Economic and Environmental Analysis of U.S.-Based Data Centers Containing Photovoltaic Power Generation

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ABSTRACT

Energy consumption and greenhouse gas emissions are two major concerns for data centers. Adopting renewable energy, such as solar energy, is a potential solution to both relieve the draw by the power grid and reduce CO_2 equivalent (CO_2e) emissions. This study quantifies the economic and environmental aspects of data center operation, and then assesses the influence of photovoltaic (PV)-based solar energy upon these aspects. The study estimates data center upfront and operating costs, and the carbon emission factor (CEF), defined here as the carbon footprint associated with each kWh of electricity consumption, for locations in all 50 U.S. states. The study includes location-specific metrics such as electricity cost, latitude and solar irradiance. The CEF is approximated based on the electric power production portfolio associated with each state. The solar availability assigned to a state is calculated using a beam and diffuse solar irradiance model based on the hourly solar irradiance data from the NREL TMY3 database. Recommendations are provided regarding the locations and data center densities with the largest economic and environmental benefit from adding PV-based power generation.

KEY WORDS: Data Center, Renewable Energy, Economic Analysis, Carbon Usage Effectiveness (CUE), CO_2e emission, Solar Photovoltaic

NOMENCLATURE

Greek Symbols

α	Altitude angle, rad
β	Slope of solar collector (from horizontal), rad
η	Averaged overall PV system efficiency
γ	Azimuth angle of collector, rad
ω	Hour angle, rad
ϕ	Observer's latitude, rad
θ	Angle of incidence, rad

Subscripts

b	Beam radiation
d	Diffuse radiation
j	Electricity generation source

Variables

A	Annualized payment
AC	Alternating current
CEF	Carbon emission factor, kg CO_2e/kWh$_{tot}$
c_{PV}	Carbon footprint from typical solar energy system, kg CO_2e/kWh
CRF	Capital recovery factor
C_{tot}	Total carbon footprint, kg
CUE	Carbon usage effectiveness, kg CO_2e/kWh$_{tot}$
DC	Direct current
DHI	Diffuse horizontal irradiance, Wh/m^2
DNI	Direct normal irradiance, Wh/m^2
EF_i	Emission factor, kg CO_2e/kg gas
E_{tot}	Total electricity generation, kWh

F_{m}	Maintenance factor
GHG	Green house gas
n	Day number
PB	Payback period, yr
PDU	Power distribution unit
P_{e}	Electricity cost
P_{PV}	PV system cost
P_{save}	Saving by implementing PV system
$P_{\mathrm{s,f}}$	Capital cost of servers and other facility
PUE	Power usage effectiveness
P_{upf}	Upfront cost of data center
Q_{IT}	Data center IT equipment energy, kWh
Q_{tot}	Total data center energy, kWh
R_{d}	Factor for diffuse radiation on a tilted plane
t	Time length, h
t_{h}	Time of the day, h
TL	Data center tier level
UPS	Uninterrupted power supply

INTRODUCTION

Published data from the Natural Resources Defense Council (NRDC) [1] indicates that roughly 91 billion kWh of electricity was consumed by America's data centers in 2013, which is projected to be almost 140 billion kWh of annual power consumption by 2020. Utilizing solar and wind energy reduces the power draw from the grid and consequently saves considerable utility costs. Many studies have looked at using renewable energy in the data center industry. Deng et al. [2] conducted research in when and where to apply renewable energy in cloud computing data centers to maximize the use of available energy. It was found that inter-data center load balancing and migration, along with job scheduling, can reduce the power draw from the grid and operate data centers within an allowed budget. Dali et al. [3] provided a theoretical study and experimental test of operating a grid-connected hybrid system, which demonstrates that the capability of the hybrid system to work safely with or without power from the grid. Liu et al. [4] integrated renewable energy supply, dynamic pricing and cooling supply into a holistic approach that reduces electricity cost and environmental impact. In order to quantify the environmental impact of an operating data center, Green Grid [5] defined a metric called the carbon usage effectiveness (CUE) in 2010, which measures the quantity of CO_2e emitted within a specific time frame. Unlike power usage effectiveness (PUE), which is a unitless measurement and evaluates data center energy efficiency, CUE considers how clean a data center is by means of the carbon footprint of a data center's power sources through units of kg CO_2e/kWh.

Any active changes in reducing CUE will impact a data center's capital and operating costs. Data center designers must examine the cost of space and construction, as well as the cost of large scale utility power and critical facility installation. Also, the heating, ventilation and air conditioning (HVAC) system, which is used to cool the servers and other networking equipment, can be particularly expensive. Plenty of literature is available regarding data economics. Turner IV et al. [6, 7] published a dollars per kW model to predict the capital cost of a data center. Xu et al. [8] built a model that studied the environmental, energy and economic performance of an operational data center. Finally, Wang et al. [9] declared an interplay between data center distributed systems and economics when analyzing the Amazon EC2 cloud service and a local cloud computing testbed.

One means to reduce a data center's CUE is to replace a portion of the grid energy with on-site photovoltaic (PV) power sources. The use of PV power results in a higher capital cost but reduces the annual power cost. Therefore, the influence of on-site PV power needs to be examined to ascertain its influence on the CUE and to determine its economic payback period. These values also depend on location due to the availability of solar irradiation and the cost of grid-based energy. Environmental impact and data center costs have become two major concerns in the data center industry. Even though CUE has been proposed for several years, few studies have discussed the calculation of this metric. Furthermore, the interaction between CUE and economics is barely documented. This study therefore illustrates a simple methodology to estimate the carbon footprint of data centers by considering the power sources (coal, natural gas, petroleum, nuclear and renewable energy) associated with their geographical locations. This paper also presents a cost model for data centers based on physical location, solar energy availability and potential carbon and economic savings. Recommendations for data center location and the use of PV sources are provided.

