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E-PowerGA: A Genetic Meta-Heuristic for Energy-Efficient and SLA aware Virtual Machine Placement

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Abstract: *Cloud computing has emerged as a ubiquitous paradigm for providing computing and storage services over the Internet. With ever-increasing demand for cloud-based services, cloud service providers need to enhance the performance, reliability, and availability of data centers while reducing operational costs. Virtualization is an effective enabler for resource optimization with reduced power consumption; however, efficient VM placement remains one of the key challenges. The paper proposes a genetic meta-heuristic approach, referred to as E-PowerGA, to optimize VM placement by consolidating VMs into a minimum number of physical machines in a cloud data center. E-PowerGA aims at minimizing energy consumption and SLA violations while considering the migration overhead of VMs. Intensive simulations based on real workload traces from PlanetLab illustrate that E-PowerGA significantly outperforms traditional heuristics like Power-Aware Best Fit Decreasing. Experimental results have shown a reduction of 31.44% in energy consumption, 47.31% fewer VM migrations, and 60% improvement in SLA violations during the evaluation period of ten days. These findings pinpoint the efficiency of the genetic meta-heuristic optimization in enhancing energy efficiency and SLA compliance within a cloud data center*

Keywords: E-PowerGA, Cloud computing, Energy Consumption, SLAV, VM Migration, VM Placement, Genetic algorithm, Virtualization, VM consolidation.

INTRODUCTION

Cloud Computing allows the efficient usage of resources and reduces the time needed for operations. Despite the many advantages, the cloud services face certain constraints such as the Quality of Service (QoS), cost, deadline for execution, usage of power, time for execution, and the Service Level Agreement (SLA) [1, 2]. The efficient handling of these factors poses a significant problem, and a common strategy used for this purpose is the placement of a virtual machine.

VM allocation is concerned with choosing suitable physical machines (PMs) to run VMs and handling VM-to-PM relationships based on varying workloads. This is one of the most crucial aspects of resource optimization as well as reducing energy consumption (EC). Proper maintenance of usage information for hosts is necessary for reducing EC [3]. VM request arrival is usually modeled based on CPU, memory, bandwidth, and storage requirements. Resource allocation algorithms try to satisfy as many VM requests as possible by following allocation policies that control VM allocation. VM virtualization of hardware resources, servers, as well as operating systems, is also one of the main factors for reducing energy consumption and cost of operation. Data centers (DCs) represent the core infrastructure of cloud computing, consisting of clusters of servers that store data and run applications. These DCs include servers, networking equipment, cooling systems, and power infrastructure, all of which consume substantial amounts of electricity and contribute to carbon dioxide (CO_2) emissions. Consequently, optimizing energy utilization in data centers has become a critical challenge.

As the number of cloud users as well as the number of cloud services being implemented is growing on a daily basis, the energy consumption in the DC is also growing steadily. But to counter such an effect, researchers proposed a VM placement algorithm with the ability to detect both the overloaded as well as underloaded hosts in real time in order to decrease energy consumption with an acceptable level of QoS [4]. The main target of the VM placement problem is the minimized EC with the optimization of energy consumption for computation, storage, processing, as well as the movement of data processes [5]. As shown in Figure 1 below, the VM placement algorithm consists of a scheduler checking the current load of the target PM; if the capacity is adequate, the placement of the VM is carried out; otherwise, the scheduler will check another available PM.

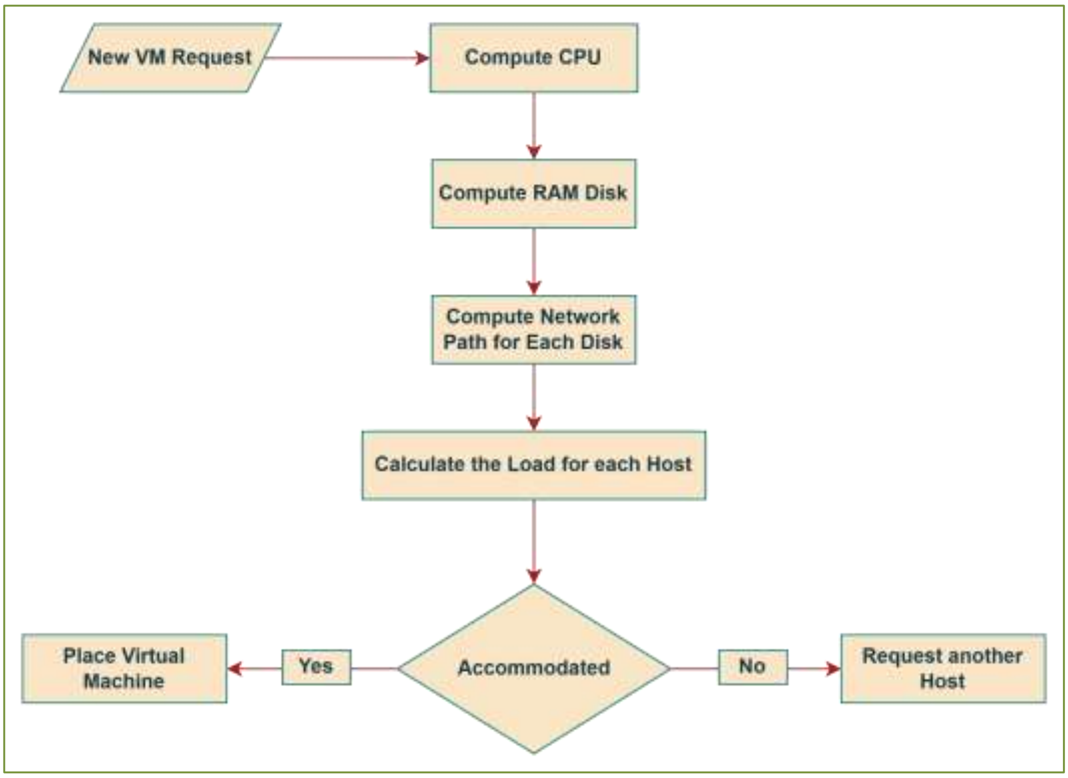

Figure 1. Virtal Machine Placement Flow

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Virtualization tries to optimize resource utilization and reduce power consumption to a great extent; hence, the important challenge of energy consumption (EC) in the management of data centers is met. The use of virtual machine placement (VMP) strategies is one of the important methods adopted to optimize the aforementioned objectives. With the current rapid expansion in the development of both IoT and cloud computing, intelligent applications have greatly fueled the adoption of cloud technology in response to the increased demand of consumers for computational services [6].

Cloud data centers consume huge amounts of energy, as processing requests from users requires substantial amounts of power, leading to the production of surplus heat, which has adverse effects on the efficiency of equipment. For optimal functionality, cooling systems are required. As a result, equipment processing as well as cooling systems are major factors in energy consumption in data centers. Research has shown that cooling systems alone account for almost 40% of the total energy expenditure in a cloud data center [7]. Moreover, carbon emissions caused by the substantial use of this energy also pose significant environmental problems, leading to the need for green computing in cloud data centers for sustainable development.

The worldwide energy use surpassed 600 TWh in 2015 [8], but is estimated to grow sharply to 2967 TWh in 2030, with hyperscale data centers also making a large contribution [9]. Data centers are estimated to emit about 2-3% of worldwide CO2 levels and use more energy than some countries, including the United Kingdom, and also digital data storage is estimated to make up nearly 14% of total emissions by 2040 [8]. The number of data centers has grown from 500,000 in 2012 to over 8 million, with energy use growing every four years [10].

As stated by PeaSoup, a cloud service provider, "Cloud computing has a large footprint, and this is primarily driven by energy consumption. Conservative estimates are that by 2025, the tech industry will account for nearly 20% of total global electricity demand, up from 10% currently, and this is primarily driven by cloud computing and related technology" [11]. Likewise, in a final report of a study that was submitted in reference [12], it was stated that cloud computing services are consuming more and more power in European cloud services, where data centers of the EU consumed 76.8 TWh of power in the year 2018, which will rise by 28% to 98.52 TWh in the year 2030.

The previous works [13] that were performed to address the energy consumption issues in the cloud environment were to propose an integrated paradigm of IoT and clouds to optimize resource usage, load balancing, and analysis of the energy efficiency of the proposed paradigm [14]. The concept of virtualization forms the basis of cloud computing, supporting the mapping of virtual machines to physical machines. This involves the concept of CPU and memory virtualization, where multiple virtual machines run multiple isolated tasks on a single physical machine. Similarly, the concept of network virtualization has been proposed to efficiently deal with energy consumption in the cloud environment.

