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Stability-Aware and Feasibility-Sensitive Aggregation in Federated Reinforcement Learning for Edge-IoT Systems: A Review

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Abstract

Federated Reinforcement Learning (FRL) provides a useful basis for distributed policy learning in Edge-IoT systems, where clients interact with local environments without transferring raw operational data to a central server. Yet aggregation becomes difficult when clients operate under different transition dynamics, workloads, resource capacities, communication conditions, and operational constraints. In these settings, local policy updates may not differ only in magnitude or direction; they may also differ in stability, reliability, resource support, and operational feasibility. Conventional averaging is therefore limited, since it does not distinguish stable and feasible updates from unstable or constraint-violating ones. This paper examines aggregation stability and feasibility-sensitive aggregation in FRL for Edge-IoT systems. It reviews and synthesizes related literature across four connected streams: heterogeneous Federated Learning, FRL-based edge decision-making, constrained and safe Reinforcement Learning, and adaptive or reliability-aware aggregation. The reviewed studies are analyzed through six dimensions: learning paradigm, type of heterogeneity, role of policy learning, treatment of operational constraints, aggregation strategy, and whether local feasibility signals influence global aggregation weights. The analysis indicates that existing studies provide valuable foundations, but they usually treat heterogeneity, constraint handling, and aggregation adaptation as separate concerns. The paper identifies a need for aggregation mechanisms that jointly account for update stability, update reliability, resource availability, and constraint feasibility. It positions aggregation as adaptive client influence regulation rather than passive averaging in future Edge-IoT FRL systems.

Article Info

Keywords:
Federated Reinforcement Learning, Edge-IoT, Adaptive Aggregation, Aggregation Stability, Constraint Feasibility.

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1. INTRODUCTION

Edge IoT systems have become an important computing paradigm for latency-sensitive and resource-constrained applications, where sensing devices, mobile users, gateways, and edge servers cooperate to process data closer to their source. Such systems commonly support task offloading, computation scheduling, bandwidth allocation, energy management, queue control, and service-level optimization under dynamic network and workload conditions [1, 2]. Recent applied work also reflects the growing relevance of the Internet of Things (IoT) and deep learning in practical monitoring systems, where latency, scalability, and reliability remain important deployment concerns [3, 4]. Reinforcement Learning (RL) is well suited to such environments because many Edge-IoT problems require sequential decisions rather than one-shot predictions. In task offloading or resource allocation, a current action may affect the future delay, energy consumption, queue evolution, and service quality. However, centralized RL is often difficult to deploy at scale because interaction data are distributed across clients, communication resources are limited, and devices may operate under privacy, energy, and intermittent connectivity constraints [1, 2, 5]. Recent local research has also highlighted the role of deep reinforcement learning in intelligent cybersecurity strategies, further supporting the relevance of RL-based decision-making in dynamic and security-sensitive computing environments [6] . Federated Learning (FL) addresses this limitation by allowing distributed clients to train collaboratively without transferring raw local data to a central server [7, 8]. Federated Reinforcement Learning (FRL) extends this principle to policy learning: clients interact with local environments, update local policies, and share policy parameters or updates for aggregation. This makes FRL relevant to Edge-IoT systems that require distributed decision-making while preserving local operational data [5, 9]. Despite this potential, aggregation in FRL is more difficult than that in conventional supervised FL. In supervised FL, local updates are primarily shaped by local data distributions and learning objectives. In FRL, local policy updates are generated through sequential environmental interactions and are affected by transition dynamics, reward feedback, exploration behavior, workload variation, resource availability, and operational constraints. As a result, clients initialized from the same global policy may still produce substantially different updates when their environments respond differently to the same actions [5, 9]. This problem becomes more critical in heterogeneous Edge-IoT systems. Clients may differ in terms of their computational capacity, bandwidth availability, residual energy, queue pressure, workload intensity, participation reliability, and service requirements. They may also experience non-IID transition dynamics, where the same state-action pair leads to different next states, delays, energy costs, or service outcomes across clients. Under such conditions, static aggregation may combine updates that are unstable, directionally conflicting, resource-limited, or associated with operational constraint violations [9, 10]. Existing studies provide useful foundations, but they do not address this problem as a single aggregation issue. Heterogeneity-aware FL explains client drift and convergence degradation under non-IID and system heterogeneity [8]. FRL studies have shown the value of distributed policy learning for edge and multi-agent decision-making [9]. Constrained and safe RL offer tools for learning under operational requirements [11]. Adaptive aggregation methods also move beyond static averaging by adjusting client influence according to reliability, fairness, robustness, and update quality [12]. What remains less developed is the connection among these directions: how local instability, resource pressure, and feasibility violations should affect a client's influence on global FRL aggregation. Therefore, the central concern of this review is the separation between local feasibility and global aggregation influence. A client may satisfy the formal structure of local constraint-aware learning but still produce updates during periods of unstable workload, low energy, weak connectivity, or repeated SLA violations. If such updates are aggregated without considering their feasibility, constraint-violating behaviors can still be propagated into the global policy. In Edge-IoT FRL, reward improvement alone is insufficient; the global policy must also remain stable and operationally feasible [9, 11, 12]. This study uses a review and research-positioning approach to examine stability-aware and feasibility-sensitive aggregation in FRL for Edge-IoT systems. This review focuses on four connected bodies of work: heterogeneous FL and client drift, FRL for edge decision-making, constrained and safe RL, and adaptive or reliability-aware aggregation. The main position of this study is that aggregation in Edge-IoT FRL should be treated as client influence regulation, not as a passive averaging step. Under this view, local updates are assessed according to update stability, update reliability, resource availability, and constraint feasibility before shaping the global policy. The contributions of this study are fivefold. First, it reviews the foundations of aggregation instability in heterogeneous Edge-IoT FRL, focusing on client drift, non-IID transition dynamics, resource heterogeneity, and policy-update divergence. Second, it clarifies why local constraint handling is insufficient when feasibility signals remain disconnected from the aggregation weights. Third, it synthesizes adaptive, reliability-aware, and resource-aware aggregation mechanisms and discusses their limitations in FRL-specific dynamics. Fourth, it identifies the need for aggregation mechanisms that jointly consider update stability, reliability, resource availability, and constraint feasibility. Fifth, it positions adaptive client influence regulation as a future direction for deployment-aware FRL in heterogeneous Edge-IoT systems. The contributions of this study are conceptual and analytical rather than algorithmic or experimental. To provide an early conceptual view of the review focus, Figure 1 summarizes how heterogeneous edge IoT clients generate local policy updates under different transition dynamics, resource conditions, and operational constraints. The figure illustrates the main flow considered in this study: local environment interaction, local policy update generation, client evaluation through stability, reliability, resource availability, and constraint feasibility indicators, adaptive aggregation weighting, and global policy formation. It also highlights the central gap addressed by this review: local feasibility signals should not remain isolated at the client level but should inform the global aggregation influence.

