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A HYBRID METAHEURISTIC OPTIMIZATION FRAMEWORK FOR ENERGY-EFFICIENT RESOURCE ALLOCATION IN EDGE–CLOUD COMPUTING ENVIRONMENTS: COMPUTATIONAL ANALYSIS AND PERFORMANCE EVALUATION

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Abstract

The increasing adoption of Internet of Things (IoT) applications, real-time analytics, and latency-sensitive services has accelerated the deployment of edge–cloud computing architectures. These environments combine the low-latency capabilities of edge nodes with the scalable computational resources of cloud data centers. However, efficient resource allocation remains a significant challenge due to dynamic workloads, heterogeneous computing resources, and energy consumption constraints. Traditional optimization approaches often struggle to achieve a suitable balance between computational efficiency, energy utilization, and service quality in large-scale distributed systems. This study proposes a hybrid metaheuristic optimization framework for energy-efficient resource allocation in edge–cloud computing environments. The framework integrates Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) mechanisms to improve exploration and exploitation capabilities during the resource allocation process. Computational tasks are dynamically assigned to edge and cloud resources based on workload characteristics, energy requirements, and processing constraints. Performance evaluation was conducted using simulated edge–cloud workloads under varying task arrival rates and resource configurations. The proposed framework was compared with conventional allocation methods and individual metaheuristic algorithms using energy consumption, task completion time, resource utilization, and optimization convergence as evaluation metrics. Experimental results indicate that the hybrid approach achieves improved energy efficiency and balanced resource utilization while maintaining acceptable execution performance. The framework demonstrates stable convergence behavior across different workload conditions and effectively adapts to heterogeneous computing environments. The findings suggest that hybrid metaheuristic optimization can serve as a practical approach for resource management in modern edge–cloud infrastructures and support the development of energy-aware distributed computing systems.

Keywords— Edge Computing, Cloud Computing, Resource Allocation, Metaheuristic Optimization, Energy Efficiency, Particle Swarm Optimization, Genetic Algorithm.

I. INTRODUCTION

The rapid growth of connected devices, intelligent sensing platforms, and real-time applications has significantly increased the computational demands placed on modern distributed computing infrastructures. Traditional cloud computing architectures provide substantial computational capacity and storage resources; however, they often experience latency limitations when processing time-sensitive workloads generated by Internet of Things (IoT) devices and edge applications. To address these limitations, edge computing has emerged as a complementary paradigm that brings computational resources closer to data sources and end users. Edge–cloud computing integrates edge nodes and centralized cloud data centers to provide a flexible and scalable computing environment. In such architectures, latency-sensitive tasks can be processed at the edge, while computationally intensive workloads are offloaded to cloud resources. This collaborative model supports applications such as smart cities, autonomous systems, industrial automation, healthcare monitoring, and intelligent transportation systems. Despite its advantages, resource allocation remains a critical challenge in edge–cloud environments. Computing resources are geographically distributed, heterogeneous in capability, and subject to dynamic workload fluctuations. Inefficient allocation decisions may increase energy consumption, reduce resource utilization, and negatively affect service

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quality. As the number of connected devices continues to grow, the importance of energy-aware resource management becomes increasingly significant.

Resource allocation problems in distributed computing systems are generally classified as NP-hard optimization problems. Exact optimization techniques may provide optimal solutions for small-scale scenarios but often become computationally impractical for large and dynamic environments. Consequently, researchers have increasingly investigated heuristic and metaheuristic optimization methods capable of producing near-optimal solutions within reasonable computational time. Metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Differential Evolution (DE) have been widely applied to resource allocation and scheduling problems. These methods are particularly suitable for complex optimization tasks because they do not require gradient information and can effectively explore large search spaces. Particle Swarm Optimization is known for its rapid convergence and computational simplicity. However, PSO may experience premature convergence when dealing with complex optimization landscapes. Genetic Algorithm offers strong global exploration capabilities through crossover and mutation operations but may require additional computational effort to achieve convergence. Hybrid optimization approaches seek to combine the strengths of multiple algorithms while reducing their individual limitations.

