Carbon Metering and Effective Tax Cost Modeling for Virtual Machines

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Abstract—With raising concerns about global warming and environmental impacts of Greenhouse Gases (GhGs) emissions, energy efficiency and carbon footprint reduction attracted many researchers to provide efficient models and tools for energy, carbon, and cost estimation and management. In this paper, a model for measuring the energy consumption and carbon footprint of an individual virtual machine is presented based on resource usage and performance monitoring counters. A simple cost model is represented in order to evaluate the energy consumption and carbon footprint models. The model evaluated on a simulated virtual private cloud with different methodologies such as server consolidation and multi-level grouping heuristic algorithms. The results show that such heuristic algorithms are able to significantly reduce the cost of energy and carbon footprint of an individual virtual machine in comparison with other methodologies such as server consolidation. The results also show that this cost reduction efficiency is positively correlated to the increase in carbon footprint tax rates.

I. INTRODUCTION

Virtualization play a big role in modern data centers nowadays. Many scientists and companies are taking advantage of this new technology for server consolidation and other management strategies for energy efficiency and quality of service [1] or try to improve it as a powerful tools [2][3]. The role of virtualization is more highlighted in carbon footprint reduction of ICT sector which its carbon footprint is about 2% of total carbon footprint of the world and is raising very fast [4].

With raising importance of energy efficiency of services, measuring the energy consumption at virtual machine or service level is becoming very important. However, since direct energy measurement of a virtual machine is not possible at hardware level, accurate models need to be used to estimate the energy consumption of an individual virtual machines or a service.

Energy accounting at VM granularity is more important and more complex when large data centers are hosting thousands of virtual machines from different customers with different CPU cores, memory size, and Service Level Agreements (SLA) which need to be billed accurately based on their energy usage.

In order to run a virtual machine, there are several other components in a data center or outside the data center which need to work together such as storage and network devices. There are also some events which do not have direct impact on individual virtual machine power consumption but has effect on overall energy consumption of a data center or a cloud over distributed data centers. The corresponding energy consumption of these events and components need to be considered in calculation of a virtual machine power usage.

In a geographically distributed cloud with data centers powered with different type of clean, semi-clean, and non-clean source of energies, the cloud energy consumption cannot represent its carbon footprint [5]. The energy consumption can be very high while carbon footprint is low in case of considering clean source of energies such as solar and hydroelectric power as data centers power source. Regarding public awareness about environmental impacts of GhG emissions, the carbon footprint of a data center is as important as its energy consumption, therefore accurate carbon footprint models for geographically distributed clouds need to be defined to measure the carbon footprint of the cloud in VM granularity.

Energy efficiency and carbon footprint reduction both are important in management of a cloud. However, carbon footprint reduction require different strategies than energy efficiency. In such environments that balance of focus on each of these goals are not clear, cost models based on both goal need to be defined based on government regulations such as carbon-tax and other cloud parameters such as service level agreements to achieve the best results.

The main contributions of this paper are as follows:

- An accurate energy measurement model for virtual machine is introduced by improvement and combination of several existing models.
- An accurate carbon measurement model for VM is introduced based on VM energy consumption parameters.
- A simple cost model is introduced for carbon-taxed environments and is validated by simulation data.

The organization of the paper is as follows. The related work to energy measurement of a virtual machine and its carbon footprint calculation are represented in section II. Then, a new energy measurement model is represented in Section III based on combination of models represented in related work section. The carbon model is represented in Section IV, and Finally, a simple cost model is introduced in Section V and is validated by collected experimental data from a simulation environment.

II. RELATED WORK

Kansal et al. introduced ”Joulemeter” to measure the power consumption of an individual virtual machines [6]. They used
a model based on runtime resource usage for power metering and applied it to virtualized environments as follows:

\[ E_{sys} = \alpha_{cpu}\mu_{cpu} + \alpha_{mem}\mu_{mem} + \alpha_{io}\mu_{disk} + \gamma \]  

where \( E_{sys} \) is the total power consumption of the server, \( \mu_{cpu}, \mu_{mem}, \) and \( \mu_{disk} \) are the resource usage for CPU, memory, and disk. \( \alpha_{cpu}, \alpha_{mem}, \alpha_{io}, \) and \( \gamma \) are the constants of model for each individual server which need to be calculated from experimental tests.

They claimed that their model has low error and low overhead processing load, however their modeling methods is simple and they didn’t use performance monitoring counters (PMC) for their model and they assume the model is valid for virtualized environment without validation [7].