The remainder of this paper is organized as follows. Section 2 describes the background and methods of the review. Section 3 reviews Federated Learning and aggregation under heterogeneity, while Section 4 discusses Federated Reinforcement Learning for Edge-IoT systems. Section 5 analyzes aggregation instability under non-IID transition dynamics, and Section 6 discusses constraint-aware Reinforcement Learning and feasibility requirements. Section 7 reviews adaptive, reliability-aware, and resource-aware aggregation mechanisms. Section 8 presents the comparative taxonomy and research gap positioning. Section 9 provides an illustrative

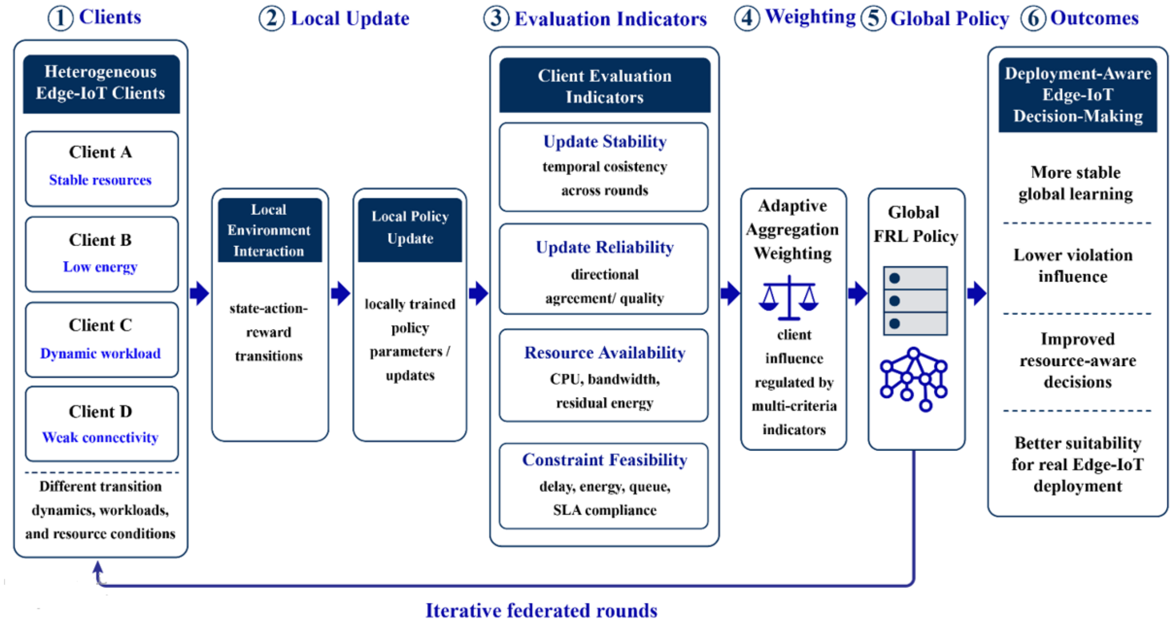

Figure 1. Conceptual flowchart of stability-aware and feasibility-sensitive aggregation in Edge-IoT FRL

Edge-IoT task-offloading case study. Section 10 outlines open challenges and future research directions. Finally, Section 11 concludes the paper.

2. BACKGROUND AND METHOD OF REVIEW

This study uses a narrative and research-positioning review approach. It does not attempt to offer a bibliometric survey or an exhaustive mapping of all studies on Federated Learning, Reinforcement Learning, or Edge-IoT. The focus is narrower: the aggregation problem that appears when FRL is deployed in heterogeneous Edge-IoT environments. This choice was deliberate because the purpose of this study was to identify and clarify an emerging research gap rather than to measure publication trends. To clarify the review boundaries, the literature search focused on peer-reviewed journal articles, conference papers, scholarly surveys, and foundational books related to Federated Learning, Federated Reinforcement Learning, Edge-IoT, constrained or safe Reinforcement Learning, and adaptive aggregation. The main sources considered included IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, MDPI, PMLR, arXiv for recent preprint developments, and the Sana'a University Journal of Applied Sciences and Technology. The representative search terms included "Federated Reinforcement Learning," "Edge-IoT," "Mobile Edge Computing," "adaptive aggregation," "client drift," "non-IID transition dynamics," "constrained reinforcement learning," "safe reinforcement learning," "resource-aware federated learning," and "federated multi-agent reinforcement learning." Foundational works and recent studies available up to 2026 were considered, with priority given to studies directly related to aggregation behavior, policy learning, operational constraints and Edge-IoT deployment conditions. The reviewed literature is grouped into four connected streams: The first concerns heterogeneous Federated Learning, including static aggregation, non-IID data, system heterogeneity, and client drift [7, 8, 10]. The second is Federated Reinforcement Learning, where clients learn policies through local environment interaction and submit policy updates to a shared global model [9]. Together, these streams explain why aggregation becomes more complex when federated learning moves from supervised model training to distributed policy learning. The third stream concerns constrained and safe Reinforcement Learning, where policies are optimized under operational or safety-related requirements, such as delay, energy use, queue stability, and service-level constraints [11]. The fourth concerns adaptive, reliability-aware, and resource-aware aggregation mechanisms, which adjust client influence using indicators such as update quality, reliability, fairness, and resource conditions [12]. These streams are particularly relevant to Edge-IoT FRL because local policy updates may differ not only in learning quality but also in their operational feasibility. Studies were included when they addressed at least one of the following aspects: aggregation under heterogeneous FL, FRL or federated multi-agent policy learning, constrained RL, adaptive or reliability-aware aggregation, and edge IoT or mobile edge computing environments. Priority was given to foundational studies, high-impact surveys, and recent publications from reputable journals and conferences. Works were not emphasized when they dealt with general machine learning, generic IoT applications, or security topics without a direct connection to federated learning, reinforcement learning, aggregation behavior, or Edge-IoT decision making. Because this paper is a narrative and research-positioning review rather than a systematic review, no formal bibliometric counting or PRISMA-style screening flow was applied. Instead, the selection emphasized conceptual relevance to the central aggregation problem: whether local update stability, reliability, resource status, and feasibility signals can influence global client weighting in Edge-IoT FRL. The selected studies were examined qualitatively using six comparison dimensions: learning paradigm, type of heterogeneity, role of policy learning, treatment of operational constraints, aggregation strategy, and whether local feasibility signals affect the global aggregation weights. These dimensions were selected because they directly reflect the paper's central question: whether current research provides a way for updating stability, reliability, resource availability, and constraint feasibility to jointly regulate client influence during FRL aggregation. Accordingly, this review should be read as a research gap synthesis rather than a new algorithmic proposal or experimental study. It examines why static and single-criterion aggregation may be insufficient for heterogeneous Edge-IoT FRL and why future aggregation mechanisms need to combine learning-oriented indicators with deployment-oriented feasibility signals before assigning client influence in global policy formation.

