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Task Classifications For Energy Efficiency Using Greedy Heuristic In Heterogeneous Cloud Computing

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Abstract
Cloud computing lead to abrupt variations resulting to immense number of data streams for storage, which are considered as tasks in a heterogeneous cloud environment. To address this problem, many researchers proposed different solutions, but still resource utilization with energy consumption remains an issue. In this research a task classification model for energy efficiency using greedy heuristic in heterogeneous cloud is proposed. The technique adopts resource requirement rate for task classification resource utilization. The CPU utilization is predictor of the overloaded and under loaded virtual and physical machines while classifying the tasks based on intensiveness. The proposed approach classified task based on intensiveness thereby reducing the energy consumption free of Service Level Agreement (SLA) violation.

Key Word: *Task Classification, Energy efficiency, Cloud Computing, Heterogeneous*

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I. Introduction

In a cloud computing context is built on the notion of virtualization which have numerous services that can ensemble the user requirements (Kumar & Sahoo, 2014). Virtual machines (VMs) are software environments that run on the server and support a variety of applications. The VMs are used to meet the application's resource requirements and provide runtime support. Server consolidation allows numerous servers to run on a single physical machine at the same time, reducing the amount of energy consumed in a data center. The workload or server consolidation problem is also known as task consolidation. In a cloud computing context, the task consolidation challenge is used to address the assigned *n* tasks to a group of *r* resources (Kumar & Sahoo, 2014). Task consolidation can be achieved through virtualization, which increases the utilization of subset of servers. Thus, task consolidation allows datacenter operators spread tasks over a smaller set of machines that are under loaded, shut down or put on sleeping mode (Armant, 2018). In a cloud virtualization technology offers an accurate method of reallocating physical resources between different physical hosts (Nasim,et al , 2018). The task/jobs are sent to different Vmsat the same time and simultaneously operate on the same physical machine PM. Datacenters vary in terms of CPU speeds, memory sizes, and power consumption requirements (Arroba*et al,* 2017) . Energy-aware VM consolidation can be thought of as a computing resource allocation challenge with the goal of reducing energy usage while maintaining the agreed-upon quality of service (QoS) (Yousafzai *et al*., 2017). Energy efficiency refers to the use of technology that uses less energy to complete the same task. Because it consumes less energy, an energy-efficient light bulb is more efficient than a filament light bulb. Increased efficiency can help to reduce greenhouse gas (GHG) emissions and other pollutants, as well as water consumption (Chang*et al,* 2015). Energy consumption measurement solutions for diverse cloud settings are relatively rare, with the majority of solutions focusing solely on cluster resource use and network monitoring. The CPU consumes around 37% of the energy in servers with local storage, while RAM, motherboard, and disk utilize 17%, 13%, and 6%, respectively. The running state, operating voltage, and a number of other constant characteristics all influence memory power usage (Hackenberg *et al.*, 2015). The DVFS methodology uses a green service level agreement between cloud users to reduce energy and cost consumption in the HCS framework. As a result, achieving the aim of minimum make span is an NP-hard problem.

Heterogeneous datacentre are dedicated computer system designed mainly for high performance parallel computing, which is obtained from the classical homogeneous cluster architecture.(Buyya *et al*., 2018). The heterogeneity of processors in a network of computers is that the processors run at different speeds. A good parallel application for a homogeneous distributed memory multiprocessor bandwidth system tries to evenly distribute computations over available processors (Riesinger*et al*, 2017). This very distribution ensures the maximal speedup on the system consisting of identical processors. Therefore, a good parallel application for the heterogeneous network must distribute computations unevenly taking into account the difference in processor speed.

More investigation is critically needed for VM consolidation particularly on the heterogeneous cloud datacenter with different CPU speed, memory size and power consumption demands (Shirvani *et al*, 2020). While VM consolidation can be as a computing resource allocation problem with objective of minimizing energy consumption while delivering quality of service (QoS) as agreed by the customers (Yavari et al, 2019). The Energy consumption reduction in by computing resources not only reduces the operation cost but also has a positive effect on the environment. Most of the clod servers are operating at half of their capacity thus wasting energy and causing unnecessary heat. Task classification is one of the methods to be used in order to reduce the consumption of energy in the heterogeneous cloud datacenter.

II. Related Works

The possible solution is to reduce the energy by transferring some of the customer tasks from least loaded resources to the active resources and make the least loaded resources in turn off mode. (Kumar *et al* 2015) study task consolidation for energy efficiency based on genetic algorithm approach. With a good resource allocation policy try to assign a task to an available virtual machine VMs on a different physical host so as to finish the task execution within a shortest possible time with aim to minimized energy consumption (Kumar *et al* 2015; Gourisiria *et al* 2018). As resource allocation is a combinatorial problem which can be describe as Non-Polynomial complete (NP-complete) (kumar *et al* 2015; Gourisiria *et al* 2018). (Kumar *et al* 2015) used a novel genetic algorithm GA task scheduling while (Gourisiria *et al* 2018) Energy conscious Task consolidation ECTC to reduce the energy consumption of the data center. The task consolidation is act of assigning N task to a set of R resource i a cloud computing environment (kumar et al 2015; Gourisiria et al 2018). While energy efficient is process where utilization of all computing node and distributing VMs in a such a way the power is efficient (Kumar *et al* 2015; Gourisiria *et al* 2018). (Kumar *et al* 2015; Gourisiria *et al* 2018) assume that all resource a homogeneous in term of their computing capabilities. To minimised the energy consumption is refer as a linear programming problem (Kumar *et al* 2015; Gourisiria *et al* 2018).

