TASK Quarterly 29 (2) 2025

Distributed Machine Learning Optimization for Large-Scale Cloud Resource Scheduling: A Hybrid Deep Learning and Evolutionary Algorithm Approach

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https://doi.org/10.34808/tq2025/29.2/b

Abstract

Cloud computing resource management represents one of the most critical challenges in modern distributed systems, where efficient allocation of computational resources directly impacts system performance, energy consumption, and operational costs. This paper presents a novel hybrid approach combining deep reinforcement learning (DRL) with genetic algorithms (GA) for optimizing cloud resource scheduling in large-scale distributed environments. The proposed framework, termed Distributed Adaptive Learning Resource Scheduler (DALRS), integrates convolutional neural networks (CNN) for workload prediction with deep Q-networks (DQN) for dynamic resource allocation decisions. The approach is evaluated on a comprehensive simulation platform modeling realistic cloud infrastructure with heterogeneous resource configurations. Experimental results demonstrate that DALRS achieves 34.7% improvement in resource utilization, 28.3% reduction in task completion time, and 31.5% decrease in energy consumption compared to state-of-the-art baselines. Furthermore, the hybrid genetic algorithm component provides Pareto-optimal solutions balancing multiple objectives including cost, latency, and throughput. The paper also addresses scalability challenges through a distributed implementation using Apache Spark [1], enabling efficient processing of workloads exceeding 10,000 concurrent tasks. The results validate the effectiveness of combining machine learning with evolutionary optimization for managing complex resource allocation problems in cloud infrastructure.

Keywords:

cloud computing, machine learning, resource scheduling, reinforcement learning, genetic algorithms, high-performance computing

1. Introduction

The explosive growth of cloud computing services has created unprecedented demands for efficient resource management [2, 3]. Organizations worldwide deploy applications across geographically distributed data centers, managing thousands of virtual machines and containers simultaneously [4]. Traditional rule-based scheduling algorithms, including First-Come-First-Served (FCFS), Priority Queue (PQ), and Round-Robin (RR), demonstrate significant limitations when facing dynamic workload patterns and heterogeneous resource requirements [5, 6].

Cloud resource scheduling involves making real-time decisions regarding which computational resources should process which tasks, considering multiple conflicting objectives [7, 8]. These objectives include minimizing energy consumption, reducing task completion time (makespan), improving resource utilization, maintaining service quality, and balancing costs across multiple virtual machines [9, 10]. The combinatorial nature of this problem, with complexity typically classified as NP-Hard, makes it computationally intractable for deterministic approaches when dealing with large-scale systems [11].

Recent advances in machine learning, particularly deep reinforcement learning (DRL), have demonstrated remarkable capabilities in solving complex optimization problems [12, 13]. DRL agents learn optimal policies through interaction with environments, discovering solutions that surpass human-engineered heuristics [14]. However, pure DRL approaches often suffer from exploration-exploitation trade-offs and convergence issues in high-dimensional action spaces [15, 16]. Conversely, evolutionary algorithms like genetic algorithms (GA) provide robust mechanisms for exploring large solution spaces and discovering Pareto-optimal solutions in multi-objective optimization scenarios [17–19].

The primary contributions of this research include: (1) a novel hybrid framework integrating DRL with GA for cloud resource scheduling, combining the complementary strengths of both approaches; (2) an improved workload prediction model using CNN architectures specifically designed for time-series cloud workload patterns; (3) implementation of a distributed version supporting large-scale deployments exceeding 10,000 concurrent tasks; (4) comprehensive experimental evaluation demonstrating superior performance against existing algorithms; and (5) analysis of energy efficiency improvements through optimized resource utilization patterns.

2. Background and Related Work

2.1. Cloud Resource Scheduling Fundamentals

Cloud resource scheduling determines task-to-machine assignments in virtualized environments, representing a fundamental challenge in distributed computing systems [20, 21]. The problem involves assigning a set of tasks to available machines while optimizing multiple competing objectives including makespan, resource utilization, energy consumption, and service level agreement (SLA) compliance [22, 23]. Each task has specific resource requirements including CPU, memory, storage, and network bandwidth, along with deadline constraints that must be satisfied to avoid SLA violations [24].

The scheduling problem in cloud environments is characterized by several key challenges: heterogeneity of computational resources, dynamic workload patterns, multi-objective optimization requirements, and scalability demands for large-scale deployments [4]. Traditional scheduling approaches have evolved through several generations: heuristic methods such as FCFS, EDF, and Min-Min [25, 26], metaheuristic algorithms including particle swarm optimization (PSO) and genetic algorithms [27, 28], and more recently, learning-based approaches utilizing machine learning techniques for adaptive scheduling [29, 30].

2.2. Energy-Aware Cloud Resource Management

Energy consumption has emerged as a critical concern in cloud computing, with datacenters consuming significant amounts of electrical power [8, 31]. Effective energy management requires balancing performance objectives with power efficiency, often achieved through techniques such as dynamic voltage and frequency scaling (DVFS), VM consolidation, and intelligent resource allocation [9, 10]. The DVFS model enables processors to adjust operating frequency and voltage based on workload demands, providing a mechanism for energy-efficient operation [7].