3. FEDERATED LEARNING AND AGGREGATION UNDER HETEROGENEITY

Federated Learning (FL) allows distributed clients to train a shared model without sending raw local data to a central server. In the classical setting, the server sends a global model to participating clients, who update it locally, and the server aggregates their submitted updates into a new global model. Federated Averaging (FedAvg) remains the standard reference point for this process, where aggregation is typically based on uniform or data-size-based weighting [7, 8]. The effectiveness of static aggregation depends on the compatibility of local updates. In practical distributed systems, clients rarely operate under the same conditions. Their data distributions, computational capacities, bandwidths, energy availabilities, and participation patterns may vary substantially. Such statistical and system heterogeneities can lead to client drift, slower convergence, and higher update variance during global training [8, 10]. Heterogeneity-aware FL methods have shown that aggregation stability is not a secondary implementation detail. For example, FedProx limits excessive local divergence by adding a proximal term to the local objective, whereas drift-control methods attempt to reduce inconsistent update directions under non-IID data [10]. These studies show that conventional averaging becomes less reliable when local updates are produced under heterogeneous conditions. However, most heterogeneity-aware FL methods are designed for supervised or prediction-based learning. In these settings, local updates are computed using fixed datasets and supervised objectives. This assumption becomes weaker in Federated Reinforcement Learning, where updates are generated through interactions with local environments. In FRL, divergence may arise not only from data heterogeneity but also from transition dynamics, reward feedback, exploration behavior, resource conditions, and operational constraints [5, 9]. Thus, heterogeneous FL provides an important starting point for understanding FRL aggregation instability, but it does not fully address this issue. Edge IoT FRL requires aggregation mechanisms that evaluate whether local policy updates are stable, reliable, resource-supported, and feasible before assigning them global influence. Therefore, the problem extends beyond data-driven client drift toward stability-aware and feasibility-sensitive client influence regulation.

4. FEDERATED REINFORCEMENT LEARNING FOR EDGE-IOT SYSTEMS

Federated Reinforcement Learning (FRL) extends the federated learning idea from distributed model training to distributed policy learning. Each client interacts with its own environment, collects trajectories, updates a local policy, and shares policy parameters or updates with the federated server. The aim is to support collaborative policy learning while keeping raw interaction data local [5, 9]. This setting is well aligned with Edge-IoT applications, in which many decisions are sequential rather than static. Task offloading, computation scheduling, bandwidth allocation, energy management, and queue control involve actions whose effects may appear later through delays, energy consumption, queue evolution, or service-level satisfaction. FRL can therefore support distributed edge intelligence when centralized RL is constrained by communication cost, privacy concerns, scalability, or limited resources [1, 2, 9]. The difficulty is that FRL changes the meaning of "local update." In supervised FL, an update mainly reflects a local dataset and loss function. In FRL, it also reflects how the local environment responds to actions. Transition dynamics, rewards, exploration, workload variation, and operational constraints can shape the direction and magnitude of policy updates. Two clients may start from the same global policy and still return incompatible updates if their environments respond differently to similar actions [5, 9]. In Edge-IoT systems, this issue is exacerbated by partial participation and resource heterogeneity. Clients may drop out or participate irregularly because of limited battery, weak connectivity, mobility issues, or heavy local workloads. Consequently, the global policy may be shaped by a changing subset of updates, some of which may be stale, unstable, resource-limited, or associated with constraint violations [8, 10]. Therefore, aggregation in Edge-IoT FRL should be treated as a methodological problem, not as a direct transfer of supervised FL averaging. The server needs to combine local policy updates while also assessing whether these updates are stable, directionally reliable, resource-supported, and feasible under operational constraints. This view motivates the discussion of non-IID transition dynamics and feasibility-sensitive aggregations.

5. AGGREGATION INSTABILITY UNDER NON-IID TRANSITION DYNAMICS

Aggregation instability in FRL appears when the server combines policy updates generated under heterogeneous and only partially compatible environmental dynamics. In supervised FL, non-IIDness usually refers to differences in the local data distributions. In FRL, heterogeneity also occurs in the transition behavior of local environments because clients learn through state-action interactions rather than by optimizing fixed datasets [5, 9]. Non-IID transition dynamics can be expressed as differences in client-specific transition functions. For two clients and , the same state-action pair may lead to different next-state distributions:

$$P_i(s' \mid s, a) \neq P_j(s' \mid s, a) \tag{1}$$

In Edge-IoT systems, such differences may result from unequal bandwidth, workload arrival rates, CPU capacity, residual energy, queue congestion, wireless channel quality, mobility, or local service requirements [1, 2]. This type of heterogeneity directly affects the policy updates. A client with stable resources and a moderate workload may produce a smooth update, whereas a client facing bursty arrivals, weak connectivity, low energy, or queue congestion may produce a noisy or highly reactive update. Because the RL updates are policy-dependent, a local policy can also change the future data it observes through its own actions. This feedback loop can amplify the divergence across clients [5, 9]. Therefore, aggregation instability may appear as oscillatory convergence, high update variance, conflicting update directions, or inconsistent policy performance across clients. In Edge-IoT FRL, such instability should also be interpreted through deployment indicators, including delay violations, energy overuse, queue instability, and SLA degradation. A policy that improves the average reward but repeatedly violates operational constraints is not necessarily suitable for deployment [2, 11]. This implies that static weighting or participation-based averaging is too limited for heterogeneous Edge-IoT FRL. The server requires aggregation-relevant signals that describe whether each client update is stable across rounds, directionally reliable, resource-supported, and feasible under local constraints. This is the basis for the feasibility-sensitive client influence regulation.

