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An Adaptive Curriculum Event-Aware Federated Averaging Framework for Resource Demand Prediction in 5G Non-Standalone Networks

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Abstract

The dynamic and heterogeneous 5G traffic complicates short-term resource-demand prediction. While federated learning (FL) enables privacy-preserving training by keeping raw data local. However, FedAvg and FedProx do not explicitly account for client traffic heterogeneity or sudden demand variations. To address these limitations, this paper proposes ACE-FedAvg, an Adaptive Curriculum Event-Aware Federated Averaging framework for next-hour downlink Physical Resource Block (DL PRB) utilization prediction in 5G Non-Standalone (NSA) networks. ACE-FedAvg jointly incorporates curriculum-based client selection, adaptive client importance estimation, and event-aware aggregation to prioritize informative clients and traffic conditions during federated training. The framework is evaluated using operational 5G NSA measurements from 127 Next Generation NodeBs (gNodeBs) collected over ten consecutive days, with the first nine days used for training and one unseen day for testing. ACE-FedAvg is compared with FedAvg and FedProx using multiple evaluation metrics. On the unseen test day, ACE-FedAvg achieves the lowest root mean square error (RMSE) of 0.654, peak RMSE of 1.715, top-5 error (1.501) and weighted RMSE of 0.773, compared with 0.670, 1.853, 1.733 and 0.799, respectively, for FedAvg. These results indicate improved overall and high-demand prediction performance for federated DL PRB utilization prediction under realistic 5G NSA network conditions.

Keywords: 5G NSA; federated learning; resource-demand prediction; physical resource blocks; curriculum learning; event-aware learning

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Academic Editors: Dipankar Mitra, Shuvashis Dey, Giovanni Andrea Casula, Rig Das and Francisco Falcone

Received: 3 September 2026
Revised: 29 September 2026
Accepted: 6 October 2026
Published: 9 October 2026

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1. Introduction

The continuous proliferation of Internet of Things (IoT) devices together with the increasing demand for mobile broadband services has significantly intensified radio resource utilization in fifth-generation (5G) networks, resulting in highly dynamic traffic patterns [1]. Accurate short-term prediction of network resource demand has therefore become essential for proactive radio resource management, efficient spectrum utilization, improved Quality of Service (QoS) and reliable support for large-scale IoT applications [2]. Among the

operational Key Performance Indicators (KPIs), Downlink Physical Resource Block (DL PRB) utilization is one of the most representative indicators of radio resource demand as it directly reflects spectrum occupancy and cell load [3]. Recent advances in Artificial Intelligence (AI) have considerably improved traffic prediction performance. However, most existing approaches rely on centralized learning, where operational data collected from multiple base stations are transferred to a central server for model training [4]. Although such methods can achieve high prediction accuracy, they raise important concerns regarding data privacy, communication overhead, scalability and regulatory compliance [5]. Federated Learning (FL) addresses these limitations by enabling collaborative model training while keeping raw data locally stored and exchanging only model parameters. Despite these advantages, conventional FL algorithms, such as FedAvg and FedProx, generally treat all participating clients equally during model aggregation [6]. In practical 5G networks, however, (gNodeBs) exhibit heterogeneous traffic characteristics, user densities and radio resource utilization patterns [7]. Consequently, assigning identical aggregation importance to all clients may limit the ability of the global model to capture dynamic traffic behavior. Moreover, most existing FL-based traffic prediction methods do not explicitly exploit client heterogeneity or account for traffic events that significantly influence short-term resource demand [8]. Recent studies have further extended intelligent and federated resource management toward emerging 6G Cell-Free architecture, including energy-efficient optimization and federated deep reinforcement learning for delay-energy trade-offs [9,10]. These studies provide an important context for the potential future generalization of adaptive federated learning frameworks toward next-generation wireless systems. However, the applicability of such approaches to operational 5G NSA resource-demand prediction and their extension to 6G Cell-Free architecture remain open research directions. To address these limitations, this paper proposes ACE-FedAvg (Adaptive Curriculum Event-aware Federated Averaging), a novel adaptive federated averaging framework for short-term DL PRB utilization prediction in operational 5G NSA networks. The proposed framework combines curriculum-based client selection, adaptive client importance estimation and an event-aware aggregation mechanism within a unified federated learning architecture. The curriculum strategy gradually introduces clients according to their learning difficulty, while the importance estimation identifies clients that provide more informative model updates. Furthermore, the event-aware mechanism prioritizes clients experiencing significant traffic conditions while preserving data privacy. The proposed framework is evaluated using a real operational 5G NSA dataset collected over ten consecutive days. The first nine days are used exclusively for model training, whereas the tenth day is reserved as an unseen test set to assess the generalization capability of the proposed framework. The training period also includes a real nationwide event corresponding to the announcement of national examination results on 14 June 2026. Since 5G deployment in Algeria was still in its early stages during the measurement period, not all mobile users were using 5G services. Thus, the event may have introduced additional communication activity among 5G users without necessarily producing a pronounced increase in 5G traffic demand, thereby providing temporal variation for evaluating the event-aware prediction capability of the proposed framework. The main contributions of this paper are summarized as follows:

