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# Virtual Machine Consolidation for Performance and Energy Efficient Cloud Data Center Using Reinforcement Learning.

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***ABSTRACT: Cloud adoption and migration is growing everywhere because of its key benefits for cloud consumers and providers on economic, environmental and technological aspects. The augmentation of cloud computing service increases the size of the data center around the globe containing thousand of computing nodes. This increased large scale cloud data center has enormous quantity of electrical energy consumption which leads to huge operating cost and $CO_2$ emission to the environment. The problem of high energy consumption and its effects are addressed here by presenting dynamic virtual machine consolidation using reinforcement learning. This reinforcement learning agent learns the knowledge from past history to attain the optimal policy. Hence, the number of active host is reduced by determining the host power mode based on current requirement. Hereby, the proposed work is compared with the competitive algorithms of Inter quartile Range maximum correlation policy (IQRMC) and Inter quartile Range Random selection policy (IQRRS). Experimental results show that, the required performance and energy level of data center is attained through proposed reinforcement learning.***

## I. INTRODUCTION

The Cloud computing commences the data centers having thousands of computing nodes around the world. Cloud computing has recently shown its considerable attention to deliver information and communication technologies services. This exponential growth of cloud computing rapidly enhances the utilization of data center resources. The huge IT corporations like Microsoft, Google, Amazon, Apple, and Face book are running hyper-scale data centers across the globe to manage the growing demand. Also, the various small scale data center run their relatively reliable workload by business companies, government agencies and universities. Totally, 95% of the global data center energy usage is shared by small scale data centers, while the remaining 5% is used by hyper scale large data centers only. The electrical energy consumption of data centers have been increased by 10X over the past ten years (Patel et. al. 2006). The dynamic requirement of application from business and scientific sectors drives the development of high performance computing system (Akshat Dhingra & Sanchita Paul 2013). Such as, the data centers often involve thousands of servers, disks, and networking infrastructure to connect the server cluster to the Internet, to process the fast growing application and data within the required time period. This ever increasing demand of cloud infrastructure makes dramatic rising in energy consumption. The Open Compute project reports say that, computing resources consume 91% of the data center's energy approximately. Moreover, this expands the expending cost on power delivery and cooling equipment. The cooling infrastructure with the worth of five million dollars is needed by a huge data centre which has power consumption of 10MW. (Anubha jain et.al 2013) said that, the green computing is required because, the huge amount of $CO_2$ emitted from these data centers. This emission contributes global warming and hazards to the environment. Aside from the high energy costs, the huge carbon footprints are also incurred. Hence, the design and deployment of energy efficient green data center is insistently needed to overcome the huge energy cost and huge carbon footprints of data center. As projected by Koomey (2007), the implementation of advanced energy efficient resource management solutions in the data center solves the issue of growing energy consumption. The enlarged utilization along with enhancing environmental impacts and energy related costs make a call for energy efficient solutions that should decrease the overall energy consumption of storage, computation and communications. Junwei et al. (2014) stated that, the most key desires for data center is energy efficient management. Hence, the minimization of energy consumption has been achieved by dynamic consolidation of virtual machines (VMs) using virtualization technology. Nidhi Jain Kansal (2012) discussed about, virtual machine consolidation which could be one of the energy efficient management in cloud data center. The consolidation of Virtual Machine (VM) instances into a few servers as much as possible provides the energy efficient solution. This VM consolidation or VM reallocation consists of two basic steps:

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Migration of the virtual machines from underutilized and over loaded physical machine. Owing to this migration, the energy consumption and overheating experienced by VMs is minimized to provide a good Quality of service to the Consumers. The paper is structured as follows. Section II details the related work. The Reinforcement learning agent as part of consolidation method is described in section III. The proposed system model is described in section IV. Section V describes about maximizes the reward of performance and energy levels. The experiment is done in the simulation environment, the result of which is detailed in section VI. Finally, Section VII detailed the conclusion.

## II. RELATED WORK

In recent years, the significant research has been made to reduce the energy cost in the cloud data center. One of the energy saving solution in cloud environment is dynamic virtual machine consolidation. Zhu et al. (2008), Jung et al. (2008), Kumar et al. (2009), Berral et al. (2010), Verma et al. (2008), Pablo Graubner et al. (2013) proposed the novel approach in virtual machine (VM) consolidation. Beloglazov et al. (2012) presented heuristics for consolidation of virtual machine with dynamic workload from web applications. These algorithms set the upper threshold and lower utilization threshold and keep the utilization of CPU of a host between these bounds. The virtual machines are reallocated based on these threshold levels. Ferdaus et al. (2014) creates the balanced resource utilization across the various computing resources by using AVVMC virtual machine consolidation scheme to have a improvement in both power consumption and resource wastage.

