Optimizing Power requirements of Cloud Services during Virtual Machine Live Migration

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Abstract - **Cloud computing is gaining more importance gradually in the field of computing services with the support of data centers across the world. A large number of enterprises and individuals are opting for cloud computing services for resource requirements. The number of requests for services is raising in cloud computing, which leads to increase in power consumption of data centers with high pace. This caused the rise in ownership cost of service providers and harmful carbon footprints into the environment. Therefore, it is imperative to optimize the power requirements in data centers to mitigate the cost of ownership and to make it environment-friendly. In today's era, virtualization plays a significant role to minimize power consumption during virtual machine live migration in data centers. This paper presents the hybrid genetic algorithm that provisions various virtual machines to hosts in such a way to optimize power requirements of cloud services during virtual machine live migrations. Simulation experiments have been carried out with a variety of characteristics as input to Power Optimizing Genetic Algorithm with different allied parameters of migration. Results have shown that proposed genetic algorithm optimize power consumption and migration overhead with defined test problems as compared to recent virtual machine placement method. The statistical approaches have been applied to validate the reliability of the simulation results.**

Keywords: Data center; Power consumption; Genetic Algorithm; Virtualization; Virtual Machines (VMs); VM Placement

I. INTRODUCTION

With the swift increase in a number of applications on cloud computing in the recent days, there is fast growth in all data centers' power consumption. Various big firms related with cloud computing like Amazon, IBM, Google, and Microsoft have deployed their servers to provide customer services globally. Consistent good quality services, fault tolerance, load balancing and data security are the crucial concerns which are considered by service providers to provide reliable services to customers [1]. Cloud computing is considered as "pay-as-you-go" functional prototype which is also observed as a profitable model for service providers. It is important to ensure uninterrupted supply of services to customers worldwide and running various servers 'ON' leads to power consumption around the clock due to the utilization of resources [2]. The rise of power consumption in data centers led to the growth in energy consumption worldwide since energy consumption is in the linear relationship with power consumption.

The Energy consumption of data centers increased on very fast pace with the escalation of data center industry. In the starting years of 21st-century energy consumption of data centers worldwide has increased twofold and now data electricity consumption is almost two percent of the world production [3]. The power and energy consumption in various data centers lead to the rise in electricity bill with CO_2 emission and the growth in global warming [4]. In addition, an annual growth rate of 30% had been estimated in energy consumption from 2012 to 2016 [5].

Many servers are running idle or without the load in the data center, that cause the power consumption equivalent to half of the fully loaded server. In spite of this, Whitney et al. have estimated twofold growth in energy consumption during the years 2010 to 2020[6]. So, highly sophisticated power efficient algorithms are required to curtail this growth rate of power consumption in data centers.

A certain number of Virtual Machines are provisioned among few hosts in data centers' network with the use of virtualization technology. The virtualization technology ensures the exploitation of data center resources that in turn curtail the energy or power usage. VM consolidation feature of virtualization technology is of vital importance for cloud computing and to mitigate the cost of ownership. The energy efficiency of data centers is achieved with the live migration of VMs to other hosts for load balancing and resource management among hosts [7].

With VM live migration feature, hosts with high power consumption shift their load of VMs to other hosts with the lesser number of VMs or running under load. The under load hosts with the lesser number of VMs are shut down after migrating their VMs to other physical machines of data centers. In this process, selection of VM for migration and placement of VM on target machine are the foremost challenges for research, which has been discussed earlier [8]. In the past few years, various VM selection and placement algorithms have been designed to tackle the same problem [9-13]. However, recent past algorithms did not consider the cost of power incurred during VM live migrations. Authors have reviewed various papers [8] and analysis have been made to study the relationship between parameters i.e. network bandwidth, VM size and migration time with energy consumption of underlying machines [14].

In this paper, results of the proposed genetic algorithm (POGA) have been compared and analyzed with the Modified Best-Fit Decreasing (MBFD) algorithm and Minimization of migrations (MM) designed by A. Beloglazov et al. [13]. Various allied parameters of power consumption were identified and observed during simulation to represent the impact of the proposed algorithm. Afterwards, proposed Genetic Algorithm was evaluated and validated using statistical parameters.

