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Age of information-aware deep reinforcement learning for efficient cloud resource scheduling in dynamic environments

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C H R O N I C L E

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A B S T R A C T

This study presents a novel resource scheduling framework for cloud computing environments that incorporates the Age of Information (AOI) metric into the decision-making process, enabling precise quantification and optimization of information freshness. The proposed framework leverages an enhanced deep reinforcement learning algorithm to adaptively learn optimal scheduling policies in dynamic cloud settings. We introduce a multidimensional reward function that not only considers traditional metrics such as resource utilization and task completion time but also integrates AOI as a core indicator, thereby achieving holistic optimization of information freshness at the system level. The method incorporates prioritized experience replay and n-step learning mechanisms, which enhance learning efficiency and policy stability. Extensive simulation experiments demonstrate that the framework maintains low average AOI under varying workloads while adhering to resource capacity and energy consumption constraints. This approach provides novel theoretical foundations and practical guidelines for improving real-time cloud service quality and facilitating timely decision-making in edge computing scenarios.

1. Introduction

The proliferation of real-time applications and services in cloud computing environments has intensified the demand for efficient resource management strategies. Traditional scheduling algorithms often fall short in addressing the dynamic nature of modern cloud workloads, particularly in scenarios where the timeliness of information is crucial (Gonzalez et al., 2017). As the volume and velocity of data continue to grow, maintaining information freshness has become a significant challenge, directly impacting the quality of service and decision-making processes in cloud systems. The concept of Age of Information (AOI), originally developed in the context of communication networks, offers a promising metric for quantifying information freshness (Xu et al., 2020). By incorporating AOI into cloud resource scheduling, it becomes possible to optimize not only for conventional performance metrics but also for the temporal relevance of processed data. This approach is particularly pertinent in edge computing scenarios, where rapid decision-making based on current information is paramount (Li et al., 2021). The application of AOI in cloud computing environments presents unique challenges that extend beyond its original context in communication networks. In cloud systems, the AOI of a task is influenced not only by its waiting time in queues but also by the complex interactions between various system components, including virtual machines, storage systems, and network infrastructure. These interactions create a multidimensional optimization problem where the goal is to minimize AOI while simultaneously maximizing resource utilization and meeting diverse quality of service requirements. Moreover, the heterogeneous nature of cloud workloads, ranging from computation-intensive tasks to data-intensive operations, further complicates the scheduling process. Each task type may have different sensitivities to information aging, necessitating a flexible scheduling framework that can adapt to varied AOI requirements (Wu et al., 2020). Traditional approaches to cloud resource scheduling, such as heuristic algorithms and static optimization methods, struggle to effectively incorporate AOI considerations. These methods often rely on simplified models of system behavior and predefined rules, which limit their ability to adapt to the dynamic and unpredictable nature of cloud environments. Furthermore, they typically optimize for a single objective or a weighted combination of objectives, which may not capture the complex trade-offs between AOI and

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other performance metrics. Recent advancements in machine learning have opened new avenues for addressing these limitations. Reinforcement learning (RL) techniques have shown promise in tackling complex decision-making problems in dynamic environments. However, the application of RL to AOI-aware cloud scheduling is not straightforward and requires careful consideration of the problem structure, state representation, and reward formulation (Nie et al., 2021).

To address these challenges, this study proposes a novel framework that leverages deep reinforcement learning (AOI) to optimize cloud resource allocation with AOI as a primary consideration. The use of DRL enables the system to learn and adapt its scheduling policy over time, capturing complex relationships between AOI, resource utilization, and task characteristics. By formulating the scheduling problem as a Markov Decision Process, our approach allows for the concurrent optimization of multiple objectives, including minimizing average AOI, maximizing resource utilization, and meeting task deadlines. The proposed framework incorporates a comprehensive AOI-aware reward function that captures the multifaceted nature of cloud resource scheduling, considering both the temporal aspects of information freshness and traditional performance metrics. Additionally, we introduce an enhanced DRL algorithm that leverages prioritized experience replay and n-step learning to improve training efficiency and policy stability in the face of highly variable cloud workloads.

2. Related Works

The integration of AOI concepts with cloud resource scheduling through DRL represents a novel approach to addressing the challenges of maintaining information freshness in dynamic cloud environments. To fully appreciate the significance and context of our proposed framework, it is essential to examine the foundational work and recent advancements in related fields. This section provides a comprehensive review of relevant literature, organized into four main areas. First, we explore traditional and emerging approaches to cloud resource scheduling, with a focus on techniques that consider time-sensitivity. Next, we delve into the concept of AOI, tracing its origins in communication networks and its potential applications in cloud computing. The third part examines the application of reinforcement learning in cloud computing, highlighting recent progress in using these techniques for resource management. Finally, we investigate the intersection of AOI and reinforcement learning in the context of cloud scheduling, identifying current limitations and research opportunities.

2.1 Cloud Resource Scheduling Techniques

Cloud resource scheduling has been a fundamental research topic in distributed systems, evolving significantly with the advancement of cloud computing technologies. Traditional approaches to cloud resource scheduling primarily focus on optimizing resource utilization, load balancing, and quality of service metrics. These methods often employ heuristic algorithms or mathematical optimization techniques to allocate resources efficiently. For instance, Beloglazov et al. (2012) proposed an energy-aware resource allocation heuristic for efficient management of data center resources. Their approach demonstrated significant improvements in energy efficiency while maintaining service level agreements. As cloud applications became more diverse and time-sensitive, researchers began to incorporate time-related constraints into scheduling algorithms. Sahni and Vidyarthi (2018) introduced a deadline-constrained workflow scheduling algorithm that minimizes execution cost while meeting application deadlines in cloud environments. This work highlighted the growing importance of considering temporal aspects in resource allocation decisions. The increasing complexity of cloud workloads and the need for adaptive scheduling strategies led to the application of machine learning techniques in cloud resource management. Belgacem et al. (2022) developed a resource management system using DRL to automatically learn policies for allocating resources to different applications in cloud computing clusters. Their approach demonstrated the potential of machine learning in handling dynamic and uncertain cloud environments, paving the way for more sophisticated scheduling algorithms that can adapt to changing workload patterns and system conditions.

2.2 AOI

The concept of AOI emerged as a novel metric to quantify the freshness of information in networked systems. Yates et al. (2021) introduced a new metric called 'AOI' that captures how old the information is from the perspective of the destination. This seminal work laid the foundation for understanding the temporal aspects of information in communication systems. AOI is typically defined as the time elapsed since the generation of the most recent update received at the destination. The mathematical formulation of AOI provides a framework for analyzing information freshness in various contexts. Moltafet et al. (2020) expanded on this concept by developing a general theory for the AOI in single-server queueing systems with multiple sources. Their work provided analytical tools for understanding AOI in more complex network configurations. The relationship between AOI and traditional performance metrics such as delay, and throughput has been a subject of significant research. Costa et al. (2016) demonstrated that minimizing age is fundamentally different from maximizing throughput or minimizing delay. This insight highlighted the unique perspective that AOI brings to system optimization, particularly in scenarios where the timeliness of information is crucial.