- We propose ACE-FedAvg, an adaptive federated learning framework that jointly integrates curriculum-based client selection, client importance estimation, and event-aware aggregation for short-term DL PRB utilization prediction in 5G NSA networks.
- We develop an adaptive client importance estimation mechanism that assigns aggregation weights according to the statistical significance of local traffic patterns.

- We design an event-aware aggregation mechanism that enhances the contribution of clients experiencing significant traffic demand variations, improving the global model's ability to capture dynamic network behavior.
- We validate the proposed framework using real operational measurements from 127 (gNodeBs) and an unseen temporal test day, and compare its performance with FedAvg and FedProx under different traffic conditions, communication rounds, and client participation rates.
- We integrate curriculum learning, adaptive client importance estimation and event-aware aggregation into a unified federated averaging framework namely ACE-FedAvg, for short-term DL PRB utilization prediction in operational 5G NSA networks.

The remainder of this paper is organized as follows: Section 2 reviews the related work. Section 3 presents the proposed ACE-FedAvg framework, discusses the experimental setup, dataset and evaluation methodology. Section 4 presents and discusses the experimental results. Finally, Section 5 concludes the paper and outlines future research directions.

2. Related Works

The development of federated learning was initiated by the FedAvg algorithm, which introduced communication-efficient collaborative model training without sharing raw data [11]. Subsequently, FedProx extended this framework by introducing a proximal optimization term to improve convergence under heterogeneous client data distributions [12]. More recently federated learning has emerged as an effective solution for traffic prediction and resource management in cellular networks while preserving data privacy. Existing studies have demonstrated the feasibility of federated traffic forecasting for 5G base stations and proposed energy-aware federated prediction frameworks that improve prediction accuracy while reducing communication overhead and energy consumption [13,14]. In parallel, curriculum learning has been introduced to enhance federated optimization under heterogeneous data distributions by progressively increasing learning difficulty, leading to improved convergence and generalization performance [15]. Furthermore, recent surveys have highlighted the growing importance of learning-based traffic prediction as a key enabler of intelligent Open RAN management and proactive radio resource optimization [16]. Recent studies have further investigated adaptive mechanisms for federated aggregation and client participation. FedMcon proposes an adaptive aggregation method based on a learnable meta-controller, which dynamically determines the contribution of heterogeneous local models to the global model [17]. This approach is related to the importance estimation mechanism of ACE-FedAvg in that both seek to adapt the contribution of participating clients rather than relying solely on conventional aggregation. However, FedMcon learns the aggregation behavior through a meta-controller, whereas ACE-FedAvg explicitly estimates client importance from resource and demand-related characteristics relevant to 5G resource-demand prediction. The weighting coefficients in ACE-FedAvg were determined through simulation-based evaluation, as described in Section 3.8, and their robustness was further examined through the ablation study. In parallel, AdaptiveFL investigates communication-adaptive federated learning under dynamic bandwidth conditions [18]. Its adaptation primarily considers the communication resources available to clients, whereas ACE-FedAvg adapts client participation and aggregation according to resource-demand characteristics, client importance, curriculum difficulty and event-related variations. AdaptiveFL therefore provides a complementary server-side baseline for evaluating ACE-FedAvg under adaptive client participation. These differences clarify that ACE-FedAvg is not intended as a general replacement for existing adaptive aggregation or communication-aware federated learning methods, rather, it is designed to jointly address resource-oriented client selection, importance estimation and event-aware aggregation for