II. Power Optimizing Genetic Algorithm

The presumption has been made that virtual machine(s) can be assigned to any physical machine on the basis of utilization, and power consumed by these machines depends on the utilization of resources. As per earlier studies, power consumption is correlative to CPU utilization of the machine [15][16][13].

The main goal of this research work is to optimize the power consumed by hosting physical machines during live migrations and allocation of virtual machines to target hosts with a minimum number of migrations to control the rise of power overhead. For the attainment of this goal, it was highly desirable to formulate the mathematical model of the problem [17] and use of Genetic Algorithm theory [18] to design the optimization policy. This portion of the paper presents a detail of Genetic Algorithm parameters like encoding scheme, crossover operator, mutation operator and fitness function with the detail of advanced Genetic Algorithm. Thereafter, simulation observations or results are presented and compared with recently designed algorithm [13] known as Primary Algorithm.

A. *Encoding Scheme*

The proposed genetic algorithm works with several chromosomes and their genes that are represented as |B| i.e. number of virtual machines. The certain positive number of physical machines is represented as |A| on which various virtual machines are to be assigned. The allotment of virtual machines to various physical machines has shown in the following figure i.e. Figure 1 in compliance with all chromosomes.

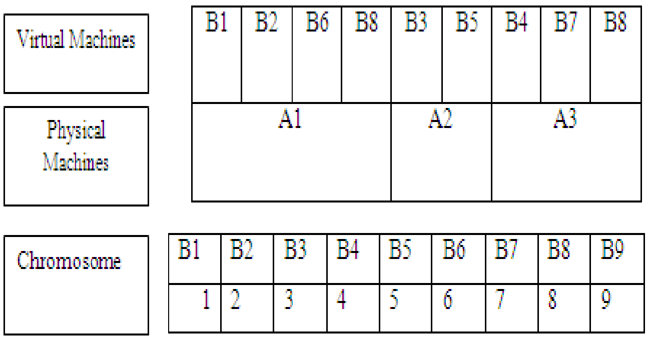

Figure 1. Allocation of VMs to Machines with chromosomes

B. *Mutation Operator*

The mutation is a genetic operator which helps to retain the variety of offspring generated from the collection of several chromosomes. This is similar to biological mutation process. Mutation changed the gene values in chromosomes from its initial state. In this context, virtual machines eligible to migrate are mutated and allocated to physical machines as per their resource requirements. The virtual illustration of mutation operator in the context of current problem is described in the given Algorithm 1.

Algorithm 1. Mutation
Input: Chromosomes, $P = c_1 c_2 c_3 c_4 \ldots\ldots c_n$
Output: Mutated , $P' = c'_1 c'_2 c'_3 \ldots\ldots c'_n$
1: $P' \leftarrow P$
2: Random generation of VMs , $v_i \in \lvert V \rvert$
3: Random generation of PMs , $p_j \in \lvert P \rvert$
4: Interchange $c'_i \leftarrow p_j$
5: Output P'

C. Crossover Operator

The genetic linkage of the population is a serious concern since the length of the chromosome is long and dealt with utmost importance. The proposed genetic algorithm practiced a bias uniform crossover operator that has been shown in Algorithm 2.

D. Fitness Function

Following expression represents the fitness function in the proposed algorithm:

Fitness Function = $@(e) Fitnessfunction(Fs, Ft, Rs, Rp, Cr_{ex}, Cr_p)$;

The given variables i.e. Fs, Ft, Rs, Rp, Crp, Crex are the optimization parameters and variable e represents the total power consumption of underlying systems. The fitness function makes it sure that fitness value of various given variables is small in amount than of any optimal and feasible solution. Thus, fitness value describes the nature and amount of power consumption in the context of the current problem.

