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ORIGINAL RESEARCH

Capping carbon emission from green data centers

Tathagata Bhattacharya[1] · Mostafa Rahgouy[4] · Xiaopu Peng[2] · Taha Takreeti[4] · Ting Cao[3] · Jianzhou Mao[4] · Amit Das[4] · Xiao Qin[4] · Apurba Sinha[5]

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Abstract
The world has witnessed a global surge in energy consumption and carbon footprint since the industrial revolution. Data centers are claimed to be the second most significant contributor of the havoc greenhouse gasses. This paper deals with modeling carbon footprint of green data centers. Initially, we use a panel dataset of a green data center that mostly relies on green energy resources for power. Our study reveals that in spite of massive renewable energy usage, the carbon footprint trend of this data center is quite significant. Alongside, due to massive nuclear energy usage in this data center, a hefty amount of nuclear waste is generated causing a global threat to sustainability. This is a novel paper that pinpoints that though green data centers claim they are zero-carbon data centers but the reality is different. We prove that green data centers also emit significant amount of greenhouse gasses and cause danger to sustainability. Alongside, we provide a nuclear footprint estimator that effectively calculates the nuclear emission and carbon footprint from the data center each hour. We also provide a remedy to this entire situation and provide a carbon footprint model in this paper that optimizes the total carbon emission from this green data center.

Keywords Energy modeling · Power management · Green energy · Brown energy · Carbon footprint · Nuclear estimator

Introduction

Starting with the aviation industry to car manufacturers, and from electrical industries to agricultural plants [1], the globe is trying to manage carbon emission smartly. Data centers are not exceptions; capping carbon footprint has become a prime focus for developing large-scale data centers. Data centers consume a massive amount of energy to fulfill its daily energy demands. Unsurprisingly, powering and cooling a data center are expensive in terms of energy demand [2]. This enormous power demand results in emitting a significant amount of carbon into the air [3]. This carbon emission causes a threat to global sustainability [4]. Nowadays, data centers are responsible for almost 2 percent of global carbon emission [5], which is causing global warming along with ice melt at the poles [6]. In what follows, we describe our motivation behind the study of global carbon footprint.

Massive brown energy usage

Electric grids burn mostly coal energy to meet the ever-increasing power demand of the data centers throughout the globe. A report of the Lawrence Berkeley National Laboratory claims that the US data centers consume up to 70 billion Kilowatt-hours of energy which costs around dollar 7 billion [7]. Another report states that these data centers consume over 1000 W/m2 of power—more than 10 times that required by a commercial office space [8]. Scientists estimate that a large-scale data center uses the energy of

✉ Tathagata Bhattacharya
tzb0063@auburn.edu

Xiao Qin
xqin@auburn.edu

Apurba Sinha
m.sinha0686@gmail.com

1 Auburn University, Montgomery, USA

2 Lander University, Greenwood, USA

3 Truman State University, Kirksville, USA

4 Department of Computer Science and Software Engineering, Shelby Center for Engineering Technology, Samuel Ginn College of Engineering, Auburn University, Auburn, AL 36849-5347, USA

5 Department of Computer Science and Software Engineering, Guru Gobind Singh Educational Society Technical Campus, Bokaro, India

almost 25,000 households [9]. One of the most crucial factors that add to the expense of powering a data center is cooling. For a standard data center, the cost of cooling can be significantly high [10]. Reports assert that an efficient cooling system of a data center consumes 24% of the total energy consumption, whereas a least efficient cooling system can consume up to 61% of total energy. On average, a cooling system consumes 40% of the total data center energy [11]. Today IT sector uses 7% of the global electricity; it is expected to consume 13% of the global electricity no sooner [12]

Power management and energy-saving techniques have been deployed to build energy-efficient data centers [13]. All these cutting-edge technologies come at the cost of huge expenditure, intensive labor, and excellent infrastructure. Most of the existing schemes overlook modeling clean energy resources (e.g., solar and wind). Renewable energy resources [14] can bring a panacea in this situation. Researchers claim that photovoltaic cells can produce up to 1.5 MW power [15]. Brown energy resources give the way to green energy resources, which further boost energy efficiency of future data centers.

Global carbon footprint

Carbon dioxide is one of the principal greenhouse gasses that causes the rise in the earth's average temperature [16]. To mitigate excessive carbon emission, engineers ought to cap the carbon emission of the data centers. Data centers are estimated to produce the fastest-growing carbon footprint [17]. Data centers are responsible for 2% of the global carbon footprint [18], and the growth is expanding. Reports claim that data centers can produce carbon dioxide of 171,630 kg [19]. Now the question arises, how do data centers produce such a hefty amount of co_2. Electric grids burn a hefty amount of brown energy resources to meet the never-ending power needs of the data centers [20]. This tremendous power consumption leads to increased emission of greenhouse gasses, especially Carbon Di Oxide causing an increase in the earth's average temperature by1.5 to 2 degrees [21].

Although a carbon tax has been imposed on the data centers to cap the carbon footprint [3], such a tax does not help the overall situation. The curve in the rapid growth of carbon dioxide ever since the industrial revolution has been steep [21]. Today parallel and cloud computing powered by virtualization has proved to be effective in capping the carbon footprint of data centers [22]. Using green energy to curb the carbon footprint is an optimum solution. It is evident that green slots reduce carbon footprint by 39% [23]. Alongside, smart grids are furnishing a green revolution for the future data centers managing their carbon footprint [24]. Therefore, green computing is expected to bring forth much-needed positive environmental changes.

Global sustainability

Fastest-growing data centers and IT industry causes impose a financial burden accompanied by environmental degradation [25]. Today the total energy cost of operating data centers is approaching $14 billion a year; such a high cost is going to be $50 billion per year in the recent future by 2020 [26]. Total cooling cost is estimated to be around $7 billion according to the reports [27]. An array of models predicts that data centers would swallow 10 percent more energy every year, thereby generating massive e-waste and greenhouse gasses. Energy resources of data centers are significantly dependent on brown energy resources such as coal and natural gas. Therefore, it is evident that by 2030, the natural resources for non-renewable energy will deplete causing an environmental dis-balance [28]. Now coming to heat dissipation, data centers are the cause of massive heat emission [29]. Apart from wasting billions of dollars in meeting the energy demand, data centers are one of the true factors behind climate change [30]. Due to the increase in atmospheric greenhouse gasses, the global temperature has increased 1.5 to 2.5 degrees [31]. This global warming results in ice melting at the poles leading to devastation.

To battle with this evil, google and yahoo have incorporated evaporative cooling techniques [32]. Governments are focusing on green energy deals to save the climate. We are shifting our focus from traditional data centers to zero-carbon data centers. Companies like Google are trying to make 100% carbon–neutral arrangements [33]. It is prudent to adopt clean energy to fulfill the energy demand of data centers. These clean energy resources intend to mitigate financial burden, to cut back carbon footprint, and most importantly, to ensure sustainability of the earth.

