An Extensive Study on Power-Efficient Nature-Inspired Techniques in Cloud computing Data Centres

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Abstract

Systematic deployment of services within the cloud as well as resources to the cloud consumers via the Internet is known as Cloud computing. The IaaS (Infrastructure as a Service) facility is offered to the cloud user by allowing better access to storage, processing power, networks and basic computational services which comprise both operating systems as well as applications. The resources are made obtainable as Virtual Machines (VMs). Services within the cloud are offered to the cloud consumers on a pay-per-use model on demand and is the utilized services are billed appropriately. The VMs are found to run on several data centers within the cloud, which possess a multitude of resources making use of energy in abundance with the side-effect of alarming carbon emission in the atmosphere. Various research studies have suggested a variant of power-efficient techniques which are intended to minimizing power usage within the data centers. One amongst the popular solutions are algorithms that are inspired by nature. In this research work, a review of those algorithms inspired by nature for the ideal power utilization within the data centers of the cloud is exercised. Proper management of energy usage in the data centers and the Power-Efficient Nature inspired techniques for the data centers within the cloud are explored and a comparative evaluation of the different power-efficient methods is executed. This research work empowers both academic researchers as well as industry personnel in the data centers of the cloud to understand the literature development for ideal power-efficient methods for the data centers in the Cloud.

Keywords: Cloud computing, Power-efficiency within Data centers, Nature-Inspired techniques.

1) Introduction

The algorithms that imitate natural phenomena are popularly known as Nature-inspired algorithms. These algorithms are classified into Evolutionary Intelligence, Bio-Intelligence and Swarm Intelligence. The idea is to mimic the self-optimizing, self-healing, self-learning and self-processing ability of nature's components be it flora, fauna or the environment. If computers are empowered with this type of intelligence, they learn to adapt to the changing complexities similar to how nature deals with complex problems. In this direction, algorithms should implement techniques from nature in order to gain efficiency and reliability. Algorithms that are inspired by nature are widely used in various fields which comprise resource allocation, optimization problems, load balancing and optimal search problems and have proven to be improved than non-nature inspired algorithms. They solve complex problems at rapid rate.

Consider the instance of Evolutionary intelligence, a Genetic Algorithm (GA) inspired by natural selection theory proposed by Darwin and is dependent on the survival of the fittest candidate in any given environment (4, Goldberg). It imitates the mechanisms of evolution such as genetic crossover and mutation. A group of natural meta-heuristics inspired by collective intelligence is called Swarm intelligence. Here, a group of homogeneous agents interrelate amongst themselves and the environment and build the collective intelligence. This behaviour may be seen in ants, flocks of birds, school of fish to mention a few. Engelbrecht (5, Engelbrecht) emphasized the essentials and advances in swarm intelligence algorithms for solving several real-life optimization problems. Bio-Intelligence algorithms are inspired by the life style and behaviour of biological organisms. The intelligence of Bio-Inspired algorithm is decentralized, distributed, self-organized and adaptive (3, Mishra). Space and time complexity continue to be a major issue in resource management of Cloud computing. Nature-inspired algorithms are efficient as the decrease the solution space by introducing high-level heuristics, like Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) alongside Simulated Annealing (SA) algorithms. Existing literature study proves that Nature-Inspired help in achieving single as well as multi-objective solutions.

2) Management of power consumption within cloud computing data centers

Geographical difference is noticed to be an important feature in energy cost especially the cost of energy and the cleanliness of the same. Energy management is classified into four subclasses. They are Static Management of Power (SMP), Dynamic Management of Power (DMP), choice of location, and Infrastructure variations (1, Beloglazov).