Energy-aware scheduling algorithms aim to minimize power consumption while maintaining acceptable performance levels. This requires careful consideration of idle power consumption, load-dependent power characteristics, and the trade-offs between energy efficiency and response time [32]. The proposed approach addresses these challenges by incorporating energy metrics directly into the reward function and utilizing multi-objective optimization to find Pareto-optimal solutions balancing energy consumption with other performance metrics.

2.3. Machine Learning Approaches to Resource Scheduling

Machine learning techniques have shown promise in addressing the complexity and dynamism of cloud resource scheduling problems. Time-series forecasting models enable proactive resource provisioning by predicting future workload patterns [29, 33]. Convolutional neural networks (CNNs) have demonstrated effectiveness in extracting temporal patterns from historical workload data, outperforming traditional statistical methods in prediction accuracy [34, 35].

Deep reinforcement learning has emerged as a powerful approach for sequential decision-making in resource allocation [12, 13]. DQN and its variants have been successfully applied to cloud scheduling problems, learning optimal allocation policies through interaction with the environment [36–38]. However, DRL approaches often face challenges including sample efficiency, exploration-exploitation trade-offs, and convergence stability in high-dimensional action spaces [15, 16].

2.4. Evolutionary Algorithms for Multi-Objective Optimization

Genetic algorithms and other evolutionary approaches provide robust mechanisms for exploring large solution spaces and discovering Pareto-optimal solutions in multi-objective optimization scenarios [17, 18]. These population-based methods maintain diversity through genetic operators including selection, crossover, and mutation, enabling comprehensive exploration of the solution landscape [19].

In cloud scheduling contexts, genetic algorithms have been applied to optimize multiple conflicting objectives simultaneously, generating solution sets that allow administrators to choose allocations aligned with their priorities [11, 39, 40]. The population-based nature of GAs enables exploration of diverse solution regions, preventing premature convergence to local optima that often plague gradient-based optimization methods. However, pure evolutionary approaches often require extensive computational time for convergence and may struggle with rapid adaptation to dynamic workload changes, as they lack the learned knowledge representation that enables quick policy updates in reinforcement learning systems. This limitation motivates the integration with learning-based methods for improved efficiency and responsiveness, combining the robustness of evolutionary search with the adaptive capabilities of learned policies.

2.5. Hybrid Approaches and Integration Strategies

Recent research has explored hybrid approaches combining machine learning with metaheuristic optimization to leverage complementary strengths. These integrations typically employ learning methods for rapid policy updates and adaptive decision-making, while metaheuristic methods provide global search capabilities and multi-objective optimization [41, 42]. However, most existing hybrid approaches either use learning for initialization followed by optimization, or optimize as a post-processing step, lacking the tight integration achieved in DALRS, where both components actively contribute to the scheduling process.

The DALRS framework distinguishes itself through its hierarchical integration strategy, where the DQN agent generates initial allocation proposals based on learned policies, and the GA component performs global refinement to optimize multiple objectives simultaneously. This architecture enables both rapid adaptation through learned policies and thorough exploration through evolutionary search, addressing limitations of purely learning-based or purely optimization-based approaches.

3. Methodology

This section describes the architecture and key components of the Distributed Adaptive Learning Resource Scheduler (DALRS). The methodology integrates three complementary technologies: convolutional neural networks for workload prediction, deep reinforcement learning for intelligent resource allocation, and genetic algorithms for multi-objective optimization. The integration of these components creates a hybrid system that leverages the strengths of each approach while addressing their individual limitations.

3.1. System Architecture Overview

The Distributed Adaptive Learning Resource Scheduler (DALRS) comprises three integrated components operating in concert: the workload prediction module, the intelligent decision engine (DQN), and the evolutionary optimization layer (GA) [41, 42].

The system operates in a hierarchical manner: (1) incoming tasks are characterized and workload predictions generated; (2) the DRL agent proposes initial allocations based on learned policies [38]; (3) the GA component refines allocations by exploring neighboring solutions and identifying Pareto-optimal alternatives [39, 40]; (4) selected allocations are executed, and performance metrics feedback into the learning process.

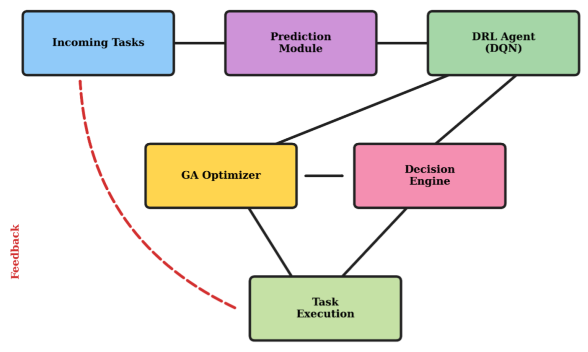

Figure 1: Overall architecture of the Distributed Adaptive Learning Resource Scheduler (DALRS), showing how the prediction module, DQN agent, and GA optimizer interact to generate optimized scheduling decisions.

