Towards Energy Efficiency and Power Trading Exploiting Renewable Energy in Cloud Data Centers

Shahzad Aslam[1], Sheraz Aslam[1,2], Herodotos Herodotou[2], Syed Muhammad Mohsin[1] and Khursheed Aurangzeb[3]

[1] Department of Computer Science, COMSATS University Islamabad, Islamabad 44000, Pakistan;
[2] Department of Electrical Engineering, Computer Engineering and Informatics, Cyprus University of Technology, Limassol 3025, Cyprus;
[3] Computer Engineering Department, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia;
Correspondence: sheraz.aslam@ieee.org, herodotos.herodotou@cut.ac.cy

***Abstract*—This study investigates the energy cost and carbon emission reduction problem in geographically distributed cloud data centers (DCs), where each DC is connected with its own renewable energy resources (RERs) for green energy generation. We consider four cloud DCs that are operated by a single cloud service provider. They consume energy from both RERs and from the commercial grid to meet the demand of cloud users. For energy pricing, we consider four different energy markets that offer varying energy prices per hour. Additionally, our proposed strategy enables DCs to sell excess electricity to the commercial grid in peak-price hours and purchase in low-cost hours according to power trading. This work also exploits energy storage devices (ESDs) to store energy for future use. We utilize real-time data requests, weather data, and pricing data for performing simulations and results affirm the effectiveness and productiveness of our proposed method to mitigate the energy cost and carbon emission of cloud DCs.**

***Index Terms*—Cloud computing; Energy efficiency; Cloud data centers; Renewable energy integration; Power trading;**

I. Introduction

Cloud computing plays an important role in providing computing resources to consumers [1]. It provides hardware and software resources anywhere and anytime on a pay-as-you-go model. Customers can enjoy cloud computing services provided by cloud data centers (DCs) that are distributed around the globe. These DCs typically host a number of servers in the order of thousands. Furthermore, cloud DCs consume a huge amount of energy that leads to both a high cost and a huge amount of carbon emissions. According to a report published in 2013 [2], the power consumption of US DCs was 91B KWh and it was estimated to increase up to 140B KWh till 2020. 91B KWh power load is equivalent to two years of load demand for New York City. Higher energy consumption leads to higher carbon emissions that adversely affect the environment. For the sake of environmental sustainability, some countries have imposed a tax on carbon emissions [3], [9], [10]. Therefore, there is an exigent need to reduce the power consumption of DCs or to install cheaper resources of energy generation that also lead to lower carbon emissions.

Energy efficiency in cloud DCs is considered a big challenge due to huge energy consumption. Researchers are proposing various solutions to enhance energy efficiency. For instance, some researchers are focusing on consolidating virtual machines on as few servers as possible and shutting down idle servers [4]; some people propose virtualization techniques to improve data center efficiency [5]; in contrary, others are trying to integrate renewable energy resources to improve energy efficiency and performance of DCs [6]. Prominent cloud service providers (CSPs), like Amazon, Google, and Microsoft, are trying to minimize energy consumption and carbon emissions through the integration of renewable energy with brown energy [7], [8]. Some CSPs have their own renewable-energy plants, while others prefer to purchase power from renewable grids (wind farms and solar parks). However, due to the intermittent nature of solar and wind energy, CSPs can not rely on it. To provide reliable and economical services to the users, CSPs prefer to integrate renewable and brown energies.

The authors of [11] propose a virtual machine (VM) placement scheme by implementing a crow search algorithm. Another energy consumption and active servers minimization scheme is presented in [12], where an ant colony optimization-based approach is implemented to achieve desired objectives. However, both studies [11], [12] did not consider the cost of carbon emissions (total energy requirement is met by fossil fuel-based electric grid). In [13], the authors aim to find the best location for a data center, based on geographical location and characteristics of the data center to alleviate energy consumption, cost, and carbon footprint. However, in this way, sometimes the data centers are located far from the end-users and this may cause delays in processing user requests. Another work [14] proposed to reduce energy consumption, cost, and carbon emission by using various optimization techniques. Furthermore, renewable energy resources (RERs) are installed to provide electricity to data centers to achieve a green environment. However, they assume consistent electricity generation from RERs, which is non-realistic, because RERs are intermittent in nature. This property of RERs can often cause high costs and delays. Yanwei et *et al.* propose a cost-efficient method to mitigate energy cost in geographically distributed cloud data centers (DCs) [15]. However, they did not consider energy storage devices (ESDs) and DCs are not able to sell excess electricity back to the commercial grid. The work [16] also addresses the energy cost minimization problem for cloud DCs that are distributed in various locations. They exploit ESDs to alleviate the energy cost and carbon emissions; however, according to their method, DCs do not participate in power trading.

