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Reinforcement Learning Based Energy Consolidation Model for Efficient Cloud Computing System

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Abstract: Cloud computing offers significant deployment services to the end-users by using various network & software resources which consumes enormous energy. Energy plays a key factor in the ubiquitous cloud system because it involves financial investment for the hardware infrastructure and also contributes for service quality. There are numerous models available the consumption of cloud data center energy. In the prevailing cloud models certain count of resources were experimented which are not providing significant energy consumption due to wide set of applications actively running in the data center. One of the classifications of Machine Learning model is Reinforcement Learning (RL) model which gives maximum support to minimizing the application energy through learning model and reward points. The Data Center (DC) in the cloud consists of a host with multiple Virtual Machines (VMs), so the energy consolidation technique is needed for minimizing energy. RL based Multi agent model is proposed for minimizing the energy in VM level to DC level by implementing three agent's levels namely VM agent, Host Agent and DC agent. The reward points are analyzed based on these agent's responses with corresponding resource level parameters. Based on the resource action, the policy determines in finding energy efficient resources and terminate the idle VM on the host which is also contributing to the considerable amount of energy. The consolidation of energy efficient virtual machine which provides a salient model for cloud data center and dynamically prevents host shutdowns have been proposed in the RL model.

Keywords: Cloud Computing, Data Center, Energy Consumption, Virtualization, Machine Learning, Reinforcement Learning.

1 Introduction

Technology related to the computing domain evolves based on various factors such as platform, architecture, application improvement. Initially desktop computing provides the result based on the user requirement but it suffers sharing of the data and resources among the host. This problem is solved by introducing a series of computing methods like client server model, distributed model, parallel model and so on. Grid computing model selects suitable resources from high-end servers and performs the task without any resource problem. Cloud computing provides all kind of resources to the customer in a service manner by following the pay as you go method. Cloud model uses virtualization techniques, which maintain multiple virtual resources with loosely coupled manners. It achieves high availability of resources, flexibility in the application development with high level of security. Cloud computing models maintain the resources in an energy efficient manner with desirable locations. The overall resource utilization is improved by handling clusters of machines during peak load situations. It reduces the maintenance cost of the user. Energy management is a challenge faced by the cloud due to workload, outsourcing of resources, consumption of energy by the resources (i.e. active and idle state) and power management problems. The energy consumed by the cloud resources are reduced by identifying unused servers with relevant methods of implementation. Energy management problems are addressed in different levels of abstraction namely network level, resource level, application and middleware layer. Network related resources and components use high energy which is minimized by following energy efficient policies. Artificial intelligence techniques are applied to cloud computing models for identifying efficient resources, which consumes less energy. Various types of learning models are used in machine learning namely supervised learning, unsupervised learning and reinforcement learning

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(RL). RL uses the feedback method for interacting with the cloud environment by performing actions through the agent. The agents collect the feedback from the environment based on the current action. Cloud energy efficient models collect the energy level of various resources and perform the action according to the collection data.

2 Related Work

Energy consumption of the cloud grows at a high rate due to CO_2 emission by the resources on a global level. CO_2 emissions are addressed by using multilevel energy aware models with various techniques like adaptation and scheduling of application. It suffers the reliability and accounting problem for developing CO2 aware models in open-source platforms [1]. QoS (Quality of Service) are measured in the cloud computing application with various factors such as cost of deployment, cost of energy, price of the service, customer retention rate, operation cost. Two types of clouds are used to share the services among the providers namely multi cloud and federated cloud. Multi cloud based on the relationship established between provider and user of the cloud. Federated cloud through agents. Federated cloud applied in two different application types that are related to optimization of energy and cloud resources with execution status [2]. Dedicated data center utilizes the resource with full capacity and consumes high energy, so it is overcome using an energy efficient cloud server. Integrated forecasting method has been proposed to reduce the noise as well as energy consumption [3]. High scalable cloud models suffer power management problems because of thermal variations in the data center. Artificial Intelligence based learning methods predict the thermal level of various clouds such as private cloud and public cloud [4]. Offloading of computing resources and its allocation is done with energy efficiency. The transmissions of energy between the resources are formulated using various energy aware constraints [5]. Green computing model minimizes the energy cost and consumption of the cloud by considering various technologies like Virtual Machine (VM) migration and consolidation of resources etc. Agent helps the cloud provisioning process to perform live migration processes. Agents are classified into static agent and dynamic agent. This agent corrects and verifies the migration process and takes the decision with optimal policy [6]. Future generation cloud infrastructure suffers an energy awareness problem due to lack of resource utilization, high-energy management cost. This issue is rectified by using Advanced RL consolidation technique with corresponding agent. It determines the dynamic policy with minimum knowledge, which is accessed from environment [7]. Consolidation of the resource in the cloud computing is categorized into static and dynamic consolidation (DC). DC methods minimize the utilization of resources which reduces energy consumption. RL based DC techniques reduce the active VMs based on the current need. This method also defines the optimal energy model with suitable policy [8]. Applications that are deployed into a single cloud computing model lack issues like flexibility and scalability problems. Cloud model needs the application scheduling, allocation to the respective resource though service level agreement. RL based micro service deployment done with minimized energy [9]. The balance between energy saves and performance is assessed using a distributed dynamic VM approach. This model achieves optimum VM placement and elimination of workload allocation. Multiple agents are used with the RL method for learning cloud environments in order to make accurate decisions [10]. The main objective of the proposed model solves the issues analyzed in the existing model and provides energy efficient solutions to cloud computing.

