Available online at www.qu.edu.iq/journalcm
JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS
ISSN:2521-3504(online) ISSN:2074-0204(print)

Task Scheduling in Cloud Computing: A Novel Approach Using Artificial Intelligence Algorithms

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ARTICLE INFO

Article history:
Received: 18/04/2025
Rrevised form: 17/07/2025
Accepted : 21/07/2025
Available online: 30/09/2025

Keywords:

Cloud Computing, Task Scheduling, NP-Complete, Makespan, Reinforcement Learning.

ABSTRACT

Task scheduling is an important problem that is encountered in distributed systems, project management, and cloud computing. Task dependencies used to model the so-called directed acyclic graphs (DAGs) and for the scheduling optimization have been widely used. However, such methods do not work well in dynamic environments and complex constraints. Task scheduling using DAGs is proposed in this paper, along with the application of Artificial Intelligence (AI) algorithms exploring Artificial Neural Networks (ANN), Artificial Intelligence algorithms, which include Genetic Algorithms (GA) and a specific type (Reinforcement Learning (RL)) as novelty addition to the scheduling problem. The proposed method is developed to enhance inventory efficiency, bound make span, and intend to dynamically cope with changes in resource availability and task priorities. The unusual effect that paper accounts for in that race was the application of artificial intelligence to enhance the process of scheduling. The workflowSim simulator is used to evaluate the proposed method on both synthetic and real-world workflows. Experimental results highlight the method's superior effectiveness when compared with alternative algorithms.

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https://doi.org/10.29304/jqcsm.2025.17.32377

1. Introduction

In such environments as cloud computing where resources are shared across multiple users or project management where task priorities change based on external circumstances, task scheduling becomes increasingly complex and hence the problem abounds in global nature. However, these changes make traditional algorithms inefficient and suboptimal[2]. Due to a natural facilitation of task dependency modeling, DAGs are a widely used scheduling problem formulation [3]. For instance, in the case of cloud computing, a DAG serves as a workflow to run a set of tasks in a sequential way[4]. It can be used to identify the critical tasks and give them the right resources based on the analysis of the DAG[5]. List scheduling and directed critical path analysis are known good static scheduling algorithms but struggle in more dynamic environments[6]. For instance, suppose a resource is no longer available or a task takes longer than anticipated, then these algorithms may not real time adjust the schedule [7]. However, the limitations can be overcome by AI techniques in the form of RL and GA[8]. GA provides a global optimization framework for driving an optimization of a wide range of possible schedules, and RL permits the system to learn from experience and adapt to changing conditions. Thus, it is possible to obtain an adaptive and optimized scheduling system by combining these techniques [10]. And this paper introduces a novel approach to DAG based task scheduling which is then optimized using AI algorithms[11]. Adaptive decision-making through RL and global optimization by GA are combined to achieve a robust solution to complex scheduling problems[12].

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Experimental results show that this approach is effective with substantial improvement over the traditional methods regarding makespan and resource utilization [13]. For instance, in cloud computing, cloudest resources such as CPUs, memory and storage are to be shared by multiple users, and resolving such complex resource allocation problems is necessary[14]. In project management, task priorities and dependencies themselves change according to expounded external factors like shifting deadlines or resource unavailability, and the traditional scheduling algorithms like the First Crow First Served (FCFS), Round Robin and heuristic based methods work to tackle these challenges. They are effective in static environment where the requirements of the task and availability of the resources are kept constant[2]. As a global optimization and an adaptive decision making strategy, in the proposed method, RL is utilized for adaptive decision making and GA is used for global optimization to resolve complex scheduling problems. Experimental results also show the effectiveness of the approach in terms of makespan and resource utilization that is far better than traditional methods.