Reducing energy consumption in cloud data centers is thus an essential requirement. Various research studies have shown a linear correlation between PM CPU utilization and energy consumption [15]. CPU utilization can thus be considered a prominent parameter in measuring the energy efficiency of the cloud data centers. Additionally, the cooling mechanism needed for heat management is another energy-intensive component. Reducing energy consumption without compromising the acceptable QoS is thus a rewarding requirement. Recent research studies have made efforts to optimize resource utilization based on energy efficiency and QoS parameters [16]. The proposed research work aims at improving efficiency and optimizing energy consumption.

Dynamic consolidation of virtual machines (DCVM) has been identified as a leading approach in the consolidation of energy consumption in a cloud data center environment [17]. The VMP problem, which is a variant of the bin-packing problem, has been solved in the past by employing the concepts of a variety of algorithms including heuristics, meta-heuristics, and soft computing algorithms [18]. For the VM placement process in this proposed model, a Genetic Algorithm (GA), building upon the original concepts expressed by Holland in [16], has been applied, which is well-known for the discovery of near optimal solutions by making use of a variety of operators inspired by nature, including selection, crossover, mutations, and evaluation, as depicted in the figure below.

In the proposed work, the fitness function will be defined on the basis of the power consumption of physical machines. In existing research works, SLA satisfaction, energy minimization, and rank-based metrics have also been considered in the evaluation of the fitness function. Several experiments on DCVM have been carried out for the purpose of improving efficiency, resource optimization, and minimizing energy use.
The task here is to detect the overutilized and underutilized PMs, forecast resource demand, choose candidate VMs, and migrate the VMs to appropriate destination PMs [21]. The aim here is to load the work on the least active number of PMs in order to overcome the inefficiencies associated with overutilization and underutilization of PMs. VM migration facilitates the shuffling of loads without disturbing the services; it also imposes performance-related overheads and may result in reduced system efficiency unless properly managed [22]. Carlos Juiz et al. studied the performance overheads of physical machines during VM consolidation for the purpose of analyzing the impact of energy efficiency on performance overheads using Speedup, Efficiency, and Scalability parameters of parallelism [23].

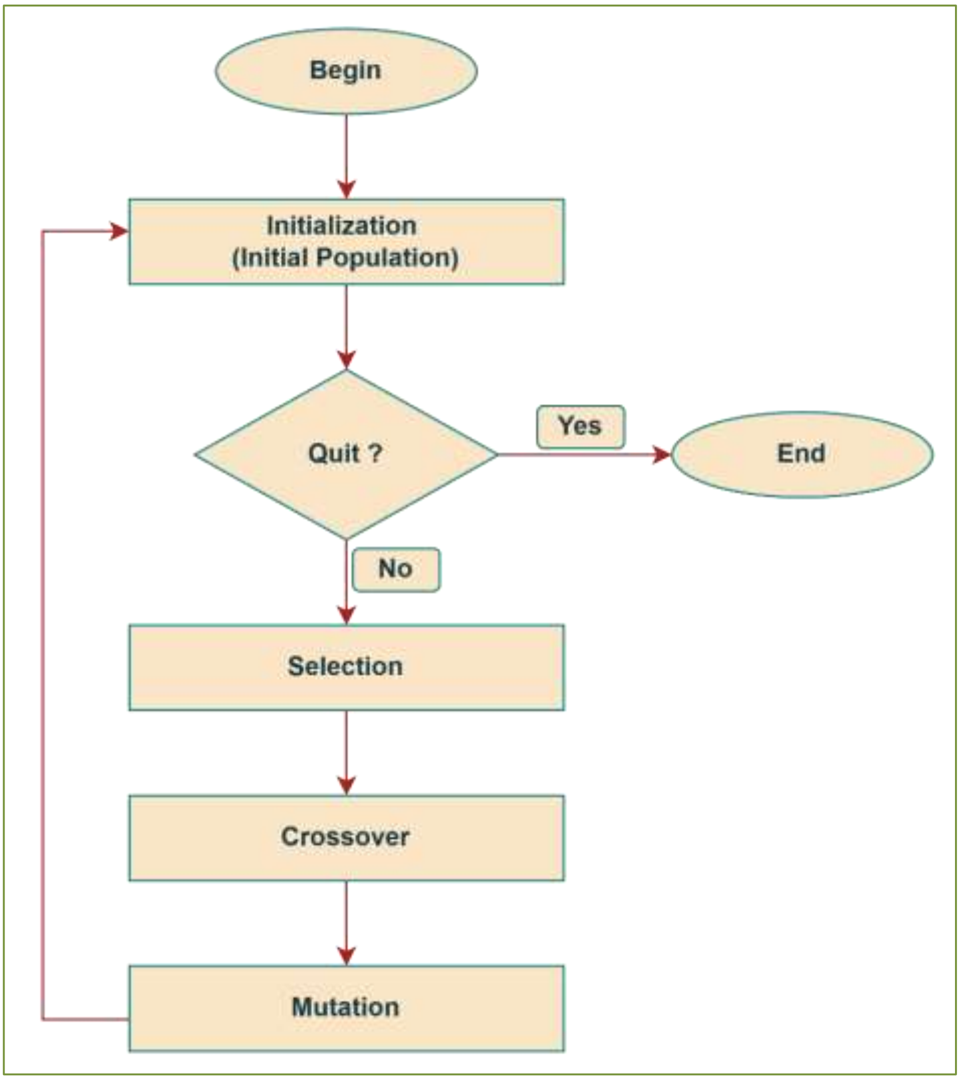

Figure 2. Genetic Algorithm (GA) Process

Through this paper, dynamic consolidation of virtual machines (DCVMs) can be accomplished by using a strategy to place VMs, which has been called E-PowerGA, based on inspiration from former research work. For identifying overloaded physical machines (PMs) and resource utilization, this paper uses a method based on local regression (LR). As a remedy to avoid overloading of physical machines, a careful selection process based on a Minimum Migration Time (MMT) algorithm [24] has been used. According to the established framework, a mechanism based on the combination of LR and MMT will provide a group of virtual machines to overloaded PMs. This group will be utilized as input to encode a process, where power consumption has been included effectively in terms of defining a fitness function. Eventually, these methods have been utilized to place virtual machines on physical machines effectively.

Through this analysis, results have been obtained, which have confirmed that this work develops a competent strategy based on meta-heuristics to handle virtual machine management on its own at a cloud data center to manage energy consumption effectively along with providing optimal QoS.

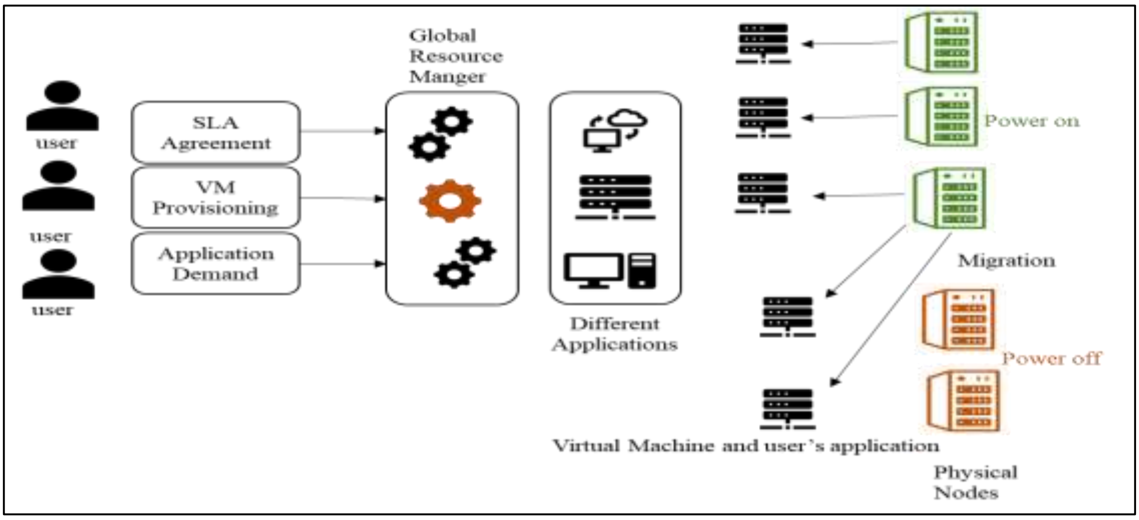

Figure 3. VM Consolidation in Cloud Computing

One of the most efficient methods to mitigate challenges regarding resource utilization as well as energy consumption in cloud data center infrastructure is the adoption of virtualization technology and VM consolidation techniques. Figure 3 shows a state-of-the-art cloud system design using virtualization technology and VM consolidation techniques [35]. In this design solution, cloud users submit service requests to cloud service providers. Finally, cloud service providers assign such service requests to VMs hosted on physical machines. Thereafter, unused machines are turned off by migrating VMs to machines that are more heavily loaded in order to decrease energy consumption attributed to idle machines.