The work cited in [11]-[16] either focused on specific production applications or failed to take full advantage of cloud and smart grid-based technologies. This work studies the issue of energy efficiency in cloud data centers that are distributed geographically. Then, we develop an intelligent mechanism to integrate renewable energy to mitigate the cost burden of DCs as well as to reduce carbon emissions. In addition, we also consider energy storage devices to store energy for future use. Thus, the DCs can efficiently manage the power demand to respond to the customers' requests.

The rest of the paper is organized as follows: the next section presents the related work and Section III uncovers the system model and mathematical formulations. Furthermore, Section IV outlines the developed methodology, while Section V presents the experimental setup along with results. Finally, the paper is concluded with Section VI.

II. Related Work

The work [17] proposed a task scheduling approach using integer linear programming to alleviate the energy cost in cloud DCs. In order to reflect the dynamic nature of the cloud environment, a genetic algorithm was developed. Furthermore, simulation results showed that the developed methods gain high performance in terms of lowering response time and minimizing energy consumption. The authors of [18] developed a mixed-integer linear programming model to alleviate the energy cost in Internet DCs (IDCs), where they considered the electricity tariffs of various locations and power management ability of IDCs. Furthermore, WorldCup '98 data is utilized to check the effectiveness of their developed model. It is evident from simulation results that the energy consumption of IDCs is reduced by the developed solution. Shamimul *et al.* focused on green cloud DCs, where they propose a hybrid energy system that consists of wind turbines, solar panels, diesel generators, and a storage system.

Abdullahi *et al.* exploited a symbiotic organisms search algorithm to minimize the energy consumption of DCs [19]. They save energy by mitigating a number of active servers using VMs migration. They perform simulations with a different number of VMs and their results validate their scheme with regards to the reduction in energy consumption. The work in [20] solves a VM placement problem to attain energy efficiency in cloud DCs. It also develops an energy-aware algorithm, namely GATA, which combines a genetic algorithm with tabu search. The key objectives of that work were to achieve energy efficiency by optimal VM placement along with maximizing load balance among different sources. Simulations have been performed to validate the performance of the newly proposed GATA algorithm. In addition, GATA is also compared with two metaheuristic benchmark algorithms and the effectiveness of GATA is confirmed from comparative analysis.

Another work [22] developed a VM allocation method with VM consolidation and modifying the VMs processing speed, aiming at high response time and energy efficiency of cloud DCs. According to their proposed method, VMs processing speed in the baseline module is switched to low speed in case of low traffic/low requests. On the contrary, in case of high traffic, VMs operate with high processing speed and consolidation will be performed with baseline module and reserved module VMs. Furthermore, they exploit the Markov chain to mathematically check the response performance and energy-saving degree.

III. System Model

In this work, we consider a cloud environment that consists of two key entities, i.e., a cloud service provider and a cloud user. A cloud service provider is an entity that own multiple DCs and provides the cloud services/resources to its consumers against payment of charges. A cloud user is an entity that consumes the services/resources offered by the cloud service provider. The physical resources of the cloud are categorized on the basis of various parameters, like architectures of processors, speed of processors, memory, and the number of cores. Besides, cloud tasks can be categorized on the basis of several parameters, such as size in millions of instructions, dependency among various tasks, and time (arrival time, waiting time, start time, and time limit). However, this work focuses on energy cost and carbon footprint reduction in a cloud environment.

A. Cloud Service Provider

The cloud service provider manages n number of DCs, $DC = \{DC_1, DC_2, ..., DC_n\}$, which are geo-distributed in various locations. Each DC is connected to a backbone network (see Figure 1) to provide services/resources to cloud consumers. It uses multiple energy resources (i.e., green energy resources and commercial grid), network equipment, and other devices. Moreover, DCs can manage their energy utilization to reduce power costs and carbon footprint. For instance, they can use power from either green energy sources g (e.g., solar panels, wind turbines) or conventional resources c, i.e., power grid. DCs also have installed diesel generators d to deal with any unpleasant circumstances (e.g., power outages). We define all power resources of DCs as $p = \{g, c, d\}$. Furthermore, each DC contains m number of servers, $S = \{s_1, s_2, ..., s_m\}$.