2. Background and Related Work

Task scheduling is a fundamental problem in computing systems, especially in the distributed and the cloud environment where resources are shared between different users and applications. Under task scheduling, this section gives away details of traditional task scheduling methods, and DAG based scheduling, as well as how Artificial Intelligence (AI) plays a crucial role in assuage the short-falls of traditional approaches. It also identifies gaps in the existing literature that motivate the proposed hybrid AI-driven approach.Traditional task scheduling algorithms have been widely studied and applied in various computing environments. These algorithms can be broadly categorized into:

Static Scheduling Algorithms like List Scheduling and Critical Path Method (CPM) assign tasks to resources based on predefined priorities and dependencies. While effective in static environments, they struggle to adapt to dynamic changes in resource availability or task priorities [12].Dynamic Scheduling Algorithms such as Round Robin and Earliest Deadline First (EDF) adjust task assignments in real-time. However, they often lack the ability to handle complex dependencies and optimization objectives.Heuristic-Based Methods heuristics like Min-Min, Max-Min, and Genetic Algorithms (GA) are used to find near-optimal solutions, The jobs' timing details are unknown at runtime under dynamic scheduling. Therefore, the task's execution schedule may alter based on user request. Compared to static scheduling, dynamic scheduling has runtime overhead. The cloud provider is unable to plan ahead of time when using dynamic scheduling. It distributes and withdraws resources as required[15].

In recent years, various DAG scheduling techniques and system models have been suggested. Virtualized, scalable cloud computing resource management and charging mode were used to build the majority of standard system models and scheduling techniques. Typically, the goal of scheduling is to maximize the usage of cloud computing resources or reduce the cost of user workflow implementation[16]. Short jobs will be carried out in parallel using the Min-Min algorithm, while lengthy jobs will come after the short ones. This algorithm's drawback is that short work are scheduled first, then longer jobs are planned and completed when the machines have more time. Min-min might result in an imbalanced load and an extended execution time for the entire batch process. Even lengthy tasks cannot be completed. The three restrictions (quality of service, dynamic priority model, and cost of service) that are added to the enhanced algorithm in comparison to the conventional Min-min algorithm can alter this condition[17].

The cloud workflow scheduling issue is resolved by the fuzzy dom-inance sort based heterogeneous earliest-finish-time (FDHEFT) algorithm. Like MOHEFT, FDHEFT is an enhanced variant of HEFT that is separated into two main stages: the instance selection phase and the task prioritization phase. In the task prioritizing step, the scheduling priorities of all tasks in the workflow are given and then in the instance selection phase, the optimum instance for each job in the scheduling list is selected[18]. described a new but promising search and optimization algorithm that was first conceived by John Holland approximately thirty years ago. A genetic algorithm (GA) differs from other traditional search and optimization methods in several ways (Goldberg, 1989): it is a stochastic search and optimization procedure; it is an abstraction of natural genetics and natural selection processes, it works with a set of solutions rather than one solution in each iteration; it works on a coding of solutions rather than solutions themselves; and it is highly parallelizable. The main reasons GAs are becoming more and more popular are their broad applicability, global perspective, and inherent parallelism[9].

In a cloud computing environment, scientific process tasks are scheduled using an intelligent DQ-HEFT algorithm. Three stages make up the algorithm's execution: the first involves updating the Q-table value using the HEFT algorithm's rank value as an instantaneous reward in Q-learning. Sorting the initial jobs based on the converged Q-table yields the best order in the second phase. The EFT allocation approach assigns the optimal processor to the job

