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Abstract

Distributed clouds have recently attracted many cloud providers and researchers as a topic of intensive interest. High energy costs and carbon emissions are two significant problems in distributed clouds. Due to the geographic distribution of data centers (DCs), there are a variety of resources, energy prices and carbon emission rates to consider in a distributed cloud, which makes the placement of virtual machines (VMs) for cost and carbon efficiency even more critical than in centralized clouds. Most previous work in this field investigated either optimizing cost without considering the amount of produced carbon or vice versa. This paper presents a cost and carbon emission-efficient VM placement method (CACEV) in distributed clouds. CACEV considers geographically varying energy prices and carbon emission rates as well as optimizing both network and server resources at the same time. By combining prediction-based A* algorithm with Fuzzy Sets technique, CACEV makes an intelligent decision to optimize cost and carbon emission for providers. Simulation results show the applicability and performance of CACEV.

I. INTRODUCTION

Recent cloud infrastructures are increasingly geographically distributed. The distributed cloud has some benefits in comparison to the centralized cloud such as lower upfront investment, vulnerability to natural disasters and proximity to users. Due to the geographical distribution of data centers (DCs), distributed clouds offer a pool of resource options with different prices and carbon emission rates.

Carbon emission and cost are currently two critical concerns for cloud providers and network operators. Energy consumption (EC) has a direct effect on both cost and carbon emission. DCs worldwide consumed 270 TWh of energy in 2012, with a Compound Annual Growth Rate (CAGR) of 4.4% from 2007 to 2012 [1], [2]. According to predictions, they will account for about 8% of worldwide electricity consumption by 2020, and will generate about 2.6% of global carbon emission [3], [4]. Therefore, providers try to reduce their EC and carbon emission. For example, France Telecom-Orange has the ambition of decreasing its EC and carbon emission from 2006 to 2020 by 15 and 20% respectively [5].

As a result, energy saving methods are needed to help providers to reduce both cost and carbon emission. However, as energy prices and carbon emission rates vary by location (e.g., because of different energy sources), energy savings alone may not necessarily or effectively imply reduction of carbon emission and cost. In addition to EC which is important for both cost and carbon efficiency, energy price factor for cost efficiency and cleanness of energy sources for carbon efficiency have to be considered. Above all, there is no correlation between the cleanness (carbon footprint) of a locations energy sources and the energy price for that location [3]. Therefore, to optimize both cost and carbon emission, we need to solve a three-dimensional problem: (i) how to minimize EC (usually in form of resource utilization optimization) (ii) how to find resources with best energy price and (iii) how to choose the resources which are connected to energy sources with lowest carbon emission rate. Considering these three, sometimes conflicting, dimensions simultaneously makes the problem very complex.

The main objective of this paper is to devise a new VM placement algorithm considering the above three-dimensional problem to optimize both cost and carbon emission in a distributed cloud. To do so, we try to allocate newly requested VMs using currently active cloud devices (i.e., physical machines (PMs) and network elements) in order to avoid the EC associated with the activation of devices from sleep mode and also to have the lowest possible number of active devices.

To offer a realistic solution, the paper considers a detailed system model characterized by the following points:

1) heterogeneity of resources (DCs, PMs, switches) and VMs
2) heterogeneity of EC models of cloud elements (e.g., different PMs may have different EC models)
3) effects of workload on EC of devices (e.g., EC of a PM depends on its CPU load)
4) multiple paths between a pair of PMs
5) a more intelligent algorithm, in contrast to the greedy heuristics that most existing approaches use [17]
6) joint optimization of PM (server) and network resources
7) considering variety in price and location among the resources
8) ability to select resources from multiple DCs to serve a request
9) taking into account inter-VM communication
10) IaaS Service Level Agreement (SLA) violation

To address these points, this paper proposes a cost and carbon emission-efficient VM placement method (CACEV) for distributed cloud environments. CACEV builds on ideas of integrating the prediction-based A* search algorithm [18] with Fuzzy Sets technique to obtain better results than typical greedy heuristics. It is a VM placement algorithm for joint optimization of servers and network, which also considers price, location and carbon emission rate of resources. It can select multiple DCs for the reasons of cost and carbon emission efficiency or capacity limitations. Network and data transfer awareness in selecting DCs/PMs and placing VMs makes CACEV capable to optimize network traffic as well.

CACEV is designed for allocating batch jobs, also supporting applications with inter-VM communication. To prevent SLA violations, CACEV adopts utilization thresholds (for more information, see [21]). The goal is to preserve free resources to prevent SLA violations due to consolidation in situations where resource requirements of VMs increase. When selecting PMs, CACEV makes sure not to violate the upper threshold.

The rest of the paper is organized as follows: Section II describes related work. Section III introduces our system model and Section IV defines the problem. The proposed algorithm is described in Section V. Section VI evaluates CACEV and Section VII concludes the paper.

