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Hybrid Optimization Algorithm for Resource Allocation in SDN Enabled Virtual Networks in Cloud Environment

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Abstract

Software-Defined Networking (SDN) is an *emerging paradigm to logically centralize the network control plane and automate the configuration of individual network elements. At the same time, in Cloud Data Centers (DCs), although network and server resources are collocated and managed by a single administrative entity, disjoint control mechanisms are used for their respective management. To overcome those problems, in this paper, a hybrid optimization algorithm is proposed for resource allocation (HOA-RA) in SDN enabled virtual networks in IaaS cloud environment. In proposed HOA-RA, to introduce improved pattern search (IPS) algorithm to SDN structure, this imparts flexibility to remove the control layer from the data transfer layer to the control plane. Then, to combine the network virtualization principles with Enhanced swallow search (ESS) algorithm to share physical infrastructure to enable multiple service providers to access the network; The flexible access requires optimal rule based fusion (ORBF) algorithm to optimize the network resources; the SDN control plane can be used for efficient management of virtual networks. The proposed HOA-RA design is implemented in Cloudsim environment. The results and performance analysis show that the proposed HOA-RA design perform very efficient than existing state-of-art designs.*

Keywords *Software-defined networking, Resource allocation, SCO, Cloud computing, CSO, Virtual network, NLP*

Introduction

Cloud-to-Cloud (C2C) migration enables the organizations to switch among various cloud environments without rebuilding the whole system on another cloud. Numerous virtual machines (VMs) placed in one cloud-computing environment during the C2C migration are moved to another [1]. Despite the increasing popularity of studies for joint resource optimization in the cloud environment with SDN technology, the realization is still limited for developing integrated management platform providing a simultaneous controllability of computing and networking infrastructures [2]. As these applications are communication-intensive, optimizing network transfer between VMs is critical to the performance of these applications and network utilization of data centers [3]. Virtual network provisioning is considered to be a main resource allocation challenge in any virtualized network environment. Software-defined networking (SDN) imparts flexibility to a network by removing the control layer from the data transfer layer of the network and moving it to the control plane. Network virtualization is further employed to share physical infrastructure to enable multiple service providers to access the network [4][5]. Such a bottleneck however does not exist in conventional physical machines or to a much lower degree [6]. One approach to accommodating IP traffic on a wavelength-routed network is to construct a virtual network topology (VNT) and reconfigure the VNT according to traffic changes. Guided by attractors, the VNT control method searches for a solution: a VNT that can accommodate the IP traffic [7].

In a cloud hosting multi-tenant applications, virtual service providers can be provided with real-time recommendation techniques to allocate their virtual resources in edge, core, or access layers in an optimal way to minimize costs and footprint. Such a dynamic technique requires a flexible and optimized networking scheme to enable elastic virtual tenants spanning multiple physical nodes. A virtual slice

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consists of optimal flows assigned to virtual machines (VMs) in a virtual data center taking into account traffic requirements, VM locations, physical network capacity, and renewable energy availability [8][9].Traditional energy-aware VM allocations either allocate VMs to PMs in a centralized manner or implement VM migrations for energy reduction without considering the migration cost in cloud computing systems. We address these two issues by introducing a decentralized multiagent (MA)-based VM allocation approach [10]. Resource allocation in Cloud Computing has been done reactively, hindering service guarantees and generating unnecessary charging of idle resources[11]. Online mechanism makes no assumptions about future demand of VMs, which is the case in real cloud settings. The proposed online mechanism is invoked as soon as a user places a request or some of the allocated resources are released and become available. The mechanism allocates VM instances to selected users for the period they are requested for, and ensures that the users will continue using their VM instances for the entire requested period [12] [13].

