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Power Aware Energy Efficient based Virtual Machine Migration Using Enhanced Pelican Remora Optimization in Cloud Center

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Abstract: Cloud computing technology is widely used in many industries to build a large-scale data center. One of the main challenges in this technology is to minimize the energy utilization in data centres. The quality of service is remarkably obsessed with percentage of power utilization in cloud centres. Many methods have been explored to minimize the energy consumption and for effective Virtual Machine (VM) migration. But failed to attend the significant outcomes in migration and consolidation problems. Consolidation of VM into the minimal number of physical machines is considered one of the best solutions to consume minimum power. This research proposed an Energy Migration Optimized using Enhanced Pelican Remora (EMOEPR) for achieving the suitable placement of VM into minimum possible physical machine to diminish the number of overload hosts as much as possible. Also, it minimizes the energy consumption without violating service level agreement. The proposed method is simulated using Cloudsim Toolkit. The experimental procedure done on different workloads with various sizes of VM and PM, shows that does not affect service level agreement and outperforms compared with the existing techniques. The proposed method reduced 5% energy consumption, 22.62% of VM migrations, 8.62% of service level agreement violation when compared with the existing techniques.

Keywords: Energy consumption, Consolidation, Migration, Mapping, Service level agreement violation.

1. Introduction

Cloud computing has gaining an incredible place in a general computing platform for receiving and sending services over the internet in past decades. This technology is mostly scalable and reproducible in various services. [1, 2]. The physical machine (PM) compiles with numerous Operating Systems (OS) securely and independently to achieve the power efficiency. Energy consumption is mainly focused for cloud datacenters since it requires more energy that is almost equivalent to 25000 household utilized. According to study, around 2% electricity is consumed by datacenter in United states. It estimated that datacenters using 18% of total energy in worldwide [3, 4]. VM can access in the particular resources and dispute with the service level agreement (SLA) cloud users [5]. Choosing the right VM is one of the important steps in consolidation. The trade-off should be considered to reduce the power utilization in cloud centers [6, 7].

One of the main problems in cloud computing is selecting the appropriate placement of VM on PMs in data center. Achieving optimal placement could minimize the energy consumption [8-10]. Several techniques have been suggested in recent times for VM placement. But these techniques are not efficient to balance the resources and to minimize the power. In this research, an energy efficient based VM migration EMOEPR is proposed. The primary contributions of the research are as follows,

- To map the migrated VMs into the best possible PMs, EMOEPR is proposed based on the hybrid strategy of enhanced pelican and remora optimization.

- It achieves the nearest optimal solution by maximizing the fitness function of remora optimization and minimum energy consumption is achieved by minimizing the fitness function of pelican optimization. It depends on the weighted parameter of both active hosts and overloaded hosts. The overall computational complexity is reduced.
- The proposed technique specifically reduces the count of overloaded hosts as much as possible by consolidating the suitable placement of VMs into the appropriate possible PMs.

The structure of the research is specified as follows; Section 2 explains some recent literature works based on energy efficient VM migrations. Section 3 explains the proposed methodology. Section 4, explains the execution outcomes and discussions of proposed method. Finally, section 5 ended up with conclusion and future work.

2. Literature survey

Some recent literatures-based son energy consumption and resource utilization is described as follows,

R. Shaw, E. Howley and E. Barrett [11] have developed a VM consolidation with automating energy efficient by applying reinforcement learning in cloud data centers. Across the data centers the distribution of VMs were optimized by applying reinforcement learning (RL) algorithms. During the learning process the reward structure was incorporated with the domain knowledge by using potential based reward shaping (PBRS).

A. Aghasi, K. Jamshidi, and A. Bohlooli [12] have presented a binary gravitational search algorithm based on fuzzy controlled binary gravitational search algorithm (FC-BGSA) algorithm. The computational time and energy consumption of FC-BGSA was minimized simultaneously by using metaheuristic approach. The optimization of the algorithm was controlled by using fuzzy logic based self-adaptive mechanism. The experiment was conducted using the google cluster and planet lab datasets.