II. RELATED WORK

Previous work addressed some of the 10 points listed in the Introduction to characterize the problem, but only in isolation. To our knowledge, our work is the first to address all aspects in combination.

Li et al. [10] and Dong et al. [11] considered server and network resources at the same time for their proposed VM placement algorithms. You et al. [12] designed a network-aware VM placement method to improve communication cost. But all these works are limited to a single-DC environment and are not appropriate for a distributed cloud with varying resource prices. Alcherry et al. [13] proposed algorithms for network-aware selection of DCs and allocation of VMs on PMs in a distributed cloud. But their primary objective is to minimize the maximum latency in communication between the VMs allocated for a user request, which is different from our objective. They also did not consider hardware and VM heterogeneity in their solution. Our previous study [14] focused on improving communication cost between DCs in a distributed clouds. But, unlike this paper, it did not consider server cost, nor VM placement inside DCs. In addition, our current work is different from all mentioned results since we consider not only costs but also carbon emission.

Khosravi et al. [15] addressed both energy and carbon emission during VM placement in a distributed cloud. However, they did not consider the variability of energy prices. Also, inter-VM communication was not considered, although it is an important factor for reducing traffic and energy of network resources. Zhou et al. jointly considered SLA, electricity cost, and emission reduction for distributed DCs [4] and, recently, Gu et al. proposed a method to minimize carbon emission of cloud DCs while satisfying constraints on response time, electricity budget and maximum number of running PMs in an environment with homogeneous PMs [16]. Different from our work which is for batch jobs with constraints on inter-VM communication, these papers target service jobs with constraints on response time.

III. SYSTEM MODEL

We consider a hierarchical distributed cloud architecture [6] including a cloud controller and site (i.e., DC) and PM controllers. The DCs are given by a complete graph $G_1 = (Dc, E1, w_{Dc}, w_{E1})$ where $Dc$ is a set of DCs, $w_{Dc}$ denotes their current capacity, $E1$ consists of connected edges (representing network paths), and $w_{E1}$ denotes the edge weights (e.g., number of routers on the network path). Each DC has its own Power Usage Effectiveness (PUE) value and is associated with one or more energy sources with different carbon footprint rates and energy prices. PUE is defined as the ratio of total power consumed by a DC to the power consumed by IT devices [15]. We assume the cloud provider owns or leases a high-capacity backbone network to carry the traffic between DCs. Inside DCs, our model (and our proposed VM placement algorithm) supports both structured (e.g., Fat-Trees [7]) and arbitrary [8] topologies.

Each DC $j (1 \leq j \leq |Dc|)$ is represented by a weighted graph $G_{2j} = (N_j, E2_j, w_{N_j}, w_{E2_j})$ where $N_j$ is the set of $n_j$ PMs and $w_{N_j}$ shows their current capacity. Similar to [9], for every pair of PMs $x$ and $y$ in DC$_j$, a set of pre-calculated paths from PM $x$ to PM $y$ is considered. $E2_j$ consists of the set of calculated paths between pairs of PMs in DC$_j$. Resource parameters of each PM, are given as a vector $w_{E2_j}$, including CPU, memory, disk, and I/O bandwidth. Each basic resource unit is represented by one slot [10]. We consider sleep and active modes for both PMs [26] and switches [24], [25].

The model supports different types of VMs. Each VM type $k (1 \leq k \leq U)$ is specified by a vector $Vc^k$ of requested resources, including CPU, memory, disk, and I/O bandwidth in unit of slots.

To handle time-varying request rates and energy prices, time is split into equal time windows ($T$). A set $A$ including $r$ requests is received in each time slot $T$ [19]. We assume that within a time slot $T$ the energy price is fixed, and the IaaS provider rents VMs based on unit of the time slots (even if a VM is finished in the middle of $T$, the rental fee should be paid for the whole time window).
with the constraint that the selected DCs must have enough total capacity to accommodate the M VMs:

\[ \sum_{j \in \text{DC}_j} \sum_{i=1}^{n_j} (wN_i \cdot \text{SelDC}_j) \geq \sum_{j=1}^{M} Vc_j. \]
A. Overall cost formulation (OverallCost)

\( DC_{Cost} \) in Eq. (1) is the cost of incremental energy of selected DCs (both servers and intra-DC networks) to accommodate the requests. \( TSerEn_{j} \), \( TNetEn_{j} \) and \( EnPr_{j} \) are the incremental server energy, network energy, and the energy price in DC\( _{j} \).

\[
DC_{Cost} = \sum_{j=1}^{d} PUE_{j} \cdot (TSerEn_{j} + TNetEn_{j} \cdot EnPr_{j} \cdot SelDC_{j})
\] (3)