We formulate a multiobjective optimization problem of resource allocation, which considers the CPU and memory utilization of virtual machines (VMs) and physical machines (PMs), and the energy consumption of data center [14] [15]. Due to the existence of resource variations, it is very challenging for Cloud workflow resource allocation strategies to guarantee a reliable Quality of Service (QoS) [16]. If prediction is available, we demonstrate that existing prediction-based control algorithms lack worst case performance guarantees for our problem, and we design two novel predictive control algorithms that inherit the theoretical guarantees of our online algorithm, while exhibiting improved practical performance [17] [18]. WebIDE is leveraged for IoT application development, which could adapt to the rapid growth of IoT applications and meanwhile facilitate the rapid development. Resource allocation is of vital significance in the WebIDE cloud service system [19]. Due to the shared nature of cloud computing, QoS may be impacted by interference with co-hosted services. In this paper, we propose an adaptive control approach for resource allocation that adaptively reacts to dynamic request workloads and resource demands [20].

The main contribution of this paper is as follows.

We formulate and proposed an proposed a hybrid optimization algorithm is proposed for resource allocation (HOA-RA) in software defined network (SDN) enabled virtual networks in IaaS cloud environment.

- This imparts flexibility to remove the control layer from the data transfer layer to the control plane
- Increasing the performance and throughput of the controller by decreasing processing delay of the flows and allocation more resources
- we provide an implementation model to recommend the optimized resource allocation schemes to virtual data center service providers based on software defined techniques
- Improving of the resource consumption by releasing the extra resources

This paper is organized as follows. Section 2 reviews previous work from the literature that is related to virtual network resource allocation. Then, section 3 describes about existing issues and system model for this framework. Section 4 presents the performance analysis of the proposed method. Simulation results are discussed in Section 5. Finally, Section 6 concludes the paper and describes the perspectives to this work

3.2 System model

Regarding to the large volume of incoming flows into the network, a problem is related to find the optimizedpaths by the controller in SDN networks. If the controller has not enough resource to handle these requests, then a performance of proposed HOA-RA is created. This module is the main part of the IAAS which plays a controller role in Cloud computing and manages system resources. It also provides virtual machines and servers based on the user requests. In this condition, to achieve the required performance and high scalability, improving performance of the controller by increasing the number of access point in a

