



Task and Resource Allocation for Energy Efficiency in Heterogeneous Cloud Environment

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ABSTRACT

Prominent amount the challenges facing heterogeneous cloud environment is resource utilization and alarming increase energy consumption which have attracted series of research attentions. However, efficiency of resource utilization and energy consumption still requires additional research efforts. The current research intends to solve resource utilization and energy consumption challenges in a heterogeneous cloud environment where tasks create enormous quantities of data streams that must be stored. The technique explored a greedy heuristic method for task and resource categorization with the goal of optimizing energy efficiency through creation of energy consumption profile. To classify tasks and resources depending on their intensity levels was proposed. The method was evaluated using CloudSim 3.0.3. version. The result obtained revealed a decrease in energy usage by 1.88% and 24.23 % in term of task and resource utilization. Despite the increased resource utilization, the execution time continues to be a significant impediment to achieving optimal energy efficiency. subsequently, this work presents a novel approach to addressing resource utilization and energy consumption challenges in a heterogeneous cloud environment. The method therefore achieved improved energy efficiency by categorizing tasks and resources based on their intensity levels by using our suggested heuristic method.

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INTRODUCTION

Cloud technology for virtualization allows for the flexible reallocation of physical resources among distinct physical nodes (Nasim et al., 2018). Assigning tasks to several virtual machines within a single time, many VMs run on the same physical machine PMS. CPU speeds, memory, and power consumption needs differ amongst data centers (Arroba et al., 2017). Energy-conscious Virtual Machine VM consolidation may be viewed as a problem in computing resource allocation with the purpose of minimizing energy consumption while preserving the agreed-upon quality of service QoS. The use of modern technology that requires less energy to achieve the same work can be defined as energy efficiency. This

improved efficiency can aid in the reduction of greenhouse gas GHG arc energy in servers with local storage, while RAM, Motherboard, and disc are utilized. Motherboard, 13%, and 6%, respectively, are used. Memory power is affected by the operating state voltage and other constant parameters (Hackenberg et al., 2015). As a result, attaining a minimum makespan is an NP-hard issue.

Heterogeneous data centers are specialized computer systems that are primarily geared for high-performance parallel computing (Buyya et al., 2018). The processors in a network of computers are heterogeneous in the sense that they run at various speeds. The goal of a successful parallel application for a homogeneously distributed memory

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multiprocessor bandwidth system is to spread calculations uniformly among available processors (Riesinger et al., 2017). Distribution guarantees that the system's speed is maximized by using identical CPUs. As a result, a heterogeneous network must distribute computing unevenly to accommodate for processor performance differences.

More research is urgently required for VM consolidation, especially on heterogeneous systems with varying CPU speeds, memory sizes, and power consumption needs (Shirvani Rahmani & Sahafi M., 2020). While VM consolidation may be phrased as a computational resource allocation issue with the goal of minimizing energy usage while providing agreed-upon quality service (Yavari et al., 2019). Reduced energy consumption by computing resources not only lowers operating costs but also has a positive influence on the environment. Because most data centers run their servers at just over half capacity, they waste energy and generate unneeded heat.

METHOD

Heterogeneity occurs when task arrival rates differ across homogeneous CPUs or CPUs with differing task processing rates. Tasks in distributed computing DCS can be executed on any computing node, and a single computing node can operate as a resource manager or scheduler to collect all global information from other computing nodes. A heterogeneous distributed computing system (HDCS) is suitable for fulfilling enormous computational needs and a diversified set of workloads.

Let $U(i,j)$ be the resource usage by the task t_j when executed on R_i , then the utilization matrix of the resource R_i at a given time τ , denoted as U_j and defined as:

$$U_i(\tau) = \sum_{j=1}^K U_{i,j} \dots \text{equation 1}$$

Where K is the number of tasks running on resource R_i at time τ . Then the energy consumption E_i of a resource R_i at time τ is defined as:

$$E_i(\tau) = (P_{max} - P_{min}) * U_i(\tau) \dots \text{equation 2}$$

Where P_{max} is the power consumption at the peak load and P_{min} is the minimum power consumption in the inactive mode. As resource utilization is directly proportional to the energy

consumption of the physical resource. Thus, energy consumption by the cloud infrastructure instant of time τ is denoted as $E(\tau)$ and can be defined as follows:

$$E(\tau) = \sum_{i=1}^m E_i(\tau) \dots \text{equation 3}$$

Where m is the total number of resources in cloud infrastructure. Therefore, total energy E consumed in time T_{max} is defined by

$$E = \Delta\tau \sum_{\tau=1}^{\tau_{max}} E(\tau) \dots \text{equation 4}$$

The main objective of the research is to minimize E on the cloud computing environment by allocating set of task T efficiently.