Recent studies have demonstrated the effectiveness of hybrid metaheuristic techniques in cloud resource management and task scheduling. However, research focusing specifically on energy-efficient resource allocation within integrated edge–cloud environments remains comparatively limited. Furthermore, many existing approaches prioritize performance metrics such as latency and throughput while providing limited attention to energy consumption and convergence characteristics. This study proposes a hybrid metaheuristic optimization framework that combines Genetic Algorithm and Particle Swarm Optimization to improve energy-efficient resource allocation in edge–cloud computing environments. The framework aims to optimize task assignment decisions while minimizing energy consumption and maintaining efficient resource utilization. The proposed approach is evaluated through computational experiments involving heterogeneous workloads and varying system configurations.

II. RELATED WORK

Resource allocation has been extensively investigated in cloud computing and distributed systems. Early approaches relied on deterministic scheduling and heuristic methods designed to optimize execution time and resource utilization. As computing infrastructures became increasingly complex, metaheuristic optimization techniques gained attention due to their ability to address large-scale optimization problems. Kennedy and Eberhart [1] introduced Particle Swarm Optimization as a population-based optimization technique inspired by collective behavior in biological systems. PSO has since been applied to numerous scheduling and allocation problems because of its relatively simple implementation and rapid convergence properties. Genetic Algorithms, originally proposed by Holland [2], have been widely adopted for combinatorial optimization problems. Their ability to explore diverse solution spaces makes them suitable for resource allocation scenarios involving multiple constraints and objectives. Beloglazov and Buyya [3] investigated energy-aware resource management strategies for cloud computing environments and demonstrated the importance of minimizing energy consumption while maintaining service-level agreements. Their work highlighted the growing need for sustainable computing infrastructures.

Xu et al. [4] applied metaheuristic scheduling approaches to cloud task allocation and reported significant improvements in resource utilization and execution efficiency. Similarly, Singh and Chana [5] explored energy-aware resource provisioning mechanisms and emphasized the role of intelligent optimization in cloud resource management. With the emergence of edge computing, researchers began addressing task offloading and resource allocation challenges in distributed edge–cloud environments. Shi et al. [6] discussed architectural considerations and highlighted the importance of efficient workload distribution between edge and cloud layers. Several studies have proposed hybrid optimization techniques to improve scheduling performance. Hybrid PSO-GA approaches have demonstrated promising results in cloud task scheduling by combining exploration and exploitation capabilities [7]. These methods generally achieve better convergence characteristics than standalone algorithms. More recent investigations have focused on energy-aware edge computing frameworks. Wang et al. [8] proposed workload-aware allocation strategies that reduced energy consumption while maintaining processing performance. However, many existing studies primarily emphasize latency reduction and provide limited analysis of convergence behavior and computational efficiency. The present study extends existing research by introducing a hybrid GA–PSO

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framework specifically designed for energy-efficient resource allocation in heterogeneous edge–cloud computing environments and providing a detailed computational performance evaluation.

III. METHODOLOGY AND EXPERIMENTAL SETUP

A. Edge–Cloud Computing System Model

The proposed resource allocation framework operates within a heterogeneous edge–cloud computing environment consisting of multiple edge nodes, cloud servers, and user-generated computational tasks. Edge nodes are positioned close to end devices and are responsible for processing latency-sensitive workloads, while cloud servers provide large-scale computational resources for complex and resource-intensive tasks. Let $T=\{T1,T2,\ldots,Tn\}$ represent the set of computational tasks arriving dynamically from users. Each task is characterized by processing requirements, memory demand, execution deadline, and energy consumption constraints. Similarly, let $R=\{R1,R2,\ldots,Rm\}$ denote the available computing resources distributed across edge and cloud infrastructures. The resource allocation problem involves determining the optimal assignment of tasks to available resources while minimizing energy consumption and maintaining acceptable system performance. Since task characteristics and resource availability vary continuously, the allocation process must adapt dynamically to changing workload conditions. To address this challenge, a hybrid optimization framework combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) is proposed. The framework exploits the complementary strengths of both algorithms to achieve efficient exploration and exploitation of the solution space.