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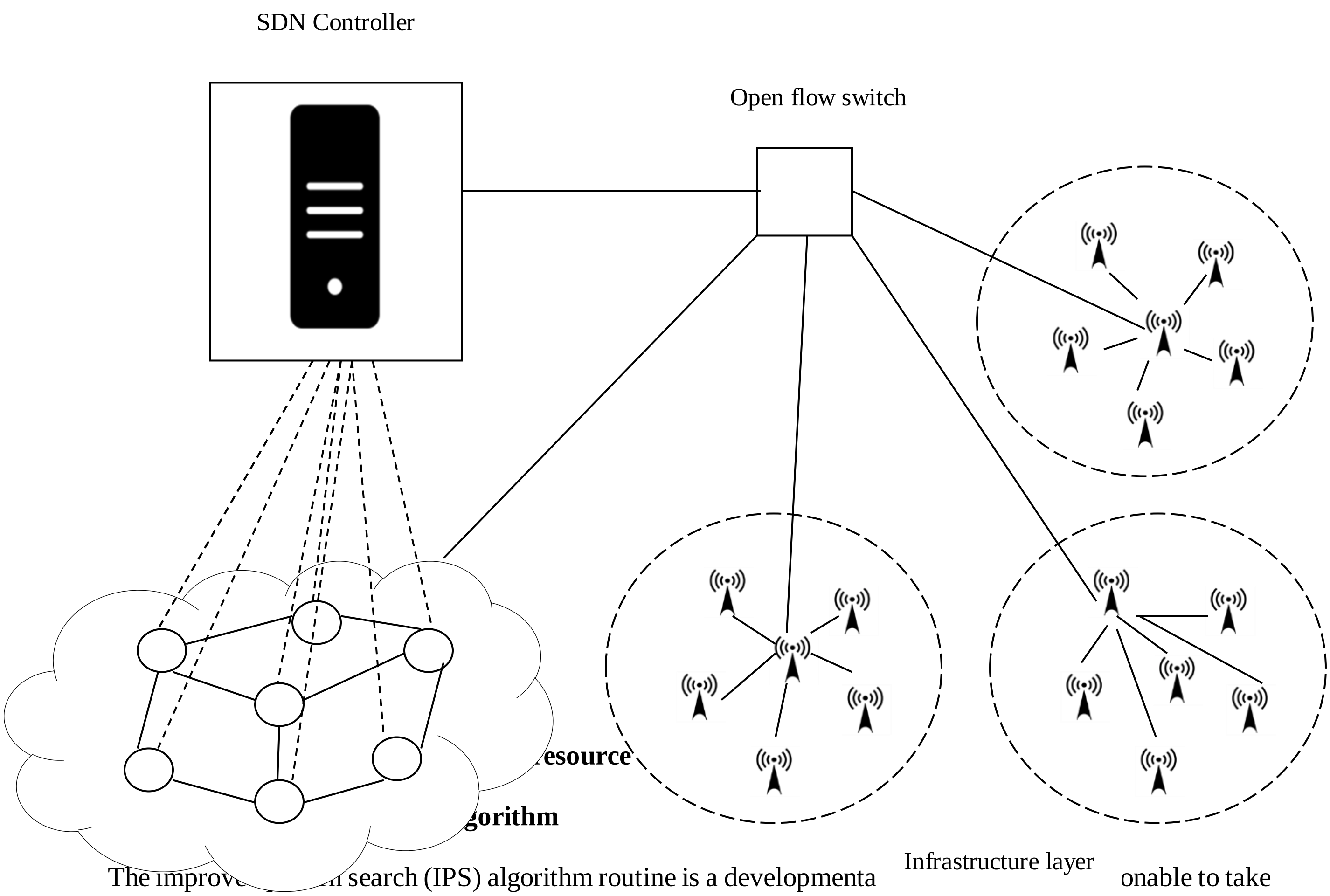
linear order can be a useful solution. In this paper, the memory as main resources of the controller is allocated adaptively. In this Section, firstly, the integration of SDN and Cloud is presented then the allocation of resources to the SDN controller in an adaptive manner is described.The system model for our proposed work is shown in Fig.1.

Fig.1 Proposed HOA-RA in SDN enabled virtual networks



esource

gorithm

The improv... search (IPS) algorithm routine is a developmenta ... onable to take ca... f advancement issues that lie outside the e... enhancement str... other heuristic calculations, for example, hereditary calculations, PS has an ada...ed administrator to upgrade and adjust the worldwide and calibrate neighborhood search. A valuable audit of direct scan strategies for unconstrained advancement, though subtleties of the execution embraced in this paper. These returns by figuring a succession of focuses that may not move toward the ideal worth. The calculation begins by building up a lot of focuses called a work, around the given point. This present point could be the underlying beginning stage provided by the client or it could be registered from the past advance of the calculation. The work is shaped by adding the present point to a scalar various of a lot of vectors called an example. In the event that a point in the work is found to improve the target work at the present point, the new point turns into the present point at the following cycle. The example inquiry improvement in bunch hub trust esteem calculation procedure is appeared in Fig. 2

