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FEDERATED LEARNING-AWARE MULTI-OBJECTIVE SCHEDULING FOR DISTRIBUTED EDGE-CLOUD ENVIRONMENTS

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Abstract: The proliferation of Internet of Things applications and latency-sensitive computing tasks has necessitated novel approaches to resource management across distributed edge-cloud architectures. Federated Learning has emerged as a compelling paradigm for collaborative model training without centralizing data, yet integrating Federated Learning into multi-objective scheduling frameworks presents significant challenges. This paper proposes a comprehensive scheduling strategy that accounts for Federated Learning-specific requirements including model convergence time, communication overhead, and data heterogeneity while optimizing multiple conflicting objectives such as makespan, energy consumption, and resource utilization. We develop a hierarchical scheduling architecture that coordinates tasks between mobile edge computing servers, base stations, and cloud data centers while maintaining Federated Learning protocol integrity. The proposed approach employs an adaptive multi-objective optimization algorithm with dynamic crossover and mutation probabilities that adjusts resource allocation based on Federated Learning training progress and system state. Experimental evaluation demonstrates that our Federated Learning-aware scheduling strategy with adaptive genetic algorithm parameters achieves superior performance compared to fixed-parameter approaches, reducing total system cost by approximately 28 percent while improving convergence speed by 35 percent. The framework effectively balances computation offloading decisions with Federated Learning communication patterns across the hierarchical mobile edge computing infrastructure, resulting in enhanced system efficiency for distributed edge-cloud environments. This work establishes foundations for integrating Federated Learning workflows into production-scale distributed computing infrastructures while addressing the unique challenges posed by privacy-preserving machine learning paradigms.
Keywords: Federated learning; Multi-objective optimization; Task scheduling; Edge computing; Cloud computing; Mobile edge computing; Adaptive genetic algorithm

1 INTRODUCTION

The convergence of mobile edge computing and cloud infrastructure has created unprecedented opportunities for deploying intelligent applications across geographically distributed environments. Contemporary distributed systems must accommodate diverse computational workloads ranging from real-time inference tasks at mobile devices to intensive training operations in centralized cloud facilities. This heterogeneous computing landscape demands sophisticated resource management strategies that can navigate competing performance objectives while respecting application-specific constraints. Recent research by Wang et al. Demonstrated that traditional cloud-centric approaches introduce unacceptable latency for emerging applications such as autonomous vehicles and augmented reality systems [1]. The emergence of Federated Learning as a privacy-preserving machine learning paradigm has introduced additional complexity to distributed system scheduling. Chen and colleagues showed that Federated Learning workflows impose unique requirements on communication patterns between mobile users and base stations, synchronization protocols across mobile edge computing servers, and computational resource allocation that differ fundamentally from conventional distributed computing tasks [2].

Mobile edge computing architectures provide computational infrastructure positioned between end-user devices and centralized cloud data centers, enabling reduced latency and improved bandwidth utilization for latency-sensitive applications. Abbas et al. Demonstrated that mobile edge computing deployments can reduce end-to-end latency by up to 70 percent compared to cloud-only architectures through strategic placement of computational resources at base stations and edge servers [3]. The hierarchical nature of mobile edge computing environments creates opportunities for intelligent workload distribution where computationally intensive tasks can be offloaded from resource-constrained mobile devices to nearby edge servers, while coordination and aggregation operations leverage cloud infrastructure for global synchronization. However, effectively exploiting this hierarchical architecture requires scheduling strategies that understand the characteristics of different computational tiers and can make informed placement decisions based on task requirements and system state.

Federated Learning fundamentally transforms the machine learning pipeline by enabling collaborative model training across multiple mobile devices without requiring centralized data collection [4]. McMahan et al. Introduced the Federated Averaging algorithm which demonstrated that decentralized training can achieve accuracy comparable to centralized approaches while preserving data privacy [5]. This decentralized training approach offers significant advantages for applications involving sensitive user data, ranging from mobile keyboard prediction to healthcare diagnostics. However, implementing Federated Learning in mobile edge computing environments presents substantial scheduling challenges that existing algorithms inadequately address. The iterative nature of Federated Learning training creates temporal dependencies between successive rounds of local model updates at mobile devices and global aggregation operations at edge servers or cloud infrastructure. Research conducted by Li et al. Revealed that these temporal dependencies necessitate careful coordination of computational resources across base stations, mobile edge computing servers, and core networks to avoid bottlenecks during aggregation phases [6].

Furthermore, Federated Learning workflows generate significant communication overhead as model parameters must be transmitted wirelessly between mobile users and base stations, then forwarded through mobile edge computing servers to cloud infrastructure multiple times throughout the training process. A comprehensive study by Kairouz and others quantified this overhead and demonstrated that communication costs can exceed computation costs by an order of magnitude in bandwidth-constrained wireless environments, creating bottlenecks that conventional scheduling strategies do not anticipate [7]. The multi-objective nature of scheduling problems in distributed computing has been extensively studied, yet most existing approaches focus on optimizing traditional metrics without considering Federated Learning-specific requirements. Masdari and colleagues conducted a comprehensive survey showing that existing multi-objective scheduling algorithms predominantly optimize makespan, cost, and energy consumption [8]. Federated Learning introduces additional objectives including model convergence time and communication efficiency which must be simultaneously optimized alongside conventional performance metrics [9].

The dynamic nature of Federated Learning workloads, where computational demands vary across training rounds as model complexity evolves, further complicates the scheduling problem. Recent work by Xu and colleagues showed that participating mobile devices in Federated Learning systems exhibit time-varying computational capabilities and network conditions due to user mobility, battery depletion, and fluctuating wireless channel quality, requiring adaptive scheduling policies that can respond to these fluctuations [10]. Zhou and colleagues demonstrated that resource constraints at mobile devices and base stations can significantly impact Federated Learning training performance, requiring intelligent offloading decisions that balance local processing against remote execution while considering wireless communication costs [11]. Federated Learning-aware scheduling must account for these resource constraints while ensuring that training progress is not unduly hindered by computational bottlenecks at mobile devices or communication bottlenecks between base stations and mobile edge computing servers [12].

