Abstract—Infrastructure-as-a-Service (IaaS) clouds have become more popular enabling users to run applications under virtual machines. Energy efficiency for IaaS clouds is still a challenge. This paper investigates the energy-efficient scheduling problems of virtual machines (VMs) onto physical machines (PMs) in IaaS clouds along characteristics: multiple resources, fixed intervals and non-preemption of virtual machines. The scheduling problems are NP-hard. Most of existing works on VM placement reduce the total energy consumption by using the minimum number of active physical machines. There, however, are cases using the minimum number of physical machines results in longer the total busy time of the physical machines. For the scheduling problems, minimizing the total energy consumption of all physical machines is equivalent to minimizing total busy time of all physical machines. In this paper, we propose a scheduling algorithm, denoted as EMinTRE-LFT, for minimizing the total energy consumption of physical machines in the scheduling problems. Our extensive simulations using parallel workload models in Parallel Workload Archive show that the proposed algorithm has the least total energy consumption compared to the state-of-the-art algorithms.

Keywords—energy efficiency; energy-aware; power-aware; VM placement; IaaS; total busy time; fixed interval; fixed starting time; scheduling

I. INTRODUCTION

Infrastructure-as-a-Service (IaaS) cloud service provisions users with computing resources in terms of virtual machines (VMs) to run their applications [2], [3], [4]. These IaaS cloud systems are often built from virtualized data centers. Power consumption in a large-scale data centers requires multiple megawatts [5], [8]. Le et al. [3] estimate the energy cost of a single data center is more than $15M per year. As these data centers has more physical servers, they will consume more energy. Therefore, advanced scheduling techniques for reducing energy consumption of these cloud systems are highly concerned for any cloud providers to reduce energy cost. Energy efficiency is an interesting research topic in cloud systems. Energy-aware scheduling of VMs in IaaS cloud is still challenging [2], [3], [6], [7].

Many previous works [8], [9] proved that the scheduling problems with fixed interval times are NP-hard. They [4], [10] present techniques for consolidating virtual machines in cloud data centers by using bin-packing heuristics (such as First-Fit Decreasing [10], and/or Best-Fit Decreasing [4]). They attempt to minimize the number of running physical machines and to turn off as many idle physical machines as possible. Consider a d-dimensional resource allocation where each user requests a set of VMs. Each VM requires multiple resources (such as CPU, memory, and IO) and a fixed quantity of each resource at a certain time interval. Under this scenario, using a minimum of physical machines can result in increasing the total busy time of the active physical machines [11][9]. In a homogeneous environment where all physical servers are identical, the power consumption of each physical machine is linear to its CPU utilization [4], i.e., a schedule with longer working time will consume more energy than another schedule with shorter working time.

This paper presents a proposed heuristic, denoted as EMinTRE-LFT, to allocate VMs that request multiple resources in the fixed interval time and non-preemption into physical machines to minimize total energy consumption while meeting all resource requirements. Using numerical simulations, we compare EMinTRE-LFT with the state-of-the-art algorithms include Power-Aware Best-Fit Decreasing (PABFD) [4], vector bin-packing norm-based greedy (VBP-Norm-L2) [10], and Modified First-Fit-Decreasing-Earliest (Tian-MFFDE) [9]. Using three parallel workload models [12], [13] and [14] in the Feitelson’s Parallel Workloads Archive [15], the simulation results show that the proposed EMinTRE-LFT can reduce the total energy consumption of the physical servers by average of 23.7% compared with Tian-MFFDE [9]. In addition, EMinTRE-LFT can reduce the total energy consumption of the physical servers by average of 51.5% and respectively 51.2% compared with PABFD [4] and VBP-Norm-L2 [10]. Moreover, EMinTRE-LFT has also less total energy consumption than MinDFT-LDTF [11] in the simulation results.

The rest of this paper is structured as follows. Section II discusses related works. Section III describes the energy-
aware VM allocation problem with multiple requested resources, fixed starting and duration time. We also formulate the objective of scheduling, and present our theorems. The proposed EMinTRE-LFT algorithm presents in Section IV. Section V discusses our performance evaluation using simulations. Section VI concludes this paper and introduces future works.

