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AN ADAPTIVE CLOUD RESOURCE RE-CONFIGURABILITY ALGORITHM FOR ENERGY AND PERFORMANCE BALANCING

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ABSTRACT

Dynamic Voltage and Frequency Scaling (DVFS) enabled cloud computing VMs has gained immense popularity in real time due to its faster execution and adaptive processing. It can achieve the primary objectives such as high energy conservation and resource allocation balancing of cloud computing VMs. To completely exploit the cloud computing systems, it is very essential to achieve a high balancing between resource allocation and reconfiguration cost to save cost and faster resource allocation in cloud computing environment. Therefore, here, an Adaptive Cloud Resource Re-Configurability ($ACRR$)model is introduced which rely upon Dynamic Voltage and Frequency Scaling ($DVFS$)cloud computing systems to attain a trade-off between resource allocation, energy and performance of information processing centers and decrease task load. Here, an effective modelling is introduced to reduce high reconfiguration cost in various information processing centers. Experimental results verify superiority of our proposed $ACRR$ technique in terms of power consumption, average power and power sum.

Keywords: *DVFS, Cloud Computing, Energy consumption, Performance Balancing.*

I. INTRODUCTION

In recent years, Cloud computing applications have taken immense growth due to their extensive ever-increasing demand and availability of numerous varieties of resources. Cloud computing model is a computational prototype, which rely upon internet for its services. It allows using its resources and information based on 'pay-per-go' prototype. Cloud computing model can distribute into three types such as Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS) [14]. In cloud computing environment, to decrease the cost of management, the position of various software and hardware resources can be migrated over the network. Cloud computing model is next generation future computing model, which can provide large amount of resources, consists high storage capabilities and instantaneous scalability and user need to pay for the time, it utilizes cloud resources [1], [2]. For an instance, $Amazon, IBM, APPLE$ and $Microsoft$ consists of its own huge cloud centers [3].

However, due to enlargement of these large information processing centers, the energy consumption in the cloud servers and resources has widely increased. Due to this high energy consumption, the cost of cloud computational processing enhances drastically as well as it is a threat for global green computing as it causes various environmental issues. The energy consumption cost is very high and essential and need to be focused. Therefore, various researchers have turned their attention towards cloud computing environment and it is widely used in software industries and enterprises. The significance of energy- efficient methods in cloud computing environment is very high.

Moreover, Heterogeneous cloud computing devices consists of various bulky processors and resources to offer different services to the subscribers. However, failure in processor capabilities can reduce the system reliability [15] and QoS (Quality of Service) for various subscribers. Therefore, the efficient scheduling of tasks in various processors and resources is the key strategy to enhance the performance in the cloud computing environment. Thus, to reduce the above mentioned drawbacks and improve the performance of the cloud computing network, various techniques are presented by different researchers in recent time. This techniques are Constrained Earliest Finish Time ($CEFT$) approach [5], Contention-Aware Energy-efficient duplication ($FastCEED$) algorithm [6], Hierarchical Reliability-Driven Scheduling ($HRDS$) algorithm [4], and Voltage and Frequency Island (VFI) technique [8] and Dynamic Voltage and Frequency Scaling ($DVFS$) [7]. However, Dynamic Voltage and Frequency

Scaling ($DVFS$) is the most essential technique in among all these techniques which is highly praised by various researchers due to its high energy consumption and effective resource scheduling facilities. $DVFS$ technique is a well-recognized energy saving technique in cloud computing environment which reduces power consumption in resources dynamically scales down the chip voltage. This technique can provides high QoS to the subscribers.

A brief literature is discussed to reduce the drawbacks such as energy consumption, ineffective resource allocation and performance degradation presented by different researchers in the field of for cloud computing environment. In [9], a mobile cloud computation prototype is adopted which rely upon the energy-saving dynamic cloudlets to decrease the power consumption in information cloud processing centers. In [10] and [16], an effective resource allocation prototype is presented to increase relationship with the subscribers and to enhance the performance of VMs and a brief review on various conventional task-scheduling techniques is introduced in cloud computing environment. In [11], an energy efficient

VM scheduling algorithm is presented considering various network components and resources. VM placement and VM migration techniques are presented to decrease the congestion in cloud environment. In [12], [13] and [17], an effective resource scheduling algorithm is presented which rely upon $DVFS$ enabled information processing centers. Here, $DVFS$ enabled energy saving technique optimizes two different energies such as computing energy and communication energy based on SLA constraints. However, this is very complex process to execute in real-time environment.

