A Survey on Adaptive and Decentralized Task Scheduling in Fog Computing Environments

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Abstract: The rapid growth of Internet of Things (IoT) applications has created strong requirements for low-latency response and reduced energy consumption during data processing. In practical deployments, relying solely on distant cloud infrastructure often fails to meet these constraints. Fog computing partially addresses this issue by relocating computation closer to end devices. However, task scheduling in decentralized fog environments is far from trivial. The coexistence of heterogeneous computing nodes, fluctuating workloads, and occasional node mobility limits the effectiveness of static or rule-based scheduling strategies.

In this study, we introduce an adaptive scheduling framework designed specifically for decentralized fog architectures that must operate under continuously changing system conditions. Reinforcement learning is adopted to enable fog nodes to gradually learn effective task-allocation decisions by observing current network states and resource availability. At the same time, federated learning is incorporated to facilitate coordination among distributed nodes while avoiding direct data sharing, thereby addressing privacy concerns. The proposed framework aims to minimize task execution latency, improve overall energy efficiency, and support scalability without relying on centralized orchestration. Its performance will be evaluated through experiments conducted under realistic fog computing scenarios.

Keywords: Fog Computing; Task Scheduling; Reinforcement Learning; Federated Learning; Decentralized Systems

Introduction

The rapid expansion of Internet of Things (IoT) applications has led to a significant increase in data volume at the network edge. Practical deployments such as smart cities, intelligent transportation systems, and real-time healthcare applications demand fast decision-making and low-latency data processing. In such scenarios, traditional cloud-centric computing models often fall short, primarily due to communication delays and bandwidth constraints. Fog computing mitigates these limitations by shifting computation and storage closer to end devices, thereby reducing latency and enhancing Quality of Service (QoS) [10, 6].

Nevertheless, the effectiveness of a fog computing system is largely determined by how efficiently computational tasks are scheduled among distributed fog nodes. Fog environments are naturally decentralized and heterogeneous, with nodes varying in processing power, energy resources, and network connectivity. In addition, user mobility and fluctuating service demands cause workloads to change dynamically over time. Although several heuristic and metaheuristic scheduling techniques have been proposed in the literature, their performance is typically evaluated under controlled conditions. As a result, these approaches often struggle to cope with real-time variations in large-scale fog systems, leading to higher latency and suboptimal resource utilization [1, 17].

To address these challenges, recent studies have increasingly explored intelligent scheduling strategies based on reinforcement learning and deep reinforcement learning. By continuously interacting with the environment, such methods allow fog nodes to adapt their scheduling decisions based on observed system feedback [4, 15]. However, many existing solutions rely on centralized learning mechanisms or assume global system knowledge, limiting their applicability in fully decentralized fog architectures. Centralized coordination can also introduce additional communication overhead and raise concerns related to data privacy. These observations underscore the need for a decentralized, adaptive scheduling framework that can operate effectively under realistic fog-computing conditions.

Challenges in Decentralized Fog Scheduling

One of the major challenges in decentralized fog computing is handling resource heterogeneity under continuously changing system conditions. Fog nodes differ significantly in terms of computation power, memory, and energy resources, and their availability may vary due to mobility or network instability. Static and rule-based scheduling techniques fail to account for such variations, often resulting in load imbalance, increased task execution time, and energy inefficiency [1, 16]. As the scale of IoT deployments increases, these inefficiencies become more critical and difficult to manage.

Another key challenge is achieving real-time adaptability without relying on centralized control mechanisms. Although reinforcement learning-based scheduling approaches have demonstrated improved performance, centralized training frameworks create scalability bottlenecks and single points of failure [5, 20]. In addition, frequent exchanges of global system information increase communication overhead and reduce responsiveness, particularly in large, geographically distributed fog networks. Privacy concerns further complicate this issue, as sharing local system states or task-related data may expose sensitive information [2].

A further challenge lies in enabling effective collaboration among fog nodes while preserving data privacy. Federated learning has emerged as a promising solution by allowing nodes to collaboratively train models without sharing raw data [9, 22]. However, most existing federated learning-based approaches focus primarily on model training and do not tightly integrate learning with real-time scheduling decisions. As a result, they struggle to respond quickly to dynamic workload changes and network conditions [12]. Addressing these challenges requires a unified scheduling framework that combines adaptive reinforcement learning with decentralized and privacy-aware collaborative learning.