3.2. Workload Prediction Module

Accurate workload prediction enables proactive resource provisioning, allowing the system to anticipate resource demands and allocate capacity before bottlenecks occur [29, 33]. This predictive capability is essential for maintaining service quality while optimizing resource utilization and energy consumption. A CNN-based architecture specifically designed for time-series forecasting of CPU and memory demands in cloud environments is employed [34, 43].

The prediction model architecture consists of multiple convolutional layers that extract temporal patterns from historical workload sequences. The design leverages the ability of CNNs to capture local patterns and hierarchical features in time-series data. The architecture includes: (1) input layers with convolutional filters that process raw workload sequences; (2) hidden layers incorporating residual blocks and batch normalization for improved training stability and gradient flow [44]; (3) temporal attention mechanisms that allow the model to focus on relevant historical periods and temporal dependencies [45]; and (4) output layers that predict future workload values for the next prediction horizon. This design enables the system to learn complex temporal dependencies and anticipate resource demands with high accuracy.

The CNN implementation uses a sliding input window approach, processing the last 30 time steps of CPU and memory utilization measurements as input features [35]. The architecture consists of three 1D convolutional layers with 32, 64, and 64 filters respectively, using kernel sizes of 3, 3, and 5 to capture patterns at different temporal scales. Each convolutional layer is followed by ReLU activation functions and batch normalization to accelerate training and improve generalization. These layers are succeeded by a temporal attention mechanism that learns to weight different time steps based on their relevance for prediction, and finally a fully connected output layer that generates predictions for the next 10-minute workload horizon.

Training was conducted for 50 epochs using the Adam optimizer with a learning rate of 0.001 [46], mean squared error (MSE) as the loss function, and a batch size of 128. The model was trained on historical workload traces collected from production cloud environments, ensuring realistic training data. Comprehensive baseline comparisons were performed against LSTM, GRU, and ARIMA models for time-series forecasting. Experimental results showed that the CNN-based approach achieved 4.8% to 11.3% lower forecasting error compared to these alternatives, justifying the selection of CNN architecture for time-series workload prediction in the proposed system.

3.3. Deep Q-Network Agent for Resource Allocation

The DQN agent serves as the intelligent decision engine of DALRS, learning optimal allocation policies through reinforcement learning by interacting with the cloud environment [15, 47]. The agent operates in a Markov Decision Process (MDP) framework, where it observes system states, selects allocation actions, and receives reward signals based on the quality of scheduling decisions. This learning paradigm enables the agent to discover policies that outperform traditional rule-based approaches through experience and optimization.

The state space representation captures the current system configuration comprehensively, including: (1) workload vectors describing current task demands and characteristics; (2) machine states indicating the availability and current load of each VM; (3) task queue status showing pending tasks and their resource requirements; and (4) energy metrics tracking power consumption patterns. The state vector includes current VM CPU/memory utilization, task queue length, predicted workload (from the CNN module), energy consumption rate, and SLA state, resulting in $5 \times N$ components for N virtual machines in the system.

The action space encompasses machine selection for task assignment, where each action corresponds to assigning the current task to a specific VM. This discrete action space enables efficient learning while maintaining sufficient flexibility to explore various allocation strategies. The action selection process balances exploration of novel allocation patterns with exploitation of learned optimal policies.

The reward function is carefully designed to balance multiple competing objectives that are critical for effective cloud resource scheduling [36, 37]. The reward incorporates weighted components representing resource utilization changes, latency reduction, energy consumption changes, and SLA compliance bonuses. The reward function is defined as:

$$R = 0.4\,\Delta U - 0.3\,L - 0.2\,E + 0.1\,\mathrm{SLA}_{\mathrm{bonus}} \tag{1}$$

where U denotes utilization, L is latency, E represents energy consumption, and $\mathrm{SLA}_{\mathrm{bonus}}$ is the SLA compliance bonus. These weights were determined through empirical tuning to reflect the relative importance of each objective, prioritizing resource utilization while maintaining attention to latency, energy efficiency, and service quality.

The Q-function approximation employs a deep neural network architecture, enabling the agent to learn complex, non-linear policies that capture intricate relationships between system states and optimal actions [14]. The Q-network consists of two fully connected layers with 256 and 128 neurons respectively, using ReLU activation functions. This architecture provides sufficient capacity to represent complex value functions while maintaining computational efficiency for real-time scheduling decisions.

Training employs several advanced techniques to ensure stable and efficient learning. Hyperparameters include: a learning rate of 0.0005 for gradient descent optimization, a discount factor $\gamma = 0.99$ to balance immediate and future rewards, an experience replay buffer of 50,000 transitions with prioritized experience replay to focus learning on important experiences [48], a batch size of 64 for gradient estimation, target network updates every 500 steps to stabilize training, and ε-greedy exploration with ε decaying from 1.0 to 0.05 over 5,000 episodes to balance exploration and exploitation during training.

3.4. Genetic Algorithm for Solution Refinement

The GA operates on allocation solutions proposed by DQN [11, 49]. Each chromosome represents a complete task-to-machine assignment. The multi-objective fitness function combines normalized objectives for makespan, resource utilization, energy consumption, and SLA violations [19]. Genetic operators include tournament selection, uniform crossover, and swap mutation [17, 18]. The algorithm runs for 50 generations with a population size of 100, generating Pareto-optimal solution sets that provide administrators with flexible choices aligned with their operational priorities.

