ISSN : 0976-8491 (Online) | ISSN : 2229-4333 (Print)

Energy Optimizing Hybrid Genetic Algorithm During VM Migrations in Data Center

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Abstract
Energy Consumption is the crucial factor in Cloud Data centers that leads to acquire high cost of running budget. As demand for resources increases in cloud computing, energy consumption of data centers also becomes high. In today's era, virtualization has become one of the most essential solutions in minimization of energy consumption. Virtual Machine Placement on hosts is the main concept which carried out during Virtual Machine migrations in data centers. Virtual Machine migration helps to utilize hardware resources of hosts, but leads to extra energy overhead in Data centers. The main objective of this work is to optimize energy consumption in the context of energy overhead during VM Live Migration. Our proposed hybrid algorithm provisions various VMs to hosts in a way that to minimize energy consumption, while delivering approved Quality of Service with minimum migration overhead. Results demonstrate that proposed EOHGA algorithm minimized energy consumption and migration overhead with defined test problems as compare to base VM Placement method.

Keywords
Data center, Virtualization, VM Placement, Energy Consumption, Virtual Machines (VMs), Genetic Algorithm

I. Introduction
Cloud computing is gaining importance day-by-day. The large number enterprises and individuals are shifting and opting for cloud computing services. Thousands of servers have been employed worldwide to cater the needs of customers for computing services by big organizations like Amazon, Microsoft, IBM and Google. The round-the-clock reliable computational services, fault tolerance and information security are the main issues to be addressed while providing services to geographically spread customer sites [1]. Cloud computing, also known as "pay as you-go" utility model is economy driven. It becomes necessary for the service provider to ensure load balance and reliable computing services to its clients round the clock worldwide and keeping services ON means consuming power all the time to use resources [2].
To reduce power consumption of Data centers is an important issue because of large amount of electricity consumption. Mekinsey & Company a consulting firm analyzed and stated that on an average only 6 to 8 percentage of total datacenter electricity power is used by their servers to perform computations [3].Thus; it is desirable to minimize energy consumption in data centers to reduce overall cost.
Virtualization technology helps to consolidate multiple VMs to lesser number of hosts and improves utilization of resources to reduce energy consumption. VM consolidation can provide significant benefits to cloud computing by facilitating better use of the available data center resources. Server consolidation using virtualization technology has become an important technology for improving the energy efficiency of data centers [4]. The basic idea behind the server consolidation technology is to perform migration of Virtual Machines (VMs) to as few energy efficient physical machines (PMs) as possible, and then switch off all the other PMs. The underlying computational problem of the server consolidation is basically a VM selection and placement problem, which has been elaborated in previous study [5]. In the past few years, many approaches to the VM consolidation problem have been proposed [6-10]. However, existing VM consolidation approaches do not consider the energy overhead during VM migration from one host to other.
In recent research studies, we have reviewed various papers [5] and analyzed the impact of VM size, migration time and network bandwidth parameters on energy consumption of subsystems [11].
A. Beloglazov et al. [10] presented the Modified Best-Fit Decreasing (MBFD) algorithm and Minimization of Migrations (MM), which is best-fit decreasing heuristic, for Power-aware VM allocation and adaptive threshold-based migration algorithms to dynamic consolidation of VM resource partitions.
The remaining paper is organized as follows: Section II presents literature review of recent studies. Section III formulates the new research problem; Section IV details the Energy Optimizing Hybrid Genetic Algorithm (EOHGA); Section V evaluates the performance of proposed genetic algorithm and finally Section VI concludes with discussion and talk about our future work.

II. Literature Review
In the past few years, many approaches to the VM consolidation problem have been proposed [6-10]. However; exiting VM placement methods do not consider energy consumption parameter optimization during migrations using genetic Algorithms. Maolin Tang et al. [12] proposed a genetic algorithm for new VM placement problem that considers the energy consumption in both the servers and communication networks in the data centers as preliminary research. Further this study was extended to improve the performance and efficiency of genetic algorithm. Heena Kaushar et al. [13] aimed to analyze various VM consolidation algorithms based on various heuristics on legitimate host. Authors also presented a comparative study of various existing energy efficient VM consolidation algorithms using real world workload traces from more than a one thousand VMs using CloudSim toolkit. Anton Beloglazov et al. [14] presented a survey of research in energy-efficient computing. The architectural principles for energy-efficient management of Clouds, energy-efficient resource allocation policies and scheduling algorithms considering QoS expectations, power usage characteristics of the devices, and a number of open research challenges are addressed. This work substantially contributes to both resource providers and consumers. The approach is validated by conducting a performance evaluation study using the CloudSim [15-16] toolkit showing significant cost savings and demonstrates high potential for the improvement of energy efficiency under dynamic workload scenarios. Bandi Madhusudhan et al. [17] designed a genetic algorithm which uses previous history and current demand of Virtual Machines in Placement decisions. Mohen Sharifi et al. [18] proposed an