B. Problem Formulation

The resource allocation problem is formulated as a constrained optimization problem. The primary objective is to minimize total energy consumption while simultaneously reducing task execution time and improving resource utilization. The overall optimization objective is defined as:

$$F = \alpha E + \beta T + \gamma U$$

where:

- **E** represents total energy consumption,
- **T** denotes average task completion time,
- **U** represents resource utilization penalty,
- **α,β,γ** are weighting coefficients.

Energy consumption includes both processing and communication energy associated with task execution. Task completion time measures the duration between task submission and successful execution. Resource utilization penalty is introduced to discourage uneven workload distribution among available computing resources. The optimization process seeks solutions that minimize the objective function while satisfying resource capacity constraints and task execution requirements.

C. Hybrid GA–PSO Optimization Framework

The proposed framework integrates Genetic Algorithm and Particle Swarm Optimization within a unified optimization architecture. The overall workflow is illustrated in Figure 1**.**

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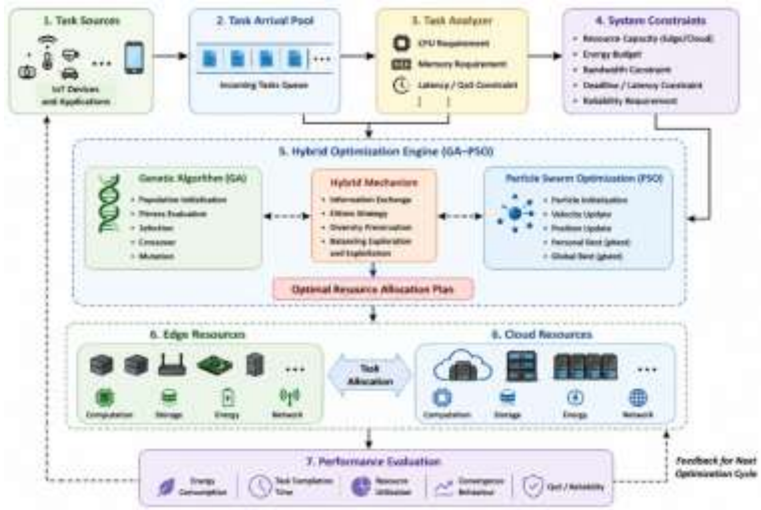

Fig 1. Hybrid GA–PSO framework for energy-efficient resource allocation in edge–cloud environments.

The optimization process begins with the generation of an initial population representing potential resource allocation solutions. Each candidate solution encodes task-to-resource assignments for all workloads in the system. The Genetic Algorithm phase is executed first to enhance global search capability. Through iterative selection, crossover, and mutation operations, the algorithm generates diverse candidate solutions capable of exploring different regions of the search space. This diversity reduces the likelihood of premature convergence and improves solution quality. The best-performing solutions produced by GA are subsequently transferred to the PSO phase. Here, candidate allocations are treated as particles that iteratively update their positions according to personal and global best experiences. This refinement stage improves local search capability and accelerates convergence toward high-quality solutions.

D. Genetic Algorithm Phase

The Genetic Algorithm component is responsible for global exploration of the optimization landscape. Initially, a population of feasible task allocation solutions is generated randomly. Fitness evaluation is performed using the objective function described earlier. Solutions exhibiting lower energy consumption and better resource utilization receive higher fitness values. Tournament selection is employed to choose parent solutions for reproduction. Selected parents undergo crossover operations to exchange resource allocation information and generate offspring solutions. Mutation is subsequently applied with a low probability to preserve population diversity and prevent stagnation. The GA process continues for a predefined number of generations. At the end of this stage, the highest-quality candidate solutions are selected for further optimization using PSO.