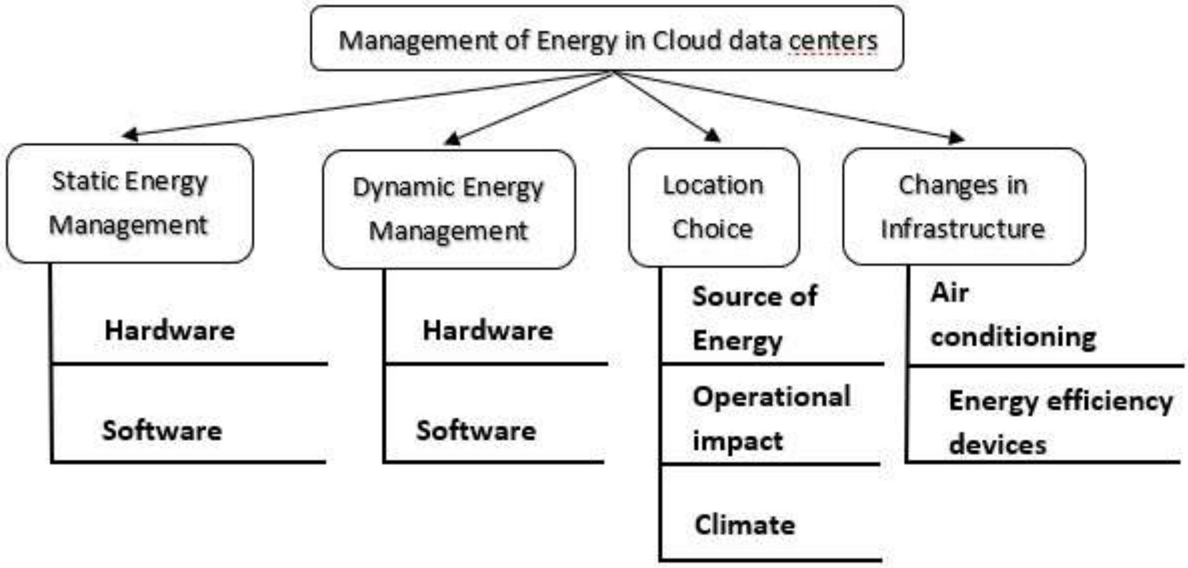

Fig. 1 Energy Classification in Cloud Data Center

• Static Management of Power (SMP)

SPM comprises all techniques of optimization that make sense at the time of design, usually on the circuit, logic and at the system architecture stages from a hardware point of view. Even if the hardware is designed perfectly, inappropriate design of software can lower the performance and cause power loss.

• Dynamic Management of Power (DMP)

The SPM method mentioned above is not scalable to solve run-time issues in data centers to respond to the changes in workload. However, the DPM method is scalable and minimizes consumption of energy at the software level. This technique entails an approach to monitor the dynamic characteristics of the state of a system and adjusts according to the existing workload requirement.

• Choice of location

The datacenters dissipate a lot of heat that needs to be cooled. The source of energy and the size of data center determine carbon emission. This primarily happens due to the statistic that the number of simultaneous users cannot be minimized just to optimize energy consumption. Considering all these cases we conclude that workload execution in datacenters located in various geographical locations may vary. The conditions of weather also have an impact on the system of ventilation a data center uses. For instance, data centers placed in cold areas don't need air conditioning.

• Infrastructure variations

The infrastructure needs to be altered to hold equipment that are energy-efficient. Servers may be changed while cooling systems can be improved. We can shift to state-of-the-art software for the optimal utilization of the data center architecture.

Energy-efficient and sustainable Cloud Computing operations can reduce energy consumption. The following sections discuss the practical approaches to minimize energy consumption within data centers.

2.1) Idle low-energy versus active low-energy based method

A device in active state performs useful work, otherwise, it will be in a sleeping state (6, Jiang). The device may be in low active state when it operates at a very low speed where the power is low in comparison with an active state. It may be noticed that in an inactive state, the components of computing do not accomplish any task. Dynamically accepting the frequency of system power is an example of active energy mode. The frequency may be brought to a constant when the workload is low. This approach is also known as Dynamic Voltage Frequency Scaling. This approach was initially made use of in CPU of laptop to align the frequency of work with energy consumption in order to save life of battery. Now this is seen to be a norm in HPC nodes and cloud datacentre servers. The performance states of DVFS, popularly referred to as p-state, talks about the operating frequency of processor.