(Kumar *et al* 2015) genetic algorithm is better than other two algorithm that random and round robin algorithms in term of makespan. Based on the research at hand it revealed that no numeric data is seen to validate the claims. It also shows that the research have not used simulator or any programming language to come up with their result. However, the research only show that it achieve makespan only where the tittle of the work was not seen clearly in the work. No future direction is for upcoming researchers.

(Gourisiria *et al* 2018) the ECTC outperform MaxMaxult algorithm in term of energy consumption but look at the result at hand find out that at 70% utilization both of have consume amount of energy. It also show that the experiment was conducted using MATLAB2012 where latest version where available. The research in silent on future upcoming research such many challenges where not solve by the research in term of task consolidation.

III. Task Consolidation

A cloud computing infrastructure can be as H is a set of physical machine (H_1, H_2, H_3 .... H_n). This cloud infrastructure resources can be used by virtualization technology, that allows one to create several VM on a PM that reduce s the amount of hardware to be use and improve the utilization of resources. Therefore, we assumed that virtual machine as a computing resource/node in a cloud model. A computing resource R is a set of VM (R_1, R_2, R_3, ...R_m). The energy consumed by the resource R_i for executing a task or services runs on the resource. Thus, energy consumed by a resource is proportional to the processor associated with the resource. Let the set of task be represented as T=(t_1, t_2, t_3, ...t_n). Each task t_j has an expected time to compute on resource Ri and broken as t(i,j) where any node can carry out the duties. Each arriving task t_j have Task ID, arrival time, an expected time to compute on a different computing node. The load balancing algorithm is of two kinds, centralized and decentralized, i.e. with/out threshold. A centralized load balancing algorithm structure is chosen because it imposes less overhead on the system than its counterpart. Also, it needs the overall information of the computing node at one location and policy initiatives from the central location. Heterogeneity takes place due to the difference in task arrival rate at homogeneous CPUs or CPUs with different task processing rate. Tasks in DCS can be executed on any computing node; a single computing node can act resource manager or scheduler to collect all global information of other computing nodes. HDCS is appropriate in a meeting of large computational demands and diverse groups of tasks.

Let u(i,j) be the resource usage by task t_j be executed on R_i . where the utilization matrix of resource R_i at give time τ donoted a U_j define as:

$$U_i\,(\tau) = \sum_{i=1}^{k} U_{i,j} \qquad \text{… equation 1}$$

Where k is the number of tasks running on the resource Ri onat time τ and energy consumption Ei of a resource Ri at a time τ is defined as:

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

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 isdirectly propotional to the energy consumption of physical resource. Then, energy consumption by the cloud infrastructure at instant of time τ is denoted as E (τ) and defined as:

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

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

$$E = \Delta\tau \sum_{\tau-1}^{\tau_{max}} E\,(\tau) \qquad \text{…equation 4}$$

Where the main research objective is to minimized E on the cloud computing environment by efficiently allocate set of task T.

Task Utilization allocation Algorithm

Input: Task Matrix

Output: Utilization Matrix

```
Initialize τ
Initialize Utilization Matrix, U*← Ø
R* ← Ø
while mainQ ≠ Ø do
    tempQ ← All jobs from mainQ where arrival time ≤ τ.
      while tempQ ≠ Ø do
        j ← MaximumResourceUtilizationTask(tempQ)
        i ← MaximumUtilizedResource(U, τ, tj)
        if i ≠ Null then
          Assign task tj to Ri
          Update Utilization Matrix U(τ, i).
          Remove task tj from mainQ and tempQ.
        else
          Remove task tj from tempQ.
        end if
        end while
      Increment τ.
end while
return U.
End Algorithm
```

The algorithm goal is to keep computing nodes available while lowering the overall power consumption. (Kumar & Sahoo, 2014) as energy efficiency management maintains the utilization of all compute node and distributes virtual machines in a power sufficient manner.

Description of The Proposed Model

Cloud datacentres stores data for processing and computational analysis based on a threshold value. The data are informed of task that then classified based on the computation procedure and assigned to appropriate VM in the cloud (Afzal & Kavitha, 2019). Though, a rapid flow of data happens due to fluctuations in the identifying area. Cloud system also allows some certain variations to select a suitable VM for the live migration process. The sudden change will lead to inaccessibility of resources known as resources starvation or scarcity in identifying environment where VM are migrated from one physical machine to another.VM migration leads to greeter resource wastage, VM-interference and energy consumption (Mosa & Paton, 2016).Though due to nonexistence knowledge of the types of tasks that may provide poor consolidation solutions and more resource waste than required (Armart, 2018).Simultaneous run of multiple VMs in single host and moved them dynamically using live migration can lead to higher resource utilization in cloud environment (Choi, 2016).