B. Cloud User

A cloud user is an important entity of the cloud environment that submits a request regarding cloud resources/services. A service request by cloud user i at time t is represented by $u_i(t)$ and consists of various parameters, such as request type, hold time, storage, start time, deadline, etc. A cloud service provider receives q number of requests R from various users at time t, denoted as $R = \{r_1, r_2, ..., r_q\}$.

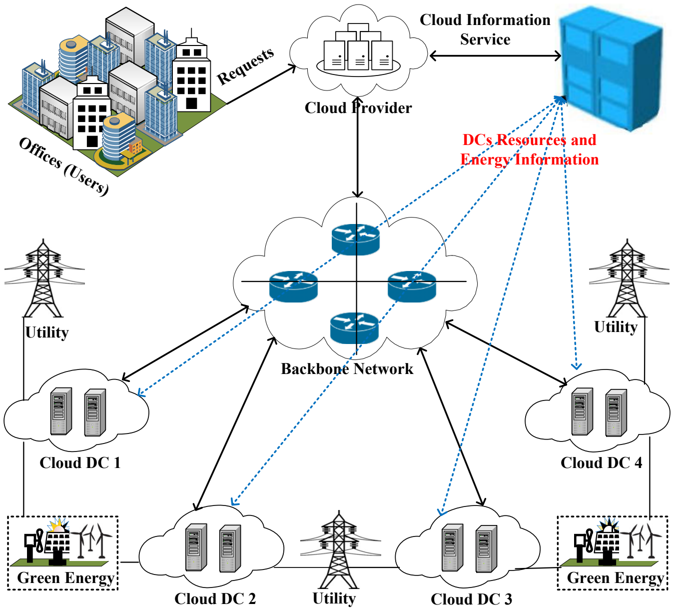

Fig. 1: Architecture of geographically distributed cloud data centers connecting a single cloud provider, several clients, and various energy supplying resources

C. Workload Model

Cloud consumers are frequently assigning tasks to the cloud service provider and then these tasks are assigned to a specific DC on the basis of available energy and computing resources. Let us denote all incoming tasks with $T = \{task_1, task_2, ..., task_N\}$, where t_N shows the maximum number of tasks. It is important to note that each task (service request) is considered as an independent task that can only be assigned to a single DC and cannot be broken down and distributed to multiple DCs. Furthermore, we can present a single task at time t as

$$task_i^t = \{A_i, D_i, L_i, S_i, F_i\}, \tag{1}$$

where, A_i and D_i denote the arrival time and deadline of task i, respectively. L_i shows the task's length. The start time of task i is denoted by S_i, while the finishing time by F_i.

D. Energy Consumption Model

According to our proposed model, each DC has several energy resources to meet its power demand while fulfilling computing requests by cloud consumers. In particular, a DC may use a combination of green sources g, conventional power grid c, or diesel generators d. However, each DC has a priority to use maximum energy from green sources g due to low cost and minimum carbon emission. Wind turbine and solar panel are explained in detail below.

1) Solar Panel: The solar panel produces electricity from sunlight and is calculated as [24]:

$$P^{sp}(t) = \eta^{sp} \times A^{sp} \times Irr(t) \times (1 - 0.005(Temp(t) - 25)) \tag{2}$$

where, hourly produced energy for time interval t is shown by $P^{sp}(t)$. The terms η^{sp} and A^{sp} denote the efficiency and area of the solar panel, respectively. The solar irradiation is denoted by $Irr(t)$ and and outside temperature by $Temp(t)$ for time interval t.

2) Wind Turbine: Wind turbines are also installed for low carbon emission electricity generation and produce power on the basis of wind speed. We can calculate energy using the following mathematical formula:

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

The $P^{wt}(t)$ shows the generated energy from a wind turbine at time interval t. A wind turbine generates power on the basis of the area swept by rotor blades A, wind speed $V^{wt}(t)$, air density ρ, rotor efficiency C_p, and constant λ. Note that energy generation is directly proportional to wind speed ($P_t{}^{wt} \propto V$).