algorithm to schedule the workload of a set of virtual machines (VMs) to a set of physical machines (PMs) in a datacenter. The goal was to minimize total energy consumption by considering the conflicts between processor and disk utilizations and the costs of migrating VMs. To identify the conflicts, authors presented four models, namely the target system model, the application model, the energy model, and the migration model. Simulative results of proposed algorithm showed 24.9% power savings compared to other methods. Fabio Lopez Pirez et al. [19] presented an extensive up- to-date most relevant VM consolidation literature review in order to identify research directions.

So, reducing power consumption is important and designing energy-efficient data centers has recently received considerable attention of research community. Energy consumption in data centers consists of two parts, including power consumed by the ICT (Information and Communications Technology) systems i.e. servers, storage and networking, and power consumed by infrastructure i.e. heating, ventilation and Air-Conditioning. Although many researchers have designed various algorithms to minimize energy consumption, but incorporation of the migration energy overhead during VM live migration with VM placement policies is very rare. Migrations through VM Placements still have enough potential to overcome the problem of energy consumption.

In this paper, we proposed Energy Optimizing Hybrid Genetic Algorithm (EOHGA) to optimize energy consumption during VM placement and VM migrations to cater extra energy overhead during migrations. Proposed Genetic Algorithm was evaluated and validated using statistical parameters.

III. Research Problem

Description of variables is given as follows:

|V|=a set of Virtual Machines

|P|=a set of Physical Machines

r_i^{cpu}=CPU requirement of Virtual Machines, $v_i \in |V|$

c_j^{cpu}=CPU capacity of Physical Machine, $p_j \in |P|$

u_j^{cpu}=CPU usage of Physical Machine, $p_j \in |P|$

V_{pj}=set of Virtual Machines allocated to $p_j \in |P|$

R_j^{cpu}=Rate of CPU Utilization of PM, $p_j \in |P|$

$u_{j,l}^{cpu}$=CPU utilization lower bound of PM, $p_j \in |P|$

$u_{j,u}^{cpu}$=CPU utilization upper bound of PM, $p_j \in |P|$

Utilization rate of CPU is written as follows:

$$R_j^{cpu} = \frac{u_j^{cpu}}{c_j^{cpu}} \quad (1)$$

As per energy consumption model given in [10], then the energy consumption of physical Machine p_j when its CPU utilization is R_j^{cpu} is given as follows:

$$E(p_j) = k.e_j + (1-k)\cdot e_j.R_j^{cpu} \quad (2)$$

Where k is the fraction of energy consumed when p_j is idle; e_j is the energy consumed when p_j is fully utilized and R_j^{cpu} is the CPU utilization rate.

It is assumed that the communication network topology in data centers is a typical three-tier tree as shown in Fig. 1 [20]. The VMs in a data center can communicate with each other through communication devices, such as switches, with different bandwidth capacities and data, which also consume a non-trivial amount of energy. It has been shown that the energy consumption of the communication network is largely dependent on bandwidth of concerned link and data transfer [11, 21]. Thus, we use the following method to approximate the energy consumption in the communication network in the data center.

We categorize the communication between a pair of VMs into four types. The first communication type is the communication between a pair of VMs on the same PM. The communication between vm2 and vm3 in Fig. 1 is an instance of the first type.