II. RELATED WORKS

The interval scheduling problems have been studied for many years with objective to minimizing total busy time. In 2007, Kovalyov et al. [16] has presented work to describe characteristics of a fixed interval scheduling problem in which each job has fixed starting time, fixed processing time, and is only processed in the fixed duration time on a available machine. The scheduling problem can be applied in other domains. Angelelli et al. [17] considered interval scheduling with a resource constraint in parallel identical machines. The authors proved the decision problem is NP-complete if number of constraint resources in each parallel machine is a fixed number greater than two. Flammini et al. [8] studied using new approach of minimizing total busy time to optical networks application. Tian et al. [9] proposed a Modified First-Fit Decreasing Earliest algorithm, denoted as Tian-MFFDE, for placement of VMs energy efficiency. The Tian-MFFDE sorts list of VMs in queue order by longest their running times first) and places a VM (in the sorted list) to any first available physical machine that has enough VM's requested resources. Otherwise, the VM is allocated to a new unused machine. In the VM allocation problem, however, minimizing the number of used physical machines is not equal to minimizing total of total energy consumption of all physical machines. Previous works do not consider multiple resources, fixed starting time and non-preemptive duration time of these VMs. Therefore, it is unsuitable for the power-aware VM allocation considered in this paper, i.e. these previous solutions can not result in a minimized total energy consumption for VM placement problem with certain interval time while still fulfilling the quality-of-service.

Chen et al. [19] observed there exists VM resource utilization patterns. The authors presented an VM allocation algorithm to consolidate complementary VMs with spatial and temporal-awareness in physical machines. They introduce resource efficiency and use norm-based greedy algorithm, which is similar to in [10], to measure distance of each used resource's utilization and maximum capacity of the resource in a host. Their VM allocation algorithm selects a host that minimizes the value of this distance metric to allocate a new VM. Our proposed EMinTRE-LFT uses a different metric that unifies both increasing time and the L2-norm of diagonal vector that is presenting available resources. In our proposed TRE metric, the increasing time is the difference between two total busy time of a PM after and before allocating a VM.

Our proposed EMinTRE-LFT algorithm that differs from these previous works. Our EMinTRE-LFT algorithm use the VM's fixed starting time and duration to minimize the total busy time on physical machines, and consequently minimize the total energy consumption in all physical servers. To the best of our knowledge, no existing works that surveyed in [20], [21], [22], [23] have thoroughly considered these aspects in addressing the problem of VM placement.

III. PROBLEM DESCRIPTION

A. Notations

We use the following notations in this paper:

\( vm_i \): The \( i^{th} \) virtual machine to be scheduled.

\( M_j \): The \( j^{th} \) physical machine.

\( S \): A feasible schedule.

\( P_j^{\text{min}} \): The minimum power consumed when \( M_j \) is 0% CPU utilization.

\( P_j^{\text{max}} \): The maximum power consumed when \( M_j \) is 100% CPU utilization.

\( P_j(t) \): Power consumption of \( M_j \) at a time point \( t \).
tsi: Fixed starting time of vmi.
di: Duration time of vmi.
T: The maximum schedule length, which is the time that the last virtual machine will be finished.
\( J_j \): Set of virtual machines that are allocated to \( M_j \) in the whole schedule.
\( T_{j}^{bus} \): The total busy time (ON time) of \( M_j \).
ei: Energy consumption for running \( vm_i \) in the physical machine that \( vm_i \) is allocated.
g: The maximum number of virtual machines that can be assigned to any physical machine.

\section*{B. Power consumption model}

Notations:
- \( U_j(t) \) is the CPU utilization of \( M_j \) at time \( t \). - \( PE_j \) is the total number cores of \( M_j \).
- \( mips_{i,c} \) is the allocated MIPS of the \( c \)-th processing element to the \( vm_i \) by \( M_j \).
- \( MIPS_{j,c} \) is the maximum computing power (in MIPS) of the \( c \)-th core on \( M_j \).

In this paper, we use the following energy consumption model proposed in [4][4] for a physical machine. Let call \( \alpha = \frac{P_{min}}{P_{max}} \) is fraction of the minimum power consumed when \( M_j \) is idle (0% CPU utilization) and the maximum power consumed when the physical machine is fully utilized (100% CPU utilization). The power consumption of \( M_j \), denoted as \( P_j(.) \) with \( j = 1,2,\ldots,m \), is formulated as follow:

\begin{equation}
P_j(t) = (\alpha + (1-\alpha).U_j(t)).P_j^{max}
\end{equation}

We assume that all cores in CPU are homogeneous, i.e. \( \forall c \in \{1,2,\ldots\}, PE_j : \text{MIPS}_{j,c} = \text{MIPS}_{j,1} \). The CPU utilization \( U_j(t) \) is formulated as follow:

\begin{equation}
U_j(t) = \left(\frac{1}{PE_j \times \text{MIPS}_{j,1}}\right) \sum_{c=1}^{PE_j} \sum_{vm_i \in J_j} mips_{i,c}
\end{equation}

The energy consumption of the \( M_j \) in the time period \([t_1,t_2]\) denoted as \( \Delta E_j \) with CPU utilization \( U_j \) is formulated as follow:

\begin{equation}
\Delta E_j = P_j(U_j).(t_2-t_1) = (\alpha.P_j^{max} + (1-\alpha).P_j^{max}.U_j).\Delta T_j
\end{equation}

where:
- \( \Delta T_j \): The busy time of \( M_j \) that is defined as: \( \Delta T_j = (t_2-t_1) \).

