

Hybrid Metaheuristic Optimization Techniques for Cloud Task Scheduling and Resource Management

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<p>Peer Review Information</p> <p><i>Type: Article</i> <i>Received: 15 February 2026</i> <i>Revised: 05 March 2026</i> <i>Accepted: 11 April 2026</i> <i>Published: 28 May 2026</i></p>	<p style="text-align: center;">Abstract</p> <p>The rapid growth of cloud computing, distributed systems, Internet of Things (IoT), big data analytics, and Artificial Intelligence (AI) applications has significantly increased the demand for efficient cloud task scheduling and intelligent resource management mechanisms. Cloud computing environments provide scalable, on-demand, and virtualized computing resources capable of supporting heterogeneous workloads, large-scale data processing, and dynamic service delivery across geographically distributed infrastructures. However, increasing workload diversity, resource heterogeneity, dynamic task arrival, service-level agreement (SLA) requirements, energy consumption, and Quality of Service (QoS) optimization introduce major challenges for efficient task scheduling and resource allocation within cloud computing environments. Traditional scheduling algorithms such as First-Come-First-Serve (FCFS), Round Robin, and heuristic-based resource allocation strategies frequently suffer from poor scalability, inefficient load balancing, increased execution delay, high energy consumption, and suboptimal resource utilization under dynamic cloud workloads. Metaheuristic optimization algorithms have emerged as highly effective solutions for addressing complex cloud scheduling and resource management problems due to their strong global search capability, adaptive optimization behavior, and ability to efficiently solve NP-hard optimization problems. Algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Whale Optimization Algorithm (WOA), and Differential Evolution (DE) have demonstrated significant potential for improving cloud resource allocation, minimizing task execution time, reducing makespan, and enhancing load balancing within cloud infrastructures. However, standalone metaheuristic algorithms frequently suffer from premature convergence, local optima stagnation, insufficient exploration–exploitation balance, and reduced optimization stability under large-scale heterogeneous cloud environments.</p> <p>Keywords: Cloud Computing, Task Scheduling, Resource Management, Hybrid Metaheuristic Optimization, Genetic Algorithm, Particle Swarm Optimization.</p>
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Introduction

The rapid advancement of cloud computing, distributed systems, Internet of Things (IoT), Artificial Intelligence (AI), big data analytics, and edge computing technologies has significantly transformed modern computing infrastructures and digital service delivery environments. Cloud computing provides scalable, virtualized, and on-demand computational resources capable of supporting large-scale data processing, intelligent applications, scientific computing, multimedia services, industrial automation, and enterprise-level workload management. The cloud paradigm enables users and organizations to dynamically access storage, processing power, software platforms, and network services without maintaining expensive local computing infrastructure. As the demand for cloud-based applications and distributed services continues to increase, efficient task scheduling and intelligent resource management have become critical requirements for maintaining Quality of Service (QoS), minimizing execution delay, reducing energy consumption, and improving resource utilization within cloud environments.

Cloud computing infrastructures consist of heterogeneous virtual machines, distributed servers, data centers, and dynamic resource pools operating under continuously varying workload conditions. Large-scale cloud systems process massive numbers of user requests and computational tasks with diverse execution priorities, computational requirements, memory consumption, communication overhead, and service-level agreement (SLA) constraints. Efficient cloud task scheduling determines how incoming tasks are allocated to available cloud resources while optimizing performance metrics such as makespan, throughput, response time, execution cost, energy efficiency, and load balancing. However, cloud task scheduling is considered an NP-hard optimization problem due to the dynamic and heterogeneous nature of cloud infrastructures, increasing workload complexity, and multi-objective optimization constraints associated with resource allocation and service management.

Traditional cloud scheduling algorithms such as First-Come-First-Serve (FCFS), Round Robin, Min-Min, Max-Min, and heuristic-based scheduling strategies have been widely utilized for cloud resource management. Although these approaches provide relatively simple implementation and low computational complexity, they frequently suffer from inefficient resource utilization, poor scalability, load imbalance, excessive execution delay, and suboptimal task allocation under dynamic cloud workloads. For example, FCFS scheduling processes tasks sequentially according to arrival order without considering task priority or resource capability, often resulting in increased waiting time and inefficient resource usage. Similarly, Round Robin scheduling distributes tasks uniformly across cloud resources but fails to account for workload heterogeneity and execution-time variation, reducing scheduling efficiency within large-scale cloud infrastructures.