H.L. Leka, Z. Fengli, A.T. Kenea, N.W. Hundera, T.G. Tohye, and A.T. Tegene [13] have presented a resource usage prediction of cloud VM using ensemble meta-learning approach based on particle swarm optimization (PSO). The cloud resource provisioning was done with the help of long short-term memory (LSTM), gated recurrent unit (GRU) and bidirectional LSTM. The availability of various variables affects the VMs CPU consumption.

S. Rahmani, and V. Khajehvand [14] has presented a burst aware VM migration to enhance the efficiency of the cloud. To control the load of PM in cloud computing, random early detection (RED) algorithm was used. RED migration time (REDMT) was used to achieve the mean load of PM. Adaptive heuristic algorithm was used for VM migration.

D. Saxena, A.K. Singh, and R. Buyya [15] have presented an Online VM Prediction based multi-objective load balancing (OP-MLB) framework for managing resources in cloud datacenter. For effective VM placement and migration multi objective load balancing was used. Unpredicted overloads in the active server leads to high SLA violation in this modal.

S. Supreeth, K. Patil, S.D. Patil, S. Rohith, Y. Vishwanath, and K.S. Prasad [16] have presented an efficient policy-based allocation and scheduling of VM in cloud computing. The VM scheduling and allocation was done by using the enhanced shark smell optimization algorithm (ESSOA). There was some security limitation identified in both allocation and scheduling.

S. Kulshrestha, and S. Patel [17] have presented a host overload detection algorithm on exponential weighted moving average (EWMA) based cloud data center. The time series forecasting was monitored by using the EWMA. This method may wrongly declare the host as overloaded based on prediction.

D. Alsadie [18] has presented an optimizing task schedule for cloud data centers using multi-objective grey wolf optimizer (MGWO). While handling conflicting objectives, optimal task scheduling performed to found nearby solution using task schedule MGWO (TSMGWO). Memory usage is not optimized in this model.

C. Jiang, L. Yang and R. Shi [19] have presented a VM migration strategy based on the three-way decision (VMM 3WD). Divide and conquer method was used to reduce the network overload. Moreover, it has high host network dependency.

A. Ibrahim, M. Noshy, HA. Ali and M. Badawy [20] suggested a framework based on Power-Aware technique depending on particle swarm optimization (PAPSO). It employed decimal encoding to map the migrated VM to the appropriate possible PMs. Moreover, minimum energy consumption was achieved

In cloud computing platform, VM migration is deeply focused on load compliment and minimizing the power in data centres. There are several existing techniques adopted to power aware concept and VM placement problems. The primary problem is to design and implement an efficient virtual machine migration algorithm that leverages the optimization technique to make data center operations more power-aware and energy-efficient. The limitations of existing approaches are,

i. Poor outcomes due to the initial decision taken by the agent [11]
ii. Poor energy consumption [12]
iii. Large number of variables [13]
iv. Dynamic value problem [14]
v. Due to unpredicted overloads leads to high SLA violation [15]
vi. Security limitations [16]
vii. Wrong prediction [17]
viii. Memory usage [18]
ix. High overload host [19]
x. VM migration was not significantly reduced [20]

This research aims to address the critical challenge of optimizing energy efficiency in cloud data centres through the utilization of virtual machine migration strategies. In this research, proposed EMOEPR technique is used to achieve the optimal placement of VM and reduce the power consumption in cloud center. The research seeks to contribute to the ongoing efforts to reduce the environmental footprint of cloud data centres and lower operational costs by enhancing the intelligence and effectiveness of virtual machine migration, thereby optimizing power consumption without compromising the quality of service.

3. Proposed EMOEPR to find the optimal placement of VM and energy consumption

In this research, an EMOEPR is proposed to achieve the appropriate placement for VM migration and efficiency energy consumption. This method combined both enhanced pelican [23] and remora optimization [24].