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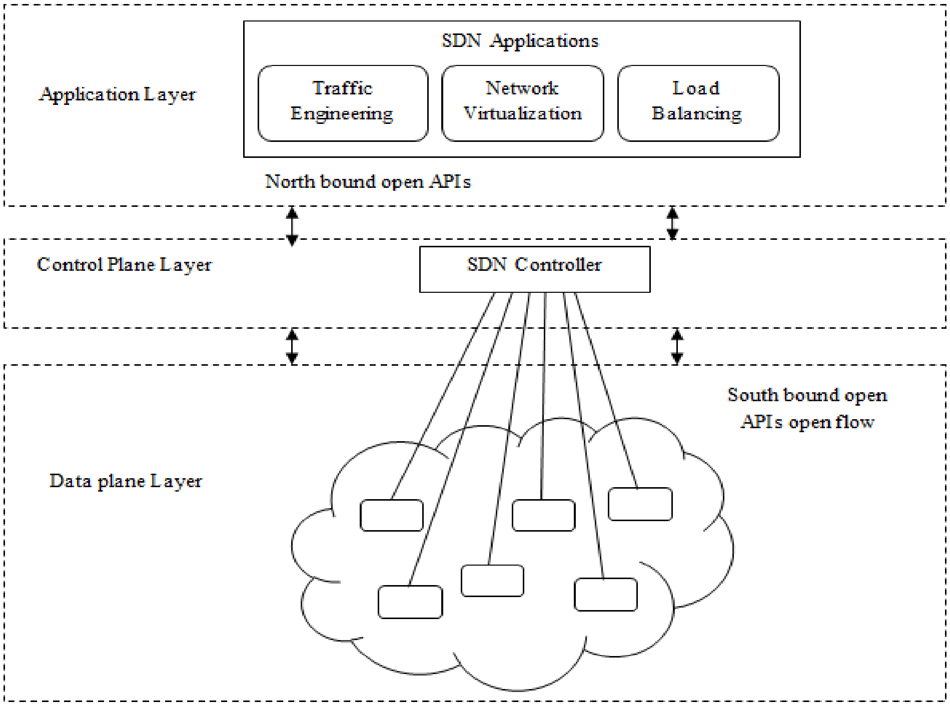

Fig.2 SDN structure using improved pattern search algorithm

4.1.1. Mathematical formulation

The detailing of the dynamic monetary dispatch comprises of the customary plan of the ED planned over some stretch of time and enhanced by certain framework limits and operational imperatives. In this segment, the plan of the DED is exhibited and the expansion of an emanation record is additionally considered. The target capacity of the common DED is as per the following

$$g_1 = G = \sum_{m=1}^{M} \sum_{i=1}^{N} G_{im}(V_{im}) \tag{1}$$

with the incremental fuel cost functions of the generation unit switch valve-point loading represented as:

$$G_{im}(V_{im}) = a_i V_{im}^2 + b_i V_{im} + c_i + | e_i \sin (g_i (V_{i\min} - V_{im})) | \tag{2}$$

Where ai; bi; ci; ei; fi are the cost coefficients of ith unit, Vim is the yield intensity of ith unit at time m, Vim in is the lower age destined for ith unit, N is the quantity of age units, M is the quantity of hours in the time skyline. In the event that the emanation file is considered, at that point the accompanying extra term ought to be added to the plan

$$g_2 = E = \sum_{m=1}^{M} \sum_{i=1}^{N} E_{im}(V_{im}) \tag{3}$$

and the amount of emission of each generator can be expressed by

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$$E_{im}(V_{im}) = \alpha_i V_{im}^2 + \beta_i V_{im} + \gamma_i + \eta_i \exp(\delta_i V_{im}) \tag{4}$$

The following term is considered as the objective function to the combined economic and emission dispatch and the minimization problem is represented as

$$Min\ (g_1 + g_2) = Min\ (G + E) \tag{5}$$

Subject to real power balance

$$\sum_{i=1}^{N} V_{im} = V_{Dm} + V_{Lm} \tag{6}$$

Real power operation limits

$$V_{i\min} \langle V_{im} \langle V_{i\max}, \quad i \in N,\ m \in M \tag{7}$$

Generating unit ramp rate limits

$$V_{im} - V_{i(m-1)} \le UR_i \quad i \in N,\ m \in M \tag{8}$$

$$V_{i(m-1)} - V_{im} \le DR_i \quad i \in N,\ m \in M \tag{9}$$

Where i=1, 2,……, T. $V_{Dm}$is the load demand at time m, V_{Lm} is the transmission line losses at time m, V_{imax} is the upper generation bound for i^{th} unit, and UR_i and DR_i are the ramp-up and ramp-down rate limits of the i^{th} generator, respectively.