In above literatures, various problems such as optimization problem, high computational complexity, energy consumption and ineffective resource utilization etc. exists which can degrade their performance and hence difficult to introduce in real time scenarios. Therefore, an effective resource scheduling technique is needed to maintain a balancing between energy consumption and high performance based on $DVFS$ due to its various energy saving capabilities for a cloud computing environment. Therefore, a Dynamic voltage and Frequency Scaling ($DVFS$) based Adaptive Cloud Resource Re-Configurability ($ACRR$) technique is presented for cloud computing devices which efficiently decreases energy consumption as well as executes operations in very less time.

The contribution of work can be classified as follows:
In this paper, a Dynamic voltage and Frequency Scaling ($DVFS$) based Adaptive Cloud Resource Re-Configurability ($ACRR$) technique is presented for cloud computing networks. The proposed $ACRR$ technique can provide high QoS by processing at low transmission rates and induces very less delay. This scheme supports effectively to achieve high interaction cost and computational energy. The $ACRR$ technique is a distributed cloud computing scheme which can generate various opportunities to work with different scientific workflows at minimum cost. Therefore, in this model, experiments are tested using various scientific workflows. This scheme schedules jobs in parallel and assigns its resources parallel and provides high scalability. The proposed $ACRR$ scheme performs superior to the basic DVFS. The proposed $ACRR$ technique also helps to achieve a great balance between energy and performance in heterogeneous cloud computing devices.

This paper is organize in following sections which are as follows. In section 3, the proposed methodology is described. In section 4, experimental results and evaluation shown and section 5 concludes the paper.

II. ADAPTIVE CLOUD RESOURCE RE-CONFIGURABILITY ($ACRR$) ARCHITECTURE:

This section describes about the architecture of the proposed $ACRR$ technique and its different components. It also provides an efficient modelling to optimize the reconfiguration and computational cost. The proposed architectural diagram is demonstrated in Figure 1. Here, a novel Adaptive Cloud Resource Re-Configurability ($ACRR$) approach is adopted to provide effective resource allocation schemes and processing cost reduction methods so that the performance of cloud computing resources and processors get enhanced. The$ACRR$ technique mainly operates based on adaptive computing to handle numerous VMs at a time in a cloud environment which can be handled using central resource controller. The cloud computing VMs, works as a self-governing unit and control each assigned task by self-handling its resources and memory. Message passing is the most effective way to communicate with intra cluster in a cloud network. When a new job is allocated, the central resource controller begin distribution of resources and admission governing simultaneously

Figure1 demonstrates the architecture of the proposed $ACRR$ technique which is presented in the below section. It consists of three vital components which is very much essential to ensure better resource allocation between cloud computing VMs from an infrastructure observation, such as information storage, switched Local Area Network (LAN) and Virtual Machine Handler (VMC) as shown in Figure 1. When a novel job is allocated to any of the cloud computing VMs, then the arrival time period of that job can be denoted as b_n and job size can be expressed as G_b in bits. The assigned work to VMs must be complete in the predicted employed time $M_b(sec)$ for an allocated job to utilize in real time environment. The proposed $ACRR$ approach utilizes only those parameters which are key to achieve the objective of an efficient resource allocation and minimization of computational cost such as assigned job size G_b, maximum bearable delay M_b in sec and job granularity which demonstrates maximum number of parallel jobs which can be embedded into one allocated work($S_M \gg 1$). Here, table 1 represents the notation representation which are used in the below equations.

Table I Notation representation for acrr

γ	Resource Utilization Factor
b_n	Arrival time period of assigned job
G_b	Size of assigned Job
M_b	Maximum bearable delay in sec
k_a	Processing rate in bps
G	Allocated task
G_d	Size of background jobs
β_a	Power consumption in VMs
$\delta(h)$	Time Period of job accomplishment
G_e	Size of assigned task to cloud computing $VM(e)$
k	Computation frequency
i_j	Reconfiguration cost in $\mu joules/(MHz)^2$
$\tilde{\mu}(\gamma)$	$virtual\ power\ consumption\ curve$
$\mathbb{T}$	Finite set contains discrete values of processing rates
$\mathbb{F}$	Frequency set of discrete values

Let, the maximum number of VMs which need to be used in the allocated jobs using the proposed $ACRR$ technique can be defined as($S_M \gg 1$) and demonstrated in Figure1. The proposed resource allocation technique operates on the norm that each VM can operates as a virtual server at a processing rate of $k_a bps$ (Bits per Second). Depending on the task size G in bits, the processing rate k_a can be scaled adaptively at implementation time. Let each task follows the interval $[0, k_a^{\uparrow}]$, where $k_a^{\uparrow}$ denotes the max acceptable processing rate.