Table 1: U.S. Electricity Production Portfolio (Thousand Megawatt hours) [12]

States	Coal	Natural Gas	Biomass	Hydropower	Petroleum	Solar PV	Wind	Nuclear	Total	Fossil Fuel Percentage
Alabama	34,186	56,731	265	6,985	31	39	0	39,902	138,139	65.8%
Alaska	487	2,977	0	1,491	780	1	169	0	5,905	71.9%
Arizona	30,403	34,042	214	7,168	52	4,725	542	32,377	109,523	58.9%
Arkansas	23,750	17,853	108	3,570	39	33	0	13,421	58,774	70.9%
California	0	84,476	4,498	28,930	40	24,616	13,498	18,908	174,966	48.3%
Colorado	29,941	12,658	162	1,891	7	999	9,417	0	55,075	77.4%
Connecticut	177	17,044	856	224	87	345	13	16,575	35,321	49.0%
Delaware	479	6,792	52	0	63	118	0	0	7,504	97.7%
Florida	39,255	157,012	2,570	175	746	354	0	29,320	229,432	85.9%
Georgia	37,674	52,420	719	3,357	84	1,076	0	34,481	129,811	69.5%
Hawaii	1,492	0	88	53	6,442	849	639	0	9,563	83.0%
Idaho	0	3,142	156	9,033	0	40	2,578	0	14,949	21.0%
Illinois	57,816	16,472	467	131	68	86	10,659	98,607	184,306	40.3%
Indiana	72,481	19,320	338	426	101	243	4,899	0	97,808	94.0%
Iowa	23,480	2,661	150	917	239	59	20,068	4,703	52,277	50.5%
Kansas	23,096	1,975	59	31	28	10	14,111	8,246	47,556	52.8%
Kentucky	66,822	7,975	105	3,478	88	32	0	0	78,500	95.4%
Louisiana	12,014	39,835	80	1,103	15	191	0	17,152	70,390	73.7%
Maine	60	3,157	1,623	2,678	99	29	1,667	0	9,313	35.6%
Maryland	13,751	4,919	417	1,392	157	728	527	14,760	36,651	51.4%
Massachusetts	1,875	20,464	1,177	708	403	1,863	194	5,414	32,098	70.9%
Michigan	40,433	28,402	1,646	1,539	116	64	4,696	31,552	108,448	63.6%
Minnesota	22,806	8,628	1,235	1,078	30	47	9,905	13,861	57,590	54.6%
Mississippi	5,342	49,680	10	0	15	6	0	5,897	60,950	90.3%
Missouri	60,269	5,890	88	1,268	78	200	1,122	9,430	78,345	84.5%
Montana	14,263	472	0	10,083	17	11	2,140	0	26,986	54.7%
Nebraska	21,551	536	80	856	0	7	3,798	9,351	36,161	61.1%
Nevada	2,167	28,578	55	1,789	11	3,252	344	0	36,196	85.0%
New Hampshire	422	4,689	1,654	1,146	22	52	432	10,761	19,178	26.8%
New Jersey	1,315	43,277	815	9	80	2,220	21	29,885	77,622	57.6%
New Mexico	18,365	9,840	18	148	52	909	3,603	0	32,935	85.8%
New York	1,437	55,677	1,828	26,827	595	1,013	3,939	41,571	132,887	43.4%
North Carolina	37,186	39,134	1,217	4,403	243	3,588	6	42,786	128,563	59.6%
North Dakota	26,472	1,051	0	1,912	30	0	8,172	0	37,637	73.2%
Ohio	68,662	28,627	463	500	212	174	1,191	16,817	116,646	83.6%
Oklahoma	18,791	36,359	15	2,573	17	9	20,069	0	77,833	70.9%
Oregon	1,898	15,199	459	34,550	5	192	7,157	0	59,460	28.8%
Pennsylvania	54,294	66,611	1,723	2,374	264	362	3,476	82,924	212,028	57.1%
Rhode Island	0	6,241	205	2	25	45	20	0	6,538	95.8%
South Carolina	20,900	16,304	829	2,224	97	41	0	55,826	96,221	38.8%
South Dakota	2,083	919	0	4,806	3	1	3,714	0	11,526	26.1%
Tennessee	30,293	10,779	84	6,774	119	165	38	29,578	77,830	52.9%
Texas	121,231	185,014	704	1,342	78	1,122	57,483	42,079	409,053	74.9%
Utah	25,502	8,210	68	759	32	1,204	822	0	36,597	92.2%
Vermont	0	1	475	1,077	4	135	291	0	1,983	0.3%
Virginia	16,214	40,266	2,331	1,463	529	62	0	29,732	90,597	62.9%
Washington	4,569	10,873	612	78,345	13	90	8,041	9,626	112,169	13.8%
West Virginia	71,401	980	0	1,143	123	6	1,432	0	75,085	96.6%
Wisconsin	32,927	15,032	835	2,620	26	38	1,508	10,151	63,137	76.0%
Wyoming	39,629	186	0	974	45	3	4,389	0	45,226	88.1%