In diverse cloud data centers, task categorization decreases energy usage and migration count, allowing for server consolidation (Ismaeel et al., 2018). The element of the three solutions is task profiling for proper VM assignment selection of highly utilized overloaded and less utilized under loaded host and VM. The CRB approach is used to determine the significantly overloaded number of active PMs. Where the PEC approach is used to find under loaded PM that may be reduced to save energy. The goal is to optimize resource utilization by lowering energy usage and matching customer expectations (Khanet al, 2018). For improved outcomes, task and resource categorization may be used to schedule activities and resources in a heterogeneous cloud environment (Patra, 2018). Task and resource classification is based on resource need rate in allocating jobs to an appropriate resource. Thus, choosing and moving highly overloaded VMs is referred to as VM selection, while distributing them to the desired PMs is referred to as VM placement. If tasks are allocated without taking into account functional needs such as resource capacity, the selection of suitable VMs would increase the potential energy consumption and the number of live migrations of virtual machines VMMs (Zhou et al., 2016). Before submitting the job, evaluate the impacts of VM resource capacity, utilization, and energy consumption on the corresponding host. A possible VM selection and allocation is described as a mapping of the host to the set of VMs such

$$\sum_{j=1}^{VM_j} \sum_{m=1}^{H_n} VM_{jm}^k = (VM_{1L}^k, VM_{2L}^k, VM_{3L}^k, \dots \dots VM_{JM}^k)$$

which must meet the following two conditions. Each VM is allotted to at least one PM, and no VM is allotted to more than one PM,

$$\cup_{VM_j \in h} VM_j^k(h_m) = VM_{j,m}^k, VM_{i=1,m=1}^r \cap VM_{j=1,m=2}^k = 0, \forall 1 \leq i, j \text{ and } i = j \text{ otherwise for every PM, the cumulative resource requirements of its hosted VMs do not surpass its available resources, i.e., Task of Type } ToT_{j,m}^x \leq \sum_{j=1}^{VM_j} VM_{j,m}^R(kc) \leq h_m(kc) \forall 1 \leq j \leq m$$

The model above depicts that sort of work, where Kc refers to resource capability. As illustrated in Figure 1, the task resource requirement rate RRR value should be smaller than the VM and PM resource capacity. Each job is assigned a set of CPU, memory, storage, and bandwidth resources based on the RRR value. Based on the RRR value, all sorted task types are updated and maintained, and tasks are allocated to their corresponding VM kinds, such as (VMCPU, VMM, VMBW, or VMStr). The task ranking scheme categorization is used to filter out overloaded hosts and is partially utilized to determine the targeted host for an accurate VMM process. Using the resource requirement, the suggested technique categorizes jobs based on CPU, storage, memory, and bandwidth requirements. To

precisely assign the job to the right VM, which decreases expectations and energy usage. The VM selection technique is based on evaluating highly loaded hosts using the CRB rating system and underloaded hosts using the PEC function, ensuring correct VM migration. As a result, all of these approaches properly anticipate a suitable VM for the work, resulting in a low process of task categorization and task allocation to the right virtual machine of the host. This process is based on an assessment of the host's resource utilization rate and energy usage. Initially, the job is received from the working platform together with the required resource pieces. The tasks are organized based on these factors. The ToT set consists of four types of tasks (task type T, where T = CPU, BW, M, or Str). When the task RRR value equals the threshold value of (CPU, memory, storage, and bandwidth), T= (CPU, BW, M, or Str). As a result, the sorted job is assigned to the host's appropriate VM. The VM migration is carried out by categorizing the hosts into two types: those with low utilization, known as under loaded VMs, and those with high utilization, known as overloaded VMs.