Our contributions

It is evident that world needs to focus on reducing the carbon emission to prevent the damage in sustainability. Extensive technologies such as workload consolidation and virtual machines (VM) migration, geographical load balancing are capable of mitigating the carbon emission issue of data centers at high cost. Leading-edge solutions like workload scheduling and power management lack efficiency standards and quality of services [34]. The globe needs easy, simple, reliable, and affordable solutions to handle the surge in carbon footprint and energy consumption. To deal with this challenging situation, we come up with a carbon footprint model to curtail carbon emission from data centers by predicting carbon footprint.

The primary contribution of the paper is detecting the flaws in the current green data center and providing the solution to overcome this situation. To execute our plan, we initially investigate the power consumption and carbon footprint of a green data center. We deliberately show that though green data centers claim they are zero-carbon data centers, eventually that is a myth. We also assert that though this data center mostly relies on green energy resources, the carbon footprint from the brown energy resources is significantly high. During peak hours, these data centers still use a massive amount of brown energy resources to meet their never-ending power demand. Also, this data center uses nuclear energy as a significant energy resource; but the nuclear waste from this data center can cause a severe threat to sustainability. Therefore, it is prudent to optimize the energy resources to cap the carbon footprint from this data center. Our model serves this purpose by effectively reducing the carbon emission from the data center while meeting its power demand. We summarize the overall contributions in this paper as follows.

We investigate and detect the flaws in green data centers.
We extend our carbon footprint calculator (see sec3.3) of the data center powered by heterogeneous energy resources to measure carbon footprint and nuclear footprint of the data center.
We display the yearly and daily energy usage trend and carbon footprint graph for the data center. We also specify the diversity of heterogeneous energy resources used in this data center.
We optimize the energy resources and their usage to limit the CO2 emission from the green data center.
Through series of evaluations, we prove the efficiency and accuracy of our model in terms of capping carbon emission from the data center.

Background of carbon capping

To maintain the ecological balance, engineers and researchers have come up with several power consumption and CO2 production models customized for data centers. This section presents the background of energy-efficient computing that brings solidarity and uniqueness to our research.

Capping carbon footprints from data centers

To control power usage effectiveness or PUE, the IBM management and management technology (MMT) is very effective in scanning the power usage of a data center [35]. Once we aim toward energy efficiency, we set a step ahead in reducing the carbon footprint. Today, green computing has opened a new horizon for the energy-efficient computing community to cap carbon dioxide elimination from data centers. Researchers delve into the development of novel technologies like virtualization, live VM migration, geographical load balancing, scheduling policies, and to name just a few. Virtualization by consuming less energy and creating negligible e-waste contributes toward reducing the carbon footprint from data centers [36]. Renewable energy-aware workload allocation algorithm to cap carbon footprint of the data center is claimed to be efficient [37]. Unlike the above techniques, our solution has its root in power modeling in a way to reduce the carbon emission from data centers by efficiently substituting green energy for brown energy resources while meeting data centers' energy requirements.

Power consumption of data center

Electric grids are a significant power resource of data centers. These electric grids are a huge consumer of brown energy (e.g., coal, hard coal, and petroleum). The data center architecture is very difficult decipher [38]. Power engineers use feature extraction, a very common technique to model the energy optimization of data centers [39]. Measuring the raw power consumption through hardware and software has been intrinsic research toward power optimization [40]. Current data centers depend on PDUs to optimize energy efficiency because these techniques are less portable [41]. Although PDUs are extremely efficient, the expensiveness and scalability issue of PDUs prevent the wide adoption of this approach. Hardware performance counters (HPC) today are ubiquitous in data centers for measuring power consumption as well as predicting energy consumption [42]. Along with these, CPU power dissipation with free cooling, clock gating or using split plane power, scientists are dealing up with the massive energy consumption of the data centers [43]. Energy-efficient cloud management and energy-efficient resource allocation have also grabbed eyes in terms of energy conservation in a data center [44]. Prior efforts have put forward several models derived from data gleaned by HPCs, but in some cases, such data are misleading and the error rate shows flaws in HPCs [45]

Power modeling

Data centers comprise a variety of components, the energy consumption models of which are summarized in this subsection. Servers are very an essential piece in a data center as the servers correspond to significant load requirements. Hence, constructing a power model for servers is crucial in reducing the total energy consumption of data centers. Server power models depend on other collaborating components. Roy et al. devised a simple yet elegant server power model, which is a summation of the load consumption of

CPU and memory [46]. Lewis et al. developed a server power-consumption model as a function of the total energy consumed by processor, memory, DD-RAM, SD-RAM, the semiconductor chips, and hard disks [47]. Apart from that, Orangerie et al. orchestrated server energy as a function of the energy consumption of system boot and system halt [48]; Li et al. constructed a power model as a function of energy consumed by active virtual machines running on servers [49].

Cooling is crucial in data centers to dispose of heat generated by the high power consumption in the server [50]. Cooling consumes approximately 50% energy of a standard data center; hence, it is imperative to model cooling energy consumption as well as maintain the quality of service or QoS [51]. Starting from the cooling fans, over the positioning of cool air into the system causes power inefficiencies [13]. To address this issue, a simple cooling power model came up to express fan power consumption as a function of the temperature of the air outside a data center and hot air exhaled by IT racks in the data center [52]. Other models capture cooling power consumption as a function of the fan speed of CRAH systems and the idle and dynamic power usage of CRAH units of data centers [53].

Machine learning techniques compel the researchers have investigated supervised and unsupervised learning models for power consumption in the data center. For instance, Beral et al. demonstrated a way of modeling expected processor and disk usage based on the M5P algorithm [54]. Khargharia et al. applied a decision tree to map a power-consumption model with current system behavior [55]. Dhiman et al. piloted a GMM-based approach for power prediction following an unsupervised learning method with an error below 10% [56]. Reinforcement learning enables power managers to dynamically create new power control policies during the run-time from information gathered via RL [57]. Moreno et al. developed a MLP-based neural network to predict power from clients' historical data [58]. Recently, *iOverbook*—an autonomous, online, and intelligent overbooking strategy—has drawn attention in the field of power modeling [59]. After analyzing the time and space complexities, Li et al. proposed an embedded software power model by the virtue of the backpropagation artificial neural network (B-ANN) [60]. Recent technology development has given birth to Data Center Energy-Efficient Resource Scheduling (DCEERS), Green Cloud, Elastic Tree, and DENS [61]. Intelligent Transportation Cloud Data Center [62], VM allocation algorithms for IoT platforms [63], auto-scaling energy-efficient VM migration [64] or dynamic workload placement [65] are current trends in capping the surge in energy consumption of the data centers.

All the aforementioned models have significantly contributed to reducing the power consumption of data centers from the perspectives of cooling and server power consumption. But no technology is a complete solution to the overall problem. Each of these models, technological developments have their flaws. Therefore, it is very complex to do a combination and permutation of all these energy-efficient technologies while running a complex data center. Therefore, it remains an open issue to the model power consumption of data centers powered by a diversity of energy resources. To fill this technological gap, we propose a power-consumption model for modern data centers that are powered by a mixture of green and brown energy to reduce the cost and carbon footprint.