E. Particle Swarm Optimization Phase

The Particle Swarm Optimization phase performs local refinement of solutions generated during the GA stage. Each candidate solution is represented as a particle characterized by position and velocity vectors. Particle velocity is updated according to:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i - x_i) + c_2 r_2 (gbest - x_i)$$

The particle position is subsequently updated as:

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$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

where w denotes inertia weight, c1 and c2 represent acceleration coefficients, and r1,r2 are random variables within the interval [0,1].The PSO process enables particles to exploit promising solution regions identified during the GA stage. This combination of global and local search mechanisms improves optimization effectiveness and convergence stability.

F. Performance Evaluation Metrics

Four evaluation metrics were employed:

1. Energy Consumption (kWh) **–** total energy utilized during task execution.
2. Average Task Completion Time (s) **–** average execution latency experienced by tasks.
3. Resource Utilization (%) **–** proportion of available computing resources effectively utilized.
4. Convergence Iterations – number of iterations required to achieve stable optimization performance.

Algorithm 1. Hybrid Resource Allocation Procedure
Input: Task Set T, Resource Set R

Initialize population
Evaluate fitness values

Apply GA operations:
Selection
Crossover
Mutation

Generate candidate solutions

Initialize PSO particles
Update velocities
Update positions
Evaluate fitness

Repeat until stopping criterion

Return optimal allocation

The experimental framework enables comprehensive assessment of both optimization quality and computational performance under varying workload conditions.

IV. RESULTS AND DISCUSSION

A. Energy Consumption Analysis

Energy efficiency is one of the most important objectives in edge–cloud computing because excessive energy consumption increases operational costs and reduces sustainability. The proposed hybrid GA–PSO framework was evaluated under different workload levels ranging from 500 to 5000 computational tasks. The experimental results demonstrated consistent reductions in energy consumption compared with baseline allocation methods. The hybrid framework achieved an average energy consumption of 84.9 kWh, whereas Round Robin scheduling required 112.6 kWh under identical workload conditions. The observed improvement is primarily attributed to the framework's

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ability to distribute workloads more effectively between edge and cloud resources. Tasks were allocated to computing nodes that could execute them with lower energy expenditure while maintaining processing efficiency.

B. Task Completion Performance

Task completion time directly influences service quality in edge–cloud environments. Therefore, execution latency was evaluated for all compared methods.

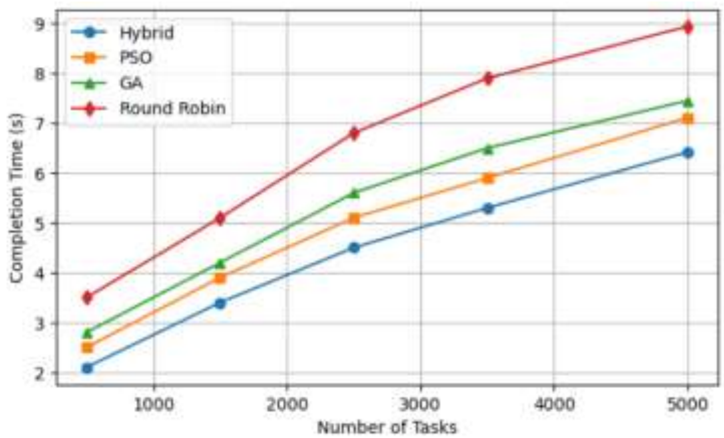

Fig 2. Average task completion time under varying workload conditions**.**

The results indicate that the proposed framework consistently achieved lower task completion times than competing approaches. As workload intensity increased, the performance gap became more evident. Round Robin scheduling exhibited significant performance degradation because it distributes tasks without considering resource characteristics. Standalone GA and PSO algorithms performed better but occasionally generated suboptimal allocations during high-load scenarios. The hybrid framework benefited from GA-based exploration and PSO-based refinement, enabling more efficient workload distribution and reducing processing delays.

