Optimizing Task Scheduling in Fog Computing with Deadline Awareness

Mohammad Sadegh Sirjani

Department of Computer Science

University of Texas at San Antonio

San Antonio, USA

mohammadsadegh.sirjani@utsa.edu

Mohammad Ahmad

Department of Computer Science

University of Texas at San Antonio

San Antonio, USA

mohammad.ahmad@utsa.edu

Somayeh Sobati-Moghadam

Department of Computer Engineering

Ferdowsi University of Mashhad

Mashhad, Iran

s.sobati@hsu.ac.ir

Abstract-The rise of Internet of Things (IoT) devices has led to the development of numerous time-sensitive applications that require quick responses and low latency. Fog computing has emerged as a solution for processing these IoT applications, but it faces challenges such as resource allocation and job scheduling. Therefore, it is crucial to determine how to assign and schedule tasks on Fog nodes. This work aims to schedule tasks in IoT while minimizing the total energy consumption of nodes and enhancing the Quality of Service (QoS) requirements of IoT tasks, taking into account task deadlines. This paper classifies Fog nodes into two categories based on their traffic level: low and high. It schedules short-deadline tasks on lowtraffic nodes using an Improved Golden Eagle Optimization (IGEO) algorithm, an enhancement that utilizes genetic operators for discretization. Long-deadline tasks are processed on hightraffic nodes using reinforcement learning (RL). This combined approach is called the Reinforcement Improved Golden Eagle Optimization (RIGEO) algorithm. Experimental results demonstrate that RIGEO achieves up to a 29% reduction in energy consumption, up to an 86% improvement in response time, and up to a 19% reduction in deadline violations compared to stateof-the-art algorithms.

Index Terms—Internet of Things, Fog Computing, Job Scheduling, Golden Eagle Optimization Algorithm, Reinforcement Learning

I. INTRODUCTION

In recent years, the Internet of Things (IoT) has become a prominent technology in the internet and networking industry [1]. It consists of a system of linked physical devices, like household items and cars, that have sensors, software, and online connectivity [2]. Although IoT has been expanding quickly, it is encountering obstacles such as traffic congestion, delays, and excessive energy usage.

Adhering to deadlines is crucial in real-time IoT applications such as: e-health in healthcare, smart grid in energy management, livestock monitoring in agriculture, and smart traffic in transportation management. These time-sensitive applications have stringent QoS requirements including response time, deadline adherence, and energy efficiency that exceed the capabilities of resource-constrained IoT devices [3]. Managing resources while minimizing energy usage and meeting deadlines remains challenging [4].

To maintain efficient resource allocation and establish QoS rules in IoT-fog networks, monitoring and analyzing network

traffic is crucial. Traffic management becomes increasingly important as the number and complexity of Internet applications grow.

Fog computing addresses these challenges by providing computational capabilities at the edge, reducing delays and energy consumption [5], [6]. However, fog computing's diverse and limited resources necessitate efficient scheduling and allocation strategies [7]. Many existing solutions rely on single optimization strategies or fail to account for the dynamic, heterogeneous nature of IoT-Fog environments [8]–[11].

Meta-heuristic algorithms are particularly valued for their speed and ability to quickly find satisfactory solutions in complex optimization problems. Among these approaches, the Golden Eagle Optimization (GEO) algorithm, inspired by the hunting behavior of golden eagles, demonstrates effectiveness in global optimization tasks. Its computational efficiency is especially crucial for preventing deadline violations in time-sensitive IoT applications.

This work proposes the Reinforcement Improved Golden Eagle Optimization (RIGEO) algorithm, an adaptive task scheduling framework. RIGEO dynamically classifies Fog Nodes (FNs) into low-traffic and high-traffic categories based on real-time network conditions. Low-traffic nodes are characterized by average network traffic that falls below a predefined threshold, whereas high-traffic nodes exceed this average. It employs Improved Golden Eagle Optimization (IGEO) for short-deadline tasks on low-traffic nodes and Reinforcement Learning for long-deadline tasks on high-traffic nodes, leveraging the strengths of each method for different operational scenarios.