3 System Model

Cloud computing technique uses the virtualization for mapping the physical machines to multiple virtual machines (VM) in order to execute the cloud requesting task. Data center holds various hosts with more number of VMs. The proposed system is formulated using an RL model with energy parameters. The energy efficiency is achieved by selecting optimal resources from the data center. Energy of the cloud resources are assessed and evaluated using a multiagent RL model. Three main elements are considered in the proposed algorithm namely Data center (DC) level, Host level and VM level. Energy of these resources are analyzed by respective agents. Cloud RL agents are performing actions for identifying the energy efficient resources that are formulated in single and multilevel agent models. Single Agent model is formulated with the attributes as **<State S, Action A, Transition T, Reward R>**. State space tree is prepared based on the VMs, Hosts and Data centers with S. Multi Agent models multiple state space trees are followed because multiple agents use different environments. The state space tree of the proposed model is shown in Figure 1.

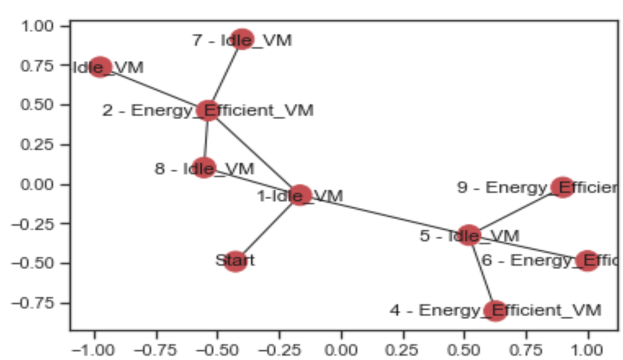

Fig. 1: State Space Tree.

VM Agent uses the action space A **<VM_{idle} , VM_{energy} , VM_{select}, $VM_{workload}$>** for performing actions from the action over the specific environment. The agent identifies idle VM in the data center; terminate that VMs. Energy level of the VM is identified based on the workload condition, and select the VM. Reward value R is calculated from the agent actions at the cloud resources. Policy π(S) is represented in single agent model as **(S,P,T,R)** and multi agent model as **(S_i,P_i,T_i,R_i).** The optimal policy π*(a|S) is represented in to the following equation (1) to (3),

$$\pi^*(a|S) = \begin{cases} \text{Energy Efficient, } a = \text{VM with correct work load} \\ \text{No,} \quad \text{otherwise} \end{cases} \tag{1}$$

$$a = \begin{cases} Enegy\ Level, VM\ Capacity == Workload\ Size \\ No \quad , otherwise \end{cases} \tag{2}$$

$$\text{Re}\,ward\ R = \begin{cases} +\gamma,\ if\ \ action = VM\ Select \\ -\gamma,\ otherwise \end{cases} \tag{3}$$

4 Architecture of Proposed RL Model

Energy efficient model with multi agent Reinforcement learning applied over the data center. The data center consists of various hosts and hosts contain different sets of VM. VMs execute the customer task by considering suitable resources. Cloud energy consumption is carried out on multiple levels because various elements are involved in cloud interaction. These elements' energy levels are analyzed with various agents such as DC agent, Host agent and VM agent. DC agent assesses the energy levels of various hosts and host energy levels are calculated from VMs of the particular host. Host agents collect consumption levels of various hosts and keep the host in a more energy efficient manner. The agent performs two types of actions namely VM selection, VM migration. If the VMs of the host perform enough number of tasks (i.e. workload) then analyze the energy level. Suppose the host VMs are holding minimum numbers of workloads then that workload is migrated to another host and terminate all VMs. This process reduces the energy consumption level because the idle host also consumes energy. Reward value is calculated based on the observation of the agents and policies that exist in the RL model. Multi-agent model maintains various policies that are analyzed and updated in an accurate manner. Figure 2 shows that the proposed multi agent model for minimizing energy consumption of cloud resources. Host consolidation process reduces the excess energy existing in the cloud.