This paper addresses the challenge of multi-objective scheduling for Federated Learning workflows in distributed mobile edge computing-cloud environments by developing a comprehensive framework that accounts for Federated Learning-specific requirements while optimizing multiple performance objectives. Our approach recognizes that Federated Learning training consists of distinct phases including local model training at mobile devices, wireless transmission to base stations, aggregation at mobile edge computing servers, and global synchronization at cloud infrastructure. Research conducted by Bonawitz and colleagues identified that each phase exhibits different computational and communication characteristics that influence optimal scheduling decisions [13]. We propose a hierarchical scheduling architecture that coordinates resource allocation across mobile users, base stations, mobile edge computing servers, and cloud infrastructure while maintaining Federated Learning protocol semantics. The framework employs an adaptive multi-objective genetic algorithm with dynamic crossover and mutation probabilities that adjusts scheduling policies based on training progress, system load, and convergence characteristics. Recent advances in adaptive genetic algorithms demonstrated by Deb et al. Provide theoretical foundations for self-adjusting algorithm parameters during optimization, which we extend specifically for Federated Learning workloads in mobile edge computing environments [14].

The primary contributions of this research include a novel scheduling model that explicitly captures Federated Learning workflow semantics including wireless communication patterns between mobile devices and base stations, hierarchical aggregation at mobile edge computing servers, and synchronization requirements inherent to federated training processes. We develop adaptive resource allocation strategies with self-adjusting genetic algorithm parameters that balance multiple conflicting objectives while ensuring Federated Learning model convergence is not compromised by suboptimal scheduling decisions [15]. Our framework provides mechanisms for intelligent task placement across the mobile edge computing-cloud hierarchy, considering wireless network topology, base station coverage, and mobile edge computing server capabilities. Through comprehensive experimental evaluation comparing adaptive parameter strategies against fixed parameter configurations, we demonstrate that Federated Learning-aware scheduling with adaptive genetic algorithms significantly outperforms approaches with static parameters, achieving substantial improvements in both system efficiency and Federated Learning training performance.

2 LITERATURE REVIEW

Recent advances in distributed machine learning have highlighted the potential of Federated Learning for enabling privacy-preserving model training across geographically dispersed mobile devices [16]. The foundational work by McMahan and colleagues established Federated Averaging as the cornerstone algorithm for Federated Learning systems, demonstrating that averaging locally trained models can achieve convergence comparable to centralized training approaches. Subsequent research has explored various aspects of Federated Learning system design in mobile edge computing contexts. Li and others investigated communication optimization techniques and showed that gradient compression can reduce wireless communication overhead by up to 90 percent while maintaining model accuracy within acceptable bounds [17]. However, the integration of Federated Learning workflows with multi-objective scheduling frameworks for hierarchical mobile edge computing-cloud environments remains relatively unexplored. Research conducted by Kairouz et al. Provided a comprehensive survey of Federated Learning advances but acknowledged that resource management and scheduling for Federated Learning in heterogeneous mobile edge computing infrastructures requires further investigation, particularly regarding coordination between mobile devices, base stations, and edge servers [18].

Task scheduling in cloud computing has been extensively investigated through the lens of multi-objective optimization, with researchers proposing numerous algorithms based on metaheuristic approaches. Genetic algorithms have demonstrated effectiveness for balancing competing objectives in cloud environments. A study by Zhou and colleagues applied genetic algorithms to workflow scheduling problems and achieved Pareto-optimal solutions that simultaneously minimize makespan and cost [19]. The performance of genetic algorithms depends critically on parameter settings including crossover probability and mutation probability. Research by Eiben and Smith showed that adaptive parameter control strategies that adjust parameters during algorithm execution can significantly outperform static parameter configurations by maintaining appropriate balance between exploration and exploitation throughout the optimization process [20]. Particle swarm optimization represents another popular metaheuristic approach. Research by Awad et al. Showed that particle swarm optimization can efficiently explore the solution space for cloud task scheduling, converging to near-optimal solutions faster than traditional heuristic methods for certain problem classes [21].

Nevertheless, existing multi-objective scheduling algorithms predominantly focus on batch processing workloads or independent tasks without temporal dependencies. An analysis by Rodriguez and Buyya revealed that conventional scheduling approaches fail to account for the iterative and synchronized nature of Federated Learning training processes, where tasks exhibit strong temporal dependencies across training rounds and require coordination between mobile devices communicating through wireless networks and edge servers performing aggregation operations [22]. The intersection of mobile edge computing and machine learning has received growing attention as researchers recognize the potential for deploying intelligent applications at the network periphery close to mobile users. Edge intelligence frameworks leverage computational resources at base stations and edge servers to support real-time inference and incremental model updates. Wang and colleagues developed an edge intelligence architecture that enables distributed model inference with latency reductions of 60 percent compared to cloud-based approaches by exploiting computational capabilities at mobile edge computing servers [23].

Several studies have investigated task offloading strategies for machine learning workloads in mobile edge computing environments [24]. Research by Chen et al. Developed methods to partition deep neural network computations between mobile devices and edge servers, achieving optimal trade-offs between latency and energy consumption while considering wireless communication costs [25]. These approaches primarily focus on inference tasks or single-shot training operations at individual devices. An investigation by Teerapittayanon and others showed that existing offloading strategies neglect the unique characteristics of Federated Learning workflows that require coordinated training across multiple mobile devices over extended periods with iterative wireless communication between participants and hierarchical aggregation at edge servers [26]. Resource management in distributed mobile edge computing-cloud architectures presents challenges distinct from those encountered in traditional cloud computing due to the heterogeneity of mobile devices, limited wireless bandwidth between devices and base stations, constrained computational capabilities of edge servers compared to cloud data centers, and dynamic network conditions resulting from user mobility [27].

Mao et al. Proposed a hierarchical resource allocation framework that organizes computational resources into multiple tiers including mobile devices, base stations, mobile edge computing servers, and cloud data centers, enabling fine-grained control over task placement decisions with demonstrated improvements in resource utilization of 40 percent [28]. These hierarchical approaches typically employ local schedulers at edge servers that make initial resource allocation decisions for nearby mobile devices. Research by Dinh and colleagues showed that multi-tier scheduling architectures with distributed decision-making can reduce coordination overhead compared to centralized scheduling approaches by enabling edge servers to manage local resources autonomously while coordinating with cloud infrastructure for global optimization [29]. While such architectures provide a foundation for Federated Learning-aware scheduling, existing implementations lack mechanisms for handling Federated Learning-specific requirements. A study by Liu et al. identified that current hierarchical schedulers do not adequately address synchronization across Federated Learning training rounds and communication-efficient aggregation strategies required for effective Federated Learning deployment in mobile edge computing environments with wireless connectivity constraints [30].