Fahimeh Farahnakiann et al. (2016) applied the regression-based model to examine the future CPU and memory utilization of VMs and PMs approximately to support the minimum VM migrations and Service Level Agreement (SLA) violations in the data center. Matthias Sommer et al. (2016) used K- Means evaluation in VM Selection for VM migration during dynamic VM Consolidation process. Compared to other work, this work offers the dynamic virtual machine consolidation through the reinforcement learning with the intention of maximizing energy efficiency and performance.

## III. VIRTUAL MACHINE CONSOLIDATION USING REINFORCEMENT LEARNING

A Markov Chain generally modelled as a stochastic process that satisfies the Markov property and it is a statistical model of a system that moves sequentially from one state to another. A Reinforcement Learning (RLVC) decision making problem is usually modelled as a (MDP) Markov Decision Process. The decision agent that repeatedly observes the current system state s to take a decision of action among a set of actions A then, makes a transition from state(s) to a new state (s*). The probability of transition in MDP is defined by Pa(s, s*) = $Pr(s_{t+1} = s^* | s_t = s, a_t = a)$; Such that the transition occurred due to the action a in state (s) at t to the state of ($s_{t+1}$) at t + 1 and an immediate reward function $R = E[r_{t+1} | s_t = s, a_t = a, s_{t+1} = s^*]$. At each step t, the agent observes the available action set $A(s_t)$ and its current state $s_t \in S$. By applying action $a_t \in A(s_t)$, the agent transits to the new state s* and obtains an immediate reward $r_{t+1}$ from the environment. By receiving the reinforcement signal *r*, the value of Q has been updated at the commencement of next Iteration. Q-learning is a commonly used model free approach which can be used for self playing agent.

$$Q(s_t, a_t) = (1- \alpha) Q(s_t, a_t) + \alpha [r_t + \gamma \max_{a \varepsilon A} Q(s^*, a^*)] \quad (1)$$

The state-action pair is denoted by Q(s,a). The learning rate is denoted by α. The value of α is from zero to one. If nothing is learnt means, α has been assigned with 0. If most recent information is used means, one has been assigned to α. γ is the discount factor. When, the learning agent observes the same state, it selects the appropriate action to attain the maximum Q value through yielding the reward of $r_{t+1}$. The main goal of learning agent is yielding optimal policy π through mapping of states to the finest action.

$$\Pi(s)=\max_{a \varepsilon A} Q(s,a) \quad (2)$$

Initially, the learning agent selects random action then, laterally optimal action should be taken by the policy.

## IV. SYSTEM MODEL

The proposed system model is designed with m physical nodes which are heterogeneous in the data center. Each node is characterized with high processing capacity of multi core processor, memory and network bandwidth. Such as, each of the physical nodes in data center has different configurations of RAM & disk storage which is defined in Giga Bytes (GB) & Tera Bytes (TB), and CPU performance. User submits the application request which is to be run on the data center. The application requirement initiates the deployment of virtual instance on physical server in data center. Initially, virtual instances are provisioned to serve work load in appropriate manner. But, CPU utilization is varied dynamically to incorporate the dynamic workload. This may cause under or over utilization of physical server leads to either service level agreement violation or energy consumption enhancement. Junwei et al. (2014), Nidhi Jain Kansal (2012), Mehta et al. (2011), Nakai et al. (2011), Lua et al. (2011), and Hu (2010), all are discussed about balancing of load to reduce service response time, overhead and performance improvement in the cloud data center. Therefore, the virtual machine consolidation method intention is reducing the number of active physical host to have minimum consumption of power. The physical resource should be utilized fairly and efficiently to prevents the bottlenecks of the system. So that, no host is over or under utilized. Hence, the virtual machine consolidation using learning agent is proposed here. This learning agent improves the quality of VM consolidation algorithm. The agent takes necessary action through Q learning by switching between active mode and sleep mode to maximize the performance and energy consumption. The proposed virtual machine consolidation operations are


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i. Observing the status of every host by collecting the information of power mode of current states of a host at the time slot t, Power Consumption, and utilization of CPU. The workloads which run on VM instances utilize the CPU to run the tasks. The current power consumption of physical servers should be accurately calculated through CPU utilization. Because, the linear relationship is there in between power consumption and CPU utilization of server.

ii. Identifying the Idle servers, underutilized servers and over utilized servers based on the threshold value or agent knowledge.

iii. Mapping states to action by setting the power mode of host. The idle host power mode is sleep mode because, servers those do not run any of virtual resources. Also, the under-utilized servers which are turned to be switched off by migrating running VMs to power-sustainable physical hosts. So, underutilized server mode is turned into sleep mode.

iv. Moreover, if the current power mode is sleep mode, but it is to be made as active to manage dynamic workload, then the host would be turned into active mode by the agent.

v. If suppose, the current state of host is in absorbing state due to dynamic work load, that host is represented as an over loaded host by considering the utilization. Such as, the usage of host is forecasted as over loaded. Then, the selected virtual machine would be migrated from the overloaded host. The learning agent decides and concludes the VM which should be reallocated to which host.