System overview

In the beginning, we design a data center framework to understand the underpinning architecture of a data center. Section 3.1 defines the overall structure of a data center.

In what follows, we outline the system architecture in Sect. 3.1. In Sect. 3.2, we discuss the methodology applied to the development of the model.

System architecture

Figure 1 describes the framework of a medium-scale green *data center*, which compromises a large number of components like physical nodes, UPS, Battery, chillers, and other heterogeneous energy resources. We elaborate on each of these components below.

- *Nodes*: Computational resources draw significant energy from data centers to provide high-performance computing and storage capacity.
- *UPS*: UPS offers an uninterrupted power supply.

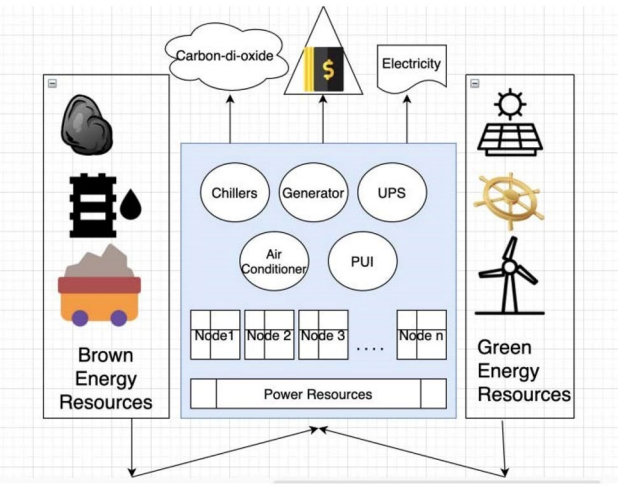


Fig. 1 The framework orchestrates a diversity of green and brown energy sources to maximize the energy efficiency of data centers

- *Air Conditioner*: Air conditioning systems are deployed to cool down the data centers.
- *Chillers*: Chillers are also used to cool down data centers with chilled water.
- *Cooling Tower*: Cooling towers work as a great source of cooling for data centers.
- *Generator*: Generators produce power from green and brown energies.
- *Battery*: Batteries facilitate energy storage for data centers.

More often than not, data centers consume a massive amount of energy from brown energy resources (see, for example, Coal and Petroleum at the left of Fig. 1), thereby releasing an enormous amount of heat and greenhouse gasses in the air to cause a major adverse impact on the environment. Recent evidence confirms that data centers consume energy as large as that of 25,000 households and 100 to 200 times of electricity consumed by standard office space[66]. This high brown energy consumption threatens the sustainability due to a massive carbon emission from this data center. The high energy cost can be curtailed by deploying green energy like solar and wind (see the green energy box at the right of Fig. 1). On the other hand, green energy causes no significant threat to the environment. Plus, green energy can be cost-effective as well while ensuring the energy supply for the data centers.

Instead of using massive coal, petroleum and fossil fuel energy, we advocate for green-energy-enabled data centers powered by solar, nuclear, wind, and hydro-energy to optimize the hefty energy demand and diminish the operational cost of the data centers. Clean energy not only reduces energy costs but also fulfills the UN sustainability goals by lowering greenhouse gas emissions in the air thus ensuring sustainability of the world [67]. Our dataset shows that solar, wind, nuclear and hydro-energies are notable sources of energy to eliminate brown energy usage. The data center in our system architecture makes use of the plenty of solar energy available during day time as a source of power while charging the UPS to use batteries during nighttime. Also, the energy from the turbine and wind can supply power demand to the data centers at night, thereby meeting the energy demand of the data center at night. Nuclear energy is employed as a backup plan. Though nuclear energy produces significantly less carbon dioxide (0.0264555 lb co2 from 12gm/kWh nuclear energy) but comes up with high amount of radioactive rays causing severity to the eco-system and mankind [68]. It is arguably true that the usage of green energy leads to the sustainability of future data centers.

Methodology

While designing a model to cap carbon emission from the data center, our second initiative is defining a creative methodology to experiment. To initialize in a methodical approach, we investigate the popular modeling approaches to obtain a rich dataset of energy usage per hour. We decided that we are not going to make a prediction with our model. Instead, we try to design a model that will prove to reduce the carbon dioxide emission from the data center in future. After harnessing the dataset, we portray the energy usage in graphical forms to come up with a clear picture of a data center's energy consumption and carbon footprint at any particular time of the day. This analysis strategy helps us in building a theoretical underpinning of our model. In what follows, we articulate our research methodology.

- **A pilot study.** Initially, we graphically plot the energy, power consumption and carbon emission trend from the data center. We categorically portray these graphical trends to illustrate the difference of energy and power usage along with carbon emission during each month, weekday and weekend, and each day.
- **Regression.** After a thorough analysis, we decide to implement linear, polynomial and lasso regression to predict a model for reducing the carbon footprint from the data center. We also determine to evaluate the efficiency and efficacy of our model in terms of their comparative study.
- **Other models** Finally, we would propose how can we bring panacea in this scenario and design the energy equation that will lower the carbon footprint for the future data centers.

Nuclear estimator

To deal with the carbon footprint of the data centers, we need to know the carbon emission from the data center per hour. Since, we did not have the data of carbon footprint from this data center, we design our own carbon footprint calculator. This calculator determines the carbon footprint of a data center if we can plug in the energy values in this calculator as an input. Therefore, we initially searched for the amount of carbon emission from the brown and green energy resources per hour. Once we get the values, we tune them in the calculator to find the total carbon footprint generated by burning the brown and green energy resources per hour. We have mentioned the heterogeneous resources and their symbols used to determine the carbon footprint of the data center in Table 1.

Let $t = \{\alpha, \beta\}$ denote a set of energy types, in which α and β represent green energy and brown energy, respectively.

Table 1 Symbol and annotation

Symbol	Annotation
$\alpha 1$	Hydro-pump energy
$\alpha 2$	Solar energy
$\alpha 3$	Nuclear energy
$\alpha 4$	Wind energy
$\beta 5$	Coal energy
$\beta 6$	Biomass energy
$\beta 7$	Fossil gas
$\beta 8$	Oil energy
$\gamma 1$	Carbon footprint of green energy
$\gamma 2$	Carbon footprint of brown energy
δ	Total carbon footprint
δ	Green energy
δ	Brown energy

The calculator presented in Algorithm 1 measures carbon footprint according to a given energy type in set t.