in the final step, where makespan serves as the goal function. During this stage, the DQ-learning algorithm's experience replay is crucial for scheduling various scientific process applications. All other comparison algorithms are outperformed by the DQ-HEFT. Moreover, the DQ-HEFT method yields the greatest speedup value[19]. Combining genetic algorithms (GAs) and reinforcement learning (RL) offers a potent AI-driven method for resource allocation optimization. The qualities of both approaches are used in this hybrid approach to handle the dynamic and intricate nature of resource management issues. Real-time decision-making and ongoing strategy development are made possible by reinforcement learning's capacity to adapt to shifting circumstances. Contrarily, genetic algorithms offer reliable solution space search, successfully locating near-optimal solutions even in extremely limited and non-linear situations[20]. offer a cloud computing platform workflow scheduling solution for numerous DAGs that is based on reinforcement learning. Create a new task scheduling method that uses reinforcement learning to maximize the deadline given the available cloud computing resources by theoretically analyzing the job execution process in a cloud computing environment in light of the system model. We do comprehensive simulations to assess the task scheduling optimization strategies. Guided by the empirical observation, we find that the job scheduling scheme can optimally utilize cloud resources and load balancing to obtain the minimal makespan with resource constraint[16]. For workflows installed and hosted on IaaS clouds, our goal was to simultaneously reduce cost and time. We proposed a novel list scheduling technique, FDHEFT, that combines the heuristic HEFT with the fuzzy dominance sort mechanism for a workflow with precedence restrictions across jobs. To confirm the efficacy of the suggested FDHEFT, two sets of simulation tests were conducted on synthetic applications and real-world processes[18]. In an effort to identify the best solution for the scheduling problem, the various advantages of Q-learning are leveraged by incorporating both historical and anticipated data. The main contribution lies in providing an optimal task scheduling solution tailored for scientific workflows through the development of a novel scheduling method that integrates deep Q-learning with HEFT techniques, enhancing decision-making and resource allocation efficiency[19].For single-user workloads, we have a modified evolutionary algorithm where the fitness is designed to promote the creation of solutions to minimize the time and compared with current heuristics. According to experimental data, the algorithm performs well even under high loads[21].

3. Considering the energy consumption brought on by various data center cooling techniques, we investigate the use of reinforcement learning for real-time job scheduling on a federated cloud. We leverage the various CSP data center locations and energy sources in the federated cloud to optimize the energy consumption and carbon emission in order to lower the data centers' energy consumption and carbon emissions. In order to replicate the randomness of task arrival in a realistic setting, we also introduce Watermark[22].

4. Load balancing and resource optimization via cloud data center is a viable mix of Reinforcement Learning (RL) and Genetic Algorithms (GA) into a hybrid optimization platform for successful and scalable cloud resource management by achieving the global optimization and successful real time adaptability, which is not possible with either choice individually [23]. This study investigates how hybrid AI techniques might improve work scheduling in cloud computing,By combining several AI strategies to balance efficiency and adaptability . When compared to traditional algorithms, the method exhibits significant promise for enhancing makespan, load balancing, and resource utilization. Better management of intricate, dynamic workloads is made possible by integrating several AI strategies. However, over-reliance on AI models may result in higher training complexity and computational overhead, and real-time responsiveness and scalability issues in large-scale cloud systems may arise during actual deployment[24]. This provides a thorough overview of the various approaches and their efficacy by methodically reviewing the load balancing and work scheduling strategies currently used in cloud computing. Strengths like better resource use and shorter execution times for numerous algorithms are highlighted by the study. However, there are drawbacks, such as a lack of consistent assessment criteria and a lack of attention to dynamic, expansive cloud settings. Furthermore, there is room for improvement in future research because many of the examined approaches have trouble adjusting to real-time workload variations and varied resource conditions[25].

3.Proposed Methodology

This part describes the proposed DAG for task scheduling in Directed Acyclic Graph (DAG) and Artificial Intelligence (AI) algorithms. To overcome the inherent disadvantages of conventional scheduling techniques, the present approach uses Reimforcement Learning assigned with Genetic Algorithms to produce a hybrid framework. It provides a methodology to optimize task scheduling in dynamic environments constrained by both different or the same set of constraints as well as different or the same set of objectives.

3.1 Overview of the Hybrid Framework

It then integrates two AI techniques, namely, unsupervised text processing and object detection.

1. Reinforcement Learning (RL): Enables real-time adaptation to dynamic changes in the environment.

2. Genetic Algorithms (GA): Enables the exploration of the solution space in an effective way to discover the global optimization.

The hybrid approach leverages the strengths of both techniques:

- RL adapts to real-time changes in resource availability and task priorities.
- GA explores the solution space to avoid local optima and improve overall scheduling efficiency.