Furthermore, the predicted time to finish the allocated work by VMsdoes not rely upon the size of the taskG_b, which is very essential for any model to be accept in real time environment. Moreover, a background jobs with size $G_d$of an allocated task G can be controlled by VMs. This background jobs comes under OS (Operating System) observation. Let that basic memory of $VMs$is utilized to store the background job-loads. Therefore, background job-loads are only concerned with computational costs, not for interaction cost. Then, resource utilization parameter γ can be describes as,

$$\gamma \triangleq k_a . (k_a^{\uparrow})^{-1} \in [0,1], \qquad (1)$$

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Here, equation (1) describes that the dynamic component of the computational energy are very important to reduce the cost of computation. Let that the complete power consumption in VMs to accomplish a job for a time period$\delta(h)$ can be expressed as $\beta_a$in joule at an accessing ratek_a. Therefore, the dimensionless ration can be defined as,

$$\mu(\gamma) \triangleq \beta_a(k_a).(\beta_a^{\uparrow})^{-1} \equiv \mu(k_a).(k_a^{\uparrow})^{-1}, \qquad (2)$$

Where, equation (2) defines the complete power Consumption by the utilized VM. For an example, CPU analytical form which rely upon $DVFS$ can be defined by the below equation,

$$\mu(\gamma) = \gamma^2, \qquad \gamma \epsilon [0,1], \qquad (3)$$

Here, $\alpha$is utilized to evaluate relative energy cost by the utilizedVM for the finishing of task.

A. Modelling For Task-Load Reduction Using Proposed ACRR Technique:

This section discuss an efficient modelling to handle heavy task-load in cloud computing environment. Let that the number of jobs which are not overlapped can be denoted as $S \triangleq \downarrow \{S_{C,}S_M\}$ and can be adaptively implement to perform tasks in parallel. Let the size of task which are allocated to the cloud computing $VM(e)$ can be denoted asG_e. The operating time of various tasks is independent from task lengthG_e. Then, the operating rate (bits/sec) can be describes as,

$$k_a(e) = G_e.(\delta)^{-1}, \qquad (4)$$

Here, equation (4) demonstrated that the max permissible task size which is $G_e^{\uparrow} = \delta.k_a^{\uparrow}(e)$. And $\gamma \triangleq k_a(e).(k_a^{\uparrow})^{-1} \equiv G_e.(G_e^{\uparrow})^{-1}$. The task size can be represented as G_b in bits and can be allocated to VMs using a task scheduler as demonstrated in Figure1 and can be represented as $G_e \gg 0, e = 1, \dots, .. S$. To decrease job loads, total job sizeG_b can be distributed into S parallel jobs whose length limit can be described as$\sum_e^S G_e = G_b$.

B. Optimization of Reconfiguration Cost Using Proposed ACRR Technique:

In this section an efficient modelling is defined for the reconfiguration cost optimization. The VM resource handler is utilized to execute two essential operations like job load balancing and handling of VMs. Virtual Machine Controller (VMC) is utilized to handle the virtualization layer as presented in Figure 1. VMC Helps to accomplish comprehensive resource mapping to compute the reconfiguration cost in cloud computing environment. The characteristic modules of VMs can be defined using equation (9) as,

$$\{\delta, k_a^{\uparrow}(e), \mu_e(\gamma_e), \beta_a^{\uparrow}(e), \alpha(e), G_d(e), \qquad e = 1, \dots \dots S\} \qquad (5)$$

