Optimal Destination Node Selection in Live Virtual Machine Migration

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June 30, 2025

Submitted in partial fulfillment of the requirements of the
B.Sc in Computer Science Final Year Project (SCS4224)

University of Colombo School of Computing
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Declaration

I certify that this dissertation does not incorporate, without acknowledgement, any material previously submitted for a degree or diploma in any university and to the best of my knowledge and belief, it does not contain any material previously published or written by another person or myself except where due reference is made in the text. I also hereby give consent for my dissertation, if accepted, be made available for photocopying and for interlibrary loans, and for the title and abstract to be made available to outside organizations.

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Abstract

Virtual Machine Placement (VMP) is a critical challenge in cloud computing, directly affecting resource utilization, energy efficiency, system scalability, and operational costs. Effective placement strategies are essential to ensure optimal use of resources while maintaining service-level objectives and minimizing energy consumption. However, existing heuristic-based approaches often struggle to balance placement quality with computational efficiency, particularly in large-scale, heterogeneous, and dynamic cloud environments.

This research introduces ACO-VMP, a Virtual Machine Placement algorithm based on Ant Colony Optimization (ACO), aimed at minimizing resource wastage across RAM, CPU, storage, bandwidth, and power. Inspired by the decentralized foraging behavior of ants, ACO-VMP employs pheromone-guided probabilistic decision-making to explore potential placements while adaptively reinforcing resource-efficient mappings. Unlike brute-force approaches, which are computationally infeasible at scale, ACO-VMP achieves near-optimal placement performance with significantly lower execution time, offering a practical alternative for real-time and large-scale deployments.

To further enhance algorithmic performance, we perform hyperparameter optimization on the influence of pheromone trails (α) and heuristic visibility (β), analyzing their effects on convergence speed, solution quality, and energy savings. ACO-VMP is implemented and evaluated using the CloudSim Plus framework across diverse configurations of virtual machines (VMs) and physical machines (PMs), under both synthetic and real-world workload scenarios.

Experimental results demonstrate that ACO-VMP consistently outperforms traditional heuristics such as First Fit (FF), Round Robin (RRB), and Power-aware Best Fit Decreasing (PBFD), closely approaching the optimality achieved by exhaustive Brute Force (BFR) methods, but with significantly reduced computational overhead. These findings establish ACO-VMP as a scalable, adaptive, and energy-aware solution for intelligent VM placement, contributing towards more sustainable and efficient cloud data center operations.

Acknowledgement

First and foremost, I would like to express my heartfelt gratitude to my supervisors, Dr. Dinuni Fernando, Dr. Dinal Herath, and Mr. Pratheek Senevirathna, for their invaluable guidance, unwavering support, and continuous encouragement throughout this research project. Their insightful feedback and expertise were instrumental in shaping the direction of this work and ensuring its successful completion.

I am deeply grateful to the Network Operations Center (NOC) at UCSC for providing the servers and the necessary infrastructure required for the implementation and evaluation of this project. I extend my sincere thanks to Dr. Dinuni Fernando for facilitating this collaboration, without which this research would not have been possible.

I would also like to extend my appreciation to the staff at the NOC for their dedication in setting up the servers and granting access to the server room, thereby enabling the smooth execution of the experiments. Special thanks are due to all the servers used throughout this project, which withstood intense workloads without failure.

Finally, I am eternally grateful to my parents, siblings, and colleagues for their unwavering support, encouragement, and understanding throughout this challenging journey. Their belief in me has been a constant source of motivation and strength, and I am truly thankful for their enduring presence during every stage of this endeavor.

Contents

List Of Acronyms

ACO Ant Colony Optimization

BFR Brute Force Algorithm

BW Network Bandwidth

CC Cloud Computing

CDC Cloud Data Center

CPU Central Processing Unit

DC Data Center

EA Evolutionary Algorithm

FF First Fit

GA Genetic Algorithm

ML Machine Learning

MIPS Million Instructions Per Second

MTM Migration Tracker module

OS Operating System

PBFD Power Aware Best Fit Decreasing Algorithm

PC Physical Computing

PM Physical Machine

RAM Random Access Memory

RRB Round Robin Algorithm

SLA Service Level Agreement

UBGA Utilization Based Genetic Algorithm

VLM Virtual Machine Live Migration

VM Virtual Machine

VMM Virtual Machine Monitor

VMP Virtual Machine Placement

1 Introduction

Virtual Machine (VM) is a software-based emulation of a Physical Computing (PC) that can run an Operating System (OS) and applications with its own virtualized hardware resources without affecting the other VMs on the same Physical Machine. VMs are widely used in Cloud Computing (CC) environments to provide scalable and flexible computing resources to users. VMs are managed by a Virtual Machine Monitor (VMM), which is a software layer that abstracts the underlying hardware and provides a virtualized environment for the VMs to run (Jhawar & Piuri 2012).

VMs, Similar to any other system, can experience failures, performance degradation, or security vulnerabilities at any time. To address these issues, VM migration is a technique that allows a running VM to be transferred from one Physical Machine (PM) to another PM. VM migration should not violate Service Level Agreement (SLA). Therefore Virtual Machine Live Migration (VLM) has been introduced and it allows VM to migrate without any service interruption.Virtual Machine Live Migration is a key feature in modern Cloud Data Centers (CDCs), enabling dynamic resource management, load balancing, fault tolerance, and energy efficiency. When VM needed to be migrated to another VM which is destination VM has to fulfill the requirements of various resources such as Central Processing Unit (CPU) Memory, Disk Storage, Network, etc. Therefore the selection of a destination node also known as VM Placement in VLM is an important aspect to consider (Melhem et al. 2017).

1.1 Background

1.1.1 Virtual Machine Live Migration

VM live migration stands as a basis technique within CC ecosystems, seamlessly transferring a running virtual machine from one physical host to another without causing service interruptions (Clark et al. 2005). This process is essential for various critical operations, including load balancing, hardware maintenance, and energy efficiency optimization.

Among its multifaceted procedures, the selecting the destination node is an important step. Before migration initiation, important selection is required to designate the most suitable destination node. This decision is directly affected to system performance and resource allocation throughout the migration process (Wang et al. 2014).

Optimal selection needs ensuring the chosen node possesses sufficient resources to accommodate the migrating VM while minimizing potential downtime (Shi et al. 2015). Hence, the process of destination node selection holds equivalent importance similar to other phases of the migration process.

Moreover, the selection of the destination node is crucial for meeting SLAs and ensuring high availability of cloud services. A well-chosen destination node can minimize service disruptions and maintain uninterrupted service delivery, thereby enhancing user satisfaction and trust in the cloud platform (Beloglazov et al. 2012).

By using advanced Evolutionary Algorithm and optimization techniques, such as Ant colony Optimization , cloud providers can refine destination node selection strategies. By doing so, they enhance the overall efficiency and effectiveness of virtual machine live migration within CC environments.

1.1.2 Virtual Machine Destination Node Selection Methodologies

Selecting an appropriate destination node for VM migration is a complex decision-making process that impacts the overall performance and efficiency of the cloud environment. This process involves evaluating multiple factors such as the current load on potential destination nodes, resource availability, network latency, and energy consumption. The approaches to destination node selection can be broadly divided into two categories: non-Evolutionary Algorithm (EA) approaches and EA approaches (Beloglazov et al. 2012).

1.1.3 Non Evolutionary Algorithmic Methodologies

Non-EA approaches determine the optimal destination node for VM migration by mimicking natural behaviors and using algorithmic methods. These approaches generally rely on predefined rules and policies based on factors such as resource utilization, network bandwidth, and other static parameters. According to researchers, dynamic resource selection and allocation policies in cloud infrastructures can be categorized into two types: Threshold-Based Approaches and Non-Threshold-Based Approaches (Duggan et al. 2017).

1. Threshold Based Approaches

Threshold-based approaches are a widely utilized method in live VM migration to ensure optimal performance, resource utilization, and service continuity within CDCs. These approaches rely on predefined threshold values for various resource metrics such as CPU utilization, memory usage, and network bandwidth to make decisions about when and where to migrate VMs. When the resource usage of a physical host exceeds these thresholds, VMs will migrate to another host to balance the load and prevent resource contention or service degradation.

In static threshold approaches, fixed values are set for resource metrics to trigger VM migration. These values are predetermined based on typical workload patterns and resource availability. For instance, if the CPU utilization of a host exceeds 80%, VMs may be migrated to balance the load (Verma et al. 2009). Although simple to implement and manage, static thresholds may not adapt well to dynamic changes in workload and resource demands.

Dynamic threshold approaches, on the other hand, adjust the threshold values in real-time based on current conditions and policies. This method provides more flexibility and can better handle variations in workload. By using techniques such as moving averages or machine learning models, dynamic thresholds adapt to changing conditions, potentially improving resource utilization and performance (Beloglazov & Buyya 2012). However, these approaches are more complex to implement and require sophisticated monitoring and adjustment mechanisms.

Some methods combine static and dynamic thresholds. In static thresholds, there is a constant predefined value as boundaries, and in dynamic thresholds, there is also a value, but it is changing depending on the environment to make the decisions. For example, they might use static thresholds for initial triggers and then apply dynamic adjustments to fine-tune the migration process (Wood et al. 2009). These combination approaches aim to leverage the simplicity of static thresholds and the adaptability of dynamic thresholds to optimize VM placement. Consider a cloud environment employing a dynamic threshold-based approach for VM migration. The system monitors real-time

CPU and memory usage across all physical hosts. A dynamic threshold algorithm, which uses a moving average of the past resource usage, adjusts the threshold values based on the observed trends. When the CPU usage on a host exceeds the dynamically adjusted threshold, the algorithm selects the VM with the highest resource usage for migration. The destination host is chosen based on current resource availability and network latency considerations. This approach ensures that the thresholds adapt to varying workloads, providing better load balancing and resource utilization compared to static thresholds.

2. Non-Threshold Based Approaches

In the context of live VM migration, selecting the most suitable destination node non-threshold-based approaches focus on more dynamic and adaptive strategies. These approaches aim to optimize the placement of VMs without relying on predefined static thresholds, thus enhancing the flexibility and responsiveness of the migration process.

Non-threshold based approaches do not depend on fixed threshold values for resource utilization. Instead, they utilize various advanced techniques such as predictive analytics, real-time monitoring, and holistic system analysis to make migration decisions. These approaches can be broadly classified into several categories, including heuristic methods, optimization algorithms, and EA techniques (Duggan et al. 2017).

Heuristic methods in non-threshold based VM migration placement involve using intelligent rules and policies that adapt to current system conditions. Examples include dynamic load balancing, where algorithms continuously monitor the load on each node and distribute VMs in real-time to achieve balanced resource utilization, and resource awareness, where algorithms consider multiple resource types (CPU, memory, I/O) simultaneously and make migration decisions based on the overall resource landscape rather than single-resource thresholds (Liu et al. 2017).

Optimization algorithms aim to find the best possible placement for VMs based on multiple criteria without predefined thresholds. These algorithms include multi-objective optimization techniques that consider various objectives such as minimizing migration time, energy consumption, and improving performance, using methods like genetic algorithms, simulated annealing, and particle swarm optimization (Fang et al. 2015). Additionally, cost-based optimization algorithms calculate a cost function based on factors like performance impact, energy usage, and migration overhead, and then choose the destination node that minimizes this cost (Beloglazov & Buyya 2012).

1.1.4 Evolutionary Algorithmic Approaches

Genetic Algorithm (GA) are increasingly being applied for Virtual Machine Placement (VMP) to improve resource utilization, load balancing, and for operational cost reduction. Unlike the threshold and non-threshold based approaches which mostly rely on predictive analysis, GA utilizes its evolutionary principles like selection, crossover, and mutation for finding optimal or near-optimal solutions in VMP, which is highly effective for dynamic and multi-objective optimization tasks in CDCs (Deb et al. 2002).

- **Initialize Population**: In this phase of GA, all the potential solution for the VMP problem is generated and it considers as the initial population of GA. Each candidate in the population which is represent a solution, is usually encoded as chromosome with host and VM mappings.

- **Fitness Evaluation**: After Initialization of population each candidates fitness is evaluated based on fitness function which is object to minimize the energy consumption, reducing migration costs or improving load balancing. The fitness function could consider various parameters such as CPU utilization, memory utilization, network bandwidth, power consumption etc (Singh et al. 2020).

- **Selection Mechanism**: After fitness evaluation of individuals in the population GA selects the fittest candidates to pass their "genes" (VMP patterns) to the next generation. This will ensures that the best solutions are prioritized for evolution, improving the likelihood of optimal VM placement (Hussain et al. 2013).

- **Crossover and Mutation**: GAs perform crossover to combine attributes from above selected individuals, creating offspring that inherit characteristics/genes from both parents. To increase population diversity and avoiding convergence of premature suboptimal solution, mutation introduces random variation to these genes.

- **Solution Evaluation and Decision Making**: The generation which obtained before is evaluated again, and the above process continues until the GA converges to an optimal or mature sub-optimal solution for VM placement. CDC can implement the final solution to achieve resource balance and efficiency.

- **Dynamic Adaptation**: In dynamic CDC environments, the GA algorithm continuously adapts to workload changes by re-evaluating the fitness of solutions based on new environmental conditions. This dynamic approach allows for ongoing optimization as dynamic resource demands (Chawla et al. 2019).