Table 1. VM Consolidation Techniques

Technique	Energy-Efficiency / Power-Saving Approach	Performance Metrics Evaluated
Online Linear Programming	B-matching theory is applied to repackage workloads efficiently	SLA compliance, minimum operational cost, and number of VM migrations
K-Nearest Neighbour (KNN) with Regression Analysis	KNN-based prediction is used to identify host over-utilization and under-utilization	SLA violation rate and energy consumption
Ant Colony Optimization (ACO)	VM consolidation is formulated as a bin-packing optimization problem	CPU utilization, memory utilization, and bandwidth usage
Distributed Parallel ACO	ACO algorithm is executed in parallel across multiple servers	CPU utilization, memory utilization, and VM migration failure rate

In addition, improving the efficiency of data centers has also been a focus in recent years. The cloud data centers run at a low processing utilization rate without stopping their enormous power consumption, thereby causing inefficient energy use. In this regard, there have been proposed methods for improving the consolidation techniques in virtual machines [36], some of which are shown in Table 1 above.

However, the process of VM consolidation can also pose new issues. When the migrated VMs run on the actual operational servers, it can lead to the overloading of some physical servers. Moreover, if the growing requirements of the existing VMs also add to the issue of server overloading, it can further increase the problem of performance issues or BREACH of Service Level Agreement.

The rest of this paper will be structured as follows: In Section II, the application of genetic algorithms in VM allocation will be briefly discussed, and existing research in the same domain will also be provided. The problem definition will be stated in Section III. In Section IV, the approach will also be explained in a comprehensive manner. The environment for the simulations will be defined in the following Section V, while the performance metrics and comparison results on the superiority of the GA-based VM allocation over the heuristics will be stated in Section VI. Eventually, the entire research will be concluded in Section VII.

LITERATURE REVIEW

This section presents reviews of resource management approaches based on genetic algorithm techniques that have been proposed for the VMP problem. Several GA-based metaheuristic methods were developed and evaluated to address energy efficiency, service level agreement violations, and resource utilisation in cloud data centres. Some representative studies are discussed in what follows.
Mustafa et al. [33] presented the Utilization-Based Genetic Algorithm (UBGA), which performs machine utilization and node distance for simultaneous minimization of energy consumption, network load, and resource wastage. Comparative evaluations performed using CloudSim revealed that UBGA achieved predominant performances regarding utilization efficiency, networking overhead, and energy reduction compared to conventional techniques in resource placement.

P. Karthikeyan [32] proposed a Self-Adaptive Immigrants GA (SAI-GA) for enhancing VM placement with the aim of maximizing the utilization of CPU and memory of PMs. This algorithm utilized several immigrant schemes. The results obtained were compared using non-parametric statistical tests to check its performance against the available methods and came out on top.

A novel Improved GA algorithm called I-GA with a virtual hierarchical architecture model was introduced by authors Jiawei Lu et al. [31]. Their results showed energy efficiency optimization with a high availability level when simulated on CloudSim compared to several baseline VMP algorithms.
In the following, the work of Hormozi et al. [30] is summarized: VMP has been formulated as a constrained optimization problem, and an accelerated genetic algorithm has been developed for minimizing the residual resource. Their strategy outperformed the existing methods of FFD and Genetic Algorithm in terms of solution quality, execution time, and energy consumption.

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Farouk A. Emara et al. [29] proposed a GA-based multi-objective task scheduling algorithm called G-MOTSA for cloud resource management. The system comprised a matrix chromosome for tasks, VMs, and servers. The simulation outcomes demonstrated the superiority of G-MOTSA over ETVMC, TSACS, and ACO algorithms in terms of parameters like Energy Consumption, Makespan, Throughput, and Resource Utilization.
Elnaz et al. [28] used the Non Dominated Sorting Genetic Algorithm III (NSGA-III) for multi-objective VMP problems. The proposed system worked on minimizing power consumption, reducing the count of activated VMs, and preventing resource wastage. The outcome of the simulations proved the efficiency of NSGA-III in comparison with various existing multi-objective VMP algorithms in regard to efficiency and complexity.

Abohamama et al. [27] presented a permutation GA to conceal power usage as well as active PM number for data center settings. The strategy provided balanced usage of resources such as PMs, memory, and bandwidth by using an improved genetic algorithm along with a resource-aware best-fit approach.
Abdelkhalik Mosa et al. [26] tackled the dynamic VM allocation problem by taking into account the CPU and memory demands. This GA-based reallocation strategy in the real-time scenario maximizes PM utilization, thereby reducing SLAVs. Experiments carried out in CloudSim proved its effectiveness in comparisons with Best Fit Decreasing (BFD).

Kaaouache Mohamed Amine et al. in [25] proposed an HGA for VM placement in order to reduce the energy consumption of PMs. The selection of parents was carried out using the roulette wheel technique. Moreover, the crossover operation was performed using the single-point method. Additionally, in the mutation phase, VMs are exchanged between randomly chosen PMs. The experimentally obtained results proved the superiority of the proposed method compared with existing ones. A meta-heuristic framework based on GA for making decisions for VM placement was proposed by Oshin et al. [24]. Comparison with existing approaches for placement has shown that the proposed method is effective for energy costs as well as for reducing SLA violations.

A brief overview of related research work is presented in Table 2 below. This work concentrates on applying a genetic algorithm to place a virtual machine, taking into account power consumption.

The key contributions of this work are summarized as follows:

1) An optimization framework using GA for effectively solving VM placement problems in cloud data centers is presented.
2) The VMP problem is defined as a multi-objective optimization problem that maximizes SLA and minimizes the total energy usage simultaneously.
3) Formula design also strives to achieve the minimum migration overhead for VMs and a minimal number of active physical machines.
4) A new approach based on GA is proposed, called E-PowerGA.
5) E-PowerGA adopts a linear matrix concept for defining the link and association between virtual machines and physical machines in a virtual machine environment.

6) The GA approach proposed here includes five traditional evolutionary steps, namely the initiation of the population, the process of evaluating fitness, the selection step, the crossover process
7) A customized fitness function is employed that calculates the quality of solutions based on the predicted CPU use of physical compute resources.
8) The efficiency of E-PowerGA is simulated and compared using a real workload trace through a CloudSim simulator and a 10-day PlanetLab trace.
9) Comparative performance analysis is done by the proposed algorithm in relation to the PABFD Heuristic-based VMP algorithm on standard SPEC benchmarks.

Table 2. Related work on current GA-based virtual machine placement strategies.

Author / Year	**Chromosome Representation**	**Fitness Evaluation Criteria**	**Selection Strategy**	**Crossover Method**	**Mutation Strategy**	**Limitation / Future Scope**
Mustafa et al. [33] **2024**	Tree-based representation	Resource wastage and communication cost	Tournament selection	Uniform-rate crossover	Random mutation	Migration overhead and SLA awareness need further investigation.
Karthikeyan [32] **2023**	Integer-based encoding	Objective function and constraint violations	Random selection	Two-point crossover	Swap mutation	Performance may degrade with frequent workload fluctuations
Jiawei Lu et al. [31] **2022**	Group-based encoding	Energy efficiency and availability	Probability-based selection	Mating with random crossover	Probabilistic mutation	High computational overhead due to hierarchical modelling
Hormozi et al. [30] **2022**	Individual-based encoding	Energy consumption and residual resources	Tournament selection	Uniform-rate crossover	Random mutation	Requires parameter tuning for large-scale data centers
Farouk A. Emara et al. [29] **2021**	Matrix-based encoding	Minimized energy and maximized system performance	Tournament selection	Single-point crossover	Probabilistic mutation	Primarily focuses on task scheduling rather than pure VM placement
Elnaz et al. [28] **2020**	Family genetic representation	Reduction in execution time and energy usage	Fitness-based selection	Single-point crossover	Random mutation	Time complexity increases for large-scale multi-objective scenarios