Here, all the factors can be specified with the help of Virtualization Layer and then this factors can be communicated to Virtual Machine Controller(VMC) as shown in Figure 1. The computational rate k_a can be scaled either up or down utilizing an efficient dynamic voltage and frequency scaling ($DVFS$) technique which is handled using VMC. Whenever VM switches from one computation frequency k_1 to other computation frequencyk_2, then the power consumption reaches to $\beta(k_1{:}k_2)$ in joule. This power consumption largely dependent on the techniques utilized and over the $CPU's$ utilized in cloud computing information processing centers. The energy function $\beta(k_1{:}k_2)$ contains few characteristics like the frequency gap$|k_1 - k_2|$ are the one thing on which the energy function $\beta(k_1{:}k_2)$ depends and the energy function goes zero at$k_1 = k_2$. Furthermore, this energy function $\beta(k_1{:}k_2)$ remains in non-decreasing in the whole frequency gap$|k_1 - k_2|$. The features of the proposed $ACRR$ technique can be presented byequation (10),

$$\beta(k_1{:}k_2) = i_j(k_1 - k_2)^2, \qquad joule \qquad (6)$$

Here, i_j describes the cost of reconfiguration for frequency switching and i_j ranges till few hundreds of $\mu joules/(MHz)^2$. In proposed $ACRR$ model, for each task the length of the task G_b remain similar over the corresponding processing timeM_b. At the time of execution, no fluctuations should occur in the job-loads. Number of task can be executed adaptively. $DVFS$enabled techniques consist of time overhead which can be up to few μsec.

From the above equations it can be conclude that the utilization parameter γ can be a continuous value parameter and it needed continuous operating rates which can be expressed as k_a. The cloud computing VMs can provide an example of $CPU's$ as a finite sets which is described in the following section,

$$\mathbb{F} \triangleq \{\hat{k}^{(0)} \equiv 0, \hat{k}^{(1)}, \dots, \hat{k}^{(\mathbb{T}-1)} \equiv k_a^{\uparrow}\}, \quad (7)$$

Here, the finite set contains discrete values of processing rates $\mathbb{T}$. The following equation (8), can be used to define the optimality loss in continuous and discrete technique which rely upon $DVFS$,

$$\mathbb{P} \triangleq \{\hat{\gamma}^{(0)} \equiv 0, \hat{\gamma}^{(1)}, \dots\dots, \hat{\gamma}^{(\mathbb{T}-1)} \equiv 1\}, \quad (8)$$

Here, frequency set $\mathbb{F}$ can be defined using discrete set of γ values as demonstrated in equation (7). A $virtual\ power\ consumption\ curve$ can be expressed as $\tilde{\mu}(\gamma)$ and constructed using $piecewise\ linear\ interpolation$ and the permissible processing points are,

$$\left\{\left(\hat{\gamma}^{(\mathbb{R})}, \mu\left(\hat{\gamma}^{(\mathbb{R})}\right)\right), \mathbb{R} = 0, \dots\dots.., (\mathbb{T}) - 1\right\} \quad (9)$$

Where, the corresponding vertex points can be represented as,

$$\left(\hat{\gamma}^{(\mathbb{R})}, \mu\left(\hat{\gamma}^{(\mathbb{R})}\right)\right)\ and\ \left(\hat{\gamma}^{(\mathbb{R}+1)}, \mu(\hat{\gamma}^{(\mathbb{R}+1)})\right) \quad (10)$$

This above mentioned virtual power consumption curve helps to sustain the continuity and can be utilized for the allocation of VM resources. The use of piecewise linear interpolation recommends that with the help of virtual power consumption curve, the typical energy cost of DVFS enabled approaches remains under the predicted interval of time period δ. Here, each VM configuration dependent onCPU type, memory size and cost per time duration. The VMs cost depends on the type of configuration used. Let the internal cost of VMsis zero in all cloud information processing centers.

III. PERFORMANCE EVALUATION

The exploitation of cloud computing VMs is enormously increased in recent time due to widespread utilization of cloud computing resources from the internet itself. These cloud computing VMs contains different digital equipment's, software gadgets and networking tools etc. However, the demand is very extensive compare to the accessible cloud resources and VMs and energy consumption in information cloud processing centers also become very extensive due to the widespread use of these cloud VMs which can damage the performance of the system. Therefore, the performance of cloud computing VMs must be increase in order to control these extensive demand of cloud resources and VMs by numerous subscribers all over the world. A well-recognized conventional $DVFS$ technique can be used to attain a balancing between proper resource allocation and reduction of reconfiguration cost for cloud computing devices. Therefore, a Dynamic voltage and Frequency Scaling ($DVFS$) based Adaptive Cloud Resource Re-Configurability ($ACRR$) technique is presented for cloud computing devices which efficiently decreases energy consumption as well as executes operations in very less time. In proposed $ACRR$ technique, various jobs are utilized like 30, 50, 100, and 1000 to evaluate execution time. In the following sections, Power sum, average power and energy consumption outcomes demonstrated in graphical form. A $Montage$ scientific dataset is utilized to verify proposed $ACRR$ architecture. In proposed $ACRR$ technique, different job sizes as 30, 60,100 and 1000 are considered using $Montage$ scientific benchmark. The proposed $ACRR$ technique simulated on 64-bit windows 10 OS with 16 $GB\ RAM$ which contains an $INTEL\,(R)$ core $(TM)\,i5 - 4460$ processor.It contains 3.20 $GHz\ CPU$. This project is simulated using $EclipseWS\ Neon.$3 editor and code is written in $JAVA$. The machine configuration used to compute these results are as follows:

Table II vms types with description used in the experiment.

Type	Memory(GB)	Core Speed (ECU)	Cores
m1.small	1.7	1	1
m1.large	7.5	4	2
m1.xlarge	15	8	4

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a) Comparative Study

In recent time, cloud computing VMs has received high praise from all over the world in different fields like healthcare solutions, software industries, trading and medical applications etc. Therefore, cloud computing has started to add $DVFS$technique support to reduce energy consumption in various information processing centers. Furthermore, to improve the efficiency of cloud computing $VMs$for future use, various $DVFS$ enabled adaptive technique are introduced in cloud computing environment. However, high energy consumption, high computing cost and inappropriate resource allocation techniques causes high degradation in performance of cloud computing systems. Subsequently, to ensure proper resource assignment, less energy consumption and balancing between proper resource allocation and reduction of reconfiguration cost for cloud computing devices, here, an Adaptive Cloud Resource Re-Configurability ($ACRR$) technique is presented. The proposed $ACRR$ technique helps to boost throughput and performance of the cloud computing VMs and provide effective adaptive resource scheduling. Here, numerous experiments are conducted using the proposed $ACRR$ technique to find energy consumption, power sum and average power results which are demonstrated in table 2 with the help of $Montage$ scientific dataset for different jobs as 30, 50,100 and 1000. The proposed $ACRR$ technique ensures very less energy consumption for $Montage$ scientific dataset such as for $Montage\,25$ is 39.18879852 Watts, $Montage\,50$ is 52.60213278 Watts, $Montage\,100$ is 95.8242739 Watts and $Montage 1000$ is 937.9076791Watts demonstrated in table 2 which is highly reduced compared to basic DVFS using similar statistics. Table 2 also demonstrates Execution time to finish the task using the proposed $ACRR$ technique for different jobs as 30, 50,100 and 1000 with the help of $Montage$ benchmark. The average power outcomes for $Montage\,25$ is 21.99901827 W, $Montage\,50$ is 21.99910567 W, $Montage\,100$ is 21.99923734 W and $Montage 1000$ is 21.99943531 W.

b) Graphical Representation

This section offers graphical representation of the simulated experiments for different jobs using $Montage$ scientific dataset and compared with basic DVFS in terms of average power, energy consumption and power sum. Here, Figure2 demonstrates Power Sum results in contrast to $DVFS$ technique using proposed $ACRR$ technique for scientific dataset $Montage$ for different jobs as 30, 50,100 and 1000.Here, Figure3 shows Average Power results in contrast to $DVFS$ technique using proposed $ACRR$ technique for scientific dataset $Montage$ for different jobs as 30, 50,100 and 1000.Here, Figure4 shows Energy consumption results in contrast to DVFS technique using proposed $ACRR$ technique for scientific dataset $Montage$ for different jobs as 30, 50,100 and 1000. These outcomes concludes the superiority of proposed $ACRR$ prototype in terms of average power, power consumption and power sum using $Montage$ scientific dataset.