In cloud computing task classification in heterogeneous cloud datacentres to reduce the energy consumption and migration count that coursing server consolidation (Ismaeel, Karim, & Miri, 2018). Task pro filling for appropriate VM assignment selection of less utilized and highly utilized overloaded host and VM selection are aspect solution. CRB method is used to identified the highly over loaded and number of active host. While PEC method is used to identified under loaded host that can be turn down in order to save the energy. The aim is to improve the resource utilization by reducing the energy consumption and meeting the customer agreement in cloud datacentres environment (Khan*et al*, 2018)

Task is one the key factor used in heterogeneous cloud computing (Panda & Jana, 2015). Task classification method can be used to schedule task in cloud computing for better (Patra, 2018). For better effective service utilization in a cloud environment task scheduling can be applied. Some of the parameters to be used for effective utilization are makespan, energy consumption, resource utilization etc. Minimum energy should be consider while handling task in cloud. Have faster execution of tasks in cloud computing scheduling can be applied. Task scheduling method is one of the produce of ordering task for effective execution in cloud computing (Sanjeevi & Viswanathan, 2018). Task allocation is a distribution of cloud system includes several computing interconnect with datacentres via backbone network for better quality of service (QoS).

One of the important aspects in cloud environment is load balancing is considered for speedy response from the cloud. When the load is properly balanced, computing resources can faster the task scheduling. Energy consumption can be minimized for cloud computing by leveraging geographically distributed heterogeneous cloud datacentres (Srichandan*et al*, 2018). Where this datacentres have a significant impact on energy consumption.

A cloud computing heterogeneous datacentres is present for great energy efficient VM selection and migration method. The main objective of the proposed method is task classification, assignment, and VMs selection and allocation mechanisms, with intention of reducing the number of active PMs. Such as, precise service provisioning, resource utilization optimization, and a reduction in costs are achieved. Virtual machine migration VMMs are being reduced despite the fact SLA guarantees are being met. Equally, total resource balance TRB ranking system process element cost PEC function, energy consumption model are all taken into consideration when classifying tasks in heterogeneous cloud datacentres. This addresses the issues raised above by maximizing the use of PMs' resources to reduce task utilization and energy consumption of cloud computing environment. As a result of the appropriate selection of VMs, referred to as VM consolidation, the unproductive use of PM resources can be eliminated. To address issue of heterogeneity cloud computing problem which mathematical models is used to forecast the performance of a systems and the migration task of multiple VMs in clusters. The aforementioned mechanism is based on predefining thresholds that is lower and upper threshold values: the upper thresholds t_u and the low threshold t_l when the PM resource utilization exceeds t_u, where the system then migrate some VMs to another PM to avoid hotspots. Consequently, when the PM resource utilization is t_l then the system will transfer all the VMs of the PM to targeted PM, to have a better performance and energy saving. As cloud is a dynamic system, where the central manager is accountable for defining these thresholds and manages all the VMs and PMs information.

Task classification divides tasks into classes with similar resource requirements and performance characteristics, allowing available resources to be distributed more efficiently. The clustering criteria that are used impact the resource allocation method's goal. In order to achieve the goal of energy-efficient resource allocation, task categorization must fully incorporate user QoS requirements while assessing task resource needs (Cheng, Chai, & Anwar, 2018). A large-scale Cloud datacentres often consists of hundreds of thousands of heterogeneous servers that provide clients with reliable computing and storage services. Multiple tenants can share datacentres resources and services using virtualization and container technologies by collocating latency-sensitive applications or services encapsulated in virtual machines or containers; at the same time, big data workloads like batch processing or streaming can be pushed into shared production cluster settings (Yang, Ouyang, Chen, Townend, & Xu, 2018). Li, Ding, Zhang, & Lai, (2018) investigates the energy efficiency of heterogeneous datacentres. The study presents a task-based resource allocation scheme for datacentres. The simulation results show that the CBRAS efficiently improves datacentres energy efficiency when compared to the classic RR and MBFD resource allocation algorithms. To increase resource usage, the task classification method was integrated with the marginal cost idea to classify jobs and servers. The datacentres energy minimization problem was solved using a work scheduling algorithm that used the marginal cost and work classification methods to optimize server energy consumption, cooling system energy consumption, and state transition cost, resulting in a reduction in total datacentres energy consumption (Ji et al., 2021)

The datacentre receives a significant number of resource requests with varying resource requirements, duration s, priorities, and performance objectives. To deploy available resources efficiently, task classification divides tasks into classes with similar resource requirements and performance characteristics. The purpose of the resource allocation method is influenced by the clustering criteria used. Task categorization must completely include user QoS requirements while assessing the task resource need in order to meet the goal of energy-efficient resource allocation (Li et al., 2018). Two types of heterogeneous data Centre configurations is considered. With Load balancing significantly lengthens connection time due to the restricted bandwidth resources on the networks. However, in order to interact with each other, the geographically dispersed activities require extra hops (Hsu, Kuwahara, Matsuda, & Matsuoka, 2019).

(Hsu et al., 2019) Study high resource sharing entails complex resource contentions at several levels of the software stack, as well as the possibility of performance degradation. The investigation also uncovered evidence that Alibaba's workload-specific schedulers for long-running and batch operations are not as well-coordinated as they should be, emphasizing the need for a more integrated, co-location-optimized solution. Intelligent scheduling algorithms will be required to solve the challenges and limitations of network service delivery (Soulegan, Barekatain, & Neysiani, 2021). Large parallel applications typically have heterogeneous computational demands, with some tasks performing more work than others, so a heterogeneous cloud is an interesting solution for their execution.