Algorithm 1: Carbon Footprint Calculator

```
Input  : α, β (KWh)
Output δ(lbph)
if α == α3 then
    return radioactive emission= 0.01 * α3
end
if t ==  α then
    return γ1= 0.04078552 * α1 + 0.110231 * α2 +
    0.0264555 * α3 + 0.0242508 * α4
end
else if t ==  β then
    return γ2 = 2.21 * β1 + (2 * 2.41) * β2 + 0.92 * β3 +
    2.11 * β4
end
δ = γ1 + γ2
```

Carbon footprint Calculator 1 detects the carbon footprint from both green and brown energy resources in a data center. Also, to modify the pre-existing carbon footprint calculators, we decide to add nuclear emission calculator. The data for carbon footprint for the brown energy resources are available at [69]. The amount of carbon footprint and nuclear emission(only for nuclear energy) generated from the green energy resources can be obtained from [70–73]. We do our little bit of calculations and play with these value and brought to a specific unit pound-per-hour(lbph). The nuclear emission is calculated in millirem per year. Then, we used simple arithmetic operations to find the amount of lbph of CO2 emissions per KWh burning of the different fuels. Though we include nuclear energy in this algorithm, one may opt for pruning the nuclear energy usage from the model. Nuclear energy resources contribute a very less carbon footprint, but such resources are highly radioactive. It is evident that nuclear energy's radioactivity causes cell damage, impotency, and cancer [74]. Because we are focusing on sustainability, we ensure that nuclear energy only plays a supporting role in our model. Also, it was initially considered that biomass is a zero-carbon energy resource [75]. Recent studies, however, indicate that burning biomass produces a carbon footprint double the amount of that produced by coal energy. For this reason, we treat biomass as brown energy in the model though it is traditionally classified as renewable energy [73].

Results and discussion

Data collection and data handling

Data collection for this research has been crucial in terms of reliability, authenticity and scalability. Although we explore a lot of information on energy efficiency, renewable energy usage, and power modeling of data centers, we could not accumulate a data center's public data on energy resources and energy usage. Fortunately, we have the detailed configuration of a data small-scale data center managed by Auburn University. We make use of the Auburn data center's configuration fed into the energy-consumption model [76] to estimate energy usage and energy resources. We opt for applying this model to project the energy usage of the Auburn data center because the model has been well validated in the literature. Thanks to our carbon footprint calculator, we could calculate the carbon emission from this data center per hour. After obtaining the panel dataset, we perform multiple machine-learning algorithms to exploit the entire scenario. We segmented the dataset into *yearly, weekday- weekend and heterogeneous* energy usage and carbon emission of the data center to proceed with the different aspects of our experiment.

Yearly energy consumption

Figure 2 orchestrates the brown and green energy usage of a data center per hour over one year. Figure 3 plots the carbon footprint of a data center per hour powered by brown and green energy resources. Figure 2 reveals that this data center uses a significant amount of green energy resources in this case(which is quite an exception). Though brown energy resource usage is quite elevated in Fig. 2, still we observe this data center uses more green energy in meeting the energy requirement. On a contrary, Fig. 3 indicates that even the less amount of brown energy usage in this data center produces much more carbon dioxide than that by the leading green energy resources. This reveals that the data center power usage needs an energy-intensive model to cap

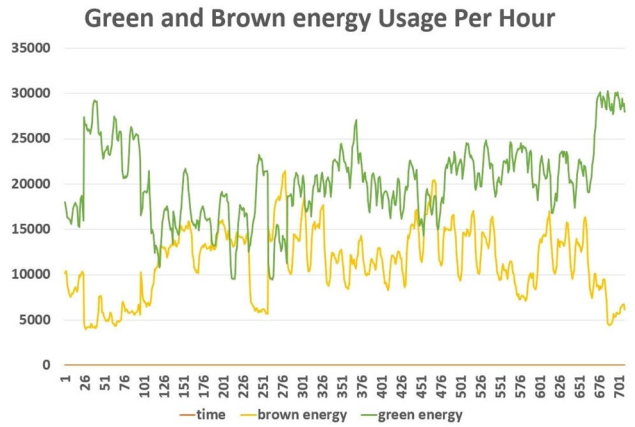


Fig. 2 This line chart defines the brown and green energy consumption of a data center per hour over a period of one year. The x-axis determines time in hour, where the y-axis denotes the energy usage in kwh. The maximum and minimum usage of brown energy resources in this figure is 22000 KWh and 3500 KWh, respectively, whereas the maximum and minimum green energy usage in this figure is 30000 KWh and 9500 KWh, respectively

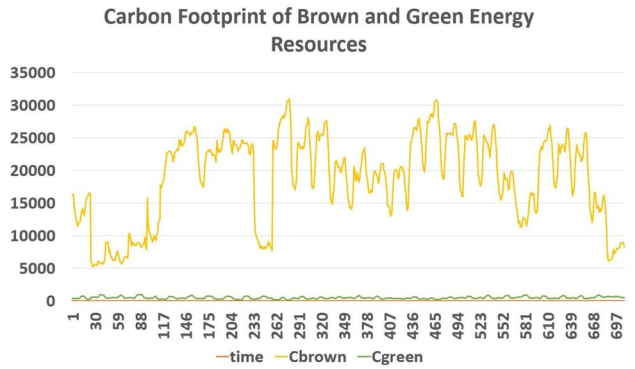


Fig. 3 This line chart defines the carbon footprint from a data center due to brown and green energy usage per hour over a period of one year. The x-axis determines time in hour, where the y-axis denotes the carbon footprint in pound per hour (lbph). The maximum and minimum carbon dioxide emission from brown energy resources in this figure is 32000 lbph and 5000 lbph, respectively, whereas the maximum and minimum carbon footprint from green energy usage in this fig is around 100 lbph and 26 lbph, respectively. Here, Cbrown and Cgreen represent carbon footprint of brown and green energy resources, respectively

its carbon footprint. To reduce the carbon emission from this data center, the energy resources must be carefully investigated and designed.

Figure 4 depicts the energy consumption cost of a data center per hour over a year. Figures 5 and 6 orchestrate the brown energy and green energy consumption of the data center per hour over a year. Figures 4 and 5 have a strong correlation. These two figures are related proportionally to each other. We notice, whenever there is a surge in energy demand and brown energy consumption increases, the cost

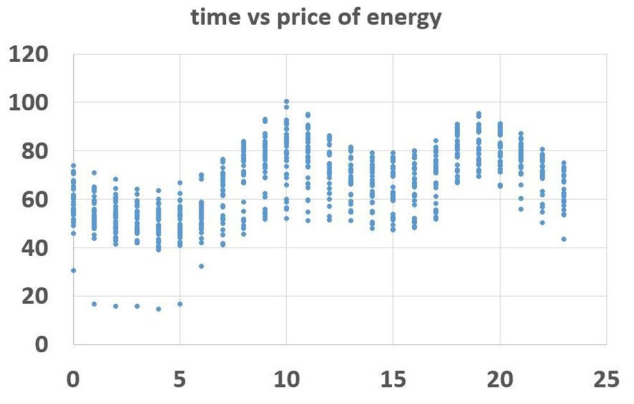


Fig. 4 The scatter plot defines the relationship between time and price of the energy consumption. The x-axis determines time in hour, where the y-axis denotes the cost of the energy usage per hour in dollar. The maximum cost in this figure is around dollar 100 per hour, whereas the minimum cost is around dollar 19 per hour

