energies

Article

Towards Energy Efficient Cloud: A Green and Intelligent Migration of Traditional Energy Sources

Syed Muhammad Mohsin [1,2,*], Tahir Maqsood [3] and Sajjad Ahmad Madani [1]

1 Department of Computer Science, COMSATS University Islamabad, Islamabad 45550, Pakistan; madani@comsats.edu.pk
2 College of Intellectual Novitiates (COIN), Virtual University of Pakistan, Lahore 55150, Pakistan
3 Department of Computer Science, COMSATS University Islamabad, Lahore 55150, Pakistan; tmaqsood@cuilahore.edu.pk
* Correspondence: syedmmohsin9@yahoo.com

Abstract: Geographically distributed cloud data centers (DCs) consume enormous amounts of energy to meet the ever-increasing processing and storage demands of users. The brown energy generated using fossil fuels is expensive and significantly contributes to global warming. Considering the environmental impact caused by the high carbon emissions and relatively high energy cost of brown energy, we propose the integration of renewable energy sources (RES), especially solar and wind energy, with brown energy to power cloud data centers. In our earlier study, we addressed the intermittency of renewable energy sources, where we replaced the random initialization of artificial neural network (ANN) edge weights with the harmony search algorithm (HSA)-optimized assignment of weights. This study incorporated reliably forecast solar and wind energy into the input parameters of our proposed green energy manager (GEM), for cost minimization, carbon emission minimization, and better energy management of cloud DCs, to make our current study more reliable and trustworthy. Four power sources, on-site solar energy and wind energy, off-site solar energy and wind energy, energy stored in energy storage devices, and brown energy, were considered in this study and simulations were carried out for three different cases. The simulation results showed that case 1 (all brown) was 58% more expensive and caused 71% higher carbon emissions than case 2.1 (cost minimization). Case 1 (all brown) was 39% more expensive and had 80% higher carbon emissions than case 2.2 (carbon emission minimization). The simulation results justify the necessity and importance of the GEM, and finally the results proved that our proposed GEM is less expensive and more environmentally friendly.

Keywords: brown energy; renewable energy; cost optimization; carbon emission minimization; green energy manager

check for updates

Citation: Mohsin, S.M.; Maqsood, T.; Madani, S.A. Towards Energy Efficient Cloud: A Green and Intelligent Migration of Traditional Energy Sources. *Energies* **2024**, *17*, 2787. https://doi.org/10.3390/en17112787

Academic Editor: Silvano Vergura

Received: 9 April 2024
Revised: 28 May 2024
Accepted: 2 June 2024
Published: 6 June 2024

1. Introduction

Fulfillment of increased storage and computation demands from users has resulted in the rapid growth of cloud data centers (DCs), both in number and scale. This swift growth in cloud DCs has produced serious concerns about operational costs and environmental implications [1]. DCs consume more energy, which leads to higher operational costs and more carbon emissions [2]. The power consumption of cloud DCs was 200 TWh in 2016, and it is expected to grow to 2967 TWh by 2030 [3]. According to [4], the energy consumption of cloud data centers was 2% of worldwide electricity consumption in 2019 and it is expected to rise to 8% of worldwide electricity consumption by 2030. The report in [5] stated that a 40% energy saving for cloud servers would help save more than USD 3 billion annually. The same report went on to state that the increasing power consumption of US cloud DCs will require the installation of nearly 50 large power plants, which will generate about 150 million tons of carbon emissions annually.

Higher energy consumption leads to higher energy costs and carbon emissions. In this context, Barasso stated that the continuously increasing trend in energy consumption by cloud DCs will make the lifetime energy costs of DC servers higher than the equipment cost itself [6]. Google consumes more than 1120 GWh and Microsoft consumes more than 600 GWh, which costs USD 67 million/year and USD 36 million/year for Google and Microsoft, respectively [7]. Cloud service providers are controlling their electricity costs and carbon emissions through integration of RESs (green energy) with brown energy sources [8,9]. Google is already powering its DCs with up to 39.4%, while Yahoo is powering its DCs with up to 56.4% green energy [10]. Some cloud service providers have their own RESs (wind or solar energy plants), while others purchase green energy produced by RESs from renewable grids, installed at different locations in the form of solar parks and wind farms.

Brown energy generation, through fossil fuels such as crude oil, natural gas, and coal, leads to excessive carbon emissions, hence polluting the environment. The study in [11] stated that 100 MWh energy generation in the US produces 50 tons of carbon dioxide. The carbon emission rates (CER) of different energy sources are shown in Table 1, which indicates that the carbon emission rates of renewable energy sources are far lower than brown energy sources [12]. The report in [13], presented that about 80% of today's energy is brown energy and being produced using fossil fuels. Widespread use of fossil fuels is connected with global climate warnings [14]. To develop sustainable, cheaper, and environmentally friendly green computing systems, green energy produced by RESs should be employed as the primary power source, and the brown energy produced using fossil fuels should be employed as a secondary power source. Therefore, clean power generation technologies, such as the use of renewable energy, are seen as a crucial path to a low-carbon electricity economy that takes into account the balance between economic development and environmental concerns [15–17].

Table 1. Carbon emission rates (CER) of different energy sources.

Energy Source		CER (gCO_2e/KWh)
Brown energy	Coal	968
	Gas	440
	Oil	890
Renewable energy	Solar energy	53
	Wind energy	22.5
	Hydro	13.5
	Nuclear	15

Carbon emissions produced by burning fossil fuels for the sake of ever increasing demands for electricity have forced the international community to consider the global warming issue very seriously, and various policies have been formulated by countries to protect the natural environment. As per the Kyoto protocol [18], European Union (EU) countries are bound to decrease their emissions of greenhouse gases, especially carbon dioxide, for environmental protection, along with economic growth. Consequently, EU countries are focusing on renewable energy production, among other programs [19,20]. To meet the objective of a green world, a series of decisions and actions encompassing all walks of life are required. The climate summit in Madrid, Spain [21], presented "The European Green Deal" [22] to make EU a "zero emission" economy by 2050. Moreover, this strategy also directed a 50% reduction in emissions of carbon dioxide by 2030. EU policy of making a "zero emission" economy involves further research and development in the renewable energy sector [23–26].

In this context, electricity cost reduction and environmental sustainability are critical challenges for governments and the research community. Considering the long-term impacts of carbon emissions through power generating units, a few countries have imposed heavy taxes on carbon emissions [27,28]. Therefore, the research community has put huge research efforts into decreasing electricity costs and carbon emissions, especially those caused by the energy consumption of cloud DCs. Further research and development in solar and wind energy is underway. A study conducted by Fitch Solutions [29] stated that the additional solar power capacity is expected to rise by 125% globally during the coming decade and it will take a 6% share of global energy generation, whereas, according to Wood Mackenzie [30], the additional global wind power capacity from 2020 to 2029 will be 77 GW, on average.

The research community has considered the higher costs and excessive carbon emissions due to the use of brown energy in cloud DCs. Therefore, most researchers proposed the integration of renewable energy sources with brown energy. However, as shown in the Table 2, the intermittency of renewable energy sources is not considered in the literature, i.e., the main contribution of our research. Integrating RESs with brown energy helps in minimizing data center operating costs, reducing carbon emissions, overcoming energy imbalances, reducing the dependence on electricity reserves, improving equipment reliability, and better scheduling various energy sources. However, the intermittency of renewable energy sources is an important issue for effective and efficient grid management.

In our previous study in [31], we addressed the highly fluctuating nature of renewable energy sources (solar and wind energy) and proposed a harmony-search-algorithm-optimized artificial neural network (HSA-ANN) to deal with the intermittency of solar and wind energy sources. We replaced the random initialization of ANN edge weights with the HSA-optimized assignment of weights. This incorporated reliably forecast solar and wind energy into the input parameters of our proposed green energy manager (GEM) for cost minimization, carbon emission minimization, and better energy management of cloud DCs, to make our current study more reliable and trustworthy. The output of our previously proposed HSA-ANN model was used in this study as input to our proposed green energy manager (GEM) under the labels $SE^t_{on-site}$ (on-site solar energy), $WE^t_{on-site}$ (on-site wind energy), $SE^t_{off-site}$ (off-site solar energy), and $WE^t_{off-site}$ (off-site wind energy). The key contributions of our study are listed below.

- The issue of the efficient power management of cloud DCs is focused on for the sake of cloud DC cost optimization and reduction in carbon emissions.
- In reviewing the literature, we found that the intermittency of renewable energy sources is not taken into account when proposing the integration of renewable energy sources together with brown energy sources. Therefore, more reliably and accurately forecast solar and wind energy are provided at the input of our proposed green energy manager using the HSA-ANN model, which we presented in our previous study [31].
- The four power sources considered in this study are $GE_{on-site}$, $GE_{off-site}$, S_{esd}, and S_{be}. Where $GE_{on-site}$ represents on-site green energy, i.e., composed of on-site solar energy and wind energy, and $GE_{off-site}$ is off-site green energy that is also composed of off-site solar and wind energy sources. S_{esd} represents energy stored in energy storage devices (ESDs), and S_{be} refers to brown energy supplied by traditional fossil-fuel-based power generating units.
- Our proposed green energy manager manages the power consumption of cloud DCs in such a way that the cloud DCs are mostly powered by green energy (renewable energy sources). This minimizes the overall energy costs of the cloud DCs and the resulting carbon emissions.

The rest of this article is structured as follows. Section 2 presents the current state of the literature and system models are revealed in Section 3. The proposed system model is explained in Section 4, whereas the experimental setup and results are explained in Section 5. The graphical and numerical performance evaluation of our proposed model is discussed in Section 6, and, finally, Section 7 concludes the study with research findings and future research directions.

Table 2. Summary of various studies on cost and/or carbon minimization.

Paper	Energy Source(s)	ESDs	Implementation Strategy	Objective(s)	Limitation(s)
[1]	Solar, wind and brown energy	Yes	(1) Data center ranking (2) Request allocation through bin packing method (3) Cplex solver to schedule different energy types	Minimization of costs and carbon emissions	RES intermittency not considered
[2]	Solar, wind, and brown energy	Yes	A smart load allocation policy using RESs	Cost minimization	RES intermittency not considered
[10]	Solar, wind, and brown energy	Yes	(1) Server scheduling for maximum utilization of renewable energy (2) Cplex solver to schedule different energy types	Minimization of costs and carbon emissions	RES intermittency not considered
[32]	Brown energy	No	Efficient VM placement through crow search algorithm	Minimization of energy consumption	RES intermittency not considered
[33]	Brown energy	No	Minimization of active servers using ant colony optimization algorithm	Minimization of energy consumption	RES intermittency not considered
[34]	Solar, wind, and brown energy	No	Selection of best location for cloud data center	Minimization of costs and carbon emissions	RES intermittency not considered
[35]	Solar and brown energy	Yes	Single DC level batch scheduling of jobs based on availability of green energy	Cost minimization	RES intermittency not considered
[36]	Solar and brown energy	No	Linear fractional programming based algorithm and effective dynamic task distribution among DCs	Cost minimization	RES intermittency not considered
[37]	Solar, wind, and brown energy	No	Decomposed the whole problem into sub-problems and solved using Cplex solver	Minimization of carbon emissions	RES intermittency not considered
[38]	Solar and wind energy	Yes	DC management problem was divided into IT sub-problem and electrical sub-problem. A game theoretic algorithm was used	Balance between power demand and supply of DCs	RES intermittency not considered
[39]	Solar and wind energy	No	A case study on greenhouse gas effect on Egyptian energy system	Carbon emission minimization	RES intermittency not considered
[40]	Solar, wind, and brown energy	No	A green-aware online control algorithm	Minimization of costs and carbon emissions	RES intermittency not considered
Ours	Solar, wind, and brown energy	Yes	Green energy manager to schedule different types of energy	Minimization of costs and carbon emissions	Considered RES intermittency in [31]

Abbreviations: ESDs: energy storage devices, RES: renewable energy source.

2. Literature Review

Various solutions have been proposed to deal with the abovementioned financial and environmental challenges. By using energy trading and ESDs, a unique scheduling architecture was developed by the authors of [1] to make cloud data centers greener at a lower cost. The proposed green scheduler considers requests that require different resources, including the CPU, memory, disc, bandwidth, and execution time. The results of their study showed that energy trading with the power grid can further reduce both overall energy costs and carbon emissions. The authors of the research in [2] proposed EcoMultiCloud for cost-efficient load management of cloud DCs. They exploited brown energy, RESs, and ESDs for geographically distributed cloud DCs and concluded that, for the considered scenario, the proposed strategy was very well suited and flexible.

Focusing on the importance of energy costs, the authors of [32] implemented a crow search algorithm for efficient VM placement, to control the energy consumption of DCs. In another study in [33], minimization of energy consumption through minimization of active servers using an ant colony optimization algorithm was proposed. Both studies presented in [32,33] did not consider environmental implications and stated no solution for controlling carbon emissions, rather they completely relied upon brown energy. The authors of [34] proposed a strategy to find the best location for a data center to minimize energy consumption, energy costs, and carbon emissions. Although it was a good effort, primarily focusing on the objective of cost and carbon minimization, the data centers were placed too far from the users, which ultimately led to delays in the processing of user requests.

The intermittent nature of renewable energy sources is an important issue that adversely affects energy management. Researchers have explored various perspectives to deal with the issue. One perspective is to take advantage of geographically distributed DCs, and another is to act at a single data level. The authors of [35] focused on the management of a single DC through the processing of batch jobs with due date constraints. They proposed an online greedy algorithm named the attractiveness-based blind scheduling heuristic (ABBSH). Experimental results confirmed a 49% decrease in consumption of brown energy and 51% cost savings.

Yanwei, Z., et al. [36] proposed a dynamic task distribution algorithm on the basis of linear fractional programming. They proposed a middleware namely, GreenWare, for effective and efficient task distribution among various data centers, to meet the budgetary constraints of the user. They discussed the diurnal pattern of renewable energy sources. However, they did not consider ESDs, and the simulation results showed that the proposed GreenWare ensured maximum utilization of renewable energy to power DCs and to meet the budgetary constraints of the user.

The authors of [37] stated that the data centers of the same cloud service provider are always geographically distributed to cover most of a region and to provide better and fast services to the users. The electricity prices incurred to power these DCs fluctuate with time zones and geographic locations. They divided the overall problem of carbon emission minimization into sub-problems. The objective of the study was to minimize carbon emissions using renewable energy, while satisfying electricity cost constraints, the intermittent nature of RESs, and the maximum number of servers in DCs. The authors of [37] used both energy sources to power cloud data centers but did not discuss ESDs. Their experimental results showed that the proposed scheduler reduced carbon emissions through effective utilization of renewable energy to power the cloud data centers.

The overall data center management problem was divided into an IT sub-problem and electrical sub-problem in [38]. An efficient power compromise was achieved using an efficient negotiating game theoretic algorithm in their study. Negotiation between both sub-systems was performed through the proposed black-box approach and semi black-box approach. The results confirmed that the semi black-box approach was better for ensuring the quality of service, stability, and execution time compared to the black-box approach. The authors only used RESs with ESDs and ignored brown energy in their research.