Task Classification Model

Resource famine follow due to heretical of the barring capacity CPU, memory, bandwidth and storage resources of the VMs and demanding resource utilization initialised the VM process. Random task allocation give to resource insufficient (Zheng*et al*, 2020). Therefore, the task classification in heterogeneous cloud datacentre method first evaluates the task resource requirement rate RRR where tasks are classified based on this rate. Hence, task is been distributed to the suitable VM by considering the resource utilization rate and bearing capacity. Therefore, VMM can be minimized which leads to a smaller number of live VMMs. Through, VM selection and placement is very significant during VMM process of a task. Selection of VM process is by sorting out the overloaded physical machine with help of TRB ranking scheme. While VM placement process is carried out by considering PEC (Zhong *et al*., 2020). The above methods where used in VMM process and directly improved the performance of servers and conserves energy consumption better than the existing system.

. **Table 1:** Summary of Used notation

Symbol	**Meaning**
VMM	Virtual machine migration
VM_{IM} & VM_{JM}	No virtual machine should be allocated to morethen one host (i≠j)
$\boldsymbol{E_i^{jm}}$	Energy of i^{th} task on j^{th} VM on m^{th} physical machine
$\boldsymbol{\gamma_i^{MIPS}}$ $(\boldsymbol{t})$	CPU utilization (million -seconds) at time interval t
$\boldsymbol{\gamma_m}$	Resource utilization rate of m^{th} host
$\boldsymbol{\rho_{ijm}^{d}}$	Required time to transfer d size of file for executing i^{th} task on j^{th} VM of m^{th} host

Table 1 explained the notations used in the research work. The Optimization in cloud computing structure of the VM migration process is very important matter in server consolidation mechanism. Two issues where considered in server consolidation that is task classification and VM selection. Task classification is done based on resource requirement by assigning task to a suitable VMs. However, VMs selection is process of relocating VMs from high loaded physical machine and allocating it to the targeted physical machine is called VM placement. When task a task is assigned without leveraging the functional requirements such as resource requirement capacity, to select suitable VMs would leads to the increase of energy consumption and live migration potentials. (Zhou et al, 2016). VM allocation and selection is an issue that evaluate the effects of resource capacity, energy consumption and resource utilization of VMs on individual physical machine before tasks is submitted. Selection of VM can be described as a mapping of PM to the set of VMs such that the two condition must be satisfied, each allocated VM is to at least one PM and no VM is allocated to more than one PM. otherwise the cumulative resource requirement of VMs should not exceeded its host available resources, i.e., Task of Type

The model indicates the type of task and kc which refers as the capacity of the resource. Task RRR should be less than the VM capacity and resource host capacity. Fig.1 shows the task classification based on the resource requirement rate. Task set comprises of four type of intensive that is CPU, memory, storage and bandwidth using the RRR value. Task are sorted updated and maintained and assigned to the respective VM type e.g., (*VMCPU, VMM, VMBW or VMStr)*. The task classification status scheme is used to sort out based on RRR value where overloaded physical machine where partially used target host for an accurate VMM process The proposed method classified the task based on the requirement for memory, CPU, storage and bandwidth resources using RRR function. To allocate task accurately to the appropriate VM, which reduce energy consumption and expectancy. Hence the method predict task for the suitable VM which leads to lower the task classification process and allocation to proper VM of the physical machine. The formulation evaluate the resource utilization rate and energy consumption of VM and host. First task where received from the working platform with resource elements requirement. Task element where sorted into various types and updated in a type of task ToT set. The ToT set element have four type of tasks (Where task type T = CPU, BW, M or Str). However if the task RRR value is equivalent to threshold value of (CPU, memory, storage and bandwidth), then T= (CPU, BW, Str and M) effectively. All sorted task is allocated to the suitable VM of the host. This process is accomplish the energy consumption and resource utilization is considered. Table 2 and 3 show the virtual machine configuration and the physical machine that would be used in the experiment.