Task Classification algorithm 1.

- Input:** 1. Task parameter set: $T = \{t_1, t_2, t_3, t_n\}, t_i \{Li, Di, li, Ci\}$.
2. Task set: $T = \{t_1, t_2, t_3, \dots, t_n\}$
3. $VM_{sub-type} = \{VM_{c-type}, VM_{M-type}, VM_{B-type}, VM_{S-type}\}$
 $VM_{c-type} \{VM_{CM-type}, VM_{CS-type}, VM_{CB-type}\}$
 $VM_{M-type} \{VM_{MC-type}, VM_{MS-type}, VM_{MB-type}\}$
 $VM_{B-type} \{VM_{BC-type}, VM_{BM-type}, VM_{BS-type}\}$
 $VM_{S-type} \{VM_{SC-type}, VM_{SM-type}, VM_{SB-type}\}$
4. Task intensive $\sigma = \{\sigma_C, \sigma_B, \sigma_M, \sigma_S\}$

Output: Task types based n intensity on resource requirement-type, S-type, C-type, M-type and B-type

```
// task classification//
for i = 1 to n do
  if ( $\sigma_C = \text{Max}$ ) then
     $\sigma_C$  intensive is C-type
  else
    if ( $\sigma_M = \text{Max}$ ) then
       $\sigma_B$  intensive is M-type
    else
      if ( $\sigma_B = \text{Max}$ ) then
         $\sigma_M$  intensive is B-type
      else
        if ( $\sigma_S = \text{Max}$ ) then
           $\sigma_S$  intensive is S-type
        endif
      endif
    endif
  endif
endif
```

```

endif
endfor
VMType ← VMsub-types using utilization algorithm 2
for each VMsub-types in VMToT ∈ VMtypes do
    if ti is fit in VMToT
        VMType ← VMToT
    endif
endfor
Return Type of Task, VMType

```

Resource allocation algorithm 2

- Input 1. Host set of H = (h₁+h₂+h₃ h_n)
2. Task set T = (t₁, t₂, t₃,.....t_n)
3. VM type set VM type = (VM_{C-type}, VM_{M-type}, VM_{S-type}, VM_{B-type})
4. Task intensive σ = (C. B. M. S)

Output Accurate VM selection

```

Ti ← useri
For i=1 to n do
[σc, σm, σs,σb] ← TaskClassification using algorithm 1
For each task ti ∈ T do
    vm ← selectVMType(ti, T) using algorithm 1
    Update VMList ← vm
End
For each hi ∈ H do
    If vm is fit in HostList, then
        hi - vm
        Update HostList h
    End end
Return select vm ∈ VMList

```

Table. 1: Host Configuration.

| Resource/Host | Host1 | Host2 | Host3 | Host4 | Host5 |
|-----------------|---------|---------|---------|---------|---------|
| MIPS | 7000 | 6500 | 4000 | 7500 | 6000 |
| Cores | 2 | 3 | 4 | 4 | 5 |
| RAM(GB) | 24 | 24 | 24 | 24 | 24 |
| Bandwidth(Mbps) | 100,000 | 100,000 | 100,000 | 100,000 | 100,000 |
| Storage(GB) | 100 | 70 | 60 | 65 | 50 |

Table. 2: VM Configuration.

| Resource/VMType | VMCPU-type | VMStr-type | VMM-type | VMBW-type |
|-----------------|------------|------------|----------|-----------|
| MIPS | 7000 | 6500 | 4000 | 7500 |
| Cores | 1 | 2 | 3 | 2 |
| RAM(MB) | 512 | 512 | 1024 | 1024 |
| Bandwidth(Mbps) | 1000 | 1000 | 1000 | 1000 |
| Storage(GB) | 6 | 5 | 10 | 7 |

RESULTS DISCUSSION

The experiment was conducted on a laptop computer system with following Intel(R) Core(TM)i5-4200U CPU @ 1.60GHz 2.30GHz Processor, with 8.00GB of RAM, System Type of 64-bit Operating System,x64-based

processor. With Windows 10 Operating System with IntelliJ IDEa community edition 2019.2 version. Where CloudSim 3.0.3 is used for the implementation. Three sample experiment where carried out and tested on the both

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classified and unclassified task and resources for validation.