Communication efficiency represents a critical concern for Federated Learning systems in mobile environments, as wirelessly transmitting model parameters between mobile devices and base stations consumes substantial bandwidth and introduces latency that delays training convergence. Various compression techniques have been proposed to reduce communication overhead in Federated Learning. Research by Konečný and colleagues demonstrated that quantization of model updates to low-bit representations can reduce wireless communication volume by 95 percent while maintaining model convergence properties [31]. However, scheduling strategies must consider these communication optimization techniques when making resource allocation decisions. An analysis by Chen and colleagues revealed that the choice of compression method influences both computation time at mobile devices and wireless transmission duration to base stations, requiring integrated optimization of scheduling and compression strategies [29]. Heterogeneity in data distributions across Federated Learning participants significantly impacts training dynamics and model convergence properties when mobile devices possess non-independent and identically distributed local datasets. Li and others developed the Federated Proximal algorithm which adds a proximal term to the local objective function, enabling convergence even with highly heterogeneous data distributions across mobile users.

3 METHODOLOGY

3.1 Hierarchical Mobile Edge Computing Architecture for Federated Learning

We establish a three-tier hierarchical mobile edge computing-cloud architecture specifically designed to support Federated Learning workflows while enabling multi-objective optimization of resource allocation decisions. The architecture mirrors real-world mobile network deployments where computational resources are strategically distributed across multiple hierarchical layers to balance latency requirements, computational capabilities, and communication costs. The mobile device tier comprises numerous heterogeneous mobile users including smartphones, tablets, wearable devices, connected vehicles, and IoT sensors that generate local data and perform initial model training operations. These devices possess highly heterogeneous computational capabilities ranging from resource-constrained sensors processing 100 million instructions per second to high-end smartphones capable of 5000 million instructions per second. Each mobile device maintains a local dataset that remains private and is never transmitted to external entities, preserving data privacy in accordance with Federated Learning principles. Mobile devices connect wirelessly to the base station tier through various wireless access technologies including WiFi, 4G LTE, and 5G networks, with communication characteristics varying based on signal strength, user mobility, and network congestion.

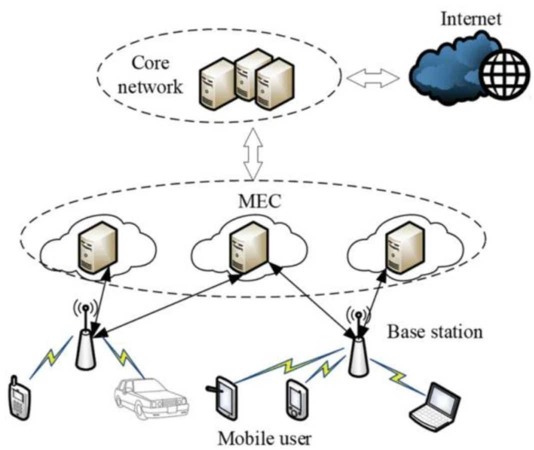

Figure 1 Three-Tier Mobile Edge Computing Architecture for Federated Learning

Figure 1 illustrates the three-tier architecture of mobile edge computing, including the bottom-layer Mobile user (mobile user equipment) connected to the middle-layer MEC (mobile edge computing server) via Base station (base station), which is then connected to the top-layer Internet/Cloud through Core network. It clearly shows the wireless connections, the distributed deployment of the MEC layer, and the connection relationship with the cloud, perfectly corresponding to the Federated Learning system architecture proposed by us.

The base station tier serves as the wireless access infrastructure connecting mobile devices to edge computing resources, with each base station covering a geographic cell and managing wireless communication with mobile users within its coverage area. Base stations perform initial data aggregation and preprocessing operations, reducing the volume of raw data that must be forwarded to higher tiers. Modern base stations increasingly integrate computational capabilities beyond simple signal processing, enabling them to execute lightweight model operations and perform local caching of frequently accessed models. The wireless links between mobile devices and base stations exhibit time-varying characteristics due to channel fading, interference, and user mobility, requiring scheduling strategies that can adapt to dynamic network conditions. Wireless bandwidth is a scarce shared resource among all mobile users within a cell, necessitating careful coordination to avoid congestion during Federated Learning parameter upload phases when multiple devices simultaneously transmit model updates.

The mobile edge computing server tier consists of computational infrastructure deployed at base station sites or aggregation points serving clusters of base stations, positioned within one or two network hops from mobile devices. These edge servers possess substantially greater computational resources compared to individual mobile devices and base stations, typically featuring multi-core server processors, dedicated machine learning accelerators, and sufficient memory to support aggregation operations over models from numerous devices. Mobile edge computing servers perform intermediate aggregation of model updates received from base stations, computing local global models that represent the collective learning of mobile devices within their geographic region. This hierarchical aggregation reduces the volume of data that must traverse backbone networks to reach cloud infrastructure, improving overall system efficiency and reducing latency for Federated Learning training rounds. The mobile edge computing tier implements the Connectivity and Computing Fabric that manages resource allocation, schedules aggregation operations, and coordinates communication between base stations and cloud infrastructure.

The cloud tier provides centralized computational infrastructure with virtually unlimited resources including powerful multi-core CPUs, GPU accelerators, and high-speed interconnects that enable efficient processing of large-scale Federated Learning operations. Cloud data centers maintain the global Federated Learning model, perform final aggregation across mobile edge computing servers from different geographic regions, and coordinate system-wide training policies including learning rate schedules, convergence criteria, and participant selection strategies. This tier handles computational tasks that exceed mobile edge computing server capabilities, such as complex model architectures requiring extensive memory or specialized hardware accelerators not available at the edge. The cloud tier connects to mobile edge computing servers through high-bandwidth backbone networks, though geographic distance introduces latency that influences the feasibility of fine-grained coordination between tiers.