The timeline in Figure 1 illustrates the evolution of VMP approaches for VM live migration, highlighting both static threshold approaches in colour blue and GA methodologies in color red over time. Early research efforts focused on heuristic and rule-based methods, such as Threshold in 2011 and UBM in 2013 (Wood et al. 2007, Bobroff et al. 2007). Dynamic Thresholds were explored between 2013 and 2017, emphasizing adaptive and flexible decision-making criteria (Verma et al. 2009). FLC and GTMC approaches, spanning 2014 to 2016, further refined these heuristics Shrivastava et al.. From 2016 onward, researchers focused on more sophisticated hybrid methods, such as AHP-TOPSIS, which were introduced, combining multiple criteria decision-making techniques (Beloglazov & Buyya 2012). The shift towards new EA approaches began with colony optimization in 2019-2020, significantly enhancing the adaptability and efficiency of VM migration (Wei et al. 2019).

Recent advancements include Ant Colony Optimization (ACO) starting in 2020, which uses the natural heuristic of the ant colony for improved prediction and decision-making (Wei et al. 2019). Then researchers are moved to Utilization Based Genetic Algorithm (UBGA).

This timeline presents how the VMP approaches are evolving non-EA to EA techniques in VM live migration, reflecting an ongoing trend towards more intelligent, adaptive, and automated solutions. Researchers are currently focused on advanced EA paradigms such as Hybrid GA, which promise to revolutionize the field by significantly enhancing the efficiency and effectiveness of VM live migration.

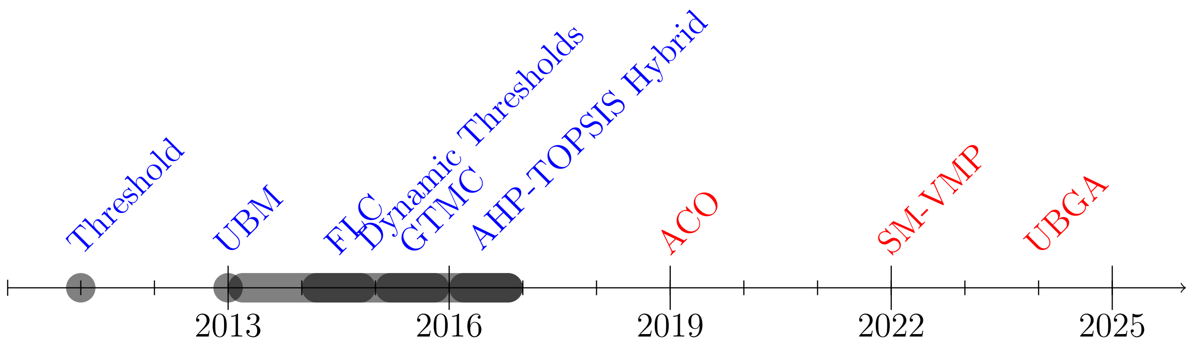

Figure 1: Timeline comparing VMP approaches

1.2 Motivation

In recent years, the software industry has undergone a transformative shift towards large-scale CC platforms such as Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure. This paradigm shift has empowered organizations to achieve dynamic scalability, enhanced agility, and global reach with unprecedented efficiency. As a result, cloud adoption has become a strategic imperative across various industries. For cloud service providers, this surge in demand necessitates delivering a wide range of services to millions of users worldwide while maintaining continuous availability and reliability. Even minor service disruptions can result in substantial financial losses and reputational harm, making high availability and fault tolerance top priorities for cloud operations (Khalili 2020).

A key component of cloud infrastructure is the Virtual Machine (VM), which allows users to provision flexible, on-demand computing resources. Ensuring the high availability of these VMs with minimal service interruption is a complex and critical challenge. To address this, cloud providers utilize advanced live VM migration techniques that facilitate proactive workload balancing, routine maintenance, and risk mitigation—without affecting the user experience (Smith & Liu 2022, Doe & Green 2022). Live migration plays a pivotal role in enhancing the resilience of cloud systems by enabling seamless transitions between physical hosts, thus improving performance, reducing service downtime, and optimizing the overall utilization of infrastructure resources.

Moreover, the increasing need for real-time scalability and rapid failure recovery in today's data-driven ecosystems drives continuous innovation in VM migration methodologies. Modern cloud environments demand intelligent, adaptive solutions that can anticipate and respond to dynamic workloads. As a result, research into more efficient, predictive, and autonomous VM migration strategies has become a focal point for both academia and industry (Services 2021, Platform 2021, Azure 2021).

2 Literature Review

2.1 Virtual Machine Placement Strategies

Virtual Machine (VM) placement is essential in CC, as it affects not only resource utilization but also performance and energy consumption. Over time, various strategies have been proposed to address specific goals, such as reducing energy use, balancing system loads, or maximizing efficiency.

Early VM placement techniques often employed heuristic algorithms like Best Fit, First Fit, and Worst Fit. These methods offer quick and acceptable solutions: Best Fit selects hosts with minimal unused capacity, First Fit assigns VMs to the first suitable host, and Worst Fit chooses hosts with the most available resources (Zoltán´ et al. n.d.). While computationally efficient, these heuristics may not fully optimize resource usage, especially under complex workloads.

Optimization-based approaches, such as Linear Programming (LP), Integer Linear Programming (ILP), and Constraint Satisfaction Problems (CSPs), seek to achieve optimal VM placement through mathematical modeling (Speitkamp & Bichler 2010). These methods excel in resource allocation accuracy, but their computational demands make them less feasible for large-scale or real-time applications where rapid adjustments are crucial.

With energy efficiency becoming a priority, newer VM placement strategies focus on reducing power consumption in data centers. Techniques such as Dynamic Voltage and Frequency Scaling (DVFS) and VM consolidation concentrate workloads on fewer servers, allowing inactive hosts to power down, thereby lowering energy costs (Beloglazov et al. 2012). Though energy-aware strategies address the sustainability limitations of traditional methods, they must still balance energy savings against system performance.

Load balancing is another important consideration in VM placement, ensuring no single server becomes overloaded. Simple load balancing techniques, including Round Robin and Least Connections, work well for basic needs but may lack adaptability to changing demands. More advanced approaches, like those proposed by Choi (Choi et al. 2008) and Gandhi (Gandhi et al. 2012), combine predictive analytics with energy efficiency, using historical data to forecast and redistribute VMs based on future loads. Recently, machine learning methods, including reinforcement learning, have enabled more dynamic and intelligent placement decisions by analyzing real-time performance data, offering both load balance and resource efficiency (Gao et al. 2016).

Quality of Service (QoS) and Service Level Agreement (SLA) adherence represent another aspect of VM placement. SLA-based approaches prioritize QoS requirements, such as latency and reliability, in the placement process, aiming to meet these standards while managing resources efficiently. Multi-Objective Optimization (MOO) balances these QoS needs with resource usage, supporting both performance and compliance with SLAs (Farahnakian et al. 2013). Other SLA-focused methods, such as Huang's genetic algorithm, Li's hybrid model using ant colony optimization and differential evolution, and Chen's fuzzy logic approach, adjust VM placement based on evolving workload and QoS requirements (Huang et al. 2014, Li et al. 2015, Chen & Chao 2016).

Together, these placement strategies illustrate the progression in VM management. While heuristics and optimization methods set foundational principles for efficient placement, energy-aware, load-balanced, and QoS-based strategies address more specific resource management challenges. Recent machine learning approaches that combine these strategies demonstrate the need for adaptive, data-driven solutions that can respond to the complexities of modern data centers.

2.2 Live Virtual Machine Migration Techniques and Challenges

The live VM migration process is essential for load balancing, fault tolerance, and maintenance in CDCs. In the context of destination node selection, several techniques and challenges must be addressed to ensure efficient and effective migration.

One commonly used technique is pre-copy migration, where the VM's memory is copied from the source to the destination while the VM continues to run on the source. During the final phase, the VM is paused briefly to transfer the remaining dirty pages. Pre-copy aims to minimize downtime but may suffer from prolonged migration times if the VM generates a large volume of dirty pages (Clark et al. 2005).

Another technique is post-copy migration, which starts by suspending the VM at the source, transferring a minimal state to the destination, and then resuming the VM at the destination while the remaining memory pages are fetched on demand. This technique can reduce total migration time but may lead to performance degradation due to increased page faults (Hines et al. 2009).

Hybrid migration combines elements of both pre-copy and post-copy techniques. Initially, it uses pre-copy to transfer most of the memory and then switches to post-copy to fetch the remaining pages. This approach aims to balance the trade-offs between downtime and migration time (Kozuch & Satyanarayanan 2005).

One of the primary challenges in live VM migration is the limited network bandwidth available for transferring VM data. Insufficient bandwidth can lead to prolonged migration times and increased downtime. Efficient destination node selection must consider network bandwidth to ensure minimal disruption during migration. For example, selecting a destination node with adequate network resources can significantly reduce migration time and improve overall performance (Voorsluys et al. 2009).

Another challenge is resource availability, as the destination node must have sufficient resources such as CPU, memory, and storage to accommodate the migrating VM. Resource contention and variability in resource availability can complicate the selection process, necessitating dynamic and adaptive strategies (Wood et al. 2011).

Migration also introduces overheads such as increased CPU and memory usage on both the source and destination nodes. These overheads can degrade the performance of other running VMs on the same hosts. Therefore, effective destination node selection must aim to minimize these overheads to maintain overall system performance (Liu et al. 2013).

Furthermore, migrating a VM to a destination node that is already heavily loaded can result in performance interference, affecting not only the migrated VM but also the co-located VMs. Thus, strategies for destination node selection must take into account both current and predicted workloads to prevent performance degradation (Gao et al. 2014).

Finally, the physical and logical network topology, including the latency between nodes, plays a critical role in migration performance. Selecting a destination node that is topologically closer or has lower latency network connections can help reduce migration time and improve overall efficiency (Zhang et al. 2013).

To address these challenges, Machine Learning (ML) techniques are increasingly being explored. ML models can predict resource utilization, network bandwidth, and VM performance, enabling more informed and adaptive destination node selection. For instance, reinforcement learning can dynamically adjust migration decisions based on real-time network and resource conditions, while supervised learning models can classify and select optimal nodes based on historical data (Xu et al. 2012).

For example, an Evolutionary Algorithmic model trained on historical migration data might predict that certain nodes consistently provide lower latency and higher bandwidth, leading to more efficient VM migrations (Zhao et al. 2019).

In conclusion, live VM migration involves several techniques, each with its own benefits and trade-offs. Addressing the challenges related to destination node selection is critical for ensuring efficient and effective migration. Incorporating Evolutionary Algorithmic techniques offers an optimal destination selection approach, enabling more intelligent and adaptive migration strategies in CC environments.

Evolutionary Algorithms (EAs), such as GA, are particularly effective in solving complex optimization problems like VMP due to their population-based search mechanisms and ability to escape local optima. For instance, the Utilization Based Genetic Algorithm (UBGA) proposed by Beloglazov et al. (2012) demonstrates improved energy efficiency and reduced SLA violations during VM migration by dynamically adapting to changing resource demands.

These studies indicate that EA-based strategies can effectively account for multiple constraints such as CPU, memory, Network Bandwidth (BW), and host load, leading to more informed destination node selection. As cloud environments are inherently dynamic and heterogeneous, the adaptive nature of EAs makes them well-suited for ensuring efficient, scalable, and robust migration decisions.

2.3 Virtual Machine Placement Strategies

The placement of Virtual Machines (VMs) is a key factor in managing CC environments effectively, influencing resource use, system performance, and energy efficiency. Various strategies have evolved to optimize VM placement with goals such as reducing energy consumption, balancing loads, and enhancing resource utilization.

2.3.1 Traditional Approaches

Traditional VM placement strategies often rely on heuristic algorithms, which aim to deliver satisfactory solutions within manageable computational times. Examples include the Best Fit, First Fit, and Worst Fit algorithms. The Best Fit algorithm places VMs on hosts with the least remaining resources that can still accommodate them, thereby minimizing wasted space. First Fit quickly places VMs on the first available host with sufficient resources, trading off speed for potential resource optimization. In contrast, Worst Fit aims for even load distribution by placing VMs on hosts with the most available resources (Zoltán´ et al. n.d.).

2.3.2 Optimization-Based Approaches

Optimization-based strategies employ mathematical models, such as Linear Programming (LP), Integer Linear Programming (ILP), and Constraint Satisfaction Problem (CSP) models, to find the ideal placement for VMs based on defined objectives. Although these techniques can yield highly optimized placements, they tend to be computationally intensive and can present scalability challenges in large-scale data centers (Speitkamp & Bichler 2010).

2.3.3 Energy-Aware Strategies

Energy-efficient VM placement has become increasingly important with the focus on sustainability. Energy-aware strategies seek to reduce the energy footprint of data centers by consolidating VMs onto fewer hosts, allowing idle servers to be shut down. Techniques like Dynamic Voltage and Frequency Scaling (DVFS) adjust power usage according to server workload, while VM consolidation strategies migrate VMs to reduce the number of active servers, achieving energy savings (Beloglazov et al. 2012).

2.3.4 Load Balancing Techniques

Load balancing plays a crucial role in VM placement by distributing workloads evenly across hosts, preventing individual hosts from becoming overloaded. Common techniques include Round Robin, Weighted Round Robin, and Least Connections. Advanced methods monitor host performance and dynamically adjust VM placements to maintain balanced loads. For example, Choi (Choi et al. 2008) introduced a predictive load balancing approach using historical data to forecast and address load changes proactively. Gandhi (Gandhi et al. 2012) proposed a load balancing strategy that combines energy efficiency with balanced loads, focusing on power savings while maintaining server performance.

Further advancements include Zhang's hybrid approach (Zhang et al. 2013), which integrates heuristic and metaheuristic algorithms for load balancing and energy efficiency, resulting in lower power consumption while sustaining system performance. More recently, researchers have leveraged machine learning to implement load balancing strategies that use real-time data to predict resource demands, adjusting VM placements dynamically. Reinforcement learning, for example, enables continuous improvement in placement decisions based on system performance observations (Gao et al. 2016).