3.1 System model

Cloud computing is widely grown in infrastructure as a service (IaaS) platform, which consists of incredible data centers along with several heterogeneous PMs. PMs utilized CPU storage in many aspects such as Million Instructions Per Second (MIPS), energy, storage and frequency. PMs optimizes only local disks to load the operating system. In addition, if VM is transmitted from one place to another, only the memory part is migrated.

Each individual PM consists a software layer to maintain a VMs, which is defined as a hypervisor. For the consideration of the energy resources, VMs are consolidated with the active hosts in the server with minimal violating SLA.

3.2 Identifying unbalancing hosts

To attain the workload consolidation, three hosts are identified based on the usage, underloaded, overloaded and normal hosts. For example, if the hosts utilized more than a specified range, it is known as overloaded hosts [21]. If the hosts are minimum utilized, then it is known as underloaded hosts. Remaining all hosts are known as normal hosts. Based on the threshold values, the hosts utilize the range. Underloaded hosts utilize 10-50% capacity which leads to the high energy consumption. Therefore, the VM migration from the underloaded servers are occupying the lower threshold value [22]. The minimization of SLA violation is possible by utilizing the free resources during the migration time between overloaded hosts and underloaded hosts to reach the upper threshold range.

3.3 EMOEPR for VM migration

After identifying the unbalancing hosts, some elected VMs are transferred from the overloaded hosts and discover the appropriate place for the migrated VMs. The current research presented a VM migration based EMOEPR technique to find the appropriate place for migrated VM and to minimize the energy consumption. The EMOEPR is evaluated through population-based algorithm which uses a learning strategy. The proposed architecture is shown in Fig. 1.

The efficient energy consumption is attained based on the principle of pelicans, which is commonly searching the position based on the population. They kept long bags and beaks in the throat and grab the prey. After identifying the location of prey, they caught it from the height of 20m. To attain the appropriate position of VMs remora optimization is used. Remora is very famous for its swimming behavior. It attacks the whales and sword fishes to achieve the specification of the host. Mainly it has two objectives namely free travel and eat attentively, which is achieved through exploration and exploitation. The main process of the designed scheme is explained through each stage.

a) Initialization stage

EMOEPR is performed based on the population searching algorithm to find the active host. To achieve the best population initialization, this method uses the stochastic contrastive learning strategy to optimize the energy consumption, expressed by Eq. (1).

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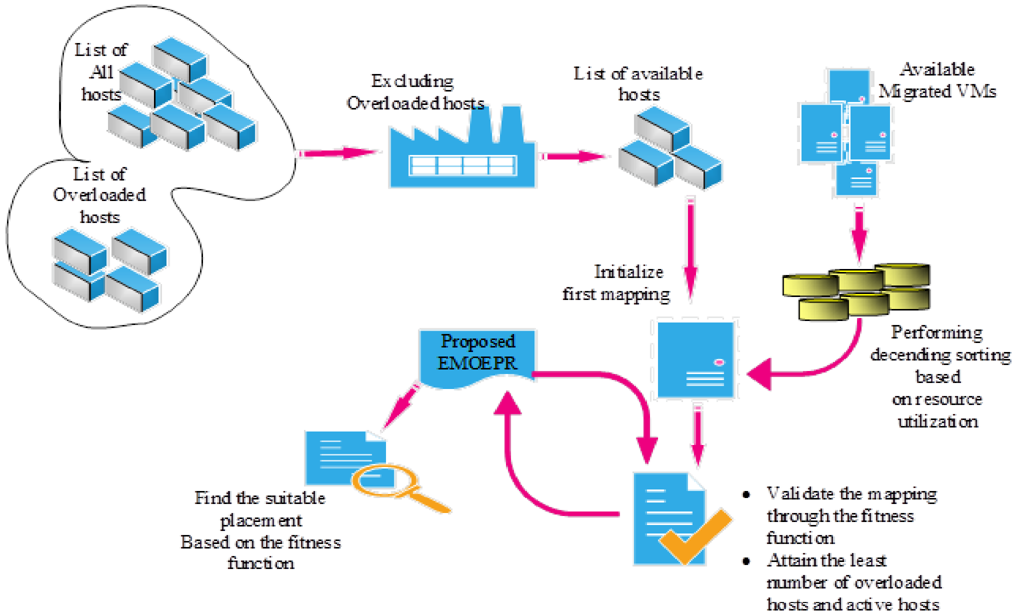