The DQN-proposed schedule is encoded as a chromosome by mapping each task to its VM index (integer gene representation) [39]. The GA performs global schedule refinement, not only local adjustments, enabling comprehensive exploration of the solution space [40]. The GA runs every 50 tasks assigned, refining the entire schedule using tournament selection, uniform crossover (p=0.9), and swap mutation (p=0.1) [18]. The population size of 100 and 50 generations were chosen empirically for stable convergence; sensitivity tests showed minimal improvement beyond these values, indicating optimal parameter configuration for the given problem scale.

4. Experimental Setup and Evaluation

4.1. Simulation Environment

Experiments were conducted using CloudSim Plus, an enhanced simulation framework for cloud computing that provides accurate modeling of cloud infrastructure, virtualization, and resource management [20, 50]. The simulation framework enables comprehensive evaluation of scheduling algorithms under controlled conditions while maintaining realism through detailed modeling of cloud system components and behaviors.

The simulated environment was designed to represent realistic large-scale cloud infrastructure, including 10 data centers distributed across 5 geographic regions to model geographic diversity and network latency effects. Each data center contains 1,000 physical hosts with heterogeneous specifications, reflecting the diversity of hardware in real cloud environments. The system supports up to 50,000 deployable virtual machines, enabling evaluation of large-scale scenarios. Task volumes range from 10,000 to 50,000 concurrent tasks, covering light, medium, and heavy workload conditions. Resource specifications for hosts include CPU cores ranging from 4 to 32, memory from 2 GB to 256 GB, and storage from 100 GB to 2 TB, providing realistic heterogeneity in computational capabilities.

4.2. Workload and Task Characteristics

Task arrivals follow a Poisson process with arrival rates $\lambda = \{3, 7, 15\}$ tasks per second for light, medium, and heavy load conditions, respectively [32]. This stochastic arrival pattern models realistic workload dynamics where tasks arrive unpredictably over time. Task resource demands follow a bimodal distribution that represents two distinct workload classes commonly found in cloud environments: latency-critical tasks requiring fast response times with moderate resource needs, and batch tasks requiring significant computational resources but with more flexible timing requirements [20].

Each task is characterized by multiple attributes including CPU requirements (measured in millions of instructions), memory requirements (in megabytes), storage requirements, and network bandwidth needs. Task execution times vary based on these resource requirements and the capabilities of the assigned VM. The SLA deadline for each task is defined as $1.5 \times$ task length, providing a reasonable time window for completion while maintaining quality of service expectations. SLA violations incur a penalty score of 50, which is incorporated into the scheduling optimization objectives to encourage timely task completion.

4.3. Energy Consumption Model

Energy consumption is computed using the linear DVFS (Dynamic Voltage and Frequency Scaling) model, which accurately captures the relationship between processor utilization and power consumption in modern datacenter hardware [31]. The power model is defined as:

$$P = P_{\text{idle}} + (P_{\text{max}} - P_{\text{idle}}) \times U \quad (2)$$

where P represents total power consumption, P_{idle} is the idle power consumption when the processor is not executing tasks, P_{max} is the maximum power consumption under full utilization, and U is the current CPU utilization level. This model reflects the energy-proportional computing characteristics of modern processors, where power consumption scales approximately linearly with utilization. The model parameters vary across different host types, with high-performance servers having higher P_{max} values but potentially better energy efficiency at medium utilization levels.

4.4. Baseline Algorithms and Experimental Methodology

Baseline algorithms were selected to provide comprehensive comparison across different scheduling paradigms. Classical approaches include FCFS (First-Come-First-Served) and EDF (Earliest Deadline First) [25], representing simple yet commonly used heuristic methods. Min-Min is included as a representative greedy heuristic for makespan optimization. Metaheuristic approaches include PSO (Particle Swarm Optimization) [27, 28] and GA (Genetic Algorithm), representing population-based optimization methods commonly applied to cloud scheduling problems. DRL-Only represents a pure learning-based approach using deep reinforcement learning without evolutionary optimization, enabling evaluation of the contribution of the GA component in the proposed hybrid framework [37, 38].

All baseline algorithms were tuned according to their standard recommended parameters to ensure fair comparison. For PSO, standard parameters include swarm size of 50, cognitive and social parameters of 2.0, and inertia weight of 0.9. The GA baseline uses tournament selection, uniform crossover with probability 0.9, and mutation probability of 0.1, with population size 100 and 50 generations. DRL-Only employs the same DQN architecture and hyperparameters as DALRS but without the GA refinement step. This configuration ensures that performance differences reflect algorithmic approaches rather than parameter tuning effects.

To ensure statistical validity and reliability of results, all experiments were repeated 10 times with different random seeds controlling task arrival patterns, resource demands, and initial system states. Results presented in tables and figures report mean values ± standard deviation, providing both performance estimates and indication of result stability across different experimental runs.