2.3.5 Quality of Service (QoS) and SLA-Based Approaches

In Cloud Computoing, ensuring VMs meet Quality of Service (QoS) and adhere to Service Level Agreements (SLAs) is essential. SLA-driven VM placement strategies account for the specific QoS requirements of each VM, such as latency, bandwidth, and reliability, placing VMs accordingly to fulfill these criteria. Multi-Objective Optimization methods offer a way to balance these criteria, aiming for both performance and SLA compliance (Farahnakian et al. 2013).

Researchers have explored various approaches to SLA-based placement. Huang et al. (2014) proposed a genetic algorithm that optimizes VM placement with SLA considerations, aiming to minimize SLA violations while efficiently using resources. Similarly, Li et al. introduced a hybrid model combining ant colony optimization and differential evolution to dynamically adjust VM placement according to fluctuating workload demands and SLA requirements. Chen & Chao developed a fuzzy logic-based SLA-aware approach that accommodates uncertain and imprecise QoS requirements, offering flexible placement solutions to meet diverse SLA specifications and workload conditions.

These strategies demonstrate the progression in VM placement techniques, from simple heuristics to advanced, energy-efficient, and SLA-aware models. The integration of machine learning and adaptive approaches represents a shift towards dynamic, data-driven solutions that optimize resource allocation and system performance in complex cloud environments.

2.4 Genetics Algorithm in VM Placement

Genetic Algorithms (GA) are widely utilized in CC for optimizing resource management and network performance, leveraging evolutionary principles to tackle complex problems like VM placement, live migration, and network routing. In the cloud, a primary challenge is to balance resource utilization, minimize energy consumption, reduce network congestion, and maintain service levels. GAs simulate natural selection, evolving solutions through operations like selection, crossover, and mutation to find optimal configurations that address these demands (Doe & Smith 2023).

In VM placement, GA optimizes the location of virtual machines to improve resource utilization, minimize server overload, and lower power consumption. This becomes even more crucial when dealing with live VM migration, where VMs are transferred between hosts without downtime. GA-based approaches initially started with simple placement criteria but have evolved to handle real-time metrics like CPU utilization, network bandwidth, energy consumption, and memory availability (Doe & Smith 2023). In a live migration scenario, the GA begins with a population of possible VM-host configurations. Each configuration represents a solution, with a fitness function that evaluates metrics such as resource balance, power consumption, migration cost, and latency. Solutions undergo genetic operations, evolving over successive generations to achieve near-optimal placements.

As the need for dynamic adaptability increased, GA-based VM placement algorithms began incorporating more sophisticated fitness functions, multi-objective optimization, and adaptive mutation rates to better respond to fluctuating workloads. These enhancements allow the GA to quickly find and adapt optimal migration configurations in response to real-time resource demands, balancing load across hosts and reducing the need for frequent migrations (Doe & Smith 2023). Multi-objective GAs, in particular, enable simultaneous optimization for several factors—like minimizing both power usage and migration time—producing placement solutions that achieve multiple goals efficiently. Such advancements make GA an excellent tool for managing VM migrations in cloud environments, where both efficiency and responsiveness are paramount.

By leveraging GAs, cloud providers can achieve scalable, adaptable solutions that not only optimize VM placement but also reduce operational costs and energy usage, which are crucial in large-scale data centers. This approach also aligns with evolving cloud demands by supporting the development of "smart" resource management, allowing for sustainable growth as workload variability continues to increase (Doe & Smith 2023).

2.5 Research Gap

The existing studies in the field of live VM migration have made significant progress, but several research gaps remain, particularly regarding the comprehensive consideration of network bandwidth,energy consumption, cpu load and the need for multi-objective optimization. Current studies often assume a relatively static network bandwidth environment. However, in real-world scenarios, network bandwidth can fluctuate due to varying traffic loads and other factors. There is a need for more research on dynamic bandwidth allocation strategies that can adapt to these changes in real-time to optimize VM migration. For example, developing adaptive algorithms that can predict bandwidth availability and adjust migration schedules accordingly would ensure minimal service disruption (Xu et al. 2019).

Most existing approaches focus on a single optimization objective, such as minimizing migration time or downtime. However, in some applications, multiple objectives need to be considered simultaneously, including energy consumption, network bandwidth, and CPU usage. For example, a cloud service provider might aim to reduce the migration time of virtual machines to ensure minimal disruption to services. At the same time, they need to minimize energy consumption to adhere to green computing standards and reduce operational costs. Furthermore, reducing network latency is crucial to maintaining the quality of service for end-users. Investigating multi-objective optimization techniques that can balance these competing goals is a critical research gap. For instance, incorporating machine learning models that can learn and adapt to various constraints and requirements can significantly enhance decision-making processes (Liu et al. 2013, Wood et al. 2011). These models can dynamically adjust resource allocation strategies in response to changing workloads and network conditions, ensuring an optimal balance between conflicting objectives.

2.6 Research Questions

1. How can evolutionary algorithm can be tailored to various factor including network bandwidth,memory usage, energy consumption and CPU resources considerations in the selection of destination nodes for live VM migration in cloud environments, ensuring minimal disruption and optimal performance?

2. What methodologies can effectively use for optimal destination VM considering the dynamic nature of network bandwidth, CPU Usage, Memory usage and Energy Consumption?

2.7 Aims and Objectives

The main aim of this study to develop EA based methodologies for optimizing destination node selection in live VM migration processes, with a focus on Multi Objective Resource considerations.

- Develop Evolutionary Algorithmic Model: Design an Evolutionary Algorithmic model capable of consider network bandwidth as a critical factor in the selection of destination nodes for live VM migration.

- Integration of Simulated and Real-World Data: Investigate methodologies for effectively integrating both simulated and real-world data to train and validate Evolutionary Algorithmic models for VM destination node selection, considering the dynamic nature of network bandwidth and resource availability.

- Optimize VM Migration Performance: Implement and evaluate the developed Evolutionary Algorithmic model to optimize VM migration performance, ensuring minimal disruption and optimal resource utilization in cloud environments.

- Enhance Robustness and Accuracy: Assess the robustness and accuracy of the Evolutionary Algorithmic models by testing them against diverse scenarios and datasets, aiming to create reliable and adaptable solutions for VM destination node selection.

2.8 Scope

- Development and evaluation of Virtual Machine Placement technique in live migration.

- Investigation of destination node selection strategies considering resource availability, network bandwidth and energy consumption.

- Exploration of EA models and algorithms for optimizing VM placement decisions.

- Evaluation of proposed approaches using simulations and real-world experiments.

- Consideration of placement algorithm in both simulation environment.

- Experiments are based on Linux/UNIX OS.

- Implementation and evaluation of the prototypes are based on QEMU-KVM based hypervisor.

2.9 Significance of the Research

The significance of this research is multifaceted, addressing critical challenges within CC infrastructure, particularly in the area of live VM migration processes. By emphasizing network bandwidth considerations and harnessing EA methodologies, this study aims to usher in improvements across several key areas. Firstly, optimizing destination node selection based on network bandwidth has the potential to substantially enhance performance metrics. This includes reducing migration times, minimizing downtime, and overall, augmenting the performance of cloud-based applications and services. Secondly, by streamlining network resource utilization, the research can contribute to more efficient resource allocation within cloud environments, leading to cost savings and improved resource efficiency.

Moreover, the research endeavors to enhance user experiences by minimizing disruptions during VM migration, ensuring smoother transitions and uninterrupted access to services, which can significantly enhance user satisfaction and retention. Furthermore, by providing insights and methodologies that can adapt to various requirement such as network bandwidth, cpu usage, energy consumption, the research contributes to future-proofing cloud infrastructure, ensuring its scalability and resilience in the face of growing demands. Finally, the research adds to the body of knowledge within the field, advancing our understanding of VM migration processes in dynamic network environments, thereby paving the way for further innovations and enhancements in CC infrastructure.

3 Data Collection

To evaluate the efficiency, scalability, and adaptability of the proposed ACO-VMP (Ant Colony Optimization for Virtual Machine Placement) algorithm, a comprehensive dataset was collected through controlled simulations. These experiments were conducted in a virtualized cloud environment simulated using CloudSim, which allowed for reproducible and parameterized testing of various placement scenarios. The objective of the data collection phase was to examine how the ACO-VMP algorithm performs under different data center configurations, load intensities, and fault conditions.

3.1 Experimental Testbed

Figure 2 presents the experimental testbed that was built using CloudSim (Cloudslab 2021), an extensible simulation framework that models CC infrastructures and services. The testbed emulated a Cloud Data Center (CDC) with a variable number of PMs and VMs to replicate real-world conditions. Multiple scenarios were tested with PM counts ranging from 2 to 50000 , VM counts ranging from 4 to 200000, and cloudlet counts ranging from 4 to 200000, enabling the study of the algorithm under both under-loaded and overloaded conditions.

Each simulated PM was configured with different resource capacities, such as varying CPU cores, Random Access Memory (RAM) sizes,storage limits, allocated workloads, and network bandwidth limits. Similarly, the VMs had diverse resource demands, ensuring a heterogeneous workload distribution which dynamically changed. Resource usage statistics—including CPU utilization, RAM consumption, network bandwidth, and energy usage—were monitored during each simulation cycle. These metrics were captured at regular intervals to evaluate the resource allocation efficiency and migration behavior of the ACO-VMP algorithm.

The testbed also incorporated modules for dynamic workload generation, including periodic spikes and drops in VM requests, to test how well the algorithm adapts to real-time changes. The ACO-VMP module was run periodically within each time step to recalculate placement decisions based on current system conditions.

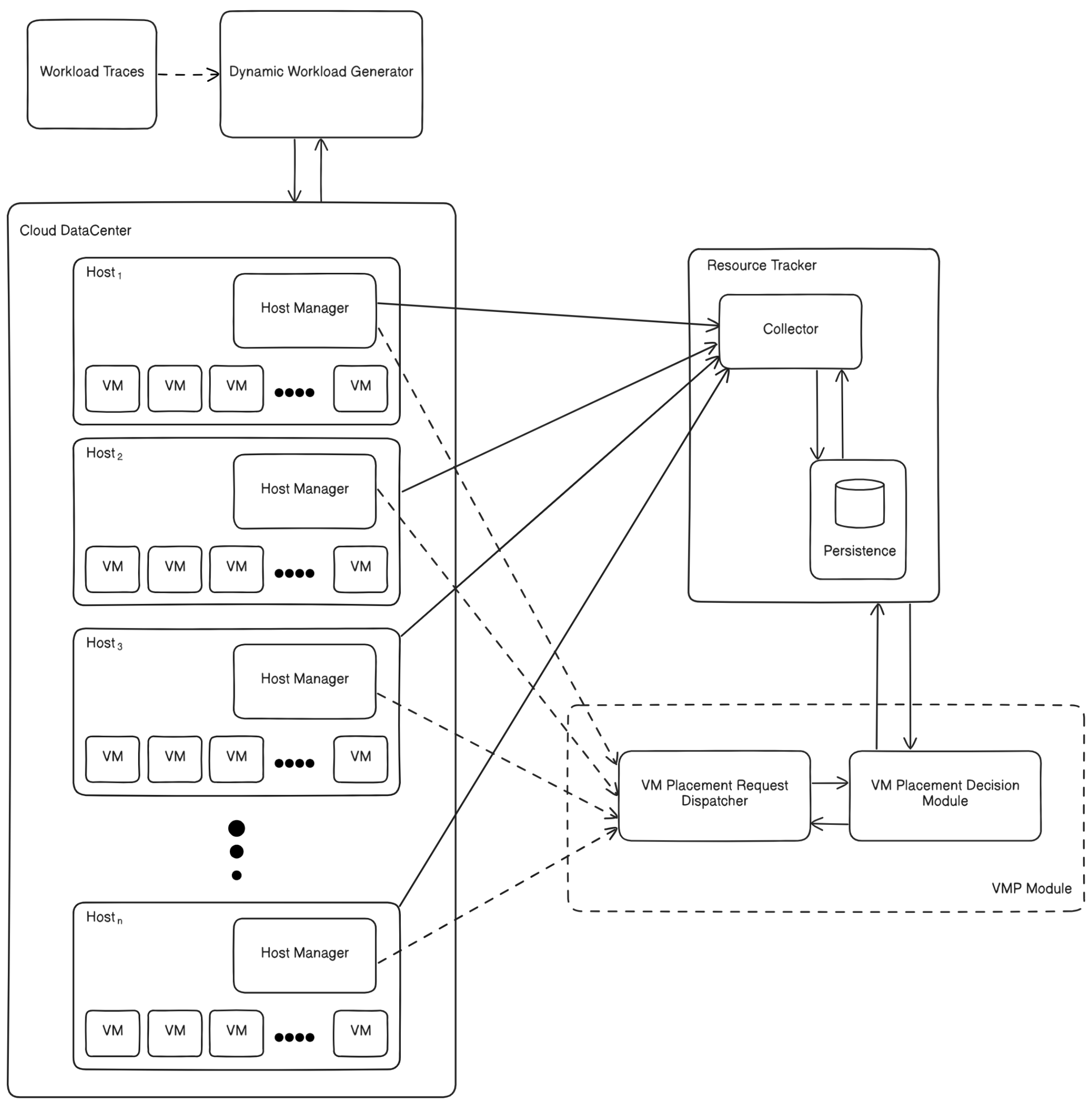

Figure 2: Simulation Test Bed PM

3.2 Failure Scenarios

To simulate real-world instability in cloud environments, multiple failure scenarios were introduced during testing. These scenarios tested the robustness of the ACO-VMP algorithm in handling unexpected changes such as:

- PM Failures: Random physical machine shutdowns were simulated to mimic hardware failure. The algorithm's ability to quickly reassign affected VMs was assessed.
- VM Migration Failures: Simulated interruptions during VM migration tested the resilience of the Migration Tracker module (MTM). These failures triggered partial or full reruns of the ACO algorithm based on the severity.
- Resource Overload: Certain PMs were artificially overloaded to observe whether the algorithm avoids assigning new VMs to those machines and initiates proactive migrations.