3.2 Reinforcement Learning Component

The RL part is tasked with the task of learning optimal scheduling policies over interaction with the environment. RL framework includes the following major elements.

1. The current state of the system described in terms of the tasks are assigned and how they are progressing; Resource availability and utilization; DAG structure and dependencies.

Example: A state could be represented as a vector of task-resource assignments and resource loads.

2. Action Space: Defines the possible actions the RL agent can take, such as: Assigning a task to a specific resource. Reallocating resources dynamically. Adjusting task priorities based on deadlines or dependencies.

Example: An action could be assigning Task A to Resource 1.

3. Reward Function: Provides feedback to the RL agent based on the quality of scheduling decisions. Rewards are designed to align with optimization objectives, such as: Minimizing makespan (total completion time).Maximizing resource utilization.Reducing energy consumption.

Example: A reward could be proportional to the reduction in makespan.

4. Training Process: The RL agent interacts with the environment, taking actions and receiving rewards. A policy network (using Q-learning or Deep Q-learning) is trained to maximize cumulative rewards.

Exploration strategies (epsilon-greedy) are used to balance exploration and exploitation.

3.3 Genetic Algorithm Component

The GA component is used to explore the solution space and evolve high-quality schedules over generations. Key steps in the GA framework include:

1. Chromosome Encoding: Each chromosome represents a potential schedule, encoded as a sequence of task-resource assignments.

Example: A chromosome could be a list of tuples, where each tuple specifies a task and its assigned resource.

2. Initial Population: A population of chromosomes is initialized randomly or using heuristic-based methods.

Example: Generate 100 random schedules as the initial population.

3. Fitness Function: Evaluates the quality of each chromosome based on optimization objectives. Example: Fitness could be inversely proportional to makespan or directly proportional to resource utilization.

4. Genetic Operators: Crossover: Combines two parent chromosomes to produce offspring, preserving good traits. Example: Use a two-point crossover to exchange task assignments between parents. Mutation: Introduces random changes to chromosomes to maintain diversity example: Randomly reassign a task to a different resource. Selection: Selects the best performing chromosomes for the next generation example: Use tournament selection to choose chromosomes with the highest fitness.

5. Evolution Process:The population evolves over multiple generations, improving the quality of schedules example: Run the GA for 50 generations, updating the population at each step.

3.4 Hybrid Optimization Strategy

The hybrid framework combines RL and GA to achieve both adaptability and global optimization:

1. RL-Guided Search: The RL agent provides real-time guidance to the GA, focusing the search on promising regions of the solution space example: Use RL to prioritize tasks with tight deadlines or high resource demands.

2. GA-Enhanced Exploration: The GA explores the solution space globally, avoiding local optima and improving overall scheduling efficiency example: Use GA to generate diverse schedules and evaluate their fitness.

3. Integration Mechanism: The RL agent and GA interact iteratively, with RL providing feedback to GA and GA generating new solutions for RL to evaluate example: After each RL episode.

Algorithm: Hybrid AI-Driven Task Scheduling Using DAGs

Inputs:

DAG: G=(V,E), where:

V={v1,v2,…,vn} is the set of tasks.

E={(v_i,v_j)| v_i,v_j ∈V} is the set of dependencies between tasks.

Resources: R={r1,r2,…,rm}, where each resource r_k has a capacity c_k and speed s_k.
RL Parameters:
Learning rate: α.
Discount factor: γ.
Exploration rate: ϵ.
GA Parameters:
Population size: P.
Crossover rate: pc.
Mutation rate: pm.
Number of generations: G.
Optimization Objectives: Minimize makespan T, maximize resource utilization U, etc.

Outputs:

Schedule = S\(kVi , r)} ∋ V_i ∋ V_k, r{R: mapping of tasks to resources.
Performance Metrics: Makespan T, resource utilization U, energy consumption E, etc.