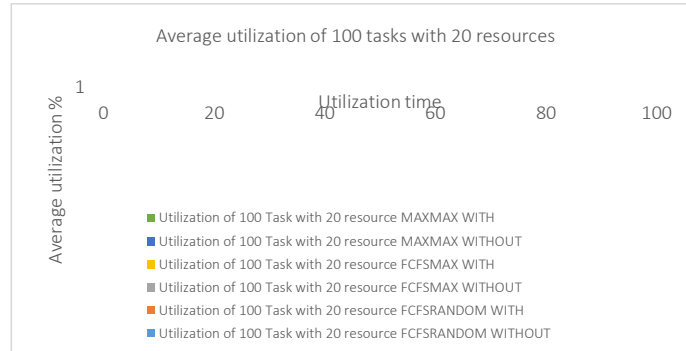


Fig. 1 Average utilization of 100 task with 20 resources

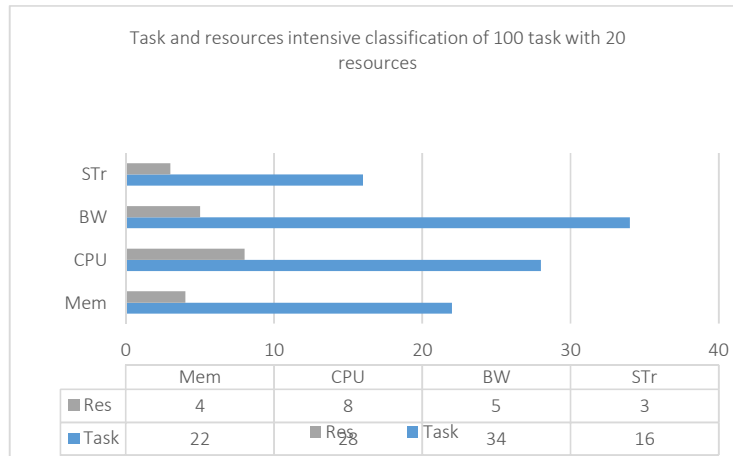


Fig. 2 Task and resource classification of 100 task with 20 resources

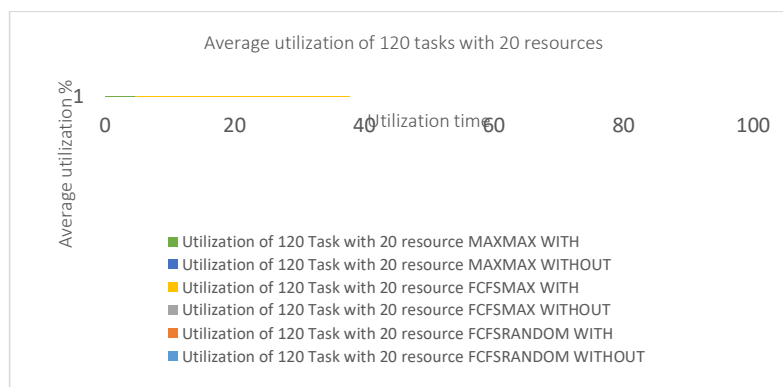


Fig. 3 Average utilization of 120 tasks with 20 resources

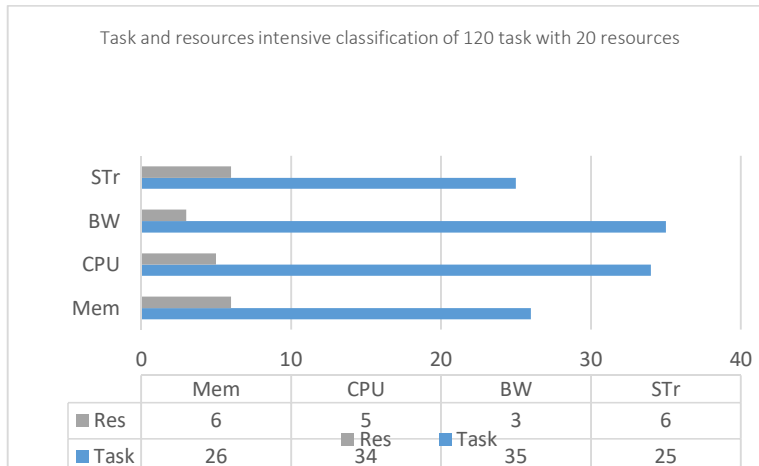


Fig. 4 Task and resource classification of 120 tasks with 20 resources

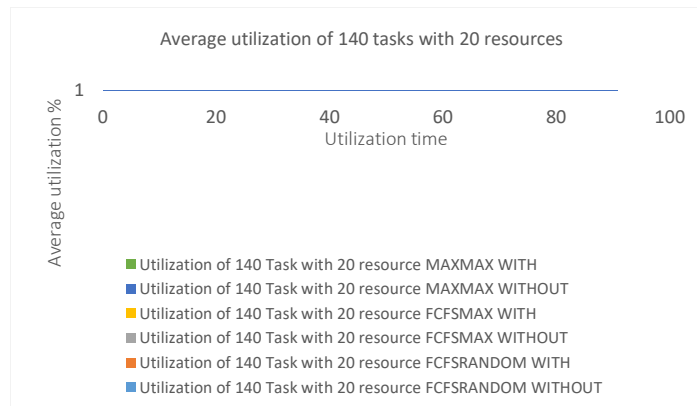


Fig. 5 Average utilization of 140 tasks with 20 resources

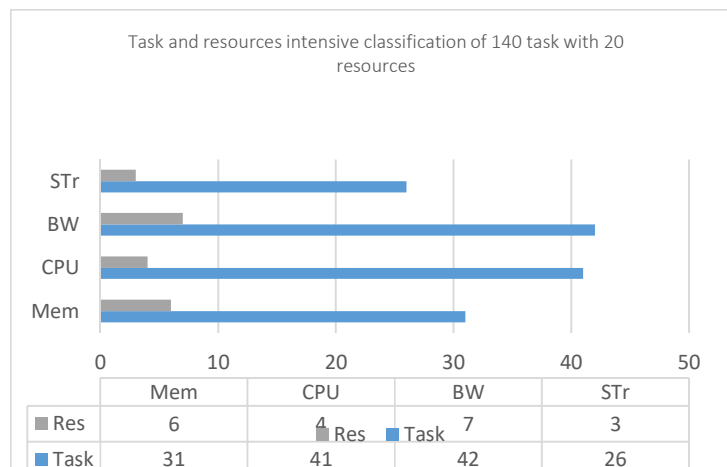


Fig. 6 Task and resource classification of 140 tasks with 20 resources

EXPERIEMENT DISCUSSION

The above figure 1 – 6 shows the average utilization of tasks ranging from 100, 120, and 140 each with 20 number of resource that is running on them with three different hybrid heuristic algorithms that are either classified or not. The figures indicate that MAXMAX has the highest utilization percentage

while FCFSRANDOM has the lowest. Moreover, figures 1 -6 indicate the task and resource classification of various tasks on constant resource to be 20 in number. The figures also reveal that CPU and BW are leading in task classification while in resource classification any of the intensive can leads.

Table 3: Energy Consumption Utilization.

| | Energy Consumption | | | | | | | | | | |
|-----|--------------------|---------|---------|---------|--------|---------|---------|---------|-------|-------|-------|
| | FCFSRAND | | FCFSMAX | | MAXMAX | | TWC | TWOC | ATWC | ATWOC | DIFF |
| | With | Without | With | Without | With | Without | | | | | |
| 140 | 401620 | 499210 | 383430 | 404130 | 464370 | 482410 | 1249420 | 1385750 | 47.41 | 52.59 | -5.17 |
| 120 | 472380 | 393550 | 390030 | 393620 | 442530 | 458430 | 1304940 | | 51.16 | 48.84 | 2.33 |
| 100 | 319880 | 367690 | 278510 | 338560 | 377420 | 406720 | 975810 | 1112970 | 46.72 | 53.28 | -6.57 |
| | | | | | | | | | | | -9.41 |
| | | | | | | | | | | | -1.88 |