Figure 1. Proposed EMOEPR structure

$$x_{j,new} = (h + v) - dx_j \tag{1}$$

$$x_j = \begin{cases} x_{j,new} & t(x_{j,new}) < f \\ x_j & else \end{cases} \tag{2}$$

where, x_j is the present VM location instructions. h and v are defined as an upper and lower limit, d is represented as a random number between $\{0,1\}$. Based on the random opposition learning approach, the respective discrete active host fitness function is estimated. Weighting both fitness values such as present individual and optimized individual is derived by Eq. (2). The fitness value is adopted to minimize the energy utilization. The current position K is represented in Eq. (3),

$$K_j = (K_{j1}, K_{j2}, K_{j3}, \ldots\ldots K_{jT}) \tag{3}$$

where, j represents a count of remora and T represents a dimension of the search space. The optimal placement is described by Eq. (4),

$$K_{best} = (K_1^*, K_2^*, K_3^* \ldots\ldots K_T^*) \tag{4}$$

where, K_{best} is defined the best optimal placement. In that each candidate responding for the fitness value. The fitness value to find the optimal placement is expressed by Eq. (5),

$$F(K_j) = F(K_{j1}, K_{j2}, K_{j3}, \ldots\ldots K_{jT}) \tag{5}$$

where, F is denoted as a fitness value to achieve the optimal placement. Therefore, the best fitness value is finding out with the help of best position of remora location. The best fitness value is defined by Eq. (6).

$$F(K_{best}) = F(K_1^*, K_2^*, K_3^* \ldots\ldots K_T^*) \tag{6}$$

b) Fitness function

Based on the obtained values, the particles searching their position until they get the appropriate position. Based on the total cost weighted parameter, the fitness function is derived by Eq. (7),

$$Fitness(FN) = min\,i\,mize\{\textstyle\sum_{j=1}^{t} v_j \times c_j\} \tag{7}$$

where, v_j and c_j is represented as weight and cost parameters of j^{th} objective. The weights have to be falls in the range of [0,1]. The fitness function helps to find the suitable mapping and consolidate the VMs into the nearest appropriate PM by maximizing the fitness value by Eq. (8),

$$Fitness(Fn) = max\,i\,mize\{F(K_{best})\} \tag{8}$$

By the way it finds out the appropriate position by maximizing the weight parameter with the help of remora optimization.

c)Exploration stage

After stabilizing global and local search capabilities, EMOEPR reaches the flight stage and the prey moving stage are expressed by Eq. (9),

$$X_{j,k}^{Q_1} = \begin{cases} X_{j,k} + \theta.rand.(q_k - J.X_{j,k}), & f_q < f_j; \\ X_{j,k} + \theta.rand.(X_{j,k} - q_k), & else \end{cases} \tag{9}$$

Table 1. Pseudo code of EMOEPR

Pseudocode: EMOEPR	
Input: Count of available hosts, count of excluded overloaded hosts, List of migrated VMs **Output:** Suitable migration	
Start *{* *Initializing parameters* x_j,h,v; *Performs descending sorting for migrated VMs based on CPU usage* *Creating mapping for migrated VMs* *Determine the number of iterations* *Calculate the fitness value for* x_j, $F(K_{best})$ *Locate the pelican and remora over the updated position*	*//formulate disturbance inhibition factor*
Update the position using $Levy(E)$,e,η, K_{j+1}; *{* $If(n < N)$ *{* $n = n + 1$ *}* *Else (appropriate optimal solution)* *}* $Migration$ $\rightarrow Mapping, VMsuitable \quad placement$ *}* **End**	*//iterations is repeated*