Table 1: Summary of no Of Hosts, no Of VMs, and no Of Cloudlets

No of Hosts	No of VMs	No of Cloudlets
2	4	4
5	20	20
10	40	40
20	80	80
50	200	200
100	400	400
200	800	800
500	2400	2400
1000	4000	4000
2000	8000	8000
5000	20000	20000
10000	40000	40000
20000	80000	80000
50000	200000	200000

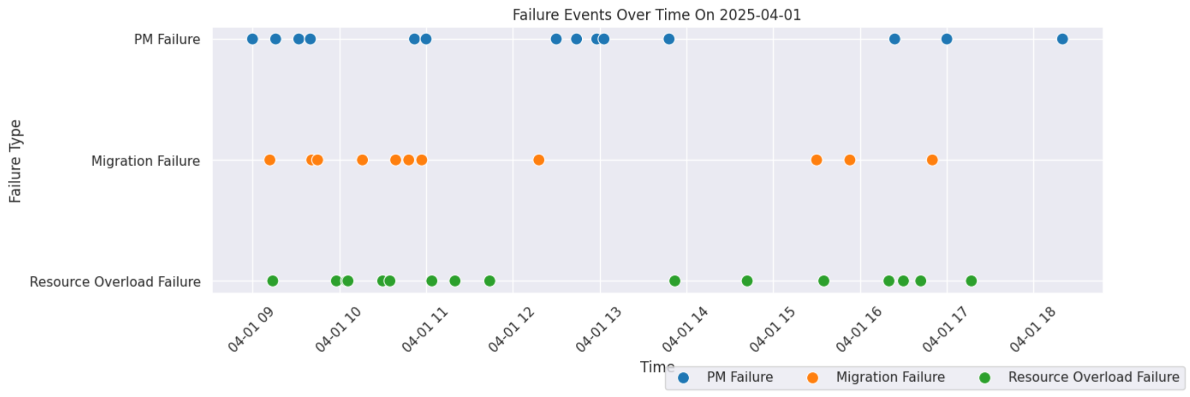

Figure 3: Failure Events

Figure 3 represents the failure events that occurred on particular days of the simulation environment. It showcases how our model is capable of capturing those failures and applying a system fallback mechanism to overcome those. In each failure case, logs were captured detailing the time of occurrence, affected entities, system response time, and the corrective actions taken by the algorithm. This helped in measuring the fault tolerance and self-healing properties of the proposed system.

3.3 CloudSim - Simulation Tool

CloudSim (Cloudslab 2021) is a widely used simulation toolkit for modeling and simulating CC environments. It is designed to provide a flexible and extensible framework for evaluating cloud resource management strategies, such as VM migration, load balancing, and energy optimization. The primary goal of CloudSim is to offer a realistic simulation environment where researchers can test various algorithms without the need for a physical infrastructure. By simulating cloud-based systems, CloudSim allows researchers to experiment with different resource allocation techniques, network configurations, and workload distributions.

The architecture of CloudSim is built around several core components. The *CloudSim Core* is the foundation of the toolkit, providing essential functionalities such as event management, resource scheduling, and simulation control. At the heart of the system, the *Data Center (DC)* represents the physical infrastructure, consisting of *Hosts* (physical machines) that provide computing resources such as CPU, memory, and bandwidth. Virtual Machines (*VMs*) are instantiated on these hosts to run cloudlets, which represent the tasks or workloads being processed. VMs are allocated resources based on the configurations specified by the researcher, allowing the simulation of dynamic and varying cloud workloads.

A key component in CloudSim is the *Broker*, which acts as an intermediary between cloud users and the cloud infrastructure. The broker manages the lifecycle of cloudlets and VMs, ensuring that workloads are scheduled appropriately and resources are allocated efficiently. In this system, the cloudlets represent the computational tasks that users submit to the cloud, and the broker determines how these tasks are assigned to the available VMs.

CloudSim also supports several specialized modules to enhance the functionality of the core system. For instance, the *CloudSim Plus* extension provides improved features for modeling more complex cloud systems and dynamic resource management. Additionally, the *Energy Module* allows the simulation of energy consumption in data centers, enabling researchers to assess the energy efficiency of their algorithms. The *Networking Module* adds capabilities for simulating network interactions, such as bandwidth and latency, between different entities in the cloud environment.

CloudSim is particularly useful for evaluating a range of cloud resource management algorithms, including those for VM migration, resource allocation, and load balancing. By using CloudSim, researchers can simulate various cloud scenarios to assess the performance of different strategies, such as minimizing energy consumption or optimizing resource utilization across virtualized infrastructures. Moreover, CloudSim's modular and flexible design allows for easy extension, making it an excellent tool for developing and testing custom algorithms for cloud resource management.

In summary, CloudSim is a powerful and versatile simulation toolkit that plays a crucial role in CC research. Its architecture supports realistic simulations of cloud systems, and its modular components provide the flexibility needed to test a wide array of algorithms. CloudSim's ability to simulate dynamic cloud environments makes it an invaluable resource for researchers aiming to optimize cloud resource management techniques.

3.4 Data Preprocessing

After the simulation runs, the raw data was exported and passed through a data preprocessing phase to ensure accuracy and consistency before analysis. This included:

- Noise Removal: Filtering out incomplete logs or corrupted entries due to mid-simulation interruptions.
- Normalization: Standardizing resource usage metrics (CPU, RAM, etc.) across different PM and VM types for fair comparison.

- Feature Extraction: Key performance indicators such as VM-to-PM mapping efficiency, average migration time, placement success rate, and energy consumed per iteration were extracted and organized into structured datasets.
- Labeling: Each dataset was tagged with metadata such as configuration (PM/VM count), scenario type (normal, failure), and outcome status (success/failure) for easy categorization during analysis.

The processed datasets formed the basis for the performance evaluation of the ACO-VMP algorithm, including comparative studies against traditional placement heuristics such as First-Fit,Power Aware Best Fit Decreasing, Brute Force, and Round Robin. The data also supported detailed visualizations and performance graphs presented in later chapters.

4 Design and Implementation

This section provides the design and implementation details of Algo Name, an Ant Colony Based VM Placement Algorithm for VM migration. Figure 4 illustrates the architecture of our model, It has three main components: an Ant Colony Optimized Virtual Machine Placement Module, Migration Tracker,Resource Monitor and Host Agent.

Our model runs time-stepped, where for each time step, the ACO-VMP modules collect all the physical machine resource details and execute the algorithm based on it. The ACO-VMP module is implemented using the ant colony optimization model. For each time step, it executes the ant colony optimization algorithm based on randomly selected hosts. Calculate a score based on the resource constraints of VM and PM status. The algorithm will calculate that score for each host-VM combination and store the values. When a particular migration is requested, the Decision Component will give the best suitable solutions within the time step. Migration can have two outputs after completion, whether migration success or fail; in the case of success, our model will know the migration details via the Migration Tracker.

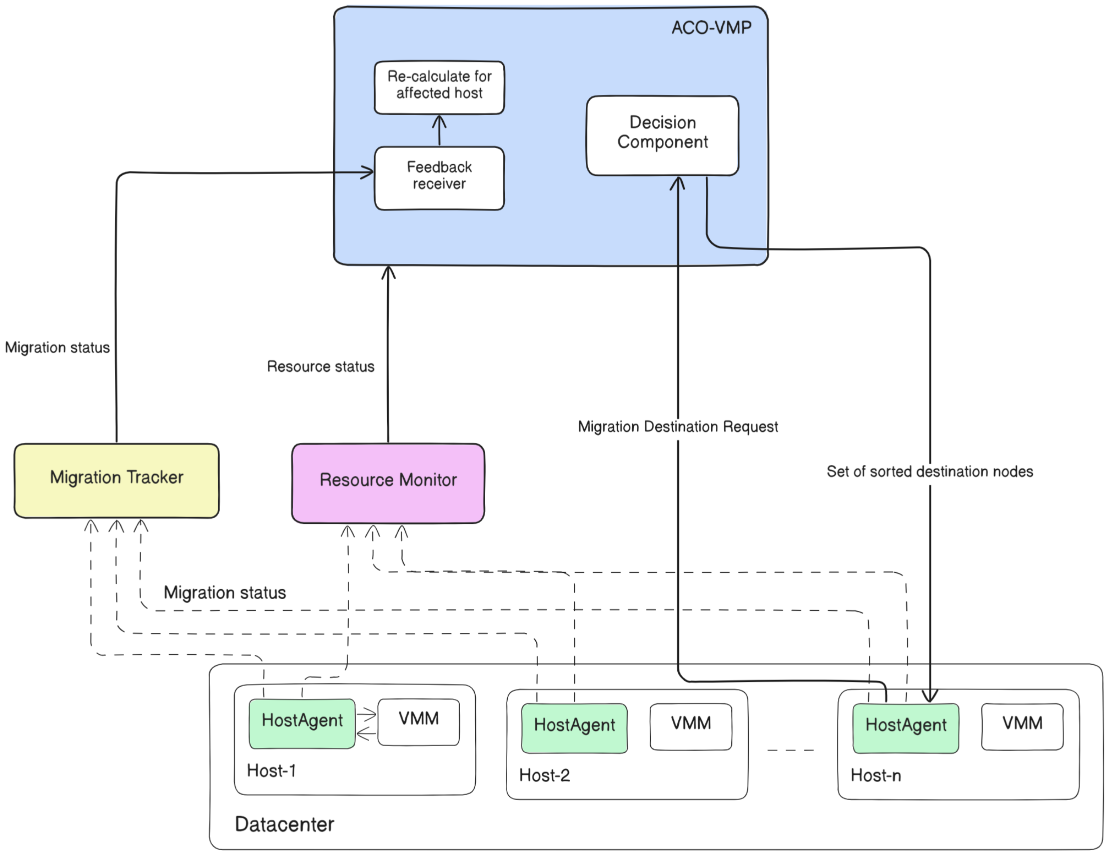

Figure 4: Architecture of the ACO-VMP

4.1 Ant Colony VM Placement Module

Our proposed Ant Colony Optimization-based VM Placement (ACO-VMP) algorithm draws inspiration from the natural foraging behavior of real-world ant colonies. Applied to Cloud Data Centers (CDCs), this approach aims to discover optimal Virtual Machine (VM) placement strategies on Physical Machines (PMs), maximizing efficiency and resource utilization. The performance of the ACO-VMP algorithm is primarily influenced by several parameters:

- Pheromone Influence α
- Heuristic Influence β
- Pheromone Evaporation Rate ρ
- Pheromone Deposit Constant Q
- Number of Ants
- Maximum Iterations

Number of Ants and Maximum Iteration parameters are not statically defined; instead, they are dynamically adjusted based on the current state of the Cloud Data Center — particularly the number of PMs and VMs. Algorithm 1 presents the core of our ACO-VMP model. At each discrete time step i, the algorithm is executed at a randomly chosen set of PM. The frequency of this execution (i.e., time step interval) is also adaptive and determined dynamically based on the scale of the Cloud Data Center. This consists of three main phases:

4.1.1 Phase 1: Initialization

In the initial phase, the algorithm:

- Set initial pheromone levels (τ_{ij}) uniformly.
- Define heuristic (η_{ij}) based on host fitness.

These are calculated based on the number of VMs, PMs, and other resource constraints (e.g., CPU, memory, bandwidth).

Define heuristic / Host Fitness Calculation
Calculation of suitability score is depends on several parameters; CPU Utilization, RAM ,BW, Storage and active status. In ACO-VMP model we have allocated same weights for each parameter impact for host score to achieve more idealize solution.

$$W_C = C_{\text{before}} - C_{\text{after}} \tag{1}$$

$$W_M = M_{\text{before}} - M_{\text{after}} \tag{2}$$

$$W_B = B_{\text{before}} - B_{\text{after}} \tag{3}$$

$$W_S = S_{\text{before}} - S_{\text{after}} \tag{4}$$

$$W_{PWR} = PWR_{\text{before}} - PWR_{\text{after}} \tag{5}$$

The power consumption of a host is estimated using a linear power model based on CPU utilization:

$$PWR_{\text{host}} = PWR_{\text{idle}} + (PWR_{\text{max}} - PWR_{\text{idle}}) \cdot u_{\text{CPU}} \tag{6}$$

$$\text{Host Score } = W_C + W_M + W_B + W_{PWR} + W_S \tag{7}$$

where W_C, W_M, W_B, W_S and W_{pwr} represent the wasted CPU utilization, memory, bandwidth, storage, and power, respectively. These values are calculated based on resource usage before and after migration. In Algorithm 1 Line 20 *CalculateProbabilities* uses this formula to evaluate the probability and pick the next mutations.