6. CONSTRAINT-AWARE REINFORCEMENT LEARNING AND FEASIBILITY REQUIREMENTS

Constraint-aware Reinforcement Learning is necessary when reward maximization does not fully describe the quality of a policy. In Edge-IoT systems, a policy may improve the average reward while still violating delay limits, consuming excessive energy, increasing queue congestion, or failing to satisfy service-level requirements. Constrained Markov Decision Processes formalize this reward–cost trade-off, whereas safe policy optimization methods provide tools for improving policies under operational or safety constraints [13, 14]. In FRL, constraint handling is more complicated because feasibility is not uniform across the clients. One edge client may be mainly latency-constrained, another may be limited by residual energy, and another may suffer from queue instability or SLA violations. Recent safe RL literature also shows that constraint formulations vary considerably across application domains, which means that feasibility assumptions must be stated clearly when policies are learned and evaluated under operational requirements [15]. The difficulty is that local constraint-aware learning does not automatically make aggregation feasibility aware. A client may train with constraints in its local objective, but its update can still be produced during temporary violations, unstable workload conditions or poor resource availability. If the server aggregates that update without considering their feasibility context, the resulting global policy may still inherit the influence of constraint-violating behavior. This distinction is central to the argument presented in this study. Local constraint handling determines whether a client can learn a feasible policy in its environment. Feasibility-sensitive aggregation asks a different question: how much influence should the client's update have on the global policy? From this perspective, delay compliance, energy budget satisfaction, queue stability, and SLA fulfillment are not only evaluation metrics, but also potential aggregation signals. In heterogeneous Edge-IoT FRL, feasibility information can help the server distinguish between updates that are useful for learning and those that are suitable for deployment. Stable and feasible clients may be assigned a stronger influence, whereas updates associated with repeated violations or unstable operating conditions may be attenuated. This provides a conceptual basis for coupling local constraint feasibility with global client influence regulation.

7. ADAPTIVE, RELIABILITY-AWARE, AND RESOURCE-AWARE AGGREGATION MECHANISMS

Adaptive aggregation has become an important response to heterogeneity in Federated Learning. Unlike static averaging, which usually relies on uniform or data-size-based weights, adaptive methods attempt to regulate client influence using additional indicators, such as update quality, reliability, fairness, contribution history, or robustness. This reflects a broader view of aggregation: it is not only a parameter-combination step but also a way to control how heterogeneous clients shape global learning [12, 16]. Reliability-aware aggregation focuses on whether a client update is dependable enough to influence the global model. Reliability may be reflected in update consistency, directional agreement, local performance, communication dependability or contribution stability across rounds. This is especially relevant in mobile edge and resource-constrained environments, where client availability, communication quality, and resource status may change from one round to another [17]. Resource-aware aggregation shifts attention to the conditions under which the updates are produced. Edge and IoT clients may differ in terms of CPU capacity, bandwidth, memory, residual energy, queue pressure, and participation reliability. These differences affect local training quality and communication timeliness; therefore, resource-aware FL methods often consider device capability and network conditions during client selection or aggregation weighting [18, 19]. However, these aggregation mechanisms remain only partially sufficient for heterogeneous Edge-IoT FRL. Many of these were designed for supervised FL, where updates are derived from local datasets and loss functions. In FRL, an update is shaped by environmental interaction, transition dynamics, reward feedback, exploration behavior, and constraint satisfaction. Indicators such as local loss, contribution history, or communication reliability, therefore, capture only part of the update's deployment relevance. Second, reliability does not necessarily imply feasibility. A client update may be directionally consistent or numerically reliable, while still being associated with delay violations, energy overuse, queue instability, or SLA degradation. Therefore, for Edge-IoT FRL, aggregation should combine learning-oriented indicators with deployment-oriented feasibility signals rather than relying on reliability, resources, or local performance alone. These limitations motivate a multi-criteria view of data aggregation. Future Edge-IoT FRL mechanisms should evaluate client updates using update stability, reliability, resource availability, and constraint feasibility. The aim is not to exclude all difficult clients or to assign equal influence to all participants but to regulate client influence so that unstable or infeasible updates are attenuated while useful diversity is preserved in federated policy learning.

8. COMPARATIVE TAXONOMY AND RESEARCH GAP POSITIONING

The reviewed literature shows that aggregation stability and feasibility-sensitive aggregation in Edge-IoT FRL sit at the intersection of several research areas. Heterogeneous FL explains why client drift and update variances degrade global learning. FRL explains why policy updates are more environment-dependent than supervised FL updates. Constrained RL clarifies why operational feasibility cannot be reduced to reward maximization. Adaptive aggregation shows that client influence need not be static. However, these streams are still only partially connected when the problem is viewed from the perspective of Edge-IoT FRL aggregation [8, 9, 13]. Table 1 summarizes these research streams and their limitations for Edge-IoT FRL. The purpose of this taxonomy is not to separate the fields rigidly but to show how each stream contributes one part of the problem while leaving some aspects unresolved. In particular, none of the streams alone provides a complete view of how update stability, update reliability, resource availability, and constraint feasibility should jointly affect the aggregation influence.

The taxonomy suggests that the gap is not caused by the absence of relevant research but by the way the relevant pieces remain disconnected. Conventional and heterogeneity-aware FL explain the risks of static aggregation under non-IID and system heterogeneity. FRL extends collaborative learning to policy optimization but often inherits aggregation assumptions from supervised FL. Constrained RL supports feasibility-aware policy learning; however, its feasibility signals are usually treated locally. Adaptive aggregation improves client weighting but often relies on limited criteria rather than a combined learning-and-deployment view [10–12]. Table 2 presents representative studies rather than an exhaustive list. The studies are arranged to help the reader follow the development from FL foundations, to FRL, constrained learning, adaptive aggregation, resource-aware FL, and recent FRL extensions. This organization is intended to clarify how each study contributes to the literature and why the specific problem of feasibility-sensitive aggregation in Edge-IoT FRL remains open.

The comparison shows that existing studies provide valuable but incomplete information. FL methods establish averaging and drift-control principles, FRL studies extend collaborative learning to policy optimization, constrained RL provides formal feasibility modeling, and adaptive aggregation introduces non-static client weighting. A unified aggregation mechanism in which update stability, update reliability, resource availability, and constraint feasibility jointly determine client influence in heterogeneous Edge-IoT FRL [9, 12, 23] is still missing.

Table 3 translates the comparative discussion into focused research-gap positioning. It identifies the limitations that are most relevant to Edge-IoT FRL and connects each limitation to the required research direction.