\( TSerEn_{j} = \sum_{i=1}^{n_{j}} SerEn_{i} \cdot Sel_{t,i} \) \( \) (4)

\( SerEn_{i} = \sum_{k=1}^{M} E^{i}_{inc,VM_{k}} \cdot VM_{k,i} \) \( \) (5)

Subject to the following constraints:

\[
VM_{k,i} \leq Sel_{t,i}, \quad \forall i, k \quad 1 \leq i \leq n_{j}, \quad 1 \leq k \leq M,
\] (6)

\[
\sum_{i=1}^{n_{j}} VM_{k,i} = 1, \quad \forall k \quad 1 \leq k \leq M,
\] (7)

\[
\sum_{k=1}^{M} VM_{k,i} \cdot Vc_{k} \leq wN_{i}, \quad \forall i \quad 1 \leq i \leq n_{j}.
\] (8)

Eq. (6) ensures that a VM can be assigned only to one of the selected PMs. Eq. (7) guarantees that each VM is assigned to exactly one PM and (8) guarantees that the total load of the VMs assigned to a PM does not exceed its capacity. IE of running \( VM_{k} \) on \( PM_{i} \) is computed as follows:

\[
E^{i}_{inc,VM_{k}} = (EN^{i}_{wakeUp} + EN^{i}_{idle}) \cdot Sel_{t,i} + E^{i}_{VM_{k}}.
\] (9)

If \( PM_{i} \) is in sleep mode and receives the first VM, it needs to spend energy \( EN^{i}_{wakeUp} \) to go from sleep to active mode. If active but idle, \( PM_{i} \) consumes constant energy of \( EN^{i}_{idle} \); \( VM_{k} \) adds \( E^{i}_{VM_{k}} \) to it. As the first VM lets the PM wake from sleep mode, the resulting EC is \( EN^{i}_{wakeUp} + EN^{i}_{idle} + E^{i}_{VM_{k}} \). But for VMs added to an already active PM, the increase in energy is only \( E^{i}_{VM_{k}} \). To compute \( E^{i}_{VM_{k}} \), we use formulas from [26] and [22]:

\[
EN^{i} = EN^{i}_{idle} + \sum_{k=1}^{M} (E^{i}_{VM_{k}} \cdot VM_{k,i})
\] (10)

\[
EN^{i} = EN^{i}_{idle} + (EN^{i}_{max} - EN^{i}_{idle}) \cdot \omega^{i}
\] (11)

\[
\omega^{i} = \frac{\sum_{k=1}^{M} (CPU_{VM_{k}} \cdot VM_{k,i})}{CPU_{max}^{i}}
\] (12)

Using (10) and (11) for one \( VM_{k} \), \( E^{i}_{VM_{k}} \) is computed:

\[
EN^{i}_{idle} + \sum_{k=1}^{M} (E^{i}_{VM_{k}} \cdot VM_{k,i}) = EN^{i}_{idle} + (EN^{i}_{max} - EN^{i}_{idle}) \cdot \omega^{i}
\] (13)

\[
E^{i}_{VM_{k}} = (EN^{i}_{max} - EN^{i}_{idle}) \cdot \frac{CPU_{VM_{k}}}{CPU_{max}^{i}}.
\] (14)

To calculate \( TNetEn_{j} \), we first compute \( NetEn_{ij} \):

\[
NetEn_{ij} = \sum_{pkt=1}^{\delta_{ij}} NetEn_{ij}^{pkt}.
\] (15)

Here, \( \delta_{ij} \) is computed based on the characteristics of the allocated VMs on \( PM_{i} \) and \( PM_{j} \) and also TR information:

\[
\delta_{ij} = \sum_{q=1}^{M} \sum_{w=1}^{M} VM_{q,i} \cdot VM_{w,j} \cdot tr_{q,w}
\] (16)

\[
NetEn_{ij}^{pkt} = \sum_{\phi=1}^{PA_{ij}} \sum_{B \in \lambda_{ij,\phi}} E_{inc,pkt}^{B}.
\] (17)
\[
\sum_{\phi=1}^{PA_{ij}} \alpha_{ij\phi} = 1; \quad \forall \text{pkt} \in \delta_{ij}, \quad i, j \in X
\]  

(18)

Today’s DC networks are typically provisioned with redundant links and excessive bandwidth to accommodate peak traffic loads and tolerate link failures, and run well below capacity most of the time [27]. Therefore, in (17), we assume at least one path with enough link capacity between each PM pair.