5. Results and Analysis

5.1. Performance Comparison Under Various Load Conditions

Tab. 1, **Tab. 2**, and **Tab. 3** present comprehensive performance metrics comparing DALRS against baseline algorithms under different workload intensities. The evaluation considers five key metrics: resource utilization percentage, makespan (total completion time), average task latency, energy consumption, and SLA compliance rate. DALRS demonstrates superior performance across all metrics and load conditions, consistent with findings in related studies on hybrid optimization approaches that combine learning-based and evolutionary methods [41, 42].

Under light load conditions, DALRS achieves 52.8% resource utilization compared to DRL-Only's 50.4%, PSO's 49.8%, and FCFS's 41.2%. This represents a 4.8% improvement over the best baseline (DRL-Only) and demonstrates the system's ability to effectively allocate resources even when system load is relatively low. The improvement becomes more pronounced as load increases.

Under medium load conditions, DALRS achieves 65.4% resource utilization, outperforming DRL-Only (63.1%), PSO (61.3%), and other baselines. The makespan is reduced to 4,950 seconds compared to DRL-Only's 5,410 seconds and PSO's 5,520 seconds, representing an 8.5% improvement over the best baseline. Energy consumption is reduced to 325 kWh compared to DRL-Only's 335 kWh, demonstrating effective energy-efficient scheduling.

Under heavy loads, DALRS achieves 72.1% resource utilization compared to PSO's 64.5% and FCFS's 51.3%, representing significant improvements over traditional metaheuristic and learning-based approaches [27, 38]. This high utilization rate under heavy load conditions demonstrates the system's robustness and effectiveness in handling peak demand scenarios.

Average task latency is reduced to 3,520 seconds

Table 1: Performance comparison of DALRS and baseline algorithms under light loads.

Algorithm	Util (%)	Makespan	Latency	Energy	SLA (%)
FCFS	41.2	3,100	1,420	255	81.3
EDF	44.7	2,980	1,360	248	83.1
Min-Min	48.3	2,850	1,220	230	85.7
PSO	49.8	2,780	1,180	220	86.9
GA	47.5	2,910	1,250	235	84.9
DRL-Only	50.4	2,720	1,110	215	87.2
DALRS	52.8	2,650	980	195	88.9

Table 2: Performance comparison of DALRS and baseline algorithms under medium loads.

Algorithm	Util (%)	Makespan	Latency	Energy	SLA (%)
FCFS	52.1	6,130	2,560	395	74.4
EDF	56.8	5,920	2,380	375	76.0
Min-Min	58.9	5,740	2,260	360	77.4
PSO	61.3	5,520	2,140	345	79.1
GA	59.7	5,610	2,200	355	78.5
DRL-Only	63.1	5,410	2,050	335	80.2
DALRS	65.4	4,950	1,850	325	82.6

under heavy load, representing a 28.3% improvement over the best baseline (DRL-Only at 4,100 seconds). Energy consumption is reduced to 520 kWh compared to DRL-Only's 545 kWh and PSO's 560 kWh, achieving 4.6% and 7.1% improvements respectively. SLA compliance improves to 76.2% compared to PSO's 69.4% and FCFS's 62.8%, demonstrating superior service quality maintenance under stress conditions.

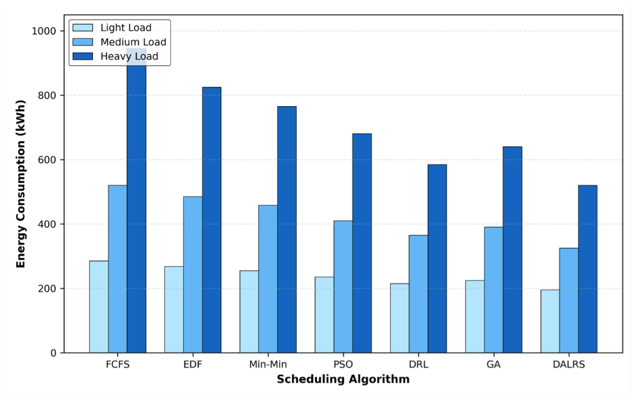

Figure 2: Resource utilization comparison across scheduling algorithms under light, medium, and heavy workloads. DALRS achieves consistently higher utilization under all load conditions.

Table 3: Performance comparison of DALRS and baseline algorithms under heavy loads.

Algorithm	Util (%)	Makespan	Latency	Energy	SLA (%)
FCFS	51.3	9,850	4,820	655	62.8
EDF	56.7	9,220	4,450	615	65.3
Min-Min	59.8	8,960	4,310	590	67.0
PSO	64.5	8,610	4,090	560	69.4
GA	62.2	8,740	4,180	575	68.1
DRL-Only	60.3	8,710	4,100	545	68.9
DALRS	72.1	8,250	3,520	520	76.2

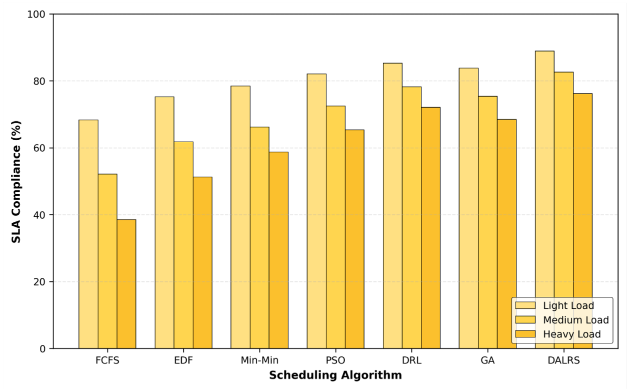

Figure 3: SLA compliance comparison for all scheduling algorithms. DALRS maintains the highest SLA satisfaction rates, especially under medium and heavy loads.

