	3.37
Improve heating efficiency	HEATING	Burner efficiency	0.80	0.90	0.80	0.90	0.80	0.90	0.80	0.90	0.80	0.90
Improve service hot water system efficiency	SWH	Heater thermal efficiency	0.81	0.90	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) [47].

[2] Retr: Retrofit model (Source: AEDG 50% Energy Savings) [48].

4. Results

This section first presents the results of energy prediction of baseline and retrofit buildings in five studied locations. Then emissions of buildings at the five locations from 2020 to 2050 under five renewable energy adoption scenarios are predicted. Finally, this section presents the emission reduction potential results of building retrofit measures in the five studied locations from 2020 to 2050 under the five scenarios.

4.1. Step 1: Energy prediction

This study predicted the hourly electricity and natural gas consumption of 50 modeled buildings (introduced in subsection 3.3). Using Denver as an example, Fig. 6 shows the results of the baseline model and retrofit model ALL with all eight retrofit measures adopted. The horizontal axis represents each day of the year, and the vertical axis represents each hour of the day. The shade of the color represents the magnitude of the value at a specific hour on a specific day. For electricity consumption, the blue color in Fig. 6. (c) is lighter than that in Fig. 6. (a), which means that the electricity consumption of retrofit model

ALL is less than the baseline model. This is because multiple energy saving measures are applied in the retrofit model ALL, such as improving lighting and equipment efficiency. Electricity consumption of the retrofit model ALL is significantly reduced.

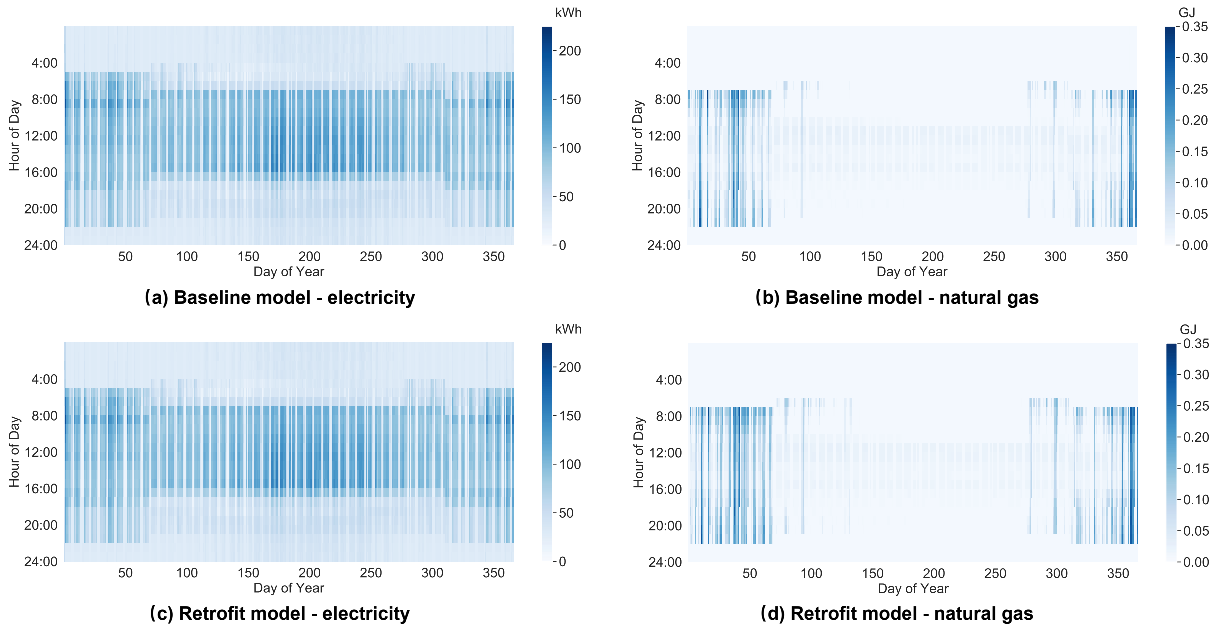


Fig. 6. Energy consumption of the baseline and retrofit model ALL in Denver.