P states = $\{P_i \mid i = 1,2,\ldots,n\}$

Here n relies on the processor that is experimented to optimize utilization of energy. Consider the example, where the CPU at P1 requires more time and lesser power in contrast to P3 (7, Snowdon). The authors have suggested energy-aware scheduling that makes use of evolutionary algorithm which is combined with DVFS to optimize power consumption within datacenters. This approach utilizes allotment of tasks to processors even with out going against the constraint of precedence.

(8, Kessaci) have suggested power-sensitive scheduling that implements evolutionary algorithm combined with DVFS to minimize the datacenter energy consumption. The method is used to allocate tasks to processors without violating the precedence constraint and the application approach that is used by the energy-conscious scheduling. (9, Kliazovich) explored DVFS technique to schedule datacenter resources. This technology merges the energy utilization of the network and server mechanisms, taking SLA into deliberation the traffic flow demand and the total energy utilization of the datacenter. (10, Meisner) use this technique to provide a clear solution for choosing one state instead of multiple states at a time with different performance, transition time, and energy consumption. The DVFS minimizes the power consumption by units (in watts) and on a single server component which is the CPU (11, Deng), (12, Sardashti). DVFS technique is not only employed to save energy for a single server and its components but also for the network resource and other related communication components in the datacenter to attain green computing (13, Shojafar). Similarly, (14, Jiang) utilized the Redundant Links Algorithms (SLRA) to detect the highest links that are in sleeping links and reverse those links to realize energy saving for the network resources in the datacenter. (15, Kim) also used power-aware DVFS scaling for energy management in Cloud datacenters. Some tasks scheduling algorithms proposed by (16, Sharma and Reddy) and (17, Yassa) used DVFS technique which allows for energy savings when the PM is not fully utilized. The power consumption of Cloud datacenters have not come down regardless of the progressions in this technology, as the DVFS technique is restricted to only the CPU. Therefore, the focus has moved from the hardware component to new techniques that are currently being implemented by datacenter administrators to optimize both hardware and software components of IaaS.

2.2) A scheme based on Energy-Aware hardware potentiality

The minimization of power is to concentrate on distinct parts of a system like the memory, the CPU, disk space and network component of the resources of the datacentre within cloud. System effectiveness can be enhanced by industries which offer optimization of hardware. Many researchers such as (18, Gabrel Torres), (19, Snowdon), (20, Ousterhout), (21, Koomey), (22, Hähnel), (23, Eom) and (24, Jiang) uses this method in their research to enhance power effectiveness and performance.

2.3) A method based on software development

In recent times, the kernel module, driver software and the applications are built with the awareness of energy consumption. Energy management functionality is offered and users are permitted to access the operating state of devices along with their power utilization. (25, Michael and Kreiger) explore multiple versions of operating systems running exactly the same application and witnessed energy utilization in a multitude of unique versions and have proven to show variations which are definitely non-negligible. The operating system is the pivotal software that defines the functionality of the system with respect to both computing and devices. They have varied energy utilizations that can be augmented to utilize minimal power, depending upon their type and version (10, Meisner).

2.4) A method based on Consolidating IT resources

An alternative method for optimizing power consumption is to consolidate and divide resources like memory, disk, CPU and power as against using many of the resources per server rack. In this way power consumption within datacenters is optimized with limited machines (26, Bianzino). Networks within datacenters have gained focus (27, Nie) and hence are consolidated. Those tasks within machines that find minimal utilization may be redirected to different machines to enable them to function with ideal capacity, using the minimal criticality method (2, Jiang). This results in the requirement of very few devices leading to low energy utilization. Likewise, substituting older servers with blade servers that utilize 10% lower energy than conventional servers are beneficial in preserving energy (28, Power) and (29, Cho).