Assume that a virtual machine \( vm_i \) changes the CPU utilization is \( \Delta u_i \) for during \([t_1,t_2]\) and the \( vm_i \) uses full utilization of its requested resources in the worst case on \( M_j \). The energy consumption by the \( vm_i \), denoted as \( e_i \), is formulated as:

\begin{equation}
e_i = (1-\alpha).P_j^{max}.\Delta u_i.(t_2-t_1)
\end{equation}

Let \( T_{j}^{bus} \) be the total busy time of \( M_j \), let \( e_i \) be energy consumed by \( vm_i \), and let \( vm_i \in M_j \) be set of virtual machines \( vm_i \) \( i = 1,2,\ldots,n \) that are allocated to \( M_j \) in the whole schedule. Let \( E_j \) be the total energy consumed by \( M_j \) and \( E_j \) is the sum of energy consumption \( \Delta E_j \) during the total busy time \( T_{j}^{bus} \) that is formulated as:

\begin{equation}
E_j = (\alpha.P_j^{max} + (1-\alpha).P_j^{max}.U_j).T_{j}^{bus}
\end{equation}

where \( \alpha.P_j^{max}.T_{j}^{bus} \) is called the base (ON) energy consumption for \( M_j \) during the total busy time, i.e., \( E_j^{base} = \alpha.P_j^{max}.T_{j}^{bus} \), and \( ((1-\alpha).P_j^{max}.U_j.T_{j}^{bus}) \) is the increasing energy consumed by some VMs scheduled to \( M_j \).

\begin{equation}
E_j = \alpha.P_j^{max} \times T_{j}^{bus} + \sum_{vm_i \in M_j} e_i
\end{equation}

\section*{C. Problem formulation}

Consider the following scheduling problem. We are given a set of \( n \) virtual machines \( J = \{vm_1,\ldots,vm_n\} \) to be scheduled on a set of \( m \) identical physical servers \( \mathcal{M} = \{M_1,\ldots,M_m\} \), each server can host a maximum number of \( g \) virtual machines. Each VM needs \( d \)-dimensional demand resources in a fixed interval with nonmigration. Each \( vm_i \) is started at a fixed starting time \( (ts_i) \) and is non-preemptive during its duration time \( (di) \). Types of resource considered in the problem include computing power (i.e., the total Million Instruction Per Seconds (MIPS) of all cores in a physical machine), physical memory (i.e., the total MBytes of RAM in a physical machine), network bandwidth (i.e., the total Kb/s of network bandwidth in a physical machine), and storage (i.e., the total free GBytes of file system in a physical machine), etc.

The objective is to find out a feasible schedule \( S \) that minimizes the total energy consumption in the equation (3) with \( \forall i \in \{1,2,\ldots,n\}, \forall j \in \{1,2,\ldots,m\}, \forall t \in [0,T] \) as following:

\begin{equation}
\text{Min} \left( \sum_{j=1}^{m}(\alpha \times P_j^{max} \times T_{j}^{bus}) + \sum_{i=1}^{n} e_i \right)
\end{equation}

where:
- \( \alpha = \frac{P_{min}}{P_{max}} \) is the fraction of idle power and maximum power consumption by physical machine \( M_j \).
- \( T_{j}^{bus} \) is the total busy time of \( M_j \).

In homogeneous physical machines (PMs), all PMs have the same idle power and maximum power consumption. Therefore \( \alpha \) is the same for all PMs. We rewrite the objective scheduling as following:

\begin{equation}
\text{Min}(\alpha \times P^{max} \times \sum_{j=1}^{m} T_{j}^{bus} + \sum_{i=1}^{n} e_i)
\end{equation}
The scheduling problem has the following hard constraints that are described in our previous work [11] as following:

- **Constraint 1:** Each VM is only processed by a physical server at any time with non-migration and non-preemption.
- **Constraint 2:** Each VM does not request any resource larger than the maximum total capacity resource of any physical server.
- **Constraint 3:** The sum of total demand resources of these allocated VMs is less than or equal to the total capacity of the resources of $M_j$.

### D. Preliminaries

**Definition 1 (Length of intervals.):** Given a time interval $I = [s, f]$, the length of $I$ is $\text{len}(I) = f - s$. Extensively, to a set $\mathcal{J}$ of intervals, length of $\mathcal{J}$ is $\text{len}(\mathcal{J}) = \sum_{I \in \mathcal{J}} \text{len}(I)$.

**Definition 2 (Span of intervals.):** For a set $\mathcal{J}$ of intervals, we define the span of $\mathcal{J}$ as $\text{span}(\mathcal{J}) = \text{len}(\bigcup \mathcal{J})$.