Bertran et al. introduced a model for power metering of CPU and memory of server based on performance monitoring counters [8] as follows:

\[ P_{total} = \sum_{j=1}^{cores} \left( \sum_{i=1}^{comps} AR_{ij} \times P_i \right) + P_{static} \]  

where \( P_{total} \) is the total power consumption of CPU and memory components in a multi-core server. \( AR_{ij} \) represent PMC-based formula accounting for activity ratio, and \( P_i \) are the formula constants. The constants need to be calculated through linear regression techniques from experimental test for each individual type of server. They define their model for single core CPUs and multi-core CPUs and evaluate it with experimental benchmarks.

They also used the same model for virtualized environments. They validated that the same model can be used for virtual machines with high accuracy [7]. Despite the accuracy of the model, there are components other than CPU and memory in a hardware server such as network cards and storage disks which their energy consumption need to be take into consideration to have an accurate total energy consumption for an individual virtual machine.

Moreover, there are other components outside a server such as Power Distribution Units (PDUs), cooling system, lighting, network devices which are necessary for a VM to run. Liu et al. considered the energy consumption and respectively carbon footprint related to these components in two categories additional to server power consumption as follows [9]:

\[ E_{total} = E_{migration} + E_{servers} + E_{utilization} \]  

where \( E_{total} \) is the total energy consumption of the data center, \( E_{migration} \) is the energy consumption corresponding to migration of virtual machines, \( E_{servers} \) represents the servers energy consumption, and \( E_{utilization} \) represents other utilities energy consumption. This model is very simple and describing the energy consumption of a data center in a very high level, but there are some missing components which need to be added to this model such as network devices energy consumption.

In [10], Van Heddeghem et al. introduced a model for carbon footprint of a distributed network of data centers. In their model they consider the manufacturing footprint and the geographical region to achieve their goal which is total carbon footprint reduction. Their model is based on calculation of chance of data centers powering by low footprint source of energies based on probability mass function of the binomial distribution. Despite the interesting result of probability estimation of carbon footprint in this research, their model is unable to accurately calculate the carbon footprint of a distributed cloud for customers. They also calculated the manufacturing carbon footprint of devices as part of their model as follows:

\[ F_m = mfI_HE_u \]  

where \( m \) is the number of data centers, \( f \) represent the manufacturing fraction, \( I_H \) represent the emission intensity for low carbon footprint source of power, and \( E_u \) denote the energy usage by a single data center. However, it is unclear that manufacturing portion of carbon footprint of devices should be considered in the investment phase at the time of purchase of the device or it should be considered in the service phase as a carbon bill to customers.

As mentioned in the Introduction section, carbon footprint and energy efficiency are not necessary correlated. Despite the importance of energy efficiency in data centers, carbon footprint reduction was the main objective of Farrahi Moghadam et al. research in [5]. They introduced a greenness factor for each source of energy to measure its cleanness as follows:

\[ C_{p_d}(t) = \rho_{d}(t)P_d(t) \]  

\[ \rho_{d}(t) = (1 - g_d(t))\rho_{max} \]  

where \( C_{p_d}(t) \) represents the carbon footprint of a data center, \( P_d(t) \) represents the power consumption of a data center, and \( \rho_{d}(t) \) represents the energy-carbon conversion rate for that particular data center. \( \rho_{max} \) represents the energy-carbon conversion rate for the dirtiest source of energy (0.9 kg per kWh [11]). \( g_d(t) \) represents the greenness factor of the data center. \( g_d(t) = 0 \) represents 0% clean data center and \( g_d(t) = 1 \) represents 100% clean and green data center at time \( t \).

This formula will convert the energy consumption of a data center to its carbon footprint. For data centers with more than one source of energy the \( \rho_{d}(t) \) is defined as follows:

\[ \rho_{d}(t) = \frac{\sum_{s \in S} \rho_{d_s}(t)P_{d_s}(t)}{\sum_{s \in S} P_{d_s}(t)} \]  

where \( S \) represents the set of power sources used in data center \( d \).