METHOD

Carbon Footprint

The Uptime Institute's Top 10 Data Center Industry Trends for 2019 [10] have indicated that "governments viewed [IT] as a positive force", and that "any downside... on energy use or carbon emissions... had largely been downplayed. But the pendulum has swung," meaning that governments are starting to show concern regarding data center carbon emissions. Thus, carbon emission calculations are needed as observable effects from climate change have indicated severe damage to the environment. This study evaluates CO_2e emissions for data centers in all 50 U.S. states. The notion here is that the power requirements for any newly built hyperscale data center will likely call for additional power generation, and a location's existing regulations will likely favor a specific type of power generation source. Therefore, it is hypothesized that the location's current power generation portfolio provides a good indicator for the likely type of power generation that would be used for any new data center construction. This enables a reasonable prediction of the carbon emissions associated with a new data center. Furthermore, existing data centers most likely draw from local power generation sources, so the local power generation portfolio also provides a means to estimate a current data center's carbon footprint. Finally, some data center owners have local utility contracts to draw from renewable power, which is important in pushing the utility industry to have more renewable sources in the long term, however the short term consequence is merely to redistribute the nonrenewable power to other utility customers.

CUE is defined as the ratio of total CO_2e emissions compared to the data center IT equipment energy consumption. By its definition, one has to consider the energy production portfolio of that specific location and their associated emissions to perform this calculation. The U.S. electricity generation information in 2016 [12] shows that 35.4% of power generation stems from nuclear and renewable sources, which generates a small amount of CO_2e compared to fossil fuel-based sources. The fossil fuels coal, natural gas and petroleum occupy 64.6% of total generation. However, Table 1 [12] shows that the electricity production portfolio depends heavily on location. In Vermont, for example, only 0.25% of generated energy is by fossil fuel in 2016, whereas in Delaware, over 97.7% of electricity stems from fossil fuel in the same year.

The analysis here assumes that CO_2e comes from multiple sources, such as petroleum, coal, natural gas, biomass, hydropower, solar photovoltaic, wind and nuclear energy. Each generation source produces largely divergent greenhouse gas (GHG) emissions through construction, operation and abandonment processes. Thus, evaluating the lifecycle CO_2e emissions of each source is extremely important. The mathematical definition of CUE is

$$CUE = \frac{C_{\text{tot}}}{Q_{\text{IT}}} \tag{1}$$

where C_{tot} is the total annual carbon footprint of the data center in kg CO_2e, and Q_{IT} is the annual data center IT equipment energy consumption in kWh. The approach introduced here for calculating CUE is to multiply the PUE by a carbon emission factor (CEF):

$$CUE = \frac{C_{\text{tot}}}{Q_{\text{tot}}} \cdot \frac{Q_{\text{tot}}}{Q_{\text{IT}}} = CEF \cdot PUE \tag{2}$$

where Q_{tot} is the total energy that data center consumed in kWh. CEF is defined here as the ratio of CO_2e emissions per kWh of facility electricity consumption:

$$CEF = \frac{\sum_j CO_2e_j}{\sum_j Q_{\text{tot}\,j}} \tag{3}$$

where CO_2e_j is the total CO_2e production from one source in kg, $Q_{\text{tot}\,j}$ is the total electricity generation from that specific source in kWh, and the subscript j represents different generation sources. Then, the equation can be written as:

$$CEF = \frac{\sum_j EF_j \times Q_{\text{tot}\,j}}{Q_{\text{tot}}} \tag{4}$$

where EF_j is the emission factor, which represents the lifecycle GHG emissions from the selected electricity generation source in kg CO_2e per kWh. Figure 1 shows the GHG emissions of multiple electricity generation sources according to the Intergovernmental Panel on Climate Change (IPCC) [23] and the World Nuclear Association (WNA) [24]. The median values of GHG emissions from each source are used in this study. It is worth noting that the lifecycle analysis of nuclear power from their research includes uranium mining, enrichment and fuel fabrication, site construction, combustion and waste management.

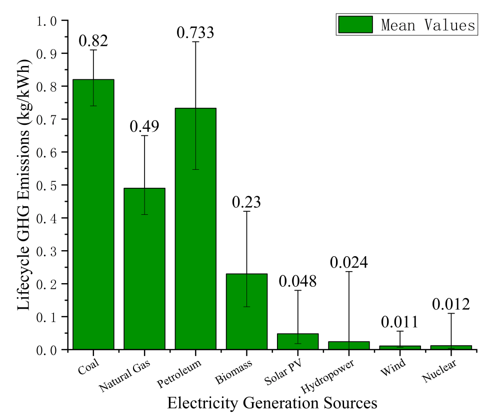

Figure 1: Lifecycle GHG emissions of Multiple Electricity Generation Sources [23, 24]