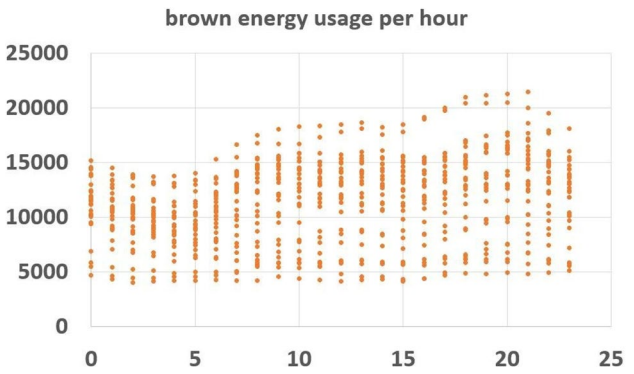


Fig. 5 This scatter plot defines the brown energy usage per hour in a data center over a period of one year. The x-axis determines time in hour, where the y-axis denotes the energy usage in kwh

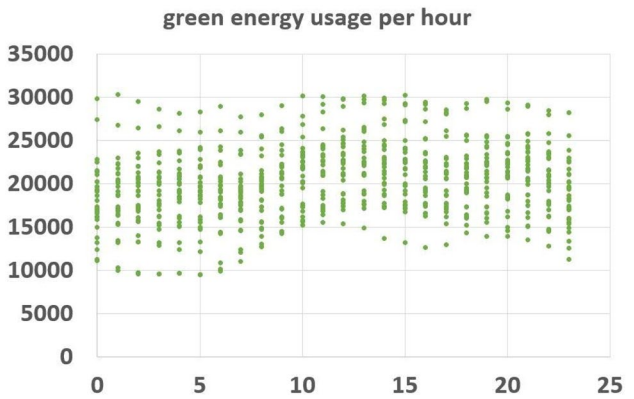


Fig. 6 This image defines the brown energy usage per hour in a data center over a period of one year. The x axis determines time in hour, where the y axis denotes the energy usage in kwh.

of energy consumption per hour also increases. For example, during the peak hours, from 10 AM to 8 PM, the cost and the brown energy usage are at their peak. Since, renewable energy resources (solar, wind, hydro-energy, etc.) are gifts of nature, they do not cost any significant amount(except nuclear energy). Therefore, we can conclude that excessive usage of brown energy solemnly increases the cost as well as the carbon footprint of the data center significantly. To deal with this situation, one needs to build a carbon footprint model comprising significant green energy resources and minimalist brown energy resources. This model can reduce power usage, increase cost efficiency and most importantly cap the

In this section, we portray the energy consumption and carbon footprint of the data center over the weekdays and weekends.

Figures 7, 8, 9 detail the energy consumption of the data center over the weekend. This scatter plot portrays that the data center uses significantly more green energy resources to meet the never energy demand. Since the total energy consumption on weekends is less, the data center uses less brown energy resources to reduce the carbon footprint. Figure 9 orchestrates the carbon footprint of the data center over the weekend. This scatterplot signifies that even less brown energy usage on the weekends could not impact the carbon emission much.

Figure 8 details the energy consumption of the data center on the weekdays. This scatter plot portrays that the data center uses significantly more brown energy resources to meet the ever-surging energy demand. Since the total

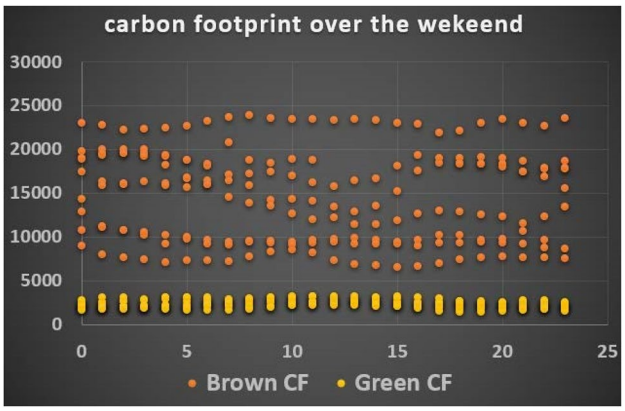


Fig. 7 The scatter plot defines the carbon footprint from brown and green energy usage over the weekend. The x-axis determines time in hour, where the y-axis denotes the carbon footprint in lbph. The maximum and minimum usage of carbon footprint from brown energy resources in this figure is 23000 lbh and 4000 lbph, respectively, whereas the maximum and minimum carbon footprint from green energy usage in this figure is 200 lbph and 11 lbph, respectively. Here, Cbrown and Cgreen represent carbon footprint of brown and green energy resources, respectively

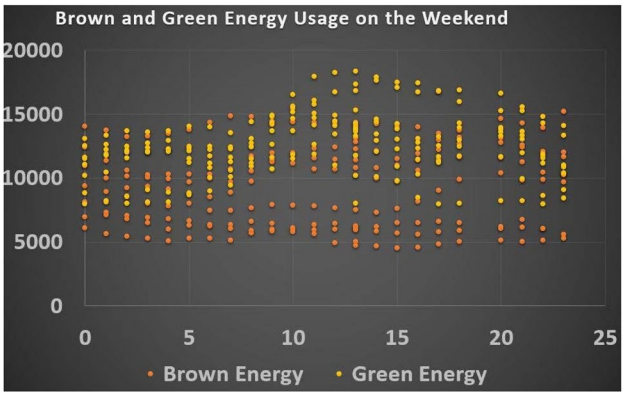


Fig. 8 The scatter plot defines the brown and green energy usage over the weekends. The x-axis determines time in hour, where the y-axis denotes the energy usage in kwh. The maximum and minimum usage of brown energy resources in this figure is 15000 KWh and 4000 KWh, respectively, whereas the maximum and minimum green energy usage in this fig is 18000 KWh and 9000 KWh, respectively

energy consumption on the weekdays is more, the data center uses more brown energy resources and less green energy resources to fulfill the energy requirement of the data center. This massive brown energy usage due to peak data traffic leads to an increase in carbon footprint significantly. Figure 10 portrays the surge in carbon emission due to the huge consumption of brown energy resources.

In terms of energy cost, the data center ends up paying more dollars on weekdays than weekends. Figure 11 portrays that weekend energy consumption cost is far less than that on the weekdays. On the same note, we observe that the amount of brown energy usage is significantly high to meet the power requirement of the data center. This indicates that the massive carbon footprint from the data center is not only

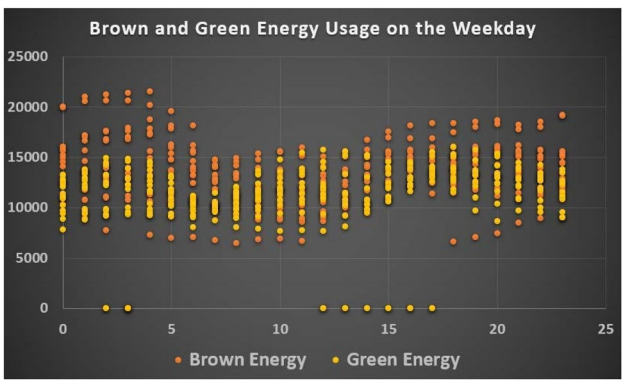


Fig. 9 The scatter plot defines the brown and green energy usage over the weekdays. The x-axis determines time in hour, where the y-axis denotes the energy usage in kwh. The maximum and minimum usage of brown energy resources in this figure is 23000 KWh and 8000 KWh, respectively, whereas the maximum and minimum green energy usage in this fig is 15000 KWh and 400 KWh, respectively