Overall, the main gap is not simply the lack of FL, FRL, constrained RL, or adaptive aggregation techniques in the literature. This gap lies in the absence of an aggregation-oriented perspective that evaluates local policy updates according to both learning behavior and deployment feasibility. In heterogeneous Edge-IoT FRL,

Table 1. Comparative Taxonomy of Related Research Streams

Research Stream	Main Focus	Limitation for Edge-IoT FRL
Conventional Federated Learning	Distributed model training without sharing raw local data.	Does not address policy learning or non-IID transition dynamics.
Heterogeneity-Aware Federated Learning	Reducing client drift and convergence degradation under non-IID and systems heterogeneity.	Mainly designed for supervised or prediction-oriented FL rather than FRL.
Federated Reinforcement Learning	Distributed policy learning through local environment interaction and federated policy aggregation.	Aggregation stability is not always treated as a central methodological objective.
Constrained and Safe Reinforcement Learning	Policy learning under operational, safety, or resource-related constraints.	Feasibility is usually handled at the local policy level, not as a direct aggregation signal.
Adaptive and Reliability-Aware Aggregation	Adjusting client influence according to reliability, fairness, robustness, or update quality.	Often lacks direct feasibility-sensitive aggregation for FRL under Edge-IoT heterogeneity.
Resource-Aware Edge Federated Learning	Learning under communication, computation, energy, and participation limitations.	Often does not model FRL-specific transition dynamics or policy feasibility.
Stability-Aware and Feasibility-Sensitive FRL	Regulating client influence under heterogeneous Edge-IoT FRL using learning- and deployment-oriented indicators.	An emerging research direction that requires deeper methodological development.

aggregation should therefore move beyond passive averaging toward stability-aware and feasibility-sensitive client-influence regulation.

9. ILLUSTRATIVE CASE STUDY: EDGE-IOT TASK OFFLOADING UNDER HETEROGENEOUS CLIENT CONDITIONS

To make the identified gap more concrete, this section uses task offloading as an illustrative edge IoT scenario. The aim is not to report experimental results but to show how heterogeneity can affect local policy updates and, in turn, global aggregation behavior. Task offloading is a useful example because each decision must balance the delay, energy consumption, queue behavior, and service-level requirements under changing workload and resource conditions [1, 2]. In this scenario, each client learns a local policy to decide whether a task should be processed locally, offloaded to an edge server, or scheduled under resource constraints. The local state may include the queue length, CPU availability, bandwidth condition, residual energy, task size, and latency requirement. Although clients participate in the same FRL process, they may experience different transition dynamics and reward–cost trade-offs [9, 22]. Static aggregation may obscure these differences. An update produced under a bursty workload, low residual energy, weak connectivity, or repeated SLA violations may influence the global policy in the same way as an update produced under stable and resource-supported conditions. This is precisely where feasibility-sensitive aggregation becomes relevant: the aggregation weight should reflect not only whether a client participated, but also the stability and feasibility of the update it produces.

To further clarify the idea of client influence regulation, Table 5 provides a simple hypothetical numerical example. The values were normalized between 0 and 1, where higher values indicated better update stability, update reliability, resource availability, or constraint feasibility. The example is not intended as an experimental result but as an illustrative explanation of how feasibility-sensitive aggregation may reduce the influence of clients associated with higher delays or SLA violations. Let the client score be computed as:

$$Score_i = \frac{Stability_i + Reliability_i + Resource_i + Feasibility_i}{4} \tag{2}$$

Then, the aggregation weight of client iis normalized as:

$$\text{Weight}_i = \frac{\text{Score}_i}{\sum_{j=1}^{N} \text{Score}_j} \tag{3}$$

where $N$is the total number of participating clients in the aggregation round.

In this illustrative trace, the client with repeated SLA violations is not removed from the aggregation, but its influence is reduced from an equal-weighting baseline of 0.25 to 0.15. In contrast, the stable client receives a stronger influence because its update is more stable, reliable, resource-supported and feasible. This example shows how feasibility-sensitive aggregation can attenuate constraint-violating updates while preserving participation diversity. This scenario illustrates why uniform or data-size-based weighting is limited in Edge-IoT FRL. A client may generate many local interactions but still produce an unstable or infeasible update if its environment is under severe resource pressure or if there is repeated constraint violation. Conversely, clients with fewer interactions may provide more stable and feasible updates. Therefore, aggregation should account for update stability, update reliability, resource availability,

Table 2. Comparative Summary of Representative Studies

Study	Research Focus	Aggregation / Stability Aspect	Constraint / Resource Aspect	Key Limitation for Edge-IoT FRL
McMahan et al. [7]	Federated Learning / FedAvg	Introduced communication-efficient averaging of client updates.	Does not explicitly model operational resources or feasibility.	Static aggregation; not designed for policy learning or transition heterogeneity.
Kairouz et al. [8]	FL foundations and open problems	Discusses heterogeneity, scalability, communication, robustness, and open FL challenges.	Addresses systems heterogeneity broadly.	Survey-level treatment; does not provide FRL-specific aggregation.
Qi et al. [9]	FRL techniques and applications	Identifies aggregation as a challenge in distributed policy learning.	Discusses FRL applications, but not feasibility-coupled aggregation.	Does not provide a unified stability- and feasibility-sensitive aggregation mechanism.
Li et al. [10]	Heterogeneity-aware FL / FedProx	Reduces local divergence under heterogeneous federated optimization.	Considers statistical and systems heterogeneity.	Designed for supervised FL, not sequential policy learning.
Achiam et al. [11]	Constrained policy optimization	Not designed for federated aggregation.	Supports safe policy improvement under cost constraints.	Does not regulate client influence in distributed FRL.
He et al. [12]	Adaptive aggregation in FL	Adjusts aggregation weights adaptively using an RL-based perspective.	Not primarily designed around Edge-IoT constraints.	Focuses on FL rather than FRL with transition dynamics and feasibility signals.
Altman [13]	CMDP foundation	Not an aggregation method.	Provides formal reward–cost modeling for constrained decision-making.	Supports local feasibility modeling but not federated aggregation.
Huang et al. [15]	Reliable and fair FL for MEC	Considers reliability-aware and fairness-oriented client contribution.	Related to resource-constrained MEC environments.	Does not jointly model FRL update stability and constraint feasibility.
Mughal et al. [17]	Adaptive FL for resource-constrained IoT	Addresses adaptive learning and edge intelligence for resource-constrained devices.	Considers resource limitations in IoT environments.	Does not focus on FRL policy-update feasibility.
Karimireddy et al. [18]	Client drift mitigation / SCAFFOLD	Uses control variates to reduce client drift under non-IID data.	Does not model Edge-IoT operational constraints.	Does not address FRL transition dynamics or feasibility-sensitive aggregation.
Zhuo et al. [19]	Early FRL formulation	Enables collaborative policy learning across distributed agents.	Limited treatment of Edge-IoT resources and constraints.	Aggregation remains relatively conventional.
Chen et al. [20]	FRL for MEC task offloading	Applies federated policy learning to edge decision-making.	Considers task offloading and resource allocation objectives.	Aggregation stability under non-IID transition dynamics is not central.
Jin et al. [21]	Constrained FRL	Connects distributed policy learning with constrained decision-making.	Explicitly considers constraints in distributed RL.	Feasibility is not fully transformed into a direct aggregation-weighting signal.
Sagar et al. [22]	Adaptive FRL for hierarchical IoT	Applies FRL to resource allocation and task scheduling.	Relevant to hierarchical IoT resource management.	Does not explicitly formulate aggregation as feasibility-sensitive client influence regulation.
Jing et al. [23]	Federated multi-agent RL survey	Reviews distributed multi-agent policy learning methods and challenges.	Discusses heterogeneous agents and application contexts.	Survey-level contribution; does not provide a specific Edge-IoT feasibility-sensitive aggregation rule.