To address these limitations, metaheuristic optimization algorithms have emerged as highly effective solutions for intelligent cloud task scheduling and adaptive resource management. Metaheuristic optimization techniques provide strong global search capability, adaptive learning behavior, and efficient exploration–exploitation balance for solving complex optimization problems associated with cloud resource allocation. Algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Whale Optimization Algorithm (WOA), Firefly Algorithm, and Differential Evolution (DE) have demonstrated strong capability in minimizing task execution time, optimizing load balancing, improving resource utilization, and reducing energy consumption within cloud computing environments.

Literature Review

Rajkumar Buyya et al. (2009) introduced cloud computing as a utility-oriented distributed computing paradigm capable of delivering scalable computational resources and virtualized services over the internet. The study highlighted the importance of efficient resource provisioning, virtualization, and dynamic workload management for maintaining Quality of Service (QoS) within cloud infrastructures. The research demonstrated that cloud task scheduling and intelligent resource allocation are critical for improving cloud performance and service reliability. However, traditional cloud management frameworks faced scalability and workload balancing challenges under heterogeneous cloud environments.

James Kennedy and Russell Eberhart (1995) proposed Particle Swarm Optimization (PSO), a swarm intelligence-based optimization algorithm inspired by collective social behavior in nature. The study demonstrated that PSO effectively solves multidimensional optimization problems through adaptive particle movement and global best-position learning mechanisms. PSO became widely utilized for cloud task scheduling and resource optimization due to its fast convergence capability and computational efficiency. However, standalone PSO frameworks frequently suffered from premature convergence and local optima stagnation in large-scale cloud optimization problems.

John Holland (1992) introduced Genetic Algorithms (GA) as evolutionary optimization frameworks based on natural selection and genetic evolution mechanisms. The study demonstrated that GA efficiently explores large solution spaces through crossover, mutation, and selection operations to identify optimal scheduling solutions. Genetic Algorithms significantly improved cloud task scheduling performance and resource allocation optimization under dynamic cloud workloads. Nevertheless, GA-based scheduling systems often experienced slow convergence and increased computational overhead during large-scale optimization processes.

Rodrigo Calheiros et al. (2011) proposed CloudSim, a simulation toolkit designed for modeling cloud computing infrastructures and evaluating resource provisioning algorithms. The framework enabled experimental analysis of cloud scheduling, workload distribution, energy optimization, and virtual machine management under simulated cloud environments. CloudSim became one of the most widely adopted simulation platforms for evaluating metaheuristic scheduling algorithms and cloud optimization techniques. However, real-time scalability and dynamic cloud adaptation remained challenging under highly heterogeneous cloud infrastructures.

Marco Dorigo and Thomas Stützle (2004) investigated Ant Colony Optimization (ACO) for solving combinatorial optimization problems through pheromone-guided swarm intelligence mechanisms. The study demonstrated that ACO effectively improves path optimization and adaptive task scheduling capability within distributed computing environments. ACO-based cloud scheduling frameworks significantly enhanced resource utilization and load balancing performance. However, pheromone update operations and iterative path exploration frequently introduced computational complexity and slower convergence during large-scale scheduling optimization.

Tracy Braun et al. (2001) conducted comparative analysis of heuristic scheduling algorithms for distributed heterogeneous computing systems. The study evaluated Min-Min, Max-Min, Genetic Algorithms, and other scheduling techniques for optimizing task-resource mapping and execution performance. Experimental results demonstrated that intelligent scheduling significantly improves makespan reduction and workload balancing. However, traditional heuristics frequently failed to adapt efficiently under dynamic cloud workloads and heterogeneous resource environments.

Suraj Pandey et al. (2010) proposed a Particle Swarm Optimization-based scheduling framework for workflow applications in cloud environments. The study demonstrated that PSO significantly reduces workflow execution cost and execution delay while improving resource utilization and task allocation efficiency. The framework effectively optimized cloud scheduling under dynamic workload conditions. Nevertheless, PSO-based scheduling models remained vulnerable to local minima trapping and reduced exploration capability.