Steps:

Step 1: Initialize

1. Initialize RL Agent:
    - Policy network: πθ, where θ represents the parameters.
    - State space: S, action space: A, reward function: R.
2. Initialize GA Population:
    - Population: P={C_1,C_2,…,C_P}, where each chromosome C_i represents a schedule.
    - Chromosome encoding: Ci={(V_k, r)|vj∈V_k ,r∈R}.
3. Initialize Environment:
    - Simulate the environment with G, R, and dynamic constraints.

Step 2: Reinforcement Learning (RL) Phase

1. For each episode t=1,2,…,$T_{episodes}$:
    - Reset the environment: s_0←initial states.
    - Initialize RL state: s←s0.
2. For each time step τ=1,2,…,Tsteps:
    - Observe the current state: s∈S.
    - Select an action:
        - With probability ϵ, choose a random action a∈A.
        - Otherwise, choose a=arg⁡max$_a$′Q(s,a′;θ).
    - Execute the action:
        - Assign task v_j to resource r_k: S←S∪{(v_j,r_k)}.
        - Update the environment state: s′←next.
    - Compute the reward:
        - r=R(s,a,s′).
    - Update the RL agent:
        - Update Q-values: Q(s,a)←Q(s,a)+α[r+γmax⁡a′Q(s′,a′)−Q(s,a)].
        - Update policy parameters: θ←θ−α∇θL(θ).
    - Check for termination:
        - If all tasks are completed or τ=Tsteps, terminate the episode.

Step 3: Genetic Algorithm (GA) Phase

1. Evaluate Fitness:

- For each chromosome Ci∈P, compute fitness f(Ci)based on optimization objectives (f(Ci)=1T(Ci).

2. Perform Selection:
   - Select chromosomes Pselected⊆P using a selection method (tournament selection).
3. Perform Crossover:
   - For each pair of parents (Ci,Cj)∈Pselected, generate offspring CoffspringCoffspring using crossover with probability pc.
4. Perform Mutation:
   - For each offspring Coffspring, apply mutation with probability pm.
5. Update Population:
   - Replace P with the new offspring and mutated chromosomes.
6. Repeat for Generations:
   - Repeat Steps 3.1 to 3.5 for G generations or until convergence.

Step 4: Hybrid Optimization

1. Integrate RL and GA:
   - Use RL to guide GA search by providing real time feedback on promising regions of the solution space.
   - Use GA to explore the global solution space and generate diverse schedules for RL to evaluate.
2. Iterative Refinement:
   - Alternate between RL and GA phases iteratively to refine the schedule.

Step 5: Output the Final Schedule

1. Select the Best Schedule:
   - S=arg⁡max⁡Ci∈Pf(Ci)S=arg maxCi∈Pf(Ci).
2. Return Performance Metrics:
   - Compute makespan T(S), resource utilization U(S), and energy consumption E(S)

Representation:

1. RL Update Rule:

   $$Q(s,a)\leftarrow Q(s,a)+\alpha[r+\gamma \max_{a'} Q(s',a')-Q(s,a)]$$

2. Fitness Function:

   $$f(Ci)=1T(Ci)$$

   where T(Ci)is the makespan of schedule Ci.
3. Crossover and Mutation

   - Crossover: Coffspring=Crossover(Ci,Cj)
   - Mutation: Coffspring=Mutate(Coffspring)

Below is a graphical representation of the proposed hybrid AI-driven approach for task scheduling using Directed Acyclic Graphs (DAGs). The graph illustrates the workflow and interaction between the Reinforcement Learning (RL) and Genetic Algorithm (GA) components. an example of a results chart that can be used to present the performance metrics of the proposed hybrid AI-driven approach for task scheduling using Directed Acyclic Graphs (DAGs). The results of the chart are compared against the baselines (FCFS, Round Robin, GA, RL, Deep Q-learning) for key metrics like Makes pan, Resource Utilization, and Energy Consumption.

4.Implementation and Experimental

We implement the hybrid AI driven DAG based approach for task scheduling and evaluate it using this setup. This section describes the details of the implementation and experimental setup used to evaluate as proposed approach for task scheduling using DAGs. Finally, the experiments attempt to validate the approach efficacy in dynamic environments and compare the performance of the approach with some standard scheduling algorithms.