The above calculation sequence illustrates that the CEF is a simple multiplier that estimates CUE for data centers assuming that each state independently produces and consumes its own power (i.e. no power crosses state borders). Since in reality power does in fact cross state borders, the CEF as defined here is only a rough approximation. However, it is reasonable to believe that the majority of power consumed in a state was produced in that same state, so the CEF provides a reasonable first approximation for CUE calculations. Table 2 shows the calculated CEF for all 50 states. One can easily observe that Vermont has the lowest CEF (0.075 kg/kWh), meaning that data centers built in Vermont will likely have lower CO_2e emissions compared with data centers built in other states for a given PUE. The states with the second and third lowest CEF value are Washington and Idaho due to their low fossil fuel consumption and large renewable or nuclear energy supply. On the other hand, West Virginia, Kentucky and Wyoming are the three states with the highest CEF (≈0.75 kg/kWh), with 96.56%, 95.39% and 88.14% of electricity generated in those three states, respectively, stemming from fossil fuel. West Virginia, a major coal producer in the nation, undoubtedly has the highest CEF because coal is their major source of power. However, Delaware, that has 97.73% of electricity comes from fossil fuel, is the state with highest percentage of fossil fuel usage but only has a medium CEF (0.504 kg/kWh) because the most of the fossil fuel burnt in Delaware is natural gas, which has a lower GHG emission factor than coal. Similar phenomena can also be observed from Rhode Island.

Table 2: CEF Values for All 50 States

State	CEF (kg/kWh)	State	CEF (kg/kWh)
Alabama	0.409	Montana	0.452
Alaska	0.418	Nebraska	0.501
Arizona	0.388	Nevada	0.442
Arkansas	0.485	New Hampshire	0.167
California	0.256	New Jersey	0.296
Colorado	0.563	New Mexico	0.608
Connecticut	0.254	New York	0.230
Delaware	0.504	North Carolina	0.396
Florida	0.482	North Dakota	0.595
Georgia	0.442	Ohio	0.607
Hawaii	0.629	Oklahoma	0.431
Idaho	0.122	Oregon	0.169
Illinois	0.309	Pennsylvania	0.372
Indiana	0.707	Rhode Island	0.478
Iowa	0.403	South Carolina	0.271
Kansas	0.425	South Dakota	0.201
Kentucky	0.750	Tennessee	0.395
Louisiana	0.421	Texas	0.468
Maine	0.228	Utah	0.685
Maryland	0.386	Vermont	0.075
Massachusetts	0.383	Virginia	0.379
Michigan	0.443	Washington	0.101
Minnesota	0.409	West Virginia	0.788
Mississippi	0.473	Wisconsin	0.551
Missouri	0.671	Wyoming	0.723

Solar Energy Integration

Traditional data center power systems include AC transformers, rectifiers, power distribution units (PDUs) and uninterrupted power supplies (PSUs). For energy conservation and carbon footprint reduction purposes, PV arrays and associated boost converters can be integrated to provide on-site power generation. The standalone power distribution system modeled in this study follows the layout shown in Figure 2.

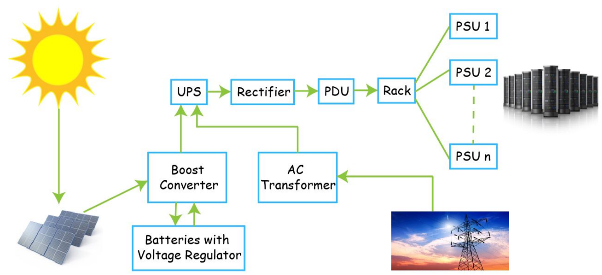

Figure 2: Integrated PV Array Model in a DC Power Distribution System

The data center draws power partially from the power grid, which goes through an AC transformer, UPS, rectifier, and PDU before reaching the racks, where the power is distributed to the servers. Another data center power source is the solar PV system, whose output DC voltage is boosted up to 480V DC and merged into 480V DC power within the UPS. The electricity generated from the PV system feeds data center energy demands during the peak loading period. If any extra electricity is generated during the data center low loading period, then it is stored in a battery bank for future use.

The solar availability for different locations is determined using the declination angle (δ), hour angle (ω) and latitude angle (ϕ) [15] and hourly solar radiation data from the NREL Typical Meteorological Year database (TMY3) [16]. The following equations are used in this study:

$$\delta = 23.45\frac{\pi}{180}\sin\left(2\pi\left(\frac{284+n}{36.25}\right)\right) \tag{5}$$

where δ is the declination angle (rad) and n is the day number. The hour angle (ω), in radians, is

$$\omega = 15^{\circ}(t_{\mathrm{h}}-12)\frac{\pi}{180} \tag{6}$$

where t_{h} is the time of day in hours, with $t_{\mathrm{h}} = 0$ occurring at midnight. The altitude angle (α) is found using

$$\sin\alpha = \sin\delta\sin\phi + \cos\delta\cos\omega\cos\phi \tag{7}$$

where α and ϕ are both in radians. The azimuth angle (γ) is calculated using

$$\gamma = \frac{\sin\omega\cos\delta}{\cos\alpha} \tag{8}$$

The angle of incidence (θ) is

$$\begin{aligned}\cos\theta = {} & \sin\delta\sin\phi\cos\beta - \sin\delta\cos\phi\sin\beta\cos\gamma \\ & + \cos\delta\cos\phi\cos\beta\cos\omega \\ & + \cos\delta\sin\phi\sin\beta\cos\gamma\cos\omega \\ & + \cos\delta\sin\beta\sin\gamma\sin\omega\end{aligned} \tag{9}$$

Here, solar collectors are placed horizontally facing up, with slope angle $\beta = 0°$. Finally, the solar availability (S), defined as the maximum solar energy that can be utilized, is

$$S = \eta\left(I_\mathrm{b}\cos\theta + I_\mathrm{d}R_\mathrm{d}\right) \tag{10}$$

where I_b and I_d are the hourly mean solar irradiance of beam and diffuse components, respectively, which are calculated based on hourly data of direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI) for different locations in the TMY3 database. R_d is a factor used to adjust the diffuse radiation quantity for a tilted plane as

$$R_\mathrm{d} = \frac{1+\cos\beta}{2} \tag{11}$$

and η is the overall average efficiency of the PV system, which is assumed to be a typical value of 18% [25].