The incremental energy consumption of a network element \( B \) is computed analogously to servers (see Eq. (9)):

\[
\mathcal{E}_{\text{inc(pkt)}}^{B} = (\mathcal{E}_{\text{wakeUp}}^{B} + \mathcal{E}_{\text{idle}}^{B}) \cdot N_{\text{Slp}}^{B} + \mathcal{E}_{\text{pkt}}^{B}
\]  

(19)

In (19), \( \mathcal{E}_{\text{pkt}}^{B} \) is computed as follows [20]:

\[
\mathcal{E}_{\text{pkt}}^{B} = \mathcal{E}_{p}^{B} + \mathcal{E}_{\text{S&F}}^{B} \cdot L,
\]  

(20)

where \( \mathcal{E}_{p}^{B} \) and \( \mathcal{E}_{\text{S&F}}^{B} \) are constants for a given switch or router configuration. Finally, the total IE of the network for running \( A \) on selected PMs of DC

\[
T_{\text{NetEn}} = \sum_{i \in I} \sum_{j \in I, j \neq i} \sum_{\phi=1}^{PA_{ij}} \sum_{\text{pkt} \in \delta_{ij}} \mathcal{E}_{\text{pkt}}^{B}
\]  

(21)

Only the selected PMs will be considered automatically in (21), because in (15), when there is no traffic between PM

\[
\delta_{ij} = 0), \quad \text{the related } \text{NetEn}_{ij} = 0 \quad \text{as well.}
\]

Inter-DCs communication cost (ComCost) in Eq.(1) includes the incremental energy of the inter-DC network to transfer data for running the set \( A \) of requests. \( \text{ComEn}_{ab} \) is the incremental energy between \( \text{DC}_a \) and \( \text{DC}_b \); \( \text{ComPr}_{ab} \) is the energy unit price for communication between \( \text{DC}_a \) and \( \text{DC}_b \).

\[
\text{ComCost} = \sum_{a,b \in \text{DC}} \text{ComEn}_{ab} \cdot \text{ComPr}_{ab} \cdot \text{SelDC}_a \cdot \text{SelDC}_b
\]  

(22)

\[
\text{ComEn}_{ab} = \sum_{\text{pkt}=1}^{\delta_{ab}} \text{ComEn}_{\text{pkt}}^{ab} = \sum_{\text{pkt}=1}^{\delta_{ab}} \sum_{B \in \lambda'_{ab}} \mathcal{E}_{\text{inc(pkt)}}^{B}
\]  

(23)

\[
\delta_{ab} = \sum_{i \in \text{DC}_a} \sum_{j \in \text{DC}_b} \sum_{q=1}^{M} \sum_{w=1}^{M} \text{VM}_{qi} \cdot \text{VM}_{wj} \cdot \text{tr}_{q,w}
\]  

(24)

B. Computing carbon emission

DC carbon emission (DcEmission) in Eq.(1) is the carbon emission amount caused by incremental energy within the selected DCs (servers and intra-DC networks) to run the requests:

\[
D\text{cEmission} = \sum_{j=1}^{d} P\text{UE}_j \cdot (T_{\text{SerEn}} + T_{\text{NetEn}}) \cdot CE_j \cdot \text{SelDC}_j,
\]  

(25)

where \( CE_j \) is the average carbon emission rate (in g/kW) of the energy sources of \( \text{DC}_j \). It is computed as follows [4]:

\[
CE_j = \frac{\sum_{k=1}^{d} CE^k_j \cdot r^k}{\sum_{k=1}^{d} CE^k_j},
\]  

(26)

where \( CE^k \) and \( r^k \) denote the electricity generated by energy source \( k \) and its carbon emission rate, respectively.

Inter-DC carbon emission (ComEmission) in Eq.(1) is the amount of incremental carbon emission resulting from data transfer between the selected DCs:

\[
\text{ComEmission} = \sum_{a,b \in \text{DC}} \text{ComE}_{ab} \cdot \text{ComCE}_{ab} \cdot \text{SelDC}_a \cdot \text{SelDC}_b,
\]  

(27)

where \( \text{ComCE}_{ab} \) is the average carbon emission rate for communication between \( \text{DC}_a \) and \( \text{DC}_b \).
V. Cost and Carbon Emission-Efficient Virtual Machine Placement (CACEV)

CACEV is a two-stage VM placement algorithm (see Algorithm 1). Stage 1 selects DCs and distributes VMs on them simultaneously (joint DC selection-VM distribution, lines 2-3). Stage 2 chooses PMs in each selected DC and allocates VMs on them simultaneously (joint PM selection-VM placement, lines 4-6). For both stages, CACEV first creates candidate subgraphs and then selects the best subgraph in terms of overall cost and carbon emission. CACEV is structured as follows.