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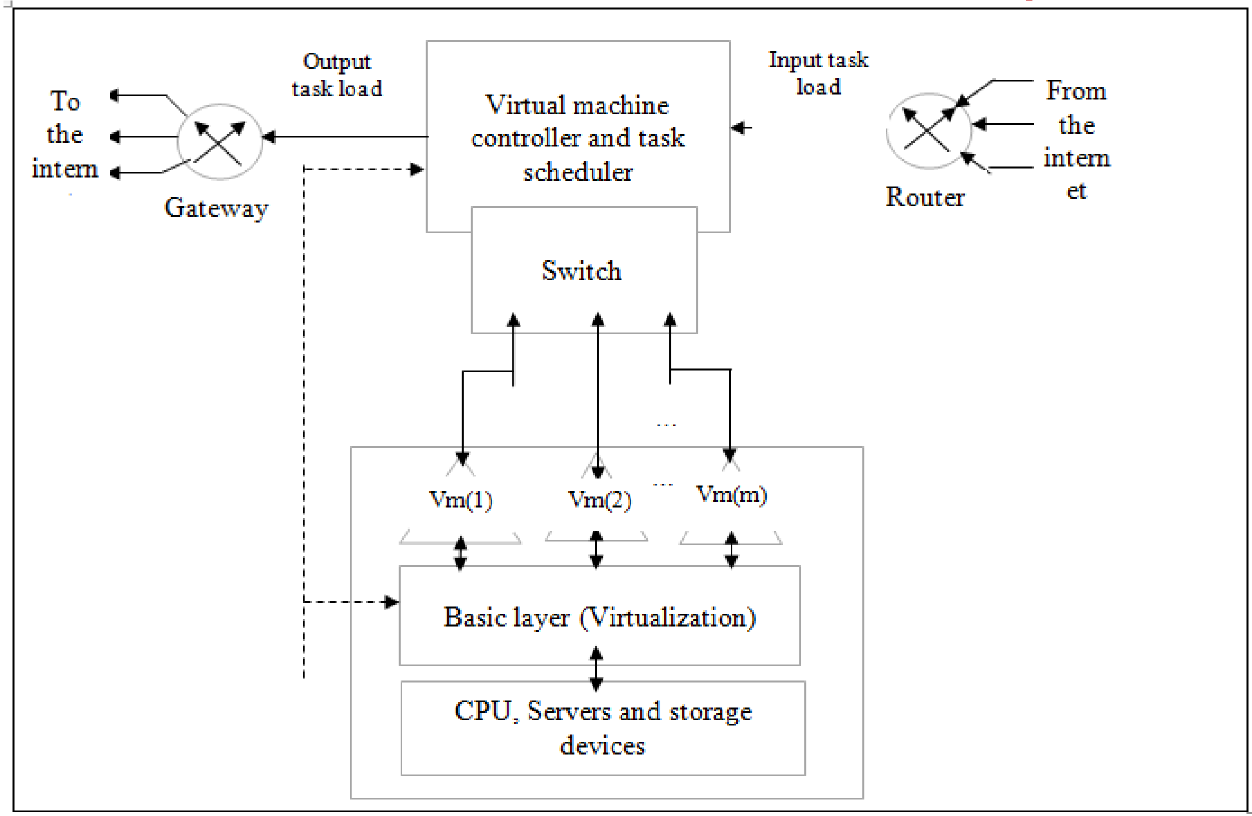

Figure 1Architecture diagram of the proposed ACRR model

Table III various parameters comparison for proposed HDSMM technique vs dvfs using scientific model Montage

Parameters	DVFS				*ACRR*			
	Montage 25	*Montage* 50	*Montage* 100	*Montage* 1000	*Montage* 25	*Montage* 50	*Montage* 100	*Montage* 1000
	VM=30	VM=30	VM=30	VM=30	VM=30	VM=30	VM=30	VM=30
Power Sum (W)	500514.37	1110499.1	2342175.63	24619248.96	126978.3334	157883.1816	249275.5583	1922348.057
Average Power (W)	28.655621	28.655677	28.6557010	28.65572049	21.99901827	21.99910567	21.99923734	21.99943531
Power Consumption (Wh)	159.32710	432.30671	1191.41619	68107.65154	39.18879852	52.60213278	95.8242739	937.9076791