4.1 System Architecture

The implementation of the proposed framework is a modular system with the following components.

1. DAG Generator: Generates synthetic DAGs with varying structures, task sizes, and dependencies. The other parameters are the number of tasks, their execution times, and edge weights (communication costs).
2. Resource Simulator: Simulates a heterogeneous computing environment with multiple resources (CPUs, GPUs, virtual machines). Parameters include resource capacities, speeds, and availability.
3. Reinforcement Learning Module: Implements the RL agent using a policy network (Deep Q-Network). Includes state representation, action selection, and reward computation.
4. Genetic Algorithm Module:Implements the GA with chromosome encoding, fitness evaluation, and genetic operators (crossover, mutation, selection).
5. Scheduler:Integrates the RL and GA modules to generate and optimize task schedules. Outputs the final schedule and performance metrics.

4.2 Datasets and Workloads

The experiments use both synthetic and real-world workloads to evaluate the proposed approach:

1. Synthetic Workloads: Generated using the DAG Generator with varying parameters: Number of tasks: 50 to 500. Task execution times: Randomly sampled from a uniform distribution.Communication costs: Proportional to task dependencies examples: Random DAGs, layered DAGs, and task graphs with specific structures.
2. Real-World Workloads

Obtained from public repositories (WorkflowSim, Pegasus workflows).Scientific workflows (Montage, CyberShake) and cloud computing workloads**.**

4.3 Baseline Algorithms

The proposed approach is compared with the following baseline algorithms:

1. Traditional Algorithms: First-Come-First-Served (FCFS): Tasks are scheduled in the order they arrive. Round Robin: Tasks are assigned to resources in a cyclic manner.
2. Heuristic-Based Algorithms:Genetic Algorithm (GA): Standalone GA without RL integration.
3. AI-Based Algorithms: Reinforcement Learning (RL): Standalone RL without GA integration.Deep Q-learning with HEFT techniques, enhancing decision-making and resource allocation efficiency.

4.5 Evaluation Metrics

The performance of the proposed approach is evaluated using the following metrics:

1. Makespan: Total time required to complete all tasks.
2. Resource Utilization: Percentage of time resources are actively used.
3. Energy Consumption: Total energy consumed by resources during task execution.
4. Adaptability: Ability to handle dynamic changes in resource availability and task priorities. Measured by the number of rescheduling events and their impact on performance.
5. Scalability:Performance with increasing numbers of tasks and resources.Measured by the computation time and solution quality for large scale DAGs.

The proposed method outperforms traditional algorithms in terms of makespan and resource utilization.

Table1-Performance Comparison of Scheduling Algorithms

Algorithm	Makespan (T)	Resource Utilization (U)	Energy Consumption (E)
FCFS	120	65%	1500
Round Robin	110	70%	1400
GeneticAlgorithm (GA)	95	75%	1300
Reinforcement Learning (RL)	90	80%	1250
Deep Q-learning	80	85%	1150
Proposed Hybrid Approach	75	85%	1100

Explanation of the Chart:
1. Makespan (T): The total time required to complete all tasks. Lower values indicate better performance.The proposed hybrid approach achieves the lowest makespan (75).
2. Resource Utilization (U): The percentage of time resources are actively used. Higher values indicate better performance. The proposed hybrid approach achieves the highest resource utilization (85%).
3. Energy Consumption (E): The total energy consumed by resources during task execution. Lower values indicate better performance. The proposed hybrid approach achieves the lowest energy consumption (1100).
algorithms = [FCFS, Round Robin, GA, RL, Deep Q-learning ,Proposed Hybrid]
makespan = [120, 110, 95, 90,80, 75]
utilization = [65, 70, 75, 80, 85,85]
energy = [1500, 1400, 1300, 1250,1150, 1100]