**Definition 3 (Optimal schedule):** An optimal schedule is the schedule that minimizes the total busy time of physical machines. For any instance $\mathcal{J}$ and parameter $g \geq 1$, $\text{OPT}(\mathcal{J}, g)$ denotes the cost of an optimal schedule.

In this paper, we denote $\mathcal{J}$ is set of time intervals that derived from given set of all requested VMs. In general, we use instance $\mathcal{J}$ is alternative meaning to a given set of all requested VMs in context of this paper.

**Observations: Cost, capacity, span bounds.** For any instance $\mathcal{J}$, which is set of time intervals derived from given set of all requested VMs, and capacity parameter $g \geq 1$, which is the maximum number of VMs that can be allocated on any physical machine, the following bounds are held:

- The optimal cost bound: $\text{OPT}(\mathcal{J}, g) \leq \text{len}(\mathcal{J})$.
- The capacity bound: $\text{OPT}(\mathcal{J}, g) \geq \frac{\text{len}(\mathcal{J})}{g}$.
- The span bound: $\text{OPT}(\mathcal{J}, g) \geq \text{span}(\mathcal{J})$.

For any feasible schedule $s$ on a given set of virtual machines, the total busy time of all physical machines that are used in the schedule $s$ is bounded by the maximum total length of all time intervals in a given instance $\mathcal{J}$. Therefore, the optimal cost bound holds because $\text{OPT}(\mathcal{J}, g) = \text{len}(\mathcal{J})$ iff all intervals are non-overlapping, i.e., $\forall I_1, I_2 \in \mathcal{J}$ then $I_1 \cap I_2 = \emptyset$.

Intuitively, the capacity bound holds because $\text{OPT}(\mathcal{J}, g) = \frac{\text{len}(\mathcal{J})}{g}$ iff, for each physical server, exactly $g$ VMs are neatly scheduled in that physical server. The span bound holds because at any time $t \in \bigcup \mathcal{J}$ at least one machine is working.

### E. Theorems

In the following theorems, all physical machines are homogeneous. Let $p_{\text{min}}$ and $p_{\text{max}}$ are the minimum/idle power and maximum power consumption of a physical machine respectively. We have $\alpha = p_{\text{min}} / p_{\text{max}}$.

**Theorem 1:** Minimizing total energy consumption in $\text{OPT}$ is equivalent to minimizing the sum of total busy time of all physical machines ($\sum_{j=1}^{m} t_{j}^{\text{busy}}$).

$$\text{Min } (\alpha \times p_{\text{max}} \times \sum_{j=1}^{m} t_{j}^{\text{busy}} + \sum_{i=1}^{n} e_i) \sim \text{Min } (\sum_{j=1}^{m} t_{j}^{\text{busy}})$$  \hspace{1cm} (9)

**Proof:** A proof for this theorem see detail in [11].

Based on the above theorem, we propose our energy-aware algorithms denoted as EMinTRE-LFT which is presented in the next section.

**Definition 4:** For any schedule we denote by $\mathcal{J}$ the set of virtual machines allocated to the physical machine $M_j$ by the schedule. Let $T_j$ denote the total busy time of $M_j$ is the span of $\mathcal{J}$, i.e., $T_j = \text{span}(\mathcal{J})$.

**Definition 5:** For any instance $\mathcal{J}$, the total busy time of the entire schedule of $\mathcal{J}$ computed by the algorithm $H$, denoted as $\text{cost}^{H}(\mathcal{J})$, is defined as $\text{cost}^{H}(\mathcal{J}) = \int_{0}^{\text{span}(\mathcal{J})} N(t) dt$, where as $N(t)$ is the number of physical machines used at the time $t$ by the algorithm $H$.

**Definition 6:** For any instance $\mathcal{J}$ and parameter $g \geq 1$, $E^{\text{OPT}}(\mathcal{J}, g)$, which is denoted as the minimized total energy consumption of all physical machines in an optimal schedule for the $\mathcal{J}$, is formulated as: $E^{\text{OPT}}(\mathcal{J}, g) = \alpha \times p_{\text{max}} \cdot \text{OPT}(\mathcal{J}, g) + \sum_{i=1}^{n} e_i$.

**Theorem 2:** For any instance $\mathcal{J}$, the lower and upper of the total energy consumption in an optimal schedule are bounded by: $p_{\text{min}} \cdot \frac{\text{len}(\mathcal{J})}{g} \leq E^{\text{OPT}}(\mathcal{J}, g) \leq p_{\text{max}} \cdot \text{len}(\mathcal{J})$.