5 Significance of Exploitation and Exploration

The workflows of the RL model need various elements for performing the learning process in an effective manner. Cloud computing domain maintains heterogeneous resources, which consumes more energy, so it leads to the performance problem. This issue is overcome by implementing energy aware models with multiple agents. Reward calculation is a major role in the RL because it decides correct action of the current state and evaluates the integrity of the agents. Reward is always represented as a scalar value, which is calculated using relevant function. This function is created based on the situations of the problem domain without any constraints. If the rewards are sparse then the agent performs the action in a longer sequence, which maintains a large number of states without any new reward value. It is solved by shaping the reward that provides the guideline to the agent for moving to the correct path. It also helps to inject domain related knowledge into the agent. The proposed RL model considers the environment as a data center, more than one agent for performing the action and multilevel policy. Three agents are used to assess the energy namely VM agent, Host agent and DC agent. VM agents select the energy aware VM from the VM list. Host agent finds the host which consumes minimum energy whereas DC agent decides which DC is energy efficient. Initially the first VM is selected by the agent and identifies energy consumption level . If the VM has workload (i.e. task for execution) then analyzing the energy level is called exploitation. Reward is calculated based on the energy level. Suppose the VM without workload is identified then the energy level is unable to calculate the reward value. The new reward value is known using the exploration method.

Exploitation process considered VM, which holds the reward value, and it ignores all other VMs that take longer time to find the best policy. It is also strict on the particular reward value of VMs without collecting additional information for improving the reward is shown in Figure 3. Exploration process of finding the new VM and calculating the reward value by using additional features with the highest reward is represented in Figure 4. It suffers convergence problems because of using more number of VMs and actions that produces large numbers of states [11]

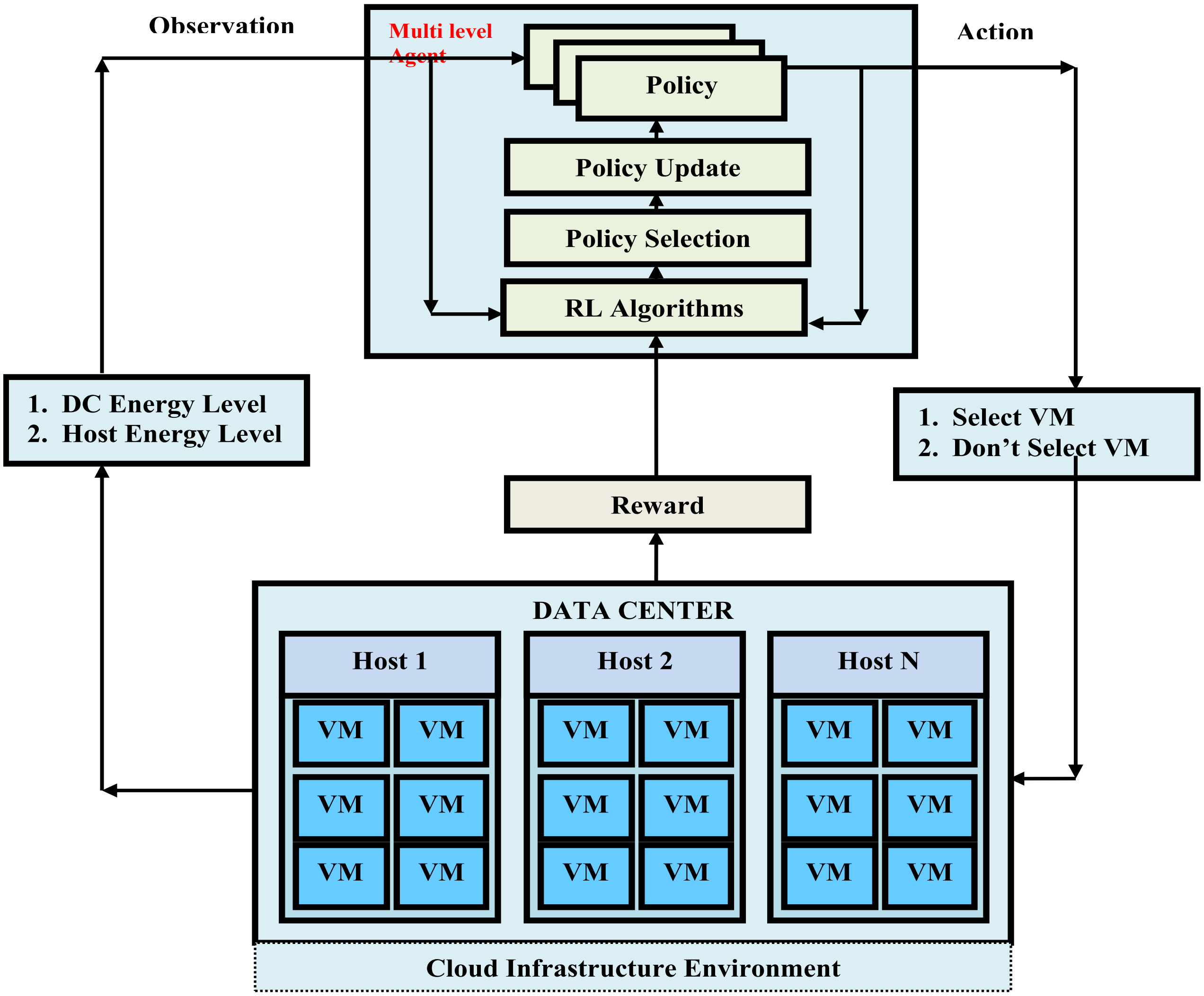

Fig. 2: Multi agent based Cloud energy model.