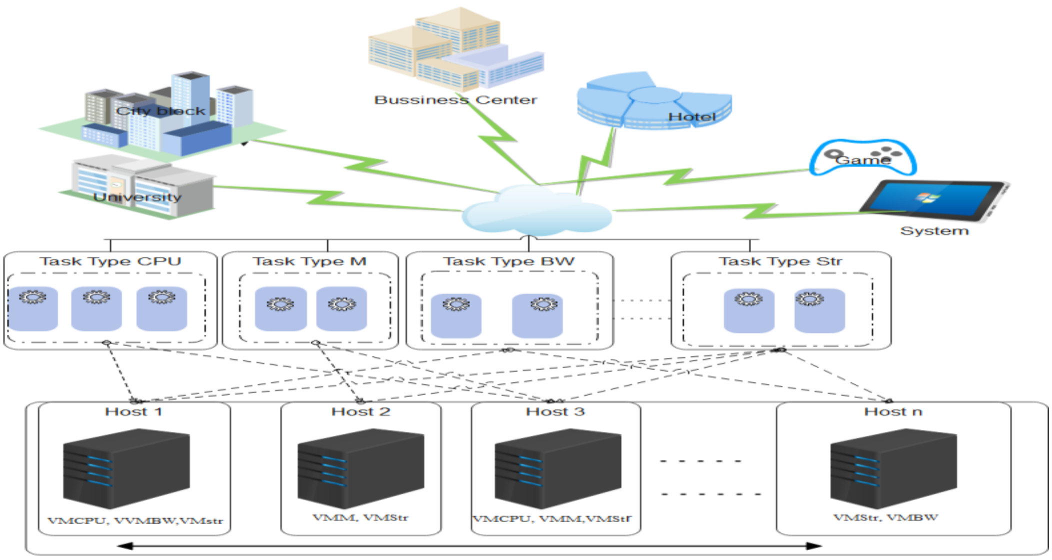

Fig: 1. Task Classification System Model

Task Classification algorithm.

Input:

1. Resource based task parameter set: $RT_i = \{ L_i, D_i, I_i, CO_i\}$.
2. Task set: $T = \{t_1, t_2, t_3, \ldots\ldots t_q\}$
3. $VM_{sub\text{-}type}$= $VM_{c\text{- type}}$: $\{VM_{CM - Type}, VM_{C1\text{-}Type}, VM_{CCO\text{-}type}\}$ $VM_{M\text{-}type}$: $\{VM_{MC - Type}, VM_{M1\text{-}Type}, VM_{MCO\text{- }Type}\}$ $VM_{1\text{-}type}$: $\{VM_{1C\text{-}Type}, VM_{1M\text{-}Type}, VM_{1CO\text{- }Type}\}$ $VM_{CO\text{-}type}$: $\{VM_{COC\text{-}Type}, VM_{COM\text{-}Type}, VM_{COl\text{- }Type}\}$

Output: $VM_{Type,}$ Types of the task based on Resource requirement-type, Str -type, CO-type

```
for t_{i=1} to T_i do
    ϕ_i ← √2/2 x (( 1 / (γCi + γMi + γCOi) )
    γCi = ϕi x γCi,  γMi = ϕi x γMi,  γ1i = ϕi x γ1i,  γCoi = ϕi x γCoi
    Update all { γCi, γMi, γ1i, γCoi}
    Max = { γCi, γMi, γ1i, γCoi}
    if ( γCi = Max) then
      The t_i is assign to Str ``-type
    else
        if (γMi = Max) then
          The t_i is assign to M-type
        else
            if ( γ1i = Max) then
              The t_i is assign to CPU-type
            end
        end
        The t_i is assign to BW-type
    end
    end
    Update Type of task [ ToT] ← {C – type, Str – type, CO – type}
    VM_Type, ← VM_sub-types using Utilization algorithm
    for each VM_sub-types and VM_ToT E VM_types do
        if t_i is fit in VM_ToT
            VM_Type ← VM_ToT
        end
    end
```

26. Return Type of Task, VM_{Type}

Table. 2: Physical Machine's Configuration.

Resource/PM	PM1	PM2	PM3	PM4	PM5
MIPS	7000	6500	4000	7500	6000
Cores	2	3	4	4	5
RAM GB	24	24	24	24	24
BamdwidthMbps	150000	150000	150000	150000	150000
Storage GB	100	80	60	65	50

Table. 3: VM's configuration.

Res./VM Type	$VM_{CPU-type}$	$VM_{Str-type}$	VM_{M-type}	$VM_{BW-type}$
MIPS	7000	6500	4000	7500
Cores	1	2	3	2
RAM Mb	1024	512	512	1024
Bandwidth Mbp	1000	1000	1000	1000
Storage Gb	6	5	10	7

3.5 Simulation, Evaluation and Performance Validation

The tools that are going to be used to implement this work is CloudSim3.0.3 using Java programming language on laptop computer system. This work is proposed to work on a 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. The system require is Windows 10 or Windows 7 Operating System with Intel IDEa community edition 2019.2 version or above. The experiment was run three time of 50, 75 and 100 tasks where tested to find the effectiveness of the algorithms.

First experiment

Table. 4: Cumulative CPU Utilization between existing and proposed systems with difference of 50 tasks

Cumulative Existing System CPU Utilization %	Cumulative Proposed System CPU Utilization %	Difference
2461	2886	4.25%