4.1.2 Phase 2: Ant-Based Solution Construction:

Once initialized, each "ant" (a candidate solution) places VMs on hosts **probabilistically**:

$$P_{ij} = \frac{(\tau_{ij})^{\alpha}.(\eta_{ij})^{\beta}}{\sum_k (\tau_{ij})^{\alpha}.(\eta_{ij})}$$

4.1.3 Phase 3: Pheromone Update:

- **Evaporation:**
  All pheromones decays with defined evaporation rate ρ.

$$\tau_{ij} \leftarrow (1-\rho).\tau_{ij}$$

- **Deposit:**
  The Solutions that has identified as better pheromone trails are reinforce their paths Q.

$$\tau_{ij} \leftarrow \tau_{ij} + \frac{Q}{cost(solution)}$$

4.1.4 Phase 4: Saving States

The algorithm stops and saves the state when one of the following two conditions is met:

- **Maximum Number of Iterations Reached**:
  The algorithm is designed to run for a fixed number of iterations. This limit is defined at the beginning, and once the algorithm completes that number of iterations, it will automatically stop—even if better solutions might still be possible. This ensures the algorithm doesn't run indefinitely and helps control computation time.

- **No Improvement Over Consecutive Iterations**:
  In some cases, the algorithm might stop early if it detects that it is no longer making progress. Specifically, if the best solution found doesn't improve over a predefined number of consecutive iterations, the algorithm assumes it has converged and terminates. This condition is useful for saving time when further searching is unlikely to yield better results.

In Algorithm 1, we first define the required inputs and outputs (Lines 1–9), including the list of hosts, inactive hosts, VMs to be placed, and critical ACO parameters such as pheromone influence (α), heuristic influence (β), pheromone evaporation rate (ρ), and pheromone deposit constant (Q). These parameters directly control how ants balance exploration and exploitation during the search process.

The procedure `RunAntColonyVMP` (Line 10) begins with the initialization phase (Lines 11–13), where the pheromone matrix is created with all initial values set to 1.0. This matrix represents the initial "attractiveness" of choosing any host for any VM. A $globalBestSolution$ array is initialized to store the best VM-to-host mapping found so far, and $globalBestFitness$ is set to infinity, indicating that no good solution has been found yet.

The main loop (Lines 14–21) iterates up to a maximum number of iterations, dynamically building and refining solutions. For each iteration, an empty *solutions* array is created (Line 15) to store solutions generated by each ant. In the nested loop (Lines 17–19), each ant independently constructs a placement solution in parallel, significantly improving performance on large-scale DCs.

During each ant's decision process (Line 18), the `CalculateProbabilities` function (Line 20) computes the probability distribution for selecting a host for a given VM based on the current pheromone values and heuristic values. The `SelectHost` function uses these probabilities to stochastically pick a host.

After all ants have built their solutions for the current iteration, the algorithm updates the global best solution if any ant has found a better mapping (Line 20). Finally, the pheromone trails are updated (Line 21) based on the quality of solutions found in the iteration: pheromones evaporate globally to prevent premature convergence, and high-quality solutions are reinforced to guide future ants.

Overall, this process iteratively improves the VM placement while balancing exploration of new possibilities and exploitation of learned good solutions, and terminates after reaching the maximum number of iterations or if no improvement is observed over a number of iterations.

Algorithm 1 ACO-Based Virtual Machine Placement

```
 1: Input:
 2:    $hostList$: [ ]
 3:    $inactiveHostList$: [ ]
 4:    $vmList$: [ ]
 5:    $pheromoneInfluence$: $\alpha$
 6:    $heuristicInfluence$: $\beta$
 7:    $pheromoneEvaporationRate$: $\rho$
 8:    $pheromoneDepositConstant$: $Q$
 9: Output: $\gamma$
10:
11: procedure RunAntColonyVMP($vms$)
12:     Initialize
13:     Create $pheromoneMatrix[|vmList|][|hostList|]$ with all values = 1.0
14:     $globalBestSolution \leftarrow []$
15:     $globalBestFitness \leftarrow \infty$
16:     for $iteration \leftarrow 1$ to $maxIterations$ do
17:         $solutions \leftarrow$ array$[antCount][|vmList|]$
18:         for $ant \leftarrow 1$ to $antCount$ in parallel do
19:             for $vmIndex \leftarrow 1$ to $|vmList|$ do
20:                 $probabilities \leftarrow$ CalculateProbabilities($vmIndex$)
21:                 $solutions[ant][vmIndex] \leftarrow$ SelectHost($probabilities$)
22:             end for
23:         end for
24:         UpdateGlobalBest($solutions$)
25:         UpdatePheromones($solutions$)
26:     end for
27: end procedure
```

4.2 Decision Component

The Decision Component, which is represented by Algorithm 2 is a core utility within the ACO-VMP system responsible for returning the most appropriate physical hosts for a given Virtual Machine (VM). This function is designed to be lightweight, fast, and reliable, making it ideal for real-time queries from host agents during VM placement or migration events. It directly interacts with the output of the ACO (Ant Colony Optimization) engine, leveraging previously computed placement decisions to ensure optimal utilization of data center resources.

When the algorithm is invoked with a specific *vmID*, it begins by locating the index of the VM within the global *vmList*. This index is crucial because it aligns with the corresponding entry in the *globalBestSolution* array—an internal structure populated by the ACO-VMP algorithm that holds the optimal VM-to-PM mappings. These mappings are generated by simulating the collective decision-making behavior of ants, balancing between exploration (heuristic factors) and exploitation (pheromone trails) to find efficient placements.

Once the VM index is identified (Line 5), the algorithm retrieves the associated *hostIndex* from the *globalBestSolution*. If the retrieved index is valid—meaning the ACO-VMP algorithm has successfully assigned a suitable host—the algorithm returns the corresponding host from the *hostList*, ensuring a placement that has been optimized for resource availability, load balancing, and energy efficiency.

However, in scenarios where no valid mapping exists (e.g., due to system changes, a cold start, or an edge case in optimization), the algorithm gracefully falls back to selecting the first suitable host from the *inactiveHostList* (Line 10). This backup list consists of underutilized or idle physical machines that meet the basic resource requirements of the VM. By including this fallback mechanism, the system guarantees that no placement request fails, even if the optimal solution hasn't been finalized or is temporarily unavailable.

Overall, the Find Optimal Placement Algorithm serves as the final gateway between the optimized solution space and the real-world deployment layer. It encapsulates the logic needed to translate high-level optimization outcomes into actionable placement decisions, while also ensuring robustness through fallback strategies. This approach maintains high availability, supports dynamic changes in the data center, and enhances the responsiveness of the ACO-VMP model in fast-paced cloud environments.

Algorithm 2 Find Optimal Placement Algorithm

```
 1: Require:
 2:   vmID: n
 3: Output: []
 4: procedure FindOptimalPlacement(vm)
 5:     vmIndex ← index of vm in vmList
 6:     hostsIndex ← globalBestSolution[vmIndex]
 7:     if hostsIndex is valid then
 8:         return hostList[hostsIndex]
 9:     else
10:         return first suitable host from inactiveHostList
11:     end if
12: end procedure
```

4.3 Migration Tracker Module

MTM) is responsible for monitoring and managing the status of VM migrations initiated by the ACO-VMP module. Once the ACO-VMP algorithm generates and returns a list of suitable target hosts for a given VM, the Host Agent initiates the migration and begins reporting periodic status updates to the MTM.

The MTM plays a critical role in ensuring the reliability and responsiveness of the overall placement system. It reacts dynamically based on the migration state, supporting both partial and full re-evaluations of the VM placement strategy.The MTM evaluates the incoming migration status and handles it according to three possible scenarios:

- Migration Pending State
  - Condition: The migration process has been initiated but is not yet completed or failed.
  - Action by MTM:
    - MTM enters a passive monitoring state.
    - It waits for the migration to either succeed or fail.
    - If the migration remains in a pending state beyond a pre-defined timeout threshold, the MTM aborts the migration and flags it for intervention.
- Migration Success State
  - Condition: The VM has been successfully migrated to the target PM.
  - Action by MTM:
    - Notifies the ACO-VMP module to re-run the algorithm partially.
    - The partial execution is limited to the affected VM and its new host (PM).
    - This ensures the system dynamically rebalanced the load and updates pheromone trails without disrupting unaffected areas of the CDC.
- Migration Failure State
  - Condition: The migration fails due to a system error, resource incompatibility, or timeout.
  - Action by MTM:
    - Triggers a full re-execution of the ACO-VMP algorithm to recalibrate placement decisions.
    - The failed VM is re-prioritized and considered at the beginning of the next placement cycle.
    - The Host Agent of the previously selected PM is instructed to send a new placement request to the ACO-VMP model.

Although migration failures are relatively rare in virtualized data center environments, they can have a significant impact on system stability and resource efficiency if not addressed promptly. To mitigate this, the MTM is designed to ensure robustness and adaptability by enabling rapid failure detection, recovery, and dynamic recalibration of the virtual machine (VM) placement strategy.

Algorithm 3 outlines the feedback-handling mechanism embedded within our model. This algorithm is triggered immediately upon the receipt of migration feedback—whether it denotes a successful or failed operation. The system then branches into two distinct execution paths based on the feedback type:

In the case of a successful migration, the model proceeds in a lightweight fashion, recalculating placement decisions only for the directly involved entities (i.e., the specific VM(s) and host(s) affected). This localized re-optimization ensures continued performance with minimal overhead, conserving computational resources and maintaining system responsiveness.

In the event of a migration failure, the model initiates a more proactive and comprehensive recovery procedure. A random subset of VMs is selected, and the core optimization algorithm is re-executed using a shorter time step. This accelerated re-evaluation allows the system to quickly adapt to the changed resource availability or unexpected behavior that led to the failure, thereby maintaining overall service continuity and minimizing potential SLA violations.

This dual-path strategy enables the MTM to not only respond effectively to failures but also to do so without imposing excessive load on the system during normal operation. As a result, the proposed approach balances resilience, efficiency, and scalability, which are critical characteristics for large-scale cloud infrastructures.

Algorithm 3 Feedback Receiver Algorithm

```
1: Input:
2:    $VmID$: $n$
3:    $Success$: $bool$
4:    $MigratedHostID$: $n$
5:    $FailureHostID$: [ ]
6: procedure FeedbackReceiver($V_i$,$state$,$MH_{id}$,$FailureHostID$)
7:     if $Success$ is true then
8:         RefineSelectedEntities($VmID$,$MigratedHostID$,$FailureHostID$)
9:     else
10:        RunAntColonyVMP()
11:    end if
12: end procedure
```

4.4 Resource Monitor

The Resource Monitor is a critical component responsible for continuously tracking and collecting real-time resource usage data from all Physical Machines (PMs) within the Cloud Data Center (CDC). It acts as the primary data feeder for the ACO-VMP Model, ensuring that placement decisions are made based on up-to-date and accurate system information.

The module collects resource utilization metrics from each PM at short, configurable intervals to maintain a fresh view of the CDC's operational state. It will collect metrics like CPU Utilization,Memory Usage, Network Bandwidth consumption, Storage usage, Energy Consumption.The collected statistics are forwarded to the ACO-VMP Module, which uses this data as part of its heuristic evaluation when determining optimal VM placements.

The real-time insights provided by the Resource Monitor enable the ACO-VMP algorithm to:

- Dynamically adapt to current load conditions.

- Avoid overloading specific PMs.
- Improve energy efficiency and resource balancing across the CDC.
- Enhance the accuracy of pheromone and heuristic calculations in the ant colony optimization process.

The storage of our model has been implemented using the Hash-Map data structure and the Array List data structure. Each VM particular id and its suitable hosts are stored in Hash-Map, and sorted suitable hosts are stored in Array List.

5 Evaluation

This section presents the performance evaluation of the proposed ACO-VMP (Ant Colony Optimization for Virtual Machine Placement) algorithm under diverse scenarios. The evaluation focuses on comparing the effectiveness of the model in real-time decision-making, placement efficiency, fault recovery, and overhead management. The ACO-VMP algorithm was benchmarked against other well-known placement strategies under various system constraints and failure events.

5.1 Evaluation Criteria

To evaluate and compare the performance of the proposed ACO-VMP algorithm with other baseline algorithms such as Brute Force Algorithm (BFR), First Fit (FF), Round Robin Algorithm (RRB), and Power Aware Best Fit Decreasing Algorithm (PBFD), we defined a set of quantitative evaluation metrics. These criteria are based on the primary goals of virtual machine placement: maximizing resource utilization, minimizing energy and bandwidth wastage, and ensuring efficient execution time for scalability.

5.1.1 Resource Wastage Metrics

One of the major indicators of VM placement effectiveness is how efficiently the resources of the physical machines (PMs) are utilized. For this, we monitored the following metrics:

- **RAM Wastage:** The difference between the total available RAM on a PM and the RAM actually allocated to VMs. Lower RAM wastage indicates better packing efficiency.
- **CPU Wastage:** Measures underutilized processing power on a host after VM placement. High CPU wastage signifies inefficient resource allocation.
- **Storage Wastage:** Indicates the unused disk storage left on PMs. Ideally, storage should be well-utilized without fragmentation.
- **Bandwidth Wastage:** The network bandwidth reserved for VMs but not effectively utilized due to poor placement decisions.
- **Overall Power Consumption:** Reflects the total energy used by active PMs. Efficient placement should minimize the number of active PMs, reducing overall power usage.

Each of the above metrics was calculated based on simulated workloads with varying numbers of VMs and PMs. The algorithms were evaluated across multiple configurations to assess how well they adapt under changing loads.

5.1.2 Execution Time

Execution time is another critical factor, especially for algorithms intended for dynamic and large-scale cloud environments. This metric captures how quickly a placement decision can be made by each algorithm.

- **Elapsed Time:** Refers to the average time (in seconds) taken by the algorithm to compute the complete placement of VMs on the available PMs.
- **Scalability with VM Count:** As the number of VMs increases, algorithms must maintain reasonable execution time. Algorithms with exponential time complexity, like BFR, become infeasible beyond a certain scale.