The total carbon footprint of geographically distributed cloud over several data centers can be calculated as follows:

\[ C_p(t) = \sum_{d \in \mathbb{D}} C_{p_d}(t) = \rho_{max} \sum_{d \in \mathbb{D}} (1 - g_d(t))P_d(t) \]  

where \( \mathbb{D} \) represents the set of data centers participating in a geographically distributed cloud.
III. VIRTUAL MACHINE ENERGY METERING

As mentioned in Section II, Equation (2) is used to measure the CPU and memory energy consumption of a multi-core server, and Equation (1) is used to measure the energy consumption of servers plus migration and utilities. To have an accurate measuring tools for energy consumption of servers, \(\alpha_{io}\) is substituted by disk usage and network usage factors in Equation (1) as follows:

\[
p^{(x)}(t) = (c)\alpha^{(x)}(t) \times (c)\mu^{(x)}(t) + (m)\alpha^{(x)}(t) \times (m)\mu^{(x)}(t) + (n)\alpha^{(x)}(t) \times (n)\mu^{(x)}(t) + (d)\alpha^{(x)}(t) \times (d)\mu^{(x)}(t) + \gamma^{(x)}
\]

where \(x\) represents the type of device; \((c)\alpha^{(x)}, (m)\alpha^{(x)}, (n)\alpha^{(x)}, and (d)\alpha^{(x)}\) represent CPU, memory, network, and disk usage factors; and \(\gamma^{(x)}\) represents the static portion of energy consumption. Each individual device \(x\) has its own parameters which are determined through experimental studies. Since the energy measurement of CPU and memory is more accurate in [7], in this research the first two terms of Equation (8) are replaced with Equation (2) as follows:

\[
p^{(x)}(t) = \sum_{j=1}^{corex} \sum_{i=1}^{compex} AR^{x}_{ij} \times P^{x}_{i} + (d)\alpha^{(x)}(t) \times (d)\mu^{(x)}(t) + \gamma^{(x)}
\]

All the \(P_{static}\)s are merged in \(\gamma^{(x)}\).

To be more accurate, more parameters are added to Equation (3) as follows:

\[
E(t, \Delta t) = E^{(S)}(t, \Delta t) + E^{(N)}(t, \Delta t) + E^{(R)}(t, \Delta t) + E^{(U)}(t, \Delta t) + E^{(F)}(t, \Delta t)
\]

The added parameters are \(E^{(N)}(t, \Delta t)\), \(E^{(R)}(t, \Delta t)\), and \(E^{(F)}(t, \Delta t)\) which represent the energy consumption regarding network devices, storage devices, and switch on/off events, respectively. \(E^{(S)}(t, \Delta t)\), \(E^{(M)}(t, \Delta t)\), and \(E^{(U)}(t, \Delta t)\) represent the server, migration, and utilization terms in Equation (3). For energy consumption of network and storage devices same equation as servers (Equation (9)) is used where \(x\) is a server, network, or storage device. It is due to the fact that all servers, network, and storage devices are microprocessor systems. All these microprocessor systems has CPU, memory, network, and storage components but with different missions. The total energy consumption of servers, network, and storage devices is as follows:

\[
E^{(S)}(t, \Delta t) = \sum_{j} O^{(S)}_{j} P^{(S)}_{j}(t) \Delta t
\]

\[
E^{(N)}(t, \Delta t) = \sum_{j} O^{(N)}_{j} P^{(N)}_{j}(t) \Delta t
\]

\[
E^{(R)}(t, \Delta t) = \sum_{j} O^{(R)}_{j} P^{(R)}_{j}(t) \Delta t
\]

where \(O^{(S)}_{j}\) represents the status of the device (on/off [5]).

Note that \(E^{(M)}(t, \Delta t)\) and \(E^{(F)}(t, \Delta t)\) are actions which involve servers, network, and storage devices processes, therefore \(E^{(S)}(t, \Delta t)\), \(E^{(N)}(t, \Delta t)\), and \(E^{(R)}(t, \Delta t)\) represent the energy consumption portion of servers, network, and storage devices without considering any migration or switch on/off events. These energy consumptions are different from actual energy readings from PDU devices. In other word, the energy consumption of servers, network, and storage devices plus energy consumption of migration and switch on/off events is equal to summation of energy readings of servers, network, and storage devices from PDU devices as follows:

\[
E^{(S)}(t, \Delta t) + E^{(N)}(t, \Delta t) + E^{(R)}(t, \Delta t) + E^{(M)}(t, \Delta t) + E^{(F)}(t, \Delta t) = E^{(U)}(t, \Delta t) + E^{(F)}(t, \Delta t)
\]

\[
(\ast)E^{(S)}(t, \Delta t) + (\ast)E^{(N)}(t, \Delta t) + (\ast)E^{(R)}(t, \Delta t)
\]

where \((\ast)E^{(S)}(t, \Delta t), (\ast)E^{(N)}(t, \Delta t), and (\ast)E^{(R)}(t, \Delta t)\) represent the total energy consumption of servers, network, and storage devices, respectively.