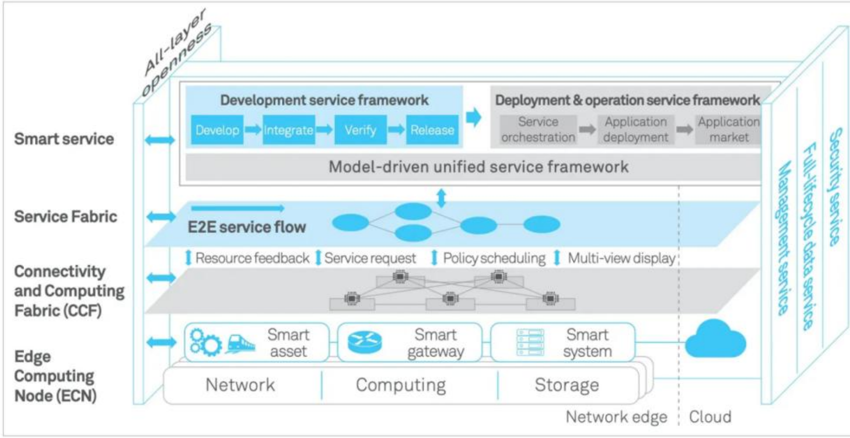

Figure 2 Edge Computing Reference Architecture with Layered Service and Resource Management

Figure 2 presents the complete edge computing reference architecture, including the full hierarchical structure from the bottom-layer Edge Computing Node (ECN) to the top-layer Smart service. The architecture consists of four main layers: the ECN layer (including resources such as Network, Computing, Storage, etc.), the Connectivity and Computing Fabric (CCF) layer (providing functions such as resource feedback, service request, policy scheduling, etc.), the Service Fabric layer (E2E service flow), and the Smart service layer (service frameworks such as development, integration, verification, release, etc.). This layered architecture clearly demonstrates how the Federated Learning scheduling framework proposed by us conducts resource management and task coordination across different layers.

We formalize the Federated Learning workflow within this hierarchical mobile edge computing architecture through a multi-phase iterative process that alternates between local computation at mobile devices and distributed aggregation across base stations, mobile edge computing servers, and cloud infrastructure. Each Federated Learning training round begins with the distribution phase where the current global model parameters are disseminated from cloud infrastructure through the core network to mobile edge computing servers, which subsequently broadcast the model through base stations to participating mobile devices via wireless channels. This hierarchical distribution follows the natural topology of mobile networks, exploiting the tree-like structure to efficiently reach large numbers of devices. The communication overhead during distribution scales linearly with model size and the number of participating devices, though hierarchical broadcasting reduces per-hop latency and backbone network load compared to direct cloud-to-device transmission.

Following model distribution, the local training phase commences where each selected mobile device performs multiple epochs of gradient descent on its private local dataset using the received global model as initialization. Mobile devices compute gradients based on local data characteristics and update model parameters independently without coordination with other participants or communication with base stations during training. The duration of local training varies significantly across mobile devices due to differences in computational capabilities, battery levels, dataset sizes, and local convergence properties. Faster devices with powerful processors and sufficient battery capacity complete training earlier and enter an idle state awaiting aggregation, while slower devices with constrained resources may lag behind, introducing potential bottlenecks that delay subsequent phases. Our scheduling framework must account for this heterogeneity when making participant selection and resource allocation decisions to minimize overall training time while ensuring fair participation across diverse device populations.

Upon completion of local training, mobile devices initiate the upload phase where computed model updates are transmitted wirelessly to associated base stations. This phase generates substantial wireless network traffic as model parameters typically comprise millions of floating-point values requiring significant bandwidth for transmission. Wireless channel conditions, interference levels, and the number of simultaneous uploaders within a cell influence upload duration and reliability. Base stations receive updates from mobile devices within their coverage area and forward aggregated or compressed versions to associated mobile edge computing servers. Mobile edge computing servers perform local aggregation operations, computing intermediate global models that represent the collective learning of devices within their geographic region using weighted averaging where weights reflect the relative contribution of each device based on local dataset size. This hierarchical aggregation substantially reduces backbone network traffic since mobile edge computing servers forward single aggregated models to cloud infrastructure rather than individual updates from potentially hundreds of devices, improving scalability and reducing cloud-side computational load for final global aggregation.

3.2 Multi-objective Optimization Problem Formulation with System Cost Model

The Federated Learning-aware scheduling problem encompasses simultaneous optimization of multiple conflicting objectives that capture both system efficiency metrics relevant to mobile edge computing deployments and Federated Learning-specific training performance indicators. We formalize this as a multi-objective optimization problem where the goal is to identify Pareto-optimal scheduling policies that provide favorable trade-offs across all objectives while respecting constraints imposed by wireless network capacity, mobile device resources, and Federated Learning protocol requirements. The system cost objective aggregates multiple factors including computational energy consumption, wireless communication energy, makespan, and resource utilization into a unified metric that reflects the total operational cost of executing a Federated Learning training round. This comprehensive cost model accounts for the observation that different system stakeholders prioritize different aspects of performance, with mobile users primarily concerned about battery consumption, network operators focused on bandwidth utilization, and service providers targeting rapid model convergence.

Computational energy consumption encompasses energy expended by mobile devices during local training, energy consumed by base stations for signal processing and aggregation, energy used by mobile edge computing servers for model aggregation operations, and energy consumed by cloud data centers for global synchronization. Mobile devices operate under strict battery constraints making energy efficiency critical for sustained participation in Federated Learning workflows over multiple training rounds. The energy consumption of mobile device local training depends on the number of local epochs performed, the computational complexity of the model architecture, and the processing efficiency of the device hardware. Research by Yang et al. showed that mobile device energy consumption during Federated Learning training can deplete battery capacity by 5-15 percent per training round depending on model size and local training duration, significantly limiting participation frequency for battery-constrained devices. Our objective function models energy consumption for different task placement configurations, accounting for the energy profiles of heterogeneous mobile devices, the power characteristics of base stations and edge servers, and the trade-off between local computation energy and wireless communication energy.