For natural gas consumption, the blue color in the Fig. 6. (d) is similar with that in Fig. 6. (b), which means that the natural consumption of retrofit model ALL is similar with the baseline model. This is because some retrofit measures reduce electricity consumption, such as improving lighting and equipment efficiency, which leads to less internal heat gain and higher natural gas consumption for heating in the winter. Although two measures improving heating and service hot water system efficiency reduce natural gas consumption, the total natural gas consumption is not reduced significantly for the retrofit model ALL due to the combined effect.

4.2. Step 2: Emission prediction

Using the energy consumption predicted in subsection 4.1 and equations (1)-(4), emissions of baseline and retrofit building models at five locations from 2020 to 2050 (on even years) under five renewable energy adoption scenarios are predicted. This results in 4,000 emission predictions (5 locations × (1 baseline model + 9 retrofit models) × 16 years × 5 scenarios). The baseline model at Denver in 2050 under the Mid scenario is used as an example to illustrate the emission prediction, as shown in Fig. 7. The Mid scenario is selected as an example because it is a reference scenario that uses median assumptions for renewable energy adoption.

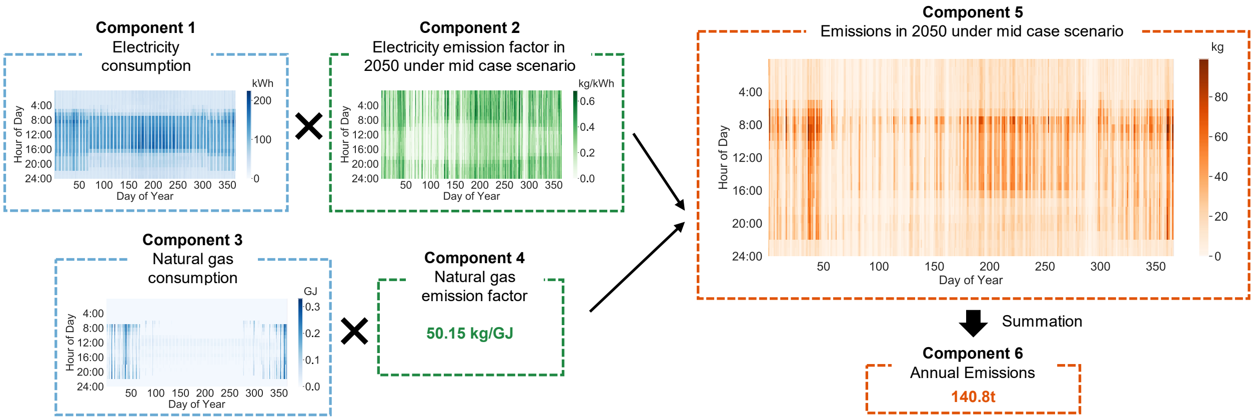


Fig. 7. Carbon emissions of the baseline model at Denver in 2050 under the Mid scenario.

There are six components involved in the calculation of annual emissions. Carbon emissions are from two sources: electricity and natural gas. The emission factor of natural gas is a constant value (component 4), while the emission factors of electricity is dynamically changing in every hour (component 2). In component 2, the color is lighter during the daytime than during the nighttime, which means that the emission factors of electricity is smaller during the daytime than the nighttime. This is because much electricity is generated from solar energy during the daytime, which has zero carbon emissions. Therefore, although the calculated dynamic emissions in component 5 still varies during the daytime and nighttime, the variation is less significant compared to the variation for electricity consumption between daytime and nighttime shown in component 1. By summing up the emissions in each hour, annual emissions can be obtained in component 6, which is 140.8 tons.

4.3. Step 3: Emission reduction potential

Using emissions predicted in subsection 4.2. and equation (2), emission reduction potential of building retrofit measures in a certain year under a specific scenario ($R_{i,j,k}$) can be calculated. Fig. 8 shows the emission reduction potentials of retrofit measures in five studied locations from 2020 to 2050 under five renewable energy adoption scenarios.