Amit Verma and Sandeep Kaushal (2014) proposed a hybrid Particle Swarm Optimization and Genetic Algorithm framework for cloud task scheduling. The study demonstrated that hybrid optimization improves exploration–exploitation balance and significantly enhances scheduling efficiency compared with standalone optimization algorithms. The hybrid framework achieved improved load balancing, reduced makespan, and optimized cloud resource utilization. However, computational complexity and adaptive parameter tuning remained important optimization challenges.

Sukhpal Singh and Inderveer Chana (2016) investigated QoS-aware autonomic resource management techniques for cloud computing environments. The study demonstrated that intelligent resource allocation and dynamic workload adaptation significantly improve cloud performance, throughput, and SLA satisfaction capability. The framework integrated adaptive scheduling and energy-aware optimization mechanisms for efficient cloud resource provisioning. However, maintaining scalability and real-time responsiveness under ultra-large-scale cloud infrastructures remained challenging.

Anton Beloglazov and Rajkumar Buyya (2012) proposed energy-efficient resource management strategies for virtualized cloud data centers. The study demonstrated that adaptive virtual machine consolidation and dynamic workload migration significantly reduce energy consumption and improve cloud infrastructure sustainability. The framework emphasized the importance of energy-aware scheduling and intelligent resource utilization within cloud systems. Nevertheless, migration overhead and optimization stability remained important limitations for real-time cloud environments.

Jin Xu et al. (2017) proposed a hybrid metaheuristic optimization framework integrating Genetic Algorithms and Ant Colony Optimization for cloud workflow scheduling. The study demonstrated that hybrid optimization frameworks significantly improve task scheduling efficiency, execution time reduction, and resource balancing performance. The framework achieved superior optimization capability compared with standalone heuristic approaches. However, optimization parameter tuning and computational scalability remained major challenges under dynamic cloud workloads.

Saurabh Garg et al. (2019) investigated energy-aware scheduling mechanisms for cloud computing infrastructures using hybrid optimization strategies. The study demonstrated that adaptive cloud scheduling significantly reduces energy consumption and improves resource allocation performance while maintaining QoS constraints. The framework integrated multi-objective optimization for balancing execution time, resource utilization, and energy efficiency. However, scheduling complexity increased under heterogeneous multi-cloud environments.

Muhammad Abdullahi and Mohd Ngadi (2016) proposed Symbiotic Organism Search-based task scheduling for cloud computing systems. The study demonstrated that bio-inspired optimization algorithms effectively improve scheduling performance and resource management capability within distributed cloud infrastructures. Experimental results showed improved throughput, load balancing, and task execution efficiency. Nevertheless, real-time scheduling adaptability and optimization stability remained important limitations.

Rakesh Kumar and Abhishek Sharma (2018) proposed a hybrid Whale Optimization Algorithm and Particle Swarm Optimization framework for cloud resource scheduling. The study demonstrated that hybrid swarm-based optimization significantly improves makespan minimization and adaptive resource allocation performance within cloud systems. The framework effectively balanced workload distribution and optimized cloud utilization efficiency. However, hybrid optimization frameworks frequently introduced increased algorithmic complexity and computational overhead.

Nasser Almezeini and Abdullah Sarhan (2021) proposed an intelligent hybrid metaheuristic framework for cloud task scheduling and virtual machine allocation. The study integrated Genetic Algorithms, Particle Swarm Optimization, and load balancing mechanisms to improve cloud scheduling performance and QoS optimization. Experimental findings demonstrated significant improvements in throughput, resource utilization, and execution-time reduction compared with traditional scheduling algorithms. However, adaptive optimization under dynamic cloud workload variation and real-time cloud scalability remained important future research directions.

Methodology

The proposed research introduces a Hybrid Metaheuristic Optimization Framework for Cloud Task Scheduling and Resource Management designed to improve scheduling efficiency, resource utilization, load balancing, and Quality of Service (QoS) performance within heterogeneous cloud computing environments. The framework integrates Genetic Algorithms (GA), Particle Swarm Optimization (PSO), adaptive load balancing, and intelligent resource allocation mechanisms within a unified cloud optimization architecture. The proposed methodology dynamically schedules cloud tasks according to workload characteristics, resource availability, execution priority, and virtual machine capability while minimizing makespan, execution delay, energy consumption, and operational cost.