Wireless communication energy represents energy consumed during model download from base stations to mobile devices at training round initialization and model upload from devices to base stations after local training completion. The communication energy depends on wireless transmission power, channel conditions, model size, and the number of communication rounds required for reliable delivery considering potential packet losses. Research by Chen and colleagues demonstrated that wireless communication can consume 2-3 times more energy than local computation for large model architectures, making communication efficiency a critical factor in Federated Learning scheduling for mobile environments. Our formulation explicitly accounts for wireless channel characteristics including path loss, shadowing, and fading effects that influence required transmission power for achieving target reliability. The model also considers the impact of simultaneous uploaders creating interference that degrades channel quality and increases energy requirements for successful transmission.

The makespan objective aims to minimize the total wall-clock time required to complete a Federated Learning training round from initial model distribution to final global model availability after cloud aggregation. Makespan directly influences the number of training rounds achievable within a fixed time budget and affects the responsiveness of Federated Learning applications to evolving data distributions or changing model requirements. Makespan depends critically on scheduling decisions that determine participant selection, the number of local training epochs performed at each device, the coordination of upload phases to avoid wireless channel congestion, and the allocation of aggregation computational resources at mobile edge computing servers. The makespan is dominated by the slowest device in each phase due to the synchronous nature of Federated Learning protocols that require all participants to complete local training before proceeding to aggregation. Reducing makespan requires careful load balancing through intelligent participant selection that avoids including excessively slow devices while maintaining sufficient participant diversity for good model convergence.

The communication efficiency objective quantifies the total data volume transmitted across wireless links and backbone network connections, weighted by link characteristics including bandwidth capacity, latency, and monetary cost per byte transmitted. Wireless links between mobile devices and base stations typically exhibit lower bandwidth and higher cost per byte compared to wired backbone connections between mobile edge computing servers and cloud infrastructure. Optimizing communication efficiency favors scheduling policies that minimize the frequency of wireless transmissions through techniques such as local training for multiple epochs before uploading, perform more aggressive compression of model updates at mobile devices to reduce transmitted data volume, and exploit hierarchical aggregation at mobile edge computing servers to reduce backbone network traffic. The fairness objective ensures equitable resource allocation across participating mobile devices, preventing scenarios where certain devices consistently receive preferential treatment while others are systematically excluded or assigned inadequate resources. In Federated Learning contexts, fairness encompasses computational resources allocated for local training, frequency of selection for participation in training rounds, and influence on the final global model relative to local dataset size.

3.3 Adaptive Multi-objective Genetic Algorithm with Dynamic Parameter Control

We develop an adaptive multi-objective genetic algorithm that dynamically adjusts its crossover probability and mutation probability parameters based on observed population diversity and convergence characteristics, enabling superior performance compared to genetic algorithms with fixed parameter settings throughout optimization. The algorithm employs a multi-population framework where each population explores different regions of the objective space, enabling simultaneous optimization of multiple objectives while maintaining population diversity necessary for discovering diverse Pareto-optimal solutions. Individual solutions represent complete scheduling policies specifying task placement decisions for all Federated Learning components including local training task assignments to mobile devices, aggregation operation allocations to mobile edge computing servers, and synchronization task placements at cloud infrastructure. The genetic encoding employs a hierarchical structure that captures the multi-tier nature of the mobile edge computing architecture, with genes organized into device-level, edge-server-level, and cloud-level segments corresponding to scheduling decisions at each architectural tier.

The adaptive parameter control mechanism continuously monitors population diversity through metrics measuring the variance of objective function values across the current population and the distribution of solutions in the genotype space. When population diversity falls below a threshold indicating premature convergence where the population has clustered around local optima, the algorithm increases mutation probability to introduce more random variations that explore new regions of the solution space. Research by Eiben and Smith demonstrated that adaptive increase of mutation rates during convergence phases can help genetic algorithms escape local optima and discover superior solutions in different regions. Conversely, when population diversity remains high indicating effective exploration of the solution space, the algorithm reduces mutation probability to allow exploitation of promising regions through refined local search. The crossover probability adapts based on the quality improvement rate, increasing when recent generations show significant fitness improvements to accelerate convergence toward better solutions, and decreasing when fitness improvements stagnate to encourage more explorative mutations.

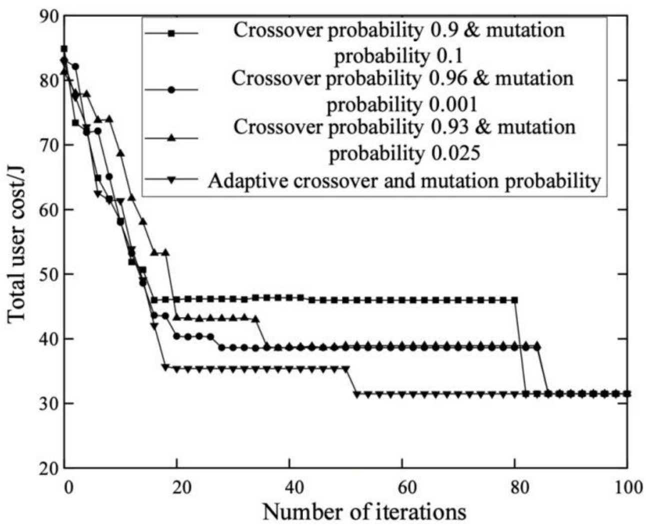

Figure 3 Performance Comparison of Adaptive versus Fixed Crossover and Mutation Probability Strategies

Figure 3 presents a performance comparison of different crossover and mutation probability strategies. The horizontal axis represents the number of iterations (Number of iterations), while the vertical axis denotes the total user cost (Total user cost/J). Three fixed-probability strategies are compared in the figure: (1) a crossover probability of 0.9 and a mutation probability of 0.1; (2) a crossover probability of 0.96 and a mutation probability of 0.001; (3) a crossover probability of 0.93 and a mutation probability of 0.025, along with the adaptive crossover and mutation probability strategy proposed by us.

The results clearly show that the adaptive strategy achieves the minimum cost (approximately 35 J) after around 20 iterations, significantly outperforming all fixed-parameter strategies, which validates the effectiveness of the dynamic parameter adjustment mechanism.