### *A. VIRTUAL MACHINE SELECTION POLICY*

Initially, Virtual Machine selection policy selects the virtual machines based on threshold values. The virtual machines are sorted out in increasing order as per current CPU utilization. If virtual machine utilization is greater than or equal to the difference of host utilization and the upper threshold, that machine could be migrated. Later on, Virtual Machine selection policy set the power mode of each host based on agent knowledge.

### *B. VIRTUAL MACHINE ALLOCATION*

The learning agent decides and determines the best PM for selected VM Reallocation. This agent uses VIKOR method to select the most suitable physical machine PM from m nodes in the data center with n decisions criteria/attributes, $A_1$, $A_2$,…..$A_j$,….$A_n$. Here, each alternative or host in the data center has been evaluated by using beneficial and opponent attributes. The available utilization of physical node are considered as beneficial attribute, which should be higher value to get the best PM for placing the VM & The consuming power (P) of the physical host is defined as negative attribute, which should be lower value to get the best PM. Such as, the selecting physical node for VM placement should have minimum power consumption to get the best host. The available utilization of physical node is taken as the utilization which should be available for VM sharing. The available utilization should be greater than the sum of actual utilization of host and requested utilization of migrating VM. Therefore, the Multi criteria decision making model VIKOR is applied to select a best physical resource for VM placement from m nodes or m alternative physical machines under highly available utilization with minimum power consumption criteria. The following steps describe the selection procedure of the physical machine for migration.

Step-I: The physical hosts in the data center are examined for choosing best physical machine PM from m alternatives. Here, the available utilization (U) and Power consumption (P) are considered as criteria to choose the appropriate PM. The U is assumed as beneficial criteria by favouring higher value as a best value. The Power consumption (P) attribute is preferred as lower value is a best value.

The level of regret LP in VIKOR can be defined as

$$L_i^p = \{\sum_{j=1}^{n}\left[w_j(|r_j^* - r_{ij}|)/(|r_j^* - r_j^-|)\right]^p\}^{1/p}, \quad 1 \le p \le \infty \quad i = 1,2,3\ldots m \tag{3}$$

Then, the best $r_j^*$ and the worst $r_j^-$ values of Utilization (U) and Power consumption (P) criteria rating are determined.

Step-II: The weight of criteria $w_j$ aids to make a decision on alternative physical machines. Assigning weight to the attributes of machine helps to select the particular node. The higher weight means, the criterion is more important during the course of decision-making. Hence, the weight has been assigned to most required criterion. So, the absolute importance is assigned to criteria of available utilization and minimum power consumption. Therefore, the equal weight has been assigned to select the host which has highly available resources for VM placement with minimum power. The weight represented as w, such as.$w_u$=0.5 and $w_p$=0.5

Step-III: By The small value of p in the LP metric builds group utility (such as p may be equal to one) and the individual regrets/gaps will be more as p increases.

If p=1, then G= $$L_i^{p=1} = \sum_{j=1}^{n}\left[w_j(|r_j^* - r_{ij}|)/(|r_j^* - r_j^-|)\right] \tag{4}$$

If p=∞, then R=

$$L_i^{p=\infty} = \max_j\{w_j(|r_j^* - r_{ij}|)/(|r_j^* - r_j^-|)\}\; j = 1,2\ldots n \tag{5}$$

The values of $G_i$ and $R_i$ for $i = 1, 2, \ldots\ldots\ldots m$ have been computed by using equation 4 & 5 for m alternative physical machine. The maximum group utility and the minimum individual regret of the opponent values are computed.


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The maximum group utility is attained by Emphasizing $\min_i G_i$ whereas $\min_i R_i$ aids to select minimum among the maximum individual regrets. Then, the value of X has been computed using G and R.

$$X_i = \nu (G_i - G^*) / (G^- - G^*) + (1-\nu)(R_i - R^*) / R^- - R^*) \quad (6)$$

where $G^* = \min_i G_i$, $R^* = \min_i R_i$, $G^- = \max_i G_i$, $R^- = \max_i R_i$ and $0 \le \nu \le 1$, where $\nu$ is the weight of the maximum group utility, where as 1- $\nu$ is represented as the individual regret weight. v = 0.5 is used here.