Table 2. Parameters and configurations

Parameters and Configurations	
Parameters	**Configurations**
Type of Hosts	HP Proliant ML110G4(2*1800MIPS 4GB) HP Proliant ML 110G5(2*2660 MIPS 4GB)
Workloads	planet lab, google cluster, clark net
Host counts	400, 800 of each type of hosts
Type of VMs	500 MIPS 1000 MIPS 2000 MIPS 2500 MIPS

Table 3. Evaluated Test Cases

Test cases	**PM counts**	**VM counts**
TI	60	60
T2	80	80
T3	100	100

where, $X_{j,k}^{Q_1}$ is described as prey moving stage and $X_{j,k}^{Q_2}$ is expressed as flight stage. θ is the disturbance inhibition factor. J represents the previous generation attack. f_j is the fitness function value of the j^{th} pelican. f_q represents the fitness function value of the q^{th} value. The corresponding values illustrate the particular position of the active hosts.

d)Exploitation stage

The developed EMOEPR efficiently solves the problem of diversity and can easily reduce active hosts in the server. Levy flight strategy is broadly used in the designed model to increase the randomness of the designed model. To optimize the exploration abilities, levy flight was merged with stage 2 of the EMOEPR is formulated by Eq. (10),

$$x_{j,new} = x_{best} + \omega.S.\left(1 - \frac{t}{T}\right).(2.rand - 1).x_{best}.Levy(\rho) \quad (10)$$

where, $Levy(\rho)$ is represented as levy flight function. ρ is represented as a dimension of the acquired problem. $\omega$is the diversity function. $\frac{t}{T}$ represents the iteration coefficient of neighborhood population.

The mathematical description of the complete process is given in pseudocode format is expressed in Table 1.

4. Results and discussions

The complete experiment procedure has been implemented in Cloudsim simulator. Cloudsim is an open accessible, programmable platform. It is very flexible to allow the model in large scale virtualized territory. The simulation done with 800 heterogeneous PMs. The parameter and their configurations owned in the executions are tabulated in Table 2.

4.1 Dataset description

Planet lab [11]: It provides a 30 days stochastic workload data, which considered as standard benchmark dataset.

Google cluster [25]: It consists of CPU resources, disk I/O request, memory and data usage of total 6,72,300 tasks executed on 12,500 servers over 29 days.

Clarknet [26]: It consists of 14 days' workload data. A total number of 3,328,587 requests were collected.10 mins time interval carried throughout the days.

4.2 Experimental outcomes

There are three types of test cases considered in the proposed technique is shown in Table 3. therefore, taking randomly counted VMs and PMs.

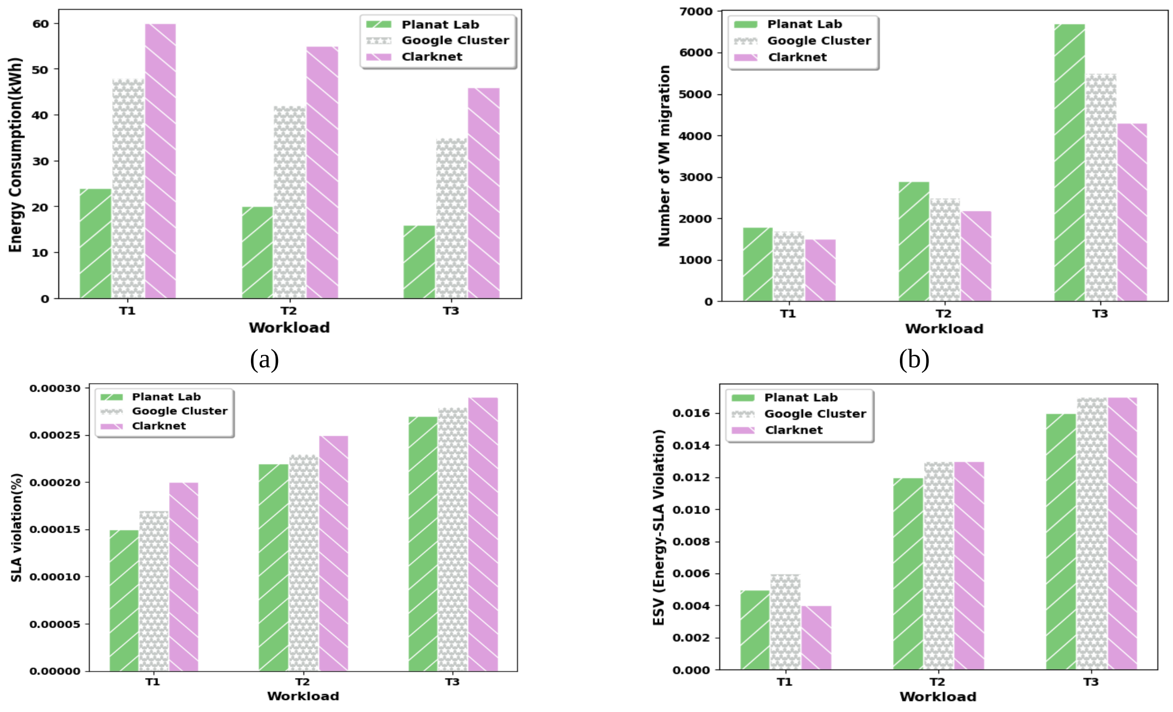
To experiment the test cases, two types of servers used, namely HP Proliant ML110G4 and HP Proliant ML 110G5 are used. Both has a CPU model Intel