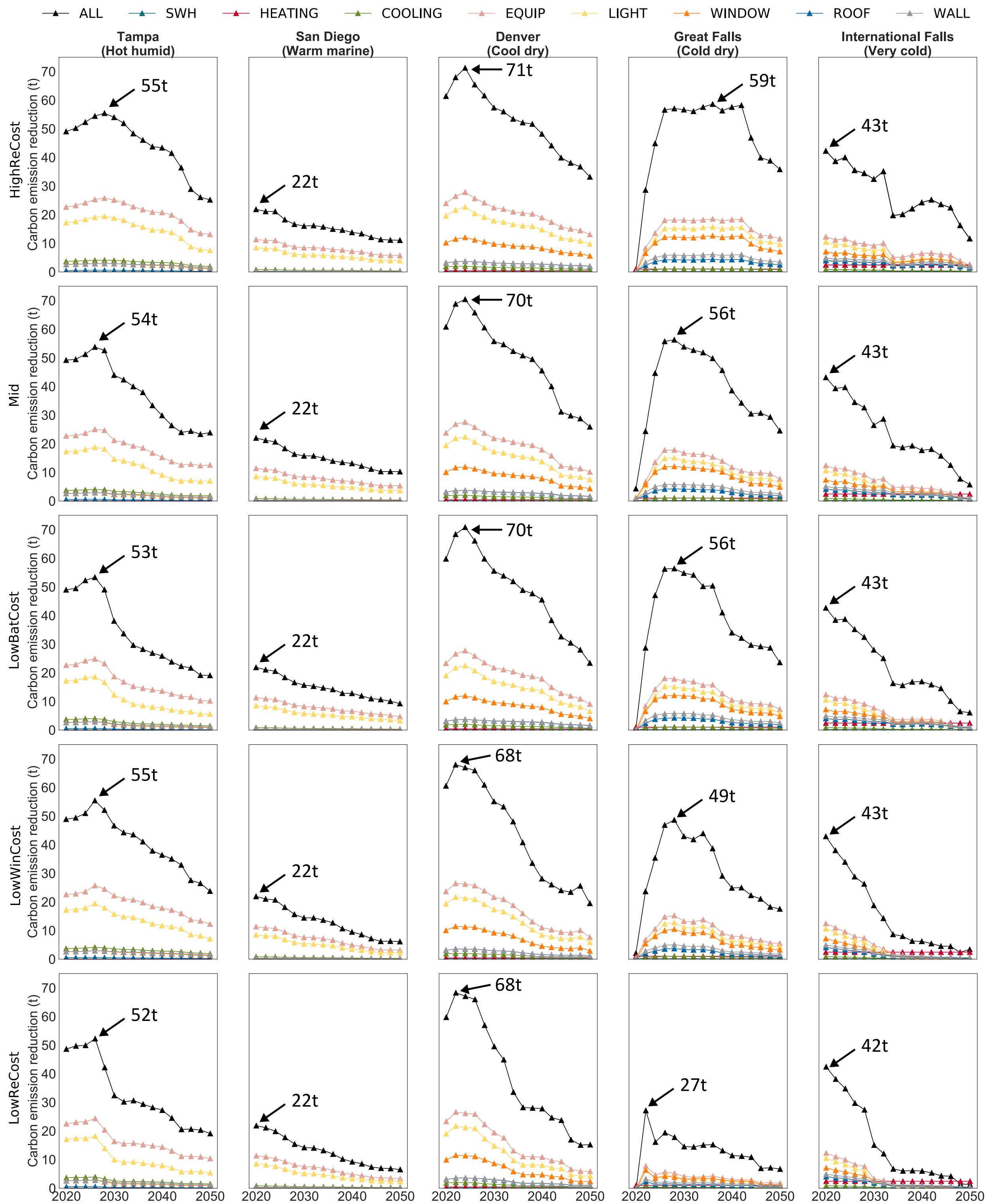


Fig. 8. Carbon emission reduction potential of building retrofit measures under five renewable energy adoption scenarios.

There are three interesting phenomena from Fig. 8. First, the highest reduction potential can be achieved in Denver because high coal usage rate (Fig. 5). As a comparison, the peak reduction potential in San Diego is the lowest among the five locations, which is 22 tons. This is because there is little coal usage in San Diego.

Second, the general trend of emission reduction potential is decreasing from 2026 to 2050. Some locations (San Diego and International Falls) are decreasing from 2020 to 2026 because the increase of clean energy (Fig. 5). Some locations (Tampa, Denver, and Great Falls) are increasing from 2020 to 2026 because the increase of coal usage (Fig. 5). The peak point occurs at different year depending on the location and scenarios. Taking the Mid scenario as an example, the peak point occurs in 2020 for San Diego and International Falls, while it occurs in 2026 for Tampa, 2024 for Denver, and 2028 for Great Falls. The peak point even postpones to 2036 for Great Falls under the HighReCost scenario.