In this research in Equation (10), \(E^{(U)}(t, \Delta t)\) will be calculated based on energy consumption readings from PDU devices and \(E^{(S)}(t, \Delta t)\) will be calculated based on Equation (9).

For \(E^{(M)}(t, \Delta t)\) and \(E^{(F)}(t, \Delta t)\) further parameters should take into consideration to calculate the corresponding energy consumptions. Each migration is a set of actions in source and destination server plus inter between network or storage devices as follows:

\[
E^{(M)}(t, \Delta t) = \sum_{m \in M_{m}} \{ \Delta p^{(S)}(m) \Delta t_{m} + \Delta p^{(N)}(m) \Delta t_{m} + \Delta p^{(R)}(m) \Delta t_{m} \}
\]

where \(M_{m}\) represent the set of migrations which happen in \(\Delta t\). \(a_{m}\) represent the source server of the migration \(m\), where \(b_{m}\) represent the destination server. \(t_{m}\) is the time when the migration \(m\) took place, and \(\Delta t_{m}\) represent the duration of migration \(m\). \(\Delta p^{(S)}(m)\) represent the extra power consumption of server \(a_{m}\) during the migration time \(\Delta t_{m}\). Respectively, \(\Delta p^{(N)}(m)\) represents the extra power consumption of server \(b_{m}\), and \(\Delta p^{(R)}(m)\) represent the extra power consumption of network and storage elements in source, destination, or inter between data centers. The extra power consumption is described as follows:

\[
\Delta p^{(x)}(m) = \sum_{j=1}^{corex} \sum_{i=1}^{compex} \Delta AR^{x}_{ij} \times P^{x}_{i} + (m)\alpha^{(x)}(m) \times (m)\mu^{(x)}(m) + (d)\alpha^{(x)}(m) \times (d)\mu^{(x)}(m) + \gamma^{(x)}
\]

where \(\Delta t\) terms indicate the extra usage regarding the migrations. Similar calculations are valid for devices switch on/off
where there is no VM running on the servers. Note that in this case all \( \Delta E \) and \( \Delta F \) represent the set of switch on/off events which happen in \( \Delta t \).

To achieve the power consumption regarding each individual VM, following parameters are calculated from Equation (10) as follows:

\[
E_{0}(t, \Delta t) = E(t, \Delta t), \text{No VM is running.} \tag{16}
\]

where \( E_{0}(t, \Delta t) \) represent the total energy consumption when there is no VM running on the servers. Note that in this case all \( AR_{ij}^{(n)}(t), \mu_{j}^{(x)} \), and \( d_{j}^{(x)} \) need to be substitute with \( 0 AR_{ij}, \mu_{j}, \) and \( 0 \mu_{j} \) in all the equations respectively, where \( 0 AR \) and \( 0 \mu \) represent the rate of CPU, memory, network, and storage components activity when there is no VM running on the servers.

\[
E_{v}(t, \Delta t) = E_{v}(t, \Delta t)\text{, only } v^{th} \text{ VM is running.} \tag{17}
\]

where \( E_{v}(t, \Delta t) \) represent the total energy consumption when there is only \( v^{th} \) VM running on the servers. Note that in this case all \( AR_{ij}^{(n)}(t), \mu_{j}^{(x)} \), and \( d_{j}^{(x)} \) need to be substitute with \( v AR_{ij}, v \mu_{j}^{(x)} \), and \( v d_{j}^{(x)} \) in all the equations respectively, where \( v AR \) and \( v \mu \) represent the rate of CPU, memory, network, and storage components activity when there is only \( v^{th} \) VM running on the servers.

\[
E_{v}(t, \Delta t) = E_{v}(t, \Delta t) - E_{0}(t, \Delta t) \tag{18}
\]

where \( E_{v}(t, \Delta t) \) represent the net energy consumption of \( v^{th} \) VM.

\[
E_{v}(t, \Delta t) = E_{v}(t, \Delta t) \times \frac{E(t, \Delta t)}{\sum_{v \in v} E_{v}(t, \Delta t)} \tag{19}
\]

where \( E_{v}(t, \Delta t) \) represent the scaled energy consumption of \( v^{th} \) VM.