E. Energy Cost Calculation

The energy cost of a cloud DC primarily depends on the energy that is purchased from the commercial grid, since RERs have fixed installation and maintenance costs. Furthermore, diesel generators are also considered (similar to [13]), which are used in the absence of other energy resources. Additionally, we have used a real-time pricing method for various DCs, based on which the utility offers new pricing $P(h)$ for each hour h. We can calculate hourly energy cost that is paid to the conventional grid as:

$$Cost_c(h) = \sum_{i=1}^{n} EnConsumed(DC_i, h) \times P(DC_i, h) \tag{4}$$

where, $EnConsumed(DC_i, h)$ denotes energy consumption by DC_i at hour h and the term $P(DC_i, h)$ presents the hourly energy price (kWh). Note that hourly prices of all DCs vary due to their geographically distributed locations.

The hourly total cost incurred by a DC against all energy resources can be calculated by equation 5.

$$Cost_{total}(h) = Cost_c(h) + \Big(Cost_d(h) \times \alpha_d(h)\Big) + Cost_g \tag{5}$$

$Cost_d(h)$ denotes hourly cost incurred by the diesel generator and $\alpha(h)$ shows the ON or OFF status of diesel generator in hour h.

$$\alpha_d(h) = \begin{cases} 1 & \textit{If diesel generator is ON} \\ 0 & \textit{If diesel generator is OFF} \end{cases} \tag{6}$$

In equation 5, $Cost_g$ represents the hourly cost of green energy resources, which are considered to have fixed operational and maintenance costs ($10/MWh) as [23].

IV. Developed Methodology

This section presents the proposed methodology for minimizing energy cost and carbon emissions. To attain our objectives, our developed method is divided into three steps, namely, ranking cloud DCs, allocating incoming requests to servers in each DC, and scheduling of several energy sources.

A. Ranking of Cloud DCs

We have ranked the DCs to attain minimum cost based on the lowest computing cost (LCC). The key aim of this strategy is to dispatch maximum requests to DCs having the minimum LCC. In this way, the DCs with LCC will have higher priority in service requests dispatching. We can calculate LCC for DC i at time interval t as [14]:

$$LCC_i^t = \frac{(P_{peak,i} \times Qd_i^t)}{C_i^t} \tag{7}$$

where, LCC_i^t shows lowest computing cost of DC i at time interval t. The term $P_{peak,i}$ and Qd_i^t denote peak power consumption of DC i and brown/diesel energy of DC i at time t, respectively. In addition, C_i^t presents total cost against DC i at time t.

B. Allocating Service Requests to Servers

We have adapted the resource vector matching (RVM) mechanism to allocate the service requests to servers of the DCs. The allocation of requests is performed through a cosine function by calculating the matching of two resource factors, as expressed below:

$$Cosine(R_j^t, H_k^t(i)) = \frac{R_j^t \times H_k^t}{|R_j^t| \times |H_k^t|}, \tag{8}$$

where, R_j^t denotes request j at time t and $H_k^t(i)$ shows available resources of server k in DC i at time t. Furthermore, a higher cosine value indicates a more suitable server for allocating service requests. In this regard, we allocate the most matching server for each service request.

C. Energy Sources Scheduling and Power Trading

After dispatching service requests to servers based on step1 and step2, the remaining problem is considered a demand-response problem. The key issue is to schedule energy resources on the basis of energy demand for cloud DCs and energy tariffs. In addition, for instance, any charging/discharging of ESDs can affect the whole scheduling decisions in subsequent time-intervals; therefore, we consider this problem for the whole period of time that is typically a mixed-integer linear problem (MILP). However, MILP can solve only a reasonable-sized problem such as the ones considered in simulations of this work. Our method decides the following in each time-interval:

- How a service request is assigned to which server of the DCs.
- Which type of energy and how much they are utilized to power DCs.
- Which type of energy is used to charge ESDs.
- When and how much energy is sold back to the commercial grid by discharging ESDs.

The exact mathematical formulations for the above are omitted due to space constraints.

TABLE I: Parameters of data centers taken from [18]

	Num servers	CPU	Memory (GB)	Storage (TB)	P_{idle} (W)	P_{peak} (W)
1	3300	8	128	2	54	90
2	2800	16	144	2	84	140
3	3200	8	128	2	65	100
4	2500	16	144	2	90	150