next-hour resource-demand prediction in operational 5G networks. Despite these advances, most existing approaches rely on conventional client participation or adaptive weighting strategies without jointly considering curriculum-based client selection, adaptive client importance estimation and event-aware aggregation [19]. In [3], the authors addressed downlink PRB utilization forecasting through multi-feature construction, demonstrating that carefully designed traffic features can improve prediction accuracy. Nevertheless, the proposed approach is based on centralized learning and does not exploit federated learning, adaptive client selection or event-aware aggregation strategies. Moreover, many studies are evaluated using simulated datasets rather than real operational network measurements.

To address these limitations, the proposed ACE-FedAvg framework integrates these three complementary components within a unified federated learning framework for next-hour DL PRB utilization prediction and validates its performance using real operational 5G NSA network measurements.

3. Proposed ACE-FedAvg Framework

This section presents the proposed Adaptive Curriculum Event-Aware Federated Averaging (ACE-FedAvg) framework for short-term DL PRB utilization prediction in 5G NSA networks. The proposed framework integrates curriculum-based client selection, client importance estimation and event-aware aggregation to improve prediction accuracy while preserving the privacy of locally stored network data.

3.1. Framework Overview

As illustrated in Figure 1, the proposed ACE-FedAvg framework consists of sequential stages: Data preparation, client construction, adaptive client selection, local model training and global aggregation. Each gNodeB is considered as an independent federated client that trains the prediction model using only its local data, while only updated model parameters are exchanged with the central server. By prioritizing informative clients during training, ACE-FedAvg improves the prediction of dynamic resource demand without exposing raw operational data.

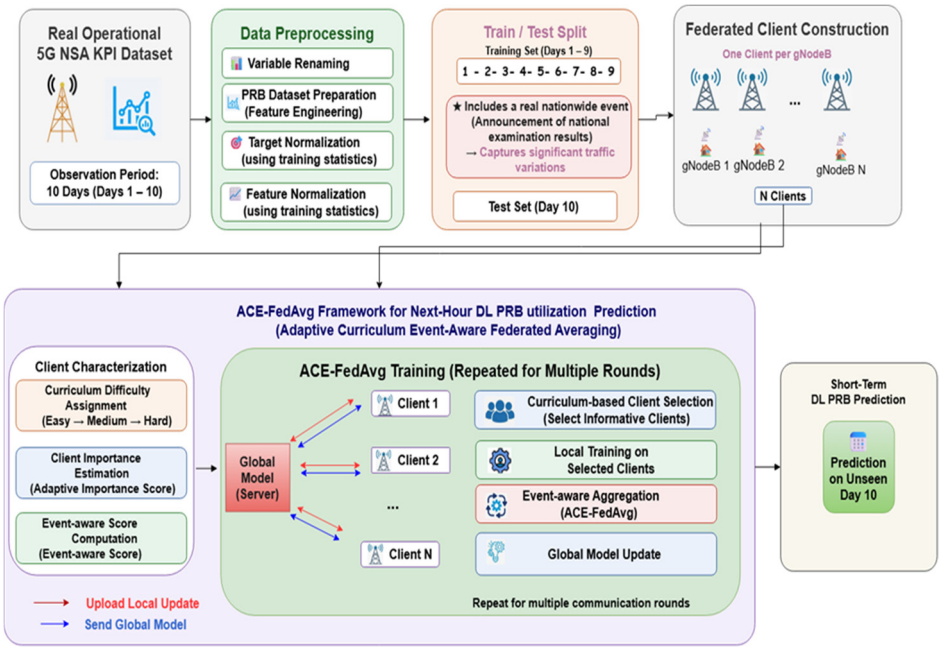


Figure 1. Overall workflow of the proposed ACE-FedAvg.