Table 3 shows the annually accumulated solar availability for the most populous cities in all 50 states. The solar availability of these cities is considered to be a rough representation for the entire state they reside in for purposes of this study. As expected, Anchorage, AK has the lowest solar availability among all other cities considered here. Seattle, WA, Manchester, NH, and Portland, OR are also low solar availability cities with slightly over 220 kWh/m^2/year. On the other hand, Phoenix, AZ, Albuquerque, NM, Honolulu, HI and Las Vegas, NV are the 4 cities with most sunlight. It is worth noting that Charleston, WV, the state with largest CEF, has an intermediate value of 259 kWh/m^2/year solar energy available.

Table 3: Yearly Solar Availability in U.S.

State	City	Solar Availability (kWh/m^2)
Alabama	Birmingham	293
Alaska	Anchorage	156
Arizona	Phoenix	369
Arkansas	Little Rock	292
California	Los Angeles	325
Colorado	Denver	301
Connecticut	Bridgeport	254
Delaware	Wilmington	264
Florida	Jacksonville	294
Georgia	Atlanta	297
Hawaii	Honolulu	349
Idaho	Boise	284
Illinois	Chicago	252
Indiana	Indianapolis	263
Iowa	Des Moines	273
Kansas	Wichita	296
Kentucky	Louisville	268
Louisiana	New Orleans	292
Maine	Portland	254
Maryland	Baltimore	266
Massachusetts	Boston	253
Michigan	Detroit	245
Minnesota	Minneapolis	249
Mississippi	Jackson	301
Missouri	Kansas City	281
Montana	Billings	269
Nebraska	Omaha	254
Nevada	Las Vegas	342
New Hampshire	Manchester	227
New Jersey	Newark	255
New Mexico	Albuquerque	355
New York	New York City	257
North Carolina	Charlotte	289
North Dakota	Fargo	249
Ohio	Columbus	247
Oklahoma	Oklahoma City	292
Oregon	Portland	228
Pennsylvania	Philadelphia	263
Rhode Island	Providence	249
South Carolina	Columbia	290
South Dakota	Sioux Falls	260
Tennessee	Nashville	283
Texas	Houston	288
Utah	Salt Lake City	295
Vermont	Burlington	240
Virginia	Richmond	277
Washington	Seattle	221
West Virginia	Charleston	259
Wisconsin	Milwaukee	252
Wyoming	Cheyenne	289

Economics Calculations

Building a data center is extremely expensive, and the cost varies widely for different data center densities and tier levels [17]. In this study, the upfront cost of a data center (P_upf) is estimated by the "dollars per kW model [18]":

$$P_\mathrm{upf} = Q_\mathrm{ITL} \cdot TL \tag{12}$$

where Q_ITL is the data center IT load in kW. TL is the data center tier level described in Table 7. Data center tier level classification is used in the model and can be found in Table 4. The operating expenses of a data center are also significant. Based on research

Table 4: Tier Level Classification [17]

Tier Level	Performance Standard	Cost Model
Tier 1	Basic Site Infrastructure	$11,500/kW
Tier 2	Redundant Capacity Components Site Infrastructure	$12,500/kW
Tier 3	Concurrently Maintainable Site Infrastructure	$23,000/kW
Tier 4	Fault Tolerant Site Infrastructure	$25,000/kW

published by the Uptime Institute [19], 22% of data center managers prefer to refresh their servers every five years and other facility equipment every 15 years. Thus, this study estimates the operating cost by breaking the total upfront cost into two parts (servers and other equipment) and amortizing them over 5 years for servers and 15 years for all other equipment, assuming a constant annual interest rate (a typical value of 5% is used in this study). The annualized operating expenses take advantage of the capital recovery factor (CRF), which converts these costs into annual values using compounding:

$$CRF(i,n) = \frac{i(1+i)^n}{i(1+i)^n - 1} \tag{13}$$

where i is the annual interest rate, and n is the number of years. Power and maintenance expenses are also incorporated in this model. The electricity price for different states was retrieved from the U.S. Energy Information Administration [20]. The maintenance cost is difficult to ascertain since it is owner-driven. Here, a 2% maintenance factor (F_{m}) is assumed. Therefore, the annualized cost of servers (A_{s}) and other equipment (A_{f}) are calculated using

$$A_{\mathrm{s,f}} = P_{\mathrm{s,f}} \cdot CRF_{\mathrm{s,f}}(i, n_{\mathrm{s,f}}) \tag{14}$$

Annualized costs of power (A_{p}) and maintenance (A_{m}) are calculated using following equations:

$$A_{\mathrm{p}} = Q_{\mathrm{tot}} \cdot P_{\mathrm{e}} \cdot t \tag{15}$$

$$A_{\mathrm{m}} = F_{\mathrm{m}} \cdot P_{\mathrm{upf}} \tag{16}$$

where E_{cost} is the average electricity price [20]. Then, the total annualized operating cost is computed using

$$A_{\mathrm{tot}} = A_{\mathrm{s}} + A_{\mathrm{f}} + A_{\mathrm{p}} + A_{\mathrm{m}} \tag{17}$$

In this study, a data center with a typical floor area of 300 m^2 and a typical PUE of 1.85 is modeled. Different data center densities (high density 150 W/sq.ft., medium density 100 W/sq.ft., and low density 50 W/sq.ft.) and different tier levels are compared.