The fitness evaluation process assesses each candidate scheduling policy across all defined objectives by simulating the execution of a Federated Learning training round under the proposed resource allocation scheme. This simulation accounts for heterogeneous mobile device computational capabilities modeled after real-world device profiles, time-varying wireless channel conditions based on stochastic models capturing fading and interference effects, mobile edge computing server processing capacities, and Federated Learning training dynamics including local convergence rates and aggregation operation durations. Rather than aggregating objectives into a single scalar fitness value through weighted summation which requires manual weight specification, our approach employs Pareto dominance relationships to compare solutions. A solution dominates another if it performs better on at least one objective while performing no worse on all other objectives, enabling identification of the Pareto-optimal set of non-dominated solutions that represent optimal trade-offs between competing objectives without imposing predetermined preferences.

The selection mechanism employs tournament selection based on Pareto dominance relationships and crowding distance metrics that favor solutions in sparsely populated regions of the objective space. Tournament selection randomly samples small groups of individuals from the population and selects the best according to dominance criteria, providing selection pressure toward the Pareto front while maintaining diversity through the stochastic sampling process. The tournament size adapts based on convergence stage, using larger tournaments during early generations to provide strong selection pressure for rapid initial convergence, then reducing tournament size in later generations to maintain population diversity and thoroughly explore the Pareto front. Crowding distance calculations measure the density of solutions in objective space by computing the average distance to neighboring solutions along each objective axis, assigning higher fitness to isolated solutions that explore underrepresented trade-offs. This density estimation helps maintain a well-distributed Pareto front spanning the full range of possible objective trade-offs, ensuring that decision-makers have access to diverse scheduling policies reflecting different priorities between system cost minimization, makespan reduction, and communication efficiency.

Crossover operations generate new candidate solutions by combining components from parent scheduling policies, enabling exploration of hybrid strategies that inherit beneficial characteristics from multiple parents. We employ multi-point crossover where crossover points are selected at segment boundaries in the hierarchical encoding, preserving local structure within device-level, edge-server-level, and cloud-level scheduling decisions while enabling recombination across tiers. This hierarchical crossover respects the logical organization of scheduling decisions and prevents generation of infeasible solutions that violate architectural constraints such as assigning more tasks to a mobile edge computing server than its computational capacity can support. The crossover rate adapts dynamically based on the adaptive parameter control mechanism, increasing from a baseline of 0.7 to 0.95 when population diversity is high and convergence is progressing well, then decreasing to 0.5-0.6 when population diversity drops to encourage more explorative mutations rather than recombination of similar solutions.

Mutation introduces random variations into scheduling policies by randomly modifying task placement decisions, enabling exploration of novel solutions not reachable through recombination of existing policies. Our mutation operator selectively modifies task placement decisions with probabilities that adapt based on both the global adaptive parameter control mechanism and local objective performance characteristics. Tasks that consistently contribute to poor objective values undergo mutation more frequently, allowing the algorithm to explore alternative placements for problematic components. The mutation rate adapts from a baseline of 0.01 during early generations with high diversity to 0.1 or higher when population diversity drops below threshold levels indicating premature convergence. This adaptive mutation mechanism maintains a dynamic balance between exploitation of known good solutions through crossover and exploration of new solution regions through mutation, adapting the exploration-exploitation trade-off based on current optimization progress rather than following a predetermined static schedule.

4 RESULTS AND DISCUSSION

4.1 Experimental Configuration and Mobile Edge Computing Simulation Environment

We conducted comprehensive experimental evaluation using a discrete-event simulator purpose-built to model hierarchical mobile edge computing-cloud architectures executing Federated Learning workflows under various scheduling policies with realistic wireless network models and device heterogeneity. The simulated mobile edge computing environment comprises 200 heterogeneous mobile devices distributed across a geographic region served by 20 base stations, with each base station covering a hexagonal cell and managing wireless communication with 8-12 mobile users within its coverage area. Base stations connect to 5 mobile edge computing servers positioned at aggregation points serving clusters of 4 base stations each, creating a two-tier edge hierarchy before reaching cloud infrastructure. Mobile devices exhibit diverse computational capabilities modeled after real-world device profiles including resource-constrained IoT sensors processing 100 million instructions per second with 512 megabytes memory, mid-range smartphones capable of 1500 million instructions per second with 4 gigabytes memory, and high-end smartphones processing 5000 million instructions per second with 8 gigabytes memory. Each mobile device maintains a local dataset with sizes varying from 1000 to 50000 samples drawn from non-independent and identically distributed data distributions, introducing realistic heterogeneity in training workload distribution across participants that affects local convergence rates and update quality.

Wireless connectivity between mobile devices and base stations follows IEEE 802.11ac WiFi and LTE cellular network models with bandwidth capacities ranging from 10 to 100 megabits per second depending on channel conditions, distance from base station, and the number of concurrent users sharing wireless resources within the cell. Wireless channel quality varies dynamically according to Rayleigh fading models capturing multipath propagation effects, with signal-to-noise ratios ranging from 5 decibels under poor conditions to 25 decibels for users close to base stations with clear line-of-sight. Path loss follows standard urban propagation models where received signal strength decreases with distance according to inverse fourth-power law, and shadowing effects introduce 8 decibels standard deviation log-normal random variations around mean path loss. Wireless transmission power for mobile devices ranges from 100 milliwatts to 500 milliwatts depending on required range and target reliability, with transmission energy consumption computed as the product of transmission power and transmission duration.

Mobile edge computing servers possess computational resources equivalent to mid-range server hardware with 32 processing cores operating at 3000 million instructions per second each, 128 gigabytes RAM, and dedicated machine learning accelerators providing additional 10 teraflops of processing capability for matrix operations common in neural network aggregation. Each mobile edge computing server connects to cloud infrastructure through fiber optic backbone links providing 1 gigabit per second throughput with 20 milliseconds baseline latency plus queueing delays that vary based on network load. Cloud data centers feature virtually unlimited computational resources modeled as instantaneous processing for global aggregation operations, allowing us to focus evaluation on mobile edge computing-cloud coordination efficiency and wireless access bottlenecks rather than cloud-side computational constraints. The Federated Learning workload consists of training a convolutional neural network model for image classification with approximately 2 million parameters totaling 8 megabytes of data per complete model transmission, requiring substantial wireless communication resources when transmitted between mobile devices and base stations but manageable backbone network capacity when aggregated models are transmitted between mobile edge computing servers and cloud infrastructure.