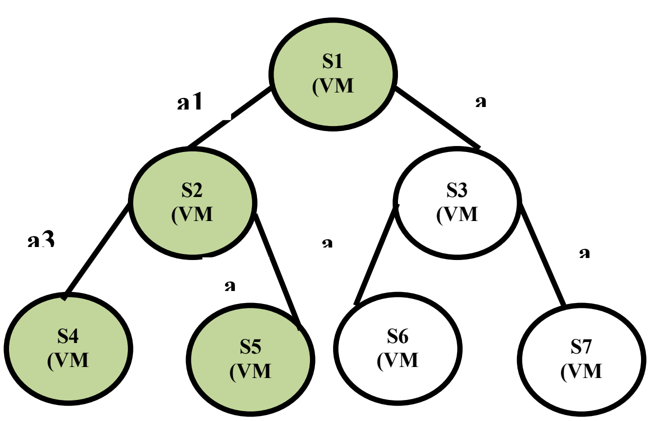

Fig. 3: Exploitation

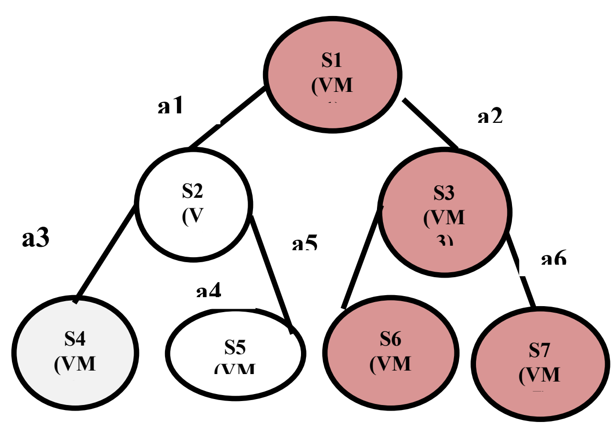

Fig. 4: Exploration

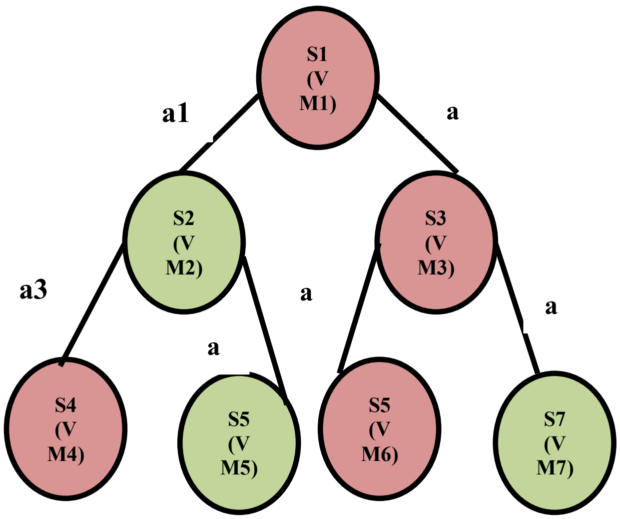

Fig. 5: Balancing of Exploration and exploitation.

The exploitation and exploration process are balanced using a simple method so that the agents use enough policy for the learning process. Excess exploration suffers the high reward without optimal policy whereas excess exploitation grows high reward with maximum number of states. Figure 5 presents the balancing process during the VM energy analysis. Reward value of the proposed RL model uses the reward value as [+5, 0, -5] related to the energy level of the cloud resources. Table I shows the representation of policy.

Table I: Policy Representation.

Agent State	**Action 1**	**Action 2**	**Action 3**	**Action 4**
State 1	0	+5	-5	0
State 2	0	0	0	+5
State 3	-5	+5	0	0
State 4	0	+5	-5	-5

6 Mathematical Analysis

Energy consumption of the data center, Host and VMs are calculated by considering the Graphics processing unit (GPU) and with CPU. It defines Microsoft VM analysis based on the power consumption [12]. The overall power of the cloud computing (E) is calculated with CPU and GPU. CPU consumes minimum energy when compared to GPU because of memory usage. CPU based Evm energy is calculated using equation (4).

$$E_{VM}\,[kWh] = \left[\frac{E_{VM} + E_{vMemory}}{1000}\right] \tag{4}$$

GPU based energy level is identified is represented in equation (5)

$$E_{VM}\,[kWh] = \left[\frac{E_{VM} + E_{vMemory} + N_{vGPU} * E_{vGPU}}{1000}\right] \tag{5}$$