RIGEO operates within a three-layered architecture: cloud, fog, and IoT devices. The fog layer comprises a controller and a network for resource management and task scheduling, while the cloud offers significant computing and storage capabilities (Figure 1). Since task scheduling is NP-hard [12], [13], machine learning and heuristic methods are essential to achieve optimal performance [14].

Task scheduling faces multiple challenges, including cost optimization, energy efficiency, meeting deadline constraints, reducing latency, ensuring reliability, and maintaining fault tolerance. The following subsections review relevant studies in these areas.

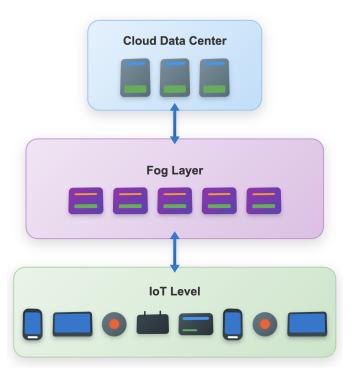


Fig. 1: The architecture of the IoT-Fog-Cloud network.

A. Energy Efficiency

The authors in [15] proposed MEETS, a new task scheduling algorithm for fog computing environments. The algorithm employs a two-step approach: determining the optimal task allocation to fog nodes, followed by scheduling tasks on each node. The results show that MEETS significantly reduces energy consumption while meeting all task deadlines. However, it assumes homogeneous fog networks and constant task arrival rates, which may not be realistic in practice.

The authors in [16] proposed Energy-Efficient Task Scheduling in Fog Computing based on Particle Swarm Optimization (EETSPSO). EETSPSO outperforms existing approaches in terms of makespan, energy consumption, and execution time. However, as fog nodes are resource-constrained, the algorithm's performance may vary across different real-world scenarios with varying resource limitations.

B. Deadline Constraints

The task scheduling approach in [7] incorporates two semi-greedy algorithms: Priority-aware Semi-Greedy (PSG) and PSG with Multi-start Procedure (PSG-M). These algorithms optimize energy consumption and minimize deadline violations for IoT tasks by effectively mapping them to fog nodes while ensuring QoS compliance. The PSG-M algorithm demonstrates a significant reduction in deadline violation time, however, the performance may vary under different real-world scenarios.

In [17], Louail et al. introduced a dynamic task scheduling algorithm considering both deadline constraints and task frequency to improve fog node efficiency in smart factories. By considering task frequency, the algorithm optimizes resource utilization, reducing idle time and improving overall efficiency. However, the complexity and computational requirements of the algorithm could pose a challenge in resource-constrained environments.

C. Latency Reduction

Authors in [18] proposed an Energy-Efficient Internet of Medical Things (EEIoMT) to Fog Interoperability of Task Scheduling framework. This framework schedules tasks efficiently by ensuring that critical tasks are executed within deadlines while balancing energy consumption. By utilizing ECG sensors to monitor heart health in smart cities, the framework processes data closer to end-users, thereby reducing latency and enhancing response times for IoMT applications. However, the study focuses on specific scenarios, and performance may vary in different real-world conditions.

The approach in [19] presents the Priority Queue Fuzzy Analytical Hierarchy Process (PQFAHP) algorithm. Using fuzzy logic and AHP, it prioritizes tasks based on completion time, energy consumption, RAM usage, and deadlines. The goal is to achieve optimal trade-offs between cost and latency in mobile fog computing environments. However, implementation complexity and computational requirements could challenge resource-constrained environments.

D. Cost Optimization

The authors in [8] proposed a Multi-Objective Cost-Aware Discrete Grey Wolf Optimization-based Algorithm (MoD-GWA) to tackle task scheduling challenges in IoT applications. This algorithm optimizes execution time, costs, and reliability by incorporating both execution and monetary cost models. Despite effectiveness, the algorithm's complexity and computational demands could pose challenges in limited-resource environments.