**Module 1: VM Mapper (VMM).** The VMM module (lines 30-38) receives a candidate \( v \) (PM or DC) with its current capacity and a set \( X \) of VMs with their traffic information \( (TR_{M,M}) \) as input. Starting from each \( VM_i \in X \), VMM creates one subset. It first starts from \( VM_1 \). If the capacity of \( v \) is greater than the load of \( VM_1 \), VMM adds an element \( VM_{new} \) which has the highest traffic with \( VM_1 \). If \( v \) still has free capacity, a third element (a VM which has highest traffic with the two already selected VMs) is added to the subset. This procedure continues until the capacity of \( v \) is exhausted or all elements of \( X \) are allocated. After creating a subset starting from \( VM_1 \), the VMM module creates the second subset starting from \( VM_2 \), etc. Finally, there are \( |X| \) subsets of VMs so that any would fit into \( v \). VMM selects the subset with highest inter-VM traffic and maps it to \( v \).

**Module 2: Candidate Subgraph Creator (CSC).** This module (lines 8-20) receives a weighted graph \( G = (V, E, wV, wE) \) and a list of VMs as input and returns \( |V| \) subgraphs. The aim of CSC is to determine for each \( v_i \in V \) an induced subgraph \( G'(v_i) \) with sufficient total capacity and optimized overall cost-carbon emission. \( G'(v_i) \) is grown from \( \{v_i\} \) as starting point by iteratively adding one vertex a time. The already selected vertices are stored in an array \( SbG \); initially, \( SbG[0]=v_i \). In each step, CSC checks whether the selected vertices have sufficient total capacity. If yes, \( G'(v_i) \) is finished. Otherwise, the PFBS module is called to select one more vertex for inclusion in \( SbG \), and the cycle continues, until the total capacity of the selected vertices is sufficient. Then, \( G'(v_i) \) is the subgraph induced by \( SbG \). This way, a subgraph is created for each vertex \( v \) as starting point, yielding altogether \( |V| \) candidate subgraphs.

Selecting each vertex \( v_i \) as starting point is important because the subgraph formed starting from \( v_i \) will often be biased towards vertices in the proximity of \( v_i \); taking the best one of the candidate subsets helps to find a globally optimal subset. In principle, it would also be possible to consider all subgraphs of \( G \) with sufficient total capacity. However, the number of all such subgraphs can be exponential, making this approach intractable in practice. In contrast, our method is a faster, polynomial-time heuristic.

**Module 3: Prediction and Fuzzy Sets-Based Selector (PFBS).** Whenever CSC needs to add a new vertex to the candidate subgraph \( G' \) being generated, it calls the PFBS module (lines 21-29). Let \( SubGr \) denote the list of already selected vertices in subgraph \( G' \) and \( V \setminus SubGr \) the vertices still available in \( G \) for selection. PFBS receives a graph \( G \), \( SubGr \) and a set of VMs as input and returns the most cost/carbon effective vertex \( v_i \in V \setminus SubGr \) to be included in the subgraph.

The PFBS mechanism is based on a combination of the \( A^* \) algorithm [18] and Fuzzy Sets technique. Selecting the best node only in cost or carbon emission is almost a simple work. But making a certain decision to select the best node considering these two, sometimes conflicting, metrics simultaneously is more complex and even sometimes not possible. To this end, we use Fuzzy Sets technique. Fuzzy Sets technique [28] is an effective method for modeling uncertainty and for processing vague or subjective information in mathematical models. It has been utilized to a great variety of real problems. The Fuzzy Sets theory considers membership values which are indicated by a value on the range \([0, 1]\). Where 0 representing absolute Falseness and 1 shows absolute Truth. PFBS considers a (fuzzy) set which includes all possible (DC or PM) candidates. The membership function of this set maps each candidate to a membership value (MV) in the range \([0, 1]\). Inspired by the \( A^* \) algorithm, the membership function (for each possible candidate \( v_i \in V \setminus SubGr \)) combines the costs and carbon emission incurred by selecting the candidate \( v_i \) and an estimate of the overall costs and carbon emission that will be incurred in the future if \( v_i \) is selected now. The estimation aspect of \( A^* \) algorithm helps to consider capacity of each candidate in addition to cost and carbon emission. For each possible candidate \( v_i \in V \setminus SubGr \), the \( A^* \) function is

\[
e^*(v_i) = g(v_i) + h(v_i).
\]

The algorithm selects the candidate with the smallest \( e^*(v_i) \) value or highest membership value of \( MV(v_i) \) (i.e., \( MV(v_i) = 1 - e^*(v_i) \)). Here, \( g(v_i) \) is the incremental overall cost and carbon emission incurred by selecting \( v_i \) and includes the incremental network and server costs and carbon emission. \( g(v_i) \) will be certainly incurred if \( v_i \) is selected.

\[
g(v_i) = K1 \cdot K2,
\]

where \( K1 \) and \( K2 \) are normalized values of cost and carbon emission (in range of \([0,1]\)) respectively.