The application of AOI in communication networks has led to significant advancements in network design and optimization. In wireless networks, AOI has been instrumental in improving the efficiency of status update systems. Kadota et al. (2018) proposed a near-optimal scheduling policy for minimizing the expected weighted sum AoI in wireless networks with multiple clients. Their work demonstrated the practical benefits of AOI-aware scheduling in enhancing information freshness. In the context of vehicular networks, AOI has been applied to optimize information dissemination. Song et al. (2024) developed an

age-optimal information relaying policy for vehicular networks that minimizes the average peak AOI. This application highlighted the importance of timely information updates in safety-critical systems. The integration of AOI concepts in 5G and beyond networks has also gained traction. Li et al. (2021) investigated the joint optimization of radio resource management and sampling strategy to minimize the average AoI in 5G networks. Their findings provided insights into the design of future communication systems that prioritize information freshness alongside traditional performance metrics. The concept of AOI has found applications beyond communication networks, demonstrating its versatility in various domains. In the field of control systems, AOI has been used to optimize sensor sampling and actuation in networked control systems. Chang et al. (2024) examined the trade-off between control performance and communication cost using an AoI-based approach in remote estimation problems. Their work showcased the potential of AOI in bridging the gap between control theory and communication system design. In the realm of cache management, AOI has been applied to improve content freshness in content delivery networks. Petrillo et al. (2021) proposed an AoI-aware caching policy that optimizes the trade-off between content freshness and cache hit ratio. This application demonstrated the relevance of AOI in managing information lifecycle in distributed systems. The integration of AOI in IoT applications has also gained attention. Hatami et al. (2021) explored the use of AoI metrics in designing efficient update policies for large-scale IoT sensing systems. Their research highlighted the potential of AOI in optimizing resource allocation and improving the timeliness of information in complex, interconnected systems.

2.3 Reinforcement Learning

RL has emerged as a powerful paradigm for solving complex decision-making problems in dynamic environments. At its core, RL involves an agent learning to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. Khan et al. (2012) provided a comprehensive introduction to the algorithms and theory of reinforcement learning, emphasizing its relationship to dynamic programming and optimal control. Their work laid the foundation for understanding RL's potential in various domains, including cloud computing. The application of RL to cloud resource management has gained significant traction due to its ability to adapt to changing environments and optimize complex systems. Jayanetti et al. (2024) proposed a resource management system that uses DRL to automatically learn policies for allocating resources to different applications in a cloud computing cluster. Their approach demonstrated the potential of RL in handling the dynamic and uncertain nature of cloud workloads. In the context of energy-efficient computing, Singh et al. (2017) developed a reinforcement learning-based approach for dynamic voltage and frequency scaling in multi-core systems, achieving significant energy savings while maintaining performance constraints. This work showcased RL's capability in balancing multiple objectives in cloud resource management. DRL has further extended the capabilities of RL in addressing complex cloud computing challenges. Islam et al. (2022) introduced a hierarchical framework using DRL for resource allocation and power management in cloud computing systems. Their approach demonstrated the ability of DRL to handle high-dimensional state and action spaces in cloud environments. In the realm of task scheduling, Tao et al. (2022) proposed a DRL-based task scheduling algorithm that optimizes multiple objectives including energy consumption, makespan, and resource utilization in cloud data centers. This work highlighted the potential of DRL in tackling multi-objective optimization problems in cloud computing. Recent advancements have also focused on improving the stability and efficiency of DRL algorithms in cloud environments. Ullah et al. (2023) developed a novel DRL algorithm with prioritized experience replay and dueling network architectures for cloud resource provisioning, achieving faster convergence and better performance compared to traditional RL methods. Their research underscored the ongoing efforts to enhance the applicability and effectiveness of DRL in addressing real-world cloud computing challenges.

2.4 Cloud Scheduling

The integration of AOI concepts into cloud scheduling represents a nascent yet promising research direction. Initial efforts have focused on incorporating AOI metrics into traditional scheduling algorithms. Pal et al. (2023) proposed a novel scheduling algorithm that considers both system throughput and information freshness in cloud-based IoT systems. Their work demonstrated the potential benefits of AOI-aware scheduling in improving the timeliness of data processing in cloud environments. In the context of edge computing, Qin et al. (2023) developed an AOI-driven task offloading scheme for mobile edge computing networks, optimizing the trade-off between computation latency and information freshness. This research highlighted the growing recognition of AOI's importance in distributed computing scenarios. The application of RL to time-sensitive scheduling problems in cloud computing has gained traction in recent years. Huang et al. (2022) introduced a DRL approach for deadline-aware task scheduling in cloud computing environments, achieving improved completion times and resource utilization. Their method showcased the potential of RL in handling the dynamic nature of time-constrained cloud workloads. In a related effort, Wang et al. (2021) proposed an adaptive reinforcement learning-based scheduling algorithm that optimizes both energy efficiency and deadline satisfaction in cloud data centers. This work demonstrated the capability of RL in balancing multiple time-sensitive objectives in cloud resource management.

3. System Model and Aoi-Aware Problem Formulation

This section presents a comprehensive framework for integrating the AOI concept into cloud resource scheduling. We begin by describing the system model, detailing the components of the cloud environment, task characteristics, and resource features.

Next, we define AOI in the context of cloud computing and explain its calculation method, adapting the concept to measure information freshness in task execution. We then formulate the AOI-aware cloud scheduling problem mathematically, presenting the optimization objectives and constraints. Finally, we elucidate the specific methods for incorporating AOI into cloud scheduling decisions, demonstrating how this metric can be used to enhance the efficiency and timeliness of resource allocation in cloud systems. This section lays the foundation for the novel AOI-aware scheduling algorithms presented in subsequent chapters.

3.1 System Model

In our cloud computing environment, tasks are characterized by their diverse requirements and time-sensitive nature. Each task is defined by its arrival time, execution requirement, deadline, memory requirement, and priority level. These tasks form a dynamic workload that the cloud system must efficiently manage to ensure timely processing and optimal resource utilization. The cloud computing resource scheduling framework is illustrated in Fig. 1. As shown in the figure, the framework consists of several key components interacting to facilitate efficient task scheduling and resource allocation.