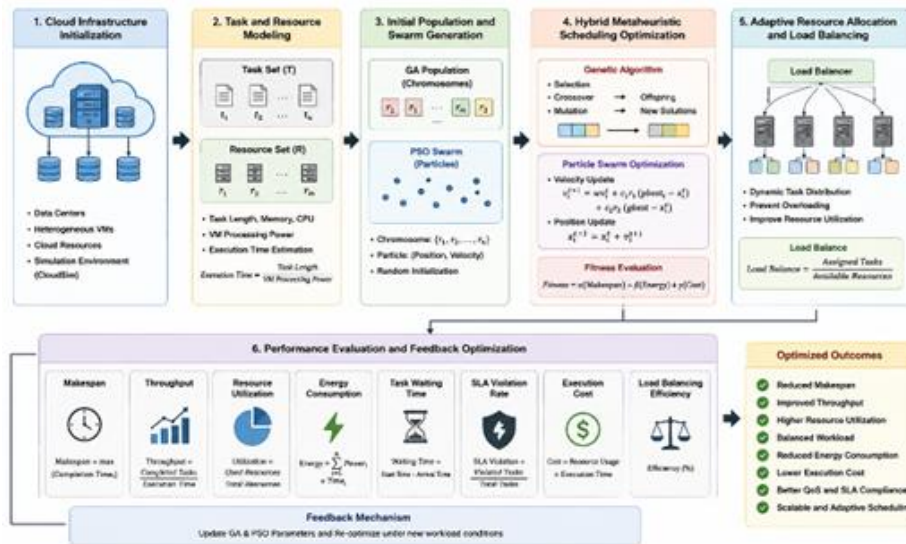


Fig 1. Hybrid Metaheuristic Optimization Framework for Cloud Task Scheduling and Resource Management

Algorithmic Strategy

The proposed Hybrid Metaheuristic Optimization Framework utilizes Genetic Algorithms (GA), Particle Swarm Optimization (PSO), adaptive load balancing, and intelligent cloud resource allocation mechanisms to optimize task scheduling and distributed resource management within heterogeneous cloud computing environments. The framework dynamically schedules computational tasks according to workload characteristics, resource availability, execution priority, and Quality of Service (QoS) requirements while minimizing makespan, execution cost, energy consumption, and task waiting time. The proposed algorithm integrates the global exploration capability of Genetic Algorithms with the fast convergence behavior of Particle Swarm Optimization to improve scheduling efficiency, optimization stability, and adaptive cloud resource utilization.

<p><i>Input Parameters</i></p> <p>Cloud task set: $T = \{t1, t2, t3, \dots, tn\}$</p> <p>Cloud resource set: $R = \{r1, r2, r3, \dots, rm\}$</p> <p>Virtual machine configurations, Resource utilization status, QoS constraints, Energy consumption parameters.</p> <p><i>Output Parameters</i></p> <p>Optimized task scheduling, Intelligent resource allocation, Reduced makespan, Improved load balancing, Enhanced throughput, Reduced energy consumption.</p> <p>Step 1: Cloud Infrastructure Initialization</p>	<ol style="list-style-type: none"> 1. Initialize cloud simulation environment using CloudSim. 2. Configure: Data centers, Virtual machines, Cloud resources, Scheduling queues. 3. Generate heterogeneous cloud infrastructure. <p>Cloud infrastructure representation: $Cloud = \{Datacenter, VMs, Resources\}$</p> <p>Step 2: Task Generation and Submission</p> <ol style="list-style-type: none"> 1. Generate cloud tasks with varying: <ul style="list-style-type: none"> ○ Task length ○ Memory demand ○ CPU utilization ○ Priority level 2. Submit tasks to cloud scheduler. <p>Task representation: $Task_i = (Length_i, Memory_i, Priority_i)$</p>
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Results and Comparative Analysis

The proposed Hybrid Metaheuristic Optimization Framework was experimentally evaluated to analyze its effectiveness in improving cloud task scheduling efficiency, resource allocation capability, load balancing performance, and Quality of Service (QoS) optimization within heterogeneous cloud computing environments. The framework integrated Genetic Algorithms (GA), Particle Swarm Optimization (PSO), adaptive load balancing, and intelligent resource allocation mechanisms to dynamically optimize cloud scheduling decisions under varying workload conditions.