Abohamama et al. [27] **2020**	Permutation-based encoding	Energy consumption minimization	Roulette wheel selection	Ordered crossover	Random mutation	Limited adaptability to highly dynamic cloud environments
Abdelkhalik Mosa et al. [26] **2019**	Dynamic mapping mutation	Physical machine utilization	Tournament selection	Uniform crossover	VM-level mutation	Focused on CPU and memory; network and storage resources are not considered
Kaaouache et al. [25] **2018**	Array encoding	Energy consumption of placement solution	Roulette wheel selection	Single-point crossover	Random mutation	Does not consider SLA violations and VM migration costs explicitly
Oshin et al. [24] **2017**	Tree-based structure	Power and resource utilization metrics	Random selection	Random crossover	Random mutation	Lack of intelligent selection mechanisms may slow convergence

Research Gap

The virtual machine placement method involves mapping of *VMs to PMs*, resulting in a total of $m \times n$ possible mappings in the search space to allocate *m VMs to n PMs*. This problem of VMP mirrors the bin packing problematic, where items with diverse sizes are packed into bins of varying capacities. In this analogy, VMs correspond to items, while PMs correspond to bins. The data center comprises *'n' PMs* $\{pm_1, pm_2, \ldots\ldots, pm_n\}$ to host the *'m' VMs* $\{vm_1, vm_2, \ldots\ldots, vm_m\}$. A function is used to allocate all virtual machines that minimizes the number of physical machines required, while still meeting energy utilization and quality of service *(QoS) constraints.*

The Best Fit heuristic is a popular method for solving bin packing problems and has been employed by Beloglazov et al. in [17] to tackle the VMP problem. They further modified the Best Fit heuristic to accommodate energy-constrained and energy-aware VM-to-PM allocation. The technique involves first arranging the list of migrating VMs in descending order with respect to their CPU utilization. Next, for the allocation of every VM, the PM providing the minimum amount of increased power consumption is chosen.

Proposed Architecture for VM Placement

The problem of Virtual Machine Placement (VMP) demands a practical method to place the virtual machines (VMs) on physical machines (PMs) efficiently. This study proposes a solution to the VMP problem using the Genetic Algorithm (GA) metaheuristic technique, as compared to other heuristic approaches. The main aim of the proposed study is to minimize the number of active physical machines

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(APMs) and minimize the energy consumption (EC) as well. A cloud platform comprises m number of VMs to be assigned to n number of physical machines. A good mapping technique must therefore try to minimize the EC and maximize the SLA. Even though various solutions and techniques exist to solve the problem of VMP, various techniques could be used to define the efficient mapping method. This paper intends to propose E-PowerGA, a method using the Genetic Algorithm to search for a superior solution to VMP in the data center.

Then, generate random solutions that do not address any feasibility constraint. After that, in each iteration, a set of crossover and mutation operations is applied to enhance the quality of VM placement solutions. In a genetic algorithm, as shown in Figure 4, a set of candidate solutions is called population, and each individual solution is represented as a chromosome.

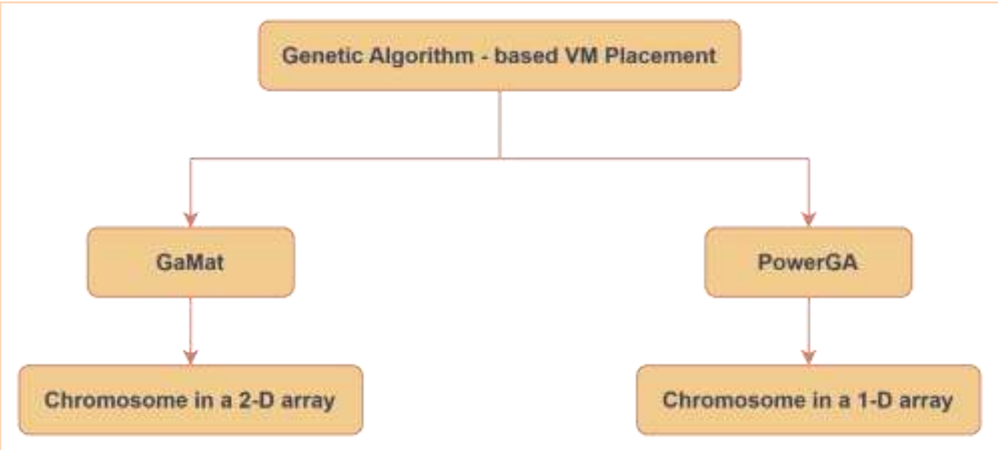

Figure 4. Genetic algorithm-based VM Placement

Populating Solution

In a genetic algorithm, the population is a representation of possible solution sets for the optimization problem. A larger population means greater genetic diversity; it can search more extensively through solution space. But in return, it is more demanding in terms of computational requirements. Figure 5 shows linear structure chromosome for E-PowerGA.

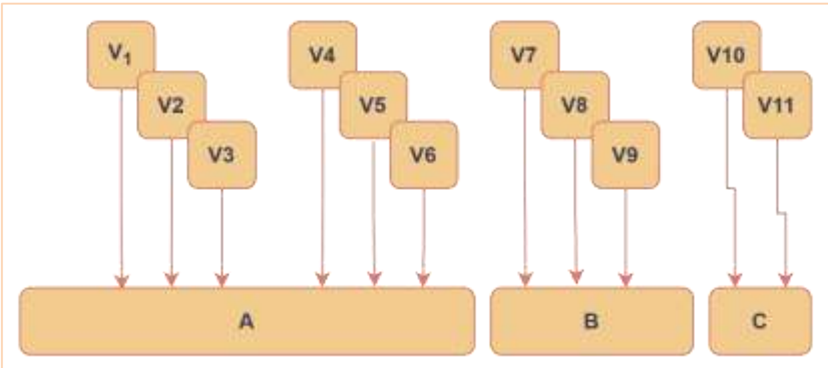

Figure 5. Chromosome Code : ABC (A: $V_1, V_2 \dots V_6$) (B: V_7, V_8, V_9) (C: V_{10}, V_{11})

Equation 1 shows that the variable x_i represents the PM_j, which hosts the VM_i.

$$x_i = PM_j, \quad if\ VM_i\ is\ allocated\ to\ PM_j \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Fitness function

The algorithm enhances candidate solutions by using a fitness function. The greater the value of the fitness, the more likely it is for an individual to be selected for reproduction, thereby favoring better solutions in subsequent generations. The fitness function evaluates the solution quality, in which the higher the fitness, the better the solution quality. In this work, the fitness value of E-PowerGA is based on the power consumption P_c of PMs. The remaining capacity ($RemCap_{PM}$) for each PM is computed using equation 2, incorporating the total capacity ($TotCap_{PM}$) of PM and the resource requirements ($ResReq_{VM}$) of all VMs in that PM. The power consumed (P_c) of PMs is determined using the LR method as described in equation 3.

$$RemCap_{PM} = TotCap_{PM} - \sum_{i}^{m} ResReq_{VM_i} \quad \forall VM \in Vm_{list} \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$P_c = Local\ Regression\ (Utilization\ History\ of\ PM) \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

As infeasible solution sets might result after applying the fitness function because the capacity of some PMs might become negative as a result of excess demand beyond capacity, such solution sets are assigned -1 as their fitness. In other cases where solution sets are feasible with positive remaining capacity for all PMs, as indicated in Equations (4) & (5), the assigned fitness is inversely proportional to Pc, which is the total power consumed by PMs shortlisted for VMP.

$$Total\ P_c = \sum_{i}^{m} Pc\ (PM_i) \quad \forall PM_j \in Pm_{cand} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

$$\eta = \begin{cases} -1, & RemCap_{PM_i} < 0 \\ \frac{1}{Total\ P_c}, & RemCap_{PM_i} > 0 \end{cases} \quad \forall PM_j \in Pm_{cand} \quad \ldots\ldots\ldots\ldots (5)$$

The above fitness function is used in the E-PowerGA algorithm. The linear chromosome in E-PowerGA undergoes a process of converting the chromosome to an array representation, and the fitness of the resulting solution is determined.

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Selection, Crossover and Mutation

Selection, crossover, and mutation are the main genetic operators adopted in the E-PowerGA framework in order to drive the evolution of the population toward the optimal solution of the VM placement problem. Through the selection process, only fitter chromosomes undergo reproduction. In this way, the subsequent generation is likely to include the best solutions. The crossover then takes place, aimed at exchanging genetic material between selected parent chromosomes and generating offspring that may have further improved characteristics. After that, mutation introduces random changes in chromosome genes for the maintenance of population diversity, with the final purpose of preventing the premature convergence toward local optimum solutions.