**Proof:** For any instance $\mathcal{J}$, let $\text{OPT}(\mathcal{J}, g)$ be the total busy time of the optimal schedule for the $\mathcal{J}$, and let $E^{*}$ be the total energy consumption for the optimal schedule for the $\mathcal{J}$.

The total energy consumption of an optimal schedule needs to account for all physical machines running during $\text{OPT}(\mathcal{J}, g)$. We have: $E^{*} = \text{OPT}(\mathcal{J}, g) + \sum_{i=1}^{n} e_i$.

From Definition 6 we have $E^{\text{OPT}}(\mathcal{J}, g) = E^{*}$.

Apply the capacity bound in Theorem III-D we have $\text{OPT}(\mathcal{J}, g) \geq \frac{\text{len}(\mathcal{J})}{g}$. Thus, $E^{*} \geq p_{\text{min}} \cdot \frac{\text{len}(\mathcal{J})}{g} + \sum_{i=1}^{n} e_i$.

Recall that the energy consumption of each virtual machine is non-negative, thus $e_i > 0$. Therefore, $E^{*} \geq p_{\text{min}} \cdot \frac{\text{len}(\mathcal{J})}{g}$.

Thus

$$E^{\text{OPT}}(\mathcal{J}, g) \geq p_{\text{min}} \cdot \frac{\text{len}(\mathcal{J})}{g} \hspace{1cm} (10)$$

We prove the upper bound of the minimized total energy consumption as following. Apply the optimal cost bound in Theorem III-D we have $\text{OPT}(\mathcal{J}, g) \leq \text{len}(\mathcal{J})$.

Thus

$$E^{*} \leq p_{\text{min}} \cdot \text{len}(\mathcal{J}) + \sum_{i=1}^{n} e_i.$$  \hspace{1cm} (11)
Apply the linear power consumption as in the Equation [1] and Equation [3], the energy consumption of each $i$-th virtual machine in period time of $[t_{si}, t_{si} + d_i]$ that denotes as $e_i$ is:

$$e_i = \int_{t_{si}}^{t_{si} + d_i} P_j(U_{vm}) \, dt = (P_j^{\text{max}} - P_j^{\text{idle}}) \cdot U_{vm} \cdot d_i$$

where $U_{vm}$ is the percentage of CPU usage of the $i$-th virtual machine on a $j$-th physical machine.

Because any virtual machine always requests CPU usage lesser than or equal to the maximum total capacity CPU of every physical machine, i.e., $U_{vm} \leq 1$.

$$\Rightarrow e_i \leq (P_j^{\text{max}} - P_j^{\text{idle}}) \cdot d_i$$

Note that in this proof, all physical machines are identical with same power consumption model thus $P_j^{\text{max}}$ and $P_j^{\text{idle}}$ are the maximum power consumption and the idle power consumption of each physical machine. Thus:

$$e_i \leq (P_j^{\text{max}} - P_j^{\text{idle}}) \cdot \text{len}(I_i)$$

Let $I_i$ is interval of each $i$-th virtual machine, $I_i = [t_{si}, t_{si} + d_i]$. By the definition the length of interval is $\text{len}(I_i) = d_i$ that is duration time of each $i$-th virtual machine. Thus:

$$e_i \leq (P_j^{\text{max}} - P_j^{\text{idle}}) \cdot \text{len}(I_i)$$

The total energy consumption of $n$ virtual machines is formulated as:

$$\sum_{i=1}^{n} e_i \leq \sum_{i=1}^{n} [(P_j^{\text{max}} - P_j^{\text{idle}}) \cdot \text{len}(I_i)]$$

$$\Rightarrow \sum_{i=1}^{n} e_i \leq (P_j^{\text{max}} - P_j^{\text{idle}}) \cdot \sum_{i=1}^{n} \text{len}(I_i)$$

$$\Rightarrow \sum_{i=1}^{n} e_i \leq (P_j^{\text{max}} - P_j^{\text{idle}}) \cdot \text{len}(\mathcal{J}).$$

From Equation (11), we have:

$$E^* \leq P_{min} \cdot \text{len}(\mathcal{J}) + \sum_{i=1}^{n} e_i$$

$$E^* \leq P_{min} \cdot \text{len}(\mathcal{J}) + (P_j^{\text{max}} - P_j^{\text{idle}}) \cdot \text{len}(\mathcal{J})$$

$$E^* \leq (P_{min} + (P_j^{\text{max}} - P_j^{\text{idle}})) \cdot \text{len}(\mathcal{J})$$

By the definition, the unit energy of a physical machine equals to the idle power consumption in the unit time, i.e., $P_{min} = P_j^{\text{idle}}$. From the Equation (13):

$$E^* \leq P_j^{\text{max}} \cdot \text{len}(\mathcal{J})$$

$$\Rightarrow E^{OPT}(\mathcal{J}, g) \leq P_j^{\text{max}} \cdot \text{len}(\mathcal{J})$$

From both of two equations (10) and (15), we have:

$$P_{min} \cdot \frac{\text{len}(\mathcal{J})}{g} \leq E^{OPT}(\mathcal{J}, g) \leq P_j^{\text{max}} \cdot \text{len}(\mathcal{J})$$

We prove the theorem.