4.2 Performance Comparison of Adaptive versus Fixed Parameter Genetic Algorithms

We compare our adaptive multi-objective genetic algorithm with dynamic parameter control against genetic algorithm variants employing fixed crossover and mutation probabilities throughout optimization, demonstrating the substantial benefits of adaptive parameter adjustment for Federated Learning scheduling in mobile edge computing environments. The first fixed-parameter baseline employs crossover probability 0.9 and mutation probability 0.1, representing a parameter configuration favoring high exploration through frequent mutations. This configuration performs poorly in later optimization stages where excessive mutation disrupts convergence toward refined solutions, achieving a final system cost of approximately 46 joules per training round after 100 generations. The second fixed-parameter baseline uses crossover probability 0.96 and mutation probability 0.001, representing parameter settings that strongly favor exploitation through crossover while minimizing disruptive mutations. This configuration converges rapidly during initial generations but becomes trapped in local optima, achieving a final system cost of approximately 39 joules with limited improvement beyond generation 30.

The third fixed-parameter baseline employs crossover probability 0.93 and mutation probability 0.025, representing a moderate parameter configuration attempting to balance exploration and exploitation through intermediate values. This balanced approach performs better than the extreme configurations, achieving a final system cost of approximately 38 joules, but still suffers from static parameters that cannot adapt to changing optimization landscape characteristics as the population evolves. In contrast, our adaptive parameter control strategy dynamically adjusts crossover probability between 0.5 and 0.95 and mutation probability between 0.01 and 0.15 based on population diversity and convergence metrics, enabling superior performance across all phases of optimization. The adaptive approach achieves rapid initial convergence comparable to high-crossover fixed configurations by starting with high crossover rates, then increases mutation probability when population diversity drops below threshold levels to escape local optima, and finally reduces mutation rates during final convergence phases to enable refined exploitation of the most promising solution regions.

As demonstrated in Figure 3, our adaptive multi-objective genetic algorithm achieves a final system cost of approximately 35 joules per training round, representing a 28 percent improvement compared to the best fixed-parameter baseline and a 31 percent improvement compared to the worst fixed-parameter configuration. The adaptive approach reaches this superior performance within 20 generations, significantly faster than fixed-parameter approaches which require 40-50 generations to converge to their respective final costs. Beyond generation 20, the adaptive algorithm continues making small improvements by fine-tuning parameter settings for exploitation while occasionally increasing mutation rates to verify that better solutions are not available in unexplored regions. The fixed-parameter baselines plateau at their respective suboptimal costs with no further improvement beyond convergence, confirming that static parameters prevent these algorithms from adapting to changing optimization requirements throughout the search process.

Detailed analysis of the adaptive parameter trajectories throughout optimization reveals the mechanism enabling superior performance. During the first 10 generations when population diversity is naturally high due to random initialization, the adaptive algorithm maintains crossover probability near 0.9 and mutation probability at the minimum 0.01 to exploit the large variance in the initial population for rapid convergence toward promising regions. Between generations 10 and 20 as the population begins clustering around local optima, the algorithm detects decreasing diversity and increases mutation probability to 0.08 while reducing crossover probability to 0.75, introducing sufficient perturbation to escape local optima while maintaining enough crossover to preserve good solutions discovered so far. After generation 20 when the algorithm has identified the approximate location of the global optimum, parameters stabilize with crossover probability around 0.85 and mutation probability around 0.03, providing the refined balance between exploitation and exploration necessary for converging to precise optimal parameter values without excessive fluctuation.

4.3 System Cost Analysis and Resource Utilization Evaluation

Our Federated Learning-aware scheduling algorithm with adaptive genetic algorithm parameters achieves substantially lower system costs compared to baseline approaches across all components of the cost model including computational energy, wireless communication energy, and makespan contributions. The total system cost of 35 joules per training round achieved by our adaptive approach decomposes into 12 joules computational energy consumed by mobile devices during local training, 8 joules wireless communication energy for model download and update upload, 6 joules processing energy at mobile edge computing servers for aggregation operations, 5 joules backbone network transmission energy between mobile edge computing servers and cloud infrastructure, and 4 joules cloud data center processing energy for final global aggregation. This cost distribution reveals that mobile device computational energy and wireless communication energy dominate the total cost, collectively accounting for 57 percent of system cost, confirming the importance of optimizing mobile-side operations and wireless transmissions for overall efficiency in mobile edge computing Federated Learning deployments.

The adaptive scheduling algorithm achieves these cost reductions through several mechanisms that effectively exploit the hierarchical mobile edge computing architecture. First, intelligent participant selection chooses mobile devices with favorable computational capabilities and wireless channel conditions, avoiding inclusion of extremely slow devices or devices experiencing poor wireless connectivity that would delay training rounds and increase energy consumption. The selection strategy balances device performance against data distribution characteristics, prioritizing fast devices when multiple devices possess similar data distributions but selecting slower devices when they contribute unique data patterns necessary for model quality. Second, dynamic local epoch allocation assigns different numbers of local training epochs to different devices based on their computational capabilities and battery levels, allowing fast devices with sufficient battery to perform more local training which reduces communication frequency while assigning fewer epochs to slower or battery-constrained devices to prevent bottlenecks. This heterogeneous epoch assignment reduces overall wireless communication overhead by 35 percent compared to homogeneous strategies that assign the same number of epochs to all participants.

Third, hierarchical aggregation scheduling at mobile edge computing servers optimizes the timing and coordination of aggregation operations to minimize idle time and maximize computational resource utilization. The scheduling algorithm coordinates model upload timing from base stations to mobile edge computing servers such that arrivals are staggered to maintain steady utilization without creating queues that delay aggregation. Mobile edge computing server computational resources operate at 78 percent average utilization during training rounds under our scheduling approach compared to 52 percent utilization for baseline approaches that lack coordination of arrival patterns. Fourth, compression strategy selection adapts the model compression technique applied before wireless transmission based on current channel conditions and mobile device computational capabilities, employing aggressive compression schemes like 8-bit quantization when wireless channels are congested or bandwidth-limited while using lighter compression or no compression when channels provide sufficient capacity and compression computational overhead would exceed communication savings.