Pattern Search Algorithm is an immediate technique proposed by Hooke and for taking care of the unconstrained advancement issue. This strategy makes hub heading move and style move on the other hand. Reason for hub course move is investigating the better heading of lessening (for taking care of minimization issue). The reason for the example search calculation is to effectively discover design in the tree which is closest neighbors of a given test design. Looking is done in a best-first way, that is, the example whose sub-tree could contain the example least removed from the inquiry example is looked straightaway. Motivation behind style move is quickening decline along great heading. This estimation of this parameter can be changed powerfully to take into account pretty much looking under different conditions, for example, time imperatives. A rundown of comparative patters is returned by the calculation. Given target work ( ) f X and hub heading (1, 2,) I ei n =, the means of Algorithm is as followings. The calculation includes a branch and bound ability which permits parts of the hunt tree to be cut-off during the inquiry: As less far off example are discovered, more prominent cut-off is accomplished. This is on the grounds that an example doesn't need to be looked if its hunt separation is more noteworthy than the separation of a recently discovered example.

4.2 Network virtualization model using ESSO algorithm

The enhanced swallow search optimization (ESSO) algorithm used to analyze the network visualization. They have social life, migrate together, and find appropriate places for resting, breeding, and feeding. Swarm moving (swarm intelligence) keeps them immune against the attacks of other birds. A pair of

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swallows has to search a wide area in order to find food, while in collective living as soon as one swallow finds food, other birds of the group fly toward that area and enjoy it. Swallows are very intelligent birds. They fly quickly, and there is a strong interaction between members of groups. They apply different sounds in different situations that the number of these sounds is more than other birds' and even signal of swallow's sound is used as a special model in signal processing. Many creatures have a social life and live in groups, including birds. A variety of birds in the small and large colonies have a social life, and each one has certain characteristics and social behaviors. By investigating these behaviors and getting inspired by them, various optimization algorithms have been presented, such as PSO. These swallows have unique characteristics and social behaviours that have attracted our attention.

4.2.1 Objective

Major idea of this new optimization algorithm is inspired by swallow swarm. There are three kinds of particles in this algorithm: Explorer particle (ei); Aimless particle (oi); Leader particle (li). These particles move parallel to each other and always are in interaction. Each particle in colony (each colony can be consisted of some sub colonies) is responsible for something that through doing it guides the colony toward a better situation.

Explorer particle: These particles encompass the major population of colony. Their primary responsibility is to explore in problem space. With just arriving at an extreme point (swallow), using a special sound guides the group toward there, and if this place is the best one in problem space, this particle plays role as a leader head (LHi). But if the particle is in a good (not the best) situation in comparison with its neighboring particles, it is chosen as a local leader LLi; otherwise, each particle (ei) regarding PLHi (velocity vector of particle toward HL),PLLi (velocity vector of particle toward LL), and competence of resultant of these two vector makes a random move.

$$P_{LH_{i+1}} = P_{LH_i} + \alpha_{LH}\, rand()(e_{best} - e_i) + \beta_{LH}\, rand()(LH_i - e_i) \tag{10}$$

$$\alpha_{LH} = \{if\,(e_i = 0 \,\|\, e_{best} = 0) \rightarrow 1.5\} \tag{11}$$

$$\alpha_{LH} = \begin{cases} if\,(e_i < e_{best})\,\&\&(e_i < LH_i) \rightarrow \dfrac{rand().e_i}{e_i.e_{best}}\; e_i,\; e_{best} \neq 0 \\ if\,(e_i < e_{best})\,\&\&(e_i > LH_i) \rightarrow \dfrac{2rand().e_{best}}{1/(2.e_i)}\, e_i \neq 0 \\ if\,(e_i > e_{best}) \rightarrow \qquad \dfrac{e_{best}}{1/(2.rand())} \end{cases} \tag{12}$$

$$\beta_{LH} = \{if\,(e_i = 0 \,\|\, e_{best} = 0) \rightarrow 1.5\} \tag{13}$$

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$$\beta_{LH} = \begin{cases} if\,(e_i < e_{best})\,\&\,\&(e_i < LH_i) \rightarrow \dfrac{rand().e_i}{e_i.LH_i}\; e_i,\; LH_i \neq 0 \\ if\,(e_i < e_{best})\,\&\,\&(e_i > LH_i) \rightarrow \dfrac{2rand().LH_i}{1/(2.e_i)}\, e_i \neq 0 \\ if\,(e_i > e_{best}) \rightarrow \qquad \dfrac{LH_i}{1/(2.rand())} \end{cases} \tag{14}$$