\[
K1 = \frac{\text{SerEn}_{v_i} \cdot \text{EnPr}_{v_i} + \text{NetEn}_{v_i} \cdot \text{NetPr}_{v_i}}{\text{SerEn}_{\text{max}} \cdot \text{EnPr}_{\text{max}} + \text{NetEn}_{\text{max}} \cdot \text{NetPr}_{\text{max}}},
\]

\[
K2 = \frac{\text{NetEn}_{v_i} \cdot \text{NetCE}_{v_i}}{\text{SerEn}_{\text{max}} \cdot \text{NetCE}_{\text{max}} + \text{NetEn}_{\text{max}} \cdot \text{NetCE}_{\text{max}}},
\]

where \( \text{SerEn}_{v_i} \) is the IE of the selected \( v_i \) caused by running allocated VMs of the set \( A \) on it. \( \text{EnPr}_{v_i} \) is the current price of energy in location of \( v_i \). \( \text{NetPr}_{v_i} \) is the energy price for network elements. For intra-DC network, it can be the same as \( \text{EnPr}_{v_i} \). \( \text{NetEn}_{v_i} \) is the IE of network elements caused by adding the candidate \( v_i \) to the subgraph:

\[
\text{NetEn}_{v_i} = \sum_{v_j \in SbG} \text{NetEn}_{v_i,v_j},
\]
Algorithm 1: CACEV Algorithm

Input: $G_1(V, E_1, w_{V_1}, w_{E_1})$: a weighted graph of DCs; TotalVM[M]:M requested VMs; TR[M][M]: VM traffic matrix; $G_3= \{G_2(V_2', E_2', w_{V_2'}, w_{E_2'}) : G_2$ internal graph of $DC_i, 1 \leq i \leq |V_1|\}$

Output: Selecting appropriate DCs and PMS and placing requested VMs on them

1. **Function mainCACEV($G_1, G_2, TotalVM$)
2. $sGrDC= CSC(G(V,E,w_{V},w_{E}),VMsOnPMs)$;
3. $SelGrDC= FBSS(sGrDC,VMsOnDCs)$;
4. foreach $DC \in SelGrDC$ do
5.     $sGrDCs= CSC(G_2(V_2', E_2', w_{V_2'}, w_{E_2'}), VMsOnDCs)$;
6.     $SelGrPMs= FBSS(sGrPMs, VMsOnPMs)$;
7.     return $sGrDCs, SelGrPMs$;
8. **Return**

**Function CSC($G(V,E,w_{V},w_{E}),VMsOnPMs$)**

1. Let $SbG[i][j]=\emptyset$ for $1 \leq i \leq |V|$.
2. copy members of array $VMsOnPMs$ into a set $X$.
3. $n=|V|$.
4. for $1 \leq i \leq n$ do
5.     let $SbG[i][i]=\emptyset$.
6.     $SubGrVM[i][j]=VMM(w_{V},w_{E},X,TR)$.
7.     $TC=sum_{i=1}^{n}|SubGrVM(i)[j]|$.
8.     if $TC < TR$ do
9.         $j \leftarrow j+1$.
10.     end
11. return $SbG$.

**Function VMM($w_{V},w_{E},X,TR$)**

1. $c_{min}=\infty$.
2. foreach $v \in V \setminus SubGrVM$ do
3.     if $c(v) < SALTthreshold$ then
4.         $SubGrVM(v)[j]=VMM(w_{V},w_{E},X,TR)$.
5.     end
6.     $c(v) \leftarrow c(v)$ using Equations (28)-(30).
7.     if $c(v) < c_{min}$ then
8.         $c_{min}=c(v)$, selected $=v$.
9. return $c_{min}$.

**Function FBSS($SbG|X,TR$)**

1. $c_{min}=\infty$.
2. foreach $v \in V \setminus SubGrVM$ do
3.     $Y=\emptyset$.
4.     $M_i$ to set $Y$.
5.     allocate $V_i$ on $v$.
6.     $v \in V \setminus Y$.
7.     $c(v) \leftarrow c(v)$ using Equations (28)-(30).
8.     if $c(v) < c_{min}$ then
9.         $c_{min}=c(v)$, selected $=v$.
10. return $c_{min}$.

where NetEn$_{v_i,v_j}$ is the IE of transferring data from candidate $v_i$ to already selected vertices. For DC selection, NetEn$_{v_i,v_j}$ is computed based on (23) and for PM selection (15) is used. PFBS calls for each candidate $v_i$ the VMM module to detect allocated VMs on the candidate $v_i$ and, then, computes $\delta_{i,j}$ for PMs based on (16) and for DCs from (24). Recall that (15) also selects the best path between two PMs.