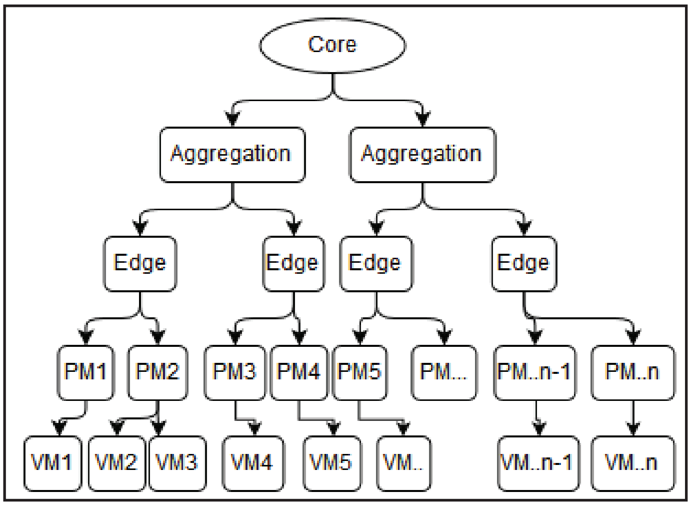

Fig. 1: Communication Network of Physical Machines and Virtual Machines

The second communication type is the communication between a pair of VMs that are placed on two different PMs, but under the same edge. The communication between vm1 and vm3 in Fig. 1 is an example of the second type. The third communication type is the communication between a pair of VMs that are placed on two different PMs under different edges, but under the same aggregation. The communication between vm3 and vm4 in Fig. 1 is an example of the third type. The fourth communication type is the communication between a pair of VMs that are placed on two different PMs under different aggregations. The communication between vm5 and vm placed on PM5 in Fig. 1 is an example of the fourth type.

Communication through these links varied with network bandwidth and size of data transferred. Therefore, the energy consumption incurred by these four types of communication links is different, as energy consumption of underlying systems varies with network bandwidth and VM size [11].

Let B1, B2, B3 and B4 be the various bandwidths defined on various communication links, Let S1, S2, S3 and S4 be the various data sizes sent on links between VM pairs. Communication type exits in VM pairs belong to the first, second, third and fourth, respectively, and let

$$B=B1 \cup B2 \cup B3 \cup B4 \quad (3)$$

$$S=S1 \cup S2 \cup S3 \cup S4 \quad (4)$$

Energy consumption for transferring data through these links is defined as follows:

ISSN : 0976-8491 (Online) | ISSN : 2229-4333 (Print)

$$e(b,s)=\begin{cases} e1, if\ b \in B1, s \in S1; \\ e2, if\ b \in B2, s \in S2; \\ e3, if\ b \in B3, s \in S3; \\ e4, if\ b \in B4, s \in S4; \end{cases} \quad (5)$$

Let $P(b,s)_{mig}$ be the power consumed by underlying systems with data transfer s amount of data with bandwidth b during live migration, $P(b,s)_{bmig}$ be the power consumed by underlying systems with data transfer s amount of data with bandwidth b before start of live migration.
Then, the energy consumption for transferring s units of data through bandwidth b on various links is given below:

$$E(b,s)_{overhead} = \left(P(b,s)_{mig} - P(b,s)_{bmig}\right) * t_{mig} \quad (6)$$

t_{mig} is the live migration time duration from source machine to destination machine through various links. Then, Virtual Machine Placement problem to assign VMs to physical Machines with minimized energy consumption and migrations is formulated as follows:

$$\sum_{p_j \in p} E(p_j) + \sum_{\substack{b \in B \\ s \in S}} E(b,s)_{overhead} \quad (7)$$

subject to the constraints

$$\bigcup_{p_j \in p} V_{pj} = V \quad (8)$$

$$\bigcap_{V_{pi}}^{V_{pj}} = \emptyset \quad p_j \neq p_i \quad (9)$$

$$u_{j,l}^{cpu} \leq u_j^{cpu} \leq u_{j,u}^{cpu} \qquad \forall\ p_j \in |P| \quad (10)$$

IV. Energy Optimizing Hybrid Genetic Algorithm

It is assumed that every physical machine can host any virtual machine, and its power consumption model is proportional to resource utilization, e.g. power consumption has a linear relationship with resource utilization (e.g. CPU utilization) [10, 22-23].
The objective of study is to optimize energy consumption of underlying systems during VM live migrations and placement of VMs on hosts with lesser number of migrations to overcome the energy overhead. To achieve the objective of study, Genetic Algorithm theory [24] was used to design solution of the formulated problem. This section discusses in detail Encoding scheme, genetic operators and fitness function of Genetic Algorithm along with description of proposed Hybrid Genetic Algorithm. Then, results of proposed algorithm were compared with latest algorithm [10] named as Base Algorithm.

A. Encoding Scheme

Genetic Algorithm consists of various numbers of chromosomes and each chromosome has various genes that can be represented as |B| that denotes to the Virtual Machine. If a gene has positive integer value between 1 and |A| where |A| denotes the Physical Machines on which VMs are to be allocated. Following Figure shows the placement of Virtual Machines in accordance with each chromosome.