A case study on the effects of greenhouse gases on the Egyptian energy system was presented in [39] to minimize carbon emissions. The authors only considered renewable energy as a power source and ignored energy storage devices in the study. The authors demonstrated significant effects on the Egyptian energy system through the proposed scheme. The authors of [40] reiterated the importance of green cloud data centers and proposed a green-aware online control algorithm (GAOA) to minimize carbon emissions and electricity costs, and to ensure service level agreement (SLA). The proposed GAOA helps find an optimal trade-off among electricity costs, SLAs, and carbon emissions. Considering multiple energy sources, the authors formulated the cost minimization problem as a constraint stochastic optimization problem. The effectiveness of GAOA was proven through extensive simulations on real-world data. Moreover, online and offline versions of the control algorithm were also discussed in the study.

The cited studies on cost minimization, electricity consumption control, and reduction in carbon emissions to curb their environmental implications are summarized in Table 2.

3. System Models

The mathematical problem formulation of the proposed solution was carried out under different system models, which are discussed in the following.

3.1. Energy Supply Model

In our proposed power setup model, we considered four main energy sources, solar energy (SE), wind energy (WE), energy stored in energy storage devices (S_{esd}), and brown energy (S_{be}). Solar and wind energy can be self-generated ($SE_{on-site}$ and $WE_{on-site}$, respectively) or purchased from off-site renewable (solar and wind) energy sources ($SE_{off-site}$ and $WE_{off-site}$, respectively). ESDs are used in the system to accommodate the intermittent nature of renewable energy supply, to smooth the power flow towards the load, i.e., cloud data centers in our case. ESDs are charged either by excessive solar/wind energy or by brown energy during low-tariff hours. The available power source(s) (P^t_{DC}) for cloud data centers are shown in following Equation (1).

$$P^t_{DC} = \{GE^t_{on-site}, GE^t_{off-site}, S^t_{esd}, S^t_{be}\} \tag{1}$$

where P^t_{DC} denotes the available power source(s) for a cloud data center at time t. $GE^t_{on-site}$ represents on-site green energy at time interval t, i.e., composed of solar and wind energy. Green energy bought from off-site green energy source(s) at time interval t is shown by $GE^t_{off-site}$, i.e., also composed of solar and wind energy, in our case. The power supply available from energy storage devices at time t is shown as S^t_{esd}, and S^t_{be} denotes the brown energy generated by fossil fuels at time interval t. Let GE^t represent both the solar and wind energy supply at time t (Equation (2)).

$$GE^t = SE^t + WE^t \tag{2}$$

Hence, we can simplify Equation (1) as shown in Equation (3) in the following.

$$P^t_{DC} = \{GE^t, S^t_{esd}, S^t_{be}\} \tag{3}$$

Let $SE^t_{on-site}(dc)$ denote the on-site solar energy required by a DC at time interval t and $SE^t_{on-site}(max)$ denote the maximum limit of the available on-site solar energy at time t. Then, the on-site solar energy requirements of any DC should be less than or equivalent to the maximum available on-site solar energy, as shown in Equation (4).

$$0 \leq SE^t_{on-site}(dc) \leq SE^t_{on-site}(max) \tag{4}$$

$WE^t_{on-site}(dc)$ denotes the on-site wind energy required by a DC at time t and $WE^t_{on-site}(max)$ denotes the maximum limit of the available on-site wind energy at time t.

Then, the on-site wind energy requirement of a DC should be less than or equivalent to the maximum available on-site wind energy, as shown in Equation (5).

$$0 \leq WE^{t}_{on-site}(dc) \leq WE^{t}_{on-site}(max) \tag{5}$$

The available on-site solar and wind energy can be used to power the DC and be stored in ESDs. Therefore, Equation (6) describes the total available on-site green energy.

$$GE^{t}_{on-site} = SE^{t}_{on-site} + WE^{t}_{on-site} + SE^{t}_{on-site}(esd) + WE^{t}_{on-site}(esd) \tag{6}$$

where $GE^{t}_{on-site}$ denotes the total available green energy produced by on-site solar and wind energy sources at time t, and $SE/WE^{t}_{on-site}(esd)$ shows the amount of on-site generated solar and/or wind energy stored in ESDs at time t for future use.

Let $SE^{t}_{off-site}(dc)$ denote the off-site solar energy required by a DC at time t and $SE^{t}_{off-site}(max)$ denote the maximum limit of the available off-site solar energy at time interval t. Then, off-site solar energy requirement of a DC should be less than or equivalent to the maximum available off-site solar energy, as shown in Equation (7).

$$0 \leq SE^{t}_{off-site}(dc) \leq SE^{t}_{off-site}(max) \tag{7}$$

$WE^{t}_{off-site}(dc)$ denotes the off-site wind energy required by a DC at time t and $WE^{t}_{off-site}(max)$ denotes the maximum limit of the available off-site wind energy at time t. The off-site wind energy requirement of a DC should be less than or equivalent to the maximum available off-site wind energy, as shown in Equation (8).

$$0 \leq WE^{t}_{off-site}(dc) \leq WE^{t}_{off-site}(max) \tag{8}$$

The available off-site solar and wind energy at time t can be used to power the DC and be stored in ESDs. This, Equation (9) describes the total available off-site green energy. Hence, the total off-site green energy can be calculated by Equation (9).

$$GE^{t}_{off-site} = SE^{t}_{off-site} + WE^{t}_{off-site} + SE^{t}_{off-site}(esd) + WE^{t}_{off-site}(esd) \tag{9}$$

where $GE^{t}_{off-site}$ denotes the total available green energy produced by off-site solar and wind energy sources at time t, and $SE/WE^{t}_{off-site}(esd)$ shows the amount of off-site solar and/or wind energy stored in ESDs at time t, for future use.

Therefore, the total available power for a cloud DC at time t (P^{t}_{DC}), including brown energy (S^{t}_{be}) and energy stored in energy storage devices (S^{t}_{esd}), in our case, can be described as shown in Equation (10).

$$P^{t}_{DC} = GE^{t}_{on-site} + GE^{t}_{off-site} + S^{t}_{esd} + S^{t}_{be} \tag{10}$$

3.2. Cloud Data Center Model

Each cloud service provider (CSP) has multiple geographically distributed data centers (DCs). In our case, $CSP = \{DC_1, DC_2, DC_3, DC_4\}$, where each DC has multiple servers in it to process the multiple incoming tasks. A DC having multiple servers is denoted as $DC = \{s_1, s_2, s_3, \ldots\ldots s_n\}$. The arriving tasks are assigned to the different servers of the data center. The set of tasks is denoted $\lambda = \{task^{t}_{1}, task^{t}_{2}, task^{t}_{3}, \ldots\ldots task^{t}_{n}\}$. The available power source(s) for a cloud data center is $P^{t}_{DC} = \{GE^{t}_{On-site}, GE^{t}_{Off-site}, S^{t}_{esd}, S^{t}_{be}\}$. The total task processing time $T = \{t_1, t_2, t_3, \ldots\ldots t_n\}$, and $task^{t}_{i}$ shows the arrival of task i at time interval t. Where task i is composed of bandwidth, memory, CPU, and disk requirements, which are different for each task and available at servers of DCs and $i \in \lambda$.

3.3. Cost Model

Data centers consume a large amount of energy, which is associated with corresponding costs. Each data center is powered by one or a combination of on-site green energy sources (solar and wind energy), off-site green energy sources (solar and wind energy), ESDs, and brown energy, as shown in the proposed system model. To calculate the energy cost for a cloud DC, we need to know the power consumption of each server in the DC and the power rate. We can calculate the power consumption of a server in a cloud data center using the following Equation (11), as mentioned in [41]. The different parameters of the considered cloud data centers are shown in Table 3 and the location-wise brown energy prices for each data center are shown in Figure 1. The green line shows the varying brown energy price at the CAPITAL site for cloud DC1, the blue line shows the brown energy price at the CENTRAL site for cloud DC2, the red line shows the brown energy price at the DUNWOOD site for cloud DC3, and the black line shows the brown energy price at the GENESE site for cloud DC4.

$$P_s = P_{min} + (P_{max} - P_{min}) * \mu \quad (11)$$

Table 3. Parameters of considered cloud data centers.

Data Center	# of Servers	# of CPUs	Memory (GB)	Disk Size (TB)	$P_{Min}(W)$	$P_{Max}(W)$
DC1	3300	8	128	2048	54	90
DC2	2800	16	144	2048	84	140
DC3	3200	8	128	2048	65	100
DC4	2500	16	144	2048	90	150

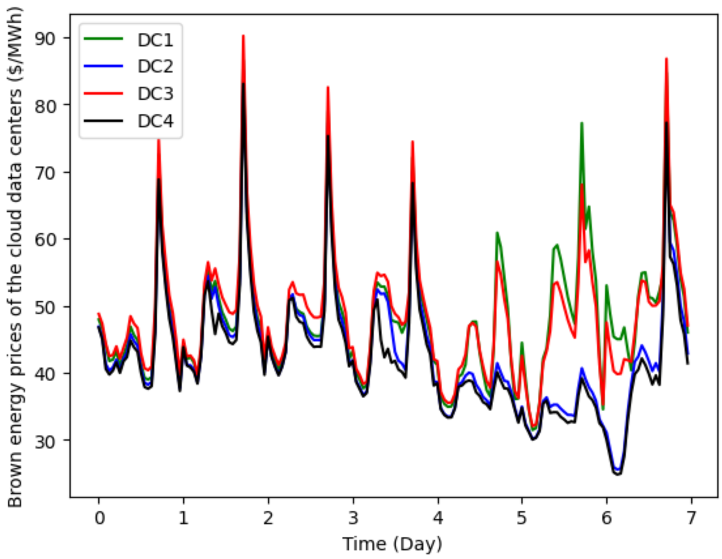


Figure 1. Location-wise brown energy prices for each DC.

Here, P_s denotes the power consumed by a server of the DC. P_{max} and P_{min} show peak load power consumption and idle state power consumption of the server, respectively. Where μ represents the CPU utilization.

Let $Cost^{total}_{GE(On-site)}$ denote the total cost of on-site green energy, $Cost^{total}_{esd}$ show the total cost of energy stored in energy storage devices, $Cost^{total}_{GE(Off-site)}$ represent the total cost of off-site green energy, and $Cost^{total}_{be}$ denote the total cost of brown energy. The energy cost of different sources can be calculated using Equations (12)–(15).

$$Cost^{total}_{GE(on-site)} = \sum_{i=1}^{n} P_{GE(on-site)}(DC,h) * Tariff_{GE(on-site)}(DC,h) \quad (12)$$

In Equation (12), $Cost^{total}_{GE(on-site)}$ represents the total energy cost incurred by usage of on-site green energy. $\sum_{i=1}^{n} P_{GE(on-site)}(DC, h)$ shows the combined on-site green energy consumed by all servers of a particular DC, whereas $Tariff_{GE(on-site)}(DC, h)$ denotes the respective hourly tariff for on-site green energy consumption.

$$Cost^{total}_{GE(off-site)} = \sum_{i=1}^{n} P_{GE(off-site)}(DC, h) * Tariff_{GE(off-site)}(DC, h) \tag{13}$$

$Cost^{total}_{GE(off-site)}$, in Equation (13), represents the total energy cost incurred from usage of off-site green energy. $\sum_{i=1}^{n} P_{GE(off-site)}(DC, h)$ shows the combined off-site green energy consumed by all servers of a particular DC, whereas $Tariff_{GE(off-site)}(DC, h)$ denotes the respective hourly tariff for off-site green energy consumption.

$$Cost^{total}_{esd} = \sum_{i=1}^{n} P_{esd}(DC, h) * Tariff_{esd}(DC, h) \tag{14}$$

In Equation (14), $Cost^{total}_{esd}$ represents the total energy cost incurred from usage of energy stored in ESDs. $\sum_{i=1}^{n} P_{esd}(DC, h)$ shows the combined ESDs power consumed by all servers of a particular DC, whereas $Tariff_{esd}(DC, h)$ denotes the respective hourly tariff for ESDs energy consumption.

$$Cost^{total}_{be} = \sum_{i=1}^{n} P_{be}(DC, h) * Tariff_{be}(DC, h) \tag{15}$$

$Cost^{total}_{be}$, in Equation (15), represents the total energy cost incurred by usage of brown energy. $\sum_{i=1}^{n} P_{be}(DC, h)$ shows the combined brown energy consumed by all servers of a particular DC, whereas $Tariff_{be}(DC, h)$ denotes the respective hourly tariff for brown energy consumption. The total energy cost of a particular cloud data center at time t can be calculated according to the following Equation (16).

$$Cost^{total}_{dc} = Cost^{total}_{GE(On-site)} + Cost^{total}_{GE(Off-site)} + Cost^{total}_{esd} + Cost^{total}_{be} \tag{16}$$

3.4. Carbon Emission Model

Green energy sources have a low CER, whereas brown energy sources, because of burning fossil fuels, have a higher CER. The total carbon emissions of a DC at time t, caused by DC energy consumption, can be calculated as per the following Equations (17)–(20).

$$CE^{t}_{GE(on-site)} = E_{rate} * SE^{t}_{On-site}(dc) + E_{rate} * WE^{t}_{On-site}(dc) \tag{17}$$

$$CE^{t}_{GE(off-site)} = E_{rate} * SE^{t}_{Off-site}(dc) + E_{rate} * WE^{t}_{Off-site}(dc) \tag{18}$$

$$CE^{t}_{be} = E_{rate} * S^{t}_{be} \tag{19}$$

$$CE^{total}_{DC} = CE^{t}_{GE(on-site)} + CE^{t}_{GE(off-site)} + CE^{t}_{be} \tag{20}$$

where CE^{total}_{DC} shows the total carbon emission of a DC from the consumption of energy from all sources at time t. Accumulative carbon emissions from on-site green energy sources, off-site green energy sources, and brown energy sources at time t are shown by $CE^{t}_{GE(on-site)}$, $CE^{t}_{GE(off-site)}$, and CE^{t}_{be}, respectively.

3.5. Objective Functions

A reduction in DC operating costs and the minimization of carbon emissions are the two primary objectives of greening cloud data centers. Both of objective functions are shown with the help of Equations (21) and (22). A list of symbols/abbreviations frequently used in system models is shown in Table 4.

$$min \sum_{task=1}^{n} . \sum_{s=1}^{n} Cost_{DC}^{total} \quad (21)$$

Subject to Equations (11)–(16)

$$min \sum_{task=1}^{n} . \sum_{s=1}^{n} CE_{DC}^{total} \quad (22)$$

Subject to Equations (17)–(20)

Table 4. List of symbols/abbreviations frequently used in system models.