and constraint feasibility. The broader implication is that resource and feasibility conditions should not remain isolated from local policy learning. They should also inform how much influence each client has during global policy formation. This supports a more stable, interpretable, and deployment-aware view of FRL in heterogeneous edge IoT systems.

10. OPEN CHALLENGES AND FUTURE RESEARCH DIRECTIONS

The review and comparative analysis suggest that stability-aware and feasibility-sensitive aggregation remains an emerging direction in Edge-IoT FRL. Heterogeneous FL, FRL, constrained RL, and adaptive aggrega-

Table 3. Research Gap Positioning

Gap Area	Current Limitation	Required Research Direction
Static Aggregation	Uniform or data-size-based aggregation ignores update quality, update stability, and operational feasibility.	Develop adaptive aggregation mechanisms that regulate client influence according to contribution quality.
FRL Heterogeneity	Many FRL methods do not fully account for non-IID transition dynamics, reward heterogeneity, and environment-dependent policy updates.	Develop aggregation-aware treatment of transition, reward, and environment heterogeneity in FRL.
Local Constraint Handling	Constraints are often handled only during local policy learning or reward design.	Propagate local feasibility signals into aggregation weight computation.
Single-Criterion Weighting	Reliability-only, resource-only, or feasibility-only weighting may capture only one aspect of client contribution quality.	Use multi-criteria aggregation based on update stability, update reliability, resource availability, and constraint feasibility.
Reward-Centric Evaluation	Average reward may hide oscillatory convergence, high update variance, cross-client inconsistency, and operational violations.	Evaluate reward together with convergence smoothness, update variance, constraint violations, SLA satisfaction, scalability, and communication cost.
Limited Interpretability	Aggregation weights may be difficult to explain when they are based on opaque or single-source indicators.	Use component-based client evaluation to make aggregation behavior more interpretable.
Deployment Gap	Simulation metrics may not fully reflect real Edge-IoT resource constraints, partial participation, and operational feasibility.	Use trace-driven simulation, digital-twin environments, or real testbed validation where possible.

Table 4. Illustrative Edge-IoT Task Offloading Scenario under Heterogeneous Client Conditions

Client Condition	Local Operating Context	Possible Update Behavior	Aggregation Implication
Stable Resources	Moderate workload, sufficient CPU capacity, stable bandwidth, and acceptable residual energy.	Produces a relatively stable and reliable policy update.	May receive stronger aggregation influence if the update remains aligned with the global learning direction.
Low Residual Energy	Limited battery level and reduced ability to perform local computation or frequent communication.	May bias the local policy toward energy-saving or aggressive offloading behavior.	Aggregation weight should consider energy status, communication capability, and participation reliability.
Bursty Workload	Rapid task arrivals, temporary queue congestion, and variable workload pressure.	May produce a noisy or highly reactive policy update.	Aggregation influence should be reduced when update instability or queue violation is high.
Weak Connectivity	Unstable wireless link, delayed communication, or intermittent participation during federated rounds.	May produce stale, delayed, incomplete, or weakly representative updates.	Aggregation should account for communication reliability, update freshness, and possible staleness.
Constraint Violations	Frequent delay, energy, queue, or SLA-related violations during local policy execution.	May generate updates that improve local reward but remain operationally infeasible.	Constraint feasibility should directly influence aggregation weight computation.

tion each provide part of the foundation, but they are not yet fully integrated into deployment-aware aggregation mechanisms for heterogeneous policy learning [9, 12, 23].

10.1. Stability-Aware Aggregation under Non-IID Transition Dynamics

The first challenge is to make non-IID transition dynamics visible to the aggregation process. Future methods need indicators that capture whether local policy updates are temporally stable and directionally consistent across communication rounds. Without such indicators, global training may suffer from oscillatory convergence, high update variance, and unstable behavior caused by incompatible client environments [9, 23].

10.2. Constraint-to-Aggregation Coupling

The second challenge is the weak connection between local feasibility and aggregation influence. Delay compliance, energy budget satisfaction, queue stability, and SLA fulfillment are often used as local metrics, but they

Table 5. Hypothetical Numerical Trace for Feasibility-Sensitive Client Influence Regulation

Client Condition	Update Stability	Update Reliability	Resource Availability	Constraint Feasibility	Client Score	Normalized Weight
Stable resources	0.90	0.88	0.86	0.96	0.90	0.35
Moderate delay pressure	0.78	0.76	0.73	0.70	0.74	0.29
Bursty workload	0.62	0.66	0.58	0.42	0.57	0.22
Repeated SLA violations	0.55	0.50	0.35	0.15	0.39	0.15

rarely regulate how strongly a client update shapes the global policy. Therefore, future FRL methods should propagate feasibility signals to the aggregation layer [13, 14, 21].

10.3. Multi-Criteria Client Evaluation

Single-criterion weighting is unlikely to be reliable in heterogeneous Edge-IoT FRL systems. Reliability-only, resource-only, or feasibility-only weighting may improve one dimension while ignoring another. A more robust approach is to evaluate clients using multiple indicators, including update stability, update reliability, resource availability, and constraint feasibility [12, 15, 17].