Host and data center energy level consumptions are specified in equation (6) and equation (7) respectively.

$$E_{Host}[kWh] = \left[Number\ of\ VM * \left[\sum_{i=1}^{N} E_{VM}[vm_i]\right]\right] \tag{6}$$

$$E_{DC}[kWh] = \left[Number\ of\ Host * \left[\sum_{i=1}^{N} E_{Host}[host_i]\right]\right] \tag{7}$$

Energy value with the threshold value ξ is represented in equation (8)

Energy value (ξ) =

$$\begin{Bmatrix} Energy\ of\ Vcpu\ , if\ E >= Nc * (Memory\ Energy) \\ Energy\ of\ Vgpu, if\ E <= Nc * (Memory\ Energy) \end{Bmatrix} \tag{8}$$

Where, N_c is number of CPU.

Total reward of the agent is specified in equation (9) with Ω is the discount factor

$$\text{Total Reward R} = \sum_{i=1}^{N} \Omega^{i=1}\ R_i \tag{9}$$

Value policy is updated using a temporal learning model [Computational Intelligence by Andries P. Engelbrecht (2007)] for performing learning operations on the data center. Two factors are needed to update them are $V(S_{vm})$ and $e(S_{vm})$, where $V(S_{vm})$ is value policy and $e(S_{vm})$ is eligibility of the VM at particular state is illustrated in equation (10) and equation (11) .

$$V(S_{vm}) = [V(S_{vm})+\eta(R+\Omega(V(S'_{vm}))- V(S_{vm})]* e(S_{vm}) \tag{10}$$

$$e(Svm) = \begin{Bmatrix} 1\ ,\ e(Svm) == e(S'\,vm) \\ 0\ ,\ Otherwise \end{Bmatrix} \tag{11}$$

Equation (12) provides the optimal value policy formula with necessary parameters.

$$V^*(Svm) = \underset{a \in A_{VM}}{MAX} \left\{ R(\mathrm{S_{VM}} + \Omega \sum_{\mathrm{S'} \in \mathrm{S}} \mathrm{T}[(\mathrm{S_{VM}}), \mathrm{a_{VM}}, \mathrm{S'_{VM}}] * (\mathrm{v} * (\mathrm{S_{VM}})), \mathrm{S_{VM}} \in \mathrm{S'_{VM}} \right\} \tag{12}$$

Multi Agent Energy efficiency of the cloud resources are formulated in equation (13)

$$\text{Energy Efficiency}\,(\omega) = \begin{cases} \text{Engery Aware VM}, & E_{VM}[kWh] <= \xi \\ \text{Energy Aware Host}, & E_{Host}[kWh] <= \xi \\ \text{Energy Aware DC}, & E_{DC}[kWh] <= \xi \\ \textit{Non Energy Aware}, & \textit{Otherwise} \end{cases} \tag{13}$$

Cloud computing energy depends on various resources which are maintained in different levels so multiple agents are used to identify the energy in particular level with RL approach [13]. Energy efficiency level is fixed with upper threshold value ξ. If the resource energy level is minimum than the threshold select those resources for performing the task execution with energy aware manner.

7 Energy Efficient Consolidation (EESC) Algorithm

Cloud service providers concentrate to reduce cost and energy consumption in order to meet the customer demand. Dynamic workload causes the problem in the energy management process that is handled by consolidation and frequency scaling method [14] [15]. Scheduling and Reservation of the cloud resources is done by providing an efficient consolidation process with efficient resource utilization. Real Time VM consolidation algorithm solves the issues of parameter selection and handling of smart applications [16]. High performance data centers minimize the energy consumption by maximizing the host utilization with the VM consolidation process. Various factors affect the energy efficiency, namely on demand service maintenance, increase of cloud user access, size of the data center and number of physical hosts and so on. Meta heuristic based approach uses the best fit and first fit combination for selecting the host [17]. Data center in the cloud consumes a huge amount of energy that leads to the cost and carbon emission problem. VM consolidation method finds and terminates the idle VM for achieving optimal resource utilization and energy consumption [18].

The EESC algorithm terminates the host and VM which are in an idle state because idle resources also consume energy. Initially the host capacity of the particular DC is identified and compares with the workload. VMs of the particular host hold maximum workload then keep that host for processing the user request. Suppose the VMs are executing a minimum task than actual VM count then those tasks are migrated to efficient host and terminate that host [19]. The reward value is calculated based on the host capacity with workload size. The learning process performs the actions based on the reward value [20].