3) Performance Metrics for cloud datacenter power efficiency

Power efficiency metrics suggest ways of measuring in order to test the operational state of the cloud datacenters. These measurements help in evaluating the power effectiveness at the various levels of cloud architecture including application, virtualization and infrastructure and their inter-dependency. Energy efficiency is a basic feature in the design and maintenance of computational systems (30, Rivoire). Power effectiveness has gained importance as a crucial measure built to determine power consumption of datacentre equipment (31, Gough). In order to effectively utilize the resouces within a data, the datacentre energy efficiency should be in compliance with that of the Green Grid Association (GGA).

The GGA analyses the given factors:

- Efficiency of Power Usage (EPU)
- Infrastructure Efficiency of Data Center (iEDC)
- Efficiency in Carbon Usage (ECU)
- Productivity of Data Center Energy (PDCe)

and acts as a measuring scale beyond determining the performance of datacentre. The most popularly used performance measure is EPU. The definition of EPU is clearly mentioned using Eq. 1.

EPU = (Cumulative Facility Energy) / (IT machine energy) (Eq. 1)

Lesser the PUE, greater the effectiveness, because a considerable portion of energy is measured by IT devices.

iEDC is inversely proportional to PUE. It is a usual metric for evaluating effectiveness within a datacentre. The Calculation is given by Eq. 2.

iEDC = (Power of IT devices) / (Cumulative Facility Power) (Eq. 2)

To get an advantageous single metric for iEDC the entire utilized energy should be measured (e.g. in kWh) for a period that is longer than the cyclic variation in efficiency, for many facilities. This may be a full year (33, Belady). ECU is another metric made use of by datacenter operators. It provides detail of certain environment efficiency relative to carbon emission. It is the total carbon emission caused by the cumulative datacenter energy divided by IT equipment energy. It has the same denominator with PUE but the numerator focuses on carbon emission, and it depends on the source of energy used by the datacenters as expressed by Eq. 3.

ECU = (Total CO_2 Emissions caused by Total Data Center Energy) / (IT Equipment Energy) (Eq. 3)

The 'Complete CO_2 Emissions' are measured in kg of CO_2 / kWh (kilowatt-hour). 'Total datacenter Energy' is the quantum of power utilized as measured by the utility meter. If a person's datacenter is running entirely on power-grid electricity, the region-wise government data will give him/her the numbers (34, Belady). PDCe is also a metric that is used to evaluate the useful work performed by the datacenter based on the quantity of energy utilization over a period of time. PDCe has been considered as the most effective and efficient method for measuring the whole of datacenter efficiency. This metric can be mathematically shown as in Eq. 4.

PDCe = (Total Useful Work was done) / (Total Data Center Energy Consumed Over Time) (Eq.4)

The PDCe considers a datacentre to be a blackbox, where power enters the box, while heat is dissipated, data goes into and out of the box, and a total quantum of beneficial work is undertaken by the black box (35, Haas). All the afore-mentioned metrics were suggested by the Green Grid with the aim of maximizing the datacenters' power efficiency. However, other metrics that are not mentioned here can be found in the energy efficiency of the distributed system by (36, Zomaya and Lee), in the best practices for energy efficient datacenter by (37, VanGeet) and in energy-efficiency metrics for datacenter by (38, Newcombe). In Table 1, we categorize the existing efficiency metrics based on their application areas and their formulae of computations.

Table 1 : Consolidated metrics for energy efficiency metrics and computation formulations

Name of the metrics	**Computational Formula**
Efficiency of Power Usage	EPU = (Cumulative Facility Energy) / (IT machine energy)
Efficiency in Carbon Usage (ECU)	ECU = (Total CO_2 Emissions caused by Total Data Center Energy) / (IT Equipment Energy)
Water Usage Effectiveness	WUE = Annual Water Usage / IT Equipment Energy
Energy reuse factor	ERF = Reuse energy outside of the data center / Total Data Center Source Energy
Energy reuse effectiveness	ERE = (Total Energy−Reuse Energy)/ Total IT Equipment Energy
Infrastructure Efficiency of Data Center	iEDC = (Power of IT devices) / (Cumulative Facility Power)
Data center productivity	DCP = Useful Work / Total Facility Power
Compute power efficiency	CPE = IT Equipment Utilization Energy / EPU
Green energy coefficient	GEC = Green Energy Consumed / Total Energy Consumed
Space, wattage, and performance	SWaP = Performance / (Space*Power)
Productivity of Datacenter energy	PDCe = Total Useful Work was done / Total Data Center Energy Consumed Over Time