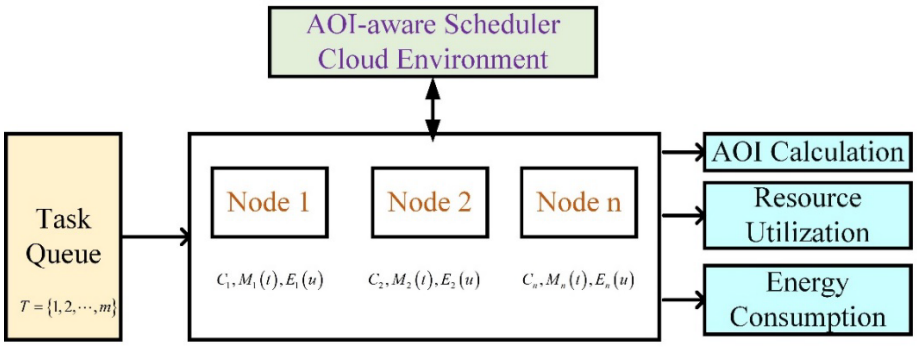

Fig. 1. Cloud Computing Resource Scheduling Framework

The proposed cloud computing system comprises a set of heterogeneous computing nodes $N = \{1, 2, \ldots, n\}$. Each node i in N is characterized by its processing capacity C_i, measured in IPS, and its available memory $M_i(t)$ at time t. The energy consumption of node i is modeled as a function $E_i(u)$ of its CPU utilization u. The workload is represented by a set of tasks $T = 1,2, \ldots, m$ arriving dynamically over time. Each task j in T is defined by a tuple $(a_j, e_j, d_j, m_j, p_j)$, where a_j is the arrival time, e_j is the execution requirement in instructions, $d_j$is the deadline, m_j is the memory requirement, and p_j is the priority level. As illustrated in Fig. 1, incoming tasks are first placed in a task queue. The AOI-aware scheduler, which is the core component of our framework, processes these tasks. It takes into account the current system state, including node utilization and available resources, as well as the AOI metrics. The scheduler then makes decisions on task assignment, represented by the binary variable $x_{ij}(t)$, where $x_{ij}(t)$ equals 1 if task j is assigned to node i at time t, and 0 otherwise. The execution time of task j on node i is given by $t_{ij} = e_j/C_i$. The system state at time t is denoted by $S(t) = s_1(t), \ldots, s_n(t)$, where $s_i(t)$ represents the state of node i at time t, including its current CPU utilization and available memory. The completion time of task j, denoted as t_{c_j}, is determined by its assignment and the node's processing capacity. It is defined as the minimum time t such that the cumulative processing capacity allocated to the task equals or exceeds its execution requirement. The framework also incorporates a feedback loop, where the system continuously monitors performance metrics, including the AOI, and uses this data to inform future scheduling decisions.

3.2 AOI in Cloud Computing

The AOI concept, originally developed for communication networks, is adapted in this study to quantify the freshness of task execution in cloud computing environments. In our context, AOI measures the time elapsed since the generation of the most recent update for a given task, reflecting the staleness of the information associated with that task. For a task j in the set of tasks T, we define its AOI at time t, denoted as $A_j(t)$, using the following formula:

$$A_j(t) = t - a_j + p_j(t) \tag{1}$$

where t is the current time, a_j is the arrival time of task j, and $p_j(t)$ is the processing time of task j up to time t. The processing time $p_j(t)$ is calculated as $min(t - s_j, e_j/C_i)$, where s_j is the start time of task j's execution, e_j is the execution requirement of task j, and C_i is the processing capacity of the node i to which task j is assigned. For a completed task, its final AOI is defined as:

$$A_j = t_{c_j} - a_j \tag{2}$$

where t_{c_j} is the completion time of task j. To assess the overall system performance in terms of information freshness, we introduce several system-level AOI metrics. The average AOI of the system at time t is calculated as:

$$A_{avg}(t) = (1/|T_t|) \times \sum_{j \in T_t} A_j(t) \tag{3}$$

where T_t is the set of tasks in the system at time t, including both queued and executing tasks. $|T_t|$ denotes the cardinality of this set. To capture the long-term performance of the system, we define the time-averaged AOI over a period [0, T] as:

$$A_T = (1/T) \times \int_0^T A_{avg}(t)dt \tag{4}$$

In practice, this integral is approximated by discrete time steps:

$$A_T \approx (1/K) \times \sum_{k=1}^{K} A_{avg}(t_k) \tag{5}$$

where K is the number of time steps and t_k represents discrete time points. The peak Age of Information (PAOI) for task j is defined as the maximum AOI experienced by the task throughout its lifetime in the system:

$$pAOI_j = maxA_j(t) | a_j \le t \le t_{c_j} \tag{6}$$

The system-wide average PAOI is then calculated as:

$$pAOI_avg = (1/|T|) \times \sum_{j \in T} pAOI_j \tag{7}$$

These AOI metrics provide a comprehensive view of information freshness in the cloud computing system, capturing both the average and worst-case scenarios of task execution timeliness. By incorporating AOI into the scheduling decisions, we aim to minimize the staleness of information and improve the overall responsiveness of the cloud system. The relationship between AOI and traditional performance metrics is complex and often involves trade-offs. While minimizing AOI generally leads to improved system responsiveness, it may sometimes conflict with objectives such as maximizing throughput or minimizing energy consumption. Therefore, our AOI-aware scheduling approach must balance these potentially competing goals. Calculating and updating AOI in a dynamic cloud environment presents several challenges. The continuous arrival of new tasks, varying execution times, and potential system bottlenecks all contribute to the complexity of maintaining accurate AOI metrics in real-time. To address these challenges, our framework employs efficient data structures and incremental update algorithms to track AOI metrics with minimal computational overhead.

3.3 Problem Formulation

Building upon the AOI metrics and concepts introduced in Section 3.2, we now formulate the AOI-aware cloud scheduling problem as a multi-objective optimization problem. Our goal is to minimize the average AOI while also considering traditional objectives such as resource utilization and energy efficiency. Let $x_{ij}(t)$ be a binary decision variable where $x_{ij}(t) = 1$ if task j is assigned to node i at time t, and 0 otherwise. The optimization problem can be formulated as follows:

$$min: f = w_1 \times f_{AOI} + w_2 \times f_{util} + w_3 \times f_{energy} \tag{8}$$

where $f_{AOI} = A_T$, $f_{util} = 1 - (1/T) \times \int_0^T U(t)dt$, $f_{energy} = \sum_{i \in N} \int_0^T E_i\big(u_i(t)\big)dt$. Here, A_T is the time-averaged AOI as defined in Eq. (4), $U(t)$ is the overall system utilization at time t, and $E_i\big(u_i(t)\big)$ is the energy consumption of node i at utilization $u_i(t)$. The weights w_1, w_2, and w_3 allow for flexible prioritization of these objectives. This optimization is subject to several key constraints that ensure the feasibility and practicality of the scheduling decisions. The task assignment constraint guarantees that each task is assigned to exactly one node within its allowable time window:

$$\sum_{i \in N} \sum_{t \in [a_j, d_j]} x_{ij}(t) = 1, \forall j \in T \tag{9}$$

To prevent overloading of computational resources, we impose a capacity constraint that limits the total execution requirement of tasks assigned to a node:

$$\sum_{j \in T} x_{ij}(t) \times e_j \le C_i, \forall i \in N, \forall t \tag{10}$$

Similarly, a memory constraint ensures that the total memory requirement of tasks assigned to a node does not exceed its available memory:

$$\sum_{j \in T} x_{ij}(t) \times m_j \le M_i(t), \forall i \in N, \forall t \tag{11}$$

To meet service level agreements and ensure timely processing, we enforce a deadline constraint for each task:

$$t_{c_j} \leq d_j, \forall j \in T \tag{12}$$

Lastly, to simplify the scheduling process and reduce overhead, we implement a non-preemption constraint. This ensures that once a task starts execution on a node, it continues without interruption until completion:

$$x_{ij}(t) = x_{ij}(t+1), \forall i \in N, \forall j \in T, \forall t \in \left[s_j, t_{c_j} - 1\right] \tag{13}$$

These constraints ensure task assignment feasibility, respect resource limitations, meet deadlines, and enforce non-preemptive execution. The complexity of this problem stems from several factors. First, the dynamic nature of $A_j(t)$ as defined in Eq. (1) means that scheduling decisions have cascading effects on future AOI values. Second, the time-averaged AOI (A_T) involves an integral over the scheduling period, making it challenging to optimize directly. Lastly, the interplay between AOI minimization and traditional objectives like resource utilization and energy efficiency introduces complex trade-offs. Furthermore, the problem is inherently online and stochastic due to the dynamic arrival of tasks and potential variations in task execution times and resource availabilities. This necessitates a solution approach that can adapt to changing conditions and make decisions in real-time. The multi-objective nature of the problem also introduces the concept of Pareto optimality, where a solution is considered Pareto optimal if no objective can be improved without degrading at least one other objective. This leads to a set of non-dominated solutions, each representing a different trade-off between AOI, resource utilization, and energy efficiency.