Table 4. Specifications of server

Server	Frequency (MHz)	Storage (GB)	Memory (GB)	Cores count	Bandwidth (Gb/s)	CPU model
HP Proliant ML110G4	1860	1000	4	2	1	Intel Xeon 3040
HP Proliant ML 110G5	2660	1000	4	2	1	Intel Xeon 3075

Table 5. List of VM characteristics

VM model	CPU(MIPS)	Cores count	RAM(GB)	Bandwidth (Mb/s)
Extra Large VM	2000	1	3.75	100
High-CPU VM	2500	1	2.5	100
Small VM	1000	1	1.7	100
Micro VM	500	1	0.613	100



(a) (b) (c) (d)

Figure. 2: (a) Energy consumption, (b)VM migration count, (c)SLA violation, and (d)ESV for three different workloads

Table 6. Power utilization of two servers

Server	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
HP Proliant ML110G4	117	114	112	108	106	102	99.5	96	92.6	89.4	86
HP Proliant ML 110G5	135	133	129	125	121	116	110	105	101	97	93.7

Xeon 3040 and Intel Xeon 3075 respectly. Four types of VMs assessed for this experiment. The specifications of the server and VM characteristics are described in Table 4 and Table 5.

The experiment results attained excellent performance in all parameters such as energy consumption, number of VM migration, SLA violation and ESV in different workloads. Hence, the different workload results are detailed in Fig. 2. Therefore, three different datasets planet lab, google cluster and Clarknet involved in three different workloads are performed. In that energy consumption, planatlab performed minimum energy consumption under T1 workload rather than other two database. To analyze the number of VM migration, clarknet performed minimum VM migration compared to other two datasets. To estimate the SLA violation, planatlab achieves the minimum SLA violation. In the ESV estimation, clarknet scored the better ESV performance in three workloads.

➢ *Energy consumption*

Among all the resources, CPU is one of the main components to utilize more power in datacenters. So, the energy utilization is estimated through the power model provided by the standard benchmark. The