The authors in [20] introduced a Cost-Aware Genetic-Based (CAG) task scheduling algorithm for fog-cloud environments. CAG improves cost efficiency in real-time applications with stringent deadlines by optimizing service and resource allocation within the three-tier IoT architecture. While effective for delay-sensitive applications, the study's limited scenarios and metrics leave room for performance variability under different real-world conditions.

E. Reliability and Fault Tolerance

In [9], the authors propose Dynamic Fault Tolerant Learning Automata (DFTLA) task scheduling, utilizing variable-structure learning automata to efficiently assign tasks to fog nodes, thereby ensuring reliable execution while optimizing response time and energy consumption. The authors in [10] proposed a Load Balanced Service Scheduling Approach (LB-SSA) for cloud-fog environments, categorizing requests into real-time, important, and time-tolerant groups while incorporating resource failure rates to enhance reliability. However, its focus on specific scenarios may limit its broader applicability.

Ref.	Year	Factors				
Kei.	rear	Energy Eff.	Deadline Const.	Latency Red.	Cost Opt.	Reliability
[15]	2018	√	✓	×	×	×
[16]	2023	√	×	×	×	×
[7]	2022	√	✓	×	×	√
[17]	2020	×	✓	×	×	×
[18]	2022	√	✓	✓	×	×
[19]	2022	√	✓	✓	×	×
[8]	2024	×	×	×	√	√
[20]	2020	×	✓	×	√	×
[11]	2017	×	×	×	√	×
[9]	2020	×	×	×	×	√
[10]	2021	×	×	×	×	√
Ours	2025	√	✓	✓	×	×

TABLE I: Comparison of factors considered in related work

Table I presents an overview of these works. This paper optimizes system response time, deadline violation time, and energy consumption in FNs. The key contributions include:

- We propose the IGEO algorithm for the efficient scheduling of short-deadline tasks.
- We introduce a Reinforcement Learning-based approach for the scheduling of tasks with long deadline constraints.
- We conduct comprehensive experiments to evaluate the performance of our proposed framework in terms of energy consumption, deadline violation rates, and response time metrics within fog computing environments.

The remainder of this paper details the methodology in Section II, presents optimization results in Section III, and concludes in Section IV.

II. METHODOLOGY

This section outlines the Task Scheduling problem in mathematical terms and provides a detailed description of the proposed method.

A. Problem Statement

Given a set of n independent tasks $T = \{t_1, t_2, \ldots, t_n\}$ that must be assigned to m heterogeneous FNs $F = \{f_1, f_2, \ldots, f_m\}$, the goal is to assign tasks to nodes in a way that minimizes energy consumption and ensures that the task deadlines are met. The fog network is represented as a graph G = (V, E) with connection links between nodes. Each task t_i has a deadline d_i in milliseconds.

The problem is to find an optimal mapping $M: T \to F$ to achieve these objectives. The parameters used in the methodology are defined as follows:

1) Response time: The response time for each task t_i is determined by the sum of the propagation delay, transmission delay, queue waiting time, and execution time as shown in Eq. (1) [2].

$$R_i = P_i + T_i + Q_i + E_i \tag{1}$$

Propagation delay, P_i , is the duration for a signal to move between locations within a communication channel. Transmission delay, T_i , is the time needed to transmit all task bits. Queue waiting time, Q_i , is the queue waiting time after task assignment, pending completion of higher-priority tasks. Execution time, E_i is the CPU processing time to process the task.

2) Deadline violation: When assessing scheduling efficiency, it is essential to consider how many IoT tasks meet their deadlines compared to the total time spent on deadline violations. A deadline violation occurs when a task's completion time exceeds its specified deadline [21].