Algorithm 2. Uniform Crossover	
Input: Parental Chromosome,	
$P^i = c_1^i c_2^i c_3^i \ldots\ldots c_n^i$ *and* $P^j = c_1^j c_2^j c_3^j \ldots\ldots c_n^j$	
Output: Single Child, $C^k = c_1^k c_2^k c_3^k \ldots\ldots c_n^k$	
1:	$g^i = fitness(P^i)$;
2:	$g^j = fitness(P^j)$;
3:	for s=1 to n do
4:	Number generation from 0 to 1, t
5:	if $t < g^i/(g^i + g^j)$ then
6:	$c_q^k \leftarrow c_q^i$
7:	Else
8:	$c_q^k \leftarrow c_q^j$
9:	End
10:	End loop
11: Output C^k	

E. Power Optimizing Genetic Algorithm

The Power Optimizing Genetic Algorithm is a holistic approach to optimize the power consumption with the proper utilization of various underlying resources. Several allied parameters played their part to affect the energy or power consumption during live migrations [14]. The concept of virtualization has ample impact on allied parameters which in turn helps to minimize power consumption of data centers. The detailed illustration of POGA algorithm is presented in Algorithm 3 and Flowchart in Figure 2.

In the simulation process of the algorithm, virtual machines are initialized with the specification of initial parameters to describe the performance measurement of live migrations. Simultaneously, hosts are being initialized with a requisite configuration to run the virtual machines hosting on it.

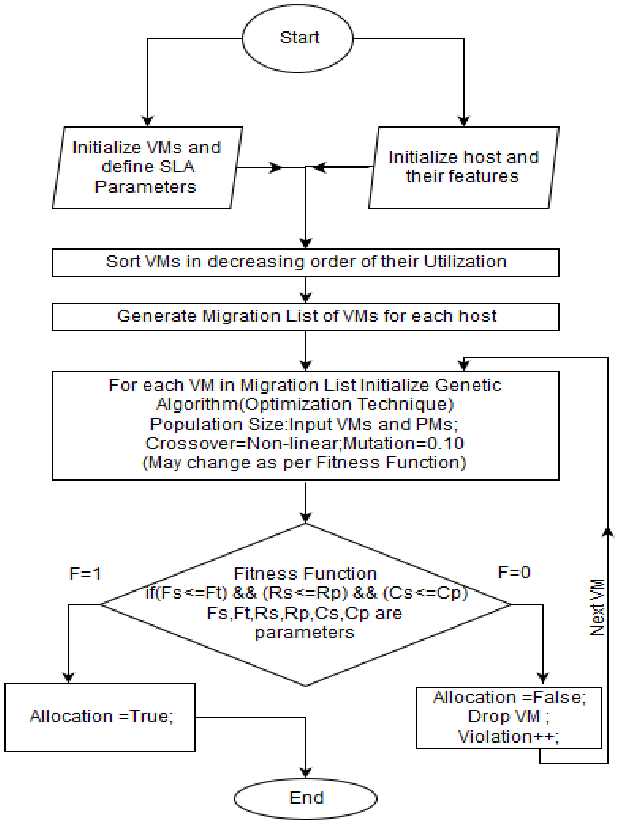

Figure 2. Flow Chart of POGA

Algorithm 3. Power Optimizing Genetic Algorithm

Input: PMs and VMs with energy utilization
Output: VM Allocation and VM Migration List
Generate population of individuals, Pop
Select the best candidate, *P* in Pop
$While\ (Condition \neq true)\ do$
    $for\ each\ P \in Pop\ do$
        Call Fitness Function
    end
    $for\ each\ P \in Pop\ do$
        Call Selection based on Utilization to pair
end
    $for\ each\ pair \in Parents\ do$
        Call Uniform crossover
end
    $for\ each\ P \in Pop\ do$
        Call Mutation function
end
    Find the best candidate P_{best} in Pop
    $if\ P_{best}\ is\ better\ than\ P\ then$
        $P_{best} = P$
    end
end
P_{best}=VM Allocation and VM Migration List

These virtual machines are open to taking requests from clients through an interface as per available services provided by the servers. In this process, some virtual machines are being overloaded which leads to an extra power consumption of underlying server in data centers. The live migration technique employed to adjust the additional workload of virtual machines to other physical machines with less power consumption. The sorting of virtual machines based on utilization in descending order helped to select the heavily loaded virtual machines as migration candidate. Every single host in the data center associated with an allocation table; it has the list of virtual machines stored in the memory of the host. Target or destination machines for virtual machine migrations are selected on the basis of their utilization and capacity to run the incoming virtual machine. Thereafter, genetic algorithm [18] have been applied to further optimize the allocations and to remove inoperative machines for perfect utilization of resources. Virtual machines with optimal workload are retained on the same host and others are migrated to other hosts as per allocation table specification. The fitness function or objective function is used to represent the associated parameters of migration.