Third, there is no significant difference in the peak emission reduction potential under different scenarios for most locations, which is within 3 tons. However, there is a significant difference in Great Falls. The peak emission reduction potential in Great Falls varies from 27 tons to 59 tons under different scenarios.

We can also quantitively analyze the trend of emission reduction potential from 2020 to 2050. Using the Mid scenario as an example (Table 2), there are two obvious phenomena: (1) emission reduction potential of the measure HEATIING and SWH doesn't change over time from 2020 to 2050 for all locations; and (2) the annualized emission reduction potential is the largest during 2020-2030, followed by 2030-2040, 2040-2050 for most locations except Great Falls. This is because the emission reduction potential in Great Falls in 2020 is extremely low due to the extremely low coal usage for electricity generation (Fig. 5). As a result, the annualized emission reduction potential is the largest during 2030-2040, followed by 2020-2030, 2040-2050 for retrofit measures in Great Falls.

Table 2. Annualized emission reduction potential under the Mid scenario.

Unit: t

Location	**Time period**	**Measures**								
		WALL	**ROOF**	**WINDOW**	**LIGHT**	**EQUIP**	**COOLING**	**HEATING**	**SWH**	**ALL**
Tampa	2020-2030	2.74	0.54	2.74	17.89	23.81	3.86	0.01	0.05	51.25
	2030-2040	2.29	0.38	2.06	12.88	19.22	3.05	0.01	0.05	39.52
	2040-2050	1.54	0.18	1.21	7.46	13.24	1.99	0.01	0.05	25.31
San Diego	2020-2030	0.26	0.22	0.21	7.53	10.27	0.73	0.00	0.08	19.71
	2030-2040	0.21	0.16	0.18	5.38	7.78	0.53	0.00	0.08	14.78
	2040-2050	0.17	0.13	0.13	4.01	5.83	0.40	0.00	0.08	11.22
Denver	2020-2030	3.48	3.47	11.06	20.57	25.54	1.86	0.44	0.12	65.28
	2030-2040	3.02	2.96	9.05	16.07	20.66	1.44	0.44	0.12	52.61
	2040-2050	2.11	2.02	5.75	9.82	13.18	0.92	0.44	0.12	33.53
Great Falls	2020-2030	4.07	2.92	8.18	9.37	11.28	0.73	1.00	0.14	37.07
	2030-2040	5.41	3.93	11.14	13.23	15.73	0.97	1.00	0.14	50.77
	2040-2050	3.21	2.31	6.41	8.08	9.86	0.68	1.00	0.14	31.31
International Falls	2020-2030	4.52	3.71	6.41	9.01	10.82	0.74	2.43	0.17	37.85
	2030-2040	3.14	2.51	3.95	4.15	5.87	0.39	2.43	0.17	22.49
	2040-2050	1.98	1.53	2.05	1.70	2.86	0.25	2.43	0.17	12.93

Note: Dark red shading means maximum value among three time periods.

Medium red shading means median value among three time periods.

Light red shading means minimum value among three time periods.

Furthermore, we use the retrofit model ALL as an example to quantitively analyze the emission reduction potential sensitivity to renewable energy adoption scenarios. As shown in Table 3, the HighReCost scenario enables the largest emission reduction potential in five locations, while the LowReCost scenario generally provides the smallest emission reduction potential in five locations.

There is one exception: the LowWinCost scenario provides the smallest emission reduction potential in San Diego from 2040 to 2050. The LowReCost scenario encourages the use of various kinds of renewable energy for electricity generation, while the LowWinCost scenario especially encourages the use of wind. In San Diego, the penetration of renewable energy, especially solar power is already very high (21% in 2020), as shown in Fig. 4. The room for further increase of solar power is very limited under LowReCost scenario. However, the LowWinCost scenario could further increase the wind power generation. Therefore, the LowWinCost scenario enables the highest rate of clean energy adoption, which leads to the smallest emission reduction potential of retrofit measures.