Vector VLHi has a significant effect on explorer particle behavior. ei is the particle current position in problem space. ebest is the best position that particle remembers from the beginning up to now. LHi is a leader particle that has the best possible response in current position. αLH and βLH are the control of acceleration coefficients that are defined adaptively. These two parameters change during the particle movements, and this change depends on the particle's position. If the particle is a minimum point (minimizing problem) and is in a better position than the ebest and LHi, probability of being a global minimum for that particle should be considered and control coefficients estimate a small amount to decrease the particle movement to the least. If the particle is in a better situation than ebest but is in worse situation than LHi, it should move toward LHi with an average amount. If the particle position is worse than ebest, consequently it is worse than LHi too, so it can move toward LHi with a larger amount. Remember that the vector of VLLi affects this movement.

$$V_{LLi+1} = V_{LLi} + \alpha_{LL} rand()(e_{best} - e_i) + \beta_{LL} rand()(LL_i - e_i) \tag{15}$$

$$\alpha_{LL} = \{if\,(e_i = 0 \,\|\, e_{best} = 0) \rightarrow 2\} \tag{16}$$

$$\alpha_{LL} = \begin{cases} if\,(e_i < e_{best})\,\&\,\&(e_i < LL_i) \rightarrow \dfrac{rand().e_i}{e_i.e_{best}}\; e_i,\; e_{best} \neq 0 \\ if\,(e_i < e_{best})\,\&\,\&(e_i > LL_i) \rightarrow \dfrac{2rand().e_{best}}{1/(2.e_i)}\, e_i \neq 0 \\ if\,(e_i > e_{best}) \rightarrow \qquad \dfrac{e_{best}}{1/(2.rand())} \end{cases} \tag{17}$$

$$\beta_{LL} = \{if\,(e_i = 0 \,\|\, e_{best} = 0) \rightarrow 2\} \tag{18}$$

$$\beta_{LL} = \begin{cases} if\,(e_i < e_{best})\,\&\,\&(e_i < LL_i) \rightarrow \dfrac{rand().e_i}{e_i.LL_i}\; e_i,\; LL_i \neq 0 \\ if\,(e_i < e_{best})\,\&\,\&(e_i > LL_i) \rightarrow \dfrac{2rand().LL_i}{1/(2.e_i)}\, e_i \neq 0 \\ if\,(e_i > e_{best}) \rightarrow \qquad \dfrac{LL_i}{1/(2.rand())} \end{cases} \tag{19}$$

$$V_{i+1} = V_{HLi+1} + V_{LLi+1} \tag{20}$$

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$$e_{i+1} = e_i + V_{i+1} \tag{21}$$

Every particle utilizes nearest particle LLi in order to compute the vector of VLLi.

5. Result and Discussion

In this section, initially we start with sample evaluation, whichdescribes the evaluation scenario with the request and host pairfurther, we demonstrate the simulation scenario with the help ofexperimental results.For this purpose, the performance,memory consumption and CPU usage are evaluated. For these evaluations, networks with different numberof switches and the tree topology are investigated. The software and hardware specifications is presented in Table.1

Table: 1 Hardware and software specifications

Physical Server type	HP Proliant DL 380 G5
16GB PC2-5300F	Total memory
Proessor model	IntelR©XeonR©CPU X5460α3.16GHz
XenServer 6.5 SP1	Hypervisor
8 CPUs x 3.166 GHz	Number of CPU cores
OpenDayLight Helium	SDN controller

5.1 Experimental evaluation

To perform sample evaluation on VM request allocation, we consider 3 requests and 3 hosts with configurations as mentionedinTable 2andTable 3respectively.Table 2 depicts evaluation ofdifferent functions used in our proposed algorithm for all possible combinations of given request and host pairs.