The deadline violation time for each task is calculated using Eq. (2), and the total violation time is determined using Eq. (3).

$$DV_i = \max(0, R_i - d_i) \tag{2}$$

$$DV_{total} = \sum_{i=1}^{n} DV_i \tag{3}$$

3) Energy Consumption: The energy used by FNs to complete all tasks is calculated by adding the energy consumed during active (E_{active}) and idle modes (E_{idle}). The coefficients α and β are user-determined parameters.

Eq. (4) shows energy consumption by f_j and Eq. (5) shows total system energy consumption [21].

$$E_j = \alpha \cdot E_{active,j} + \beta \cdot E_{idle,j} \tag{4}$$

$$E_{total} = \sum_{j=1}^{m} E_j \tag{5}$$

B. Proposed Method (RIGEO)

This work proposes RIGEO, a hybrid optimization approach that dynamically adapts to network conditions by classifying nodes based on traffic levels and applying different scheduling strategies based on task deadline requirements.

This work divides the network into two classes: low- and high-traffic. FNs are classified based on the median of observed network traffic. Nodes with traffic below the median are classified as low-traffic; otherwise, they are classified as high-traffic. Similarly, tasks are classified using the 25th percentile of the deadline distribution as the threshold, distinguishing time-critical tasks from those with relaxed time constraints. These thresholds are periodically recalculated to adapt dynamically to changing conditions.

Although periodic re-evaluation allows adaptation to evolving traffic patterns, handling sudden traffic spikes remains a challenge for future investigation. When network traffic is high, faster algorithms must be used to ensure that tasks are executed within their deadlines.

The proposed RIGEO algorithm considers deadline tasks in two stages:

- Short-deadline tasks execute on low-traffic FNs to prevent queue waiting.
- Long-deadline tasks are processed using Reinforcement Learning on high-traffic FNs, as meta-heuristic overhead isn't justified for tasks with more relaxed timing constraints.

1) Reinforcement Learning: RL is one of the main types of Machine Learning alongside Supervised, Unsupervised, and Semi-supervised Learning. RL algorithms train agents to make optimal decisions in complex environments by providing feedback and observing outcomes. The agent interacts with the environment, receives reinforcement signals, and learns to maximize long-term rewards by selecting optimal actions, enhancing decision-making capabilities through experience. The model comprises environmental states, agent actions, reinforcement signals, and an input function determining agent perception.

Initially, we create an array with a length equal to the long-deadline task count, where each cell references a task and its assigned FN. FNs can accommodate multiple tasks, with initial assignments randomly determined. This array evolves based on environmental feedback: RL evaluates the configuration, returning rewards when state T+1 improves upon state T, and penalties otherwise. Through this feedback mechanism, optimal scheduling is determined.

2) Golden Eagle Optimization (GEO): GEO is a swarm-based meta-heuristic inspired by the hunting behavior of golden eagles. GEO's search mechanism balances exploration (searching new areas) and exploitation (refining solutions). It adjusts speed during different hunting stages to find global optima while avoiding local optima.

In GEO, each eagle selects a target, calculates its cruising vector, and circles the best location found. The prey represents the optimal solution, with each eagle tracking its own best discovery. The attack vector for eagle i is calculated through Eq. (6).

$$\vec{A}_i = \vec{X}_f^* - \vec{X}_i \tag{6}$$

The step vector for eagle i at iteration t is given by Eq. (7). Random vectors \vec{r}_1 and \vec{r}_2 have elements in [0,1], with user-defined coefficients p_a (attack) and p_c (cruise). Position updates follow Eq. (8).

$$\Delta x_i = \vec{r}_1 p_a \frac{\vec{A}_i}{\|\vec{A}_i\|} + \vec{r}_2 p_c \frac{\vec{C}_i}{\|\vec{C}_i\|}$$
 (7)

$$x^{(t+1)} = x^t + \Delta x_i^t \tag{8}$$

3) Improved Golden Eagle Optimization (IGEO): Since task scheduling is discrete, GEO must be discretized using genetic operators that enhance both exploration and exploitation capabilities, enabling the discovery of optimal solutions in a minimal amount of time. IGEO enhances GEO through genetic operators for discrete task assignment [22].