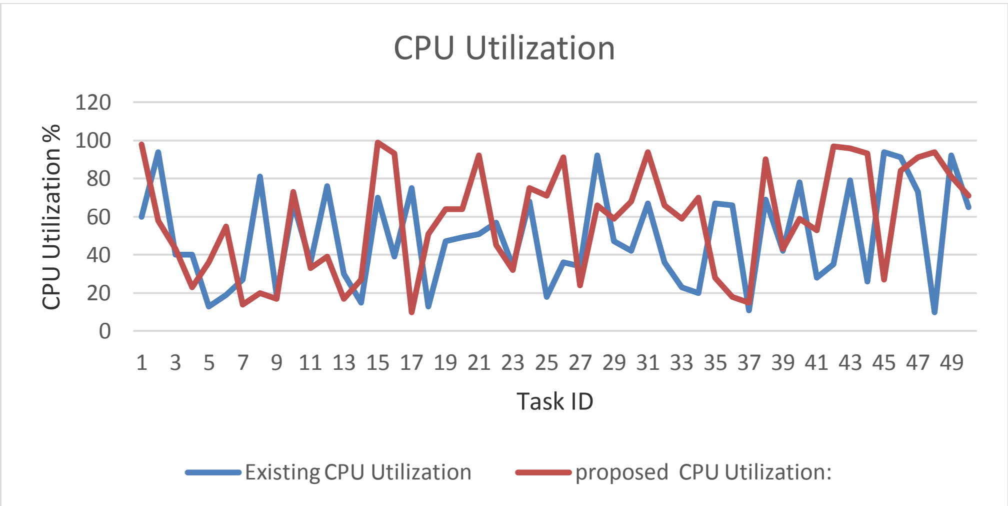

Fig. 4: CPU Utilization of existing and proposed systems of 50 tasks

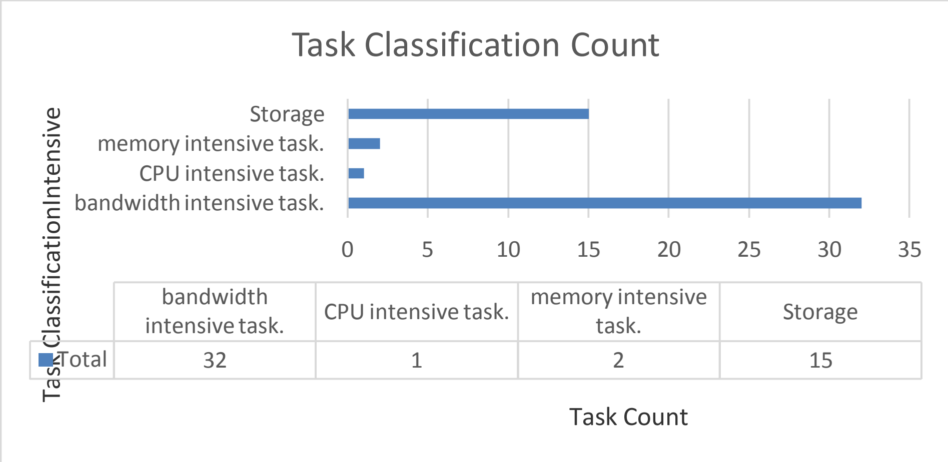

Fig. 6: Tasks classification counts of proposed systems 50 tasks

3.7 Second experiment

Table. 5: Cumulative CPU Utilization between existing and proposed systems with difference of 75 tasks

Cumulative Existing System CPU Utilization %	Cumulative Proposed System CPU Utilization %	Difference
4244	3830	-4.14%