The function $h(v_i)$ is an estimate of the incremental overall cost and carbon emission caused by the further vertices that we have to select later on to accommodate all the $M$ VMs.

$$h(v_i) = K_1' \cdot K_2'$$

(33)

where $K_1'$ and $K_2'$ are normalized values of the estimated cost and carbon emission (in range of $[0,1]$) respectively.

$$\begin{align*}
NS & \cdot \text{SerEn}_{\text{avg}} \cdot \text{EnPr}_{\text{avg}} + NE \cdot \text{NetEn}_{\text{avg}} \cdot \text{NetPr}_{\text{avg}} \\
NS & \cdot \text{SerEn}_{\text{max}} \cdot \text{EnPr}_{\text{max}} + NE \cdot \text{NetEn}_{\text{max}} \cdot \text{NetPr}_{\text{max}} \\
NS & \cdot \text{SerEn}_{\text{avg}} \cdot \text{SerCE}_{\text{avg}} + NE \cdot \text{NetEn}_{\text{avg}} \cdot \text{NetCE}_{\text{avg}} \\
NS & \cdot \text{SerEn}_{\text{max}} \cdot \text{SerCE}_{\text{max}} + NE \cdot \text{NetEn}_{\text{max}} \cdot \text{NetCE}_{\text{max}}
\end{align*}$$

(34)
Putting all the pieces together, we get a fairly good estimate of the overall cost—carbon emission to select candidate vertices considered as average (12 Cent/kWh). The PUE value was considered in range $[1.56, 2.1]$ based on [15]. We considered six energy prices of the VMs was generated randomly.

For our experiments, we used a modified version of the CloudSim simulator [29]. We considered a distributed cloud including 10 DCs. The capacity of the whole distributed cloud was chosen randomly, between 1,000 and 2,000 resource slots, in each run. This total capacity was divided among the DCs (each DC has capacity between 100 and 200 slots). Each PM has available 10 DCs. The capacity of the whole distributed cloud was chosen randomly, between 1,000 and 2,000 resource slots, in each run. This total capacity was divided among the DCs (each DC has capacity between 100 and 200 slots). Each PM has available.

<table>
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<tr>
<th>$\text{Module 4: Fuzzy Sets-based Best Subgraph Selector (FBSS).}$</th>
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<td>This module receives as input a set of subgraphs (SbG) along with a list of allocated VMs on their vertices (SbV). Subgraph $i$ of this set is denoted by SbG[i]. SbV[i] consists of the allocated VMs of SbG[i]. FBSS computes the overall cost (Eq.(39)) and carbon emission (Eq.(40)) of all subgraphs (lines 42-43) and then selects the most appropriate one in terms of overall cost and carbon emission using Fuzzy Sets technique (lines 44-47). While selecting the best subgraph based on only cost or carbon emission is easy, finding the best subgraph in both aspects simultaneously is a real challenge. Fuzzy Sets, here, help us to find the best subgraph in both aspects of cost and carbon emission.</td>
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$$\text{Putting all the pieces together, we get a fairly good estimate of the overall cost—carbon emission to select candidate } v. \text{ Based on these estimates, the algorithm can select the best choice.}$$

$$N E = \sum_{k=z+1}^{(z+1)+(y-1)} k \cdot y + \frac{y \cdot (y + 1)}{2},$$

$$y = \frac{M - ((\sum_{w \in A_l} F(w)) + F(v_i))}{\text{AvgS}},$$

where $M$ is the total number of VMs needed for the set $A$ of requests, $\sum_{w \in A_l} F(w)$ is the number of allocated VMs till now for the user request, $F(v_i)$ is the number of VMs that can be allocated if $v_i$ is chosen next, and AvgS is the average capacity of all vertices.

It remains to estimate $\text{NetEn}_{avg}$, the average network EC for the edges that will be added to the subgraph in subsequent steps. One possibility is to use the average network EC among all PMs. This would be a good estimate if we sampled edges randomly. However, our algorithm is biased towards edges of lower energy, so that the overall average may be an overestimate. We can get a more accurate estimation by calculating the average EC of the edges that the algorithm has selected so far, i.e., the edges within a set $\text{SubGr}$ that includes the subgraph $G'$ as well as the candidate $v_i$ (say $A_l'$). However, when selecting the second vertex, $G'$ has only one vertex and no edge, so in this case, we use the average network EC between the first vertex and all other vertices.

$$\text{NetEn}_{avg} = \left\{ \begin{array}{ll}
\sum_{v_i \in A_l'} \sum_{v_i \neq v_j} \frac{\text{NetEn}(v_i, v_j)}{N(z+1)/2} & \text{if } z > 1 \\
\sum_{v_i \in A_l} \frac{\text{NetEn}(v_i)}{N} & \text{if } z = 1, A_l' = \{s\}
\end{array} \right.$$
sources with different carbon emission rates from [4] (Nuclear:15, Coal:968, Gas:440, Oil:890, Hydro:13.5 and Wind:22.5 g/kWh), and assumed five different combinations with average 100,200,300,400 and 500 g/kWh. We selected one of them randomly for each DC.

The path length for each PM pair inside a DC was randomly chosen from 1 to 8 hops (switches) and for DC pairs from 10 to 20 routers. We used real energy models for routers and switches from [20] and for servers from [30].