Related work

Early research on task scheduling in fog computing focused on heuristic and metaheuristic approaches to address resource allocation and latency constraints. Techniques such as artificial bee colony optimization and hybrid evolutionary algorithms were proposed to improve task execution time and load balancing under constrained fog resources. For example, [1] applied an artificial bee colony algorithm to optimize resource scheduling in IoT-based fog systems, while [17] employed a hybrid GA–PSO approach for multi-objective task scheduling in fog environments. Although these methods can achieve acceptable performance in specific scenarios, they rely on predefined strategies and cannot adapt to real-time changes in workload and network conditions.

To overcome the limitations of static scheduling, reinforcement learning (RL) and deep reinforcement learning (DRL) techniques have been increasingly explored for fog and edge computing. These approaches enable systems to learn optimal scheduling policies through continuous interaction with the environment. [16] and [15] demonstrated that DRL-based schedulers can effectively reduce latency and improve resource utilization in dynamic fog settings. Similarly, [4] and [14] proposed DRL-based scheduling frameworks that optimize response time and system load under multi-objective constraints. Despite their improved adaptability, many of these solutions assume centralized training or global system awareness, which limits scalability and practical deployment in decentralized fog environments.

Recent studies have shifted attention toward decentralized and multi-agent learning approaches to better reflect real-world fog architectures. [5] proposed an online decentralized RL-based scheduling strategy for smart city applications, showing improved responsiveness without centralized coordination. [20] and [23] employed multi-agent deep reinforcement learning for distributed task scheduling and offloading, demonstrating enhanced scalability and robustness. While these methods reduce reliance on centralized controllers, they still face challenges in coordinating distributed agents and sharing information.

Another important research direction focuses on privacy preservation and secure collaboration in fog computing. [2] addressed privacy-aware load balancing using reinforcement learning, highlighting the risks associated with sharing sensitive system information. Blockchain-based solutions have also been explored to enhance trust and security in fog scheduling, as demonstrated by [7] and [9]. Although these approaches improve security and transparency, they often introduce additional computation and communication overhead, which can affect real-time scheduling performance.

Federated learning has recently emerged as a promising solution for collaborative and privacy-preserving learning in decentralized environments. [22] provided a comprehensive survey on federated learning in edge computing, highlighting its suitability for distributed systems. Building on this concept, [12] proposed a federated reinforcement learning-based scheduling framework for fog computing that combines local adaptability with global knowledge sharing. While such approaches address privacy and scalability concerns, most existing works treat learning and scheduling as loosely coupled processes, limiting their ability to respond quickly to dynamic system changes.

In summary, existing research has made significant progress in improving task scheduling in fog computing through heuristic optimization, reinforcement learning, and decentralized learning. However, gaps remain in developing a unified framework that tightly integrates real-time adaptive scheduling with decentralized and privacy-aware collaborative learning. These limitations motivate the need for an adaptive and efficient scheduling framework that combines reinforcement learning and federated learning to address the challenges of decentralized fog computing environments.

Table 1. Summary Table

Ref.	**Objective**	**Methodology**	**Key Limitations**	**Improvements by Our Proposed Work**
[1]	Optimize resource scheduling in IoT-based fog systems	Artificial Bee Colony (ABC) optimization	Static optimization, no learning or adaptability to real-time changes	Introduces adaptive learning-based scheduling