Figure 3 shows the data center upfront cost versus tier levels and densities. It is clear that upfront cost

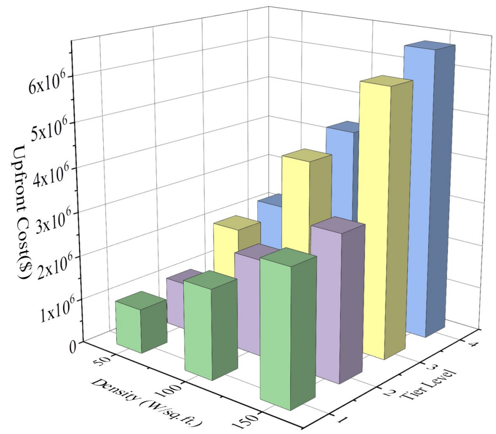

Figure 3: Data center Upfront Cost versus Tier Levels and Densities (non-PV)

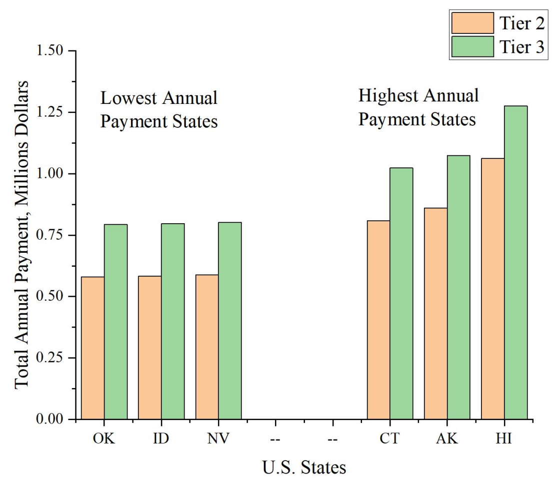

Figure 4: Annual Payment for Different States at Tier 2 & 3 (non-PV)

increases with data center density and tier level. A tier 4, high density data center costs over 6 times than a tier 1, low density data center for a given location.

The annualized operating expense varies with location and tier level as shown in Figure 4. Only the 3 states with the highest annualized payment and the 3 states with the lowest annualized payment are shown. Hawaii is the state with the highest annual payment due to its high electricity cost. On the contrast, Oklahoma has the lowest annual payment because of the its cheap electricity price. It should be noticed that Idaho may be a good data center location since the state has a clean energy production portfolio (ranked the 3rd lowest CEF state) and inexpensive electricity.

Obviously, investing in a PV system will lead to a higher upfront cost. The payback analysis for a typical PV system installation is

$$PB = \frac{P_{\text{PV}}}{P_{\text{save}}} \tag{18}$$

The PV arrays, with an averaged overall efficiency 18%, are sized to fully capture the average daily solar energy within 7 hours sunlight time. Solar panels are expensive, especially when considering the large power requirements of data centers. The average PV panel cost in the U.S. is 3.14 \$/W [21]. However, a 30% federal solar tax credit with no cap on its value, also known as an investment tax credit (ITC), gives solar system owners a significant deduction on the total cost of solar energy system installation. For a given data center with 300 m^2 roof area for PV panels, the payback calculation result is seen in Figure 5. The figure shows that the payback period is not favorable, ranging from roughly 20-60 years. It is obvious that the payback period is negatively correlated with electricity cost. Hawaii is the state with fastest payback for PV solar energy applications due to its expensive electricity and relatively high solar energy availability. On the contrast, Oklahoma, whose electricity is the cheapest among all states, has the longest payback period. The results in the figure only consider the 30% federal tax credit, so the payback period shown is still conservative when considering financing, incentives and rebates from their own state.

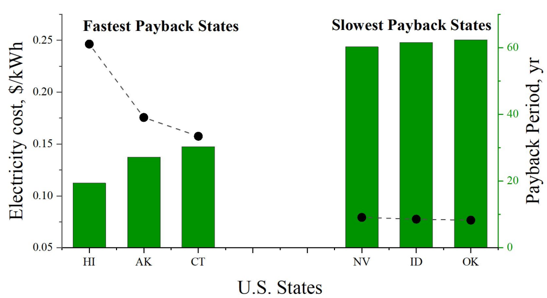

Figure 5: Payback Period & Electricity Cost Among States (30% Federal Tax Credits Included)

RESULTS AND COMPARISON

Influence of PV System

The CUE for a PV system implemented data center ($CUE_{\text{w/PV}}$) is calculated using:

$$CUE_{\text{w/PV}} = \frac{E_{\text{tot,grid}} \cdot CEF + E_{\text{tot,PV}} \cdot c_{\text{PV}}}{Q_{\text{IT}}} \tag{19}$$

with an inherent carbon footprint 0.048 kg CO_2e/kWh [23] PV system (c_{PV}). Table 5 shows the calculated