Furthermore, the annualized emission reduction potential is the largest during 2020-2030, followed by 2030-2040, 2040-2050 for most locations under all five scenarios. However, for Great Falls, the annualized emission reduction potential is the largest during 2030-2040, followed by 2020-2030, 2040-2050 under the HighReCost, Mid, LowBatCost, and LowWinCost scenarios. As mentioned before, this is because the emission reduction potential in Great Falls in 2020 is extremely low, which makes the annualized emission reduction potential during 2020-2030 low.

Table 3. Annualized emission reduction potential of retrofit model ALL under five renewable energy adoption scenarios.

Unit: t

Location	**Time period**	**Scenario**				
		HighReCost	**Mid**	**LowBatCost**	**LowWinCost**	**LowReCost**
Tampa	2020-2030	52.30	51.25	50.62	51.37	48.54
	2030-2040	48.82	39.52	31.32	42.67	30.17
	2040-2050	33.59	25.31	21.99	30.37	22.07
San Diego	2020-2030	19.81	19.71	19.71	19.49	19.20
	2030-2040	15.52	14.78	14.56	13.19	12.71
	2040-2050	12.15	11.22	10.96	7.32	7.59
Denver	2020-2030	65.54	65.28	64.99	64.47	63.61
	2030-2040	54.14	52.61	51.58	46.17	36.86
	2040-2050	40.05	33.53	33.06	24.46	20.57
Great Falls	2020-2030	37.80	37.07	37.51	31.32	16.11
	2030-2040	57.07	50.77	50.11	39.30	14.49
	2040-2050	46.21	31.31	29.56	21.51	9.05
International Falls	2020-2030	38.19	37.85	37.49	34.00	34.50
	2030-2040	25.91	22.49	20.36	11.20	9.21
	2040-2050	20.57	12.93	11.67	4.41	3.78

Note: Yellow shading means maximum value among five scenarios.

Green shading means minimum value among five scenarios.

5. Discussion

5.1. Impact of measures

Emission reduction potential of retrofit measures changes over time except for improving heating and service water heater efficiency. This is because these two retrofit measures only impact the consumption of natural gas. With a constant emission factor of natural gas, the emission reduction due to these two measures doesn't change over time. By constantly reducing carbon emissions via reduced natural gas usage, improving heating efficiency can provide a constant reduction of carbon emission, while the emission reduction of other measures decreases over time with the increased renewable generation for electricity. Our study shows that improving heating efficiency in International Falls becomes the most efficient carbon reduction measure after 2046, as shown in Fig. 9 (a).

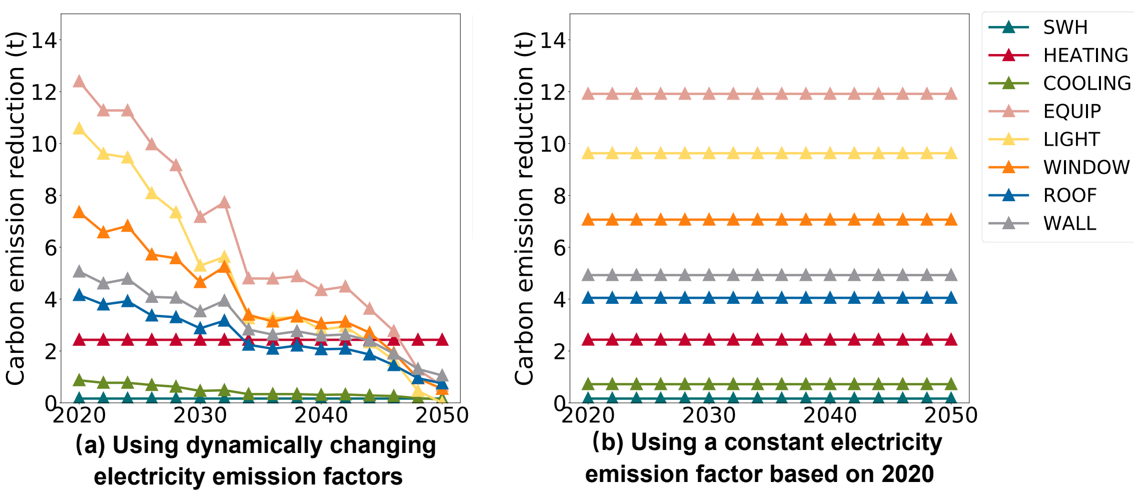


Fig. 9. Carbon emission reduction potential of building retrofit measures in International Falls under the Mid scenario.