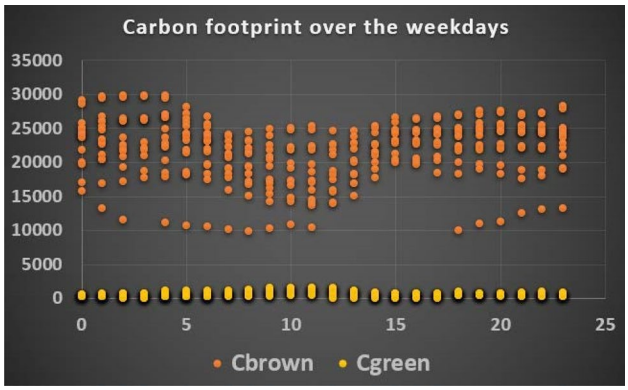


Fig. 10 The scatter plot defines the carbon footprint from brown and green energy usage over the weekend. The x-axis determines time in hour, where the y-axis denotes the carbon footprint in lbph. The maximum and minimum usage of carbon footprint from brown energy resources in this figure is 32000 lbph and 11,000 lbph, respectively, whereas the maximum and minimum carbon footprint from green energy usage in this figure is 167 lbph and 98 lbph, respectively. Here, Cbrown and Cgreen represent carbon footprint of brown and green energy resources, respectively

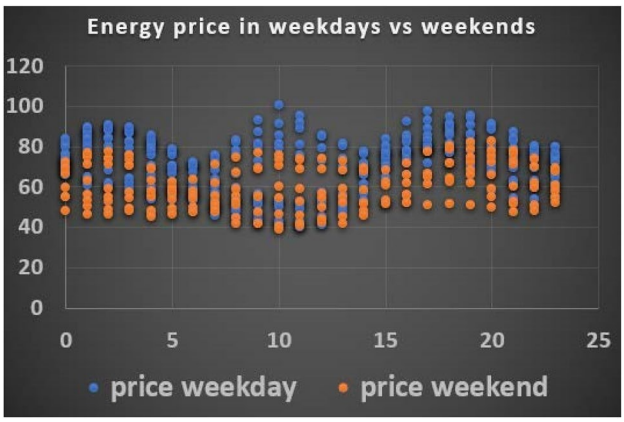


Fig. 11 The scatter plot defines the energy cost over the weekend and weekdays. The maximum energy cost on a weekday is dollar 110 during 10 AM to 3 PM and that during a weekend is dollar 75

significant damage due to brown energy usage, but ends up spending billions of dollars to buy those energy resources. Therefore, it is evident that this data center needs an efficient carbon footprint model that will cut down brown energy resources significantly while using more clean energy.

Heterogeneous energy resources

Figures 12 and 13 show the histogram of brown and green energy consumption of our data center. This histograms plot the frequency of brown and green energy usage. Figures 12 and 13 advocate that the frequency of high green energy consumption is evident in this data center.

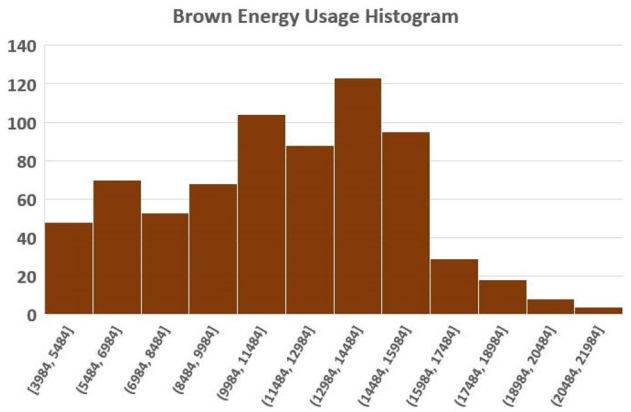


Fig. 12 The histogram details the brown energy consumption of our data center. The x-axis represents the amount of energy usage in KWh, and the y-axis represents the frequency of the energy consumption. The highest frequency (120) of brown energy lies between 12,984 and 14,484 KWh

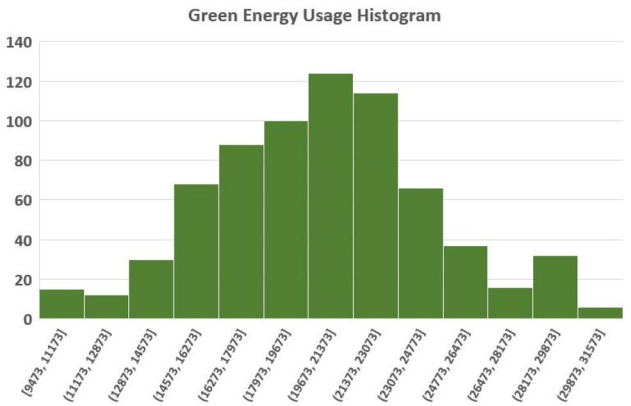


Fig. 13 The histogram details the green energy consumption of our data center. The x-axis represents the amount of energy usage in KWh, and the y-axis represents the frequency of the energy consumption. The highest frequency (120) of green energy lies between 19,673 and 23,373 KWh

Figure 14 depicts the details of various brown energy resources used to meet the power requirement of the data center. This image describes that hard coal and oil are significant sources of powering the data center, whereas biomass and coal also contribute to the carbon footprint of the data center. We describe, how hard coal and oil produce massive carbon footprint with regard to other brown energy resources like coal, biomass, etc. (see Sect. 3.3).

Figure 15 depicts the details of various green energy resources used to meet the power requirement of the data center. This image describes that wind, nuclear, and water reservoirs are the significant green energy resources to power the data center. Whereas solar, hydro-pumps, waste, and rivers also contribute to the energy supply of the data center. We describe, how nuclear energy produces

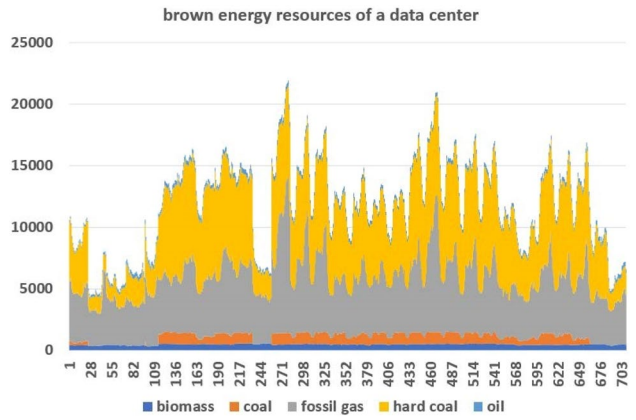


Fig. 14 This 2D chart depicts the various brown energy resource usage in a data center. Among all the other energy resources, hard coal and oil contribute to the maximum energy supply for the data center. Here, y-axis represents energy usage in KWh for various brown energy resources