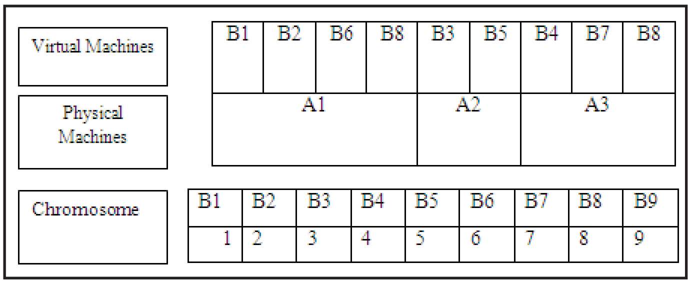

Fig. 2: Virtual Machine Allocation and its Chromosomes

B. Crossover Operator

Since the length of chromosome is potentially long, linkage is a potential problem that should be considered. Because of this consideration, the Genetic Algorithm adopts a biased uniform crossover operator, which is described in Algorithm 1.

Algorithm 1: Uniform Crossover

Input: Parent Chromosomes,
$P^i = c_1^i c_2^i c_3^i \dots\dots c_n^i$ and $P^j = c_1^j c_2^j c_3^j \dots\dots c_n^j$
Output: Single Child, $C^k = c_1^k c_2^k c_3^k \dots\dots c_n^k$

1: $g^i = fitness(P^i)$;
2: $g^j = fitness(P^j)$;
3: for s=1 to n do
4: Generate a number 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

C. Mutation Operator

Mutation operator work by arbitrarily collecting a gene from the collection of chromosomes and then reverse its value. Below algorithm 2 shows the mutation working:

Algorithm 2:Mutation

Input: Chromosomes, P= $c_1 c_2 c_3 c_4 \dots\dots c_n$
Output: Mutated , $P' = c_1' c_2' c_3' \dots\dots c_n'$
1: $P' \leftarrow P$
2: Generate randomly VM , $v_i \in |V|$
3: Generate randomly PM , $p_j \in |P|$
4: Exchange $c_i' \leftarrow p_j$
5: Output P'

D. Fitness Function

Fitness Function can be represented as below:
Fitness Function =

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

Where Fs, Ft, Rs, Rp, Crp, Cr_{ex} are parameters for optimization and e is the total energy consumption. The fitness function insures that fitness value of infeasible solution is less than that of any feasible solution. Then greater fitness value leads to minimization of energy consumption and VM migrations.

E. Hybrid Genetic Algorithm

Energy Optimizing Hybrid Genetic Algorithm (EOHGA) is a method to optimize energy consumption and to minimize VM migrations that leads to reduce migration energy cost.

First initialize the VMs and define its parameters to describe the performance of VM Live migration for power consumption. At the same time initialize hosts to accept VMs after migration to accommodate the extra workload. Virtual Machines are sorted in decreasing order as per their utilization to provide services. One Allocation table of VMs is generated against each defined host. Then for each VM and host in VM allocation table initialize Genetic Algorithm [24] to improve the allocations and remove faulty VMs for proper utilizations. VMs with optimum threshold value or who are producing optimum value for all the defined parameters are accepted and placed on corresponding hosts as per allocation table.

Then fitness function is applied with various defined parameters and allocation of VMs accepted/rejected on basis of threshold value of target host. Algorithm 3 presents the high level description of Energy Optimizing Hybrid Genetic Algorithm:

Algorithm 3: EOHGA

Input: Hosts and VMs with energy utilization
Output: VM Allocation and VM Migration List
Generate a population of individuals, Pop
Select the best individual, 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

V. Performance Evaluation

The EOHGA was implemented in MATLAB [25]. Randomly generated test problems were managed to test and validate Genetic Algorithm because there is no benchmark available for the VM Placement Problem.

Set of experiments were conducted to evaluate proposed genetic Algorithm with respect to energy optimization and migration overhead. Characteristics of the randomly generated test problems are shown in Table 1:

Table 1: Characteristics of Test Problems

Test Problem No.	VMs	PMs	Test Problem No.	VMs	PMs
1	80	20	7	120	16
2	90	20	8	120	24
3	100	20	9	120	28
4	110	20	10	120	32
5	120	20	11	120	36
6	130	20	12	120	40

In the experiments, the population size for EOHGA algorithm varied from 80 to 130 for VMs, 16 to 40 for hosts, the probabilities for crossover and mutation were non linear and 0.10, respectively, and the termination condition was 'no improvement' in the best solution for 10 generations. The various statistical parameters were used to validate the significance of results drawn after set of experiments.