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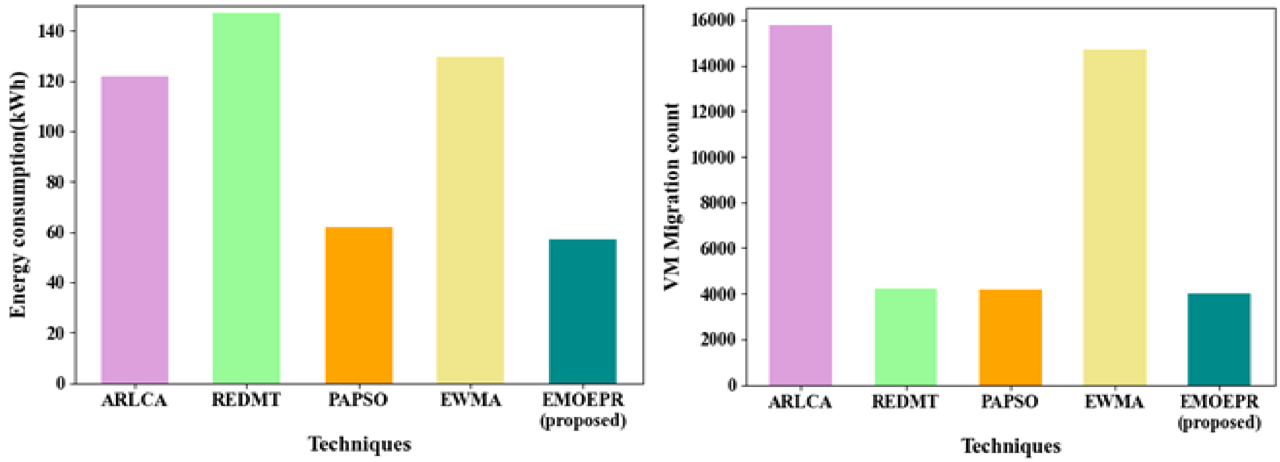
Table 7. Parameter description of existing techniques

Parameter	Description			
	FC-BGSA [12]	**ARLCA [11]**	**REDMT [14]**	**PAPSO [20]**
CPU core count	16-22	-	-	8
Workload	30-day	30-day	30-day	30-day
Server type	2	2	2	2
Memory	4 GB	-	4 GB	4 GB
Bandwidth	256MBps	-	1860-2660 MHz	500-2500MIPS
VM requests workload	May 2019	-	April 2020	-
VM types	-	-	4	4



(a) (b)

Figure. 3: (a) energy consumption and (b) number of VM migration

Table 8. Comparison of SLA violation and ESV

Technique	SLA violation	ESV
ARLCA [11]	0.000567	9.7583
REDMT [14]	0.0000028	0.00041
PAPSO [20]	0.000253	0.017
EMOEPR (Proposed)	0.0000025	0.0003

energy usage of two types of servers is tabulated in Table 6.

Moreover, the energy consumption is calculated over the time interval is described in Eq. (11).

$$Energy = \int_{t_0}^{t_1} E(v(t))dt \tag{11}$$

Time interval t is calculated over $(0,1)$, E is described as energy consumption variable.

➢ *Count of VM migration*

The minimized active servers can improve the CPU utilization in all hosts way to reduce the underloaded servers. This minimization of VM migration achieve the great impact on the solution quality to end users.

➢ *SLA Violation*

The combined SLA violation is achieved by the two independent parameters, which is obtained through Eq. (17),

$$SLAV = PDM \times SLATAH \tag{17}$$

where, PDM is defined as performance degradation due to migrations. $SLATAH$ is defined as SLA violation Time per Active Host. $SLAV$ is defined as SLA Violation.

➢ *Energy SLA violation*

In VM allocation problems, energy and SLA violation is considered as a trade-off problem. Especially cloud users consolidate into the minimum count of active hosts. By other vision, users pivot on the service performance, which is not forced by the consolidation action. So, the cloud service contributor pivot to minimize power consumption without violating SLA. Subsequently a combination of trade-off metric is formed, which works on the power consumption and SLA violation to estimate the appropriate VM placement.

The overall comparison of previous techniques such as ARLCA [11], FC-BGSA [12] REDMT [14], PAPSO [20] compared with the proposed EMOEPR is illustrated in Fig. 3. The parameter settings of the existing techniques are provided in Table 7.

From Fig. 3 (a), ARLCA method achieves 121.66 kWh energy consumption under the average of 30-day workload condition. REDMT method attains 146.77 kWh energy utilization, which is performed under different mean values of migration time.