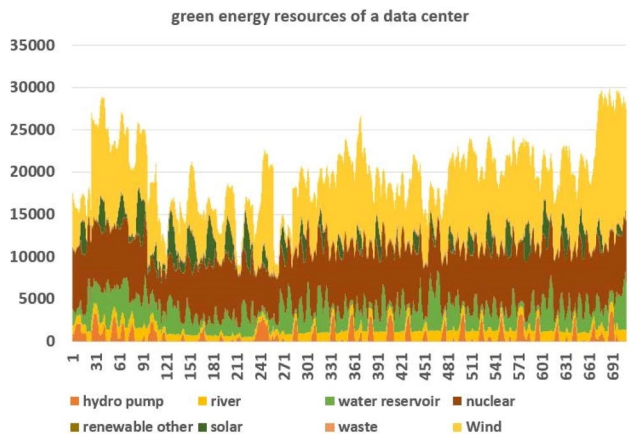


Fig. 15 This 2D chart depicts the various brown energy resource usage in a data center. Among all the other energy resources, hard coal and oil contribute to the maximum energy supply for the data center. Here, y-axis represents energy usage in KWh for various brown energy resources

radioactive emissions causing damage to mankind and animals (see Sect. 3.3). This signifies that the power source of brown energy needs to be designed properly to reduce the carbon emission and nuclear emissions from the data center.

Figure 16 represents the carbon footprint of the data center intrinsically. This line chart depicts that the rise in the total carbon footprint of the data center is solely due to the carbon footprint of brown energy resources over time. If we carefully investigate Fig. 16, we will find that the carbon footprint of the green energy resource is significantly less than that of the brown energy resources. Despite focusing on more green energy usage, this data center fails to cap the carbon dioxide emission from it. Therefore, this gives

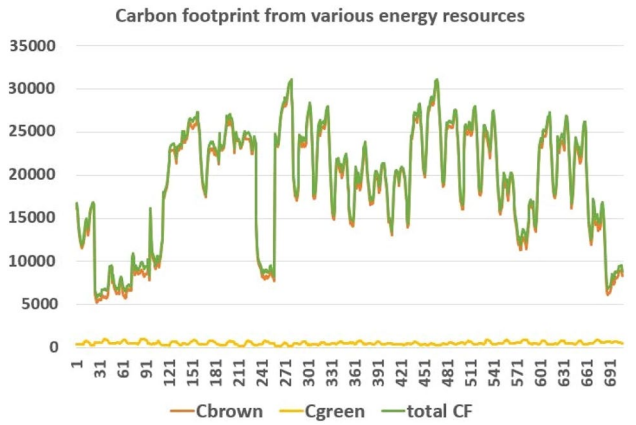


Fig. 16 The line chart plots the carbon footprint trend from brown and green energy along with the total carbon footprint. The Y-axis represents the carbon emission per hour in lbh. This chart signifies that though the overall brown energy usage is lesser than green energy resources, the carbon footprint of brown energy exceeds the carbon footprint of green energy. Thus, total carbon footprint also increases significantly. Here, Cbrown and Cgreen represent the carbon footprint of brown and green energy; whereas total CF represents the total carbon footprint of the data center

us a strong motivation to build an efficient carbon footprint model that will lower the carbon emission intensity from this data center.

Modeling energy usage

In our prior study reported in [5], we developed a power model to predict the power usage of a data center. This paper focused on the prediction accuracy of the algorithm in determining the future power consumption of the data center. But our current paper centers around capping the carbon footprint from a data center.

The aim of this paper is to build a model using maximum green energy resources. Also, our model should cap maximum carbon footprint from this data center. To provide a model for capping carbon footprint, we apply three different regression models, i.e., linear regression, polynomial regression, and lasso regression. These three models predict the carbon footprint of the green data center using the same energy resources but based on different statistical parameters. Turns out, all these three statistical models work fine to predict the carbon footprint of the data center. But here, we do not focus on prediction accuracy and efficacy. Rather our goal here is to determine the model that caps maximum carbon footprint from this data center. We plot the graph of actual and predicted carbon footprint from these models to determine the best model for capping carbon footprint for the green data centers. The best model from this graph (see 17) will provide an important measure for the network and

power engineers in reducing carbon dioxide emissions by just plugging in the energy values.

To do a pilot study, we initialized our experiment by checking the flaws of the data. After a quick reshaping and removing the skewness of the data, we start our experiment. We decide to proceed further in the following way:

- Initially, we decide to plot the dataset and find the relationship among each of the attributes. This gave us an idea of selecting the modeling strategy.
- Next, we split the dataset into random training and testing dataset. We finalize linear, polynomial, and lasso regression strategies to create the carbon footprint model for the data centers.
- Later, we decide to evaluate these models based on R squared value, p value, and other decision parameters.
- To understand the importance of each model, we came up with model plotting and thus decide the best model for capping the carbon footprint.
- Once figuring out the best possible modeling strategy, we design the carbon footprint reduction model of the data center.

The model evaluation is done based on p value, R squared value, mean squared error adjusted R squared values. Also, we plot the relationship between each attributes of the panel dataset to provide readers with a detailed graphical view. Also, once we plot the actual vs predicted carbon footprint for each model. We provide the details on how and why we claim that the particular model is great for capping the carbon emission from the data center.

Initially, we decide to use three candidate modeling techniques: linear regression, polynomial regression and lasso regression to predict the carbon footprint for future. In this case, we try to incorporate as much green energy as possible. The reason behind incorporating more green energy is to reduce the energy price as well as the carbon emission from the data center. But to meet the power hunger during the peak hours the data center requires some brown energy resources. Therefore, we decide to include fossil gas as one of the brown energy resources for the carbon footprint model. Though fossil gas is a traditional energy resource, but it causes less carbon emission and provides high power with lesser amount. Once we build the models with linear, polynomial and lasso regression, we intend to evaluate our model efficiency in predicting the future carbon footprint for future. We decide to define the efficiency parameters of these three models via Table 2.

Table 2 denotes the evaluation parameters of three modeling techniques. In terms of significance (denoted by the p value), all the models reject null hypothesis and prove to be significant. The standard R squared value suggests that these models have goodness of fit.