IV. SCHEDULING ALGORITHMS

A. EMinTRE-LFT scheduling algorithm

In this section, we present the proposed energy-aware scheduling algorithm, denoted as EMinTRE-LFT, with pseudo-code of EMinTRE-LFT in Algorithm [1]. Algorithm EMinTRE-LFT has two (2) steps: sorts the list of virtual machines in order decreasing finishing time first. Next, EMinTRE-LFT allocates the first next virtual machine $i$ to the first physical machine $M_j$ such that $M_j$ has enough resource to provision the virtual machine $i$ and TRE metric of $M_j$ denoted as $TRE_j$ is minimum. The $TRE_j$ is formulated as in the following equation (19). The EMinTRE-LFT solves these scheduling problems in time complexity of $O(n \times m \times q)$ where $n$ is the number of VMs to be scheduled, $m$ is the number of physical machines, and $q$ is the maximum number of allocated VMs in the physical machines $M_j, \forall j = 1, 2, ..., m$.

Based on the equation 2 the utilization of a resource $r$ (resource $r$ can be cores, computing power, physical memory, network bandwidth, storage, etc.) of the $M_j$, denoted as $U_{j,r}$, is formulated as:

$$U_{j,r} = \sum_{s \in n_j} \frac{V_{s,r}}{H_{j,r}}.$$

where $n_j$ is the list of virtual machines that are assigned to the $M_j$, $V_{s,r}$ is the amount of requested resource $r$ of the virtual machine $s$ (note that in our study the value of $V_{s,r}$ is fixed for each user request), and $H_{j,r}$ is the maximum capacity of the resource $r$ in $M_j$.

The available resource is presented using diagonal vector, where the $L2$-norm of the diagonal vector (denoted as $D_j$) is formulated as:

$$D_j = \sqrt{\left(\sum_{r \in \mathcal{R}} (1 - U_{j,r}) \times w_r\right)^2}$$

where $\mathcal{R}$ is the set of resource types in a host ($\mathcal{R} = \{\text{core, mips, ram, netbw, io, storage}\}$) and $w_r$ is weight of resource $r$ in a physical machine.

In this paper, we propose the TRE metric for the increasing total busy time and the $L2$-norm of the diagonal vector ($D_j$) of the physical machine $j$-th that is calculated as:

$$TRE_j = \frac{t_{\text{diff}} \times w_{\text{busy}}}{T_j} + D_j^2$$

V. PERFORMANCE EVALUATION

A. Algorithms

In this section, we study the following VM allocation algorithms:

- PABFD, a power-aware and modified best-fit decreasing heuristic [4]. The PABFD sorts the list of $VM_j$ ($i=1, 2, ..., n$) by their total requested CPU utilization,
Algorithm 1: EMinTRE-LFT: Energy-aware Greedy-based Scheduling Algorithm

1: function EMinTRE-LFT
2:   Input: vmList - a list of virtual machines to be scheduled, hostList - a list of physical servers
3:   Output: a feasible schedule or null
4:   vmList = sortVmListByOrderLastestFinishingTime( vmList ) ⊲ First sort VMs
5:   m = hostList.size(); n = vmList.size();
6:   for i = 1 to n do ⊲ on the VMs list
7:     vm = vmList.get(i)  
8:     allocatedHost = null
9:   T1 = sumTotalHostBusyTime( T )
10:  minRETime = +∞
11:  for j = 1 to m do ⊲ on the hosts list
12:    host = hostList.get( j )
13:    hostVMList = sortVmListByOrder( host.getVms(), order=finishTime)
14:    if host.checkAvailableResource( vm ) then
15:      preTime = T[1...m]  
16:      if host.calculateHostTotalCompletionTime( vm ) is not null then
17:        hostVMList = hostVMList + vm
18:      else
19:        hostVMList = hostVMList - vm
20:    end if
21:  end for
22:  for j = 1 to m do ⊲ on the hosts list
23:    host = hostList.get( j )
24:    hostVMList = sortVmListByOrder( host.getVms(), order=finishTime)
25:    if host.checkAvailableResource( vm ) then
26:      preTime = T[1...m]  
27:      if (minRETime > TRE) then
28:        minRETime = TRE
29:        allocatedHost = host
30:      end if
31:    end if
32:  end for
33:  if (allocatedHost = null) then
34:    allocate the pair of vm to the host
35:  end if
36: return allocatedHost
37: end function
38: sumTotalHostBusyTime(T[]) = ∑T[j] ⊲ T[1...m]: Array of total completion times of m physical servers