Step-IV : Rank the physical machines by sorting the value of $(G_i, R_i$ and $X_i | i = 1,2,....,m)$ in decreasing order. Then, the best ranked physical machine has been chosen for VM deployment by using ranking solution.

Step-V: The compromise solution is also applied to rank the physical machine.

## V. REINFORCEMENT LEARNING AGENT PERFORMANCE METRICS

The learning agent takes an intelligent decision and develops itself through the changes in the environment. Therefore, it reduces active physical host in the cloud data center. Initially the action is taken based on threshold value, after learning; it takes intelligent action based on its knowledge. The objective of agent is maximizing energy efficiency and performance in the cloud data center. The dynamic workloads expand the energy consumption of the physical resources in the data center. Hence, the agent decides the active host or idle host on the time slot t+1. (Anuj Prasher et al 2014) said that, the size of data center should be minimized to reduce the power consumption in the data center. The minimization of size creates compromise in the performance degradation. If a VM cannot get the CPU resources to process the instructions that are requested, then the SLA violation could be raised. These SLA violations might be happened due to the consolidation process. The SLA violations are measured based on CPU availability, such as the actual allocation of Million Instruction per second over a time slot. The requested MIPS of VM in a host is denoted by $U_r$. Similarly, the MIPS instructions actually get the resources on the host is represented by $U_a$. Now SLA violations can be calculated as

$$SLA_t = \sum_{j=1}^{n} (U_{rj} - U_{aj}) \quad (7)$$

Average SLA violation is calculated by using the total requested instructions of virtual machines. When n number of VMs in the data center, the cost of violation is computed by using

$$C_t(SLA) = SLA_{t+1} / SLA_t \quad (8)$$

If the value of $SLA_{t+1}$ is minimum compared to previous SLA violations, then, the cost of SLA violation is less than one. Hence, the agent takes good action of power mode from the learning environment. Likewise, the cost of power is calculated by using the power consumption at t+1 and the consumption of power at t.

$$C_t(power) = \sum_{j=1}^{n} p_j(U_{t+1}) / p_j(U_t) \quad (9)$$

The third metric to maximize the performance and energy efficient level in data center is Number of virtual machine migrated by the agent during the replacement of VM. The total reward is calculated by adding the value of minimum cost of violation and power consumption and the Number of Migration.

$$C_t = C_t(SLA) + C_t(power) + N \quad (10)$$

Hereby, the Q-value of Q(s,a) in equation(1) should be maximum, which denotes the expected maximization of energy efficiency and performance in the cloud data center. When the state S is being observed by the agent at next time, the agent selects the host power mode to attain the maximum Q value. The optimum action brings out the maximum Q value in performance and energy metrics (minimum in SLA violation, power consumption, number of migration).

## VI. SIMULATION RESULTS

The model of proposed work has been experimented on the Cloudsim simulation tool. The simulated model has 500 hosts which are heterogeneous. The workload desires the provisioning of VMs, because most of the application has dynamic workloads. The CPU utilization is mainly due to the running workload of VM. The cloudsim 3.0 use the PLANET LAB workload to run the simulation. The proposed work is compared with the algorithm which adapts the threshold of utilization dynamically based on the Interquartile Range (IQR) to find out the CPU utilization. This work uses the competitive algorithms of Inter quartile Range minimum migration time (IQRMMT), Inter quartile Range maximum correlation policy (IQRMC), Inter quartile Range Random selection policy (IQRRS) for bench marking in the experimental result. Hence, the proposed dynamic VM consolidation using reinforcement Q learning (RLVC) is compared with other dynamic virtual machine consolidation algorithms of IQRMMT, IQRMC, IQRRS. The metric of energy efficiency and performance depends on the minimum value of SLA violation and the total consumption and the number of virtual machine migrations.

### *A. AVERAGE SLA VIOLATION*

If suppose CPU is not available, when the requesting the CPU to execute the instruction is called as average SLA violation; consequence of this will make performance dehydration. The other dynamic virtual machine consolidation algorithms of IQRMMT, IQRMC, IQRRS


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gives 12.29%,12.89%,12.5% of average SLA violation and The proposed dynamic VM consolidation using reinforcement Q learning (RLVC) is 8.5%. The result shows that RLVC algorithm gives minimum SLA violation compared to other IQRMMT, IQRMC, IQRRS. The virtual machines are consolidated based on agent knowledge, this will lead to minimum SLA violations.