Table 2 The residual standard evaluation parameters

Parameter	Linear	Polynomial	Lasso
P value	< 2.2e−16	< 2.2e−16	< 2.2e−16
R^2	0.8957	0.8964	0.8257
Adjusted R^2	0.8956	0.8962	0.8981
Residual SE	1927	1920	2032
Mean squared error	4887	5016	3971

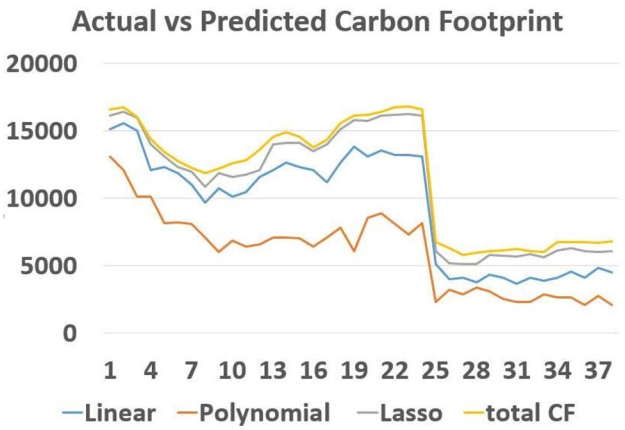


Fig. 17 This plot determines the relation between actual carbon footprint from the data center with predicted carbon footprint of the data center based on linear, polynomial and lasso regression model. The x-axis determines time, while the y-axis denotes the carbon footprint per hour

Error and mean squared error (MSE) suggest that lasso regression predicts the carbon footprint quite accurately, whereas linear regression and polynomial regression models have significant MSE. There lies the conflict. We can say that though lasso regression does a phenomenal job in predicting the carbon footprint accurately, the linear and polynomial model actually caps the carbon footprint of the data center. These two models of carbon footprint produce less carbon footprint and thus point toward sustainability. In other words, polynomial regression turns out to cap maximum carbon footprint from the data center than lasso regression and linear regression model. We have to always remember, here our aim is to build such a model that will reduce the current carbon footprint of this green data center for a better sustainable approach. Though in Fig. 17, the lasso regression has a high prediction accuracy, here we are more eager to see a model that will deplete the current carbon emission of this data center.

Figure 17 suggests that the polynomial regression is doing a phenomenal job in reducing the carbon footprint. The figure advocates that lasso regression is doing a phenomenal job in terms of prediction accuracy. But to cap the carbon footprint, we need to rely on linear and polynomial

regression. Now the question comes why we are saying both the linear and polynomial models are effective in terms of capping the carbon footprint. When we were modeling the carbon footprint of the data center, we introduced some linear parameters in the polynomial equation along with their second degree. This helped us in tuning the polynomial model to cap the carbon emission from the data center.

$$\begin{aligned} CarbonFootprint = & -2.291e+03 \times solar + 4.746e \\ & + 03 \times solar^2 + -1.069e + 04 \times wind \\ & + 2.2369e + 01 \times waste + -2.581e \\ & + 04 \times waterreservoir + -3.247e \\ & + 04 \times river + -2.763e + 04 \times river^2 \\ & + -2.753e + 00 \times hydropump \\ & + .240e + 00 \times fossilgas \end{aligned} \tag{1}$$

In Eq. 1, we have used mostly green energy resources. It is worth noting that, to reduce wastage and balancing sustainability, we incorporate waste energy in our equation. Including waste energy and eliminating nuclear energy in out carbon footprint equation makes the model efficient, sustainable and green. Also, Eq. 1 is incorporated only one brown energy resource which is fossil gas. It is worth depicting that burning small amount of fossil gas produces significantly large amount of energy while contributing to less carbon footprint; hence, adding a single brown energy resource in our research equation has produced a better, stable and efficient model to reduce carbon emission. Our experiment gives rise to two case studies. The case studies are mentioned in Sect. 6.

Case studies

While experimenting with carbon footprint capping from data centers we come across two significant case studies. These case studies are mentioned below:

- Weekend carbon footprint capping(see 6.1)
- Carbon capping during peak hours(see 6.2)

These two case studies are described in the following subsections.

Weekend carbon footprint capping

While experimenting with the data, we decide to evaluate our model on the weekday weekend data. Though for weekdays, the model fits perfectly and there is no exception, model evaluation for weekends depicts a different scenario.

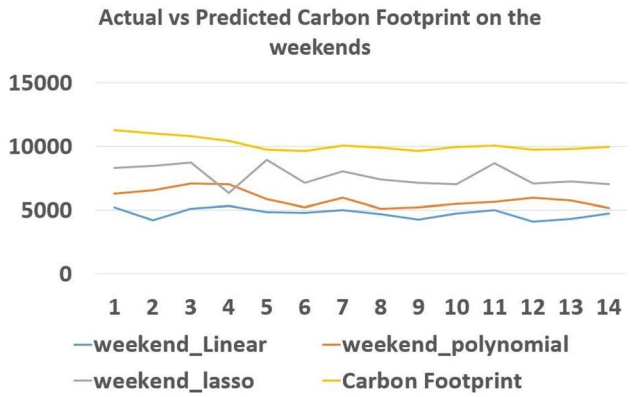


Fig. 18 This plot determines the relation between actual carbon footprint from the data center with predicted carbon footprint of the data center based on linear, polynomial and lasso regression model over the weekends. The x-axis determines time, while the y- axis denotes the carbon footprint per hour

Therefore, we feed the weekend data into three regression models and it turns out that the linear regression model caps maximum carbon footprint.

Figure 18 depicts the actual vs predicted carbon footprint over the weekends. Figure 18 reveals that the linear model works best in capping the carbon footprint of the data center over the weekends. This is probably because the data center power load over the weekends is significantly less. Limited brown energy usage over the weekends probably contributed to determining the best model to reduce carbon emission over the weekends. This result compels us to determine that along with our general carbon footprint model to limit the carbon footprint from the data center, we will look into more specific models in future research.

Carbon capping during peak hours

While analyzing the energy trend and carbon emission from the data center during peak hours, we realize, data centers burn massive brown energy resources during peak hours(see Sect. 4). Therefore, to meet the power demand during peak hours, we propose to store maximum green energy during non-peak hours. To store green energy resources, we may use various technical products like UPS(for solar energy), large above-ground tanks or in underground caverns (for wind energy), or pumped hydroelectric storage(for hydro-energy), etc. Modern technology today allows us to efficiently manage waste. We may think to use the waste energy efficiently to supply power during the peak hours for this data center.

Conclusion

In this study, we aim to construct a carbon footprint model to optimize the energy efficiency of green data centers. Thanks to the various modeling strategies, we propose a model to cap the carbon footprint of a green data center. More specifically, we updated our carbon footprint calculator with an effective algorithm to detect nuclear emissions from nuclear energy resources. Our intensive experiments demonstrate that our model is conducive to capping the carbon footprint of the data centers powered by brown and green energy. Our experimental results confirm that our model consistently declines carbon and nuclear emission from the data center.

As mentioned in the objectives(see Sect. 1), the main aim of this project was to limit massive brown energy usage of the data centers, capping the global carbon footprint, and make the data centers more sustainable. Our paper has produced a significant model that relies massively on clean energy resources that cause minimum carbon emission. Also, we focus on sustainability by not including nuclear energy as a power resource of this data center as it is still difficult to manage nuclear waste. Our nuclear and carbon footprint calculator is strong evidence that we are extremely dedicated to ensuring our mission and our objectives are properly maintained. Summarizing as a whole, we can claim that our paper ensures traditional energy usage reduction along with sustainability and carbon emission reduction.

As a future research direction, we intend to design statistical models at a micro-level. We want to develop an individual carbon footprint model for peak–non-peak hours of the day, weekend–weekdays, etc. In a second future direction, we want to explore the horizon of geographical load balancing strategy in capping power demand and carbon emission. Combining our carbon footprint model and the geographical load balancing will achieve superior efficiency, sustainability, and novelty in our research.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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