III. Results And Discussion

The predefined test configurations based on randomness were used to perform the experiments with proposed genetic algorithm since no benchmark is available for virtual machine placement policies. All simulation experiments were conducted with MATLAB [19] on Windows 7 (Ultimate 32-bit operating system). The Dell machine with Intel Core i3 (1.70 GHz) and 4GB RAM was used to perform simulations with defined characteristics.

The simulation experiments were conducted and observed with genetic algorithm for identified performance parameters i.e. power consumption, VM migrations, Response time and SLA violations during migrations. The random test problems are created and applied as an input to Power Optimizing Genetic Algorithm. These simulation experiments were conducted using variable population size i.e. 100 to 500 of virtual machines and 5 to 20 of physical machines. The Crossover and mutation operator's probabilities were selected non-linear and 0.10 respectively, and ten generations were chosen as a limit to reach the best optimal solution. During simulation, all parameters were observed for changes taken place in their results. Thereafter, mean of recorded observation is taken as a result for all the parameters and compared with the Primary Algorithm (PA).

For the significance level test of the result statistics, the authors carried out a t-test with a different variance for the difference between two samples of various parameter values with POGA and Primary Algorithm. The significance level of the t-test was chosen at 5%. The null hypothesis and alternate hypothesis designed for given parameters are given as follows:

$$H_0: \mu_1 = \mu_2 \qquad \text{Null Hypothesis} \qquad (1)$$

$$H_A: \mu_1 < \mu_2 \qquad \text{Alternate Hypothesis} \qquad (2)$$

Here, μ_1 represents mean of various parameter values of VM migrations, power consumption, SLA violations and response time with POGA algorithm. The μ_2 represents mean of various parameter values with Primary Algorithm. The hypothesis testing is done on the basis of P value of t-test conducted on sample sets of results generated from two algorithms (i.e. POGA and Primary algorithm) for various parameters. The statistical analysis based on P values for various defined parameters to validate the hypothesis as per eq. 1 and eq.2 is given in the following sections:

A. VM Migrations

For hypothesis testing (as given in eq.1 and eq.2) for VM migrations, the P value 0.033896(see Table I.) is less than 0.05 that means the rejection of the null hypothesis. Thus alternate hypothesis H_A (see eq.2) is accepted. It shows that difference between dataset values is actual and not by chance. The POGA algorithm performed lesser number or count of VM migrations as compared to Primary Algorithm.

An analogy has been drawn between the observations or results produced with Power Optimizing Genetic Algorithm and the algorithm which is based on recent research named Primary Algorithm [13]. The results illustrate that the proposed optimizing algorithm minimized the extra energy cost of migration from a source machine to destination in a data center [20]. The graphical representation of analogy between POGA and Primary Algorithm (PA) has been

given in the figure 3. The pictorial representation of VM migration results clearly indicates that Power Optimized Genetic Algorithm outperformed the Primary Algorithm.

TABLE I. VM Migrations with POGA and Primary Algorithm	
No of VMs	P value=0.033896
100	
200	
250	
300	
400	
500	