Unit vectors indicate direction without size information. Vector sizes depend only on \vec{r}_1p_a and \vec{r}_2p_c . When $|r_1p_a| < |r_2p_c|$, the cruise tendency is higher, employing mutation for a high search power. When $|r_1p_a| > |r_2p_c|$, the attack tendency is higher, using crossover operators.

Negative step vectors in Eq. (7) indicate exploration tendency; positive vectors indicate exploitation. IGEO employs

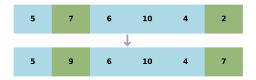


Fig. 2: Mutation operator

different genetic operators accordingly. For negative step vectors, mutation replaces addition in Eq. (8), randomly altering the parental genetic material as shown in Figure 2.

Eq. (9) shows the IGEO operation for negative step vectors, where x_{best} is the best found location and x_t is the current iteration location.

$$x_{t+1} = \begin{cases} \text{Mutation}(x_{best}) & \text{if } r \ge 0.5\\ \text{Mutation}(x_t) & \text{if } r < 0.5 \end{cases}$$
(9)

For positive step vectors, crossover operators provide efficiency. Genes from two parents exchange at predetermined cutting points, shown in Figure 3. Eq. (10) shows the update for positive operations.

$$x_{t+1} = \begin{cases} \text{single-point crossover}(x_{best}, x_t) & \text{if } r \ge 0.5\\ \text{two-point crossover}(x_{best}, x_t) & \text{if } r < 0.5 \end{cases}$$
 (10)

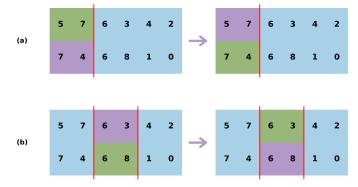


Fig. 3: Crossover operation. (a) One-point crossover. (b) Two-point crossover

Algorithm 1 shows how short-deadline tasks are sent to low-traffic FNs for IGEO processing, while long-deadline tasks go to high-traffic FNs for RL processing.

III. RESULTS

This section presents an appraisal of the RIGEO approach's performance through various metrics. The experimental configuration utilizes a laptop with an Intel Core i7 processor at 2.80 GHz, 16 GB RAM, and Windows 10 64-bit. Algorithms were implemented as simulations in MATLAB 2016, leveraging its computational capabilities to model the fog computing scenario, running 50 times using parallel processors.

Algorithm 1 RIGEO Task Scheduling Algorithm

```
Require: Task T with deadline D, Set of Fog Nodes
    F = \{f_1, f_2, \dots, f_n\}, traffic\_threshold \text{ (median)},
    deadline_threshold (25th percentile)
Ensure: Scheduled and processed task
 1: Low\_Traffic\_FNs \leftarrow \emptyset
 2: High\_Traffic\_FNs \leftarrow \emptyset
 3: for each f \in F do
 4:
      if f.traffic\_level < traffic\_threshold then
         Add f to Low\_Traffic\_FNs
 5:
      else
 6:
         Add f to High\_Traffic\_FNs
 7:
      end if
 8:
 9: end for
10: if T.deadline < deadline threshold then
      f \leftarrow SELECT(Low\_Traffic\_FNs)
11:
      result \leftarrow IGEO\_PROCESS(T, f)
12:
13: else
      f \leftarrow SELECT(High\ Traffic\ FNs)
14:
15:
      result \leftarrow RL \ PROCESS(T, f)
16: end if
```

Results are compared against GEO [23], GWO [24], WCLA+GA [7], and ETFC [25] algorithms to showcase RIGEO's performance. Each experimental configuration was executed 50 times with different random task distributions and node initializations. The results presented represent average values across these runs.