EESC Algorithm

Begin

For each DC Є Cloud do
  For each Host Є DC do
    Find the capacity of the Hosti;
    For each host Є Hosti do
      Find the active VMi and Idle VMi;
      Find

$$Host\_Space_i = Total\ \ Number\ of\ VM - Number\ of\ \ Active\ VM$$

        Find the associate resources of the VMi;
        Identify the energy level;
        Calculate the reward;
          If Host_Spacei > Host_Spacei+1 then
            If Host_Spacei > Idle_VMi then
              Migrate to Hist_Spacei
              Terminate the host with all VMs;
              Reward ← +δ
          Else
              i ← i+1
              Reward ← -δ
          End;
        End;
      End
End
Return reward;
End;

VM migration and consolidation process is carried out over data center resources for terminating the idle host and VMs and also achieves reduced energy. Figure 6 workload execution traces of active machines in the efficient host. Figure 7 provides the host level energy analysis. The proposed analysis is efficient when compared to DWC, RTVMC and Meta-Heuristic consolidation Algorithms.

which VM is suitable for processing the task. Global agent

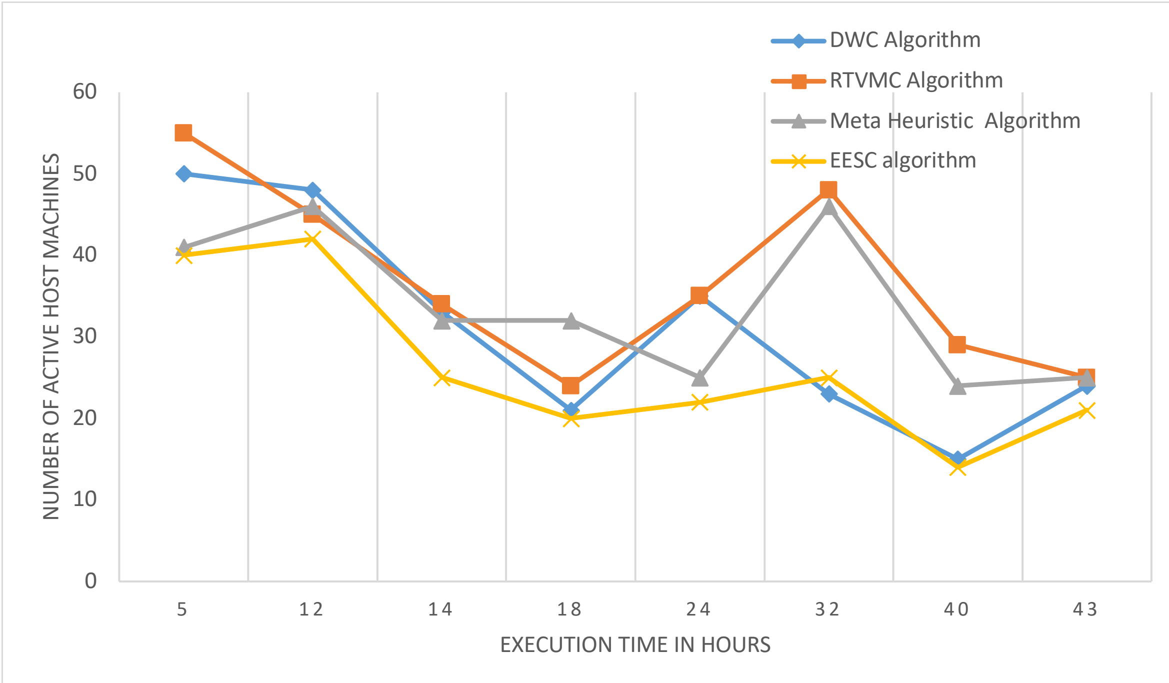

Fig. 6: Active host machine Vs Exectuion Time.