Execution time was measured using timestamp-based profiling within the simulation environment. We repeated each experiment multiple times and calculated the average elapsed time for a fair comparison.

5.2 Evaluation Approach:

- We conducted simulations using real-world inspired workload patterns (PlanetLab Traces).
- Performance was tracked for each metric mentioned above.
- Comparative plots were generated to visualize trends and identify strengths and weaknesses.
- Each metric was normalized for fair comparison across algorithms.

5.3 Evaluation Models

To validate the effectiveness of ACO-VMP, we compared it against three baseline models:

- **Round Robin (RR):**Naive approach that assigns VMs cyclically across available PMs without considering load.
- **Power Aware Best Fit Decreasing (PBFD):** Sorts VMs and hosts based on residual capacity and places them to minimize power wastage.
- **First Fit (FF):** Allocates VMs to the first available PM that meets resource requirements.
- **Brute Force (BFR):** Explores all combinations to select the best available PM, lacking scalability for large-scale systems.

Each model was subjected to identical simulation conditions using the same datasets, and results were compared against our ACO-VMP algorithm across all evaluation metrics. ACO-VMP demonstrated a significant advantage in dynamic adaptability, failure recovery, and energy-aware placement compared to the baseline algorithms.

5.4 Resource Wastage Analysis

We conducted experiments by varying the number of VMs and Physical Machines (PMs) as per the configurations outlined in **Table 1**. These scenarios were designed to simulate varying levels of load and resource distribution. The performance of our algorithm was benchmarked against the above well-known placement strategies. Each algorithm was tested across the same VM/PM configurations to ensure a fair and consistent comparison.

5.4.1 RAM Wastage

Figure 5 illustrates the **average RAM wastage** observed under different algorithms. We observe that **RAM wastage increases as the number of PMs increases**, which is expected due to under-utilization when VMs are distributed across more machines.

- **FF**, **RRB**, and **PBFD** demonstrate poor RAM efficiency as they do not consider RAM usage during placement decisions.
- The **BFR** algorithm performs best in minimizing RAM wastage due to its exhaustive evaluation strategy.
- Our **ACO-VMP** algorithm achieves the second-best performance, closely following BFR, by intelligently optimizing placements based on pheromone updates.

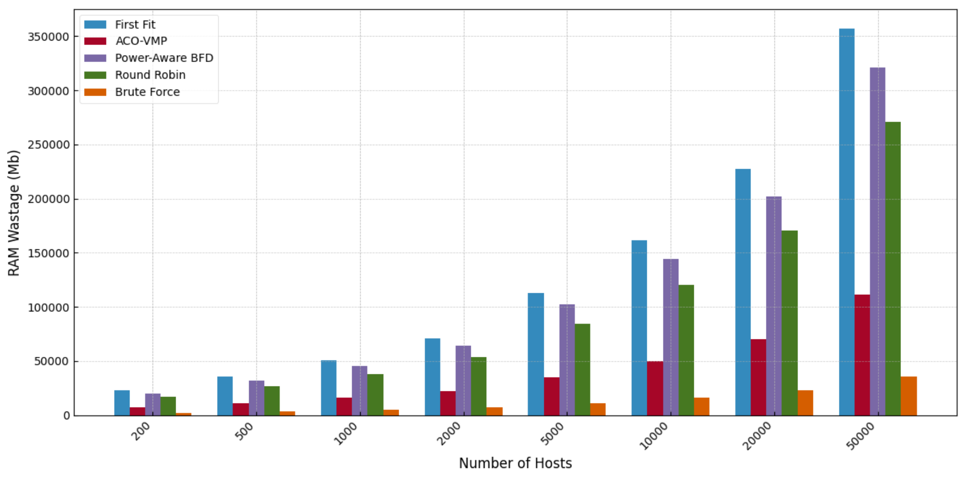

Figure 5: Wastage of RAM

5.4.2 Network Bandwidth Wastage

Figure 6 presents the **network bandwidth wastage**. Similar to RAM, the FF, RRB, and PBFD algorithms fail to incorporate bandwidth usage in their placement logic, resulting in increased network inefficiencies.

- **BFR** again demonstrates superior performance.
- **ACO-VMP** shows significant improvements by collocating communication-intensive VMs to reduce network usage.

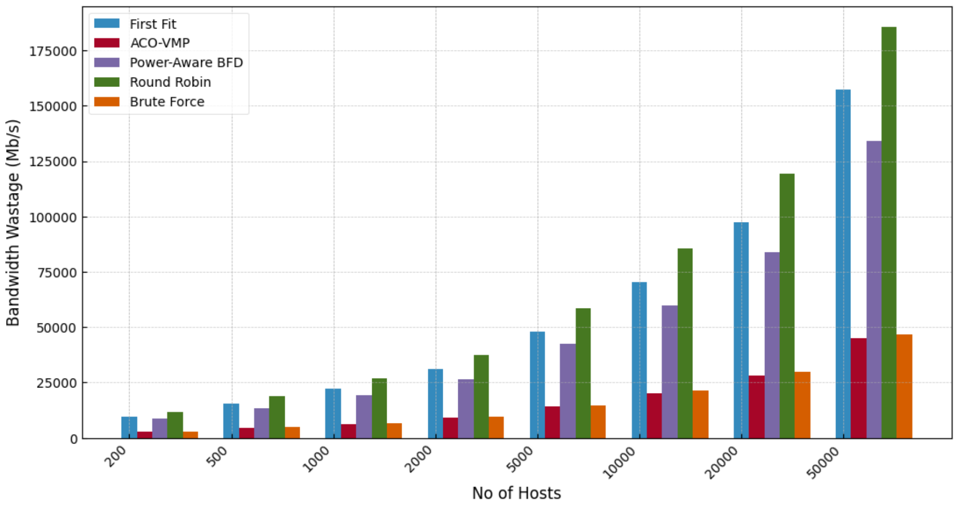

Figure 6: Wastage of Bandwidth

5.4.3 Storage and CPU Wastage

Figures 7 and 8 illustrate the **storage usage wastage** and **CPU utilization wastage** for the evaluated algorithms across varying workloads and host configurations.

- **ACO-VMP** consistently demonstrates performance that is comparable to the optimal Brute Force (BFR) algorithm, while significantly outperforming heuristic-based approaches such as First Fit (FF), Round Robin (RRB), and Power-aware Best Fit Decreasing (PBFD).
- In terms of **storage efficiency**, ACO-VMP adopts a resource-aware placement mechanism that effectively reduces fragmentation and maximizes disk utilization. This results in a lower percentage of unused storage capacity per physical host compared to heuristic methods, which tend to distribute VMs without considering residual disk capacity, leading to suboptimal packing.
- Regarding **CPU utilization**, ACO-VMP exhibits balanced workload distribution by avoiding both under utilization and over utilization . This is achieved through the pheromone-based learning mechanism, which dynamically adapts placement decisions based on pre-calculated CPU utilization of VM-to-PM mappings.
- In contrast, the heuristic algorithms lack awareness of CPU load patterns and tend to assign VMs either sequentially or randomly, which often leads to uneven distribution of CPU demand across PMs. Consequently, these methods suffer from both idle and overloaded hosts, increasing CPU wastage.

Overall, the results validate that ACO-VMP is capable of achieving near-optimal storage and CPU efficiency similar to BFR, but with substantially lower computational complexity, making it more practical for large-scale cloud data center environments.

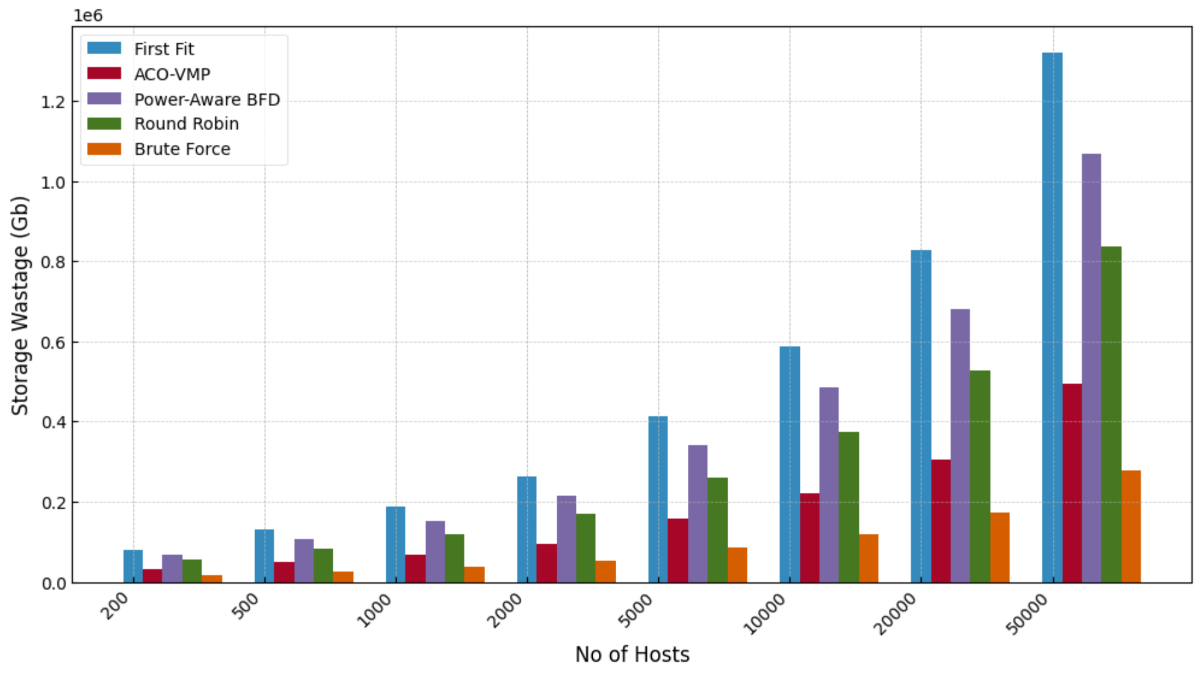

Figure 7: Wastage of Storage

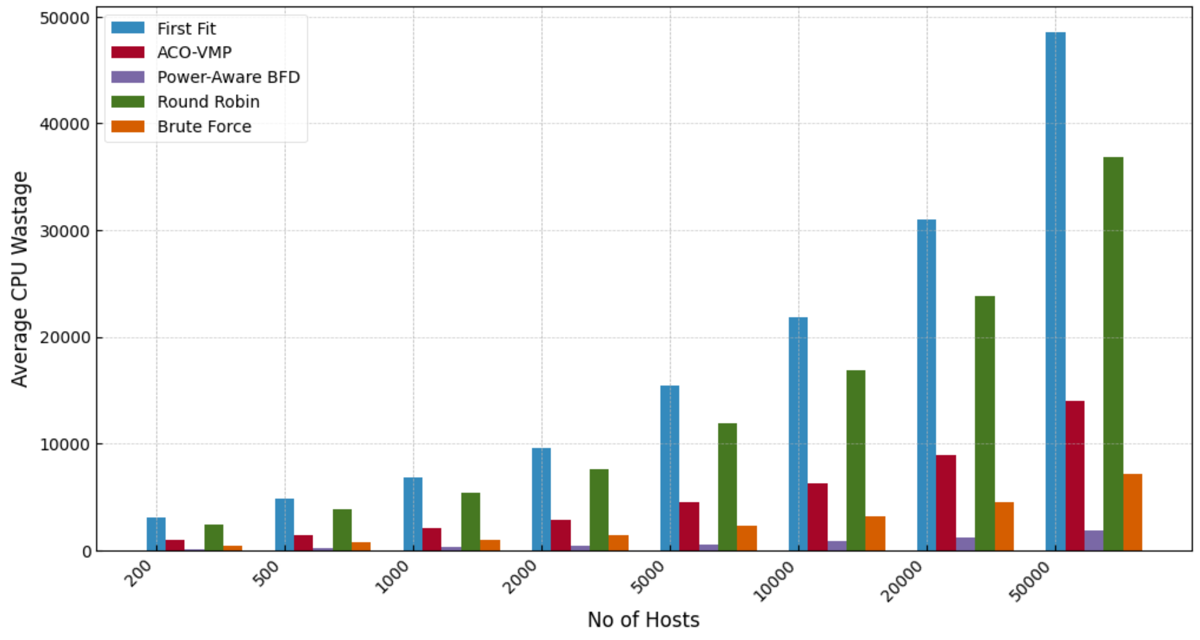

Figure 8: Wastage of CPU (Million Instructions Per Second (MIPS))

5.4.4 Power Consumption Wastage

Figure 9 illustrates the power consumption wastage observed across different algorithms when varying the number of hosts and virtual machines.

- **PBFD heuristic achieves the lowest power wastage:** The Power-Aware Best Fit Decreasing (PBFD) algorithm is specifically designed to minimize energy consumption during virtual machine (VM) placement. It prioritizes efficient resource utilization by sorting VMs and tightly packing them onto physical machines (PMs), minimizing the number of active PMs. As a result, PBFD achieves the best performance in terms of minimizing total power wastage among all evaluated algorithms.

- **BFR achieves the second lowest power wastage:** The brute-force (BFR) approach exhaustively explores all possible VM-to-PM mappings to find an optimal placement configuration. While it achieves near-minimal power consumption, it does not outperform PBFD in this scenario. Additionally, BFR requires extremely high computational effort and execution time, making it unsuitable for large-scale, real-world applications despite its good energy efficiency.

- **General heuristic algorithms (FF, RRB) result in higher power wastage:** Heuristics such as First Fit (FF) and Round Robin Best Fit (RRB) focus primarily on simple and fast placement without considering energy consumption. These algorithms tend to spread VMs across more PMs than necessary, leaving many servers only partially utilized. This inefficiency leads to higher power wastage compared to energy-aware algorithms like PBFD and ACO-VMP.