IV. VIRTUAL MACHINE CARBON METERING

To obtain the carbon footprint of a geographically distributed cloud, Equation (5) is used in combination with previous section Equations. Similar to Equation (10) and Equation (11), total carbon footprint of distributed cloud is defined as follows:

\[
C(t, \Delta t) = C^{(S)}(t, \Delta t) + C^{(N)}(t, \Delta t) + C^{(R)}(t, \Delta t) + C^{(U)}(t, \Delta t) + C^{(F)}(t, \Delta t) \tag{20}
\]

\[
C^{(S)}(t, \Delta t) = \rho_{m} \sum_{j \in S} O_{j}^{(S)}(t)\Delta p_{j}^{(S)}(t)\Delta t \tag{21}
\]

\[
C^{(N)}(t, \Delta t) = \rho_{m} \sum_{j \in N} O_{j}^{(N)}(t)\Delta p_{j}^{(N)}(t)\Delta t \tag{21}
\]

\[
C^{(R)}(t, \Delta t) = \rho_{m} \sum_{j \in R} O_{j}^{(R)}(t)\Delta p_{j}^{(R)}(t)\Delta t \tag{21}
\]

where \( \rho_{m} = \rho_{max} \) and \( r_{d_{j}}(t) \) represent the redness of a data center defined as follows:

\[
r_{d_{j}}(t) = 1 - g_{d_{j}}(t) \tag{22}
\]

where \( r_{d_{j}}(t) = 0 \) represent a 100% green data center. Similar equation as Equation (12) is valid for carbon footprint as follows:

\[
C^{(S)}(t, \Delta t) + C^{(N)}(t, \Delta t) + C^{(R)}(t, \Delta t) + C^{(M)}(t, \Delta t) + C^{(F)}(t, \Delta t) = (\ast)C^{(S)}(t, \Delta t) + (\ast)C^{(N)}(t, \Delta t) + (\ast)C^{(R)}(t, \Delta t) \tag{23}
\]

To calculate the carbon footprint corresponding to migration process, all the energy terms in Equation (13) need to be multiplied to \( \rho_{m} r_{d_{j}}(t) \) as follows:

\[
C^{(M)}(t, \Delta t) = \sum_{m \in M_{\Delta t}} \rho_{m} \left\{ \Delta p_{m}^{(S)}(t) + \Delta p_{m}^{(N)}(t) + \sum_{j \in N_{m}} O_{j}^{(N)}(t)\Delta p_{j}^{(N)}(t) + \sum_{j \in R_{m}} O_{j}^{(R)}(t)\Delta p_{j}^{(R)}(t) \right\} \Delta t \tag{24}
\]

Same calculation need to be done for switch on/off events as follows:

\[
C^{(F)}(t, \Delta t) = \sum_{f \in F_{\Delta t}} \rho_{m} \left\{ \Delta p_{m}^{(S)}(t) + \Delta p_{m}^{(N)}(t) + \sum_{j \in N_{f}} O_{j}^{(N)}(t)\Delta p_{j}^{(N)}(t) + \sum_{j \in R_{f}} O_{j}^{(R)}(t)\Delta p_{j}^{(R)}(t) \right\} \Delta t \tag{25}
\]

Finally, similar equations to Equation (16), Equation (17), Equation (18), and Equation (19), represent the carbon footprint corresponding to an individual virtual machine as follows:

\[
C_{0}(t, \Delta t) = C(t, \Delta t), \text{No VM is running.} \tag{26}
\]

\[
C_{v}(t, \Delta t) = C_{v}(t, \Delta t), \text{only } v^{th} \text{ VM is running.} \tag{27}
\]

\[
C_{v}(t, \Delta t) = C_{v}(t, \Delta t) - C_{0}(t, \Delta t) \tag{28}
\]

\[
C_{v}(t, \Delta t) = C_{v}(t, \Delta t) \times \frac{C(t, \Delta t)}{\sum_{v \in v} C_{v}(t, \Delta t)} \tag{29}
\]

where \( C_{v}(t, \Delta t) \) represent the scaled carbon footprint of an individual virtual machine. Equation (19) and Equation (29) will be used in next section in simple cost model for energy consumption and carbon footprint of a distributed cloud.
V. CARBON-TAXED COST MODELING

To evaluate the proposed model for carbon and energy, model is applied to the data collected from an enhanced version of [12] on a virtual private cloud. In this research a distributed cloud is optimized for its carbon footprint with different methodologies as shown in Figure 1. Three scenarios for methodologies are Multi-Level Grouping Genetic Algorithm (MLGGA), Server Consolidation (SRV-CONS), and No Optimization (NO-OPT). Applying the model which introduced in this paper, the carbon footprint and energy consumption of an individual VM is measured and shown in Figure 2 and Figure 3 during 48 hours of a day for different methodologies.