10.4. Resource-Aware and Energy-Aware FRL

Resource variability is unavoidable in practical Edge-IoT systems. Clients may face limited energy, variable bandwidth, intermittent connectivity, dropouts, or delayed updates. Therefore, stability-aware aggregation needs to be extended to asynchronous or semi-synchronous FRL, where clients may participate irregularly or submit stale updates under changing resource conditions [17, 22].

10.5. Privacy-Preserving Indicator Reporting

Feasibility-sensitive aggregation may require clients to report additional information on stability, reliability, resources, and constraint satisfaction. These indicators can improve aggregation decisions, but they may also reveal the operational patterns. Future work should examine secure aggregation, privacy-preserving metric reporting, compression, and quantization so that additional indicators do not create excessive communication or privacy costs [7].

10.6. Benchmarking and Deployment Validation

Finally, the field requires stronger evaluation protocols. Many Edge-IoT FRL studies still rely on simplified simulation settings that may not capture workload heterogeneity, transition dynamics, resource constraints, partial participation, or feasibility requirements. Trace-driven simulations, digital twin environments, and real testbeds would make evaluations more reproducible and deployment-relevant [1, 2, 23]. Future work may also investigate the use of metaheuristic and swarm-intelligence optimization methods, such as Particle Swarm Optimization (PSO), to tune the parameters of multi-criteria aggregation in Edge-IoT FRL. In sensor-driven IoT systems, PSO has been used to optimize control parameters by exploiting sensor feedback, such as in PID-PSO-based smart-irrigation systems. By analogy, PSO or related optimization methods can be explored to adjust the relative importance of update stability, update reliability, resource availability, and constraint feasibility when computing aggregation weights. However, such optimization should be evaluated carefully under FRL-specific requirements, including convergence stability, communication overhead, privacy of reported indicators, and satisfaction of operational constraints. [24] These challenges point to the same conclusion: Edge IoT FRL requires aggregation methods that are both learning- and deployment-aware. Static or single-indicator aggregation is unlikely to be sufficient when clients differ in their dynamics, resources, and feasibility. The next step is to design mechanisms that regulate client influence while remaining scalable, interpretable, privacy-aware and experimentally reproducible.

11. CONCLUSION

This study examined stability-aware and feasibility-sensitive aggregation in federated reinforcement learning for edge IoT systems. The review was motivated by a specific limitation in current FRL research: aggregation is often treated as a routine model-combination step, although local policy updates in Edge-IoT environments are shaped by heterogeneous transition dynamics, workload, resource conditions, communication reliability, and operational constraints. The reviewed literature shows that several research streams contribute to this problem, but none of them fully resolve it alone. Heterogeneity-aware FL explains why client drift and system diversity

Table 6. Open Challenges and Future Research Directions

Open Challenge	Research Need	Expected Benefit
Non-IID Transition Dynamics	Develop stability-aware aggregation metrics for policy updates generated under heterogeneous transition dynamics.	Smoother global policy learning and lower update variance.
Constraint-to-Aggregation Coupling	Use local feasibility signals as direct aggregation indicators, including delay, energy, queue, and SLA compliance.	Lower influence of constraint-violating updates on the global policy.
Multi-Criteria Client Evaluation	Combine update stability, update reliability, resource availability, and constraint feasibility in client evaluation.	More balanced, interpretable, and deployment-aware aggregation.
Resource and Participation Variability	Support asynchronous, semi-synchronous, and staleness-aware FRL under variable resources and partial participation.	Better scalability and robustness under realistic Edge-IoT conditions.
Privacy of Client Indicators	Develop secure, compressed, or privacy-preserving reporting of stability, reliability, resource, and feasibility indicators.	Safer deployment with reduced privacy risk and lower communication overhead.
Benchmarking and Validation	Use trace-driven simulation, digital-twin environments, and real testbeds for heterogeneous Edge-IoT FRL evaluation.	More reproducible, realistic, and deployment-relevant validation.

can destabilize global learning. The FRL extends collaboration to distributed policy optimization. Constrained and safe RL provides formal tools for feasibility-aware policy learning. Adaptive aggregation improves static averaging. However, these streams do not fully explain how local instability, resource pressure, and constraint violations should affect global client influence in Edge-IoT FRL. The main gap identified in this study is the weak coupling between local feasibility and global aggregation. In many existing approaches, constraints such as delay, energy consumption, queue stability, and SLA satisfaction are handled mainly through local policy learning or reward designs. When these signals remain outside the aggregation process, unstable, resource-limited, or constraint-violating updates may influence the global policy. Therefore, future Edge-IoT FRL systems should treat aggregation as adaptive client influence regulation rather than passive averaging. Local updates must be evaluated using both learning-oriented indicators, such as update stability and update reliability, and deployment-oriented indicators, such as resource availability and constraint feasibility. This direction can support more stable, interpretable, scalable, and deployment-aware federated policy learning under heterogeneous edge IoT conditions. As this study is a review and research-positioning study, it does not claim experimental quantitative improvements over existing FRL aggregation methods. However, the comparative analysis indicates that future stability-aware and feasibility-sensitive aggregation mechanisms should be evaluated quantitatively against representative baselines, such as FedAvg, reliability-only adaptive aggregation, resource-only aggregation, and constraint-aware local policy learning without aggregation-level feasibility coupling. Relevant comparison metrics may include convergence smoothness, update variance, delay violation rate, energy constraint violation rate, queue stability, SLA satisfaction, communication overhead, and normalized client-weight distribution. These metrics can help determine whether multi-criteria client influence regulation provides measurable improvements in both learning stability and deployment feasibility under heterogeneous Edge-IoT conditions.

12. DECLARATIONS

12.1. Ethical Approval:

This study did not involve any experiments on humans or animals. This is a review and research-positioning paper based on the previously published literature. Therefore, ethical approval was not required for this study.

12.2. Conflict of Interest:

The authors declare that they have no conflict of interest.

12.3. Competing Interests:

The authors declare that they have no financial or proprietary interest in any material discussed in this article.

12.4. Authors' Contributions:

All authors contributed to the conception, design, literature review, analysis, discussion, and preparation of the manuscript. All authors have reviewed and approved the final version of the manuscript.

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12.6. Availability of Data and Materials:

No new datasets were generated or analyzed in this study. This paper is based on previously published literature, and all cited sources are listed in the references.

12.7. Consent for Publication

All authors have read and approved the final manuscript and consent to its publication.

12.8. Consent to Participate

Not applicable, as this study did not involve human participants.