4) **Power-effective methods that are inspired by nature for data centers within Cloud**

Many different power-efficient scheduling techniques have been built and implemented using Nature-Inspired algorithms to evade underutilization of resources which is amongst the key attributes responsible for suffering high energy consumption (39, Lee). The energy-efficient methods are separated into two important classes; Non-nature inspired i.e., Heuristics and Nature Inspired i.e., Meta-Heuristics. In this research work, we concentrate only on the algorithms that are inspired by nature. Nature-Inspired optimization is further split into single or multi-objective (SOO or MOO) depending on the objective function.

5) Comparative assessment of energy-efficient techniques

Table 2 depicts comparisons of the algorithms inspired by nature and remarks about their achievements.

• Algorithm

Looking into Table 2, we understand that few of the algorithms are hybrid in nature. An instance of similar hybrid algorithms comprises, DVFS-MODPSO, given by (38, Yassa), (55, Javanmardi), (56, Shojafar), and Hybrid ACO & CS presented by (57, Moganarangan). We observe that in order to attain good output we go for hybrid algorithms. We also understand that a major part of the algorithms suggested under this method are Swarm, Evolutionary and Bio Intelligence algorithms. Applying these algorithms yield better results beyond doubt.

There is a need for more research into the algorithms inspired by nature that may improve the existing algorithms in order to attain better output.

Table 2. Comparison of Nature-Inspired energy-efficient techniques

Algorithm	Energy efficient technique	Approach	Scheduling method	Problem formulation	System resource	Measured parameter	Benchmark	Advantage	Limitation	Energy-Efficiency
H-DVFS-MODPSO (17,Yassa) (2013)	Energy -Aware	MOO	Static / Dynamic	Work flow scheduling	PM	Execution time, Cost & EC	HEFT Heuristic	Improves energy consumption and makespan	Not implemented, not reliable	N/A
MOCell, NSGA-II and IBEA algorithms (64, Guzek) (2014)		MOO	Static / Dynamic	Task scheduling	CPU	Execution time & Makespan	HEFT algorithm	Provide accurate solution for the addressed problem that converge to good solutions	Dependent on task & processor number	Low
EA-ACO (43, Feller) (2011)		SOO	Dynamic	Resource Allocation	CPU, RAM, Disk & Network	RU & EC	First Fit Decreasing (FFD)	Achieve higher energy saving & resource utilization	Does not support heterogeneity	Medium
EAVM-ACO (32, Liu) (2014)		SOO		Resource Allocation	CPU & Memory	Count of VM & Servers	FFD Algorithm	Minimize energy consumption & resource wastage	High convergence time	Low
FOA (44, Kansal and Chana) (2016)		SOO	Dynamic	Resource Allocation		EC, RU & Migration time	ACO based & FFD based algorithms	Maintained good energy efficiency & performance	No performance guarantee	High
Pre Ant Policy (45, Duan) (2016)		SOO		Resource Allocation	CPU & PM	EC, CPU utilization & CPU load	FF, Round-Robin & MM	Minimize energy consumption	Under-utilization of resources	Medium
EMOA (51, Phan) (2012)	Virtualization	MOO	Dynamic / Static	Resource Allocation	PM	Renewable EC, Cooling & User-to-Service Distance	Static & Dynamic Placement Algorithms	Improves renewable energy consumption	SLA violation has not been consider, slow response time	High
EOA (52, Pascual) (2015)		MOO	Dynamic	Resource Allocaiton	PM & Network	EC, ET & RU	NSGA-2, SPEA-2 & Hype	Reduces power & faster processes of request	High Communication overhead	Medium
OL-PICEA-g (53, Lei) (2016)		MOO	Dynamic	Task Scheduling	PM	EC, Makespan, Utilization of Renewable Energy & Task Satisfaction	PICEA-g Algorithm	reduces makespan & energy consumption	It does not handle parallel task scheduling	Low