Considering the stochastic nature of the Genetic Algorithm, experiments were repeated 10 times and recorded the solutions. The mean values and variance for all experiments were computed to draw the expected results in comparison with Base Algorithm (BA).

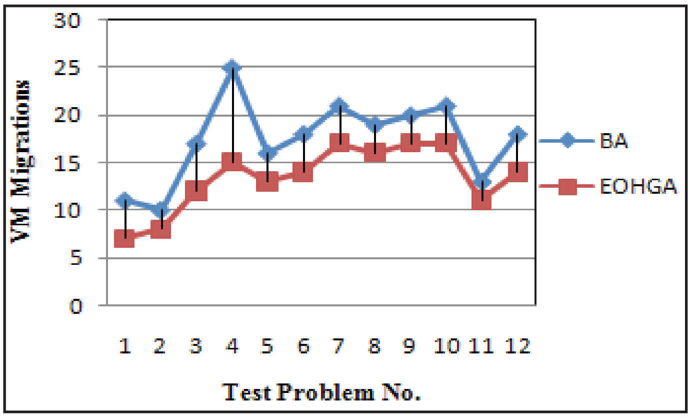

Fig. 3: VM Migrations in BA and EOHGA

P value for VM migrations is 0.0158 < 0.05, which means that there is statistical difference between two measures for all the characteristics. It has been shown in fig. 3 graph that few VM migrations were taken place using EOHGA as compare to Base Algorithm. Statistical results obtained from this experiment proved our earlier claim of fewer migrations with HVMA [26].

Table 2: Comparison of BA and EOHGA

Test Problem No.	Energy Consumption(kwh)		t-test Results		
	Base Algorithm	EOHGA Algorithm	t-stat	p Value	t-Crit
1	7.69695	1.4981	7.0658	0.000816	2.57
2	3.16121667	0.65775	8.1766	0.000848	2.57
3	16.5346667	13.77515	2.2927	0.049948	2.57
4	6.51528333	3.590433	2.7785	0.040784	2.57
5	20.6049333	3.688133	5.4709	0.001744	2.57
6	2.01401667	1.01525	3.4781	0.023912	2.57
7	12.5347667	8.372383	2.2412	0.035874	2.57
8	14.1612167	2.734517	5.0116	0.002866	2.57
9	5.46303333	3.063283	2.9004	0.044849	2.57
10	2.74893333	0.776417	4.6848	0.008257	2.57
11	5.91943333	3.55965	3.7474	0.036983	2.57
12	1.94115	0.9593	3.9070	0.034831	2.57

It is proved from the t- test result statistics in Table 2 that the EOHGA is significantly outperforms than the applied Base algorithm. The mean total energy consumption of the EOHGA Algorithm for the 12 different test problems of the same configurations is 33.20%-77.19% less than that of the applied Base Algorithm.
In order to prove the significance of the statistics in Table 2, we conducted a Paired two samples one tailed t-Test with different variance for each set of experiments. The confidence level of the t-Test was 95%. The null hypothesis and alternate hypothesis are given as follows:

$H_0: \mu_1 = \mu_2$ Null Hypothesis

$H_A: \mu_1 > \mu_2$ Alternate Hypothesis

Where μ_1 represents energy consumption by Base Algorithm and μ_2 represents energy consumption by EOHGA algorithm for various characteristics of test problems. Since for all the t-Tests performed on various set of problems, the p value is significantly less than the α value, which is 0.05, and the t-stat is greater than the t-critical value mostly for all set of problems, then null hypothesis was rejected and alternate hypothesis was accepted, which means, the difference between the two set of samples of energy consumption for 12 test problems is significant.
Which depicts that proposed EOHGA algorithm is a potential candidate for energy optimization in data centers during VM migrations.

VI. Conclusion

This paper has presented EOHGA algorithm to optimize energy consumption of VM placement problem and to cater extra energy overhead during VM migrations to different hosts. Statistical parameters were determined to evaluate the performance of EOHGA algorithm compared with the defined base algorithm for various set of problems. The results of the EOHGA algorithm have been found to be good enough in comparison to the base algorithm in terms of energy optimization and VM migrations. Results have been proved with statistical paired two samples one tailed t-Test with different variance values. On average the solutions produced by the EOHGA algorithm are 33.20%-77.19% better than those produced by the applied Base Algorithm.
In future research, we would extend this research to optimize some more performance parameters during VM Live migrations with different scenario and within defined Quality of Service constraints.

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