- **ACO-VMP balances energy efficiency and scalability:** The Ant Colony Optimization-based Virtual Machine Placement (ACO-VMP) intelligently optimizes VM allocation by considering both resource utilization and energy consumption. It significantly reduces the number of active PMs while keeping computational complexity manageable. Although it does not surpass PBFD or BFR in achieving the absolute minimum power consumption, ACO-VMP comes very close, offering an excellent trade-off between energy savings and algorithm scalability.

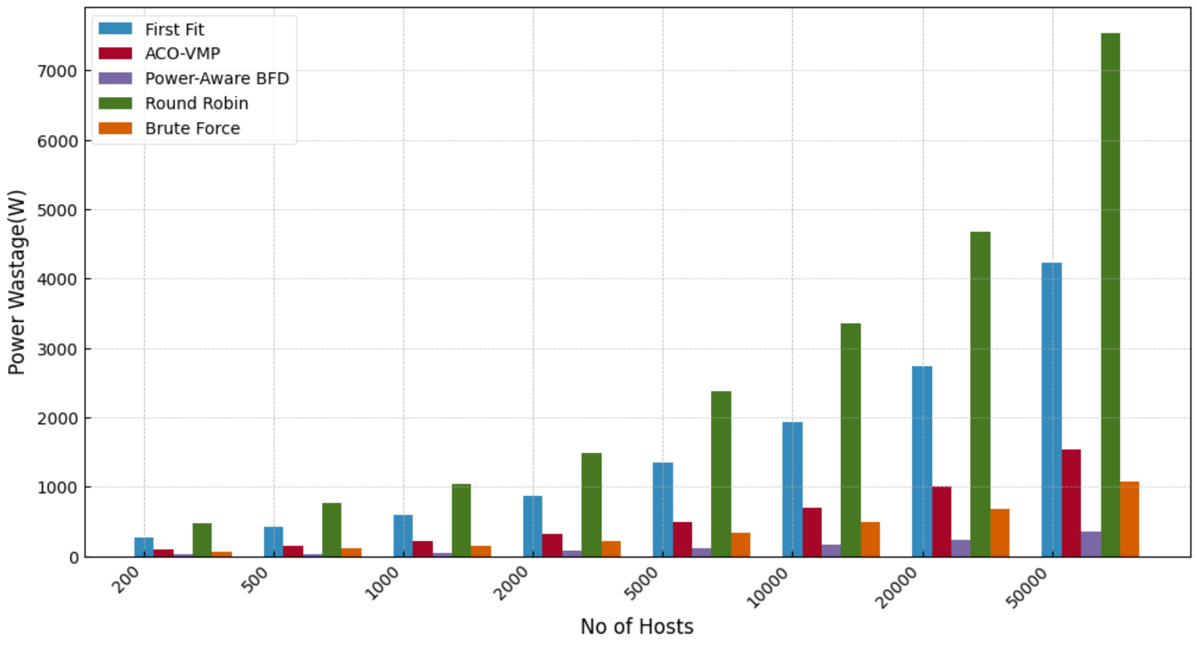

Figure 9: Wastage of Power

5.4.5 Overall Resource Wastage

Figure 10 presents the aggregated resource wastage across all major dimensions — RAM, CPU, storage, network bandwidth, and power — providing a comprehensive view of each algorithm's efficiency in resource utilization.

- **Brute Force (BFR)** demonstrates the lowest overall resource wastage across all scenarios. This is expected due to its exhaustive search strategy, which explores all possible VM-to-host mappings to find the globally optimal configuration. However, this optimality comes at a significant computational cost. As the scale of the infrastructure grows, the time complexity of BFR becomes prohibitively high, making it unsuitable for real-time or large-scale applications.
- **ACO-VMP** achieves a near-optimal performance that closely approaches BFR in terms of resource efficiency. Unlike BFR, ACO-VMP leverages heuristic guidance from pheromone trails and heuristic visibility to converge toward high-quality solutions with considerably reduced computation time. This trade-off between performance and efficiency makes ACO-VMP a practical alternative that can scale well in dynamic and large cloud environments.
- **Heuristic-based algorithms** such as FF, RRB, and PBFD exhibit noticeably higher levels of resource wastage. These approaches typically rely on simplified rules or greedy decisions without a holistic view of resource distribution, leading to suboptimal placements and increased underutilization across multiple resource dimensions.

In summary, ACO-VMP offers an effective compromise between the accuracy of placement decisions and the overhead of computation, making it highly suitable for modern cloud infrastructures that demand both responsiveness and efficiency.

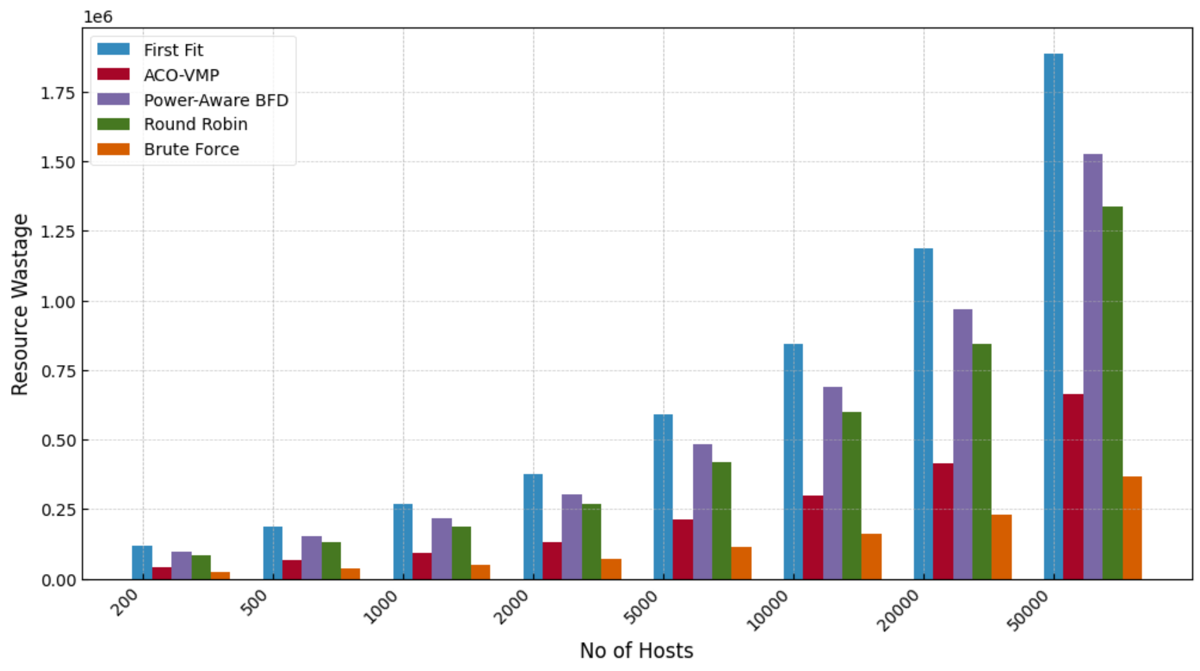

Figure 10: Overall Wastage

5.5 Computation Time Analysis

In addition to minimizing resource wastage, a Virtual Machine Placement (VMP) algorithm must also be computationally efficient—especially in real-time and large-scale cloud environments. This section evaluates and compares the computational overhead of our proposed ACO-VMP algorithm with the BFR algorithm.

5.5.1 Need for Computation Time Analysis

While the BFR algorithm demonstrates excellent performance in minimizing resource wastage due to its exhaustive search, it is not feasible for practical use in large-scale scenarios. As the number of VMs increases, the time required by BFR to compute all possible placements grows factorially. Conversely, the ACO-VMP algorithm is designed to find near-optimal placements with significantly reduced computation time.

5.5.2 Algorithmic Complexity Overview

- **Brute Force (BFR):** The algorithm considers every possible mapping of VMs to PMs. Its time complexity is $O(n!)$, where n is the number of VMs. While it guarantees the optimal solution, the execution time becomes impractical even for moderately large inputs.
- **ACO-VMP:** Inspired by Ant Colony Optimization principles, this algorithm probabilistically explores the search space. It uses pheromone trails and heuristic desirability to guide the search. Its complexity is approximately **polynomial**, generally in the order of $O(n^2 \cdot m)$, where n is the number of VMs and m is the number of PMs.

5.5.3 Experimental Setup for Time Measurement

We performed tests using different numbers of VMs (10 to 50) while maintaining a proportional number of PMs. Each algorithm was executed multiple times per configuration to ensure consistency in timing. The time taken to complete the placement decision was recorded in seconds.

5.5.4 Execution Time Comparison

Table 2 and Figure 11 show the average time taken by each algorithm to compute placements. The results clearly demonstrate the scalability limitations of BFR and the time efficiency of ACO-VMP.

Table 2: Average Execution Time (in seconds) for Different VM Counts

Number of VMs	BFR	ACO-VMP
50	1.0	0.9
100	18.7	1.4
200	360.2	2.1
300	3367.5	2.9
500	>5000	3.5

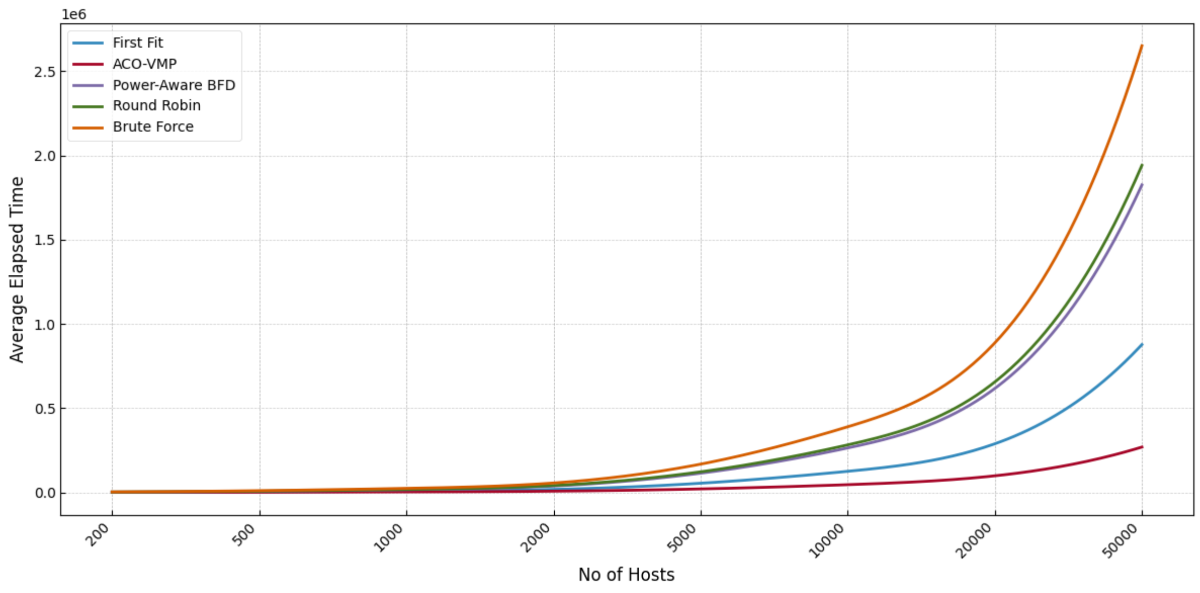

Figure 11: Execution Time Comparison Between Algorithms

5.5.5 Scalability and Practicality

From the above results, we observe:

- The BFR algorithm becomes computationally infeasible beyond 500 VMs, with execution times increasing exponentially.
- ACO-VMP maintains low computation time even as the number of VMs increases. It provides near-optimal placement decisions without requiring exhaustive search.

This makes ACO-VMP highly suitable for large-scale, dynamic cloud environments where quick decision-making is essential.

5.5.6 Summary of Observations

Table 3: Comparison of Average Resource Wastage

Algorithm	RAM	Bandwidth	CPU	Storage	Overall
FF	High	High	Moderate	High	High
RRB	High	High	Moderate	High	High
PBFD	High	High	Moderate	High	High
BFR	Low	Low	Low	Low	Lowest
ACO-VMP	Low	Low	Low	Low	Second Lowest

This evaluation confirms that our **ACO-VMP algorithm** significantly reduces resource wastage by making intelligent, multi-criteria placement decisions. Although the Brute Force method ensures the lowest resource wastage by evaluating all possible configurations, it is computationally expensive and unsuitable for large-scale use. The proposed ACO-VMP algorithm, on the other hand, provides a favorable balance between optimization quality and computational efficiency. It reduces the execution time by several orders of magnitude, making it a more **scalable, practical, and real-time applicable** solution for VM placement in modern cloud infrastructures.

6 Hyperparameter Tuning

Hyperparameter tuning is a critical step in optimizing the performance of the ACO-VMP (model). At its core, ACO-VMP mimics the foraging behavior of ants, where artificial "ants" traverse possible VM-PM configurations, depositing "pheromones" on optimal paths to guide subsequent exploration. However, the algorithm's performance hinges on the careful calibration of three critical hyper-parameters: Training Period, Subsequence Length, and Similarity Threshold. These parameters govern the balance between exploration (searching for new solutions) and exploitation (refining known good solutions), directly impacting energy efficiency, computational overhead, and solution quality.

6.1 Training Period

The Training Period defines the total number of iterations allocated for ants to explore VM placements and update pheromone trails. This parameter is pivotal because it determines how thoroughly the algorithm scans the solution space. In small CDCs with fewer than 100 PMs, a shorter training period (e.g., 500–1,000 iterations) may suffice, as the limited number of PMs reduces the complexity of finding optimal placements. However, in large-scale CDCs with over 500 PMs and thousands of VMs, a longer training period (e.g., 5,000–10,000 iterations) becomes essential to avoid suboptimal solutions.