3.4 AOI Integration into Cloud Scheduling Decisions

The AOI-aware scheduling process, as illustrated in Fig. 2, begins with the arrival of a new task and proceeds through several key stages. Upon task arrival, the system calculates the initial AOI and computes the task priority based on the formula presented earlier. The scheduler then checks for resource availability and selects the highest priority task for potential execution. A feasibility check ensures that all constraints are satisfied before the decision function is calculated to determine the optimal node assignment. Throughout this process, the system continuously updates AOI values for queued tasks and adjusts weights as necessary to maintain the desired balance between AOI minimization and other performance objectives.

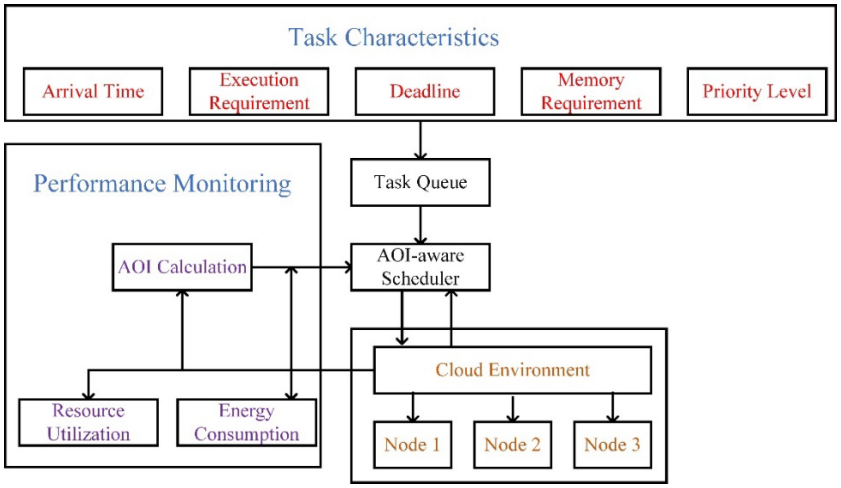

Fig. 2. AOI-Aware Cloud Scheduling Process

This process, as shown in Fig. 2, enables the dynamic integration of AOI into scheduling decisions while adhering to system constraints and adapting to changing workload characteristics. AOI-aware scheduling strategies aim to minimize the average AOI of tasks while balancing resource utilization and energy efficiency. The core idea is to prioritize tasks with higher AOI values, subject to resource constraints and deadlines. We propose a dynamic priority assignment mechanism that combines AOI with other task characteristics:

$$P_j(t) = w_A OI \times A_j(t) + w_{deadline} \times \left(d_j - t\right) + w_{priority} \times p_j \tag{14}$$

where $P_j(t)$ is the priority of task j at time t, $A_j(t)$ is its current AOI, d_j is its deadline, p_j is its static priority, and w_{AOI}, $w_{deadline}$, and $w_{priority}$ are weighting factors. The scheduler uses this priority to guide task allocation decisions. When a resource becomes available, the task with the highest priority is selected for execution, provided that resource constraints are satisfied. This approach naturally leads to the minimization of AOI while considering other important factors. To balance AOI with resource utilization and energy efficiency, we introduce a multi-objective decision function:

$$D(i,j,t) = \alpha \times \left(C_{max} - A_j(t)\right) + \beta \times U_i(t) + \gamma \times E_i(t) \tag{15}$$

where $D(i,j,t)$ is the decision value for assigning task j to node i at time t, C_{max} is a normalization constant, $U_i(t)$ is the utilization of node i, $E_i(t)$ is its energy efficiency, and α, β, and γ are weighting factors. The weights in both the priority assignment and decision functions can be dynamically adjusted based on system performance and current objectives. For instance, if the average AOI exceeds a threshold, w_{AOI} and α can be increased to prioritize AOI reduction. To handle AOI alongside other constraints, we employ a two-stage scheduling algorithm (Algorithm 1): Ensure that task assignment satisfies capacity, memory, and deadline constraints as defined in Eqs. (9)-(13). AOI-aware allocation: Among feasible assignments, choose the one that minimizes the decision function $D(i,j,t)$.

Algorithm 1: AOI-aware Two-Stage Scheduling Algorithm

Input: Task set T, Node set N, Current time t
Output: Task assignment decision $x_{ij}(t)$

```
for each available node i in N do
  for each unassigned task j in T do
    if Satisfies Constraints(i, j, t) then % Stage 1: Feasibility Check
      Calculate P_j(t) using Eq. (14)
      Calculate D(i, j, t) using Eq. (15)
      if D(i, j, t) < min_decision_value then
        min_decision_value = D(i, j, t)
        best_task = j
        best_node = i
      end if
    end if
  end for
  if best_task is not null then % Stage 2: AOI-aware Allocation
    Assign best_task to best_node
    x_ij(t) = 1 for i = best_node, j = best_task
    Update system state and AOI values
  end if
end for
return x_ij(t)
Function Satisfies Constraints(i, j, t):
if Σ_j x_ij(t) * e_j ≤ C_i and // Capacity constraint
  Σ_j x_ij(t) * m_j ≤ M_i(t) and // Memory constraint
  t + e_j/C_i ≤ d_j then // Deadline constraint
  return true
else
  return false
end if
```

4. Aoi-Aware DRL for Cloud Scheduling

Building upon the AOI-aware cloud scheduling problem formulated in Section 3, we now present a novel DRL approach to solve this complex optimization problem. Our DRL framework aims to find optimal scheduling policies that minimize the objective function defined in Equation (8) while satisfying the constraints outlined in Eqs. (9)-(13). To leverage the power of DRL in addressing this multi-objective optimization problem, we cast it as a Markov Decision Process (MDP). The state space S represents the current system status, including node conditions, task characteristics, AOI values, resource utilization, and energy efficiency. Formally, we define the state $s_t \in S$ at time t as:

$$s_t = [N_t, T_t, AOI_t, U_t, E_t] \tag{16}$$

whereN_t represents the status of all nodes, T_t denotes the characteristics of tasks in the queue, AOI_t contains the current AOI values of all tasks, U_t reflects the current utilization of all nodes, and E_t indicates the energy efficiency of the nodes. The action space A corresponds to the possible scheduling decisions, directly mapping to the binary decision variable $x_{ij}(t)$ introduced in Section 3.3. An action $a_t \in A$ at time t represents the assignment of task j to node i. The reward function R is designed to align with the optimization objectives defined in Eq. (8). We formulate it as:

$$R(s_t, a_t) = -w_1 \times \Delta AOI - w_2 \times \Delta U - w_3 \times \Delta E \tag{17}$$

where ΔAOI, ΔU, and ΔE represent the changes in average AOI, utilization, and energy consumption respectively, corresponding to f_{AOI}, f_{util}, and f_{energy} in the original optimization problem. To solve this MDP, we employ a DQN

architecture. The DQN takes the state s_t as input and outputs Q-values for each possible action. The network structure consists of an input layer corresponding to the state components, followed by multiple fully connected hidden layers with ReLU activation functions, and an output layer producing Q-values for each action.