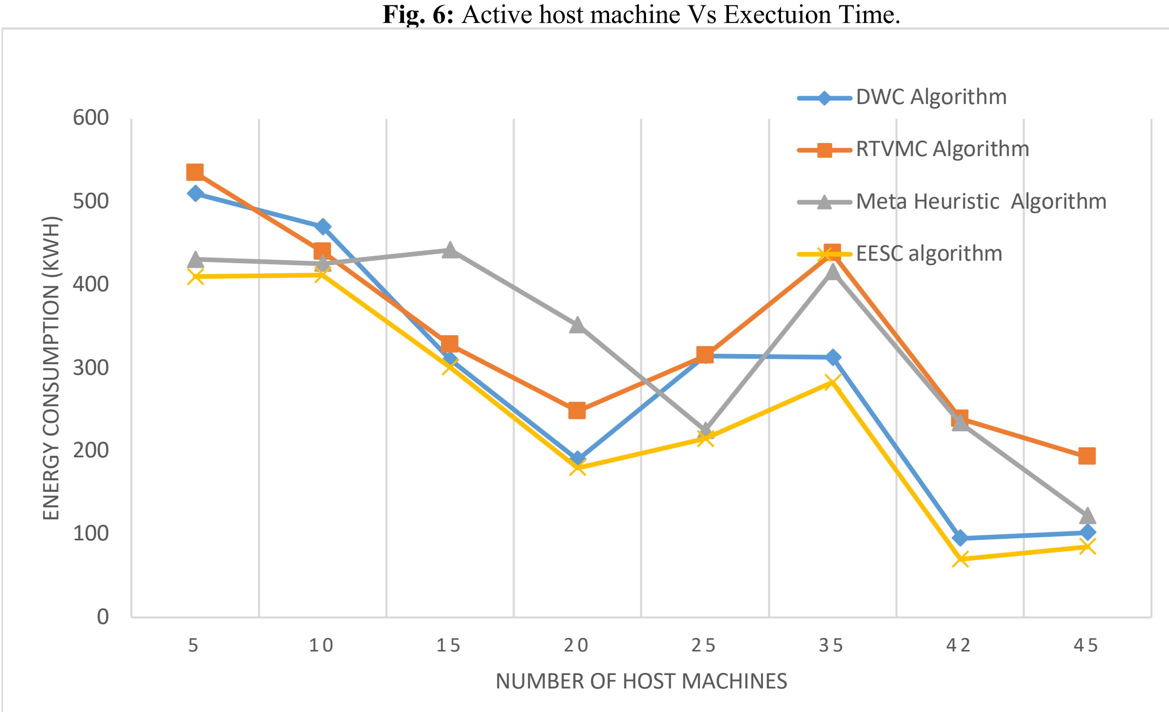

Fig. 7: Energy Analysis of Host Machines.

8 Results and Discussion

Multi Agent (MA) model is done for consolidating the user task to the VM in dynamic manner using two types of agent namely local agent and global agent. A local agent decides places the VM based on the local agent's assessment. The energy reduction ratio of MA based dynamic consolidation (MADC) is 31.9% [21]. MA based self-adaptive (MASA) models manage the cloud resources in an energy efficient manner. Physical Machine with threshold limit is applied for adjusting the CPU, memory and other devices using the RL model with 5.9% energy reduction [22]. Two phases (TP) optimized algorithm with parallel execution (TPOE) model performs RL based operation that decides virtual resources selection. It uses the MARL reduces the number of states and action values by considering value function [23]. Twig is a task management cloud service that follows the RL model by reducing the latency and energy. It uses optimal policy that guides the agent to perform action over The cloud with 38 % and 99% as energy saving and service quality respectively [24]. The Proposed MAEC algorithm uses three types of agents for calculating the energy in the data center namely VM agent, Host agent and DC agent. These agents select and terminate the resources based on the situation of the data center energy consumption at particular time. The cumulative energy level decides the reward and agents action over the cloud environment. Table II represents the workload analysis of the host and VM [25].

Table II: RL Analysis of PlanetLab Workload.

Host	Virtual Machine	Requested Workload Size for VM (MIPS)	VM Size (MIPS)	Active Workload	VM Idle Workload
Host 0	26	172.64	1000	17.26%	82.80%
	27	985.15	1000	98.52%	1.48%
	39	367.84	500	73.57%	26.43%
Host 1	0	744.4	2500	29.78%	70.22%
	1	275.68	2500	11.03%	88.97%
Host 2	28	47.71	1000	4.77%	95.23%
	29	860.22	1000	86.02%	13.98%
	40	399.13	500	79.83%	20.17%
Host 3	2	1681.84	2500	67.27%	32.73%
	3	1213.12	2500	48.52%	51.48%
Host 4	30	422.69	1000	42.27%	57.73%
	31	235.2	1000	23.52%	76.48%
	41	305.38	500	61.08%	38.92%
Host 5	4	1369.53	2500	54.78%	45.22%
	5	900.81	2500	36.03%	63.97%
Host 6	32	298.15	1000	29.82%	70.18%
	33	110.66	1000	11.07%	88.93%
	42	86.61	500	17.32%	82.68%
Host 7	6	2306.96	2500	92.28%	7.72%
	7	1838.25	2500	73.53%	26.47%
Host 8	34	673.13	1000	67.31%	32.69%
	35	485.64	1000	48.56%	51.44%
	43	492.87	500	98.57%	1.43%
Host 9	8	1994.65	2500	79.79%	20.21%
	9	1525.93	2500	61.04%	38.96%