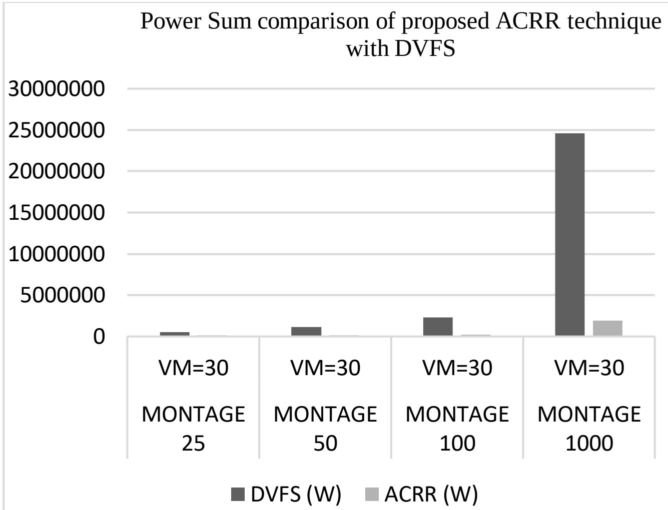

Figure2 Power Sum comparison using theACRR technique with DVFS

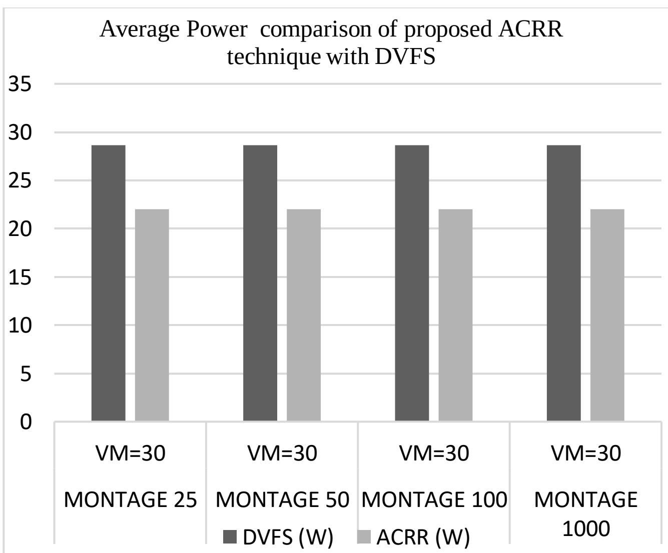

Figure 3 Average Power comparison using theACRR technique with DVFS

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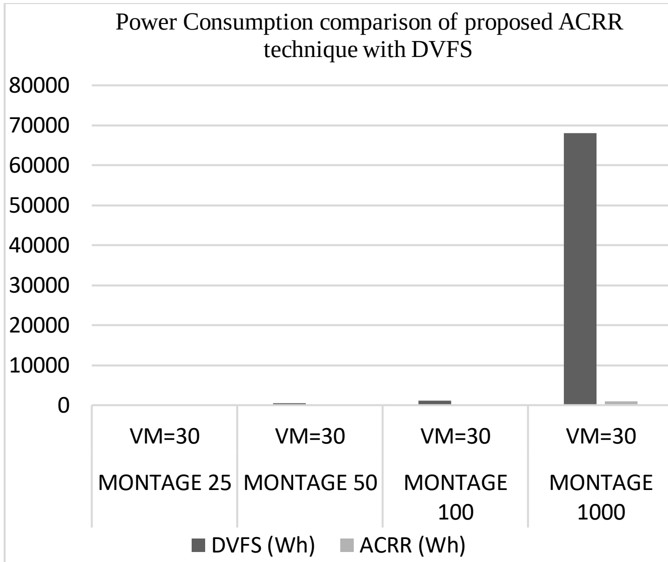

Figure 4 Power Consumption comparison using our $ACRR$ technique with DVFS

IV. CONCLUSION

The importance of controlling high power consumption and achieving high balancing between proper resource allocation and reduction of reconfiguration cost is very essential for cloud computing VMs. Therefore, here, a Dynamic voltage and Frequency Scaling ($DVFS$) based Adaptive Cloud Resource Re-Configurability ($ACRR$) technique is adopted for cloud computing devices which efficiently decreases energy consumption as well as executes operations in very less time. Hence, enhance the efficiency of the system. DVFS-enabled proposed $ACRR$ technique helps to decrease task load and achieve better resource utilization due to high speed and effective energy reduction. An effective modelling is presented to decrease reconfiguration cost, reduce task load, and enhance performance. Experimental outcomes are compared with basic DVFS in terms of average power, energy consumption and power sum. The proposed $ACRR$ technique ensures very less energy consumption for $Montage$ scientific dataset for $Montage$ 25 is 39.18879852 Watts, $Montage$ 50 is 52.60213278Watts, $Montage$ 100 is 95.8242739 Watts and $Montage$1000 is 937.9076791 Watts, which is very less in contrast to basic DVFS and conclude high superiority of the proposed $ACRR$ technique. In future work, an effective modelling to computational and interaction cost reduction for cloud computing VMs is presented.

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