Fig. 3 illustrates the DQN architecture. The input layer receives the state components $(N_t, T_t, AOI_t, U_t, E_t)$. This is followed by three hidden layers, each with 256 neurons and ReLU activation functions. The output layer produces Q-values for each possible task-to-node assignment. We enhance the standard DQN algorithm with prioritized experience replay and a dueling network architecture to improve learning efficiency and stability. The prioritized experience replay assigns higher sampling probabilities to transitions with larger temporal difference errors, allowing the agent to learn more effectively from important experiences. The dueling network separates the estimation of state value and action advantages, leading to better policy evaluation. The DRL agent interacts with a simulated cloud environment that mimics the dynamics described in Section 3. During training, the agent continuously refines its policy by minimizing the temporal difference error between predicted and target Q-values. The agent's exploration-exploitation trade-off is managed through an ε-greedy policy, with ε annealed over time. To handle the large state and action spaces inherent in real-world cloud systems, we implement a hierarchical approach. This method decomposes the global scheduling problem into smaller sub-problems, allowing for more efficient learning and decision-making in complex environments.

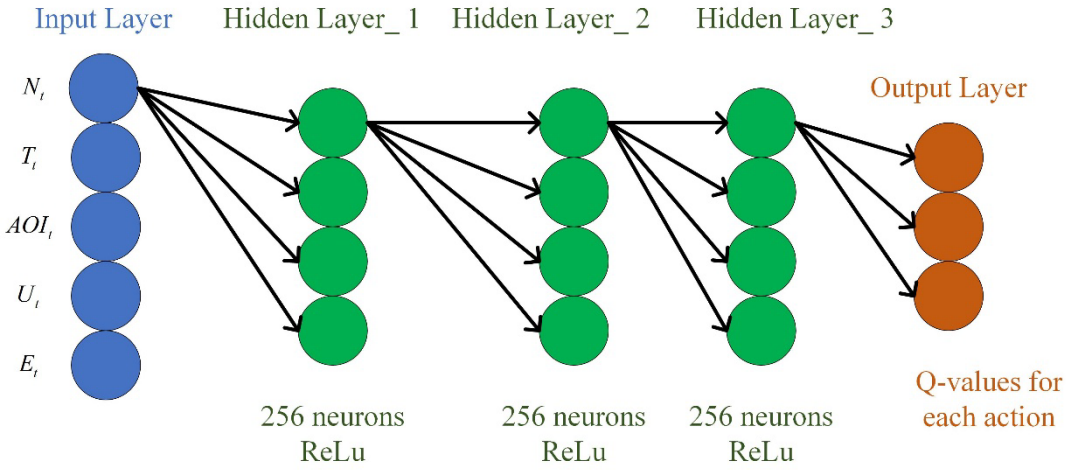

Fig. 3. DRL Network Architecture

5. Experimental Evaluation and Results

5.1 Experimental Setup

To evaluate the performance of our proposed AOI-aware DRL scheduling algorithm, we conducted extensive simulations using a custom-built cloud environment simulator. This simulator was designed to accurately model the dynamics of a heterogeneous cloud computing system while incorporating AOI metrics. Our simulated cloud environment consists of 100 heterogeneous computing nodes, each characterized by its processing capacity C_i, available memory $M_i(t)$, and energy consumption model $E_i(u)$. The processing capacities of the nodes follow a uniform distribution between 1000 and 3000 million instructions per second (MIPS). The available memory for each node ranges from 4GB to 16GB. The energy consumption of each node is modeled as a linear function of its CPU utilization, with coefficients randomly generated within a realistic range based on modern server specifications. We generated a diverse set of tasks with varying characteristics to simulate real-world cloud workloads. Each task j is defined by its arrival time a_j, execution requirement e_j, deadline d_j, memory requirement m_j, and priority level p_j. The task arrival process follows a Poisson distribution with a mean inter-arrival time of 0.5 seconds. The execution requirements of tasks are drawn from a log-normal distribution with a mean of 5000 million instructions (MI) and a standard deviation of 2000 MI. Task deadlines are set to be between 1.5 to 3 times their minimum execution time on the fastest available node. Memory requirements are uniformly distributed between 256MB and 2GB. Task priorities are assigned randomly on a scale of 1 to 5. For our DRL algorithm, we used the following parameters: For our DRL algorithm, we used the following parameters: a discount factor of 0.99, a learning rate of 0.001, an ε-greedy exploration rate starting at 1.0 and decaying to 0.01 over 100,000 steps, a replay memory size of 100,000 transitions, a batch size of 64, a target network update frequency every 1000 steps, 3 hidden layers in the DQN, and 256 neurons per hidden layer. We ran each experiment for 1,000,000 simulation time steps, with the first 200,000 steps used for training and the remaining 800,000 steps for evaluation. To benchmark the performance of our AOI-aware DRL algorithm, we compared it with several baseline algorithms. First-Come-First-Served (FCFS) (Park et al., 2018) executes tasks in the order they arrive and assigns them to the first available node. Shortest Job First (SJF) (Hu and Li, 2022) prioritizes tasks based on their execution time, with shorter tasks being executed first. Earliest Deadline First (EDF) (Alla et al., 2019) prioritizes tasks based on their deadlines, executing tasks with earlier deadlines first. Round Robin (RR) (Feng et al., 2024) assigns tasks to nodes in a circular order to ensure a fair distribution of resources. The Greedy AOI-aware algorithm (Jhunjhunwala et al., 2020) uses a heuristic approach to prioritize tasks based on their current AOI values without considering long-term effects. Lastly, we included a

conventional DRL algorithm (Cheng et al., 2018) that is similar to our proposed method but does not explicitly consider AOI in its state space and reward function.