Symbol	Description	Symbol	Description
SE	Solar energy	WE	Wind energy
S_{esd}	Energy stored in energy storage devices	S_{be}	Brown energy
$SE_{on-site}$	On-site solar energy	$WE_{on-site}$	On-site wind energy
$SE_{off-site}$	Off-site solar energy	$WE_{off-site}$	Off-site wind energy
$GE_{on-site}$	On-site green energy	$GE_{off-site}$	Off-site green energy
$SE_{on-site}^{t}(dc)$	On-site solar energy required by a cloud DC at time t	$WE_{on-site}^{t}(dc)$	On-site wind energy required by a cloud DC at time t
$SE_{off-site}^{t}(dc)$	Off-site solar energy required by a cloud DC at time t	$WE_{off-site}^{t}(dc)$	Off-site wind energy required by a cloud DC at time t
$SE_{on-site}^{t}(max)$	Maximum limit of the available on-site solar energy at time t	$WE_{on-site}^{t}(max)$	Maximum limit of the available on-site wind energy at time t
$SE_{off-site}^{t}(max)$	Maximum limit of the available off-site solar energy at time t	$WE_{off-site}^{t}(max)$	Maximum limit of the available off-site wind energy at time t
λ	Set of tasks	P_s	Power consumed by a server of DC
P_{max}	Peak load power consumption of a server	P_{min}	Idle state power consumption of a server
$Cost_{GE(On-site)}^{total}$	Total cost of on-site green energy	$Cost_{GE(Off-site)}^{total}$	Total cost of off-site green energy
$Tariff_{GE(on-site)}(DC,h)$	Hourly tariff against on-site green energy consumption at DC	$Tariff_{GE(off-site)}(DC,h)$	Hourly tariff against off-site green energy consumption at DC
$Cost_{be}^{total}$	Total cost of brown energy	$Cost_{esd}^{total}$	Total cost of energy stored in ESDs
$CE_{GE(on-site)}^{t}$	Carbon emission of on-site green energy at time t	$CE_{GE(off-site)}^{t}$	Carbon emission of off-site green energy at time t
CE_{be}^{t}	Carbon emission of brown energy at time t	CE_{esd}^{t}	Carbon emission of energy stored in ESDs at time t
P_{DC}^{t}	Available power for a cloud DC at time t	$Demand_{DC}^{t}$	Power demand of a cloud DC at time t
$Cost_{DC}^{total}$	Total energy cost of a cloud DC	CE_{DC}^{total}	Total carbon emission of a cloud DC

4. Proposed Framework

Integration of renewable energy (solar and wind) with brown energy sources has been the focus of recent research, because of its low operational cost and carbon-free production. However, reliable forecasting of renewable energy sources is an important issue and needs keen attention. Therefore, in this study, we used reliably forecast solar and wind energy from our HSA-ANN model previously proposed in [31]. We considered brown energy, EDSs, and green energy (solar and wind) sources in our proposed system model, as shown in Figure 2. Solar energy and wind energy are intermittent in nature. Their power generation can be calculated with the help of Equations (23) and (24), respectively, as mentioned in [42].

$$P^{SE}(t) = \eta^{sp} \times A^{sp} \times Irr(t) \times (1 - 0.005(Temp(t) - 25)) \tag{23}$$

In Equation (23), $P^{SE}(t)$ indicates the produced solar energy at time interval t, whereas the solar efficiency and area of the solar panel are shown by η^{sp} and A^{sp}, respectively. The outside temperature and solar irradiation for the time interval t are denoted by $Temp(t)$ and $Irr(t)$, respectively.

$$P^{WE}(t) = 0.5 \times C_p \times \lambda \times \rho \times A \times (V^{wt}(t))^3 \tag{24}$$

Wind power is generated from wind turbines, and the wind power generated by a wind turbine in Equation (24) is shown by $P^{WE}(t)$, i.e., directly proportional to wind speed ($P_t{}^{wt} \propto V$). Wind speed $V^{wt}(t)$, rotor efficiency C_p, area swept by rotor blades A, constant λ, and air density ρ affect the energy generated by a wind turbine.

The proposed system model, shown in Figure 2, can be broadly divided into the on-site power setup and off-site power setup. Both power setups have two power sources. The on-site power setup model has an on-site green energy source and ESDs, whereas the off-site power setup model includes brown energy and off-site green energy sources. Brown energy refers to traditional energy produced using fossil fuels. The blue dotted lines in the model represent communication signals.

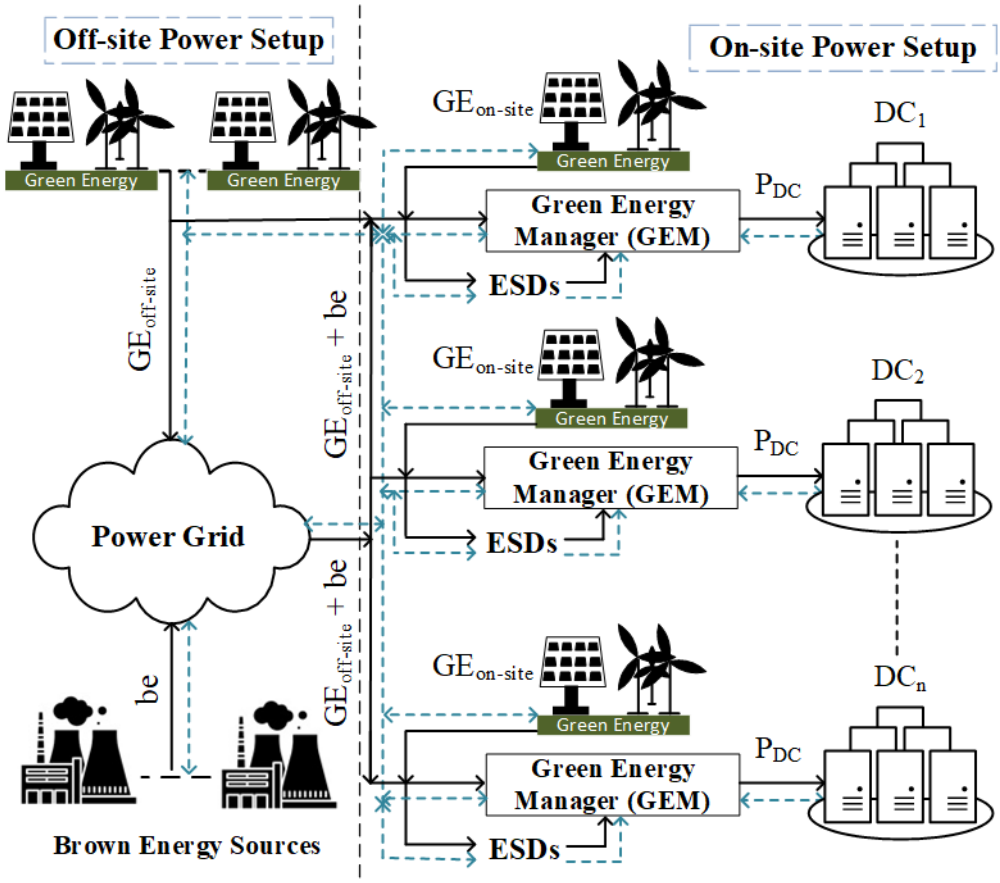


Figure 2. Proposed on-site and off-site power setup model.

4.1. On-Site Power Setup Model

An on-site power setup represents solar and wind energy production at a site by the cloud service provider (CSP) itself, to be used by an on-site data center. The prominent benefits of on-site green energy include

- Lower transmission losses;
- Lower distribution losses;
- Minimum effects from grid outages, on cloud power supply.

An on-site green energy source can fully or partially power a cloud data center, depending upon its power generation capacity and the data center's power requirements. Moreover, the energy produced by an on-site green energy source can be stored in energy storage devices or sold back to the utility, in case of excess energy. Low-cost brown energy can also be stored in ESDs for future use, and an ESD facility can be used to accommodate for the mismatch between the demand and supply of power using renewable energy sources.

A green energy manager (GEM) is an important part of an on-site power setup and is responsible for efficient and intelligent power management of a cloud data center to minimize the DC operational costs and reduce carbon emissions. The GEM controls various power sources on the basis of the available power, load demand, energy costs, and carbon emissions. Algorithm 1 of our proposed green energy manager (GEM) describes the selection of power sources for the cloud DC to meet $Demand^t_{DC}$. The different power sources considered in this study and their associated costs/data are shown in Equation (25), and the input data files (brown energy prices of all cloud DCs, solar and wind energy data, and hourly power demand of each cloud DC) of our proposed GEM are available at (https://github.com/syedmmohsin1214/SelfJ2_Cloud_InputData.git, accessed on 4 June 2024). Our proposed GEM will always select and utilize the best power source as per requirement/case, as evaluated in Section 6 of this study.

$$Cost^t_{GE(on-site)},\ Cost^t_{GE(off-site)},\ Cost^t_{esd},\ Cost^t_{be} \tag{25}$$

where $Cost^t_{GE(on-site)}$ represents the cost of on-site green energy at time interval t, and the cost of off-site green energy is shown by $Cost^t_{GE(off-site)}$. The cost of ESD supply at time interval t is depicted by $Cost^t_{esd}$, whereas $Cost^t_{be}$ describes the cost of brown energy supply for the DCs at time interval t.

The selection of the best power source(s) on the basis of availability is shown in Algorithm 1, which selects the optimal power source(s) on the basis of the availability, load demand of cloud DCs, and the associated costs to meet $Demand^t_{DC}$. It is assumed that our proposed GEM has a built-in smart meter for keeping record of electricity consumption, electricity demand, type of energy source, electricity supply, etc. At first, the GEM checks whether the on-site green energy source is sufficient to meet the DC demand at time t ($Demand^t_{DC}$) and if it is the cheapest available power source ($Cost^t_{GE(on-site)} \leq Cost^t_{GE(off-site)}$, $Cost^t_{esd}$ and $Cost^t_{be}$). If yes, then the DC will be powered by $GE^t_{on-site}$ only, as shown in Equation (26). Otherwise, the next available cheapest power source, e.g., an off-site green energy supply ($GE^t_{off-site}$) will also be included in P^t_{DC} for the DC, to meet its energy demands ($Demand^t_{DC}$) if $Cost^t_{GE(off-site)} \leq Cost^t_{esd}$ and $Cost^t_{be}$, as shown in Equation (27).

$$P^t_{DC} = GE^t_{on-site} \qquad \begin{array}{l}\text{If;}\\ Cost^t_{GE(on-site)} \leq Cost^t_{GE(off-site)},\ Cost^t_{esd} \text{ and } Cost^t_{be}\end{array} \tag{26}$$

$$P^t_{DC} = GE^t_{on-site} + GE^t_{off-site} \qquad \begin{array}{l}\text{If;}\\ Cost^t_{GE(off-site)} \leq Cost^t_{esd} \text{ and } Cost^t_{be}\end{array} \tag{27}$$

Algorithm 1 Selection of power source for cloud DC to meet $Demand^t_{DC}$

```
Initialize GE^t_{on-site}, GE^t_{Off-site}, S^t_{esd}, S^t_{be}, Cost_{GE^t_{on-site}}, Cost_{GE^t_{off-site}}, Cost_{S^t_{esd}}, Cost_{S^t_{be}},
    Demand^t_{DC}, P^t_{DC}
if GE^t_{On-site} ≥ Demand^t_{DC} and Cost^t_{GE(on-site)} ≤ Cost^t_{GE(off-site)}, Cost^t_{esd} and Cost^t_{be} then
    P^t_{DC} ← GE^t_{on-site} to meet Demand^t_{DC}
else if GE^t_{on-site} + GE^t_{Off-site} ≥ Demand^t_{DC} and Cost^t_{GE(off-site)} ≤ Cost^t_{esd} and Cost^t_{be} then
    P^t_{DC} ← GE^t_{On-site} + GE^t_{Off-site} to meet Demand^t_{DC}
else if GE^t_{on-site} + GE^t_{Off-site} + S^t_{esd} ≥ Demand^t_{DC} and Cost^t_{esd} ≤ Cost^t_{be} then
    P^t_{DC} ← GE^t_{On-site} + GE^t_{Off-site} + S^t_{esd} to meet Demand^t_{DC}
else
    P^t_{DC} ← GE^t_{On-site} + GE^t_{Off-site} + S^t_{esd} + S^t_{be} to meet Demand^t_{DC}
end if
```

Our proposed GEM again checks whether the DC's power requirement $Demand^t_{DC}$ is met or not. If the DC power demand is fulfilled then fine, otherwise the next available cheapest power source, e.g., S^t_{esd} will be added, if $Cost^t_{esd} \leq Cost^t_{be}$, into P^t_{DC} and following power (see Equation (28)) becomes available to the DC.

$$P^t_{DC} = GE^t_{on-site} + GE^t_{off-site} + S^t_{esd} \qquad \begin{array}{l} \text{If;} \\ Cost^t_{esd} \leq Cost^t_{be} \end{array} \tag{28}$$

If $Demand^t_{DC}$ is fulfilled, then brown energy will not be used, otherwise brown energy (be) will also be included in P^t_{DC} to meet the power demands of the DC ($Demand^t_{DC}$). Finally, the DC utilizes all available power sources (P^t_{DC}) to meet its $Demand^t_{DC}$, as shown in Equation (29).

$$P^t_{DC} = GE^t_{on-site} + GE^t_{off-site} + S^t_{esd} + S^t_{be} \tag{29}$$

However, Equation (30) must be satisfied to meet the DC's power requirements.

$$P^t_{DC} \geq Demand^t_{DC} \tag{30}$$

4.2. Off-Site Power Setup Model

An off-site power setup comprises off-site green energy sources and brown energy sources. In this study, we considered off-site solar and wind energy ($SE_{off-site}$ and $WE_{off-site}$) only. The availability of on-site green energy is appealing; however, it may not be the best option because of its higher installation costs and likely less favorable on-site environment for the generation of green energy. Off-site green energy sources refer to solar and wind energy sources far away from the data center site, which are installed at more conducive locations with a better production capability. Off-site energy is purchased by the cloud data center through grid. Off-site green energy sources and brown energy sources both feed the power grid, which then transmits power to the user, i.e., a cloud data center in our case. Cheap off-site energy supplied from the power grid and green energy sources can also be stored in ESDs for future use.

5. Experimental Setup and Results

Below is a brief description of the experimental setup, the incoming workload in the cloud data centers, the on-site and off-site solar and wind power generation, and the power requirements of each data center.

5.1. Experimental Setup

In view of our objective functions to minimize costs and carbon emissions (Equations (21) and (22)) by integrating renewable energy and energy storage devices, we considered four geographically distributed cloud data centers, four on-site solar and wind energy sources, four off-site solar and wind energy sources, and energy storage devices in this study. Details of the experimental setup for the cloud data centers can be found in Table 5, while Table 6 contains details of the solar and wind power generation models and energy storage devices.

Table 5. Experimental setup for cloud data centers.