Table 5: CUE Comparison

State	CUE (kg/kWh)	CUE w/PV (kg/kWh)	Percentage Difference
Alabama	0.758	0.736	2.89%
Alaska	0.773	0.762	1.44%
Arizona	0.718	0.693	3.47%
Arkansas	0.898	0.872	2.89%
California	0.473	0.460	2.65%
Colorado	1.041	1.011	2.91%
Connecticut	0.470	0.460	2.28%
Delaware	0.933	0.909	2.63%
Florida	0.892	0.867	2.88%
Georgia	0.817	0.795	2.80%
Hawaii	1.164	1.124	3.46%
Idaho	0.226	0.222	1.77%
Illinois	0.572	0.559	2.27%
Indiana	1.308	1.274	2.59%
Iowa	0.746	0.727	2.58%
Kansas	0.786	0.764	2.74%
Kentucky	1.388	1.351	2.68%
Louisiana	0.779	0.758	2.79%
Maine	0.422	0.413	2.27%
Maryland	0.714	0.696	2.50%
Massachusetts	0.709	0.692	2.46%
Michigan	0.819	0.801	2.26%
Minnesota	0.756	0.739	2.28%
Mississippi	0.874	0.850	2.82%
Missouri	1.241	1.207	2.76%
Montana	0.837	0.815	2.64%
Nebraska	0.927	0.904	2.52%
Nevada	0.818	0.791	3.31%
New Hampshire	0.309	0.304	1.77%
New Jersey	0.548	0.535	2.37%
New Mexico	1.124	1.086	3.44%
New York	0.425	0.416	2.13%
North Carolina	0.733	0.713	2.74%
North Dakota	1.100	1.074	2.39%
Ohio	1.123	1.096	2.46%
Oklahoma	0.797	0.775	2.72%
Oregon	0.312	0.307	1.56%
Pennsylvania	0.688	0.672	2.43%
Rhode Island	0.885	0.863	2.43%
South Carolina	0.502	0.489	2.70%
South Dakota	0.372	0.364	2.11%
Tennessee	0.731	0.712	2.70%
Texas	0.866	0.842	2.81%
Utah	1.267	1.231	2.90%
Vermont	0.138	0.137	0.57%
Virginia	0.701	0.683	2.62%
Washington	0.187	0.185	1.09%
West Virginia	1.458	1.420	2.60%
Wisconsin	1.019	0.995	2.44%
Wyoming	1.337	1.299	2.88%

CUE and CUE w/PV of a typical data center that has PUE = 1.85 and roof area 300 m^2 for PV panels. The percentage difference is also given. It is observed that Arizona, which has 3.47% of GHG emissions saved, is the state that would get most benefits from solar PV applications due to their huge solar energy availability. In Vermont, only 0.57% of GHG emissions can be saved because it has a clean energy production portfolio (lowest CEF state) and small solar energy (ranked 4th lowest solar availability state).

Influence of PV Array Size

PV array size has a significant impact on data center power consumption, payback period and carbon footprint. This subsection examines these aspects of a medium density data center (100 W/sq.ft.) built in Philadelphia, PA. The PV arrays are sized to have 100%, 80%, 60% and 40% of the maximum solar energy availability capacity in order to compare the carbon footprint and data center expenses under the influence of various PV array sizes.

Table 6 shows that as PV array size increases, then the solar energy absorbed increases, which reduces the grid power consumption. It is observed that the large payback time is insensitive to the PV array size, because increasing the PV array size increases the cost of the PV yet reduces the power draw from the grid. The carbon footprint slightly decreases with increasing PV array size: For Philadelphia, PA, assuming 100% solar energy captured, the CUE drops from 0.688 kg CO_2e/kWh to 0.672 kg CO_2e/kWh, saving roughly 2.35% of CO_2e emissions.

Table 6: Calculations for Different PV Array Sizes

Solar energy absorbed (MWh/year)	79	63	47	32
Percentage of total availability	100%	80%	60%	40%
PV array size (kW)	171.4	137.1	102.8	68.5
Power consumption (grid) (GWh)	2.76	2.78	2.79	2.81
Payback (Year)	51.8	51.8	51.8	51.8
CUE w/o PV(kg/kWh)	0.688			
CUE w/ PV(kg/kWh)	0.672	0.675	0.678	0.682

Influence of Location

This subsection examines the carbon footprint associated with an installed PV system and annualized expenses for various locations. A Tier 2, medium density (100 W/sq.ft.) data center with 300 m^2 floor area is used. Figure 6 shows the correlation of $CUE_{w/\ PV}$ and the annualized payment. The figure shows that most states allow for an annualized cost below \$0.95M/yr, but some specific locations (e.g., ID, VT and WA) can maintain this cost with a $CUE_{w/PV}$ below 0.25 kg CO_2e/kWh, and therefore these locations are favorable both economically and environmentally for data center construction. On the other hand, Honolulu, HI has the highest annual payment because the abundant solar energy available requires a large power output from the PV system, which drives the PV expenses higher. The high electricity cost of Hawaii also plays an important role in the economics of installing PV systems there..

The CO_2e emission savings by implementing PV solar energy in various locations, and the associated payback time, are shown in Figure 7. The figure shows that generally a greater reduction in carbon footprint is associated with a larger payback period, with the most favorable exception being HI due to the high electricity cost, large solar availability, and high CEF. Therefore, an existing data center in HI would most benefit from the addition of on-site PV power. Furthermore, the figure shows that one could save 3.47% in total CO_2e emissions in AZ by utilizing PV based solar energy due to that state's abundant solar energy and original 'unclean' power production portfolio. On the other hand, only a small decrease in CUE of 0.57% for VT is seen due to the fact that the inherent on-site PV carbon footprint does not help that much from reducing the power draw from the state's clean portfolio. Clean portfolio states like WA, AK and OR also show small amount of CO_2e savings from roughly 1.5% of CUE decreasing.