It is worth to mention that previous research [17,21] predicted constant emission reduction potential of building retrofits over time while this study predicts that the potential will reduce for most locations. The over-prediction of previous research is because they adopted a constant emission factor of electricity, while this study adopted dynamically changing factors. Fig. 9. shows that the emission reduction potential of building retrofits in International Falls will be over predicted if using a constant electricity emission factor. As showed in Fig. 5, the electric grid is expected to be cleaner over time thanks to renewable energy adoption, which results in a low emission factor of electricity. Therefore, even with the same amount of energy reduction, the emission reduction of building retrofits will decrease over time.

5.2. Impact of locations

For locations where there is little coal usage for electricity generation, such as San Diego, the change in emission reduction potential according to time is trivial. There are two kinds of non-clean energy: coal and natural gas. The carbon emission factor of coal is 95.74 kg/GJ, which is significantly higher than natural gas (50.15 kg/GJ) [30]. The carbon emission factors of clean energy are zero. For the location where there is little coal usage, the energy used for electricity generation is already very clean. Therefore, electricity emission factors won't change much over time, which lead to little change in emission reduction potential. As shown in this study, San Diego has little coal power (Fig. 5), and the change in emission reduction potential is less significant in San Diego than other locations (Fig. 8).

For locations where emission reduction potential has significant change over time, the trend of emission reduction potential is the same as the trend of coal usage. Since the carbon emission factor of coal is significantly higher than other energy sources, coal usage has the major impact on electricity emission factors and emission reduction potential. The similar trend is also found in China, whose electricity is largely based on coal. For instance, Lin and Ouyang [49] also claimed that coal played a key role in the total carbon emissions in China. Fig. 10 shows the carbon emission reduction potential of retrofit measure ALL and share of coal for electricity generation from 2020 to 2050 under the Mid scenario. San Diego is not included in this figure since the coal usage in San Diego is zero. Fig. 10 shows that the trend of emission reduction potential is the same as the coal usage for all locations under five scenarios. Carbon emission reduction potential and coal usage both increase first, then decrease from 2020 to 2050 in Tampa, Denver, and Great Falls. Carbon emission reduction potential and coal usage both decrease directly from 2020 to 2050 in International Falls.