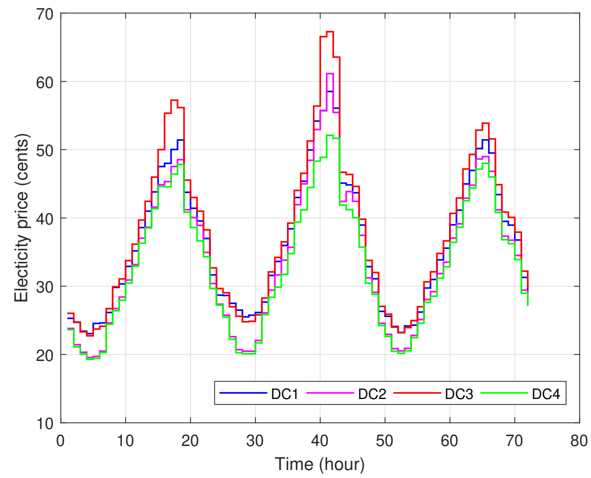

Fig. 2: Electricity tariff for three days (Aug. 1, 2018 to Aug. 3, 2018) [26]

V. Performance Evaluation

This section evaluates the effectiveness and productiveness of the proposed methodology with respect to the key objectives of this study, i.e., low energy cost and minimum carbon emissions.

A. Simulation Setup

We perform extensive simulations, where four geographically distributed cloud DCs are considered, which are owned by a single cloud provider. Our work uses the same configuration parameters of DCs as [18] (presented in Table I). For energy supply to these DCs, multiple sources of energy are assumed, like green energy resources and conventional energy resources. Utility companies charge dynamic energy prices according to DC locations. We have performed simulations for three days (from August 01, 2018 to August 03, 2018) using one-hour time intervals.

We calculate the solar and wind energy generation as [24]. Simulations of this work exploit the weather data, i.e., wind speed, temperature, and irradiance from the MIDC dataset of the National Renewable Energy Laboratory [25]. Moreover, data from the following four locations are used: Lanai Hawaii, Los Angeles California, Oak Ridge Tennessee, and San Luis Valley Colorado. For energy cost calculation that is purchased from the commercial grid, we consider the hourly tariff of the four locations [26], presented in Figure 2. In order to calculate the operational cost of renewable energy sources, we have considered 10 $/MWh for all DCs [27].