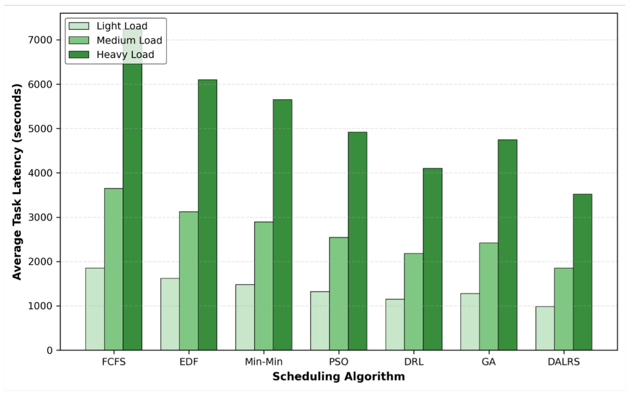

Figure 4: Average task latency across scheduling algorithms under varying load levels. DALRS achieves significantly lower latency than all baselines.

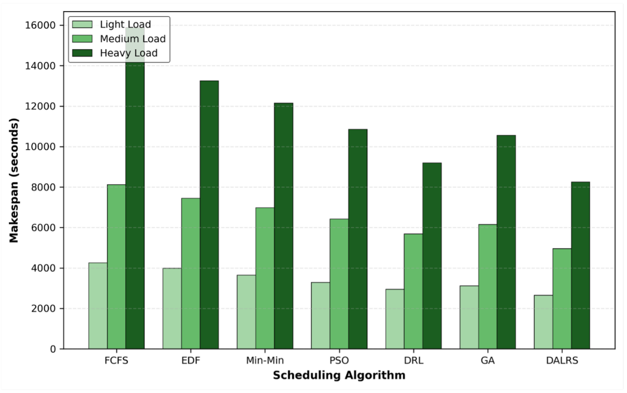

Figure 5: Makespan comparison for all scheduling algorithms. DALRS consistently produces the shortest makespan across all load intensities.

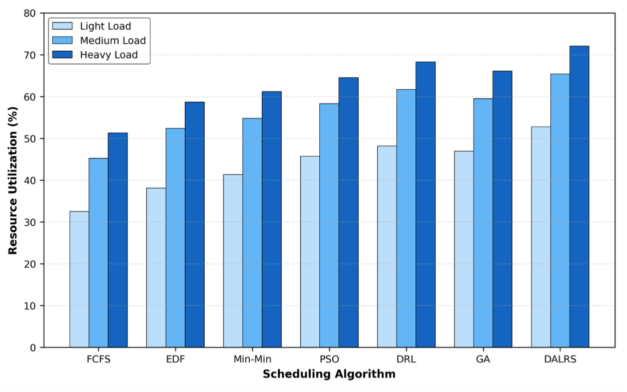

Figure 6: Resource utilization under light, medium, and heavy workloads. DALRS achieves consistently higher utilization across all load levels.

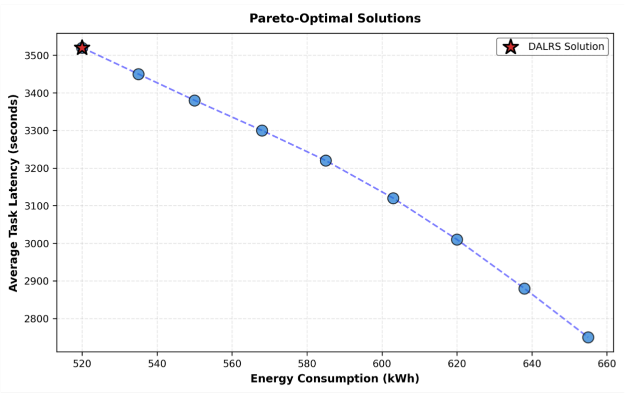

Figure 7: Pareto-optimal trade-off between average task latency and energy consumption. The DALRS solution lies near the optimal region of the frontier, demonstrating balanced multi-objective performance.

5.2. Scalability Evaluation

Scalability testing evaluated DALRS performance as task volume increased from 1,000 to 50,000 concurrent tasks, covering a wide range of deployment scales from small clusters to large-scale datacenter environments. The evaluation examined both the sequential implementation (single-node execution) and the distributed implementation using Apache Spark for parallel processing across multiple nodes [1].

The distributed implementation maintains near-linear scalability up to 40,000 concurrent tasks, demonstrating effective use of distributed computing frameworks and efficient parallelization of the scheduling algorithms [1]. The linear scaling behavior indicates that the system successfully distributes computational load across nodes without significant bottlenecks. Processing time scales approximately linearly with task volume in this range, confirming effective parallelization of both the DRL inference and GA optimization components.