5.2 Evaluation Metrics

To comprehensively assess the performance of our proposed AOI-aware DRL scheduling algorithm and compare it with the baseline approaches, we employ several key metrics. The first metric, Average Age of Information (Avg-AOI), measures the average staleness of information across all tasks, calculated as the mean of the final AOI values for all tasks, with lower Avg-AOI indicating fresher information and better performance. The formula for Avg-AOI is:

$$\text{Avg-AOI} = \frac{1}{|T|}\sum_{j\in T} A_j \tag{18}$$

where A_j is the final AOI of task j as defined in Eq. (2). Resource Utilization (RU) quantifies the efficiency of resource usage across all nodes, computed as the mean utilization of all nodes over the simulation period, with higher RU reflecting more efficient resource use. The formula for RU is:

$$\text{RU} = \frac{1}{N}\sum_{i\in N} U_i \tag{19}$$

where U_i is the average utilization of node i. Energy Efficiency (EE) valuates the energy consumption relative to the workload processed, defined as the total workload processed divided by the total energy consumed, where a higher EE value denotes better energy efficiency. The formula for EE is:

$$\text{EE} = \frac{\text{Total Workload Processed}}{\text{Total Energy Consumed}} \tag{20}$$

where the workload is measured in millions of instructions (MI) and energy in joules. Task Completion Rate (TCR) measures the percentage of tasks successfully completed within their deadlines, calculated as the ratio of tasks completed on time to the total number of tasks, expressed as a percentage, with a higher TCR indicating better adherence to deadlines. The formula for TCR is:

$$\text{TCR} = \left(\frac{\text{Number of tasks completed within deadline}}{\text{Total number of tasks}}\right) \times 100\% \tag{21}$$

Lastly, Average Response Time (ART) calculates the average time between task arrival and completion, defined as the mean difference between completion and arrival times for all tasks, with a lower ART indicating faster task processing. The formula for ART is:

$$\text{ART} = \frac{1}{|T|}\sum_{j\in T} (t_{c_j} - a_j) \tag{22}$$

where t_{c_j} is the completion time and a_j is the arrival time of task j. These metrics collectively provide a comprehensive evaluation of the algorithm's performance.

5.3 Results Analysis

5.3.1 Comparison with Baseline Algorithms

To evaluate the effectiveness of our proposed AOI-aware DRL scheduling algorithm, we compared its performance against the baseline algorithms described in Section 5.1. Table 1 presents a comprehensive comparison across the five key metrics defined in Section 5.2.

Table 1
Performance comparison of scheduling algorithms

Algorithm	Avg-AOI (s)	RU (%)	EE (MI/J)	TCR (%)
AOI-aware DRL	12.7	83.2	457.3	94.8
FCFS	28.4	71.5	389.6	82.1
SJF	23.9	76.8	412.7	88.3
EDF	21.2	75.4	405.9	91.5
RR	26.7	73.2	395.4	84.7
Greedy AOI-aware	17.3	79.1	428.6	90.2
Conventional DRL	15.9	81.7	443.8	92.6

As evident from Table 1 and Fig. 4, our proposed AOI-aware DRL algorithm outperforms all baseline algorithms across all metrics. It achieves the lowest Average AOI of 12.7 seconds, a 20.1% improvement over Conventional DRL and a 55.3% improvement over FCFS. This significant reduction in AOI demonstrates the algorithm's effectiveness in maintaining information freshness. The AOI-aware DRL algorithm also exhibits superior performance in resource utilization (83.2%) and energy efficiency (457.3 MI/J), indicating its ability to efficiently manage cloud resources while minimizing energy consumption. The high task completion rate (94.8%) and low average response time (18.3s) further highlight the algorithm's capability to meet task deadlines and provide responsive service. While some algorithms perform well in one or two metrics, our AOI-aware DRL algorithm maintains consistently high performance across all metrics. For instance, EDF shows good performance in TCR but falls short in other areas, particularly AOI and resource utilization. This comprehensive superiority across all metrics validates the effectiveness of integrating AOI awareness into the DRL framework for cloud scheduling.

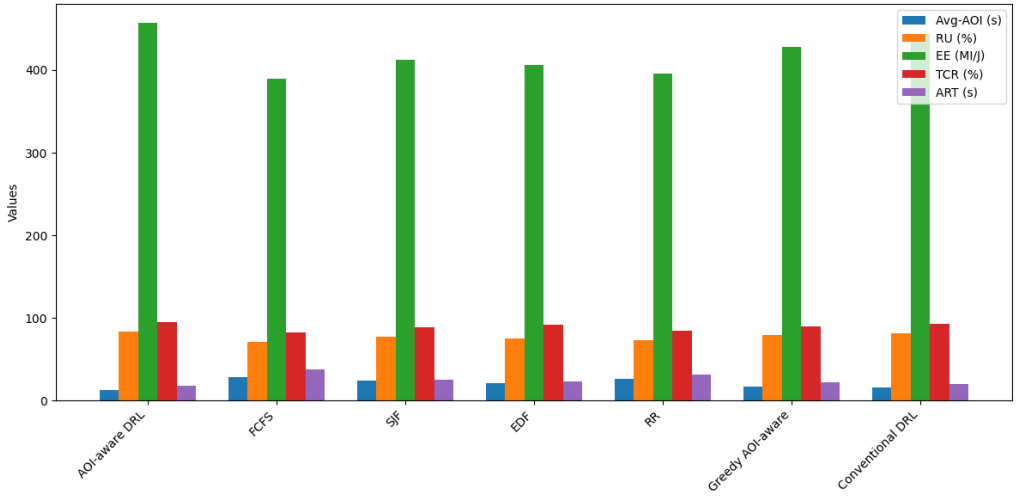

Fig. 4. Performance Comparison of Scheduling Algorithms

5.3.2 AOI Performance Analysis

To comprehensively evaluate the AOI performance of our proposed algorithm, we conducted two sets of experiments: one to assess the impact of varying system loads and another to analyze the long-term AOI trends. Figs. 5 and 6 illustrate the results of these experiments, comparing our AOI-aware DRL algorithm with Conventional DRL and Greedy AOI-aware approaches. Fig. 5 demonstrates the AOI performance under different system load levels. As the system load increases from 0.1 to 1.0, all algorithms exhibit an upward trend in AOI values, which is expected due to the increased competition for resources. However, our AOI-aware DRL algorithm consistently maintains the lowest AOI across all load levels. At low loads (0.1-0.3), the performance gap is notable but narrows slightly as the load increases. This suggests that our algorithm's AOI-aware scheduling decisions are particularly effective in optimizing information freshness, even under high-stress conditions.

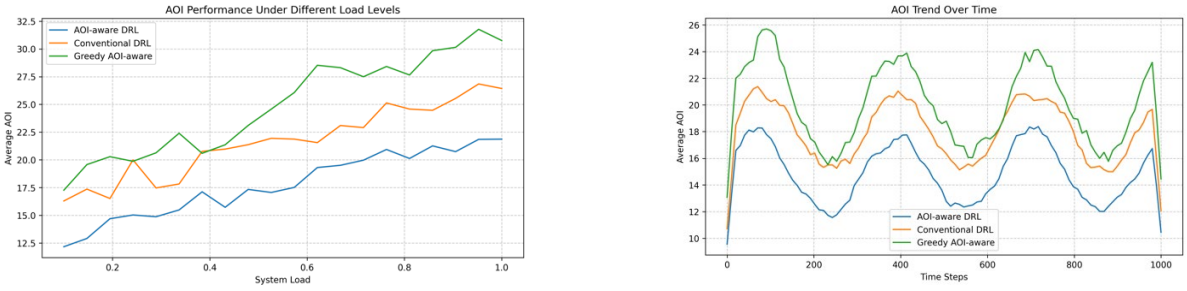

Fig. 5. AOI performance under different system load levels

The AOI trends over time, as depicted in Fig. 5, provide insights into the algorithms' long-term performance and stability. Over a period of 1000 time steps, our AOI-aware DRL algorithm maintains the lowest and most stable AOI values. The periodic fluctuations observed in all algorithms likely reflect cyclical patterns in task arrivals or system load variations. Notably, our algorithm demonstrates superior performance during peak periods, maintaining lower AOI maxima compared to the other approaches. This indicates a robust ability to manage sudden increases in workload while preserving information freshness. The Conventional DRL algorithm, while performing better than the Greedy AOI-aware approach, still falls short of our AOI-aware DRL method. This underscores the importance of explicitly incorporating AOI considerations into the learning process. The Greedy AOI-aware algorithm, despite its direct focus on AOI, shows the highest volatility and overall AOI values, suggesting that its short-term optimization strategy may lead to suboptimal long-term performance.