Table 3. Selection, Crossover and Mutation in the Proposed Method

S. No.	Selection	Crossover	Mutation
1.	Select which candidates will become the parents for the next generation of candidates.	Decide how to generate offspring from the parents.	Determine how to randomly mutate some offspring to introduce additional diversity.
2.	The selection process chooses individuals from the present reproduction methods to form the next generation.	During the crossover, GA joins two separate solutions or chromosomes to form the next generation.	Mutation involves making small, random changes to an individual's genetic information, thereby increasing diversity in solutions.
3.	Parent solutions are chosen to generate new solutions.	Two parent solutions from the population are selected for single-point crossover.	Aims to decrease the quantity of active PMs in a solution.
4.	Based on their fitness.	Single-point crossover is applied.	Random mutation occurs.

E-PowerGA Approach

The process begins in E-PowerGA by generating the initial population, composed of k solutions created randomly, where each solution is encoded into a chromosome. At this stage, it does not consider the quality of the solution; hence, some chromosomes could represent infeasible solutions. In the next phase of crossover, two parent solutions, p1 and p2, are randomly chosen from the population in order to proceed with single-point crossover. The crossover point is randomly determined between zero and the total number of migrating virtual machines.

Based on this point, genetic material is exchanged between the parent chromosomes to generate a new offspring solution. The final phase is mutation, which focuses on the minimization of the number of active PMs within a solution. This is achieved by shifting genes representing migrating VMs from one PM to another with the goal of improving the overall fitness value. While mutation may generate infeasible solutions, at each iteration, the fitness function is evaluated to check the validity of solutions. The main goal of this phase is to reallocate the VMs in such a way that minimizes the number of active PMs within the chromosome.

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Algorithm 1: Population Initialization for E-PowerGA

Input:
(m): List of migrating Virtual Machines (VMs)
(n): List of available Physical Machines (PMs)
Output:
A randomly generated initial solution (chromosome)

Steps:

1. Initialize all elements of the solution matrix to zero.
2. Randomly generate an index *PMIndex* within the range *[0, n]*.
3. For each physical machine *PM* in the PM list, set its temporary utilization value to zero.
4. For each virtual machine *VM* in the migrating VM list:
   - Add the *VM* to the list of candidate VMs.
5. Initialize the variable *allocatedVM* as *null*.
6. For each VM *i* from *1* to *m:*
   - Select the i^{th} candidate VM.
   - Assign the selected VM to the PM indicated by *PMIndex* in the solution matrix.
   - Update *PMIndex* by generating a new random value within the range *[0, n]*.
7. Construct the solution chromosome from the updated solution matrix.
8. Return the generated solution.

This algorithm produces a randomly populated initial solution for E-E-PowerGA without considering feasibility constraints, allowing genetic operators to refine solutions in subsequent phases.

Algorithm 2: Crossover Function (E-PowerGA)

Input:
p1, p2 : Two parent chromosomes (VM placement solutions)
Output:
offspring : A new chromosome generated after crossover

Steps:

1. Begin
2. Select a random integer *t* such that
   $0 < t \leq \text{Total number of migrating VMs}$
3. Compute the crossover point:
   $csPoint \leftarrow numberOfVMs / t$
4. Initialize *offspring* as a copy of parent *p1*.
5. For each index *i* from *1* to *csPoint* do:
6. Swap the genes of *p1* and *p2* at position *i + csPoint.*
7. Update *p1* with the modified chromosome.
8. Assign the updated chromosome to *offspring*.
9. Return *offspring*.
10. End.

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This algorithm performs a single-point crossover operation by selecting a random crossover point based on the number of migrating virtual machines. Genetic material from two parent solutions is exchanged beyond the crossover point to generate a new offspring, thereby promoting solution diversity in the E-PowerGA-based VM placement process.

Simulation and Ordinal Measures

Due to the limited accessibility of real-world data center environments, many studies conduct experimental evaluations using simulation tools. In this work, CloudSim is employed as a virtual simulation platform to perform the experiments. In data centers, various components such as memory, CPU, disk storage, power supply units, and cooling infrastructure significantly contribute to overall energy consumption. Previous work by Fan et al. [12] demonstrated that server power consumption can be effectively modelled using a linear relationship between energy consumption and CPU utilization.

Accordingly, this study utilizes real power consumption data obtained from SPECpower benchmark results to estimate energy usage. The SPECpower benchmark is adopted in the proposed algorithm for energy consumption calculation. Table 4 presents the specifications of two server models, PowerEdge R610 and PowerEdge R710, equipped with dual-core processors, along with their corresponding virtual machine (VM) and physical machine (PM) configurations. Furthermore, Table 5 reports the energy consumption values, measured in watts, for different levels of CPU utilization. To enhance the practical relevance of the evaluation, real workload traces from the PlanetLab dataset are employed, as summarized in Table 6.

Table 4. Simulation Ordinal Measures

Specification	PM Specification (Dell Server)		VM Specification			
	PowerEdge R610	PowerEdge R710	Type I	Type II	Type III	Type IV
RAM	4096 MB	4096 MB	613 MB	1.7 GB	1.7 GB	0.85 GB
CPU Capacity	2660 MIPS	1860 MIPS	500 MIPS	1000 MIPS	2500 MIPS	2500 MIPS
CPU Cores	2	2	1	1	2	2
Storage	1 TB	1 TB	10 GB	20 GB	30 GB	15 GB
Bandwidth	1 Gbps	1 Gbps	100 Mbps	200 Mbps	300 Mbps	150 Mbps
Power Model	SPECpower	SPECpower	–	–	–	–
Virtualization	Host-based	Host-based	Xen/KVM	Xen/KVM	Xen/KVM	Xen/KVM

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Table 5. Average Energy Utilisation (in watt) at Diverse Computing Load

Computing Load	Idle	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Dell PowerEdge R650	78	82	87	93	99	105	112	118	125	131	138
Dell PowerEdge R750	85	90	96	102	109	116	123	130	137	143	150

Table 6. Workload Datasheet

Days	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
Total VMs	1840	1725	1962	2210	2054	2386	2294	2148	1987	1896

RESULTS AND DISCUSSION

E-PowerGA integrates the Local Regression and Minimum Migration Time techniques (LrMmt) to detect overloaded physical machines (PMs) and to identify virtual machines (VMs for migration) from these overloaded PMs. Subsequently, the E-PowerGA algorithm is applied to perform virtual machine placement (VMP) for the selected VMs.

The performance of E-PowerGA is evaluated in comparison with the Power-Aware Best Fit Decreasing (PABFD) VMP technique using several performance metrics. Among these metrics, energy consumption is a primary indicator of data center efficiency. Energy consumption is calculated based on the power usage of hosts, as presented in Table 4. Another important metric is the number of VM migrations (VMM) carried out during the VMP process after selecting VMs from under-utilized hosts.

Service Level Agreement Violations (SLAVs) during the workload consolidation phase are quantified using two components: Performance Degradation due to Migration (PDM) and SLA Time per Active Host (SLATAH). PDM measures the overall performance loss caused by VM migrations, whereas SLATAH represents the fraction of time during which active hosts experience 100% CPU utilization.

Energy Consumption

Fan et al. derived a linear equation based on the energy consumption (EC) of a physical machine (PM) and the CPU usage [12]. This study employs the CPU usage of the PM to predict the energy consumption.

Therefore, the equation forming the relationship of EC to the utilisation of the CPU of the PM is given by:

$$P_{total} = P_{idle} + (P_{max} - P_{idle}) \times U \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

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Where P_{total} is the total power consumption of the physical machine (PM), P_{idle} is the power consumption during the idle time of the PM, P_{max} is the power consumption during the time the host is maximally utilized, and U is the CPU usage ratio.

The proposed E-PowerGA method removes all Pms with zero predicted utilization, since these computers are likely to remain underutilized in the following time intervals. Thus, resource underutilization is minimized, resulting in the prevention of wasteful consumption. As seen from Table 7 and Figure 6, the proposed method effectively reduces total Energy Consumption and simultaneously optimizes service efficiency.