The study simulated a fog environment with interconnected nodes having diverse energy capacities and consumption rates. Tasks from IoT devices (200-600) were distributed among nodes with 2000-6000 MIPS processing power and 80-200 Joules energy usage. The traffic threshold was set at the median of observed traffic, and the deadline threshold at the 25th percentile of task deadlines, both recalculated periodically.

Experimental results demonstrate that RIGEO reduces response time, minimizes deadline violation time, and optimizes energy consumption compared to other algorithms. The following sections examine RIGEO's performance on each parameter.

A. Energy Consumption

17: return result

Figure 4 illustrates the energy usage of FNs with varying task numbers (200 to 600) and 20 FNs. Energy consumption is calculated using Eq. (5).

RIGEO optimizes FN energy consumption by effectively distributing tasks among nodes, reducing overall usage. At maximum load (600 tasks), RIGEO achieved approximately 29% lower energy consumption than GEO and 26% lower than GWO. Comparison with other scheduling techniques reveals RIGEO's consistent success in minimizing energy consumption across all task loads.

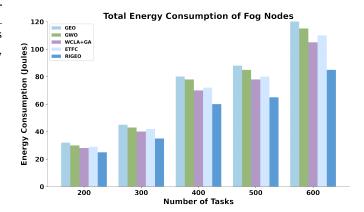


Fig. 4: Average Total Energy Consumption (Joules) with varying task numbers (200-600) and 20 FNs over 50 runs

B. Deadline Violation

RIGEO improves deadline adherence compared to other methods, as indicated by the decrease in violation times shown in Figure 5. The method consistently selects nodes with the shortest violation times, even in the presence of node shortages, demonstrating flexibility in addressing deadline breaches.

At 600 tasks, RIGEO demonstrated approximately 19% improvement over WCLA+GA and 14% improvement over ETFC in terms of deadline violation time. This capability proves especially beneficial in real-world scenarios where adherence to deadlines is critical for optimal performance and user satisfaction. RIGEO shows promise in enhancing system efficiency by minimizing deadline violations, evaluated using (3).

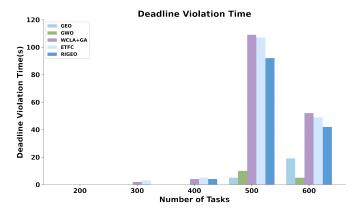


Fig. 5: Average Deadline Violation Time (ms) with varying task numbers (200-600) and 20 FNs over 50 runs

C. Response Time

Response time, the period required for the system response to a task, was systematically integrated into the fitness function as a critical parameter. Figure 6 illustrates RIGEO's superior performance in minimizing response time compared to other approaches with 20 FNs.

RIGEO achieved approximately 86% faster response time than GEO and 80% faster than GWO at maximum load. Response time computation is based on Eq. (1). The results demonstrate RIGEO's effectiveness in significantly reducing system latency across all task loads.

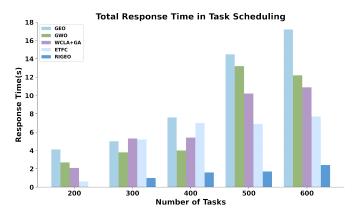


Fig. 6: Average Total Response Time (ms) with varying task numbers (200-600) and 20 FNs over 50 runs

IV. CONCLUSION

This work proposes the Reinforcement Improved Golden Eagle Optimization algorithm to address task scheduling challenges in IoT-fog computing environments. RIGEO dynamically classifies networks into low and high traffic categories, applying IGEO for low-traffic scenarios and Reinforcement Learning for high-traffic conditions.

Experimental results demonstrate that RIGEO achieves up to a 29% reduction in energy consumption, up to an 86% faster response time, and up to 19% fewer deadline violations compared to state-of-the-art algorithms. The proposed framework successfully balances computational efficiency and scheduling performance through the adaptive selection of algorithms. Future work will explore statistical validation and adaptive threshold optimization.

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