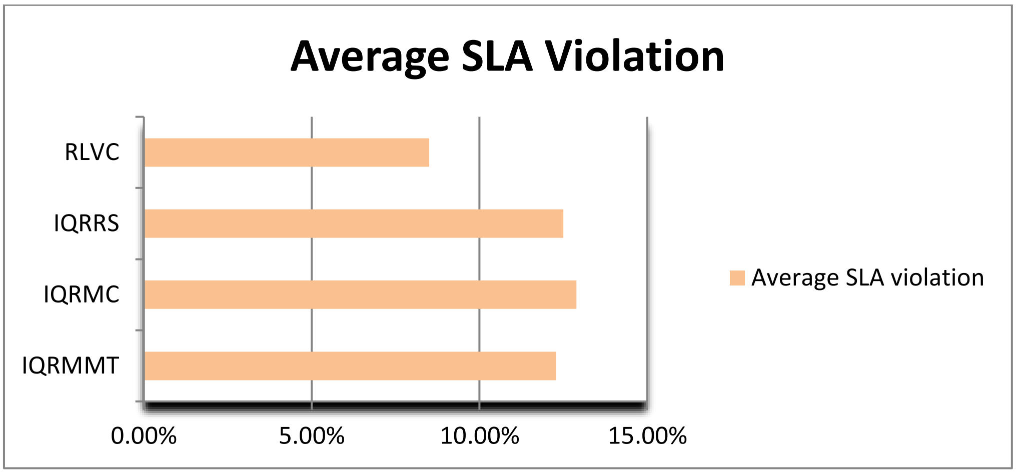


**Figure 1. Average SLA violation**

*B. ENERGY CONSUMPTION*

The Energy consumption (E) of a physical machine is desired by the integration of power consumption function over a period of time.

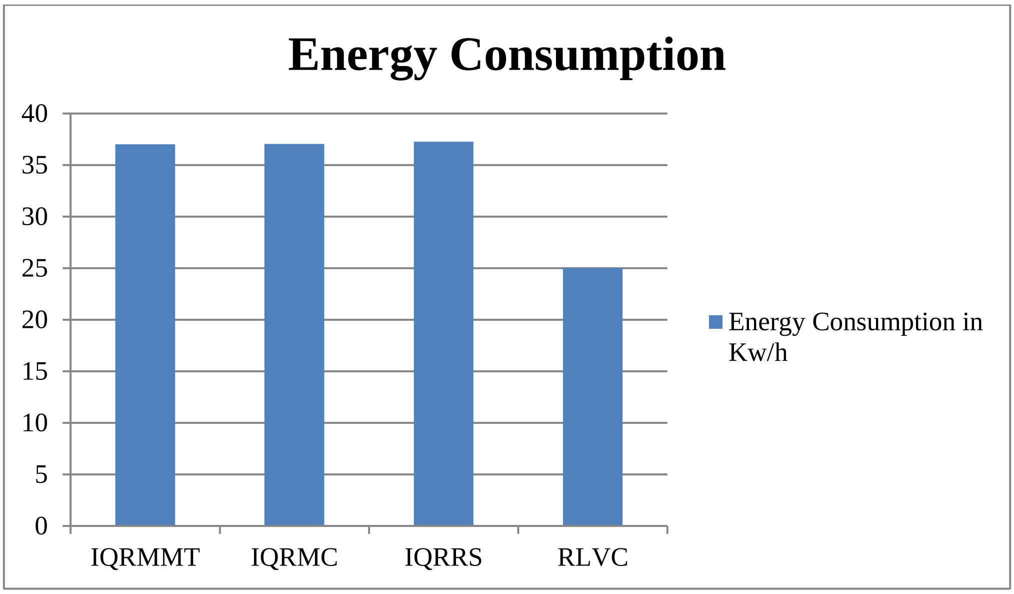


**Figure 2. Energy Consumption**

The underutilized host is detected through the learning agent. This agent makes the power mode of underutilized host is as a sleep mode, so VMs are reallocated to other physical machine which has minimum power and capacity to share the resources. Hence the significant reduction could be achieved through this learning, which is shown in figure2. The learning environment also yields minimum number of migration.

## VII. CONCLUSION

In this work, the reinforcement learning has been applied for virtual machine dynamic consolidation method to maximize energy efficiency and performance in cloud data center. The simulation of proposed consolidation method is simulated in cloud sim simulator and also compared with the existing virtual machine consolidation method. The experimental result reveals that, the virtual machine consolidation using reinforcement learning gave better result in saving energy as well as performance.

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