CONCLUSIONS

This study addresses the carbon footprint and economic aspects of data centers built in the United States. A simple method for estimating CUE of data centers, and for including on-site PV power, is proposed. The results show that Idaho is a favorable location for data centers when factoring annualized cost and carbon footprint, and Washington is also favorable when the data center is supplemented with on-site PV power. It also suggests that data centers in Vermont and West Virginia have the lowest and highest CO_2e emissions, respectively, and that Oklahoma has the lowest annualized cost. Existing data centers in HI would most benefit from PV installation, providing the lowest payback period and second largest CUE reduction. The CEF calculation should be refined to allow for power transfer across state borders. Finally, data centers in VT, WA, and ID would have least benefit environmentally from on-site PV installation due to their existing clean energy production.

Future work should also consider more flexible PV systems, such as fixed power output with varying floor area. Incorporating state tax incentives and benefits are needed to provide a more accurate payback estimation. Finally, the balance of available wind energy (with associated tax incentives), solar energy, and airside/waterside economization potential should be examined for each location to determine the strategy that optimizes economic and environmental benefit.

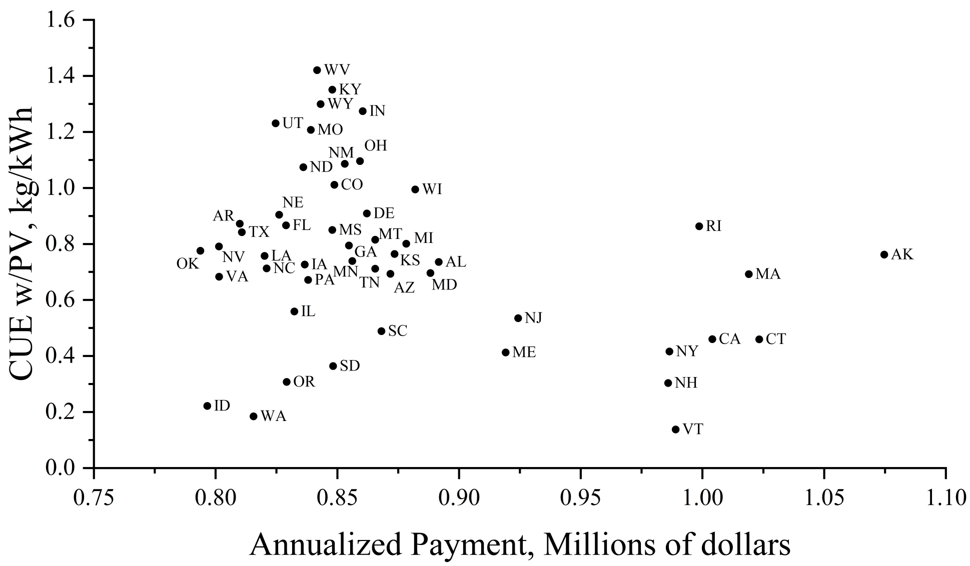

Figure 6: Annualized Payment & CUE$_{w/PV}$ for Various Locations[1]

HI has CUE w/PV = 1.124 kg/kWh and annualized payment $1.28M

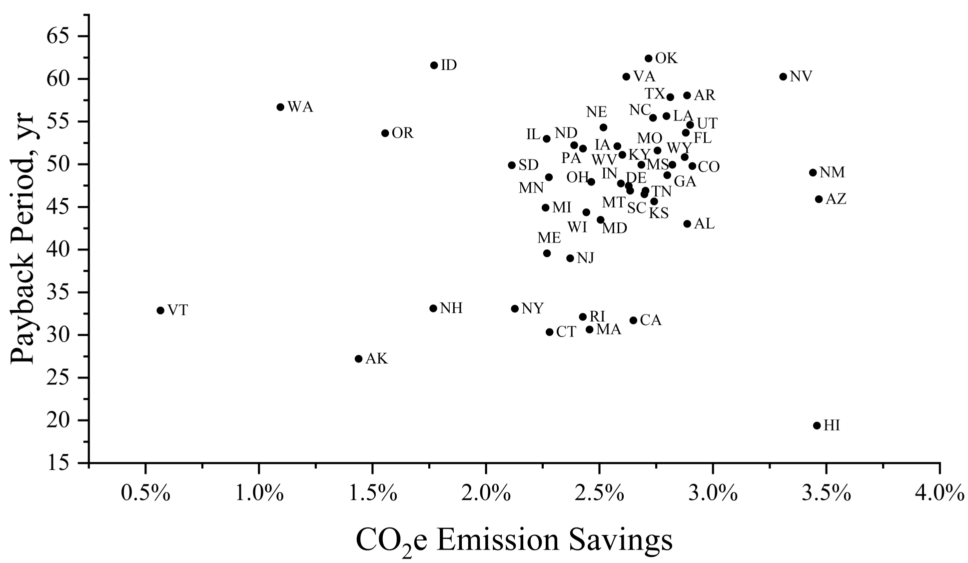

Figure 7: CO_2e Savings & Payback Period for from PV Installation Various Locations

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant No. IIP-1134810. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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