In this environment 600 virtual machines are hosted on 120 servers in 24 data center located in 24 different city around the world. The accumulative amount of energy and carbon footprint for an individual virtual machine is reported in Table I.

<table>
<thead>
<tr>
<th>Method</th>
<th>Energy consumption (kWh)</th>
<th>Carbon footprint (kgC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLGGA</td>
<td>4.87</td>
<td>1.66</td>
</tr>
<tr>
<td>Server consolidation</td>
<td>6.43</td>
<td>2.52</td>
</tr>
<tr>
<td>No optimization</td>
<td>8.11</td>
<td>3.17</td>
</tr>
</tbody>
</table>

As it is shown in Figure 2 and Figure 3, the energy consumption is almost constant, but carbon footprint has large variations. If the VM owner charged based on energy consumption, then the cost is a flat rate, but if carbon tax take into consideration then the rate is variable during hours of the day. A simple cost model for energy and carbon footprint of a virtual machine is as follows:

\[ M_v(t, \Delta t) = \alpha_e E_v(t, \Delta t) + \alpha_c C_v(t, \Delta t) \]  

(30)

where \( \alpha_e \) and \( \alpha_c \) are electricity fee and carbon tax respectively. To have a better understanding of carbon tax, Equation (30) is rewritten as follows:

\[ M_v(t, \Delta t) = \alpha_e (E_v(t, \Delta t) + r_{c/e} C_v(t, \Delta t) / \rho_m) \]  

(31)

where \( r_{c/e} = \rho_m (\alpha_c / \alpha_e) \) represent the ratio of carbon-tax to electricity price. \( C_v(t, \Delta t) \) is divided per \( \rho_m \) to achieve the corresponding equal dirty electricity amount. Note that in Equation (30) and Equation (32), it is assumed that electricity price is equal in all data centers (10 cents per kWh in our experiments) which are participating in the cloud, otherwise, for each data center an individual \( \alpha_e \) needs to be defined and cost of each data center need to be calculated separately. The graph of an individual VM cost is depicted for hours of a day in Figure 4 under different tax rates, where the percentage number infront of each methodology indicate the \( r_{c/e} \). As is shown, the MLGGA methodology on a distributed cloud is able to significantly reduce the cost of a running VM in comparison with server consolidation techniques. The amount
of cost saving is higher when the tax rate for carbon footprint is higher.

For a period of 48 hour the results from Table I are used in Equation (32) to have a simple cost model for different methodologies:

\[
\begin{align*}
M_{V_{MLGGA}} &= 0.48 + 0.18 \frac{c}{e} \text{[$/48h]} \\
M_{FSBV콘도209} &= 0.64 + 0.28 \frac{c}{e} \text{[$/48h]} \\
M_{NO-OPT} &= 0.81 + 0.35 \frac{c}{e} \text{[$/48h]}
\end{align*}
\]  

(32)

The graph of 48 hours total cost of an individual VM is shown in Figure 5 versus the tax rate. According to the results, as tax rate raise, green virtual private cloud type of infrastructure becomes more beneficial in cost, and its performance on cost reduction is more evident in higher tax rates.

VI. CONCLUSION AND FUTURE WORK

In this paper, a model for measuring the energy consumption and carbon footprint of an individual virtual machine is presented based on resource usage and performance monitoring counters. The model considers all type of energy consumptions and carbon footprints which are involved in running a virtual machine such as energy consumption and carbon footprint of VM migration, cooling systems, PDUs, lighting, network devices and storage devices inside and outside data centers. The proposed model is applied to the results of a simulated environment to evaluate its performance. The results provide the energy consumption and carbon footprint of a virtual machine in different hours of a day.

A simple cost model is introduced in order to calculate the total cost of energy consumption and carbon footprint of an individual virtual machine. The results of applying the cost model to the energy consumption and carbon footprint data shows that multi-level grouping methodologies such as MLGGA can significantly reduce the cost in comparison with server consolidation methods. The amount of cost reduction is positively correlated to the increase in tax rate which means that the importance of such methodologies such as MLGGA on virtual private clouds is more noticeable when high tax rates are charged for carbon footprint.

For future work, more advanced cost models will be considered to cover the different price of electricity in different geographically distributed location and different time of a day.

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