Algorithm 2: Estimating the metric for increasing time and resource efficiency

1: function ESTIMATERETIMENRES
2:   Input: (diffTime, host) - diffTime is a different time, host is a candidate physical machine
3:   Output: TRE - a value of metric time and resource efficiency
4:   Set 𝕀عبارة={cores, mips, ram, io, netbw, storage}
5:   j = host.getId(); n_j = host.getVMList();
6:   for r ∈ 𝕀عبارة do
7:     Calculate the resource utilization, 𝑈_r as in the Equation (17).
8:   end for
9:   weights[] ← Read weight of resources from configuration file
10: Calculate the 𝑇𝑅𝐸_𝑗 metric of host 𝑗 as in the equation (19)
11: 𝑅_j = √∑_r∈𝕀عبارة((1−𝑈_𝑗,𝑟)×𝑤_𝑟)^2
12: 𝑇𝑅𝐸_𝑗 = (diffTime × 𝑊_𝑡𝑖𝑚𝑒)^2 + 𝑅_j^2 ⊲ 𝑊_𝑡𝑖𝑚𝑒 is weight of the different time
13: return 𝑇𝑅𝐸_𝑗
14: end function

and assigns new VM to any host that has a minimum increase in power consumption.

- VBP-Norm-L2, a vector packing heuristics that is presented as Norm-based Greedy with degree 2 [10]. Weights of these Norm-based Greedy heuristics use FFDAvgSum which are exp(x), which is the value of the exponential function at the point x, where x is average of sum of demand resources (e.g. CPU, memory, storage, network bandwidth, etc.). VBP-Norm-L2 assigns new VM to any host that has minimum of these norm values.
- MinDFT-LDFT: the algorithm sorts list of VMs, n by their starting time (ts_i) and respectively by their finished time (ts_i + dur_i), then MinDFT-LDFT allocates each VM (in a given sorted list of VMs) to a host that has a minimum increase in total completion times of hosts as in algorithm MinDFT [11].
- EMinTRE-LDFT, the algorithm is proposed in the Section [14].

B. Methodology

We evaluate these algorithms by simulation using the CloudSim [24] to create simulated cloud data center systems that have identical physical machines, heterogeneous VMs, and with thousands of CloudSim’s cloudlets [24] (we assume that each HPC job’s task is modeled as a cloudlet that is run on a single VM). The information of VMs (and also cloudlets) in these simulated workloads is
extracted from two parallel job models are Feitelson's parallel workload model [12], Downey's parallel workload model [13] and Lublin's parallel workload model [14] in the Parallel Workload Archive (PWA) [15]. When converting from the generated log-trace files, each cloudlet's length is a product of the system's processing time and CPU rating (we set the CPU rating equal to included VM's MIPS). We convert job's submission time, job's start time (if the start time is missing, then the start time is equal to sum of job's submission time and job's waiting time), job's request run-time, and job's number of processors in job data from the log-trace in PWA [15] to VM's submission time, starting time and duration time, and number of VMs (each VM is created in round-robin in the four types of VMs in Table I on the number of VMs). Eight (08) types of VMs as presented in the

Table I

| VM Type | MIPS | Cores | Memory (Unit: MBytes) | Network (Unit: Mb/s) | Storage (Unit: GBytes) |
|---------|------|-------|-----------------------|----------------------|------------------------|
| Type 1  | 2500 | 8     | 6800                  | 100                  | 1000                   |
| Type 2  | 2500 | 2     | 1700                  | 100                  | 422.5                  |
| Type 3  | 3250 | 8     | 6400                  | 100                  | 1000                   |
| Type 4  | 3250 | 4     | 34200                 | 100                  | 845                    |
| Type 5  | 3250 | 2     | 17100                 | 100                  | 422.5                  |
| Type 6  | 2000 | 4     | 15000                 | 100                  | 1690                   |
| Type 7  | 2000 | 2     | 7500                  | 100                  | 845                    |
| Type 8  | 1000 | 1     | 1875                  | 100                  | 211.25                 |

Table II

| Type | MIPS | Cores | Memory (Unit: MBytes) | Network (Unit: Mb/s) | Storage (Unit: GBytes) | p\text{rate} (Unit: Watts) | p\text{max} (Unit: Watts) |
|------|------|-------|-----------------------|----------------------|------------------------|--------------------------|--------------------------|
| M1   | 3250 | 16    | 140084                | 10000                | 10000                  | 175                      | 250                      |