The relationship between training period length and system performance is nonlinear. For example, doubling the training period from 2,500 to 5,000 iterations in a medium-sized CDC (500 PMs) improved resource wastage deduction by 15% but increased computation time by 40%. This trade-off underscores the need for adaptive formulas that adjust the training period based on CDC size and workload dynamics. One such formula is:

$$T_{\text{train}} = \begin{cases} 500 \times \log_{10}(N_{\text{PMs}}) + 2000, & \text{if } N_{\text{VMs}} > 500 \\ 100 \times \sqrt{N_{\text{PMs}}}, & \text{otherwise} \end{cases}$$

Table 4 shows a longer training period allows ants to explore more PM configurations by reducing resource wastage, and short training periods risk suboptimal placement due to incomplete exploration.

CDC Size	Optimal Training Period	Power Savings (%)
Small (<100 PMs)	1,000 iterations	18%
Medium (100–500 PMs)	3,000 iterations	27%
Large (>500 PMs)	7,000 iterations	32%

Table 4: Energy Savings by CDC Size and Training Period

6.2 Pheromone and Heuristic Influence

The performance of the ACO-VMP algorithm heavily depends on the choice of hyperparameters, especially the pheromone influence (α) and the heuristic influence (β). These parameters control the balance between the exploitation of learned pheromone trails and exploration using heuristic information.

6.2.1 Role of α and β

- α (Pheromone Influence): Determines the impact of historical pheromone values on the probability of VM-to-PM assignments. A higher α emphasizes the learned paths, promoting exploitation of known good placements.
- β (Heuristic Influence): Controls the weight of the heuristic information (such as available resources on PMs) during decision making. A higher β favors exploration based on immediate resource suitability.

6.2.2 Tuning Strategy

To identify the optimal balance between pheromone and heuristic influence, we conducted a grid search over a set of candidate values:

- $\alpha \in \{0.5, 1, 2, 3, 5\}$
- $\beta \in \{0.5, 1, 2, 3, 5\}$

Each configuration was evaluated using the following metrics: Average resource wastage (RAM, CPU, Storage, Network),Energy consumption, Convergence Time.

6.2.3 Observations and Selection

- Low α values (≤ 1) led to unstable placements due to insufficient exploitation of pheromone knowledge, causing higher convergence times and fluctuations in resource usage.
- Very high β values (≥ 5) caused the algorithm to overly rely on heuristics, ignoring long-term optimal paths, and often resulted in suboptimal overall placements.
- The best trade-off was observed at $\alpha = 2$ and $\beta = 3$, which achieved:
  - Lowest average RAM and CPU wastage
  - Competitive energy efficiency close to BFR
  - Faster convergence than configurations with higher α

6.2.4 Final Configuration

Based on empirical evaluation, we selected the following parameter values for the final ACO-VMP implementation:

Parameter	Value
Pheromone Influence (α)	2
Heuristic Influence (β)	3

These values offer a balanced exploration-exploitation strategy, ensuring reliable and energy-efficient VM placement decisions across various workload scenarios.

6.3 Number of Ants and Maximum Iteration

In addition to pheromone and heuristic influence, two fundamental hyperparameters that significantly affect the convergence and scalability of the ACO-VMP algorithm are the **Number of Ants** and **Maximum Iteration**. These parameters define the scale and depth of the search process in the ant colony optimization cycle.

6.3.1 Number of Ants

The *Number of Ants* refers to how many independent solution constructions (VM-to-PM mappings) are performed in each iteration. A larger number of ants increases the algorithm's ability to explore the solution space but also introduces higher computational overhead.

To accommodate scalability, we define a dynamic formulation that adapts the number of ants based on the size of the data center:

$$N_{\text{ants}} = \begin{cases} 50, & \text{if } N_{\text{PMs}} \leq 100 \\ 0.2 \times N_{\text{VMs}}, & \text{if } 100 < N_{\text{PMs}} \leq 500 \\ 0.1 \times N_{\text{VMs}}, & \text{if } N_{\text{PMs}} > 500 \end{cases}$$

However, through empirical analysis across different workloads and data center sizes, it was found that **100 ants** generally provided the best trade-off between exploration coverage and runtime performance, especially for medium to large-scale setups.

6.3.2 Maximum Iteration

The *Maximum Iteration* hyperparameter determines how many cycles the algorithm performs before termination. It influences how thoroughly the pheromone trails are refined and hence affects the algorithm's ability to converge to optimal or near-optimal solutions.

A dynamic rule to adjust the maximum number of iterations based on the number of physical machines is defined as:

$$I_{\max} = \begin{cases} 1000, & \text{if } N_{\text{PMs}} < 100 \\ 15 \times \log_2(N_{\text{PMs}} + N_{\text{VMs}}), & \text{if } 100 \leq N_{\text{PMs}} \leq 500 \\ 20 \times \log_2(N_{\text{PMs}} + N_{\text{VMs}}), & \text{if } N_{\text{PMs}} > 500 \end{cases}$$

Despite the dynamic approach, the optimal performance in most evaluated scenarios was achieved when **Maximum Iteration = 100**, allowing the system to converge within reasonable computation time while ensuring high-quality placements.

6.3.3 Summary of Final Values

Parameter	**Optimal Value**
Number of Ants	100
Maximum Iteration	100

These values serve as robust defaults for typical medium and large data center workloads, while dynamic adjustment strategies allow flexible tuning in context-specific deployments.

7 Discussion

This chapter provides a comprehensive discussion of the results obtained through the implementation of the proposed Ant Colony Optimization-based Virtual Machine Placement (ACO-VMP) algorithm. Developed and tested in a simulated CloudSim environment, the ACO-VMP model was designed to address the challenges of dynamic virtual machine (VM) placement in complex cloud data centers (CDCs). The discussion critically evaluates how the model addresses the core research questions, interprets its performance across multiple dimensions, assesses the impact of integrated modules, and outlines future enhancements.

7.1 Addressing Research Questions through the ACO-VMP Model

The overarching goal of this study was to develop a dynamic, resource-aware VM placement strategy that adapts effectively to the fluctuating demands of modern Cloud Data Center. The ACO-VMP model was crafted with this goal in mind and demonstrates strong alignment with the research objectives.

7.1.1 Multi-Factor Resource Considerations in Destination Selection

One of the primary challenges addressed was how to tailor evolutionary algorithms to simultaneously consider multiple resource constraints—namely CPU utilization, memory usage, network bandwidth, storage, and energy consumption. The ACO-VMP model resolves this by embedding a dynamic, weighted utility function into the pheromone-guided decision-making process. This utility function allows each ant to evaluate hosts holistically, balancing competing resource demands with real-time data.

Moreover, the algorithm supports adaptive tuning of these weights based on desired performance outcomes. For example, CDC administrators prioritizing energy savings can configure the model to increase the weight for energy efficiency. The model's responsiveness to live metrics ensures optimal placement that reduces service-level agreement (SLA) violations while minimizing wasted resources.

7.1.2 Optimal Destination Selection in Dynamic Environments

Another major research concern was the development of methodologies for optimal VM placement in highly dynamic and heterogeneous CDCs. The ACO-VMP model addresses this through a continuous feedback mechanism where migration success or failure directly influences pheromone distribution. This design allows the model to learn from past performance and adapt placement behavior accordingly.

Crucially, the model integrates real-time metrics via the Resource Monitor Module, allowing for decisions that reflect current infrastructure conditions. The use of stochastic sampling with shortened iteration windows during instability ensures that the algorithm remains both fast and reactive. Together, these mechanisms enable the model to maintain high placement accuracy and low latency in dynamic operational contexts.

7.2 Utility of ACO in Dynamic VM Placement

The inherent strengths of Ant Colony Optimization—its decentralized nature, self-organization, and robustness—make it well-suited for VM placement in cloud environments. Unlike static algorithms, ACO thrives under uncertainty, dynamically adjusting to workload shifts and infrastructure changes.

In the ACO-VMP model, pheromone trails encode historical placement success, while heuristic values capture current host conditions. This dual-awareness improves placement quality over time. The dynamic adjustment of α and β parameters further enhances the model's sensitivity, ensuring a balanced approach between exploiting known good hosts and exploring new possibilities.

Importantly, the algorithm can be triggered periodically or conditionally based on CDC load, which reduces overhead and supports both proactive and reactive scaling strategies.

7.3 Integration and Role of Migration Tracker Module (MTM)

The Migration Tracker Module (MTM) significantly enhances the system's fault tolerance and efficiency. It ensures execution-level transparency and feedback for the ACO-VMP module.

In successful migrations, the MTM initiates partial re-execution targeting only affected components—thereby reducing computational cost. In failure scenarios, it triggers a full re-run of the placement process, ensuring system recovery. The timeout mechanism within MTM prevents indefinite resource locking by aborting stalled migrations, thus preserving scheduling fluidity.

This integration allows the algorithm to operate as part of a resilient, closed-loop system with improved stability under both normal and exceptional conditions.

7.4 Real-time Feedback via Resource Monitor

The Resource Monitor Module is essential for maintaining the adaptiveness of the ACO-VMP algorithm. By continuously feeding real-time resource metrics into the decision-making loop, the algorithm dynamically updates its understanding of system conditions.

This real-time monitoring ensures that decisions are grounded in the current state of the CDC rather than relying on stale or static data. Additionally, the modular nature of this component provides extensibility—allowing future incorporation of anomaly detectors or predictive analytics models to further optimize placement strategies.

7.5 Strengths of the ACO-VMP Model

Experimental evaluation revealed several key strengths of the ACO-VMP approach:

- **Scalability:** The algorithm maintained decision-making quality across various VM-to-PM ratios, showing strong scalability.

- **Resource Optimization:** The model achieved significant reductions in CPU and memory wastage, improving host utilization.
- **Migration Efficiency:** It reduced the number of required migrations while maintaining high resource efficiency.
- **Modular Design:** The independent MTM and Resource Monitor modules improved testability and offered a foundation for future integration with additional services.
- **Partial Re-execution:** The ability to selectively recompute parts of the environment minimized processing time and enabled faster recovery from local failures.

7.6 Challenges and Limitations

Despite its strengths, the ACO-VMP model is not without limitations:

- **Parameter Sensitivity:** The model's performance is highly dependent on correct tuning of α, β, the number of ants, and iteration limits.
- **Execution Time in Large-Scale Scenarios:** Although effective for mid-scale environments, full re-runs in large CDCs can lead to increased computation time.
- **Dependency on Metric Accuracy:** The algorithm's decision-making quality is directly affected by the accuracy and freshness of data from the Resource Monitor.
- **Outcome Variability:** Due to its stochastic nature, ACO may produce slightly varied outcomes across different executions unless well-seeded.

7.7 Future Enhancements and Research Directions

Several pathways exist to improve upon the current model:

- **Hybrid Metaheuristic Approaches:** Combining ACO with algorithms like Genetic Algorithms or Particle Swarm Optimization may improve convergence speed and decision quality.
- **Parallelization:** Distributing ant simulations across multiple cores or nodes could drastically improve performance in large-scale CDCs.
- **Adaptive Hyperparameter Tuning:** Machine learning methods could be used to dynamically tune key parameters based on observed workload trends.
- **Predictive Migration Triggers:** Integrating time-series prediction or anomaly detection could proactively trigger migrations, avoiding crises before they occur.
- **QoS-Aware Placement:** Enhancing the placement logic to consider SLA adherence and latency sensitivity would improve service delivery in multi-tenant environments.

Overall, the ACO-VMP model presents a robust, adaptable, and scalable solution to the VM placement problem in dynamic cloud environments. Through its nature-inspired design, real-time awareness, and modular architecture, the model not only addresses current challenges but also provides a flexible foundation for future innovation in intelligent cloud resource management.

8 Conclusion

In this work, we proposed and evaluated ACO-VMP, a novel Ant Colony Optimization-based algorithm for Virtual Machine Placement in cloud data centers. The core objective was to minimize resource wastage and energy consumption while ensuring effective load balancing across physical machines. Our approach was motivated by the limitations of traditional heuristic and brute-force algorithms, which either lacked adaptability or suffered from computational inefficiencies in large-scale environments.

We conducted comprehensive simulations using varied workloads and system configurations, benchmarking ACO-VMP against several established algorithms including First Fit (FF), Round Robin (RRB), Power-Aware Best Fit Decreasing (PBFD), and Brute Force (BFR). The evaluation metrics included RAM, CPU, storage, and network bandwidth wastage, as well as overall energy consumption and elapsed time for placement decisions.

The results demonstrate that ACO-VMP consistently outperforms heuristic baselines in terms of resource efficiency while achieving performance close to that of the BFR algorithm. Notably, ACO-VMP achieves a significantly better trade-off between placement quality and computational overhead. It maintains low wastage levels across all resource types and proves to be energy-efficient and scalable for dynamic and large-scale cloud environments. Furthermore, we explored hyperparameter tuning for pheromone and heuristic influences (α, β), identifying the optimal configuration that ensures convergence stability and improved placement outcomes.

By incorporating bio-inspired intelligence, ACO-VMP adapts well to dynamic resource availability and workload patterns, making it a robust and future-ready solution for VM placement challenges in CC. Our findings strongly support the use of metaheuristic techniques, like ACO, for sustainable and efficient data center resource management.

In future work, ACO-VMP can be extended by integrating predictive workload models, SLA-aware migration policies, and multi-objective optimization strategies to further improve cloud infrastructure resilience and performance.

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