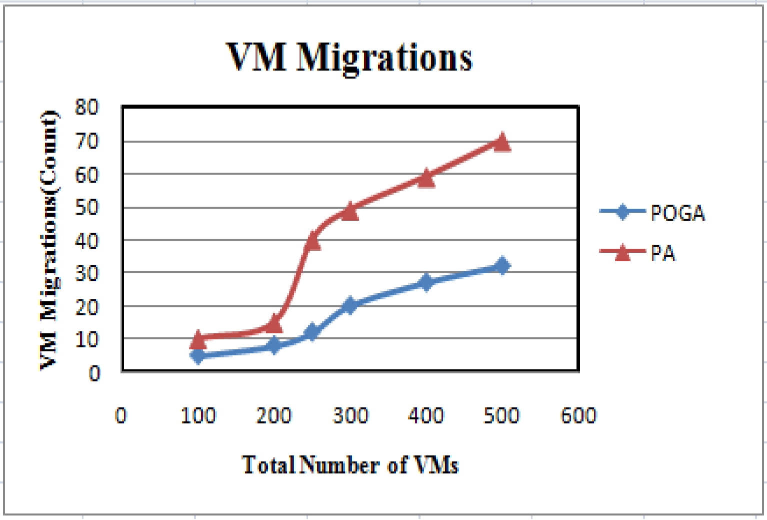

Figure 3. Count of Virtual Machine Migrations

B. Power consumption

The P value 0.000209 (see TABLE II.) is less than 0.05 in power consumption parameter that means the rejection of the null hypothesis. Thus, alternate hypothesis H_A (see eq.2) is accepted for power consumption. It has been proved that with various numbers of VM migrations, power consumption was reduced with POGA algorithm and there is a significant difference between two dataset values. The confidence interval 95% ensures that this is not happened by chance, but in reality, there is a significant difference between two dataset values.

As per pictorial representation of observations shown in figure 4, Power consumed by machines using proposed genetic algorithm outperformed the Primary algorithm with regard to count of virtual machines to be migrated from one machine to other in data centers. It specifies that power consumed by machines using Primary Algorithm is more than POGA and varied with the number of VM machines migrated to other machines. As earlier study illustrated that decline in migrations of Virtual Machines to other hosts caused the reduction in energy consumption of host machines in the data center [21].

TABLE II. Power Consumption with POGA and Primary Algorithm	
No of VMs	P value=0.000209
100	
200	
250	
300	
400	
500	

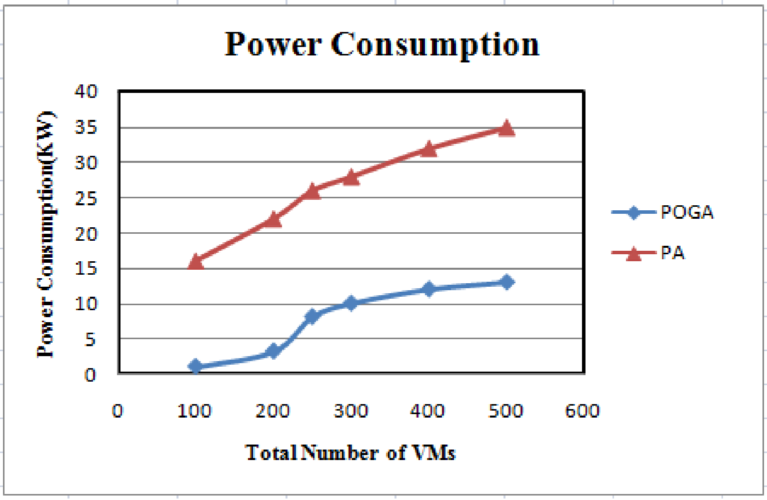

Figure 4. Power Consumption analogy for various VM migrations

C. SLA violations

The P value 0.000141 (see TABLE III.) is less than 0.05 that means the rejection of the null hypothesis. Thus alternate hypothesis H_A (see eq. 2) is accepted for SLA violations. It has been proved that with various numbers of VM migrations, SLA violations were reduced with POGA algorithm and there is a significant difference between two data set values. The confidence interval 95% ensures that there is a significant difference between two data set values.

One of the main key parameters in this proposed algorithm is the Service Level Agreement (SLA) violation, and SLAV comparative analysis with the Primary Algorithm (PA) has been presented in figure 5. The SLA violation occurs when actual service response time takes longer than pre-defined response time in SLA. In this simulation, SLA violation occurred when a given virtual machine could not get the amount of million instructions per second (MIPS) that were requested.