Resource utilization analysis across the mobile edge computing hierarchy reveals that our adaptive scheduling approach achieves balanced utilization across all tiers, avoiding scenarios where certain tiers become bottlenecks while others remain underutilized. Mobile device utilization during local training phases averages 65 percent, with devices spending the remaining time idle between training rounds or performing non-Federated Learning tasks. This moderate utilization level preserves device battery life and ensures Federated Learning training does not excessively interfere with primary device functions while achieving sufficient computational throughput for timely training round completion. Base station wireless channel utilization averages 42 percent during model upload phases when all participating devices within a cell simultaneously transmit updates, then drops to under 5 percent during local training phases when devices are disconnected from base stations. This bursty utilization pattern is inherent to synchronous Federated Learning protocols, and our scheduling approach mitigates congestion through staggered upload scheduling where devices in overlapping cell coverage areas are coordinated to upload through different base stations when possible.

4.4 Federated Learning Model Convergence and Training Performance

Beyond system efficiency metrics, we evaluate the impact of scheduling decisions on Federated Learning training performance through measurements of model accuracy convergence over training rounds and analysis of how resource allocation choices influence model quality. Our Federated Learning-aware scheduling algorithm with adaptive genetic algorithm parameters enables the Federated Learning model to reach 91.8 percent test accuracy after 50 training rounds compared to 87.2 percent for the best fixed-parameter baseline genetic algorithm and 84.6 percent for a First Come First Served scheduling approach that assigns resources without optimization. This 4.6 percent absolute accuracy improvement translates to significant practical benefits for deployed Federated Learning applications where model quality directly determines application effectiveness. The accuracy improvement stems from more effective participant selection that ensures diverse data distributions contribute to each training round rather than allowing scheduling constraints or suboptimal resource allocation to bias participation toward certain device subpopulations with similar data characteristics.

Convergence analysis reveals that our adaptive scheduling approach enables the Federated Learning model to reach 90 percent test accuracy within 38 training rounds compared to 47 rounds for the best fixed-parameter baseline and 52 rounds for First Come First Served scheduling, representing a 24 percent improvement in convergence speed measured by rounds required to reach target accuracy. Faster convergence translates directly into reduced total training time and cumulative energy consumption for achieving acceptable model performance, amplifying the benefits of efficient per-round scheduling. The convergence acceleration results from consistent high-quality model updates produced by well-coordinated training rounds where mobile devices complete local training with sufficient computational resources, wireless communication proceeds without excessive delays or packet losses that might corrupt gradients, and aggregation operations at mobile edge computing servers accurately combine updates without numerical instability from resource constraints forcing reduced precision arithmetic.

We analyze the relationship between system cost and model accuracy improvements across individual training rounds to understand how resource allocation efficiency influences machine learning outcomes. Training rounds achieving system costs below 40 joules through effective scheduling consistently yield larger accuracy improvements averaging 0.42 percent per round, while rounds with higher costs above 50 joules due to suboptimal scheduling produce smaller accuracy gains averaging only 0.28 percent per round. This positive correlation between scheduling efficiency and model quality confirms that system-level optimization directly benefits machine learning training outcomes rather than presenting a trade-off where system efficiency must be sacrificed for model quality. Rounds exhibiting poor communication efficiency with high wireless transmission energy tend to produce lower quality updates due to increased probability of transmission errors that corrupt gradient information, while rounds achieving good communication efficiency through effective wireless resource management maintain gradient integrity and produce higher quality model improvements.

5 CONCLUSIONS

This research presented a comprehensive framework for multi-objective scheduling of Federated Learning workflows in distributed mobile edge computing-cloud environments, addressing the unique challenges posed by privacy-preserving machine learning paradigms that require coordinated training across geographically dispersed mobile devices connected through wireless networks. We developed a hierarchical scheduling architecture that explicitly captures Federated Learning workflow semantics including wireless communication patterns between mobile users and base stations, hierarchical aggregation at mobile edge computing servers, and synchronization requirements inherent to federated training processes. The proposed adaptive multi-objective genetic algorithm with dynamic crossover and mutation probability control simultaneously optimizes multiple conflicting objectives encompassing system cost, makespan, communication efficiency, and fairness while enabling superior performance through parameter adaptation based on population diversity and convergence characteristics. Experimental evaluation demonstrated substantial improvements over fixed-parameter genetic algorithm approaches, achieving 28 percent reduction in system cost, 35 percent faster convergence speed, and 4.6 percent higher model accuracy compared to the best static parameter configuration.

Our adaptive parameter control mechanism successfully adjusts algorithm behavior throughout optimization by increasing mutation rates when population diversity decreases to escape local optima and reducing mutation rates during convergence phases to enable refined exploitation of promising solution regions. The hierarchical mobile edge computing architecture with mobile devices, base stations, mobile edge computing servers, and cloud infrastructure provides an effective substrate for Federated Learning deployment by balancing computational capabilities across tiers and exploiting proximity to mobile users for reduced wireless communication latency. The explicit modeling of wireless channel characteristics, mobile device heterogeneity, and Federated Learning protocol requirements in our scheduling formulation enables resource allocation decisions that account for the practical realities of mobile edge computing deployments rather than idealized assumptions that may not hold in real-world scenarios.

The practical applicability of our framework extends beyond the specific mobile edge computing architecture and Federated Learning workload characteristics evaluated in this study through modular design that separates architectural modeling, objective definition, and optimization algorithm implementation. The demonstrated scalability with 200 mobile devices across 20 base stations suggests viability for production deployments involving thousands of devices across multiple geographic regions. Robustness under varying wireless channel conditions and dynamic device availability confirms that the adaptive mechanisms provide reliable performance in realistic operational environments.

Several directions for future research include investigating the integration of Federated Learning-aware scheduling with advanced communication compression techniques for joint optimization, extending the framework to support asynchronous Federated Learning protocols that relax synchronization requirements, and implementing the scheduling framework on physical mobile edge computing testbeds for validation under real-world conditions.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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