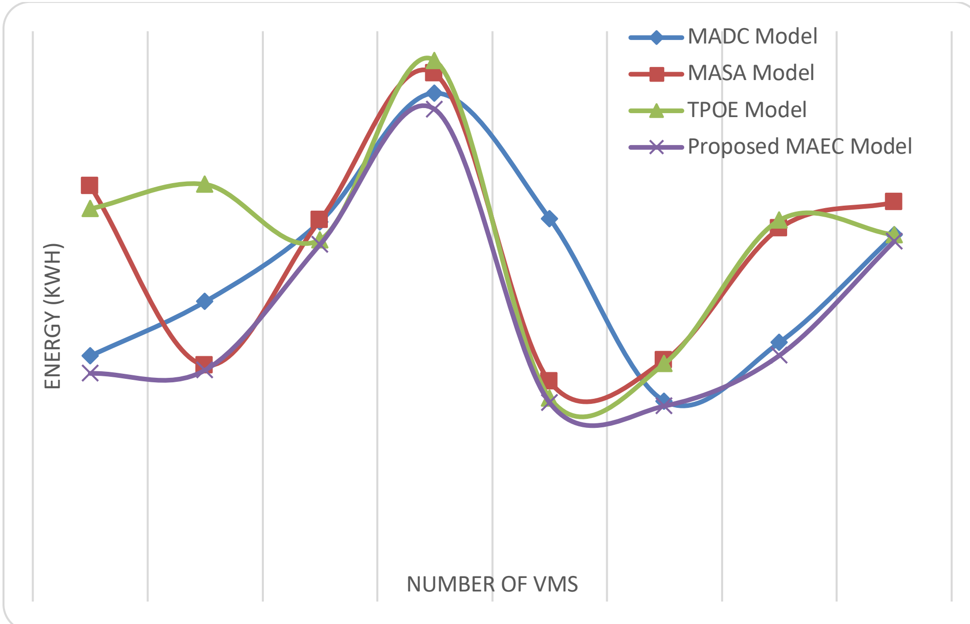

Fig. 8: VM Agent Energy Analysis.

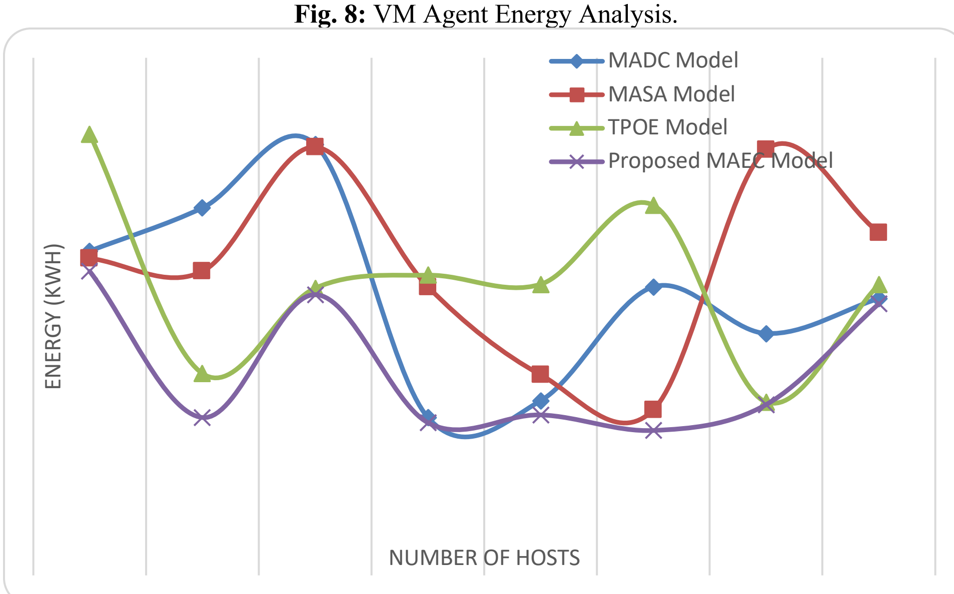

Fig. 9: Host Agent Energy Analysis.

Experimental result uses the cloudsim model with PlanetLab workloads with corresponding traces for analyzing the energy efficiency over the cloud resources. VM level energy analysis is done by using a VM level agent whereas a host level agent performs the host energy. The idle VMs are identified by setting the threshold level. If the VMs idle workload level is higher than threshold then these VMs are terminated. The remaining workloads are moves to energy efficient host. Figure 8 consumes minimum energy than existing models related to VM level. Host level analysis of energy is shown in Figure 9. The proposed MAEC model achieves high energy consumption when compared to MADC model, MASA model and TPOE model.

9 Conclusions and Future Work

Data centers maintain a huge number of elements and resources for executing cloud user tasks with high quality service. Existing power models are analyzed and identified the causes for performance degradation. Energy in the resources directly affects the service quality so it is handled in an efficient way. Generic and machine learning models minimize the resource energy but it is not efficient. RL based single agent models are not suitable for the entire cloud. This is achieved by implementing a multi agent RL model with multiple agents and policies. Reward value is calculated based on the actions of various agents and predicts future reward. Idle VMs on the hosts are identified and terminated successfully. Minimum workload hosts are also identified and those workloads are migrated to other efficient hosts. Host also terminated in order to minimize the energy consumption by the low utilized host. The proposed MAEC model achieves high efficiency with reduced energy consumption of the cloud resources when compared to other RL models. In future, this model can be applied to real workload and container-based environments.

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