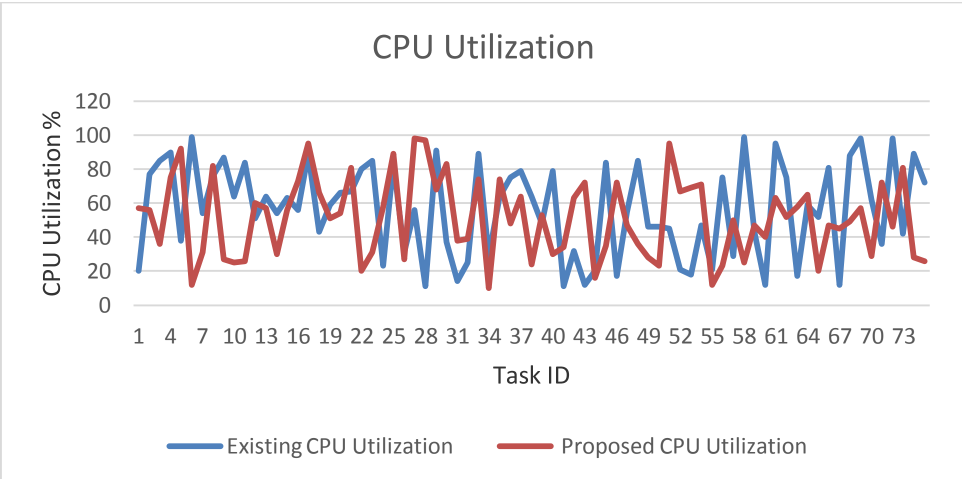

Fig. 8: CPU Utilization of existing and proposed systems 75 tasks

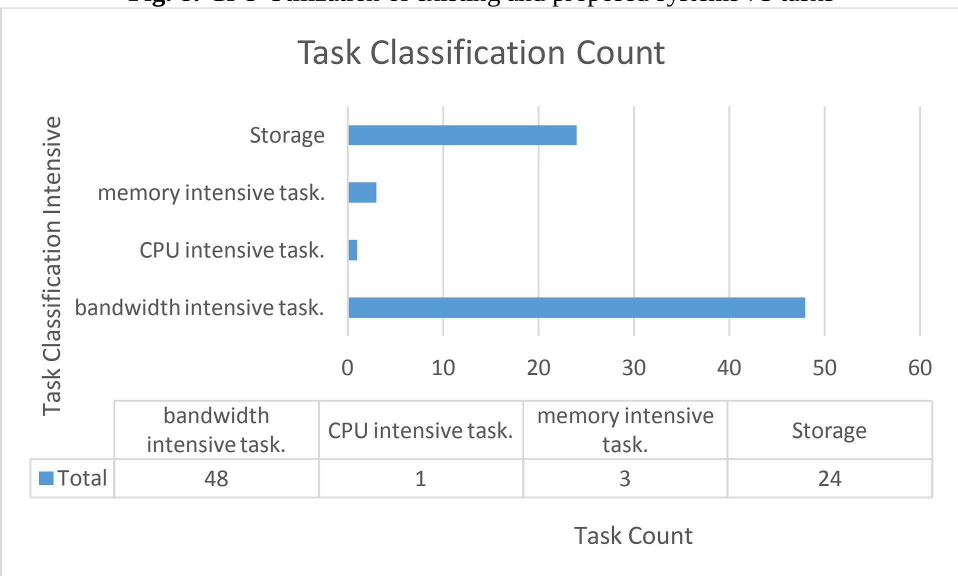

Fig. 9: Tasks classification counts of proposed systems 75 tasks

3.8 Third experiment

Table. 6: Cumulative CPU utilization between existing and proposed systems with difference of 100 tasks

Cumulative Existing System CPU Utilization %	Cumulative Proposed System CPU Utilization %	Difference
5297	5827	5.3

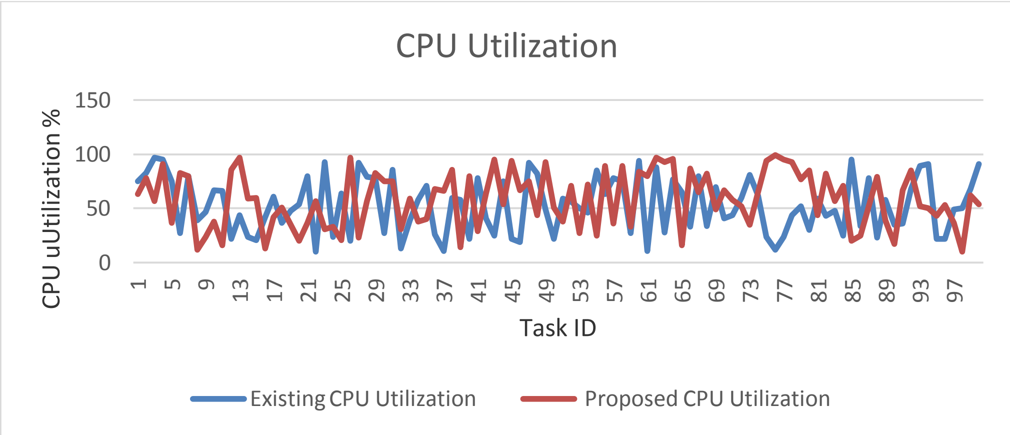

Fig. 11: CPU Utilization of existing and proposed systems 100 tasks

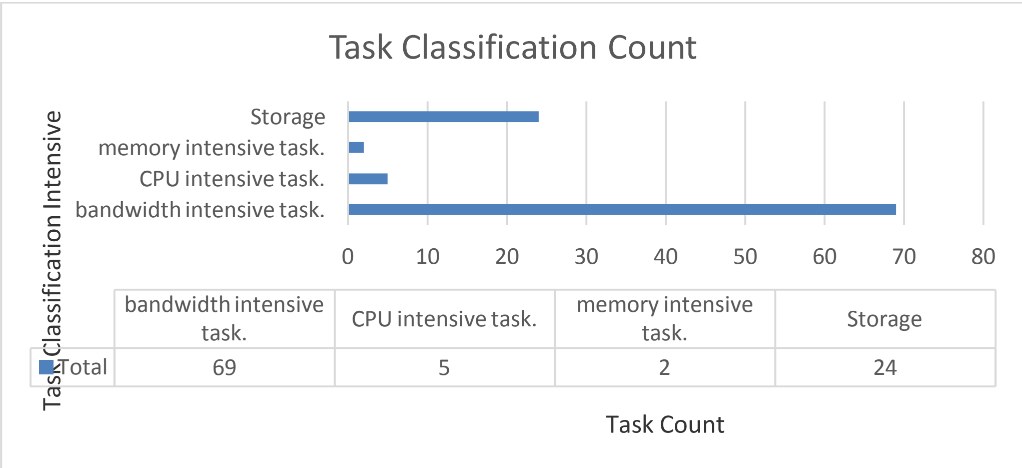

Fig. 12: CPU Utilization of existing and proposed systems 100 tasks

Table. 7: Energy consumption between existing and proposed system of 50, 75 and 100 tasks

Energy consumption											
	Magma		MaxFCFS		FCFSRandom						
Tasks	Existing	Proposed	Existing	Proposed	Existing	Proposed	Total Energy of System	Total Proposed system	Existig Enegy %	Proposed Energy %	Difference
50	185270	181260	367370	327700	166420	146550	719060	655510	52.31	47.69	-4.62
75	297570	288670	613950	507390	292320	221460	1203840	1017520	54.19	45.81	-8.39
100	409540	406660	816090	793040	378460	345130	1604090	1544830	50.94	49.06	-1.88
Total											**-14.89**
Average											**-4.96**