Table: 2 Request configurations

Req ID	RAM	No. of cores	CPU	Cd	Uti
R1	1740	1	2500	0.26	20
R2	1740	2	2000	0.5	30
R3	512	4	2000	0.67	50

Table: 3 Host configurations

Host ID	RAM	No. of cores	CPU	Pmax	Pmin	Tsi	Tai	Uti

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H1	4096	2	1000	170	105	30	24	60
H2	4996	4	1500	169	130	20	40	40
H3	4996	4	2500	120	100	40	8	80

As shown in Table 4, tuple 3 for R1 and tuple 5 and 9 for R2 and R3 respectively depictthat it chooses the request-host pair having the minimum energy consumption and less SLA violations. Hence, their linear combination presented by functionCal, gives minimum value. So, for theconsidered host-request pair, R1 and R2 are allocated to H3 andR3 is allocated to H2. We can analyze from theTable 4that it optimizes the resource allocation by selecting the host with the mini-mum value of both the parameters. We simulated our algorithm for performance and energy-efficient resource allocation. Simulation approach is used to repeatthe experiments under an analogous environment. Thus, the comparison of different scheduling strategies is possible.The CloudSim has been chosen as a simulation platformsince it allows the demonstration of virtualized environments withon-demand resource provisioning and management. Also, to use workload traces collectedfrom a real system, PlanetLab workload is used,that consist different readings of CPU utilization collected at interval of 5 min of VMs of different host scattered around the world.We have considered random total 288 readings of different VMsfor 24 h of different host. Planet Lab workloadcovered readings of around 5000 virtual machines. In our experiments, we consider physical machine with multi-core having same core capacity for each core. VMs considered to be a resourcerequest type, and the request characteristics are consider as theattributes of VM, which include the

5.4 Simulation analysis

Although several experiments are performed by varying the values of user's preference, in this section, we discuss the only key results having the values showing the equal priority (k=0.5) to each objective. Experiments are run for multiple times and average values of result are considered as final results as shown in Tables 5. The comparisons of results are summarized in fig.3and fig.4. Further, we generate random values off, to assign random priority to objectives.

Table 5: VM configuration

VM types	VM PES	VM MIPS	VM Storage	VM RAM	VM BW
1	1	2500	1000	1000000	2500
2	1	2000	1800	1000000	2500
3	1	1500	1800	1000000	2500
4	1	500	700	1000000	2500

We compare the utilization of 5 hosts included in the experiment and select the host with the average utilization. To identify the average utilized host, utilization is calculated for the period of 24 h. Thesimulation results presented in Table 5show that selection of average utilized host brings higher energy saving compared with other allocation policies. It can be noticed that while applying proposed HOA-RA technique for selection of (request, host)pair, it predicts the possible power consumption of host and n

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Accordinglyselects the most appropriate host. Energy consumptions measured in average value of KW/hr over the simulation period of 24 h. From the Table 6, we can notice that using proposed HOA-RA technique, power consumption is about 30.2 Kw/hr, the values are nearer tobest energy efficient technique WPC. This clearly shows the importance of selection of appropriate host, which can result in efficientpower consumption in data center.Fig. 3 & 4depicts the comparisons of energy consumption and SLAV with proposed HOA-RA and existing state-of-art.