Table 7. Energy Consumption

Day	PABFD Energy Consumption (kWh)	E-PowerGA Energy Consumption (kWh)
Day 1	173.43	133.23
Day 2	130.62	100.95
Day 3	150.74	113.43
Day 4	187.69	138.22
Day 5	163.05	119.70
Day 6	233.48	180.73
Day 7	191.53	143.44
Day 8	189.41	140.99
Day 9	161.58	121.91
Day 10	139.14	100.14

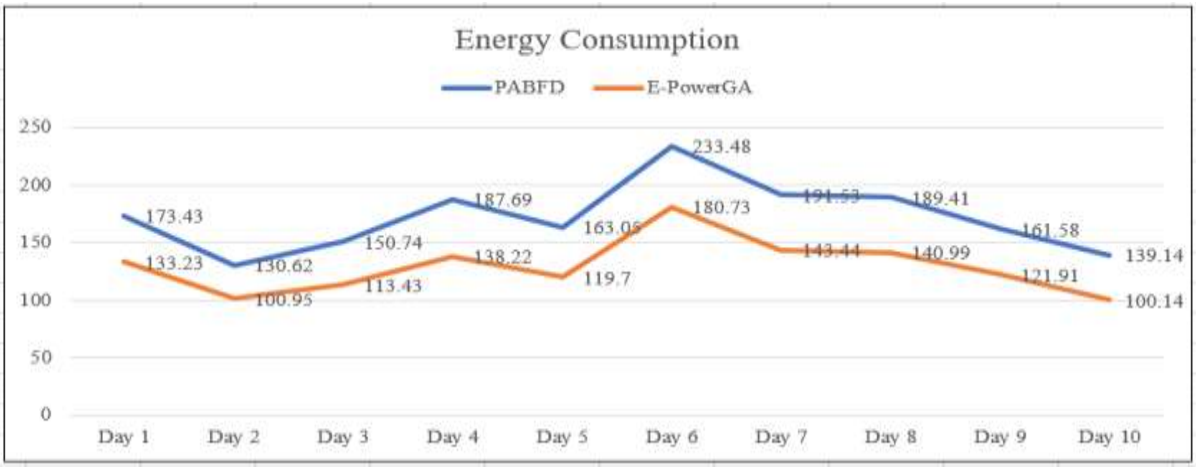

Figure 6. Improvement in Energy Consumption

VM Migration

Optimal Data Center Virtualization Management (DCVM) is considered a very challenging task, mainly because of the issue of virtual machine migrations that facilitate the smooth movement of virtual machines from one physical machine to another. The issue of virtual machine migrations directly affects system performance, where a 10% increase in CPU use indicates a corresponding degradation of system performance in terms of reduced system throughput, leading to the violation of the Service Level Agreement (SLA) [18].

Equations (7) and (8) yield the migration time and performance degradation caused by the VM migration. With an increase in the rate of VM migrations, the efficiency of the system decreases. Thus, the rate of VM migrations becomes a key performance indicator in the proposed approach. Despite the significance of VM migration in DCVM, it is important to minimize unnecessary VM migrations to maintain the stability of the system.

$$Tm_j = \frac{M_j}{B_j} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

$$Ud_j = 0.1 \times \int_{t_0}^{t_0 + Tm_j} u_j(t)dt \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

where, Tm_j is the total migration duration, $u_j(t)$ is the CPU utilisation by VM_j, M_j is the memory utilised by VM_j, and B_j is the available network bandwidth. Ud_j is the entire degradation in system performance, t_0 is the time when the migration is initiated, the VM migration causes a 10% performance degradation.

The proposed DCVM mechanism was evaluated using real workload traces, and the number of VM migrations was analysed. Experimental results indicate that E-PowerGA consistently outperforms the PABFD-based DCVM approach in terms of reducing VM migration count and migration improvement, as illustrated in Table 8 and Figure 7.

Table 8 VM Migration

Days	PABFD	E-PowerGA
Day 1	29152	15040
Day 2	21413	11757
Day 3	25551	14756
Day 4	33073	19693
Day 5	28690	16149
Day 6	40200	22729
Day 7	33159	18795
Day 8	32864	17698
Day 9	27239	15689
Day 10	25887	15304

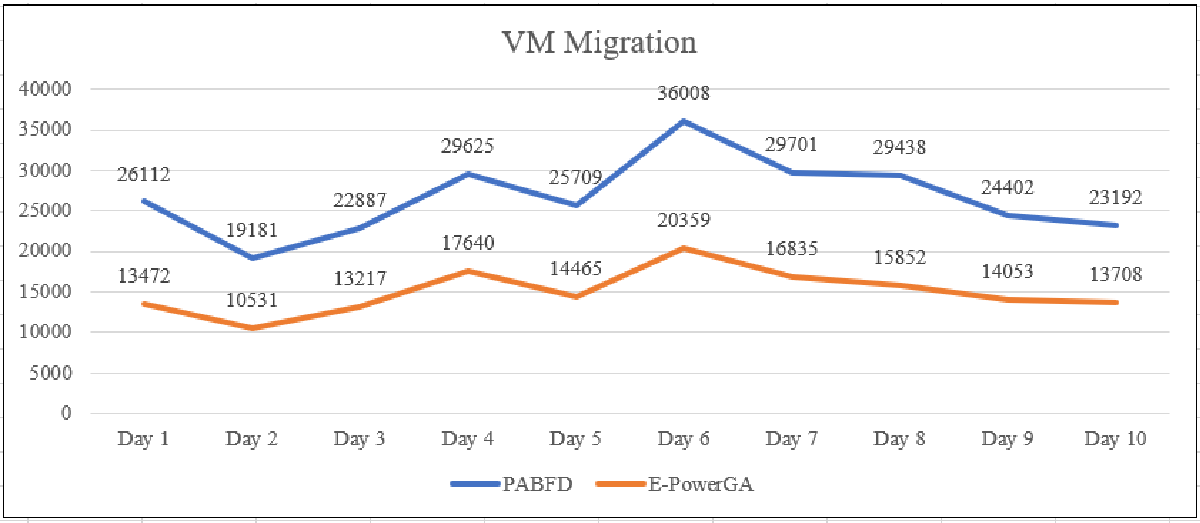

Figure 7 Improvement in Migration of VMs

SLA Violations (SLAV)

As shown in Equation (9), SLAV is also evaluated to assess operational efficiency by accounting for performance degradation during VM migration, specifically through Performance Degradation due to Migration (PDM) (Equation (10)) and SLATAH (Equation (11)). A study by Beloglazov *et al.* [20] reported that when a physical machine (PM) becomes overloaded, the source PM may experience SLA violations before the VM migration process is completed. During this migration interval, system throughput is reduced, leading to temporary performance loss.

The following subsections describe PDM and SLATAH in detail:

$$SLAV = SLATAH \ X \ PDM \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (9)$$

$$PDM = \frac{1}{N}\sum_{i=1}^{M}\frac{C_{dj}}{C_{rj}} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (10$$

$$SLATAH = \frac{1}{N}\sum_{i=1}^{N}\frac{T_{Si}}{T_{ai}} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (11)$$

Where C_{dj} denotes the expected performance loss of VM_j and Cr_j represents the total CPU capacity requested by VM_j. Let N be the number of physical machines (PMs), T_{si} the total duration for which PM_i operates at 100% utilisation resulting in an SLA violation, and T_{ai} the total time for which the host remains in the active state.

As illustrated in Figure 7, the proposed methods substantially reduce SLA violations and enhance overall service efficiency.