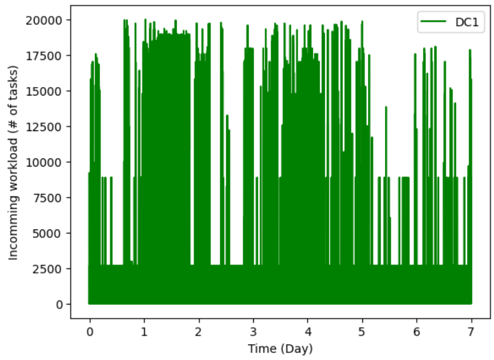
Parameters	Value
Machine specifications	Corei7, 8 GB, 1TB
Programming language	Python 3.9.18
Cloud data centers	DC1, DC2, DC3, DC4
Location/control zone of cloud data centers	CAPITAL, CENTRAL, DUNWOOD, GENESE
Considered duration	18 November 2012 to 24 November 2012
DC workload source	Intel Netbatch grid clusters (Pool A, B, C, D) [43]
Brown energy prices data source	New York Independent System Operator (NYISO) [44]

Table 6. Details on the simulation setup for the energy storage devices (ESDs), and solar and wind energy.

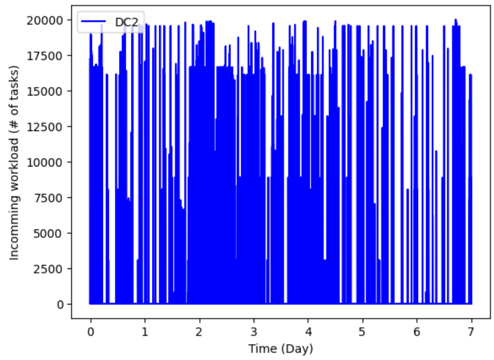
Type of Energy	Parameters	Value
ESDs	Capacity	3 MWh
	ESDs power price ($/MWh)	10
Solar power	Data source	Measurement and instrumentation data center (MIDC) of National Renewable Energy Laboratory (NREL) [45]
	Data locations	Loyola Marymount University, University of Arizona, National Energy Laboratory Hawaii Authority and Solar Technology Acceleration Center
	Applied equation	Equation # (23) of this study
	Solar panel	BP-MSX-120, 24 V [46]
	# of on-site solar panels considered in this study	20 K
	# of off-site solar panels considered in this study	40 K
	Solar panel efficiency	10.88% [46]
	Solar panel dimensions	1108 mm × 991 mm [47]
	On-site solar power price ($/MWh)	10 [1,11]
	Off-site solar power price ($/KWh)	Price of brown energy + 18 cents [1,36]
Wind power	Data source	Measurement and instrumentation data center (MIDC) of National Renewable Energy Laboratory (NREL) [45]
	Data locations	Loyola Marymount University, University of Arizona, National Energy Laboratory Hawaii Authority and Solar Technology Acceleration Center
	Applied equation	Equation # (24) of this study
	Wind turbine	Vestas V90-3.0 (3 MW) [48]
	Rated power	3.00 MW
	# of on-site wind turbines considered in this study	400
	# of off-site wind turbines considered in this study	600
	Diameter	90 m
	Swept area	6362 m^2
	Blade length	44 m
	# of blades	3
	Air density	1.23 kg/m
	Rotor efficiency	50%
	On-site wind power price ($/MWh)	10 [1,11]
	Off-site wind power price ($/KWh)	Price of brown energy + 1.5 cents [1,36]

5.2. Incoming Workload of Cloud DCs

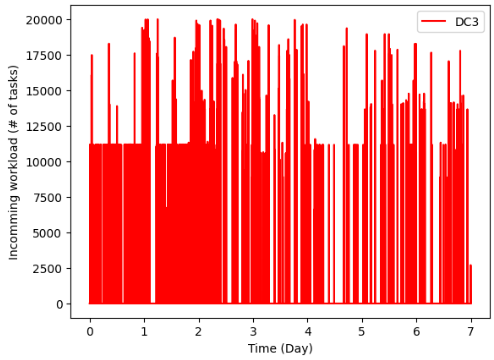
The incoming workloads of all considered cloud DCs (DC1, DC2, DC3 and DC4) installed at the CAPITAL, CENTRAL, DUNWOOD, and GENESE sites, respectively, were taken from Intel Netbatch Grid clusters (Pool A, B, C, D) [43] and are shown in Figure 3.



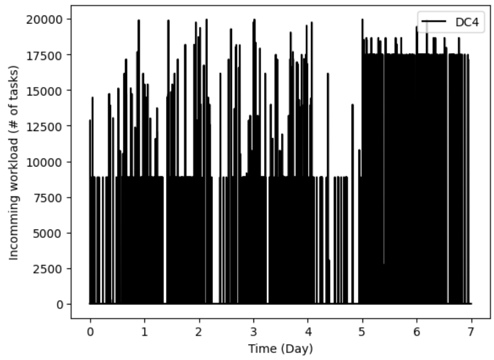
(**a**) Incoming tasks (λ) of DC1



(**b**) Incoming tasks (λ) of DC2



(**c**) Incoming tasks (λ) of DC3

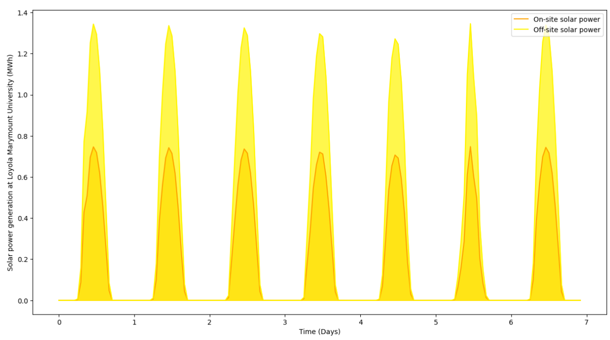


(**d**) Incoming tasks (λ) of DC4

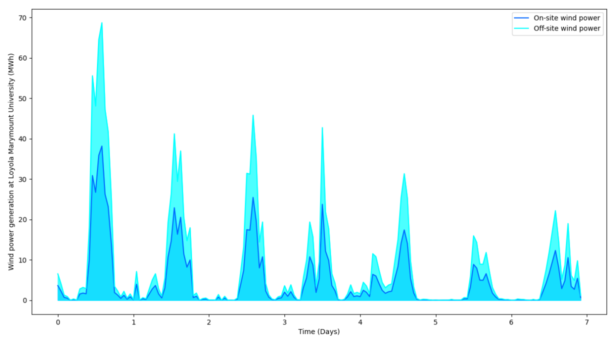
Figure 3. Incoming tasks (λ) of each DC.

5.3. On-Site and Off-Site Solar and Wind Power Generation

The weather data for the calculation of on-site and off-site solar and wind power generation according to Equations (23) and (24) for the Loyola Marymount University, University of Arizona, National Energy Laboratory Hawaii Authority, and Solar Technology Acceleration Center sites were taken from the Measurement and Instrumentation Data Center (MIDC) of the National Renewable Energy Laboratory (NREL) [45] and are shown individually in Figures 4–7. The weather data for on-site and off-site solar and wind power generation were run through our previously proposed solar and wind energy forecasting model [31] and then used as input to the green energy manager proposed in this study.

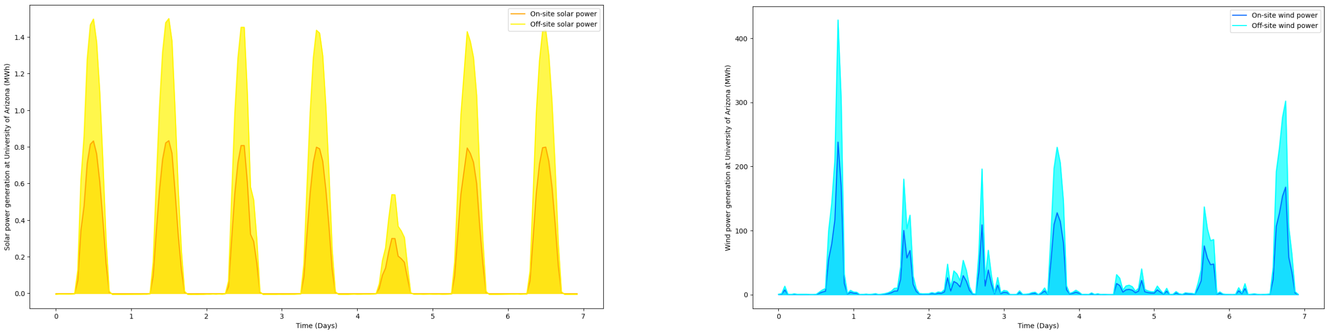


(**a**) Solar power generation



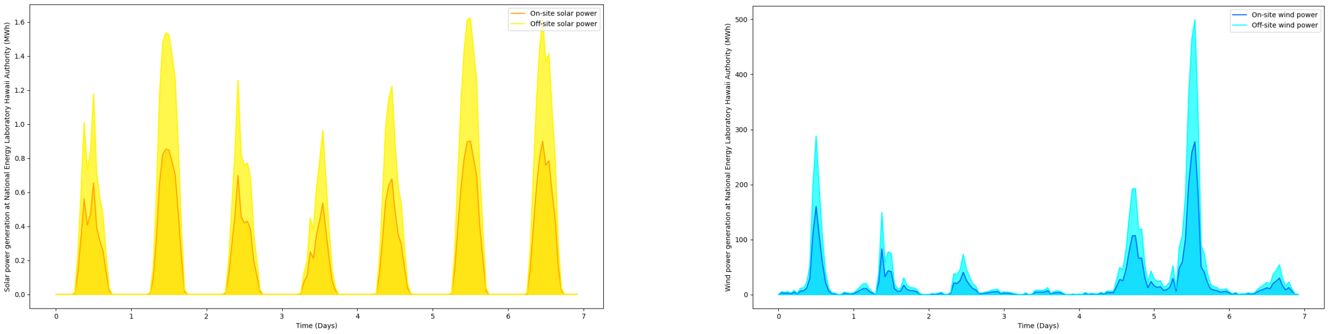
(**b**) Wind power generation

Figure 4. On-site and off-site solar and wind power generation at "Loyola Marymount University" site.



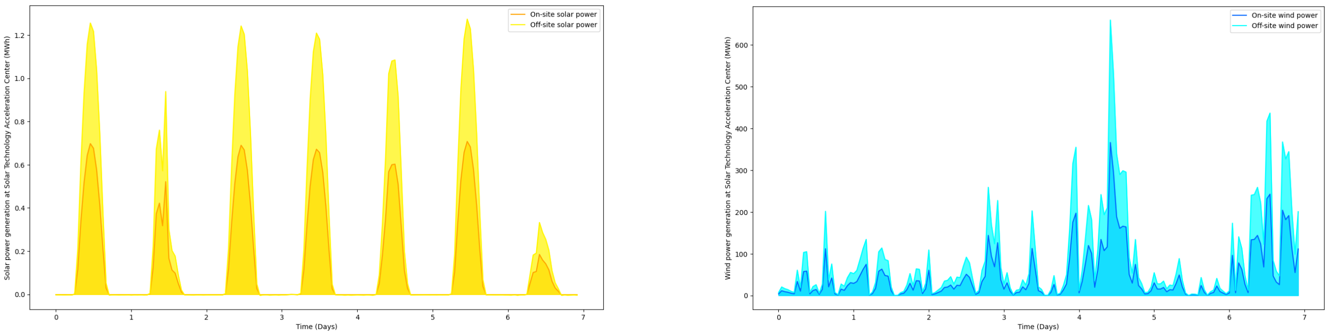
(**a**) Solar power generation (**b**) Wind power generation

Figure 5. On-site and off-site solar and wind power generation at "University of Arizona" site.



(**a**) Solar power generation (**b**) Wind power generation

Figure 6. On-site and off-site solar and wind power generation at "National Energy Laboratory Hawaii Authority" site.



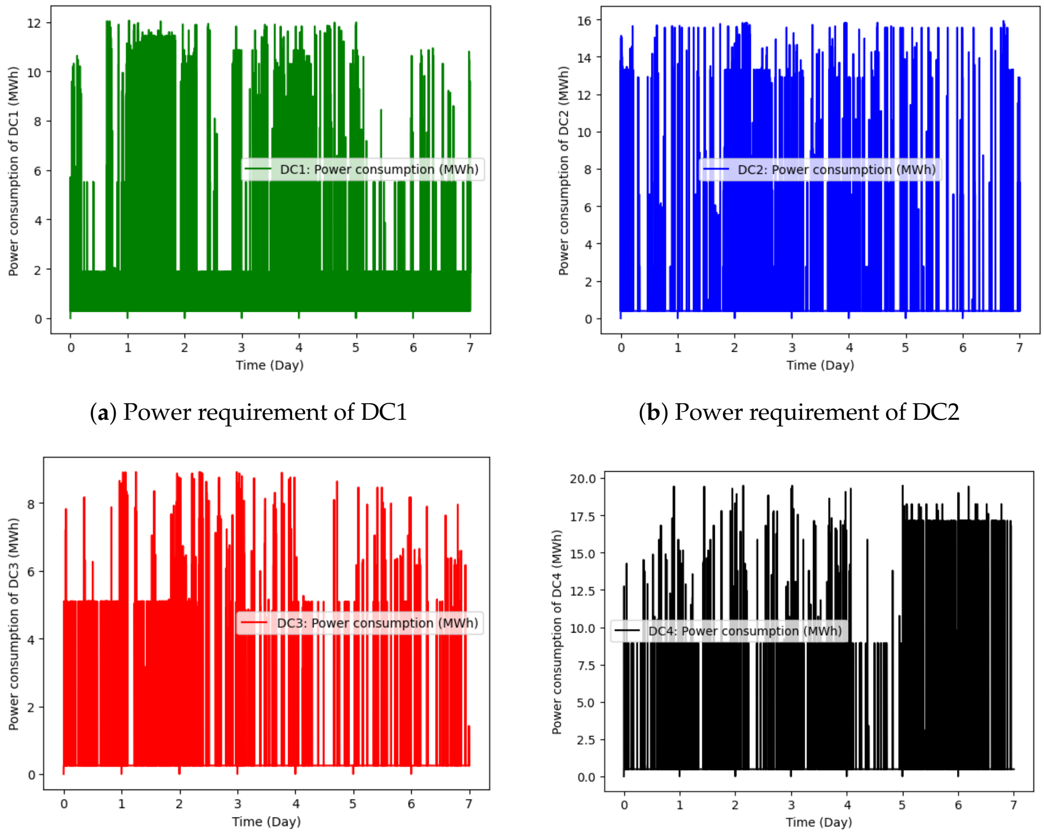
(**a**) Solar power generation (**b**) Wind power generation

Figure 7. On-site and off-site solar and wind power generation at "Solar Technology Acceleration Center" site.

The on-site and off-site solar and wind power generated at the Loyola Marymount University, University of Arizona, National Energy Laboratory Hawaii Authority, and Solar Technology Acceleration Center sites is shown in Figure 4, Figure 5, Figure 6, and Figure 7, respectively. Given the limited availability of weather data, we assumed that the data shown in Figures 4–7 were available for cloud data centers at the CAPITAL (DC1), CENTRAL (DC2), DUNWOOD (DC3), and GENESE (DC4) locations/load control areas in New York, USA, respectively.