PAPSO attains 62 kWh energy consumption, which used power aware technique with minimum violating SLA.EWMA achieved 129.7 kWh energy consumption. The proposed EMOEPR achieved 57 kWh energy consumption, which shows that proposed model consumes less energy when compared with the state-of-art techniques. From Fig. 3 (b), ARLCA reached 15,769 VM migration over 30-day workload condition. REDMT reached 4226 VM migration under different migration time. PAPSO reached 4200 VM migration, with the average of three work load condition. EWMA reached 14684 VM migration, with the average of four host overload detection polices. The proposed EMOEPR reached 4000 VM migration, which attains the lowest VM migration when compared with the existing techniques. Thus, the reduced VM migration provides excellent effect on the quality of service to end users. The comparison of SLA violation and ESV of existing techniques over proposed scheme are illustrated in Table 8.

From Table 8, ARLCA has 0.000567 SLA violation and 9.7583 ESV under the average of 30-day workload condition. REDMT has 0.0000028 SLA violation and 0.00041 ESV over the different mean values of migration time. PAPSO has 0.000253 SLA violation and 0.017 ESV while minimum violating SLA. The EMOEPR achieved minimum 0.0000025 SLA violation and minimum 0.0003 ESV. Hence it clearly shows that the proposed model achieved minimum SLA violation and ESV when compared to the existing techniques. The ESV parameter decreasing the power utilization and achieve the minimum SLA violation. So, that the better performance is yielded throughout the process. EMOEPR minimize the utilized energy in active hosts by consolidated VMs into a smaller number of servers. Execution outcomes proved that EMOEPR minimize an average <5% energy consumption, <22.62% of VM migrations, <8.62% of SLA violation is minimized, hence the efficiency of the EMOEPR is remarkably achieved. The main concern of EMOEPR is, power aware energy consumption without violating SLA. Hence, it achieves the better performance compared to existing techniques. Additionally, it performed to reduce the overloaded hosts and underloaded ones, also the VM migrations count can be significantly decreased.

5. Conclusion

This research paper presented an energy efficient VM migration in cloud center by proposing EMOEPR. The consolidation of VM in the active servers is very challenging to minimize the power consumption. The proposed EMOEPR helps to minimize the power utilization without violating SLA. The appropriate optimal placement is identified to achieve the migrated VMs. The pelican algorithm is optimized for minimize the energy consumption and reduce the active hosts and overloaded hosts. Moreover, the remora algorithm is optimized to find the optimal placement of VM. Thus, hybrid strategy is significantly decreasing the VM migrations and active hosts. The proposed methodology shown a notable reduction in power consumption of 57 kWh, minimum VM migrations of 4000, 0.0000025 SLA violations and minimum of 0.0003 ESV is attained, which demonstrates the excellent performance of proposed method when compared to the existing techniques. As a future work, EMOEPR can be analyzed for energy consumption to consider the bandwidth and RAM of the host machine during live migration.

List of notations

x_j	Present VM location instructions
h	Upper limit
v	Lower limit
K	Current position
j	Count of remora
T	Dimension of the search space
K_{best}	Best optimal placement
F	Fitness value
v_j	Weight parameters of j^{th} objective
c_j	Cost parameters of j^{th} objective
$X_{j,k}^{Q_1}$	Prey moving stage
$X_{j,k}^{Q_2}$	Flight stage
θ	Disturbance inhibition factor
$Levy(\rho)$	Levy flight function
ρ	Dimension of the acquired problem
ω	Diversity function
t	Time interval
E	Energy consumption variable
η	Iteration count
x_{best}	Best position of the initial population
J	previous generation attack
f_j	fitness function value of the j^{th} pelican.
f_q	fitness function value of the q^{th} value.
$\frac{t}{T}$	iteration coefficient of neighborhood population.
PDM	Performance degradation due to migrations
$SLATAH$	SLA violation Time per Active Host
$SLAV$	Sla violation

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Data availability statements

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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Conflict of interest

The authors declare that they have no potential conflict of interest.

Author contribution

Conceptualization, Rukmini S; methodology, Rukmini S; software, Rukmini S; validation, Dr Shridevi Soma; writing—original draft preparation, Rukmini S; writing—review and supervision, Dr Shridevi Soma.

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