Hybrid ACO & CS (57, Moganarangan) (2016)		SOO	Dynamic	Task Scheduling	PM	EC & Makespan	ACO	Substantially reduce energy consumption	Consider the energy consumption of processors only	Medium
GAHO-ILP (54, Rocha and Cardozo), 2014)		SOO	Dynamic	Resource Allocation	PM & Network	EC, PACKET LOSS & SPEED	OSPF	Trade-off between server energy consumption & network	Takes longer time to reach the nondominated solutions	Medium
DVFS-GA (16, Sharma and Reddy) (2015)		SOO	Static	Resource Allocation	PM	EC & RU	Multi-objective Genetic Algorithm	Save energy with 0% SLA Violation	Lack VM migration concept	Low
Hybrid ACO & CS (57, Moganarangan) (2016)		SOO	Dynamic	Task Scheduling	PM	EC & Makespan	ACO	Substantially reduce energy consumption	Substantially reduce energy consumption	Medium
GeNePi (58, Saber) (2014)	Consolidation	MOO	Dynamic	Resource Allocation	RAM & CPU	Reliability, Migration Cost & EC	Firs Fit (ff), Balancing Bin (BB) & Random Fit (RF)	Finds non-dominated solution easily	SLA Violation is not consider	Low
ACS-VMC (59, Farahnakian) (2015)		MOO	Dynamic	Resource Allocation	PM & Network	SLAV, EC & VM Migration	MAD, IQR, LR & THR Heuristics	Reduces Ec & maintained QoS	Low workload utilization level	High
CSO-A (60,Sait) (2016)		MOO	Dynamic	Resource Allocation	CPU	Convergence Rate, Reliability, EC& RU	GGA, RGGA, ILL& IFFD	GGA, RGGA, ILL& IFFD	Not reliable	Low
PSO-AE (63, Gabaldon) (2016)		SOO	Dynamic	Resource Allocation	PM	EC	JPR-E, FCFS, Min-Min & HILL	Faster convergence with lowest energy consumption	Low sensitivity to workloads	Low
MPSO (65, Li) (2016)		SOO	Dynamic	Resource Allocation	CPU & Disk	EC, Migration, Load & Balancing	Modified Best Fit Decrease	Indicate better energy efficiency and reduces VM migration	Lack SLA violation, consider only CPU & Disk	Low
SA-MILP (96, Marotta and Avallone) (2015)		SOO	Static	Resource Allocation	CPU & RAM	EC, Migration, RU & Makespan	First Fit Decreasing (FFD) & Sercon	Can find feasible assignment easily	The consolidation decision does not consider traffic among the VMs	Medium

VMC-ACO (97, Ferdaus) (2014)		SOO	Static	Resource Allocation	CPU, Memory & I/O	Resource Wastage & Runtime	Max-Min Ant System, Vector Greedy Algorithm, Modified FFD-Volume & FFD-L1Norm	Applicable in large virtualize data centers	Did not consider network utilization and live VM migration	Low

• Techniques

From table, we understand that there exist 3 major power efficient methods used in data centers within cloud namely, Energy-aware, virtualization and consolidation methods. The suggested methods are expected to find resources that are over-utilized and make use of more energy. It may be seen that virtualization and consolidation is used best part of the time. This is attributed to flexibility and ease of implementation which make them profound in comparison with other methods.

• Parameters

The parameters are identified either from the consumers' perspective or the service provider. The parameters mainly consider effective utilization of resources and concentrate on the application performance. Keeping this in mind the parameters from the point of view of consumers include response time, time for execution, fairness, turnaround time and makespan, while the parameters from the point of view of cloud service providers comprise efficient utilization of energy, resource utility, migration of VM, throughput, workload, budget and other constraints including reliability and priority. We consider all the parameters within the objective function of any given algorithm that is inspired by nature during cloud resource scheduling.