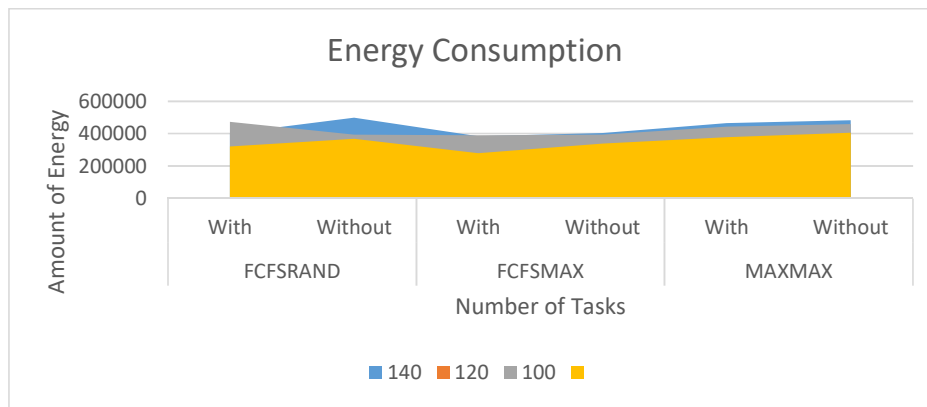


Fig.7: Energy consumption of 100 to 140 Number of Tasks

Table. 4 Utilization Execution Time.

| | Utilization Execution Time | | | | | | | | | | |
|-----|----------------------------|---------|---------|---------|--------|---------|-----|------|-------|-------|-------|
| | FCFSRAND | | FCFSMAX | | MAXMAX | | TWC | TWOC | ATWC | ATWOC | DIFF |
| | With | Without | With | Without | With | Without | | | | | |
| 140 | 95 | 42 | 76 | 51 | 94 | 22 | 265 | 115 | 69.74 | 30.26 | 39.47 |
| 120 | 72 | 46 | 114 | 51 | 124 | 20 | 310 | 117 | 72.6 | 27.4 | 45.2 |
| 100 | 46 | 36 | 84 | 41 | 74 | 18 | 204 | 95 | 68.23 | 31.77 | 36.45 |
| | | | | | | | | | | | 121.1 |
| | | | | | | | | | | | 3 |
| | | | | | | | | | | | 24.23 |

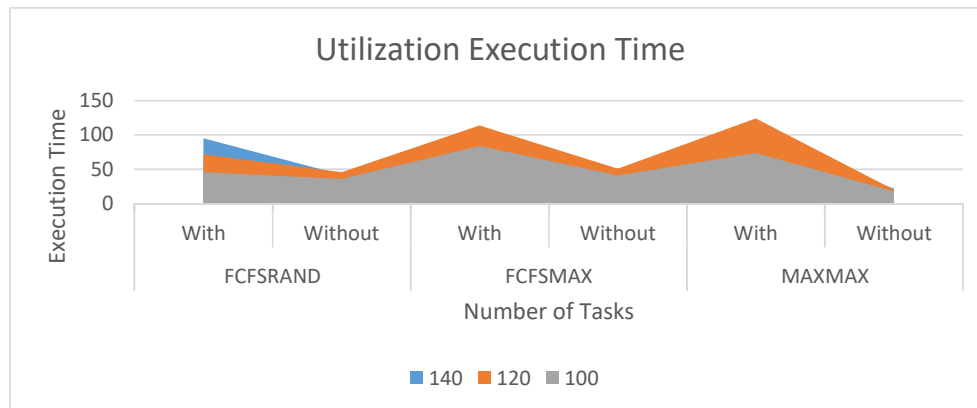


Fig. 8: Execution Utilization Time of 100 to 140 number of Tasks

CONCLUSION

The experiment was conducted on 100, 120, and 140 tasks with and without categorization on 20 resources. The results shows that tasks and resources categorization consume 1.88% less energy than tasks and resources without categorization. While utilization execution time, indicate that task and resources with categorization have a 24.23% longer execution time than task and resources without categorization. As a result, the longer the execution time, the less energy is consumed. The graphical depiction of energy consumption and execution time in several hybrid heuristic algorithms. As a result, the experiment yields the following performance metrics: energy consumption, execution time, and utilization.

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