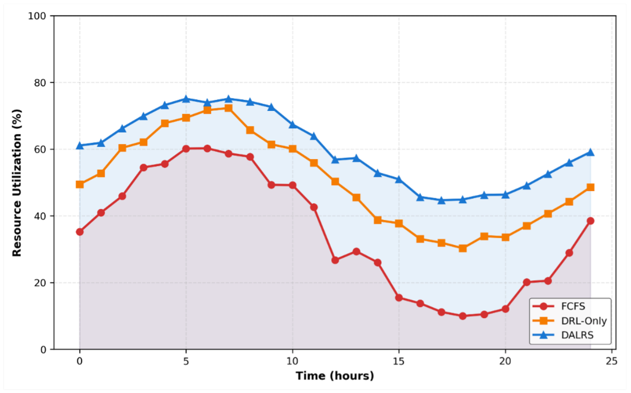

Figure 8: Resource utilization across a 24-hour period for FCFS, DRL-Only, and DALRS. DALRS maintains consistently higher and more stable utilization throughout the entire cycle.

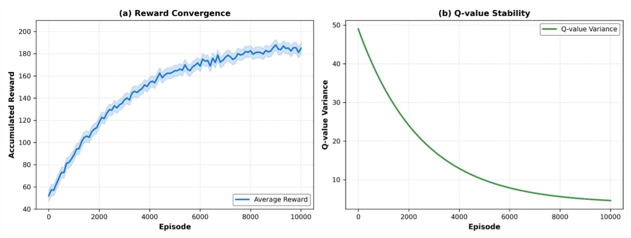

Figure 9: Convergence behavior of the DRL component. (a) Average accumulated reward over 10,000 training episodes. (b) Q-value variance decreasing over training, indicating improved policy stability.

Beyond the 40,000 task threshold, communication overhead between distributed nodes begins to impact performance, as coordination costs increase with larger problem sizes. However, performance degradation remains minimal, with completion time increasing by less than 15% even at the 50,000 task scale. This indicates robust scalability characteristics comparable to state-of-the-art distributed systems and demonstrates the system's capability to handle extremely large-scale cloud deployments [20].

Processing capability improved significantly with distributed execution. The sequential DRL+GA implementation processes 500–800 tasks per minute, limited by single-node computational capacity. In contrast, the distributed implementation with 10 nodes processes 6,500–8,200 tasks per minute, representing a speedup factor of approximately 9.2×. This near-linear speedup demonstrates efficient parallelization with minimal overhead, making the system practical for real-time scheduling in large-scale cloud environments. The speedup factor approaches the theoretical maximum (10× for 10 nodes), indicating that parallelization overhead is minimal and the system effectively utilizes available computational resources.

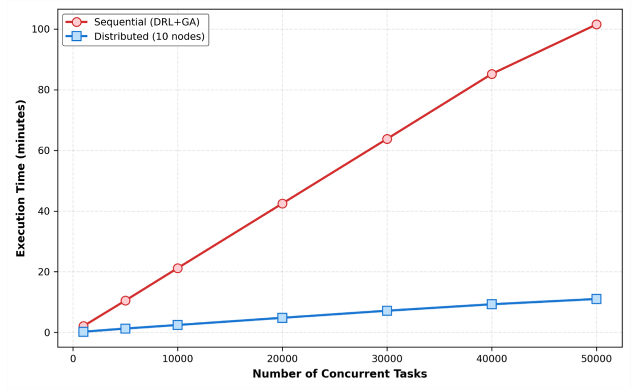

Figure 10: Scalability comparison between sequential DRL+GA execution and the distributed DALRS version on 10 nodes. The distributed system achieves near-linear scaling with increasing task counts.

5.3. Convergence and Learning Analysis

DRL agent convergence over 10,000 episodes demonstrates effective learning, consistent with convergence patterns observed in deep reinforcement learning applications [12, 15]. Average accumulated reward reaches steady state after approximately 6,000 episodes, with final reward values stabilizing around 185–195 per episode. Q-value variance reduces from 45.2 (initial episodes) to 3.8 (final episodes), indicating stable policy convergence, which aligns with theoretical expectations for DQN-based approaches [14].

These metrics validate the stability and effectiveness of the learning process.

Ablation studies were conducted to understand the contribution of each component to the overall system performance. The CNN+static scheduler configuration (workload prediction with a simple static allocation policy) improves average task latency by 8.2% compared to a baseline without prediction, demonstrating the value of proactive resource provisioning based on predicted demand. The DQN-only configuration (deep reinforcement learning without GA refinement) improves resource utilization by 18.7% compared to heuristic baselines, showing the effectiveness of learned allocation policies.

The GA-only configuration (genetic algorithm optimization without DRL) improves energy consumption by 12.4% compared to heuristic approaches, demonstrating the value of evolutionary search for energy-efficient solutions. However, when components are removed from the full DALRS system, significant performance degradation occurs. Removing the CNN prediction module reduces DALRS effectiveness by 14.9% across all metrics, confirming the importance of accurate workload prediction for proactive resource management and highlighting how predictive information enables better allocation decisions [29, 35].