Table 8. SLAV for each VM placement policy

Days	PABFD	E-PowerGA
Day 1	0.0044	0.00133
Day 2	0.00417	0.00151
Day 3	0.00549	0.00241
Day 4	0.00434	0.00208
Day 5	0.00483	0.00185
Day 6	0.00428	0.00165
Day 7	0.00428	0.00164
Day 8	0.00447	0.00162
Day 9	0.00438	0.00196
Day 10	0.00659	0.00366

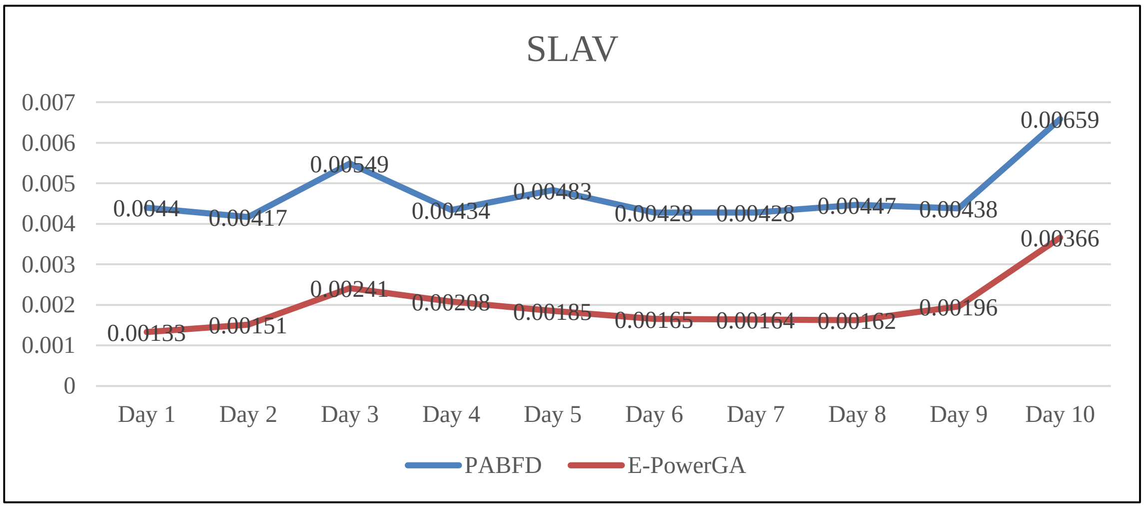

Figure 7. Improvement in for SLA violation

Comparative analysis between E-PowerGA and PABFD

The simulation results for different parameters using the CloudSim simulator has been summarised in Table 9.

Table 9. Consolidated Results of PABFD and E-PowerGA Simulation

Day	Number of VMs	PABFD Simulation	E-PowerGA Simulation	PABFD Simulation	E-PowerGA Simulation	PABFD Simulation	E-PowerGA Simulation
		EC KWh		VM Migration		SLAV	
Day 1	1840	173.43	133.23	29152	15040	0.0044	0.00133
Day 2	898	130.62	100.95	21413	11757	0.00417	0.00151
Day 3	1061	150.74	113.43	25551	14756	0.00549	0.00241
Day 4	1516	187.69	138.22	33073	19693	0.00434	0.00208
Day 5	1078	163.05	119.7	28690	16149	0.00483	0.00185
Day 6	1463	233.48	180.73	40200	22729	0.00428	0.00165
Day 7	1358	191.53	143.44	33159	18795	0.00428	0.00164
Day 8	1233	189.41	140.99	32864	17698	0.00447	0.00162
Day 9	1054	161.58	121.91	27239	15689	0.00438	0.00196
Day 10	1033	139.14	100.14	25887	15304	0.00659	0.00366

Table 10. Average outcome Results of PABFD and E-PowerGA Simulation

Algorithm	EC KWh	VM Migration	SLA
PABFD	172.067	29722.8	0.004723
E-PowerGA	117.974	15661	0.001851

The percentage improvement is calculated as:

$$Improvement\ (\%) = \frac{PABFD - EPowerGP}{PABFD} X100 \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

Table 11. Improvement in the Results of PABFD and E-PowerGA Simulation

Algorithm	EC (kWh)	VM Migration	SLA
Percentage of Improvement (%)	31.44%	47.31%	60.80%

Table 11 below shows the percentage of results that demonstrate the improvements made by the E-PowerGA algorithm in comparison to the PABFD algorithm on important factors such as energy, the number of migrations, and the number of SLA violations. The results from the table show that the E-PowerGA algorithm provides a 31.44% reduction in the use of energy, a 47.31% reduction in the number of migrations, and a 60.80% reduction in the number of SLA violations.

Conclusion and Future Work

The proposed work uses a genetic meta-heuristic technique for dynamic consolidation of virtual machines for finding optimal solutions using crossover and mutation processes on a randomly generated population. The main aim is to assess the efficiency of genetic algorithm usage in energy consumption (EC), while also considering service efficiency in cloud data centers. The developed E-PowerGA technique is based on some past works and aims to satisfy several constraints, such as energy consumption constraints, SLAs, and virtual machine overheads in migrating them.

The important performance improvement in key metrics obtained by the E-PowerGA fitness function mainly driven by power consumption can be further improved by other resource management parameters: disk I/O, memory usage, and network bandwidth. Simulation results confirm that the GA methods outperform the conventional autonomous management in keeping the EC and SLA constraints. Such findings promise that this kind of technique is one of the most promising candidates for tackling a wider resource management problem in cloud computing and may provide further research development. In recent years, with the rapid development of cloud services, cloud service providers are under high pressure to increase their system performance, reliability, and availability. Virtualization of servers is one of the core elements that helps to achieve this goal by sharing resources of physical machines between multiple VMs logically isolated from each other. Since overall cloud performance is directly affected by the efficiency of virtualization, VM placement optimization plays an important role in multi-objective balancing. Approaches considering machine utilization, VM consolidation, and node proximity can simultaneously reduce resource wastage, network overhead, and energy consumption, thereby improving efficiency in cloud data centers by orders of magnitude.

Declarations

- **Funding:** The authors declare that no external funding was received for this research.
- **Conflicts of Interest:** The authors declare no conflict of interest.
- **Availability of Data and Materials:** The datasets used during the current study are available from publicly accessible repositories (PlanetLab traces).
- **Ethical Approval:** Not applicable.
- **Consent to Participate:** Not applicable.

- **Consent for Publication:** All authors have reviewed and approved the final manuscript for publication.
- **Author Contributions:**
  - **Krishan Tuli** conceived the main research idea and formulated the overall problem statement related to energy-efficient and SLA-aware virtual machine placement in cloud data centers. He designed the proposed E-PowerGA genetic meta-heuristic, defined the fitness function, and developed the algorithmic framework. He also carried out the simulation setup using CloudSim, performed experimental evaluations using PlanetLab workload traces, analyzed the results, and led the interpretation of findings. Additionally, he prepared the initial draft of the manuscript and coordinated the overall research work as the corresponding author.
  - **Priyanka Tuli** contributed to the literature survey and critical analysis of existing VM placement, consolidation, and genetic algorithm-based approaches. She assisted in refining the problem formulation, research gap identification, and comparative analysis with existing heuristics such as PABFD. She also supported the design of performance metrics, validation of experimental results, and improvement of the manuscript structure, language, and technical clarity.
  - **All authors read, reviewed, and approved the final manuscript.**

REFERENCES

[1]. Bharathi, P. D., Prakash, P., & Kiran, M. V. K. (2017, April). Virtual machine placement strategies in cloud computing. In *2017 Innovations in Power and Advanced Computing Technologies (i-PACT)* (pp. 1-7). IEEE. DOI: 10.1109/IPACT.2017.8244949

[2]. Tuli, K., & Malhotra, M. (2024). Optimal Meta-Heuristic Elastic Scheduling (OMES) for VM selection and migration in cloud computing. *Multimedia Tools and Applications*, *83*(12), 34601-34627. Available: DOI : https://doi.org/10.1007/s11042-023-16820-w

[3]. Tuli, K., Kaur, A., & Malhotra, M. (2022, September). Efficient virtual machine migration algorithms for data centers in cloud computing. In *International Conference on Innovative Computing and Communications: Proceedings of ICICC 2022, Volume 1* (pp. 239-250). Singapore: Springer Nature Singapore. DOI: https://doi.org/10.1007/978-981-19-2821-5_20

[4]. Tuli, K., & Kaur, A. (2021, September). Load balancing scheme for optimization of virtual machine migration using swarm in cloud environment. In *2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO)* (pp. 1-6). IEEE. DOI: 10.1109/ICRITO51393.2021.9596463

[5]. Hazra, A., Das, B. K., & Roy, S. PROCEEDINGS OF 1ST INTERNATIONAL CONFERENCE ON SMART TECHNOLOGY FOR EMERGING PROBLEMS (STEP2K25). DOI: 10.70965/STEP.2025.1

[6]. Tan, J., Zhang, T., Zhang, C., Wang, C., Li, X., & Wang, X. (2026). Energy-efficient user allocation and cache updating in mobile edge computing networks based on user geographical aggregation. *Journal of Cloud Computing*, *15*(1), 15. DOI: https://doi.org/10.1186/s13677-025-00827-9

[7]. Tan, J., Zhang, T., Zhang, C. *et al.* Energy-efficient user allocation and cache updating in mobile edge computing networks based on user geographical aggregation. *J Cloud Comp* **15**, 15 (2026). https://doi.org/10.1186/s13677-025-00827-9