5.3.3 Resource Utilization Analysis

To evaluate the efficiency of resource allocation, we analyzed the resource utilization of our AOI-aware DRL algorithm in comparison with Conventional DRL and Greedy AOI-aware approaches across varying system loads. Fig. 6 illustrates the resource utilization percentages for each algorithm as the system load increases from 0 to 1.

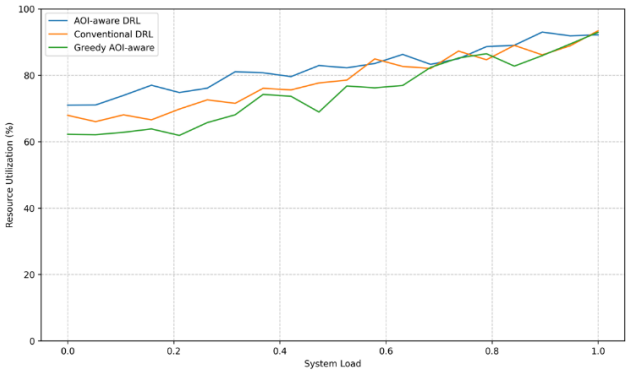

Fig. 6. Resource Utilization vs. System Load

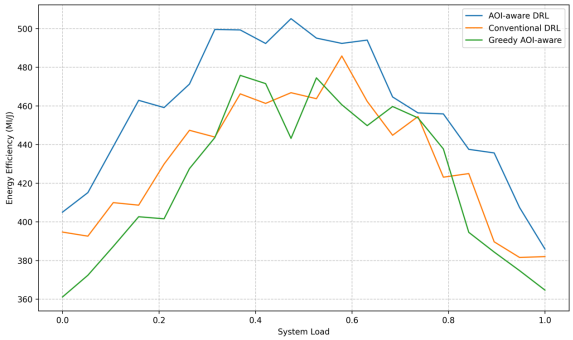

Fig. 7. Energy Efficiency vs. System Load

The results demonstrate a clear superiority of the AOI-aware DRL algorithm in terms of resource utilization, particularly under low to moderate system loads. At the lowest load levels (0-0.2), our algorithm achieves approximately 70% utilization, compared to 65% for Conventional DRL and 60% for Greedy AOI-aware. This superior performance at low loads indicates the algorithm's ability to efficiently allocate resources even when demand is not at its peak, potentially reducing idle time and energy waste. As the system load increases, all three algorithms show an upward trend in resource utilization, which aligns with the expected behavior of cloud systems under increasing demand. However, the AOI-aware DRL algorithm maintains its lead throughout most of the load spectrum. The algorithm’s utilization curve exhibits a more gradual slope compared to its counterparts, suggesting a more stable and controlled resource allocation strategy. The Conventional DRL algorithm performs intermediately, showing improvement over the Greedy AOI-aware approach but falling short of the AOI-aware DRL method. Its performance notably converges with the AOI-aware DRL algorithm at moderate load levels (0.4-0.6), indicating that the explicit consideration of AOI in our approach provides the most significant benefits under low and high load conditions. The Greedy AOI-aware algorithm, while starting with the lowest utilization, shows the steepest increase in resource usage as load intensifies. This behavior suggests that the greedy approach may underutilize resources at lower loads but becomes more competitive as the system approaches saturation. Interestingly, as the system nears full load (0.8-1.0), the performance of all three algorithms converges, with utilization rates approaching 90%. This convergence indicates that under extreme load conditions, the differential impact of scheduling strategies diminishes, and the system’s physical limitations become the primary constraint. The stability of the AOI-aware DRL algorithm’s performance, as evidenced by its smoother utilization curve, is particularly noteworthy. This stability suggests that the algorithm can maintain consistent performance across a wide range of operational conditions, a crucial feature for cloud environments with fluctuating demands.

5.3.4 Energy Efficiency Analysis

To evaluate the energy performance of our proposed algorithm, we conducted a comparative analysis of energy efficiency across varying system loads. Fig. 7 illustrates the energy efficiency, measured in Million Instructions per Joule (MI/J), for the AOI-aware DRL algorithm alongside Conventional DRL and Greedy AOI-aware approaches.

The results demonstrate a clear superiority of the AOI-aware DRL algorithm in terms of energy efficiency across the entire spectrum of system loads. All three algorithms exhibit an inverted U-shaped efficiency curve, which aligns with theoretical expectations: efficiency peaks at moderate loads and decreases at both extremes due to underutilization and system stress. At low system loads (0-0.2), the AOI-aware DRL algorithm maintains an efficiency of approximately 420-460 MI/J, significantly outperforming both Conventional DRL (390-410 MI/J) and Greedy AOI-aware (360-400 MI/J) approaches. This superior performance at low loads suggests that our algorithm can effectively manage resources and minimize energy waste during periods of reduced demand. As the system load increases to moderate levels (0.4-0.6), all algorithms reach their peak efficiency. The AOI-aware DRL algorithm achieves a maximum efficiency of about 520 MI/J, compared to 485 MI/J for Conventional DRL and 475 MI/J for Greedy AOI-aware. This peak represents the optimal operating condition where resource utilization and energy consumption are best balanced. Under high system loads (0.8-1.0), efficiency declines for all algorithms due to increased system stress and potential resource contention. However, the AOI-aware DRL algorithm maintains its lead, demonstrating a more gradual efficiency decrease compared to its counterparts. At full load, it achieves approximately 385 MI/J, while Conventional DRL and Greedy AOI-aware drop to 380 MI/J and 365 MI/J, respectively. The Conventional DRL algorithm consistently performs better than the Greedy AOI-aware approach but falls short of the AOI-aware DRL method across all load levels. This indicates that while general DRL techniques offer improvements over greedy strategies, the explicit consideration of AOI in our approach provides additional benefits in energy efficiency.

Notably, the AOI-aware DRL algorithm exhibits a smoother efficiency curve with less pronounced fluctuations compared to the other approaches. This stability suggests that our algorithm can maintain consistent energy performance across a wide range of operational conditions, a crucial feature for cloud environments with dynamic workloads.