TABLE III. SLA violations with POGA and Primary Algorithm

No of VMs	
100	P value=0.000141
200	
250	
300	
400	
500	

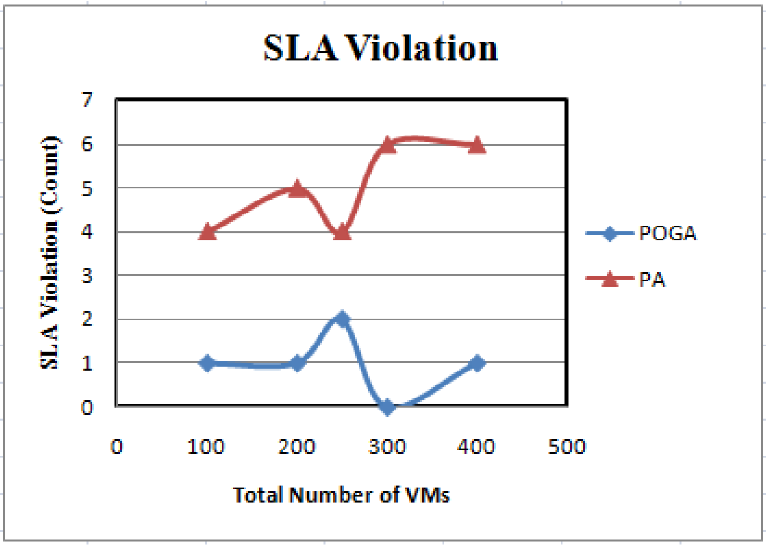

Figure 5. SLA Violation Comparison of POGA and Primary Algorithm (PA)

This can happen in the cases where virtual machines are sharing CPU cycles for the performance of host and that cannot be provided due to a consolidation of virtual machines. This metric shows the level by which the Quality of Service (QoS) requirements negotiated between the resource provider and consumers are violated due to the energy-aware resource management. The SLA violation decreased with proposed Genetic Algorithm as compared to an earlier primary algorithm with the variation in a number of virtual machines. This fact ensured better Quality of Service to customers as per negotiation in predefined Service Level Agreement.

D. Response time

The P value 0.000107 (see TABLE IV.) is less than 0.05 that means a difference between two datasets of two algorithms is not by chance. Thus, the null hypothesis is rejected on the basis of 5% significance level. Thus, alternate hypothesis H_A (see eq.2) is accepted for response time parameter. It has been proved that with various numbers of VM migrations, VM response time was reduced with POGA algorithm and there is a significant difference between two data set mean values. Figure 6 shows the comparison of response time parameter (measured in milliseconds) using a proposed algorithm and Primary Algorithm (PA). The response time is the time interval taken by the system to respond to a particular service till the change of the state. The service response time can be taken as a prime parameter for QoS to satisfy the customer requirement.

TABLE IV. Response Time with POGA and Primary Algorithm

No of VMs	
100	P value=0.000107
200	
250	
300	
400	
500	

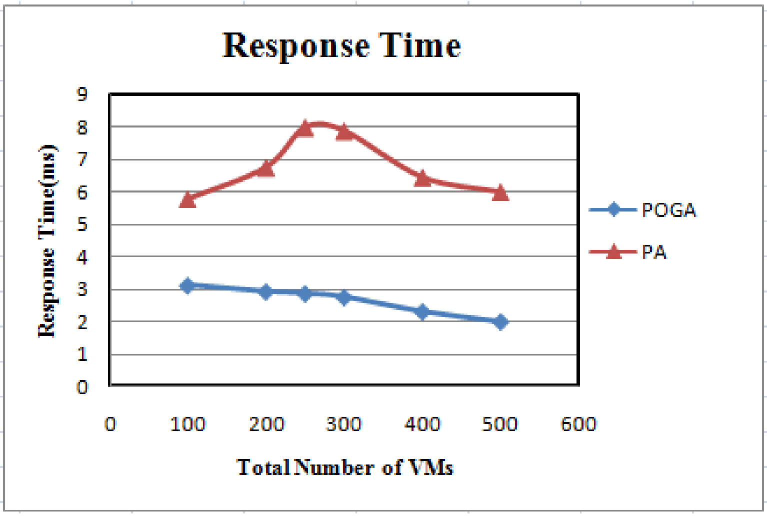

Figure 6. Response Time parameter with POGA and Primary Algorithm (PA)

The POGA has shown a drastic impact on the response time quality parameter of virtual machines. With the increase in a number of migrations, there is a slight decrease in response time parameter as shown in figure 6. The quality parameter (i.e. Response Time) ensures the timely delivery of services to the customers. The overcrowding of virtual machine migrations over the network caused hindrance and led to decline in the response time of services [22, 23]. In contrast to the results of POGA, primary algorithm caused longer response time for services provided by virtual machines.