12.9. Declaration of AI-Assisted Technologies:

The authors declare that artificial intelligence (AI) tools were used only for limited purposes, including language editing, grammar improvement, formatting assistance, and manuscript consistency checking. The authors reviewed and verified all the scientific content, interpretations, conclusions, citations, and final revisions. The authors take full responsibility for the integrity, accuracy, and originality of this work.

REFERENCES

[1] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," *IEEE Internet Things J.*, vol. 3, no. 5, pp. 637–646, 2016. DOI: 10.1109/JIOT.2016.2579198.

[2] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Commun. Surv. & Tutorials*, vol. 19, no. 4, pp. 2322–2358, 2017. DOI: 10.1109/COMST.2017.2745201.

[3] M. A. Al-Hadi, G. H. Al-Gaphari, I. A. Al-Baltah, and F. B. Julian, "A promising smart healthcare monitoring model based on internet of things and deep learning techniques," *Sana'a Univ. J. Appl. Sci. Technol.*, vol. 2, no. 2, pp. 147–153, 2024. DOI: 10.59628/jast.v2i2.811.

[4] H. H. Al-Hamadi, I. A. Al-Baltah, and N. A. Al-shaibany, "Survey on intelligent anomaly detection techniques in iot security," *Sana'a Univ. J. Appl. Sci. Technol.*, vol. 4, no. 1, pp. 1596–1621, 2026. DOI: 10.59628/jast.v4i1.2234.

[5] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*, 2nd ed. Cambridge, MA, USA: MIT Press, 2018. [Online]. Available: https://incompleteideas.net/book/the-book-2nd.html.

[6] A. A. Alshamiri and G. H. Al Gaphari, "Smart cybersecurity strategies based on deep reinforcement learning: A literature review," *Sana'a Univ. J. Appl. Sci. Technol.*, vol. 4, no. 4, pp. 2025–2033, 2026. DOI: 10.59628/d80zj848.

[7] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Artificial Intelligence and Statistics*, PMLR, 2017, pp. 1273–1282. [Online]. Available: https://proceedings.mlr.press/v54/mcmahan17a.

[8] P. Kairouz and H. B. McMahan, "Advances and open problems in federated learning," *Found. Trends Mach. Learn.*, vol. 14, no. 1–2, pp. 1–210, 2021. DOI: 10.1561/2200000083.

[9] J. Qi, Q. Zhou, L. Lei, and K. Zheng, "Federated reinforcement learning: Techniques, applications, and open challenges," *arXiv preprint arXiv:2108.11887*, 2021. DOI: 10.20517/ir.2021.02.

[10] T. Li, A. K. Sahu, M. Zaheer, M. Sanjabi, A. Talwalkar, and V. Smith, "Federated optimization in heterogeneous networks," *Proc. Mach. Learn. Syst.*, vol. 2, pp. 429–450, 2020. [Online]. Available: https://proceedings.mlsys.org/paper/2020/hash/1f5fe83998a09396ebe6477d9475ba0c-Abstract.html.

[11] J. Achiam, D. Held, A. Tamar, and P. Abbeel, "Constrained policy optimization," in *International Conference on Machine Learning*, PMLR, 2017, pp. 22–31. [Online]. Available: https://proceedings.mlr.press/v70/achiam17a.html.

[12] J. He, W. Chen, and X. Zhang, "Fedaa: A reinforcement learning perspective on adaptive aggregation for fair and robust federated learning," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 39, 2025, pp. 17 085–17 093. DOI: 10.1609/aaai.v39i16.33878.

[13] E. Altman, *Constrained Markov Decision Processes*. Boca Raton, FL, USA: CRC Press, 1999. DOI: 10.1201/9781315140223.

[14] A. Wachi, X. Shen, and Y. Sui, "A survey of constraint formulations in safe reinforcement learning," *arXiv preprint arXiv:2402.02025*, 2024. DOI: 10.48550/arXiv.2402.02025.

[15] X. Huang, L. Han, D. Li, K. Xie, and Y. Zhang, "A reliable and fair federated learning mechanism for mobile edge computing," *Comput. Networks*, vol. 226, p. 109 678, 2023. DOI: 10.1016/j.comnet.2023.109678.

[16] L. U. Khan et al., "Federated learning for edge networks: Resource optimization and incentive mechanism," *IEEE Commun. Mag.*, vol. 58, no. 10, pp. 88–93, 2020. DOI: 10.1109/MCOM.001.1900649.

[17] F. R. Mughal et al., "Adaptive federated learning for resource-constrained iot devices through edge intelligence and multi-edge clustering," *Sci. Reports*, vol. 14, no. 1, p. 28 746, 2024. DOI: 10.1038/s41598-024-78239-z.

[18] S. P. Karimireddy, S. Kale, M. Mohri, S. Reddi, S. Stich, and A. T. Suresh, "Scaffold: Stochastic controlled averaging for federated learning," in *International Conference on Machine Learning*, PMLR, 2020, pp. 5132–5143. [Online]. Available: http://proceedings.mlr.press/v119/karimireddy20a.html.

[19] H. H. Zhuo, W. Feng, Y. Lin, Q. Xu, and Q. Yang, "Federated deep reinforcement learning," *arXiv preprint arXiv:1901.08277*, 2019. DOI: 10.48550/arXiv.1901.08277.

[20] X. Chen and G. Liu, "Federated deep reinforcement learning-based task offloading and resource allocation for smart cities in a mobile edge network," *Sensors*, vol. 22, no. 13, p. 4738, 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/13/4738.

[21] H. Jin, L. Zhang, and Z. Zhang, "Federated reinforcement learning with constraint heterogeneity," *arXiv preprint arXiv:2405.03236*, 2024. DOI: 10.48550/arXiv.2405.03236.

[22] A. S. M. Sharifuzzaman Sagar, A. Haider, and H. S. Kim, "A hierarchical adaptive federated reinforcement learning for efficient resource allocation and task scheduling in hierarchical iot network," *Comput. Commun.*, vol. 229, p. 107 969, 2025. DOI: 10.1016/j.comcom.2024.107969.

[23] Y. Jing, B. Guo, N. Li, R. Xu, and Z. Yu, "Federated multi-agent reinforcement learning: A comprehensive survey of methods, applications and challenges," *Expert Syst. with Appl.*, vol. 293, p. 128 729, 2025. DOI: 10.1016/j.eswa.2025.128729.

[24] S. Oleiwi, H. Khaleel, R. Khaleel, M. M. Msallam, and A. Humaidi, "Smart iot irrigation system using pid-pso optimization method," *Adv. Technol. Innov.*, vol. 11, pp. 70–78, 2026. DOI: 10.46604/aiti.2026.15357.