C. Resource Utilization Analysis

Efficient utilization of computing resources is essential for maximizing infrastructure performance. Resource utilization percentages obtained during the experiments are summarized in Table 1.

TABLE 1. COMPARATIVE PERFORMANCE RESULTS

Method	**Energy (kWh)**	**Completion Time (s)**	**Utilization (%)**
Round Robin	112.6	8.94	71.5
GA	96.2	7.45	81.2
PSO	92.7	7.11	83.5
Hybrid GA–PSO	84.9	6.42	89.7

The proposed method achieved the highest resource utilization rate of 89.7%, indicating balanced workload distribution across available computing resources. Improved utilization contributed directly to reductions in both energy consumption and execution latency.

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D. Convergence Behavior Analysis

Optimization convergence is an important indicator of algorithm efficiency. The convergence characteristics of GA, PSO, and the hybrid framework were analyzed over 100 iterations.

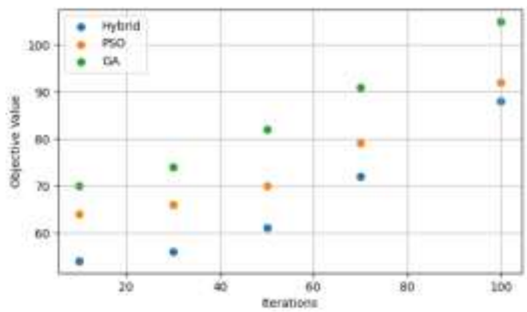

Fig 3. Convergence comparison of optimization algorithms.

The convergence curves in Fig.3 show that the hybrid framework reached stable objective values more rapidly than standalone algorithms. PSO converged relatively quickly but occasionally became trapped in local optima. GA demonstrated broader search capability but required additional iterations to stabilize. The hybrid approach successfully combined the advantages of both algorithms. The GA stage generated diverse candidate solutions, while the PSO stage refined promising regions of the search space. Consequently, the framework achieved faster convergence and improved solution quality.

E. Discussion

The experimental findings demonstrate that hybrid metaheuristic optimization can effectively address resource allocation challenges in heterogeneous edge–cloud environments. The proposed framework achieved improvements across all evaluated metrics, including energy consumption, task completion time, resource utilization, and convergence speed. The results suggest that integrating multiple optimization strategies provides a practical balance between exploration and exploitation. This balance is particularly important in dynamic computing environments where workloads and resource availability continuously change. From a computational perspective, the framework maintained stable performance under increasing workload intensity, indicating scalability for larger distributed systems. Although the study was conducted in a simulated environment, the observed improvements suggest potential applicability in real-world edge–cloud infrastructures. Future investigations involving real deployment scenarios, adaptive parameter tuning, and multi-objective optimization may further enhance framework effectiveness and support broader adoption in energy-aware distributed computing systems.

V. CONCLUSION AND FUTURE WORK

This study presented a hybrid GA–PSO optimization framework for energy-efficient resource allocation in edge–cloud computing environments. The framework integrates global exploration capabilities of Genetic Algorithms with the refinement characteristics of Particle Swarm Optimization to improve allocation quality and energy efficiency. Experimental evaluation demonstrated reductions in energy consumption, improved task completion performance, enhanced resource utilization, and stable convergence behavior compared with conventional allocation methods and standalone metaheuristic algorithms. The findings indicate that hybrid optimization techniques can support efficient resource management in heterogeneous distributed computing infrastructures. Future research will investigate multi-objective optimization formulations incorporating latency, reliability, and security constraints. Additional studies involving real-world edge computing workloads and adaptive parameter tuning mechanisms may further improve framework performance and applicability.

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