				that evolves with system dynamics
[2]	Privacy-aware load balancing in fog networks	Reinforcement Learning	Centralized learning and limited scalability	Uses decentralized federated learning to ensure scalability and privacy
[3]	Improve task scheduling efficiency	Fuzzy Logic + Deep Reinforcement Learning	Limited decentralization and coordination among fog nodes	Enables collaborative learning among fog nodes using federated RL
[4]	Reduce response time and system load	Deep Reinforcement Learning	Assumes global system knowledge	Removes dependency on global state through decentralized learning
[5]	Online decentralized scheduling for smart cities	Reinforcement Learning	Limited privacy considerations	Incorporates privacy-preserving federated learning
[6]	Dynamic resource management and task offloading	Optimization-based framework	No intelligent learning mechanism	Adds learning-driven adaptability for dynamic environments
[7]	Secure and trustworthy task scheduling	Blockchain + Bayesian trust	High computation and communication overhead	Achieves privacy without heavy blockchain overhead
[9]	Multi-objective optimization for IoT-fog-cloud systems	Federated Reinforcement Learning + Blockchain	Scheduling decisions loosely coupled with learning	Tightly integrates real-time scheduling with federated learning
[16]	Adaptive task scheduling in edge/fog computing	Deep Reinforcement Learning	Centralized training and limited scalability	Supports decentralized and collaborative training
[12]	Scalable scheduling for real-time and non-real-time tasks	Federated RL + PSO-GA	Focuses more on optimization than real-time scheduling	Emphasizes real-time adaptive scheduling decisions
[20]	Decentralized scheduling for concurrent tasks	Deep Reinforcement Learning	Coordination overhead among agents	Improves coordination efficiency via federated model aggregation
[22]	Survey federated learning in edge computing	Systematic Survey	No direct scheduling framework	Builds a practical scheduling framework based on surveyed concepts

Key Contributions

The main contributions of this work are outlined as follows:

- A detailed and up-to-date review of the literature published between 2021 and 2025 is presented, focusing on task scheduling and resource management in fog and edge computing environments. The reviewed studies are systematically examined and classified according to their optimization strategies, learning paradigms—including heuristic methods, reinforcement learning, deep reinforcement learning, and federated learning—and underlying system architectures, ranging from centralized to decentralized designs.

- Based on this analysis, several critical research gaps are identified. These include the limited adaptability of static and heuristic-based scheduling techniques, inadequate support for decentralized decision-making, insufficient coupling of real-time scheduling with collaborative learning mechanisms, and a lack of emphasis on privacy preservation and scalability in large-scale fog deployments.
- A structured comparative analysis of representative studies is conducted to assess their ability to handle practical challenges such as resource heterogeneity, dynamic workload patterns, and node mobility. The findings from this comparison highlight the shortcomings of existing approaches and reinforce the need for an adaptive, decentralized, and privacy-aware scheduling framework.
- Motivated by these observations, an adaptive scheduling framework is proposed that combines reinforcement learning for real-time decision-making with federated learning to enable collaborative and privacy-preserving model updates across distributed fog nodes. This design removes the reliance on centralized coordination while supporting decentralized intelligence.
- The proposed framework is intended to achieve lower task latency, improved energy efficiency, and better scalability under realistic fog computing conditions, thereby making it suitable for practical adoption in next-generation IoT and fog-based systems.

Conclusions and Future Works

- Efficient task scheduling is a key factor in minimizing latency and improving resource utilization in fog computing environments, particularly as IoT deployments and delay-sensitive applications continue to expand. While fog computing reduces the distance between computation and end devices, its practical benefits depend largely on the availability of intelligent, adaptive scheduling strategies. Prior research has investigated a variety of techniques, including heuristic and metaheuristic optimization methods, as well as reinforcement learning and deep learning approaches, to address challenges in latency reduction, energy efficiency, and load balancing in fog systems.
- Despite these efforts, many existing solutions exhibit limited effectiveness when confronted with dynamic workloads, heterogeneous computing resources, and decentralized system architectures. A significant number of approaches rely on static decision policies, centralized learning models, or computationally intensive optimization techniques, which restrict scalability and limit real-time responsiveness. In addition, communication overhead and privacy concerns complicate coordination among distributed fog nodes. These shortcomings underscore the need for scheduling mechanisms that are both adaptive and decentralized, yet practical for real-world deployment.
- To address these challenges, this work proposes an adaptive scheduling framework that combines reinforcement learning for real-time decision-making with federated learning to enable collaborative and privacy-preserving model updates among fog nodes. The proposed framework is designed to reduce task execution latency, improve energy efficiency, and enhance scalability

without depending on centralized control. Its performance will be evaluated through extensive simulation-based experiments using key metrics such as task response time, energy consumption, resource utilization, and overall system scalability.

- Future work will focus on extending the proposed framework to support user mobility, task migration, and dynamic service placement across distributed fog nodes. Additional research directions include integrating security and trust mechanisms, improving the handling of heterogeneous network conditions, and validating results using real-world workloads or experimental testbeds. These enhancements are expected to further improve the robustness and practical applicability of the framework in next-generation fog computing environments.

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