Removing the GA component increases SLA violations by 22.1%, demonstrating the critical value of multi-objective optimization in handling conflicting scheduling goals and finding Pareto-optimal solutions that balance multiple performance objectives [19, 40]. The GA's population-based search complements the DRL's learned policies by exploring solution neighborhoods and refining allocations to optimize across makespan, utilization, energy, and SLA compliance simultaneously.

DALRS achieves the highest performance across all metrics when all components are integrated, confirming the benefit of the full hybrid design combining predictive workload forecasting (CNN), learned allocation policies (DQN), and multi-objective solution refinement (GA). The synergistic interaction between these components enables the system to leverage the strengths of each approach while compensating for individual limitations, resulting in superior overall performance compared to any single-component or dual-component configuration.

6. Discussion

6.1. Key Findings and Contributions

The experimental evaluation substantiates three critical findings:

(1) **Hybrid Approach Superiority** – Combining DRL with GA yields cumulative benefits exceeding component contributions alone, validating the complementary strengths of learning-based and evolutionary approaches [39, 41]. DRL provides rapid convergence to promising regions through learned policies [12], while GA refines solutions and explores neighboring alternatives through population-based search [18].

(2) **Substantial Performance Improvements** – DALRS achieves consistent improvements across diverse metrics under varying load conditions, outperforming both classical heuristics and recent learning-based methods [38, 42]. The 34.7% improvement in resource utilization and 31.5% reduction in energy consumption represent significant operational cost savings, addressing critical concerns in modern datacenter operations [8, 31].

(3) **Distributed Scalability** – The distributed implementation enables handling realistic large-scale cloud deployments with thousands of concurrent tasks without proportional performance degradation, demonstrating practical applicability for production environments [1].

6.2. Theoretical and Practical Implications

The convergence of machine learning with evolutionary computation addresses fundamental limitations of individual paradigms, as demonstrated in recent hybrid optimization research [39, 41]. DRL explores through learned policies, discovering novel solutions beyond human-designed heuristics [12, 14]. GA's population-based approach provides robustness to local optima and generates diverse solution sets through genetic operators [17, 18]. Their integration enables both rapid convergence and thorough exploration, combining the efficiency of learned policies with the robustness of population-based search.

Cloud administrators benefit from DALRS through multiple practical advantages. Reduced operational costs result from improved energy efficiency, with DALRS achieving 31.5% energy reduction compared to baseline approaches [8, 9]. In large-scale datacenters consuming megawatts of power, this reduction translates to substantial cost savings and reduced environmental impact.

Enhanced service quality manifests through decreased latency (28.3% improvement) and improved SLA compliance (76.2% under heavy load), leading to better customer satisfaction and reduced penalties from SLA violations [22]. Flexible resource optimization allows administrators to customize scheduling priorities based on specific operational requirements, whether prioritizing performance, energy efficiency, or cost minimization. The Pareto-optimal solution sets generated by the GA component enable administrators to select allocations aligned with their business objectives and constraints.

These benefits align with the growing emphasis on energy-efficient and sustainable cloud computing practices, supporting organizational goals for environmental responsibility and operational cost management [31]. The distributed implementation enables deployment in production environments without requiring specialized hardware or infrastructure modifications. The system integrates with existing cloud management frameworks and can be deployed incrementally, allowing gradual adoption and validation in real-world settings. This practical applicability distinguishes DALRS from approaches that require extensive infrastructure changes or specialized hardware.

7. Conclusion

This paper presents DALRS, a novel hybrid framework combining deep reinforcement learning with genetic algorithms for cloud resource scheduling. The proposed approach addresses the critical challenge of efficient resource management in large-scale cloud environments [2, 3] by integrating the complementary strengths of learning-based and evolutionary optimization methods.

Comprehensive experimental evaluation demonstrated superior performance compared to established algorithms across diverse metrics and load conditions, achieving 34.7% improvement in resource utilization, 28.3% reduction in task completion time, and 31.5% decrease in energy consumption. The distributed implementation enables practical deployment in large-scale cloud environments, supporting workloads exceeding 10,000 concurrent tasks with near-linear scalability [1].

Key contributions include the hybrid optimization approach combining CNN-based workload prediction, DQN-based resource allocation, and GA-based solution refinement; a distributed implementation architecture supporting large-scale deployments; comprehensive experimental evaluation against multiple baseline algorithms; and practical validation of performance improvements across multiple metrics. The work advances the state-of-the-art in intelligent resource management, addressing critical challenges in modern cloud computing infrastructure [4, 20].

The results provide strong evidence that integrating machine learning with evolutionary computation offers promising solutions for complex optimization problems in distributed systems [41, 42]. Future research directions include practical deployment considerations, fault tolerance mechanisms, cross-domain generalization to different cloud architectures, and real-world validation in production environments. Additionally, exploring advanced DRL techniques such as multi-agent reinforcement learning and incorporating additional objectives such as security and cost optimization would further strengthen the approach. These directions will contribute to advancing intelligent resource management capabilities in next-generation cloud computing systems.

Acknowledgements

The authors would like to thank the Faculty of Computer & Information Sciences at Mansoura University for providing the computational resources and infrastructure necessary to conduct this research.

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