3.2. Data Preparation and Client Construction

The experiments were conducted using operational 5G NSA measurements collected over ten consecutive days from a commercially deployed 5G network in Algeria. The collected measurements include time-stamped traffic, radio-resource utilization and user-related network indicators at the cell/gNodeB level, including downlink and uplink traffic, LTE and New Radio (NR) traffic components and downlink and uplink PRB utilization. The measurements were cleaned, temporally aligned and processed to construct the input features used by the proposed framework. The first nine days were used exclusively for model training, while the tenth day was reserved for testing the one-hour-ahead resource-demand prediction to evaluate the model under real operational conditions. After removing incomplete records, lag-based and trend-based temporal features are generated and the prediction target is defined as the next-hour DL PRB utilization. To simulate the federated learning environment, the processed dataset is partitioned according to the serving gNodeBs, where each gNodeB represents an independent client. Local model training is performed using only local measurements, while updated parameters are exchanged with the central server to preserve data privacy. The relatively short observation period limits the assessment of long-term seasonal and holiday-related variations; therefore, future work will consider a longer-term dataset covering more diverse temporal conditions. The experimental configuration is summarized in Table 1.

Table 1. Configuration parameters of the proposed framework.

Parameter	Value
Observation Period	10 Days
Training days	From da 1 to day 9
Test day	Day 10
Prediction target	Next-hour DL PRB utilization
Number of clients	127 gNodeBs
Communication rounds	60
Client participation rate	20%
Mini-batch size	32

3.3. Prediction Model Architecture

The local prediction model is implemented as a fully connected Multilayer Perceptron (MLP) for one-step-ahead DL PRB utilization forecasting. The proposed framework uses a 39-dimensional numerical feature vector comprising 28 operational network KPI variables and 11 engineered temporal and historical features. The operational KPIs include radio-resource, traffic, throughput, quality, retransmission, modulation and coding, noise/interference and LTE/NR traffic-split indicators. The engineered features consist of four temporal variables (Hour, Day, Month and Weekday), four DL PRB lag variables (PRB values at t-1, t-2, t-3 and t-24 h) and three DL PRB trend variables (PRB changes over 1, 3 and 24 h). The model predicts the DL PRB utilization at (t + 1) from the 39-dimensional feature vector at time (t). Therefore, no explicit sequential input is used; instead, temporal dependencies up to 24 h are represented through the engineered lag and trend features. In a real-time deployment, the proposed framework can operate as a predictive intelligence layer, where each participating gNodeB locally processes recent network measurements and generates a one-hour-ahead resource-demand prediction, while federated training and global model aggregation are performed periodically. The resulting prediction can support proactive network management tasks such as resource allocation, load balancing and congestion mitigation, although real-time deployment and integration with operational network control loops remain future work.

The architecture and the main training settings required for reproducibility are summarized in Table 2.

Table 2. Architecture and training configuration of the local prediction model.

Parameter	Configuration
Prediction model	Fully connected MLP regression
Input	Dimensional feature vector-39
Hidden layers	2
Neurons	$1 \rightarrow 32 \rightarrow 64 \rightarrow 39$
Activation functions	ReLU $\rightarrow$ ReLU
Total trainable parameters	4.673
Dropout	None
Input sequence	No explicit sequence
Temporal dependency	Up to 24 h through engineered lag/trend features
Lag features	PRB values at t-1, t-2, t-3 and t-24 h
Trend features	PRB changes over 1, 3 and 24 h
Forecast horizon	(t + 1) hour ahead 1
Loss function	Mean Squared Error (MSE)
Optimizer	Adam
Learning rate	0.001
Early stopping criterion	Stop if loss does not improve for 2 consecutive epochs
ACE-FedAvg local epochs	Maximum 3

3.4. Adaptive Curriculum Client Selection

Since different gNodeBs experience different traffic conditions, the proposed framework adopts curriculum-learning strategy that progressively introduces clients according to their learning difficulty [16]. The client difficulty score is computed as:

$$D_i = 0.4\ T_i + 0.4\ P_i + 0.2\ U_i\ , \tag{1}$$

where T_i, P_i and U_i denote the normalized traffic demand, average DL PRB utilization and average number of connected users, respectively. Based on the obtained scores, clients are classified into three curriculum levels (Easy, Medium and Hard). During the early communication rounds, training mainly focuses on easier clients, while progressively including medium and hard-level clients as training proceeds. This strategy improves training stability and accelerates model convergence [20].