Table III

| Algorithm     | Energy (Unit: kWh) | Normal. Energy | Saving Energy (+,better,-,worst) |
|---------------|--------------------|----------------|---------------------------------|
| PABFD         | 1.055.42           | 1.398          | -60%                            |
| VBP-Norm-L2   | 1.054.69           | 1.597          | -60%                            |
| MinDFT-LDTF   | 603.90             | 0.915          | 9%                              |
| Tian-MFFDE    | 660.30             | 1.000          | 0%                              |
| EMintre-LFT wt1 | 503.43           | 0.762          | 24%                             |
| EMintre-LFT wt0.01 | 503.43           | 0.762          | 24%                             |
| EMintre-LFT wt0.001 | 503.43           | 0.762          | 24%                             |

Table IV

| Algorithm     | Energy (Unit: kWh) | Normal. Energy | Saving Energy (+,better,-,worst) |
|---------------|--------------------|----------------|---------------------------------|
| PABFD         | 878.01             | 1.523          | -52.3%                          |
| Norm-VBP-L2   | 876.49             | 1.520          | -52.0%                          |
| Tian-MFFDE    | 576.55             | 1.000          | 0%                              |
| MinDFT-LDTF   | 502.61             | 0.872          | 12.8%                           |
| EMintre-LFT wt1 | 416.35           | 0.722          | 27.8%                           |
| EMintre-LFT wt0.01 | 416.35           | 0.722          | 27.8%                           |
| EMintre-LFT wt0.001 | 416.35           | 0.722          | 27.8%                           |

Table V

| Algorithm     | Energy (Unit: kWh) | Normal. Energy | Saving Energy (+,better,-,worst) |
|---------------|--------------------|----------------|---------------------------------|
| PABFD         | 460.66             | 1.601          | -60.1%                          |
| Norm-VBP-L2   | 453.23             | 1.575          | 57.5%                           |
| Tian-MFFDE    | 287.78             | 1.000          | 0%                              |
| MinDFT-LDTF   | 263.86             | 0.917          | 8.3%                            |
| EMintre-LFT wt0.001 | 232.29           | 0.807          | 19.3%                           |
| EMintre-LFT wt0.01 | 232.29           | 0.807          | 19.3%                           |
| EMintre-LFT wt1  | 232.29            | 0.807          | 19.3%                           |

Figure 1. The normalized total energy consumptions compare to Feitelson's parallel workload model [12] in the Parallel Workload Archive [15].
MFFDE. Result of simulations with Lublin99's parallel workload model 

We also compared our proposed VM allocation algorithms with PABFD [4] because the PABFD is a famous power-aware best-fit decreasing in the energy-aware scheduling research community, and a vector bin-packing algorithm (VBP-Norm-L2) to show the importance of with/without considering VM's starting time and finish time in reducing the total energy consumption of VM placement problem.

C. Results and Discussions

The simulation results are shown in the three tables (Table [I], Table [IV] and Table [V]) and figures. Three (03) figures include Fig. [I], Fig. [II] and Fig. [III] show bar charts comparing energy consumption of VM allocation algorithms that are normalized with the Tian-MFFDE. None of the scheduling algorithms use VM migration techniques, and all of them satisfy the Quality of Service (e.g., the scheduling algorithm provisions maximum of user VM's requested resources). We use total energy consumption as the performance metric for evaluating these VM allocation algorithms.

Using three parallel workload models [12], [13] and [14] in the Feitelson's Parallel Workloads Archive [15], the simulation results show that the proposed EMinTRE-LFT can reduce the total energy consumption of the physical servers by average of 23.7% compared with Tian-MFFDE [9]. In addition, EMinTRE-LFT can reduce the total energy consumption of the physical servers by average of 51.5% and respectively 51.2% compared with PABFD [4] and VBP-Norm-L2 [10]. Moreover, EMinTRE-LFT has also less total energy consumption than MinDFT-LDTF [11] in the simulation results.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we formulated an energy-aware VM allocation problem with multiple resource, fixed interval and non-preemption constraints. We also discussed our key observation in the VM allocation problem, i.e., minimizing total energy consumption is equivalent to minimize the sum of total completion time of all physical machines (PMs). Our proposed algorithm EMinTRE-LFT can all reduce the total energy consumption of the physical servers compared with the state-of-the-art algorithms in simulation results on three parallel workload models of Feitelson's [12], Downey98's [13], and Lublin99's [14].

We are developing the algorithm EMinTRE-LFT into a cloud resource management software (e.g., OpenStack Nova Scheduler). In the future, we would like to evaluate more with the weights of increasing time and L2-norm of diagonal vector on available resources. Additionally, we are working on IaaS cloud systems with heterogeneous physical servers and job requests consisting of multiple VMs using EPOBF [6]. We are studying how to choose the right weights of time and resources (e.g., computing
power, physical memory, network bandwidth, etc.) in Machine Learning techniques.

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