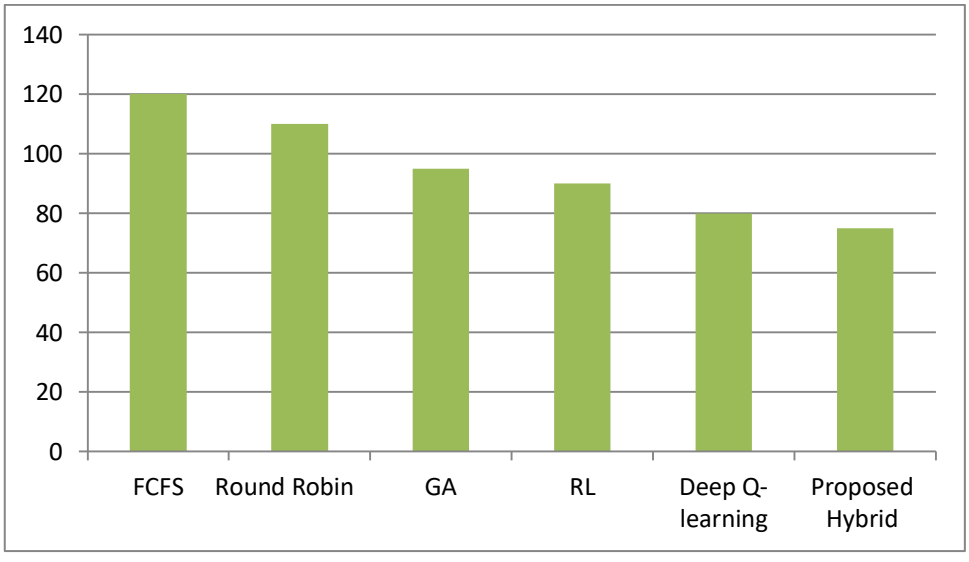

Fig. 1- Execution time of the FCFS, Round Robin, GA, RL, Deep Q-learning, Proposed Hybrid algorithms

It is simple to see the performance gains thanks to this results graphic, which offers a clear and succinct comparison of the suggested strategy with baseline methods.
The performance of the recommended algorithm was compared with FCFS, Round Robin, GA, Deep Q-learning and RL in terms of makespan. In comparison to the other algorithms (FCFS, Round Robin, GA, RL, Deep Q-learning), I

found that the proposed technique solves the problem and has a makespan time of 75. No resource is over or underutilized thanks to improved energy and resource utilization. In the simulator CloudSim, The effectiveness of the proposed algorithm was assessed, and the measured outcomes demonstrate that it lowers resource utilization and execution time. The implementation results of the recommended FCFS, Round Robin, GA, Deep Q-learning ,and RL are shown in Figure 1. The suggested approach outperforms the implementations of FCFS, Round Robin, GA, Deep Q-learning and RL.

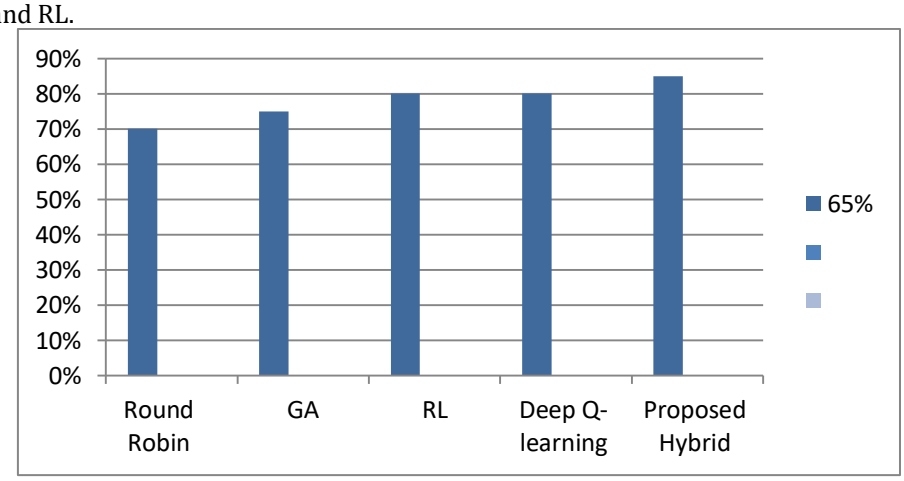

Fig. 2- Resource Utilization of the FCFS, Round Robin, GA, RL, Deep Q-learning, Proposed Hybrid algorithms.