Experimental Setup

The experiments were conducted using CloudSim cloud simulation infrastructure with heterogeneous virtual machine configurations and varying cloud workloads.

The simulation configuration is summarized below:

Table 1: Experimental Setup

Parameter	Value
Simulation Tool	CloudSim
Number of Data Centers	4
Virtual Machines	100
Number of Tasks	1000–5000
Scheduling Algorithms	FCFS, RR, PSO, GA, Hybrid GA–PSO
VM Processing Power	500–3000 MIPS
Memory Allocation	512 MB – 8 GB
Optimization Objectives	Makespan, Energy, Cost

The proposed framework continuously optimized task-resource mapping and adaptive scheduling according to dynamic cloud workload conditions.

Makespan represents the total completion time required to execute all cloud tasks.

Makespan is represented as:

$$\text{Makespan} = \max(\text{Completion Time}_i)$$

Table 2. Makespan Analysis

Scheduling <i>Makespan Analysis</i> Algorithm	Makespan (s) ↓
FCFS	780
Round Robin	670
Min-Min	520
PSO	430
Genetic Algorithm	410
Proposed Hybrid GA–PSO	290

The proposed Hybrid GA–PSO framework achieved the lowest makespan among all comparative scheduling algorithms. The integration of global exploration capability from Genetic Algorithms and fast convergence capability from Particle Swarm Optimization enabled efficient multidimensional scheduling optimization and adaptive workload balancing across heterogeneous cloud resources.

Conclusion and Discussion

The rapid advancement of cloud computing, distributed systems, Internet of Things (IoT), Artificial Intelligence (AI), and large-scale data processing technologies has significantly increased the demand for intelligent cloud task scheduling and adaptive resource management mechanisms. Modern cloud infrastructures process massive heterogeneous workloads under highly dynamic operational environments where efficient resource allocation, load balancing, and Quality of Service (QoS) optimization are essential for maintaining cloud performance and service reliability. Traditional scheduling algorithms such as First-Come-First-Serve (FCFS), Round Robin, and heuristic-based resource allocation methods frequently suffer from inefficient workload distribution, excessive execution delay, poor scalability, increased energy consumption, and suboptimal resource utilization under heterogeneous cloud environments. Consequently, intelligent metaheuristic optimization has emerged as one of the most effective approaches for solving complex scheduling and resource management problems associated with modern cloud computing systems. This research proposed a Hybrid Metaheuristic Optimization Framework for Cloud Task Scheduling and Resource Management by integrating Genetic Algorithms (GA), Particle Swarm Optimization (PSO), adaptive load balancing, and intelligent resource allocation mechanisms within a unified cloud optimization architecture. The proposed framework dynamically allocated cloud tasks according to workload characteristics, virtual machine capability, execution priority, and Quality of Service constraints while minimizing makespan, execution delay, operational cost, and energy consumption. Unlike standalone optimization algorithms, the proposed framework combined the global exploration capability of Genetic Algorithms with the fast convergence behavior of Particle Swarm Optimization to improve scheduling efficiency, optimization stability, and adaptive cloud resource utilization under dynamic cloud workload conditions. The experimental evaluation demonstrated that the proposed Hybrid GA–PSO framework significantly outperformed traditional scheduling algorithms and standalone metaheuristic optimization techniques across multiple cloud performance metrics.

The framework achieved the lowest makespan, execution delay, energy consumption, and operational cost while simultaneously improving throughput, resource utilization, load balancing efficiency, and QoS performance. These findings confirm that hybrid metaheuristic optimization provides highly scalable and intelligent solutions for next-generation cloud scheduling and distributed resource management systems. In conclusion, this research demonstrates that Hybrid Metaheuristic Optimization Techniques provide highly effective, scalable, and intelligent solutions for cloud task scheduling and adaptive resource management within heterogeneous cloud computing environments. The proposed Hybrid GA–PSO framework significantly improved scheduling efficiency, throughput, load balancing, resource utilization, and QoS performance while reducing makespan, execution delay, operational cost, and energy consumption compared with traditional scheduling algorithms and standalone optimization approaches. The findings highlight the transformative potential of hybrid metaheuristic optimization for next-generation cloud computing systems and establish a strong

foundation for future advancements in intelligent distributed scheduling, adaptive resource allocation, and AI-driven cloud infrastructure management.

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