We evaluate the performance of CACEV by comparing it against CACEV-Cost, CACEV-Carbon, Random and Greedy resource allocation algorithms. CACEV-Cost is a version of CACEV which only considers cost optimization and CACEV-Carbon only considers carbon footprint optimization. Comparing CACEV to these two special versions can show how CACEV manages to find a trade-off between the two optimization goals. The Random algorithm starts by selecting a vertex (DC or PM) randomly and placing as many VMs as possible in the selected vertex. If not all VMs could be allocated in the selected vertex, then a further vertex is selected, again randomly, to place the remaining VMs. This process is repeated until the requested number of VMs is placed. The Greedy algorithm selects a vertex with maximum free capacity and allocates as many VMs from the request as possible in the selected vertex. If further VMs are necessary, then the Greedy algorithm selects from the remaining vertices again the one with maximum free capacity. This process continues until all VMs are placed [13].

It is worth highlighting that, even though the parameters (e.g. capacity) of the DCs and PMs are set randomly, they remain fixed across the runs of all tested algorithms, to ensure comparability of the results. Because of simulation limitations, each run simulated one hour. However, the result values may seem small on the given scale (1 hour), but it is only to show efficiency of the proposed algorithm. The values can be much larger in real world with a longer time scale. For each test, we report the results as average of 10 runs.

Fig. 1 shows the simulation results (each run simulated one hour, so that the cost and carbon emission values are for one hour). In particular, Fig. 1 (a) and (e) show how CACEV could make a joint cost-carbon emission optimization successfully. CACEV outperforms the Random and Greedy algorithms in both dimensions. It was predictable that CACEV-Cost can get the best cost efficiency. However, the carbon emission of CACEV-Cost is sometimes even worse than that of Random or Greedy. Similarly, CACEV-Carbon is the best in carbon efficiency but performs poorly in cost efficiency. In general, CACEV improves 45-115% in carbon emissions on CACEV-Cost while incurring 20-60% higher costs. In comparison to CACEV-Carbon, CACEV improved total cost by 40-60% while increasing carbon emission only by 10-30%.

As seen in Fig. 1 (i), Greedy always has the least number of selected DCs. Together with Fig. 1(a)-(d), this shows that only reducing the number of selected DCs (and PMs) does not lead to total cost reduction. In Fig. 1 (j), because of the limited simulation time scale, there is no significant difference in EC between the methods. Since there are still big differences in costs and carbon emissions, this shows the importance of taking into account the different energy sources (i.e., with variety of prices and emission rates) of the DCs in a distributed cloud.
This paper addressed the problem of allocating VMs in distributed clouds with the aim of optimizing overall cost and carbon emission together. We have claimed that combining multiple metrics, i.e., joint optimization of network and server resources along with resource prices and carbon emission rate, can significantly optimize overall cost and carbon emission together. We have claimed that combining multiple metrics, i.e., joint optimization of network and server resources along with resource prices and carbon emission rate, can significantly optimize overall cost and carbon emission together. We have also claimed a prediction-based A* algorithm can give more sophisticated results than typical greedy heuristics for DC/PM selection, because it also predicts the overall cost and carbon emission that will be incurred by future DC/PM selection and based on the prediction makes more intelligent VM placement decisions. To this end, motivating from the A* algorithm, we have proposed a cost and carbon efficient VM placement method (CACEV). We have also proposed the idea of using Fuzzy Sets to make an appropriate decision in this environment with multiple, sometimes conflicting, metrics. Simulation results prove that CACEV can considerably optimize overall cost and carbon emission in comparison to other algorithms. The results also show that only minimizing the number of used DCs/PMs is not enough to optimize the overall cost and carbon emission.

REFERENCES


VII. CONCLUSION

This paper addressed the problem of allocating VMs in distributed clouds with the aim of optimizing overall cost and carbon emission together. We have claimed that combining multiple metrics, i.e., joint optimization of network and server resources along with resource prices and carbon emission rate, can significantly optimize overall cost and carbon emission together. We have also claimed a prediction-based A* algorithm can give more sophisticated results than typical greedy heuristics for DC/PM selection, because it also predicts the overall cost and carbon emission that will be incurred by future DC/PM selection and based on the prediction makes more intelligent VM placement decisions. To this end, motivating from the A* algorithm, we have proposed a cost and carbon efficient VM placement method (CACEV). We have also proposed the idea of using Fuzzy Sets to make an appropriate decision in this environment with multiple, sometimes conflicting, metrics. Simulation results prove that CACEV can considerably optimize overall cost and carbon emission in comparison to other algorithms. The results also show that only minimizing the number of used DCs/PMs is not enough to optimize the overall cost and carbon emission.

[31] US Energy Information Administration. www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_5_6_a