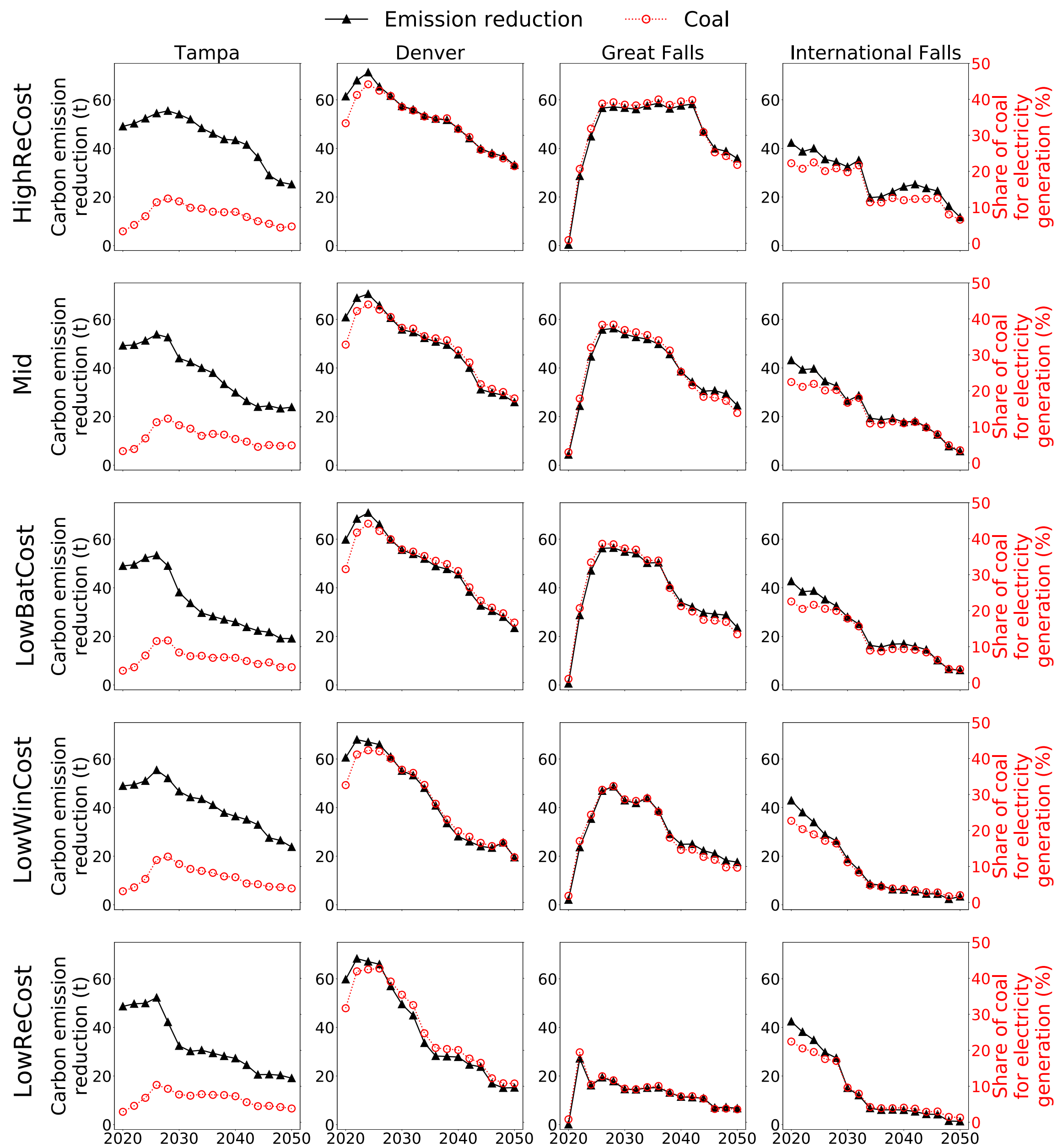


Fig. 10. Carbon emission reduction potential of retrofit measure ALL and share of coal for electricity generation.

5.3. Impact of scenarios

The five renewable energy adoption scenarios lead to different carbon emission reduction potentials. In general, the HighReCost scenario leads to the most carbon emission reduction potential, and the LowReCost scenario leads to the least reduction potential. The HighReCost scenario discourages the use of renewable energy, which lead to higher electricity emission factors than the Mid scenario. As a result, the same amount of energy saving will result in more emission reduction potential. On the contrary, the LowReCost scenario encourages the use of all kinds of renewable energy, which lead to lower electricity emission factors than the Mid scenario. Although the LowWinCost and LowBatCost scenarios also encourage the use of renewable energy, they only encourage a part of renewable energy sources. Therefore, the LowReCost scenario leads to the lowest the electricity emission factors, but least emission reduction potential for building retrofits.

In addition, the impact of the scenarios on emission reduction potential varies significantly in different locations. Some locations already have high renewable energy penetration and the potential for further increase of renewable energy power is limited despite of scenarios. Thus, electricity emission factors are similar under different scenario, and the emission reduction potential of retrofit measures is less sensitive to the scenarios. For instance, because San Diego already has high renewable energy penetration, emission reduction potential of retrofit measure ALL has a minor difference under different scenarios (Fig. 11). On the contrary, some locations have low renewable energy penetration and thus electricity emission factors are sensitive to different scenarios. For example, Denver and Great Falls have low renewable energy penetration. As a result, they see large differences for emission reduction potential of retrofit measure ALL under different scenarios, as shown in Fig. 11.