• Benchmarking

This method of comparison proves the enhancement in the algorithms that are suggested with respect to energy-effectiveness. A small number of the methods are assessed in comparison with heuristic algorithms like HEFT Heuristics, First Fit Decreasing, Round-Robin and Modified First Fit Decreasing algorithms even as other algorithms are compared with those algorithms inspired by nature like CSO, GA, PSO and ACO. It may be seen that dynamic allotment of workload or migration of VM, allocation of VM and placement and other approaches are made used of in the evaluation of power-effectiveness in the suggested algorithms. Various simulated set ups with traces are real data are used to implement this method. They prove to be really helpful in the validation of the empirical analysis and the hypothesis tests to prove their performance in drastically bringing down the energy consumption within data centers in the cloud.

• Advantage

Those algorithms that are an inspiration of nature are fool proof and are useful when assessed along with algorithms that are not inspired by nature, even as we talk about best answers and ideal computational complexity. Table 2 proves that the suggested algorithms as well as the methodologies come with a multitude of benefits like extremely good performance, dynamism, improvement in power-efficiency and reasonable allocation.

• Limitation

We observe that the algorithms referred have limitations as well. These could be SLA violation, computational complexity that is substandard and resource utilization which is single instead of multiple resource utilization, task dependency, resource utilization which is improper and also energy-intense parts like I/O resources and network is neglected. The drawbacks of each and every method is given below:

The technique of virtualization has no assurance of energy-optimization because of the communication overhead which is mostly on the higher side and goes with utilization of single resource. The method suggested by (46, 47, Wang), (48, Ramezani) and (49,Yao) have been noticed to consume more time to give the ideal solution due to the concept of poor migration brought about to overcome poor utilization of data center and power utilization. The method of consolidation has removed the disadvantages with virtualization technique as suggested by (62, Ferdaus), (61, Marotta and Avallone) and (60, Sait). But this method is affected by poor sensitivity to traces of workload. This has resulted in poor usage of workload and also the cost of network communication upon VM migration is not studied thoroughly. The problem of consolidating PM with network simultaneously just as the migration of VM which shifts between PM is not considered in this study. The methods which incorporate Energy-Aware suggested by authors like (40, Mezmaz), (41, Malakooti), (42, Raju) and (44, Kansal and Chana) concentrate on VM migration and powering on/off PM to bring down the overall power utilized by the PMs. It may be noted that this scenario causes issues like SLA violation, resource under-utilization, no guarantee of performance, convergence on the higher side.

• Energy Efficiency

It may be noticed that all the methods are efficient with respect to energy as suggest by the authors. In spite of this the mediocre performance is because of few limitation and factors in the formulation of the problem and further implementation. Hence, we divide the algorithm into low, medium and high performing energy-efficient algorithms.

6) **Conclusion**

This research paper studies algorithms inspired by nature, technologies used and the methodology generally used to alleviate power utilization of data centres within the Cloud. These techniques were then evaluated and compared based on their objectives, methodology applied, benefits and weaknesses. The algorithms were assessed based on the factors that set up energy efficiency. Even as studies prove that the methods work reasonably well in IaaS, the assessment of computational complexity suggests many drawbacks in these techniques. Quite a number of the current scheduling methods involve large amount of resources which in turn utilize more power within cloud data centers. Those strategies employed for the allotment of resources are considerably slow and causes maximum power utilization. There exist situations where the data centers operate in silos (single data centers) as against the ideal multi data centers. It is noticed that the infrastructure within data center is under-utilized and consume energy. With the given disadvantages of the current methods, better approaches are to be built to enhance power optimization and proper usage of resources within the cloud data centers. Such techniques must be designed to control resource and energy wastage without ignoring energy consumption made by networking components, and input-output devices. In this approach is strictly practiced, carbon emission at global level may be brought down phenomenally, thereby ensuring environmental sustainability and hence minimizing its adverse effects on life on planet earth. However, most of the findings are at their early stage and many of the existing methods are assessed in a simulated test set up. Building a simulated framework makes a contribution that is noteworthy due to the event simulation which is discrete in nature and also one among the initial steps in the procedure towards building Cloud computing environments.

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