5.4. Power Requirement of Each DC

The power consumption of all DCs in relation to the incoming workload is shown in Figure 8. These were calculated using Equation (11), the various parameters of the cloud data centers under consideration (Table 3), and the location-based brown energy prices of the individual data centers, as shown in the Figure 1.



(**a**) Power requirement of DC1 (**b**) Power requirement of DC2

(**c**) Power requirement of DC3 (**d**) Power requirement of DC4

Figure 8. Power requirement of each DC with regards to incoming workload (λ).

6. Performance Evaluation

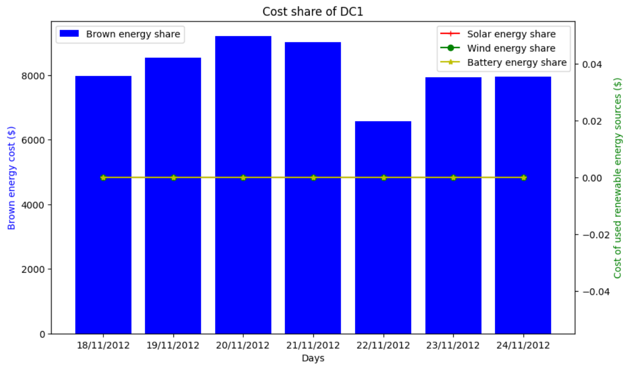
For the support and better understanding of both beginners and experienced readers, we present the performance evaluation with graphical and numerical means below.

6.1. Graphical Evaluation of the Proposed Model (GEM)

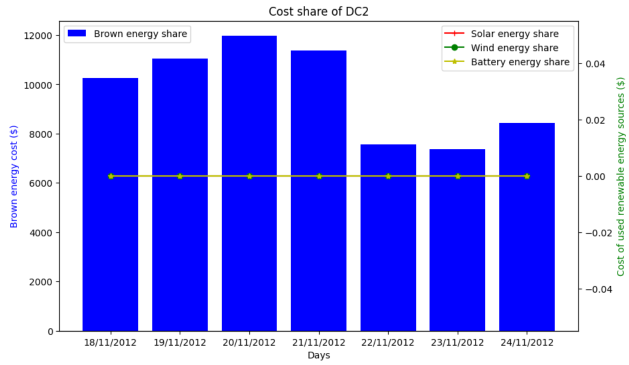
To determine the accuracy, reliability, resilience, and overall performance of a proposed model in real-life situations, an evaluation is required. In this study, we evaluated our proposed green energy manager (GEM) in the three cases described in Sections 6.1.1 and 6.1.2. The blue bars in Figures 9–20 show the cost share and carbon emissions caused by brown energy in meeting the energy demand shown in Figure 8. Green lines represent the cost share and carbon emissions caused by wind energy, red lines refer to the cost share and carbon emissions caused by solar energy, while yellow lines represent the cost share and carbon emissions caused by energy stored in ESDs. In Figures 9–20, the days are shown on the x-axis, the costs/carbon emissions of the brown energy source on the left side of the y-axis, and the costs/carbon emissions of the renewable energy source(s) are shown on the right side of the y-axis.

6.1.1. Case 1: All Brown

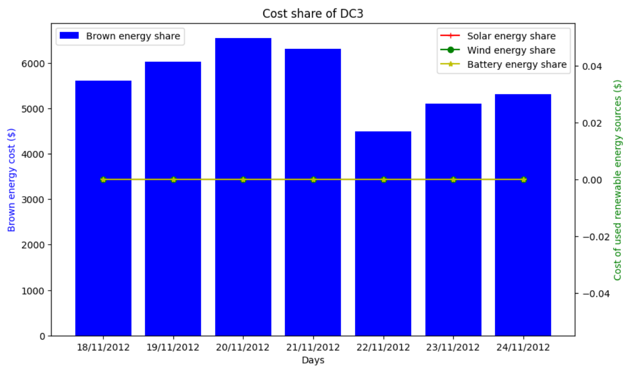
In this case, we supplied all DCs with brown energy only, depending on the load, and neither on-site solar or wind energy source(s), off-site solar or wind energy source(s), nor energy storage devices (ESDs) were considered. This case served as a benchmark for comparing the efficiency and effectiveness of our proposed GEM. The simulation results regarding the individual cost share of all DCs are shown in Figure 9 and regarding the collective cost of all DCs in Figure 10.



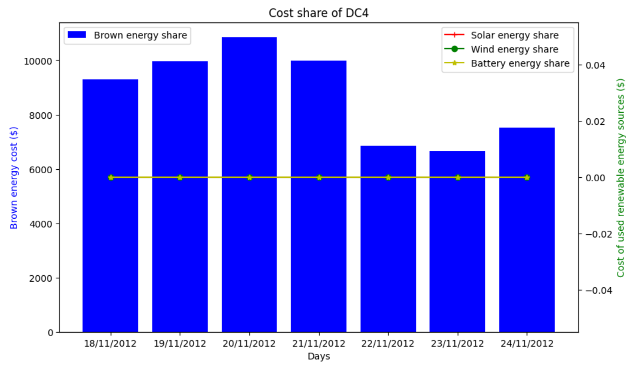
(**a**) Cost share of each energy source for DC1



(**b**) Cost share of each energy source for DC2



(**c**) Cost share of each energy source for DC3



(**d**) Cost share of each energy source for DC4

Figure 9. Case 1: Cost share of each energy source for DC1, DC2, DC3, and DC4.

As already mentioned, the cost share of the individual DCs in $ for case 1 (all brown) is shown in Figure 9. It can be seen that the share of solar energy, wind energy, and battery energy was zero in this case. Consequently, the cost share was also shown to be zero. As case 1 was the reference case, we powered each cloud DC with brown energy only, and the resultant costs are shown in $ with blue bars. The varying graph bars show the cost of brown energy depending on the incoming workload, as discussed in Section 5.2, and the respective DC power requirements, as discussed in Section 5.4.

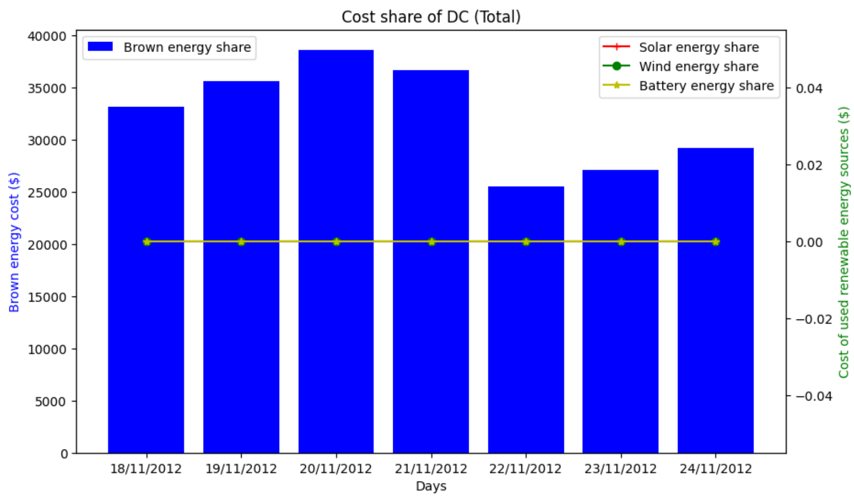
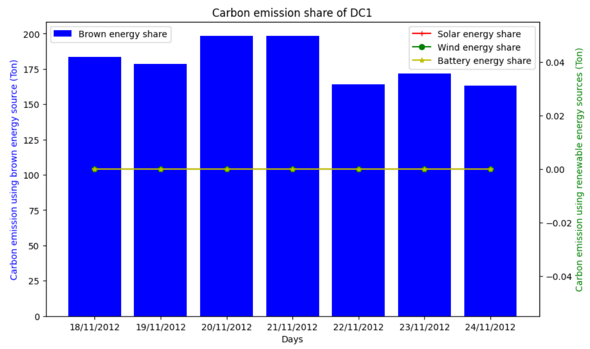
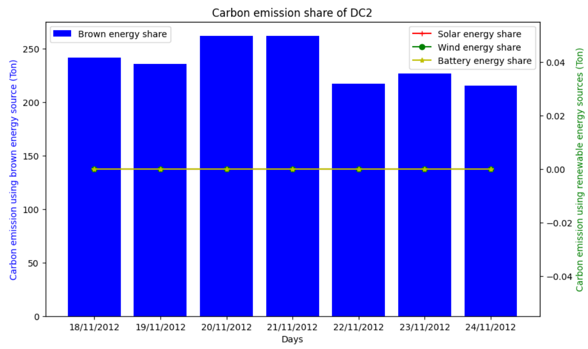


Figure 10. Case 1: Collective cost of all DCs.

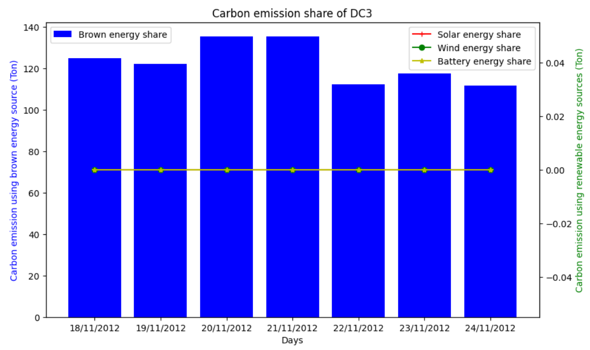
Collective cost of all DCs (DC1, DC2, DC3, and DC4) for case 1 (all brown) is shown in Figure 10. The simulation results regarding the carbon emissions of the individual DCs are shown in Figure 11, and regarding the collective carbon emission of all DCs in Figure 12.



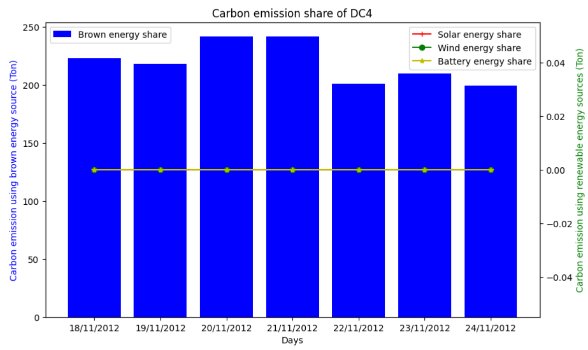
(**a**) Carbon emission share of each energy source for DC1



(**b**) Carbon emission share of each energy source for DC2



(**c**) Carbon emission share of each energy source for DC3



(**d**) Carbon emission share of each energy source for DC4

Figure 11. Case 1: Carbon emission share of each energy source for DC1, DC2, DC3, and DC4.

Case 1 used only brown energy, which is why it had higher carbon emissions, as can be seen from the carbon emission rates (CER) of the individual energy sources in Table 1. The share of carbon emissions (tons) of the individual DCs is shown in Figure 11 with blue bars. Meanwhile, the collective carbon emissions of all DCs (DC1, DC2, DC3, and DC4) are shown in Figure 12 using blue bars.

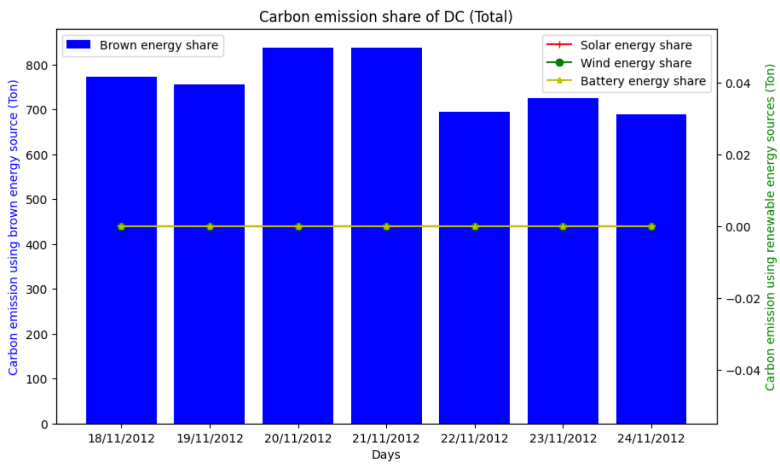


Figure 12. Case 1: Collective carbon emissions of all DCs.

6.1.2. Case 2: Proposed Green Energy Manager (GEM)

In the case 2, we considered four on-site solar and wind energy sources ($SE^{t}_{on-site}$ and $WE^{t}_{on-site}$, respectively), four off-site solar and wind energy sources ($SE^{t}_{off-site}$ and

$WE^t_{off-site}$, respectively), and energy storage devices, together with brown energy, to meet the total power demand of the cloud DCs ($Demand^t_{DC}$) based on their availability (Algorithm 1), cost (Algorithm 2), and carbon emissions (Algorithm 3).

Algorithm 2 Selection of the cheapest power source to meet $minCost^{total}_{DC}$

Initialize $GE^t_{on-site}$, $GE^t_{Off-site}$, S^t_{esd}, S^t_{be}, $Cost_{GE^t_{on-site}}$, $Cost_{GE^t_{off-site}}$, $Cost_{S^t_{esd}}$, $Cost_{S^t_{be}}$, $Demand^t_{DC}$, P^t_{DC}
if $Cost^t_{GE(on-site)} \leq Cost^t_{GE(off-site)}$, $Cost^t_{esd}$, $Cost^t_{be}$and it is available for use **then**
    $P^t_{DC} \leftarrow GE^t_{on-site}$ to meet $Demand^t_{DC}$
else if $Cost^t_{GE(off-site)} \leq Cost^t_{GE(on-site)}$, $Cost^t_{esd}$, $Cost^t_{be}$and it is available for use **then**
    $P^t_{DC} \leftarrow GE^t_{Off-site}$ to meet $Demand^t_{DC}$
else if $Cost^t_{esd} \leq Cost^t_{GE(on-site)}$, $Cost^t_{GE(off-site)}$, $Cost^t_{be}$and it is available for use **then**
    $P^t_{DC} \leftarrow S^t_{esd}$ to meet $Demand^t_{DC}$
else
    $P^t_{DC} \leftarrow S^t_{be}$ to meet $Demand^t_{DC}$
end if

Algorithm 3 Selection of the power source with least carbon emission to meet $minCE^{total}_{DC}$

Initialize $CE_{GE^t_{on-site}}$, $CE_{GE^t_{off-site}}$, $CE_{S^t_{esd}}$, $CE_{S^t_{be}}$, $Demand^t_{DC}$, P^t_{DC}
if $CE_{GE^t_{on-site}}$ is the minimum and it is available to use **then**
    $P^t_{DC} \leftarrow GE^t_{on-site}$ to meet $Demand^t_{DC}$
else if $CE_{GE^t_{off-site}}$ is the minimum and it is available to use **then**
    $P^t_{DC} \leftarrow GE^t_{Off-site}$ to meet $Demand^t_{DC}$
else if $CE_{S^t_{esd}}$ is the minimum and it is available to use **then**
    $P^t_{DC} \leftarrow S^t_{esd}$ to meet $Demand^t_{DC}$
else
    $P^t_{DC} \leftarrow S^t_{be}$ to meet $Demand^t_{DC}$
end if

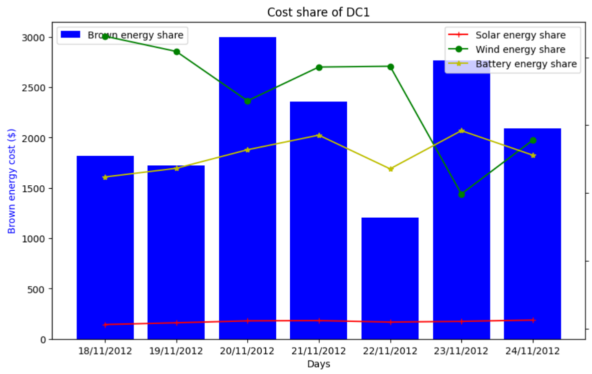
Our proposed green energy manager (GEM) compared the available power sources with the power demand, and used the power source with the lowest cost (Case 2.1) and the lowest carbon emissions (Case 2.2). As the brown energy prices fluctuated, as shown in Figure 1, it is worth noting that there may have been a situation where the price of brown energy was the lowest. Of course, the GEM preferred brown energy in this case. GEM algorithms always prefer power sources based on the selection criteria, and there may be cases where one of the power sources is not used because a relatively cheaper and less carbon-emitting energy is available. The upper limit for purchasing external power may be the power requirements of the cloud DC. In this study, we assumed that the availability of brown energy could cover the entire power demand of the cloud DCs. Case 2 had the following two sub-cases.