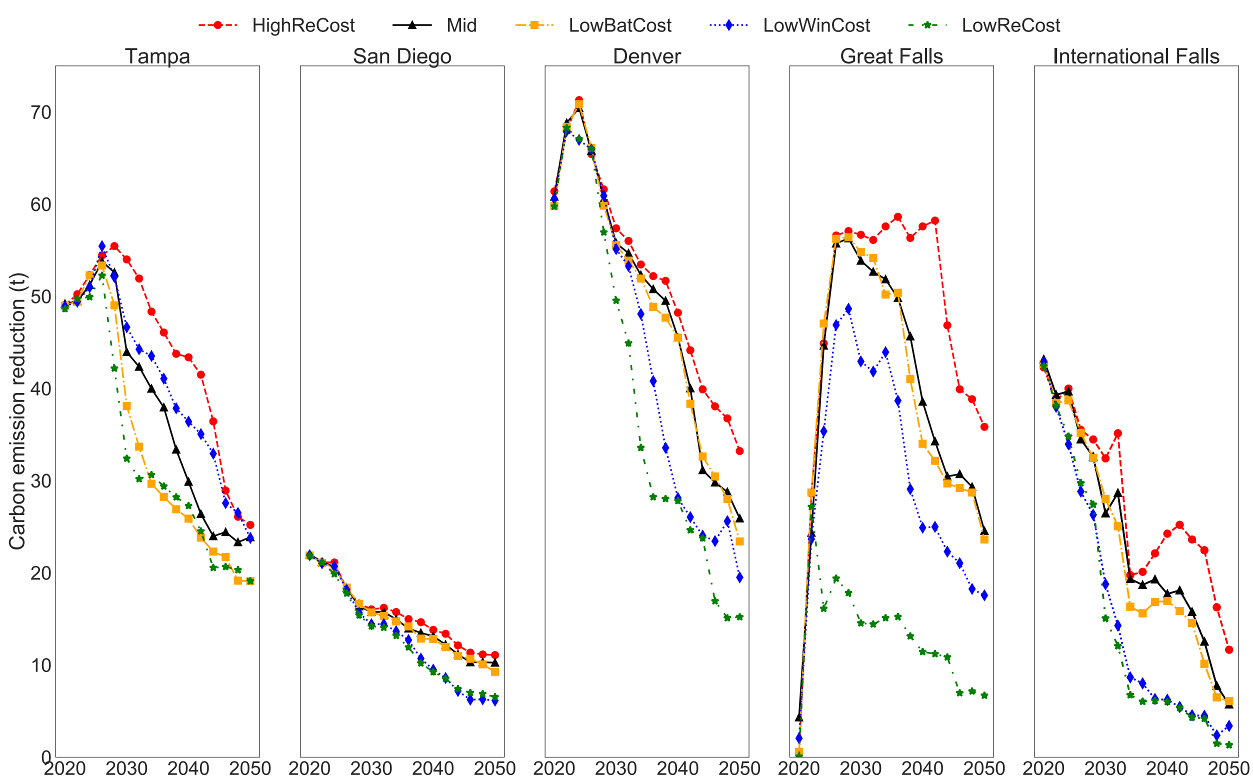


Fig. 11. Carbon emission reduction potential of retrofit measure ALL under five renewable energy adoption scenarios.

5.4. Implication to building retrofit policy

Based on the above analysis, we identified three areas that future building retrofit policies should focus on to make large impact in carbon emission reduction for medium office buildings. First, incentives on building retrofits for medium office buildings should focus on improving lighting and equipment efficiency. The total emission reduction potentials of these two retrofit measures from 2020 to 2050 are the top two among all eight studied measures. Second, the same building retrofit policy implemented in locations with high coal usage rate will achieve larger emission reduction potential than the ones with low coal usage rate. For instance, this study shows that Denver, which has the highest coal usage rate, has the largest emission reduction potential among all five studied locations. Third, because the electricity generation is more carbon intensive under the HighReCost scenario than other scenarios, building retrofits can have the highest carbon reduction potential under this scenario. Thus, building retrofit policy should be emphasized for locations under the HighReCost scenario.

6. Conclusion

This study develops a novel method to estimate the emission reduction potential of building retrofits by using dynamically changing electricity emission factors. Compared to the current approach of using a constant emission factor, the new method predicts the emission reduction potential considering the era of increased renewable energy adoption. To demonstrate the usage of the method, we used medium offices as an example. The results reveal several new phenomena on emission reduction potential of building retrofits for medium offices in the U.S.: (1) it decreases from 2026 to 2050; (2) it has the same trend with coal usage; and (3) it reaches the maximum under the HighReCost scenario. Based on the results, it is recommended that building retrofits should focus on 1) improving lighting and equipment efficiency; 2) locations with higher coal usage rate, and 3) buildings under the high renewable cost scenario.

The new method of predicting emission reduction potential of building retrofit can be applied to other building types and regions. Using this workflow, carbon emission reduction potential of the building sector in the U.S. can be predicted by providing retrofit measures, estimated building energy consumptions, and expected emission factors of other building types and regions.

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