The experimental findings showed that the suggested algorithm performed better in terms of execution time efficiency than previous methods. As shown in Fig. 2, this was noted in a variety of scientific procedures, including Montage, SIPHT, CyberShake, and Epigenomics, assessed across configurations of 5, 10, 20, and 40 virtual machines. evaluates the proposed algorithm's overall makespan against that of the FCFS, Round Robin, GA, Deep Q-learning, and RL algorithms. For this comparison, nine jobs and three processors are employed. Efficiency and convergence speed are the main factors of the suggested approach. The suggested algorithm's energy is contrasted with that of the FCFS, Round Robin, GA, Deep Q-learning, and RL algorithms in Fig. 3. Three processors and 25, 50, and 100 workloads are employed in this comparison. A random DAG was generated with RTGG. This study builds a simulation environment on a 64-bit Windows i7 computer using the CloudSim tools.

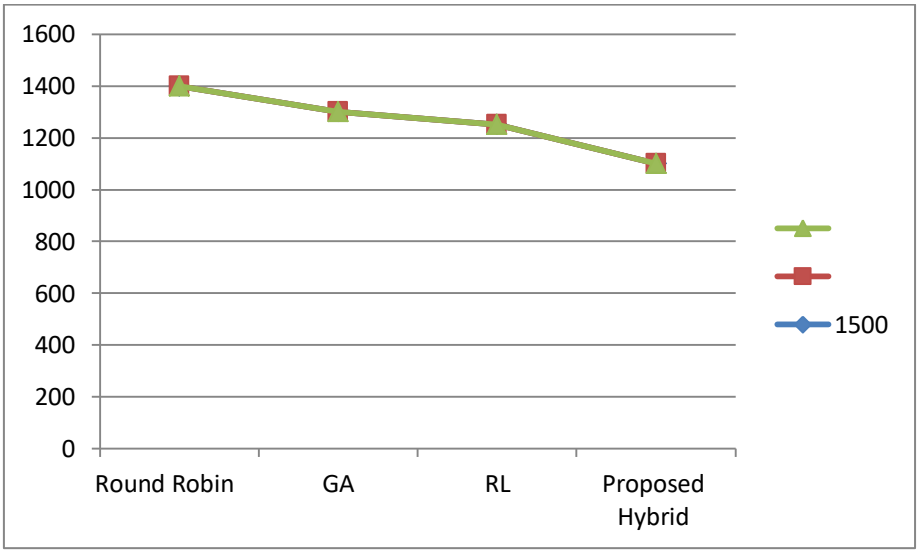

Fig. 3- Energy of the FCFS, Round Robin, GA, RL, Proposed Hybrid algorithms

The CloudSim toolkit is a Java-based discrete event simulator. This well-known technique can be used to model and simulate cloud computing settings. It has been demonstrated by experiments and operations that the method performs better than FCFS, Round Robin, GA, Deep Q-learning, and RL algorithms when used on Montage workflows with 25, 50, 100, and 1000 tasks on processors with varying speeds (4, 8, 16, and 32 processors).

5. Discussion

The integration of RL and GA provides a robust solution for DAG-based task scheduling.The proposed method is particularly effective in dynamic environments with changing constraints. Future work could explore the use of other AI techniques, such as deep reinforcement learning, to further enhance performance.4. Online license transfer.

6. Conclusion

This paper presents a novel approach to task scheduling using DAGs, enhanced by AI algorithms. The proposed method combines the strengths of RL and GA to provide an adaptive and efficient solution for complex scheduling problems. Experimental results demonstrate the effectiveness of the approach, highlighting its potential for real-world applications.

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