[8] Divya, V., & Divyasri, Y. (2026). Optimized Battery Management: A Comparative Analysis of Controller Systems for Enhanced Energy Efficiency. In *E3S Web of Conferences* (Vol. 692, p. 01017). EDP Sciences. DOI: https://doi.org/10.1051/e3sconf/202669201017

[9] Biswas, N. K., Das, D., Banerjee, S., & Biswas, U. (2026). Energy-Aware VM Consolidation Using Similarity-Driven Intelligence in Green Cloud Environments. *IEEE Transactions on Sustainable Computing*. DOI: 10.1109/TSUSC.2026.3660014

[10]. Vijarania, M., Gupta, S., Agrawal, A., Adigun, M. O., Ajagbe, S. A., & Awotunde, J. B. (2023). Energy Efficient Load-Balancing Mechanism in Integrated IoT-Fog-Cloud Environment. Electronics, 12(11), 2543. MDPI AG. Retrieved from http://dx.doi.org/10.3390/electronics12112543. **https://doi.org/10.3390/electronics12112543**

[11]. Panwar, S.S., Rauthan, M.M.S., Barthwal, V., Gaur, S., Mehra, N. (2024). Study of Energy-Efficient Virtual Machine Migration with Assurance of Service-Level Agreements. In: Chaturvedi, A., Hasan, S.U., Roy, B.K., Tsaban, B. (eds) Cryptology and Network Security with Machine Learning. ICCNSML 2023. Lecture Notes in Networks and Systems, vol 918. Springer, Singapore. https://doi.org/10.1007/978-981-97-0641-9_52.

[12]. Fan X, Weber WD, Barroso LA., (2007), Power provisioning for a warehouse-sized computer. Proceedings of the 34th Annual International Symposium on Computer Architecture, ACM New York, NY, USA, 13-23 Available:

[13]. S. H. H. Madni, M. S. A. Latiff, Y. Coulibaly, S. M. Abdulhamid, (2016), Resource scheduling for infrastructure as a service (IaaS) in cloud computing: Challenges and opportunities, Journal of Network and Computer Applications 68, 173–200. DOI: https://doi.org/10.1016/j.jnca.2016.04.016

[14]. S. S. Panwar, M. M. S. Rauthan and V. Barthwal, (2022), "Energy Consumption Analysis of Various Dynamic Virtual Machine Consolidation Techniques in Cloud Data Center," *2022 International Conference on Advances in Computing, Communication and Materials (ICACCM)*, Dehradun, India, pp. 1-8, **DOI:** 10.1109/ICACCM56405.2022.10009565

[15]. Barthwal, V., Rauthan, M.M.S., Varma, R. *et al.* Efficient Virtual Machine Placement Strategy Based on Enhanced Genetic Approach. *SN COMPUT. SCI.* **5**, 466 (2024). https://doi.org/10.1007/s42979-024-02832-2

[16]. Holland J. (1992) "Adaptation in natural and artificial systems, University of Michigan press," Ann Arbor, MI, MIT press, Cambridge, MA. Available: Adaptation in Natural and Artificial Systems: An Introductory Analysis with ... - John H. Holland - Google Books

[17]. Beloglazov A, Abawajy J, and Buyya R (2012) Energy-aware resource allocation heuristics for efficient management of data centers for cloud computing, Future Generation Computing System, vol. 28, no. 5, pp. 755_768. DOI : https://doi.org/10.1016/j.future.2011.04.017

[18]. Voorsluys W, Broberg J, Venugopal S, Buyya R (2009) Cost of virtual machine live migration in clouds: a performance evaluation. In Proceedings of the I International Conference on Cloud Computing (CloudCom), Vol. 2009.Springer: Beijing, China. DOI: https://doi.org/10.1007/978-3-642-10665-1_23

[19] Juiz, C., Bermejo, B., (2024), On the scalability of the speedup considering the overhead of consolidating virtual machines in servers for data centers. *J Supercomput* . https://doi.org/10.1007/s11227-024-05943-y

[20]. Beloglazov, R. Buyya, (2012), "Optimal online deterministic algorithms and adaptive heuristics for energy and performance efficient dynamic consolidation of virtual machines in cloud data centers", Concurr. Comput. 24 (13) pp. 1397–1420.
Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/cpe.1867

[21]. Tang, M., Pan, S., (2015), A Hybrid Genetic Algorithm for the Energy-Efficient Virtual Machine Placement Problem in Data Centers. Neural Processing Letters, 41**,** 211–221. DOI : https://doi.org/10.1007/s11063-014-9339-8

[22]. Christina Terese Joseph, K. Chandrasekaran, Robin Cyriac, (2015), A Novel Family Genetic Approach for Virtual Machine Allocation, Procedia Computer Science, Volume 46, Pages 558-565, ISSN 1877-0509. DOI: https://doi.org/10.1016/j.procs.2015.02.090

[23]. Arianyan E, Taheri H, Sharifian S (2016): Multi Target Dynamic VM Consolidation in Cloud Data Centers Using Genetic Algorithm, Journal of Information Science and Engineering 32, 1575-1593 (2016). Available: Multi Target Dynamic VM Consolidation in Cloud Data Centers Using Genetic Algorithm. | EBSCOhost

[24]. Sharma, Oshin & Saini, Hemraj. (2017). Performance Evaluation of VM Placement Using Classical Bin Packing and Genetic Algorithm for Cloud Environment. International Journal of Business Data Communications and Networking. DOI: 10.4018/IJBDCN.2017010104

[25]. Mohamed Amine Kaaouache, S. Bouamama, (2018), "An energy-efficient vm placement method for cloud data centers using a hybrid genetic algorithm", *Journal of Systems and Information Technology*, vol. 20, no. 4, pp. 430-445. DOI https://doi.org/10.1108/JSIT-10-2017-0089

[26]. A. Mosa and R. Sakellariou, "Dynamic Virtual Machine Placement Considering CPU and Memory Resource Requirements," *2019 IEEE 12th International Conference on Cloud Computing (CLOUD)*, Milan, Italy, 2019, pp. 196-198, **DOI:** 10.1109/CLOUD.2019.00042

[27]. Abohamama, Abdelaziz & Hamouda, Eslam. (2020). A Hybrid Energy-Aware Virtual Machine Placement Algorithm for Cloud Environments. Expert Systems with Applications. https://doi.org/10.1016/j.eswa.2020.113306

[28]. Parvizi, Elnaz & Rezvani, Mohammad. (2020). Utilisation-aware energy-efficient virtual machine placement in cloud networks using NSGA-III meta-heuristic approach. Cluster Computing. DOI https://doi.org/10.1007/s10586-020-03060-y

[29]. Emara, F. A., Gad-Elrab, A., Sobhi, A., & Raslan, K. R. (2021). Genetic-Based Multi-objective Task Scheduling Algorithm in Cloud Computing Environment. *International Journal of Intelligent Engineering & Systems*, *14*(5).
Available:researchgate.net/profile/Aly-Emara/publication/355361732_Genetic-Based_Multi-objective_Task_Scheduling_Algorithm_in_Cloud_Computing_Environment/links/626e361db277c02187da333a/Genetic-Based-Multi-objective-Task-Scheduling-Algorithm-in-Cloud-Computing-Environment.pdf

[30]. Hormozi, Elham, Hu, Shuwen, Ding, Zhe, Tian, Yu-Chu, Wang, You-Gan, Yu, Zu-Guo, and Zhang, Weizhe (2022), *Energy-efficient virtual machine placement in data centres via an accelerated Genetic Algorithm with improved fitness computation, Energy, 252*, 123884, ISSN 0360-5442, pages 1-15, https://doi.org/10.1016/j.energy.2022.123884

[31]. Lu, J., Zhao, W., Zhu, H. *et al.* (2022), Optimal machine placement based on improved genetic algorithm in cloud computing. *J Supercomput* **78**, 3448–3476 (2022). DOI: https://doi.org/10.1007/s11227-021-03953-8

[32]. P. Karthikeyan, (2023), Genetic algorithm with self adaptive immigrants for effective virtual machine placement in cloud environment, International Journal of Intelligent Networks, Volume 4, Pages 155-161, ISSN 2666-6030, https://doi.org/10.1016/j.ijin.2023.07.001

[33]. Mustafa Can Çavdar, Ibrahim Korpeoglu, Özgür Ulusoy, (2024), A Utilisation Based Genetic Algorithm for virtual machine placement in cloud systems, Computer Communications, Volume 214, Pages 136-148, ISSN 0140-3664, https://doi.org/10.1016/j.comcom.2023.11.028