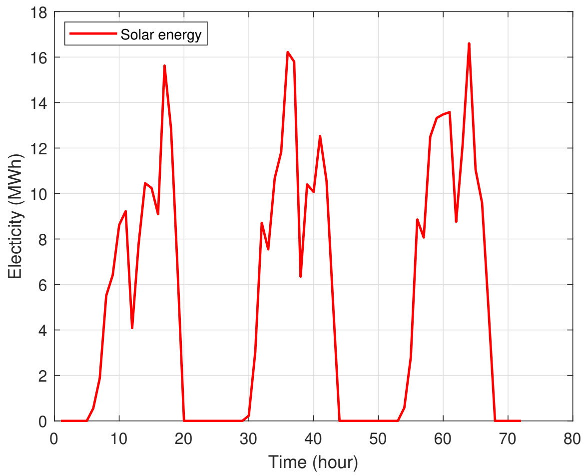

Fig. 3: Electricity generation from solar panels

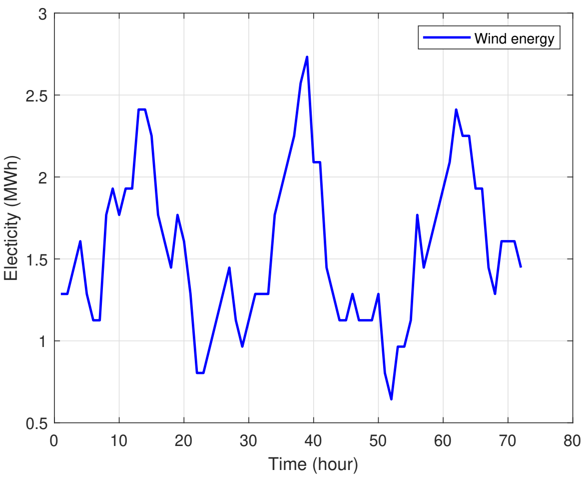

Fig. 4: Electricity generation from wind turbines

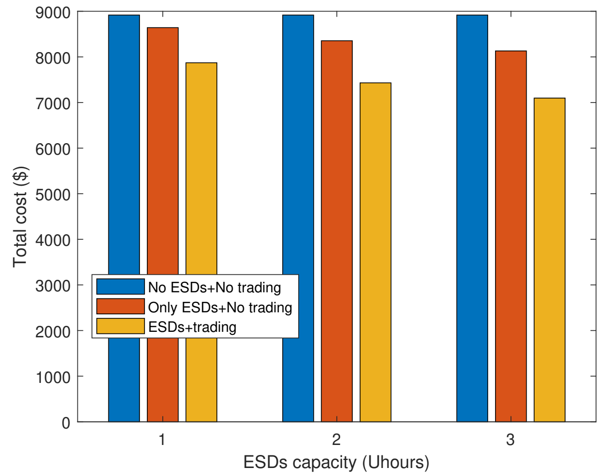

Fig. 5: Total energy cost

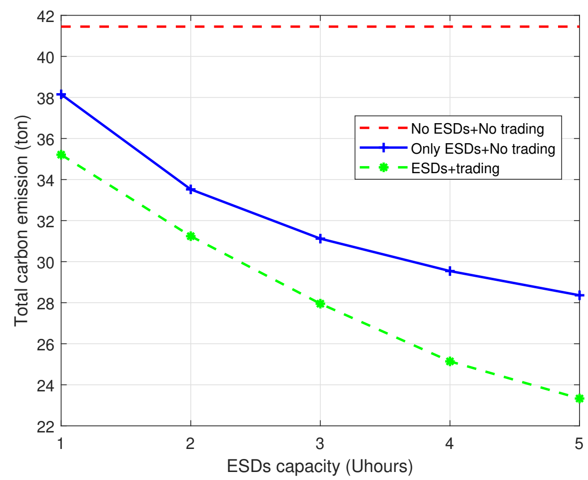

Fig. 6: Total carbon emission

We assumed that 10000 solar panels (BP-MSX 120) and 1000 wind turbines (NE-3000), as [15], are installed at each plant to fulfill the power demand of cloud DCs. Figure 3 shows the hourly energy generation from all solar panels for three days (August 01, 2018 to August 03, 2018). It can be clearly noted that solar panels generate minimum energy generation at night times and maximum energy when solar has high irradiance. Hourly energy generation from wind turbines is presented in Figure 4. It can be observed from the figure that energy generation from wind turbines is stochastic in nature.

B. Experimental Results

To verify the productiveness of our proposed method, we have performed a comparison with two benchmark works:

1) No ESDs+No trading: Only RERs are considered to make green cloud DCs (no ESDs and power trading) [15].
2) Only ESDs+No trading: Only RERs and ESDs are considered but no power trading [16].
3) ESDs+Trading: Our proposed method exploits RERs with ESDs and power trading to alleviate energy cost and make DCs greener.

The total energy cost of cloud DCs is depicted in Figure 5. It is observed from this figure that our DCs will pay the minimum cost with our proposed method. It is important to note that energy cost may be reduced because of three key factors: (1) energy prices that vary based on time and location, (2) varying capacities of ESDs, and (3) power trading. We can choose the DC to provide services to cloud users, which is purchasing electricity against minimum energy tariff. Let the capacity of ESDs, expressed in Uhour, equal the total power consumption of a DC in peak hours. Usually, most DCs exploit ESDs to avoid interruption during operations and they consider capacity at most 30 minutes in peak consumption time. To test our proposed method, we perform simulation by considering fluctuating ESDs capacities. We consider Uhour=1, Uhour=2, and Uhour=3, as presented in Figure 5. In all cases, our proposed method shows efficacy with regards to minimum energy cost.

We have calculated the total carbon emissions using carbon emission rate (CER) that shows kilograms of carbon equivalent per kWh electricity, as can be seen in Table II. Figure 6 presents the total amount of carbon emissions (tons) for all DCs using our proposed method and the two benchmark methods. It can be noticed from the figure that carbon emission is reduced by increasing the capacity of ESDs (Uhour).

TABLE II: CER of various energy resources [28]

Source of energy	Grid	Solar	Wind
CER (gCO_2e/kWh)	968	53	22.5

VI. Conclusions and Future Work

In modern economies, substantial growth of cloud data centers (DCs) across the world leads to power management issues. These DCs are usually distant from the user and consume large amounts of energy for their operations. Fulfillment of DC energy demand through brown energy leads to economic issues, power transmission issues, and excessive carbon emission. All these issues are very critical and need keen attention from the research community. In this study, we have presented a solution of cost and carbon reduction problem in cloud DCs by integrating energy storage systems and power trading with commercial grids. We consider four geographically distributed DCs, where each DC is able to produce its own electricity from green energy resources. We have performed extensive simulations to affirm the validity of our proposed method. Simulation results show that cloud providers can reduce energy costs and carbon emissions (when ESDs = 1 Uhour) by 11.73 % and 15.05 %, respectively.

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