5.5 Performance metrics

Performanceof application is affected by fluctuation in CPU demands of host.If VM request of CPU demand exceeds to CPU capacity of host, itresults into performance degradation and hence, violations ofSLA. When CPU demand is higher than CPU capacity, VM will be migrated to new host to improve performance. When performance of application degrades, it affects to SLA. To evaluate SLA Violations(SLAV), we have considered SLA violation Time per Active Node(SLATAN) and the overall performance degradation due to VMmigration(PDM). We are interested in selecting a host with less SLAV. Two measurement metrics are used to calculate SLAV:

- SLA violation time per active node (SLATAN) (where node experience maximum utilization)
- Performance degradation due to migration(PDM) of virtual machine

$$SLATAN = \frac{1}{M}\sum_{j=1}^{M}\frac{D_{cj}}{D_{sj}} \tag{23}$$

$$PDM = \frac{1}{N}\sum_{j=1}^{N}\frac{A_{bj}}{A_{dj}} \tag{24}$$

$$SLAV = SLATAN \times PDM \tag{25}$$

Technique	Energy consumption	SLAV	SLATAN	VM migration	PDM
ProposedHOA-RA	28.5	3.21	10.14	4800	0.22
MOOA	30.2	5.41	9.81	4778	0.26
Watts per core	29.8	10.78	-	-	-
LLC	34.96	6.32	7.30	3345	0.47
Round robin	30.33	11.10	-	-	-
NPA	150.68	-	-	-	-
DVFS	615.8	-	-	-	-

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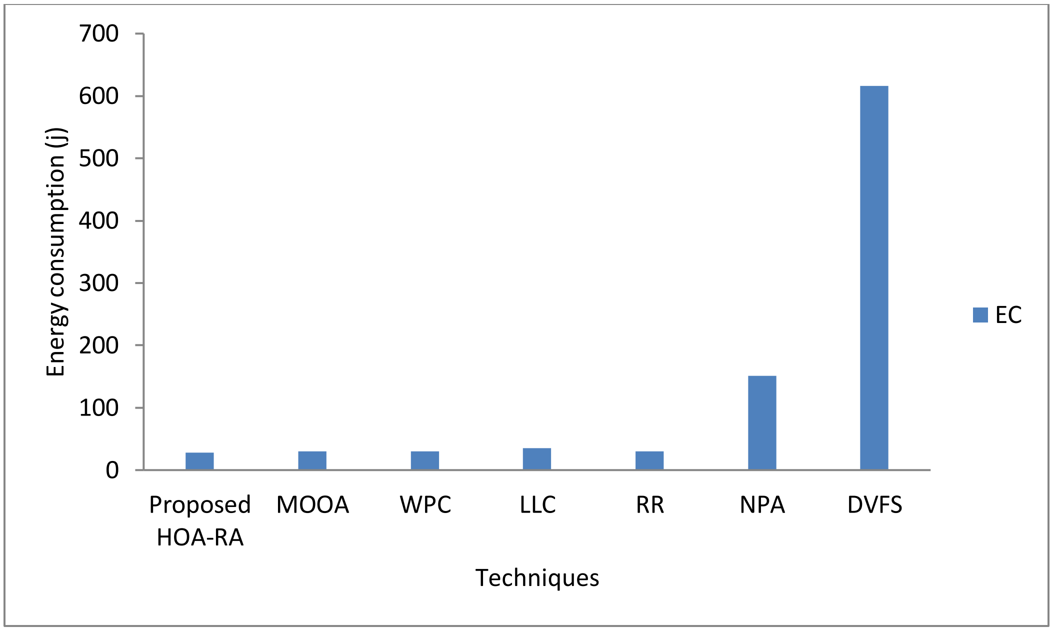

Conclusion

In this paper, a proposed HOA-RA technique is implemented for improvingstorage resource allocation in network using load distribution clusters. Since in the proposed method, improved pattern search method is used for making SDN structure, network load balance ispreserved by preserving load balancing of clusters and byallocating high quality groups in terms of average numberof hubs and average delay between server and user, qualityof service and network efficiency can be increased for datawith higher recall. On the other hand, increasing number ofclusters is directly related to storage capacity of the net-work and by increasing number of cluster, network storage can be increased. The proposed HOA-RA method can be used as a preprocessing in networks to store high-volume data. Inaddition, considering priority of groups, users can beclassified and provide each class with desired quality level.

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