Case 2.1: MinCost ($minCost^{total}_{DC}$)

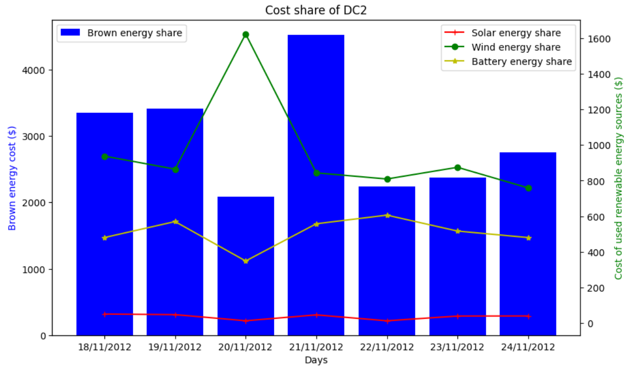
Considering the objective function defined in Equation (21), cost minimization was the top priority in case 2.1 ($minCost^{total}_{DC}$). Consequently, the carbon emissions were slightly increased as a trade-off. Therefore, the power source of each DC was selected on the basis of the lowest cost for the selected week, regardless of the carbon emissions of the selected power source(s). Selection of the cheapest power source to meet the cloud DC power requirement was carried out as per Algorithm 2 to meet the objective function of $minCost^{total}_{DC}$.

The costs of all energy sources ($Cost_{GE^t_{on-site}}$, $Cost_{GE^t_{off-site}}$, $Cost_{S^t_{esd}}$, $Cost_{S^t_{be}}$) together with the total energy demand ($Demand^t_{DC}$) of the cloud DC and the power available to the cloud DC (P^t_{DC}) were provided at the input of Algorithm 2. In this case ($minCost^{total}_{DC}$), the cost and availability of each power source were checked to see if the costs were the lowest and then the respective power source was used to meet the power demand of the cloud DCs. In this way, the maximum power requirement of the cloud DC was met with the power source with the lowest cost. Consequently, the total operating costs of the cloud DCs were reduced compared to case 1, i.e., all brown.

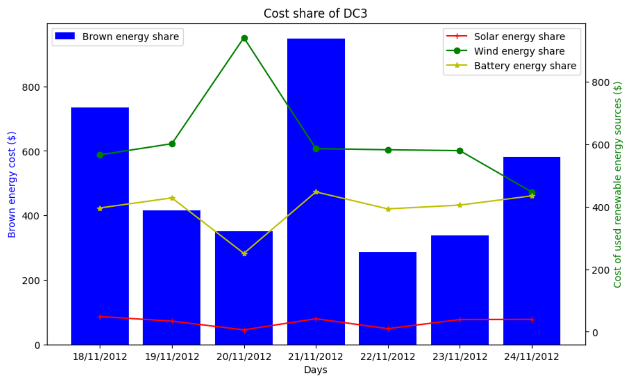
The simulation results in relation to individual cost share of all DCs are shown in Figure 13, and in relation to the collective cost of all DCs in Figure 14.



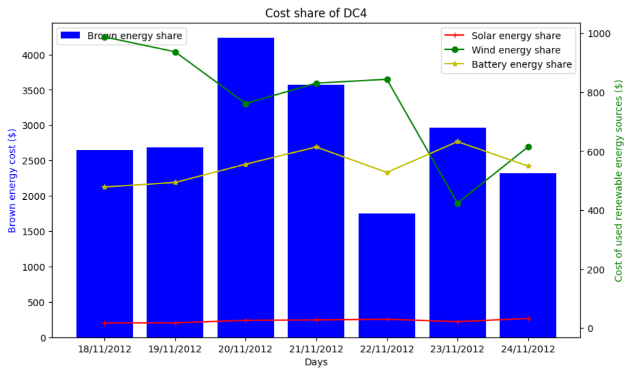
(**a**) Cost share of each energy source for DC1



(**b**) Cost share of each energy source for DC2



(**c**) Cost share of each energy source for DC3



(**d**) Cost share of each energy source for DC4

Figure 13. Case 2.1: Cost share of each energy source for DC1, DC2, DC3, and DC4.

The cost share of the individual DC in $ for case 2.1 (MinCost) is shown in the Figure 13. In this case, minimizing energy costs was the top priority, which is why each energy source was used as and when it was the cheapest. The blue bars in Figure 13 represent the cost of brown energy, the red line shows the share of solar energy, the green line shows the share of wind energy, while the yellow line represents the cost of energy provided by ESDs. The results show that all four available energy sources ($GE_{on-site}$, $GE_{off-site}$, S_{esd}, and S_{be}) were used by the GEM in this case, with the main objective of minimizing costs.

Collective costs of all DCs (DC1, DC2, DC3, and DC4) for case 2.1 (MinCost) are shown in Figure 14. The simulation results in relation to the carbon emissions of the individual DCs are shown in Figure 15. and in relation to the collective carbon emissions of all DCs in Figure 16.

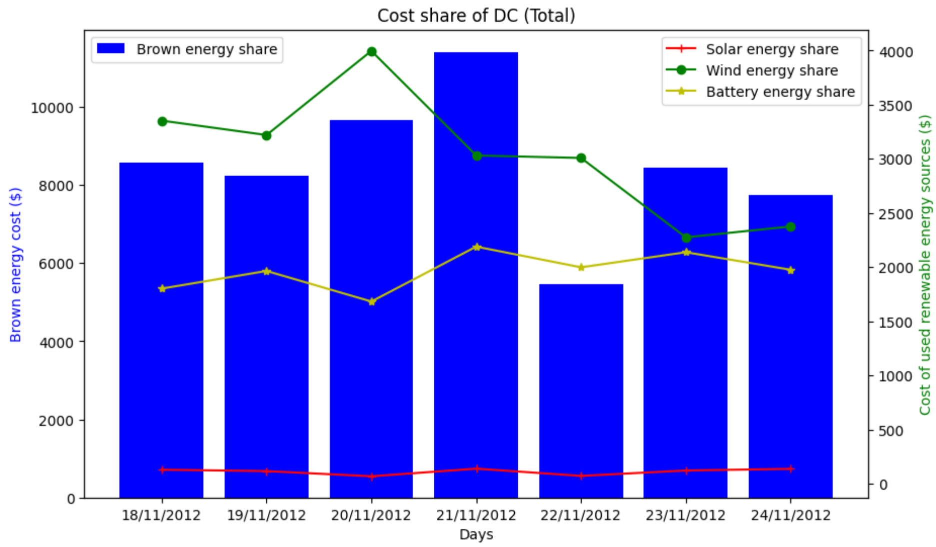
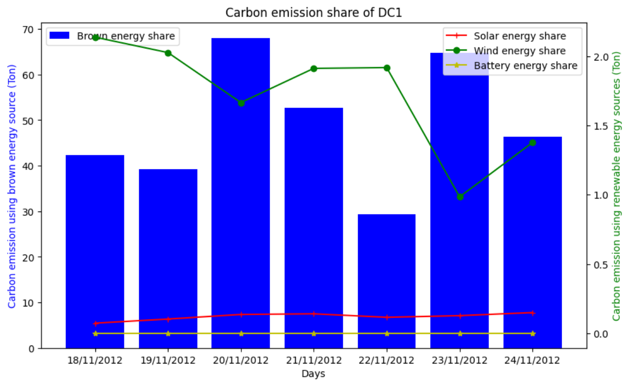
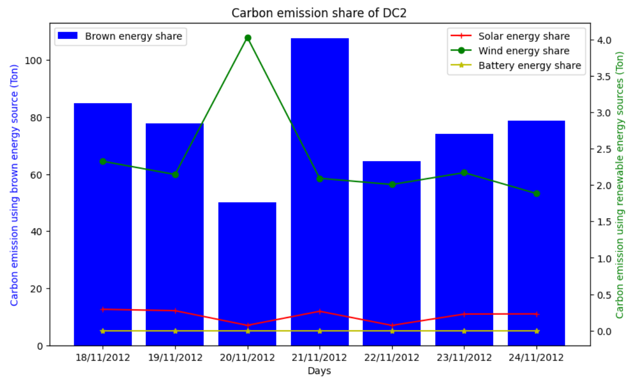


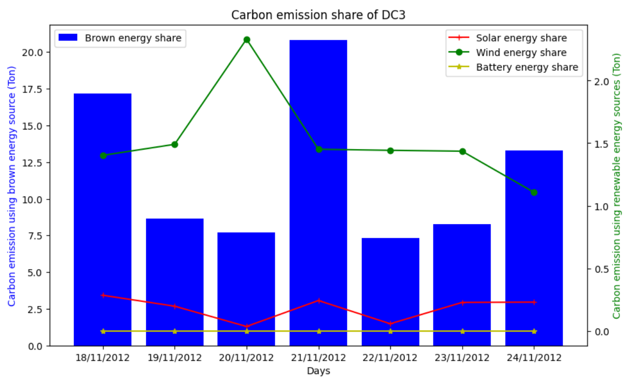
Figure 14. Case 2.1: collective price of all DCs.



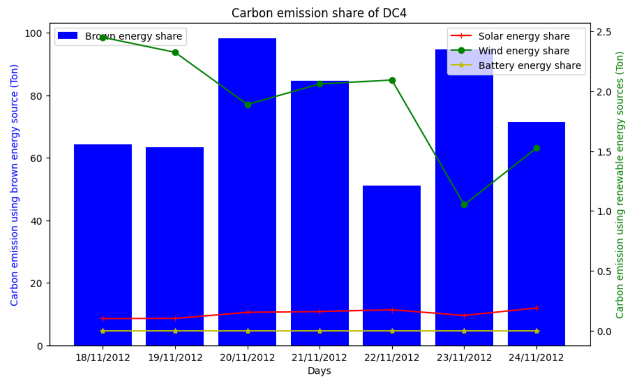
(**a**) Carbon emission share of each energy source for DC1



(**b**) Carbon emission share of each energy source for DC2



(**c**) Carbon emission share of each energy source for DC3



(**d**) Carbon emission share of each energy source for DC4

Figure 15. Case 2.1: Carbon emission share of each energy source for DC1, DC2, DC3, and DC4.

In case 2.1 (MinCost), our proposed GEM used all four energy sources ($GE_{on-site}$, $GE_{off-site}$, S_{esd}, and S_{be}), with the carbon emission rate for each source as given in Table 1. The blue bars in Figure 15 represent the proportional share of carbon emissions caused by the use of brown energy, the red line shows the proportional share of carbon emissions caused by the use of solar energy, and the green line shows the proportional share of carbon emissions caused by the use of wind energy. Although the energy stored in ESDs was also used in this case, it is worth noting that the proportion of carbon emissions caused by the energy stored in ESDs was assumed to be zero, as it was only the storage of energy. The collective carbon emissions of all DCs (DC1, DC2, DC3, and DC4) are shown in Figure 16, where the blue color bars are used for brown energy, red color line indicates solar energy, green color line shows wind energy, and yellow color line represents ESDs.

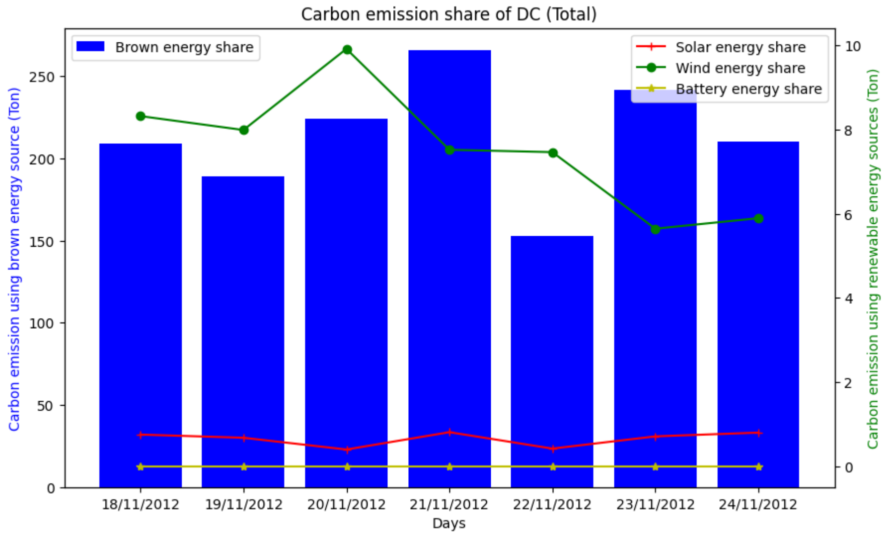


Figure 16. Case 2.1: Collective carbon emissions of all DCs.