E. Optimization performance trend

The optimization trends are generated by the difference of values for various parameters applied with competing algorithms i.e. Power Optimizing Genetic Algorithm and Primary Algorithm. The coherent study of different parameters have been shown in TABLE V and plotted in figure 7. The trends of results for various parameters have shown incredible improvement in the observations with the proposed algorithm (POGA). The mean of difference values calculated for a various number of VM migration in power consumption parameter is 71.66 percent, which shows the extent of power saving using the proposed algorithm. In the same pattern, an average of means for various parameters is 65.87 percent. This percentage describes the coherent optimization of a set of parameters with the proposed algorithm. All these competing parameters have been graphed to give a pictorial view of the trends.

TABLE V: Optimization Trends using POGA (%)

No. of VMs	VM Migrations	Power Consumption	SLA Violations	Response Time	Average
100	50	93	75	46	65.87
200	46	83	77	56	
250	70	66	50	64	
300	59	64	95	64	
400	54	62	83	64	
500	54	62	78	66	
Average	55.5	71.66	76.33	60	

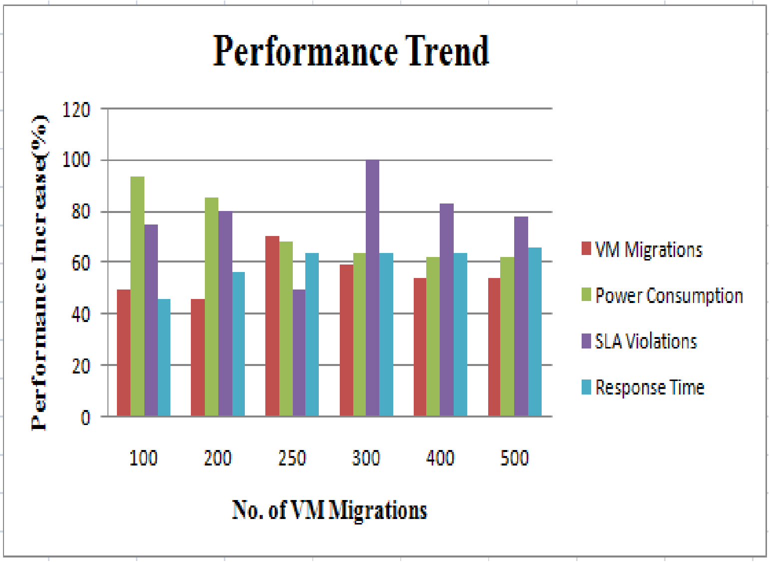

Figure 7. Trends of competing parameters using POGA

IV. Conclusion And Future Scope

Experiments conducted in this research showed valuable insights for power consumption during Virtual Machine Live migration in cloud data centers. This paper presented Power Optimizing Genetic Algorithm (POGA) to optimize power consumption and some other associated parameters i.e. VM migrations, SLA violations and response time. The simulation experiments were performed to evaluate and compare POGA algorithm with a defined primary algorithm with respect to some allied parameters. In this, the solution produced by the POGA algorithm is 65.87 percent better than those produced by the Primary Algorithm. In terms of power consumption, proposed POGA algorithm is saving 71.66 percent of power as compared to a primary algorithm with specified Quality of Service constraints. After this, trends have maintained to analyze optimization factor of various parameters. The percentage of performance trends have shown that various competing parameters are leading towards optimization with large impact of POGA algorithm.

In future research, conducting an experiment with other evolutionary computation techniques such as Particle Swarm Optimization (PSO) or Ant Colony Optimization (ACO) for power optimization and comparing the results with proposed study would be interesting. A comparative analysis and contrasting the performance of different evolutionary computation techniques including genetic algorithms for power optimization is essential to establish a detailed understanding of their strengths and limitations. It would be significant to check the performance of the proposed algorithm on some real data traffic.

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