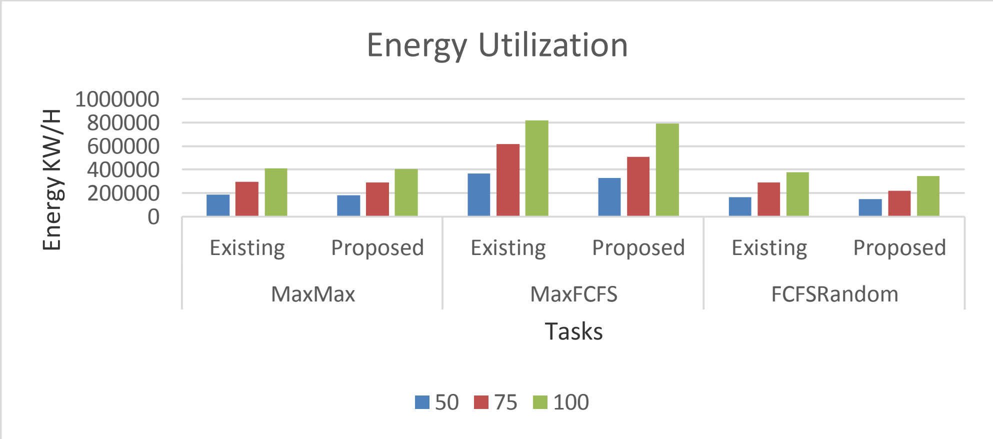

Fig. 13: Energy consumption between existing and proposed system of 50, 75 and 100 tasks

Table.8: Tasks execution time of 50, 75 and 100 tasks

Time											
	MaxMax		MaxFCFS		FCFSRandom						
Tasks	Existing	Proposed	Existing	Proposed	Existing	Proposed	Total Existing Time	Total Proposed Time	Existing %	Proposed %	Difference. %
50	15	15	17	20	21	22	53	57	48.18	51.82	3.64
75	23	20	25	27	29	32	77	79	49.36	50.64	1.28
100	27	33	30	37	36	45	93	115	44.71	55.29	10.58
Total											**15.50**
Average											**5.17**

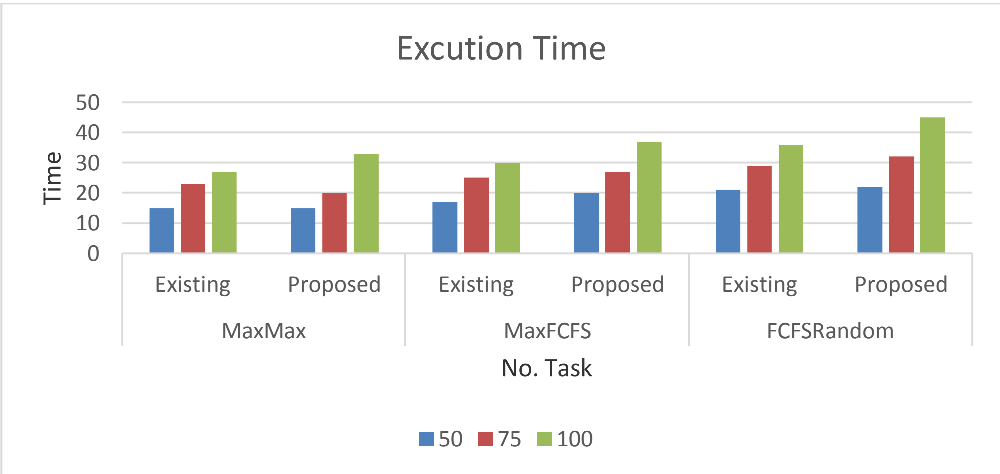

Fig. 14: Tasks execution time of 50, 75 and 100 tasks

Result Analysis

Figures 5 and 6 shows the utilization of CPU of 50 tasks between the existing and proposed systems, where the proposed system is higher than the existing system by 4.25%. In figures 7 and 8, the CPU utilization shows that the proposed system is less by 4.14% than the existing system. While in figures 10 and 11 indicated an increase of 5.3% of the existing system against the proposed.

In figures 6, 9 and 11, the task classification utilization count where CPU and bandwidth present with high utilization then memory and i/o tasks, but in task classification count bandwidth have more than 50% of the total task count followed by i/o where CPU have the less count at figures 5, 7 and 9 and the figure 13 indicating the energy consumption between existing and proposed system based on 50, 75 and 100 tasks, reveals that the average percentage of 4.96% decrease than the existing system.

However, in terms of tasks execution time, fig. 14 reveals that the proposed system has an increase of 5.17%. Thus, indicated that more research is needed in task classification, utilization and energy efficiency concerning heterogeneous cloud computing datacentres.

IV. Conclusion

The proposed system model reduces energy consumption of the cloud server without affecting the quality of service. The tasks are classified and sorted; the results show an increase of 5.17% of the execution time and average utilization by 4.96% also reduce the energy by 4.96%. The adoption of the suitable target is accomplished with an energy efficient resource based on VM selection method.

Future research direction is intended to test our method in a real world cloud computing environment. The decision can be taken to have live migration portion of application to cloud using edge and fog environment for small intended applications that lead to higher performance with global and local execution.

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