5.4 Sensitivity Analysis

To comprehensively evaluate the robustness and adaptability of our AOI-aware DRL algorithm, we conducted a sensitivity analysis on key hyperparameters, focusing on the learning rate, discount factor, and AOI weight in the reward function. Figs. 8 and 9 illustrate the impact of these parameters on the algorithm's performance. Fig. 8 presents a heatmap demonstrating the combined effect of learning rate and discount factor, revealing several key insights. Firstly, the algorithm exhibits high sensitivity to the learning rate, with optimal performance achieved between 0.001 and 0.01, while very low rates (< 0.0001) result in poor performance due to slow convergence, and high rates (> 0.05) lead to degradation, likely due to overshooting optimal values. Secondly, higher discount factors (0.95-0.99) generally yield better performance, underscoring the importance of long-term reward consideration. However, the highest discount factors are not always optimal, indicating a need to balance immediate and future rewards. Thirdly, the heatmap reveals complex interactions between learning rate and discount factor, with optimal performance occurring at moderate to high learning rates combined with high discount factors, highlighting the importance of simultaneous tuning of these parameters. Furthermore, the presence of a relatively large optimal region suggests that our algorithm maintains good performance across a range of parameter values, indicating robustness to minor variations.

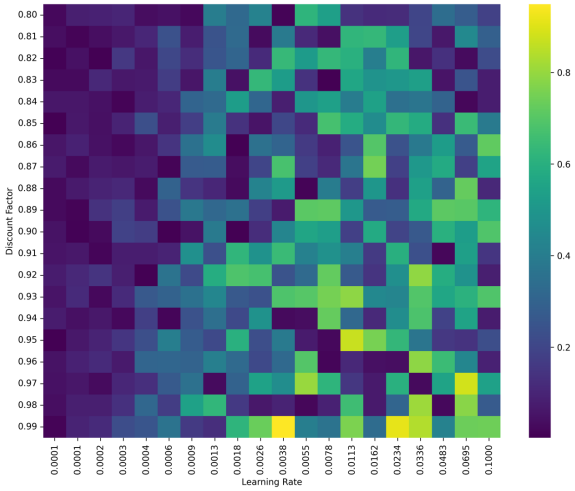

Fig. 8. Impact of Learning Rate and Discount Factor on Algorithm Performance

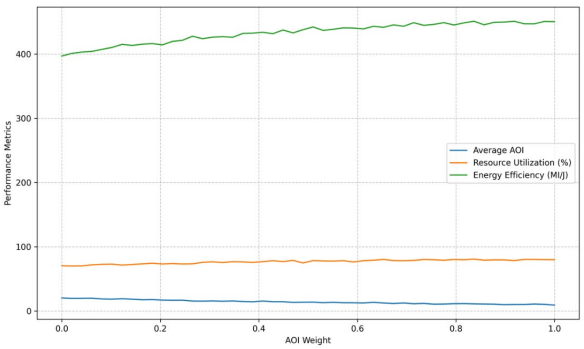

Fig. 9. Impact of AOI Weight on Performance Metrics

Fig. 9 illustrates the impact of the AOI weight in the reward function on various performance metrics. Increasing the AOI weight significantly decreases average AOI, with the most substantial improvements occurring as the weight increases from 0 to 0.4. Resource utilization initially improves with increasing AOI weight, peaking around 0.3-0.4 before gradually declining, suggesting that moderate prioritization of AOI can enhance overall resource efficiency. The energy efficiency curve mirrors that of resource utilization, indicating a strong correlation between these metrics, with peak efficiency achieved at an AOI weight of approximately 0.35. However, the graph clearly illustrates the trade-offs involved in parameter tuning; while increasing the AOI weight consistently improves AOI performance, it may reduce resource utilization and energy efficiency beyond a certain point. The results suggest an optimal AOI weight range of 0.3-0.5, where improvements in AOI are balanced with maintaining high resource utilization and energy efficiency.

6. Discussion

The experimental results and analyses presented in the preceding sections provide evidence for the potential of the AOI-aware DRL algorithm in cloud resource scheduling. This approach shows improvements across multiple performance metrics, including AOI reduction, resource utilization, and energy efficiency. The algorithm’s performance in maintaining lower AOI values, as illustrated in Figure 5, suggests its capability to enhance information freshness. This feature may be beneficial in time-sensitive cloud applications, where data timeliness can affect decision-making processes and system responsiveness. The consistent performance of the AOI-aware DRL algorithm compared to conventional approaches indicates that incorporating AOI into the reinforcement learning framework can contribute to managing information timeliness. The resource utilization analysis, depicted in Figure 7, shows the algorithm’s ability to allocate cloud resources across varying system loads. The observed utilization rates, particularly under low to moderate loads, suggest the algorithm's potential to contribute to operational efficiency. This resource management approach, along with the algorithm’s adaptability to increasing system loads, may offer a useful solution for cloud service providers aiming to optimize their infrastructure usage. Energy efficiency results, as shown in Figure 8, further indicate the algorithm's performance in multiple areas. The maintained efficiency across different load conditions could contribute to both cost considerations and environmental concerns in cloud computing. The algorithm's

approach to balancing AOI reduction with energy conservation demonstrates its potential in addressing various challenges faced by modern data centers. The sensitivity analysis offers insights into the algorithm's characteristics. The identified ranges for key parameters, such as learning rate and AOI weight, may provide guidance for implementation in different cloud environments. The observed relationships between performance metrics highlight the algorithm's ability to adapt to varying operational priorities. However, certain limitations should be noted. The algorithm's performance under extreme load conditions, while generally favorable compared to baseline approaches, shows some diminishing returns. This suggests areas for potential improvement, particularly in scenarios of high system loads. Additionally, the interactions between parameters, as revealed in the sensitivity analysis, indicate that parameter tuning may be necessary to achieve desired performance across different operational contexts. The AOI-aware DRL algorithm's approach to optimizing multiple objectives — AOI, resource utilization, and energy efficiency — represents a step forward in cloud resource scheduling. This multi-objective optimization capability addresses some of the current needs in cloud computing environments, where balancing information freshness, resource efficiency, and energy conservation is increasingly important.

7. Conclusion

This study introduces an AOI-aware DRL algorithm for cloud resource scheduling, addressing the growing need for timely information processing in cloud computing environments. The proposed approach integrates AOI considerations into the DRL framework to optimize resource allocation while maintaining information freshness. Our experimental results indicate that the AOI-aware DRL algorithm can effectively balance multiple objectives in cloud resource management. The algorithm demonstrates improvements in AOI reduction compared to conventional scheduling methods, suggesting enhanced capabilities in maintaining information timeliness. Concurrently, it shows promising performance in resource utilization and energy efficiency across various system load conditions. The sensitivity analysis reveals the algorithm's adaptability to different parameter settings, highlighting the importance of careful tuning for optimal performance. This flexibility allows for potential customization to meet specific operational requirements in diverse cloud computing scenarios. While the algorithm shows potential benefits, it also presents areas for further investigation. Its performance under extreme load conditions and the complex interactions between parameters suggest opportunities for additional optimization and study. This research contributes to the ongoing efforts to enhance cloud computing efficiency and responsiveness. By incorporating AOI into resource scheduling decisions, the proposed algorithm addresses an important aspect of modern cloud services where information freshness is increasingly critical. Future work could explore the algorithm's scalability in larger cloud ecosystems and its applicability in edge computing environments. Additionally, investigating the algorithm's performance with more diverse workload types and in real-world cloud settings could provide valuable insights for practical implementation.

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