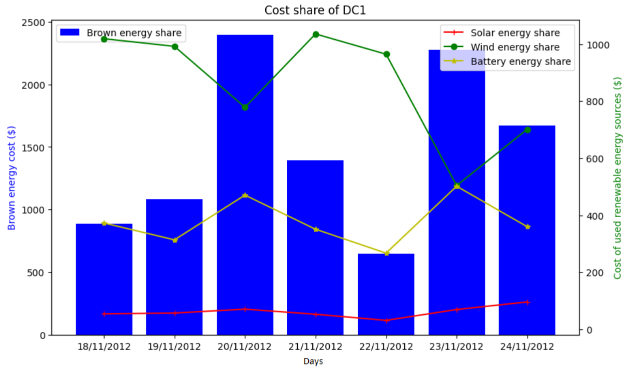
Case 2.2: MinCE ($minCE_{DC}^{total}$)

Considering the objective function defined in Equation (22), carbon emission minimization was the overriding priority in case 2.2 ($minCE_{DC}^{total}$). Consequently, the cloud DCs' operating costs were slightly increased as a trade-off. Therefore, the power source for each DC was selected on the basis of the lowest carbon emissions for the selected entire week, regardless of the cost of the selected power source(s). Selection of the power source with least carbon emission to meet cloud DC power requirements was carried out as per Algorithm 3 to meet the objective function of $minCE_{DC}^{total}$.

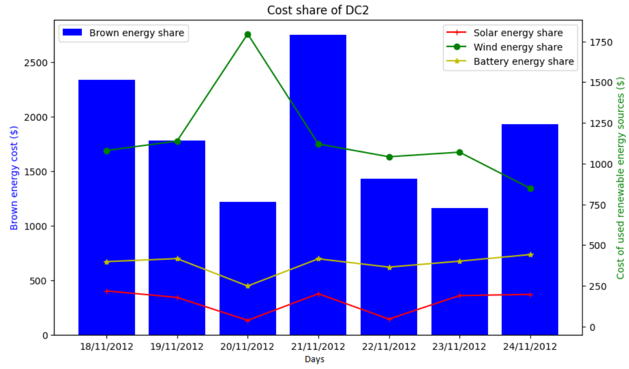
The carbon emissions of all energy sources ($CE_{GE^t_{on-site}}$, $CE_{GE^t_{off-site}}$, $CE_{S^t_{esd}}$, $CE_{S^t_{be}}$,) together with the total energy demand ($Demand^t_{DC}$) of the cloud DC and the available power for the cloud DC (P^t_{DC}) were provided at the input of Algorithm 3. In this case ($minCE_{DC}^{total}$), the carbon emissions and availability of each power source were checked to see if the carbon emissions were the lowest, and then the respective power source was used to meet the power demand of the cloud DCs. In this way, the maximum power requirement of the cloud DC was met with the power source with the lowest carbon emissions. Consequently, the total carbon emissions of the cloud DCs were reduced compared to case 1, i.e., all brown.

The simulation results regarding the individual cost share of all DCs are shown in Figure 17 and regarding the collective cost of all DCs in Figure 18.

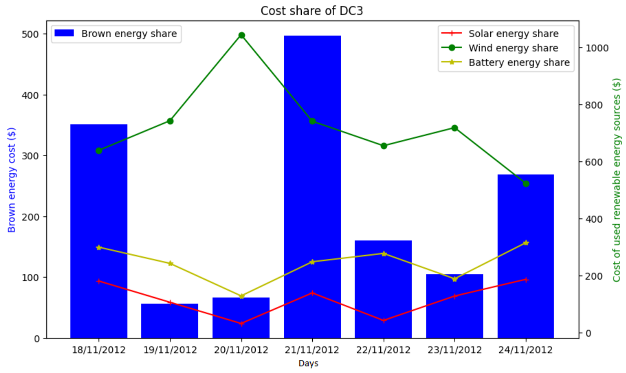
The cost shares of the individual DCs in $ for case 2.2 (MinCE) are shown in Figure 17. In this case, minimizing carbon emissions was the top priority, which is why each energy source was used as and when it had the lowest carbon emission rate, as per Table 1. The blue bars in Figure 17 represent the cost of brown energy, the red line shows the share of solar energy, the green line shows the share of wind energy, while the yellow line represents the cost of energy provided by ESDs. The results show that all four available energy sources ($GE_{on-site}$, $GE_{off-site}$, S_{esd} and S_{be}), were used by GEM in this case, with the main objective of minimizing carbon emissions.



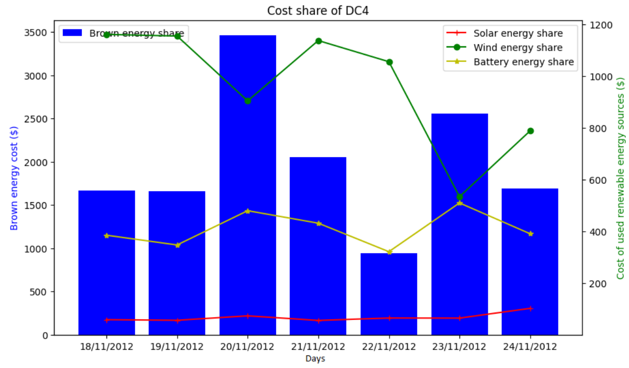
(**a**) Price share of each energy source for DC1



(**b**) Cost share of each energy source for DC2



(**c**) Cost share of each energy source for DC3



(**d**) Cost share of each energy source for DC4

Figure 17. Case 2.2: Cost share of each energy source for DC1, DC2, DC3, and DC4.

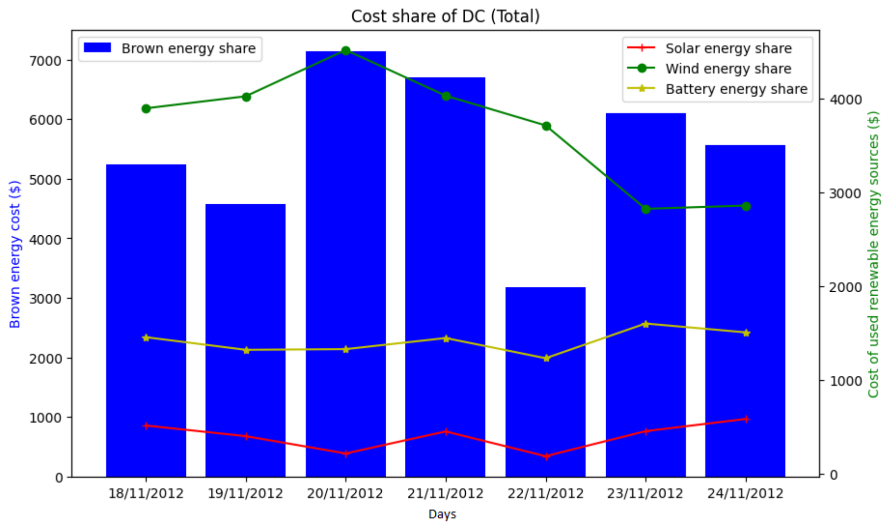
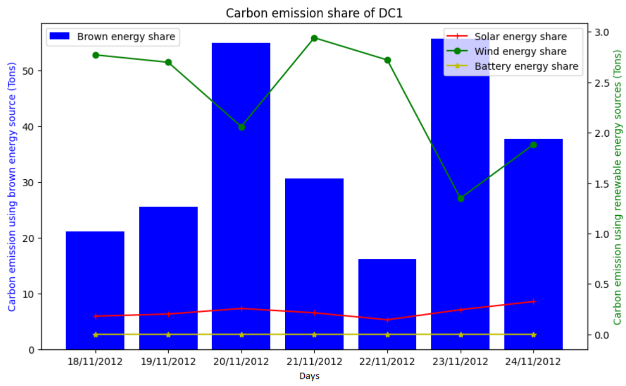


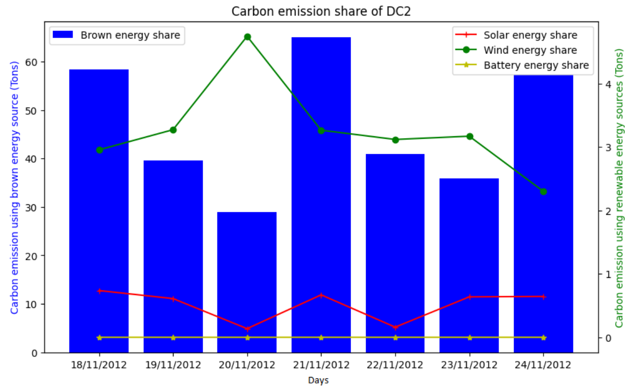
Figure 18. Case 2.2: Collective price of all DCs.

Collective costs of all DCs (DC1, DC2, DC3, and DC4) for case 2.2 (MinCE) are shown in Figure 18. The simulation results regarding the carbon emissions of the individual DCs are shown in Figure 19 and regarding the collective carbon emission of all DCs in Figure 20.

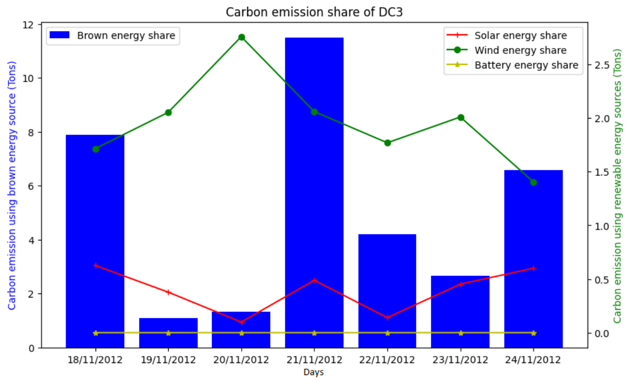
In case 2.2 (MinCE), our proposed GEM used all four energy sources ($GE_{on-site}$, $GE_{off-site}$, S_{esd}, and S_{be}) with the carbon emission rate of each source as given in Table 1. The blue bars in Figure 19 represent the proportional share of carbon emissions caused by the use of brown energy, the red line shows the proportional share of carbon emissions caused by the use of solar energy, and the green line shows the proportional share of carbon emissions caused by the use of wind energy. Although the energy stored in ESDs was also used in this case, it is worth noting that the proportion of carbon emissions caused by the energy stored in ESDs was assumed to be zero, as it was only the storage of energy. The collective carbon emissions of all DCs (DC1, DC2, DC3, and DC4) are shown in Figure 20, where blue color bars are used for brown energy, the red color line indicates solar energy, green color line shows wind energy, and yellow color line represents ESDs.



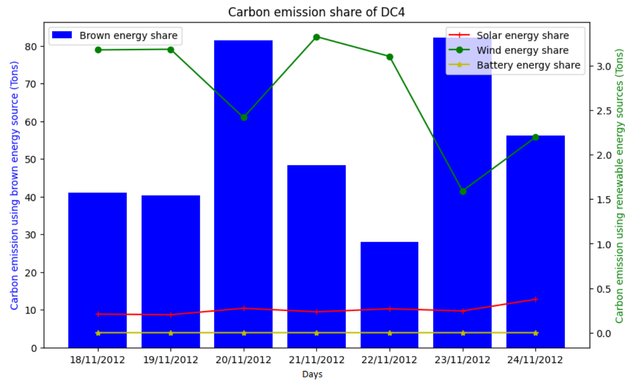
(**a**) Carbon emission share of each energy source for DC1



(**b**) Carbon emission share of each energy source for DC2



(**c**) Carbon emission share of each energy source for DC3



(**d**) Carbon emission share of each energy source for DC4

Figure 19. Case 2.2: Carbon emission share of each energy source for DC1, DC2, DC3, and DC4.

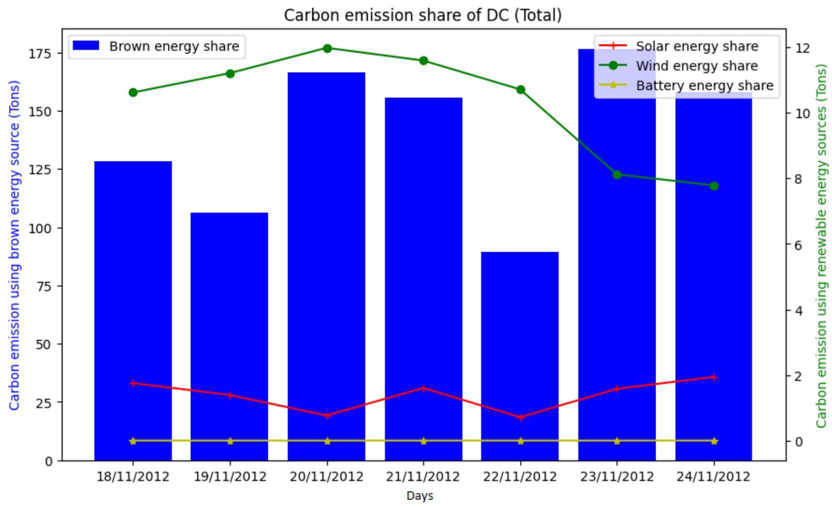


Figure 20. Case 2.2: Collective carbon emission of all DCs.

6.2. Numerical Evaluation of the Proposed Model (GEM)

The total cost of case 1 (all brown) for all DCs was USD 225,768.48, while the CO_2 emissions for all DCs were 5311.67 tons. The total cost of case 2.1 ($minCost_{DC}^{total}$) for all DCs was USD 95,331.25, while the CO_2 emissions for all DCs were 1549.97 tons. In case 2.2 ($minCE_{DC}^{total}$), the total costs for all DCs were USD 136,746.89, while the CO_2 emissions were 1062.42 tons. A summary of the simulation results for the three considered cases is shown in Table 7.

Table 7. Summary of the simulation results for the different cases.

Case	Total Cost of All DCs (USD)	Total CO_2 Emission of All DCs (Tons)
Case 1 (All brown)	225,768.48	5311.67
Case 2.1 ($minCost_{DC}^{total}$)	95,331.25	1549.97
Case 2.2 ($minCE_{DC}^{total}$)	136,746.89	1062.42

A cost comparison of cases 1 and 2.1 is shown in Equation (31), while a carbon emission comparison of the two cases is shown in Equation (32). A cost comparison of cases 1 and 2.2 is shown in Equation (33), and a carbon emission comparison of the two cases is given in Equation (34). A cost comparison of cases 2.1 and 2.2 is shown in Equation (35), while a carbon emission comparison of the two cases is given in Equation (36).

$$\text{Case 1 vs. Case 2.1 (Cost)} = \frac{\text{Total cost of case 1} - \text{Total cost of case 2.1}}{\text{Total cost of case 1}} * 100 \quad (31)$$

$$\text{Case 1 vs. Case 2.1 (CO}_2\text{ emission)} = \frac{\text{Total CE of case 1} - \text{Total CE of case 2.1}}{\text{Total CE of case 1}} * 100 \quad (32)$$

The above Equations (31) and (32) gave the conclusion that case 1 (all brown) was 58% more expensive and caused 71% more carbon emissions than case 2.1 ($minCost_{DC}^{total}$).

$$\text{Case 1 vs. Case 2.2 (Cost)} = \frac{\text{Total cost of case 1} - \text{Total cost of case 2.2}}{\text{Total cost of case 1}} * 100 \quad (33)$$

$$\text{Case 1 vs. Case 2.2 (CO}_2\text{ emission)} = \frac{\text{Total CE of case 1} - \text{Total CE of case 2.2}}{\text{Total CE of case 1}} * 100 \quad (34)$$

The abovementioned Equations (33) and (34) concluded that Case 1 (all brown) was 39% more expensive and had 80% higher carbon emissions than case 2.2 ($minCE_{DC}^{total}$).

$$\text{Case 2.1 vs. Case 2.2 (Cost)} = \frac{\text{Total cost of case 2.2} - \text{Total cost of case 2.1}}{\text{Total cost of case 2.2}} * 100 \quad (35)$$

$$\text{Case 2.1 vs. Case 2.2 (CO}_2\text{ emission)} = \frac{\text{Total CE of case 2.2} - \text{Total CE of case 2.1}}{\text{Total CE of case 2.2}} * 100 \quad (36)$$

The above equations showed that case 2.2 ($minCE_{DC}^{total}$) was 30% more expensive and caused 46% less carbon emissions than case 2.1 ($minCost_{DC}^{total}$). These results indicated a trade-off between cost and carbon emissions. Lower carbon emissions (up to 46% in this case) caused higher costs (30% in this case) and vice versa. A comparative analysis of the simulation results is summarized in Table 8.

Table 8. Comparative analysis of the simulation results for the different cases.

Cases	% Rise or Fall in Total Cost (USD)	% Rise or Fall in Total CO_2 Emission (Tons)
Case 1 (all brown) vs. Case 2.1 ($minCost_{DC}^{total}$)	Case 1 is 58% more costly	Case 1 produces 71% more CO_2 emission
Case 1 (all brown) vs. Case 2.2 ($minCE_{DC}^{total}$)	Case 1 is 39% more costly	Case 1 produces 80% more CO_2 emission
Case 2.1 ($minCost_{DC}^{total}$) vs. Case 2.2 ($minCE_{DC}^{total}$)	Case 2.2 is 30% more costly	Case 2.2 produces 46% less CO_2 emission

7. Conclusions and Future Work

The ever-increasing demand for power in cloud data centers (DCs) creates significant problems, including higher energy prices for service providers and harmful carbon emissions for the environment. To solve these serious problems, researchers have advocated the use of renewable energy sources. However, the erratic nature of solar and wind energy requires more accurate forecasting techniques. In this study, we presented a green energy manager (GEM), a solution that optimizes the use of renewable energy sources, energy storage devices, and traditional (brown) energy to reduce costs and CO_2 emissions. To improve the reliability of the feed-in of renewable energy, we used the HSA-ANN model to accurately forecast solar and wind energy. The GEM aimed to reduce expenses and carbon emissions, while successfully managing energy resources, both on-site and off-site. We evaluated its performance by comparing it to a reference scenario in which the DCs relied entirely on brown energy. The simulation results clearly showed the superiority of our GEM technique. Case 1 (brown energy only) was 58% more expensive and produced 71% higher carbon emissions than Case 2.1 ($minCost_{DC}^{total}$). Similarly, Case 1 was 39% more expensive and produced 80% higher carbon emissions than Case 2.2 ($minCE_{DC}^{total}$). Case 2.2 was 30% more expensive and produced 46% less carbon emission than case 2.1. Our future research plans include merging our proposed GEM with demand-side management measures to create a more robust and responsive energy ecology for dynamic demand-side management, by leveraging smart grid technologies and real-time data analytics to reduce overall energy costs and carbon footprints, while promoting a more resilient and responsive energy ecosystem. The ultimate goal of our research is to improve energy management systems, to achieve a greener and more sustainable approach to energy generation and consumption in cloud data centers and elsewhere.

Author Contributions: Methodology, S.M.M., T.M. and S.A.M.; Software, S.M.M.; Validation, T.M. and S.A.M.; Formal analysis, S.M.M. and T.M.; Investigation, T.M. and S.A.M.; Data curation, S.M.M.; Writing—original draft, S.M.M.; Writing—review and editing, T.M.; Visualization, S.M.M.; Supervision, T.M. and S.A.M.; Project administration, T.M. and S.A.M.; Funding acquisition, S.M.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no known conflicts of interest.

References

1. Gu, C.; Fan, L.; Wu, W.; Huang, H.; Jia, X. Greening cloud data centers in an economical way by energy trading with power grid. *Future Gener. Comput. Syst.* **2018**, *78*, 89–101. [CrossRef]
2. Laganà, D.; Mastroianni, C.; Meo, M.; Renga, D. Reducing the operational cost of cloud data centers through renewable energy. *Algorithms* **2018**, *11*, 145. [CrossRef]
3. Katal, A.; Dahiya, S.; Choudhury, T. Energy efficiency in cloud computing data centers: A survey on software technologies. *Clust. Comput.* **2023**, *26*, 1845–1875. [CrossRef]
4. Naomi Xu, E. The Internet Cloud Has a Dirty Secret. 2019. Available online: https://fortune.com/2019/09/18/internet-cloud-server-data-center-energy-consumption-renewable-coal/ (accessed on 6 February 2024).
5. Heyd, E. America's Data Centers Consuming Massive and Growing Amounts of Electricity. 2014. Available online: https://www.nrdc.org/media/2014/140826 (accessed on 6 February 2024).
6. Barasso, L.A. The price of performance: An economic case for chip multiprocessing. *ACM Queue* **2005**, *3*, 48–53. [CrossRef]
7. Qureshi, A. Power-Demand Routing in Massive Geo-Distributed Systems. Doctoral Dissertation, Massachusetts Institute of Technology, Cambridge, MA, USA, 2010.
8. Bosker, B. Google Buys 20 Years Worth of Wind Energy to Power Data Centers. 2010. Available online: https://www.huffpost.com/entry/google-wind-farm-purchase_n_653146 (accessed on 6 February 2024).
9. Deng, W.; Liu, F.; Jin, H.; Li, B.; Li, D. Harnessing renewable energy in cloud datacenters: Opportunities and challenges. *IEEE Netw.* **2014**, *28*, 48–55. [CrossRef]
10. Gu, C.; Huang, H.; Jia, X. Green scheduling for cloud data centers using ESDs to store renewable energy. In Proceedings of the 2016 IEEE International Conference on Communications (ICC), Kuala Lumpur, Malaysia, 22–27 May 2016; pp. 1–7.
11. Ren, C.; Wang, D.; Urgaonkar, B.; Sivasubramaniam, A. Carbon-aware energy capacity planning for datacenters. In Proceedings of the 2012 IEEE 20th International Symposium on Modeling, Analysis and Simulation of Computer and Telecommunication Systems, Washington, DC, USA, 7–9 August 2012; pp. 391–400.

12. Gao, P.X.; Curtis, A.R.; Wong, B.; Keshav, S. It's not easy being green. *ACM SIGCOMM Comput. Commun. Rev.* **2012**, *42*, 211–222. [CrossRef]
13. Christina, N. Fossil Fuels, Explained. 2019. Available online: https://www.nationalgeographic.com/environment/energy/reference/fossil-fuels/ (accessed on 6 February 2024).
14. Li, W.; Yang, T.; Delicato, F.C.; Pires, P.F.; Tari, Z.; Khan, S.U.; Zomaya, A.Y. On enabling sustainable edge computing with renewable energy resources. *IEEE Commun. Mag.* **2018**, *56*, 94–101. [CrossRef]
15. Popescu, G.H.; Andrei, J.V.; Nica, E.; Mieilă, M.; Panait, M. Analysis on the impact of investments, energy use and domestic material consumption in changing the Romanian economic paradigm. *Technol. Econ. Dev. Econ.* **2019**, *25*, 59–81. [CrossRef]
16. Simionescu, M.; Albu, L.L.; Raileanu Szeles, M.; Bilan, Y. The impact of biofuels utilisation in transport on the sustainable development in the European Union. *Technol. Econ. Dev. Econ.* **2017**, *23*, 667–686. [CrossRef]
17. Zhao, Q.; Chen, Q.; Xiao, Y.; Tian, G.; Chu, X.; Liu, Q. Saving forests through development? Fuelwood consumption and the energy-ladder hypothesis in rural Southern China. *Transform. Bus. Econ.* **2017**, *16*, 199.
18. UNFCCC. Kyoto Protocol Reference Manual on Accounting of Emissions and Assigned Amount United Nations Framework Convention on Climate Change. 2008. Available online: https://unfccc.int/resource/docs/publications/08_unfccc_kp_ref_manual.pdf (accessed on 6 February 2024).
19. Álvarez, R.; Zubelzu, S.; Díaz, G.; López, A. Analysis of low carbon super credit policy efficiency in European Union greenhouse gas emissions. *Energy* **2015**, *82*, 996–1010. [CrossRef]
20. Climate Strategies & Targets. European Commission. Available online: https://climate.ec.europa.eu/eu-action/climate-strategies-targets_en (accessed on 6 February 2024).
21. COP25 Summary Report. 2019. Available online: https://ieta.b-cdn.net/wp-content/uploads/2022/12/IETA_Report_COP25SummaryReport_2019.pdf (accessed on 10 May 2024).
22. 2050 Long-Term Strategy. European Commission. Available online: https://climate.ec.europa.eu/eu-action/climate-strategies-targets/2050-long-term-strategy_en#:~:text=Striving%20to%20become%20the%20world's%20first%20climate%2Dneutral%20continent%20by%202050.&text=The%20EU%20aims%20to%20be,to%20the%20European%20Climate%20Law%20 (accessed on 6 February 2024).
23. Boeters, S.; Koornneef, J. Supply of renewable energy sources and the cost of EU climate policy. *Energy Econ.* **2011**, *33*, 1024–1034. [CrossRef]
24. Shivakumar, A.; Dobbins, A.; Fahl, U.; Singh, A. Drivers of renewable energy deployment in the EU: An analysis of past trends and projections. *Energy Strategy Rev.* **2019**, *26*, 100402. [CrossRef]
25. Swain, R.B.; Karimu, A. Renewable electricity and sustainable development goals in the EU. *World Dev.* **2020**, *125*, 104693. [CrossRef]
26. Brodny, J.; Tutak, M. Analyzing Similarities between the European Union Countries in Terms of the Structure and Volume of Energy Production from Renewable Energy Sources. *Energies* **2020**, *13*, 913. [CrossRef]
27. Hepburn, C. Regulation by prices, quantities, or both: A review of instrument choice. *Oxf. Rev. Econ. Policy* **2006**, *22*, 226–247. [CrossRef]
28. Aslam, S. An Optimal Home Energy Management Scheme Considering Grid Connected Microgrids with Day-Ahead Weather Forecasting Using Artificial Neural Network. Masters's Thesis, COMSATS University Islamabad, Islamabad, Pakistan, 2018.
29. Zhong, Z.; Yang, C.; Cao, W.; Yan, C. Short-term photovoltaic power generation forecasting based on multivariable grey theory model with parameter optimization. *Math. Probl. Eng.* **2017**, *2017*, 5812394. [CrossRef]
30. Wood M. Global Wind Power Capacity to Grow by 112% over Next 10 Years. 2020. Available online: https://www.woodmac.com/press-releases/global-wind-power-capacity-to-grow-by-112-over-next-10-years/ (accessed on 6 February 2024).
31. Mohsin, S.M.; Maqsood, T.; Madani, S.A. Solar and Wind Energy Forecasting for Green and Intelligent Migration of Traditional Energy Sources. *Sustainability* **2022**, *14*, 16317. [CrossRef]
32. Satpathy, A.; Addya, S.K.; Turuk, A.K.; Majhi, B.; Sahoo, G. Crow search based virtual machine placement strategy in cloud data centers with live migration. *Comput. Electr. Eng.* **2018**, *69*, 334–350. [CrossRef]
33. Liu, X.F.; Zhan, Z.H.; Deng, J.D.; Li, Y.; Gu, T.; Zhang, J. An energy efficient ant colony system for virtual machine placement in cloud computing. *IEEE Trans. Evol. Comput.* **2016**, *22*, 113–128. [CrossRef]
34. Khosravi, A.; Andrew, L.L.; Buyya, R. Dynamic vm placement method for minimizing energy and carbon cost in geographically distributed cloud data centers. *IEEE Trans. Sustain. Comput.* **2017**, *2*, 183–196. [CrossRef]
35. Grange, L.; Da Costa, G.; Stolf, P. Green IT scheduling for data center powered with renewable energy. *Future Gener. Comput. Syst.* **2018**, *86*, 99–120. [CrossRef]
36. Zhang, Y.; Wang, Y.; Wang, X. Greenware: Greening cloud-scale data centers to maximize the use of renewable energy. In Proceedings of the ACM/IFIP/USENIX International Conference on Distributed Systems Platforms and Open Distributed Processing, Lisbon, Portugal, 12–16 December 2011; Springer: Berlin/Heidelberg, Germany, 2011; pp. 143–164.
37. Gu, C.; Liu, C.; Zhang, J.; Huang, H.; Jia, X. Green scheduling for cloud data centers using renewable resources. In Proceedings of the 2015 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Kowloon, Hong Kong, 26 Apri–1 May 2015; pp. 354–359.
38. Thi, M.T.; Pierson, J.M.; Da Costa, G.; Stolf, P.; Nicod, J.M.; Rostirolla, G.; Haddad, M. Negotiation game for joint IT and energy management in green datacenters. *Future Gener. Comput. Syst.* **2020**, *110*, 1116–1138. [CrossRef]

39. Abdallah, L.; El-Shennawy, T. Reducing carbon dioxide emissions from electricity sector using smart electric grid applications. *J. Eng.* **2013**, *2013*, 845051. [CrossRef]
40. He, H.; Shen, H.; Liang, D. Cost minimizing online algorithm for internet green data centers on multi-source energy. *Concurr. Comput. Pract. Exp.* **2019**, *31*, e5044. [CrossRef]
41. Fan, X.; Weber, W.D.; Barroso, L.A. Power provisioning for a warehouse-sized computer. *ACM Sigarch Comput. Archit. News* **2007**, *35*, 13–23. [CrossRef]
42. Aslam, S.; Javaid, N.; Khan, F.A.; Alamri, A.; Almogren, A.; Abdul, W. Towards efficient energy management and power trading in a residential area via integrating a grid-connected microgrid. *Sustainability* **2018**, *10*, 1245. [CrossRef]
43. Parallel Workloads Archive. Available online: https://www.cse.huji.ac.il/labs/parallel/workload/logs.html (accessed on 10 May 2024).
44. New York Independent System Operator (NYISO). Available online: http://mis.nyiso.com/public/P-24Alist.html (accessed on 6 February 2024).
45. Measurement and Instrumentation Data Center (MIDC) of National Renewable Energy Laboratory (NREL). Available online: https://midcdmz.nrel.gov/ (accessed on 6 February 2024).
46. Solar Modules from BP Solar. Available online: http://www.posharp.com/photovoltaic/database.aspx?cid=e45192d8-cc48-4941-a617-33f81eab7296 (accessed on 6 February 2024).
47. Solar Panel. Available online: https://www.secondsol.com/en/anzeige/12318/solar-panel/crystalline/poly/bp-solar/bp-solarex-msx-120-msx-120 (accessed on 6 February 2024).
48. Schubel, P.J.; Crossley, R.J. Wind turbine blade design review. *Wind. Eng.* **2012**, *36*, 365–388. [CrossRef]