3.5. Client Importance and Event-Aware Scoring

Besides curriculum learning, ACE-FedAvg estimates the contribution of each client according to its historical network activity. The use of client relevance or importance for selecting participating clients is consistent with importance-aware client-selection strategies in federated learning [21,22]. The client importance is computed as:

$$I_i = 0.5\ P_i + 0.2\ V_i + 0.2\ U_i + 0.1\ T_i, \tag{2}$$

where P_i, V_i, U_i and T_i denote the normalized average DL PRB utilization, PRB variability, number of users and average DL traffic respectively.

The event-aware score used for client prioritizing is then computed as:

$$E_i = 0.35\ I_i + 0.30\ P_i + 0.20\ T_i + 0.15\ F_i, \tag{3}$$

where I_i, P_i and T_i denote the normalized client importance, mean DL PRB utilization and trend score, respectively.

The performance-related term F_i is derived from the local training loss L_i as:

$$F_i = \frac{1}{(1 + L_i)}, \tag{4}$$

and subsequently normalized across clients. The resulting event-aware score is used to rank candidate clients according to their relevance under dynamic network conditions.

3.6. Training and Global Aggregation

The selected clients independently optimize their local models by minimizing the mean squared error (MSE) as:

$$L_i = \frac{1}{N_i} \sum_{K=1}^{N_i} (\hat{y}_K - y_k)^2, \tag{5}$$

where N_i denotes the number of local training samples of client i, y_k is the ground-truth next-hour DL PRB utilization and $\hat{y}_K$ is the corresponding predicted value.

Local optimization is performed using the Adam optimizer with mini-batch training and an early stopping strategy. The Adam optimizer is widely used adaptive first-order optimization method for stochastic objective functions [23]. After local training, the updated model parameters are transmitted to the central server, without sharing the underlying local measurements. Unlike conventional FedAvg, ACE-FedAvg assigns each selected client an aggregation weight that jointly accounts for its local data contribution and its event-aware relevance.

Specifically, the aggregation weight of client i at communication round t is defined as:

$$a_i^{(t)} = \alpha \frac{n_i}{\sum_{j=1}^{K} n_j} + \beta \frac{E_i^{(t)}}{\sum_{j=1}^{K} E_j^{(t)}} \quad and \quad \alpha + \beta = 1, \tag{6}$$

where n_i is the number of local training samples, $E_i^{(t)}$ is the event-aware score of client i and K is the number of participating clients. In this study, α = 0.60 and =0.40, giving greater emphasis to the statistical contribution of local data while explicitly incorporating client relevance under dynamic network conditions.

The resulting global model is then obtained as:

$$W^{(t+1)} = \sum_{i=1}^{K} a_i^{(t)} W_i^{(t)}, \tag{7}$$

where $W_i^{(t)}$ denotes the locally updated parameters of client i. This formation extends conventional sample-based federated aggregation principle introduced in FedAvg [24] by incorporating event-aware client relevance into the global update.

3.7. Adaptive Federated Learning (AdaptiveFL)–Based Comparative Approach

To broaden the comparative evaluation with a recent communication-adaptive federated learning approach, AdaptiveFL was incorporated into the experimental evaluation. AdaptiveFL was proposed to address dynamic-bandwidth constraints in federated learning by allowing each device to select a best-fit sub-model according to its available bandwidth, while employing a tailorable local training strategy for different sparsity levels [18]. In this study, the communication-adaptation principle of AdaptiveFL was adapted to the 5G NSA resource-demand prediction scenario. Each gNodeB was considered as a federated client and normalized communication-capacity levels of 0.20, 0.50, 0.75 and 1.00 were

used to represent different communication conditions. Client selection was performed by jointly considering the available communication capacity, client importance and event relevance. Accordingly, clients were ranked according to a combined selection score and the highest-ranked clients were selected for the local training. The number of participating clients was dynamically adjusted according to the mean communication capacity of each communication round. The adapted approach was evaluated using the same 5G NSA dataset, prediction task, model architecture, data partitioning, training configuration and evaluation metrics as FedAvg, FedProx and the proposed ACE-FedAvg framework.

3.8. Weight Selection and Ablation Analysis

The weight coefficients used in ACE-FedAvg were selected according to the characteristics of 5G NSA resource-demand prediction. The curriculum weights emphasize traffic demand and DL PRB utilization since they are the main indicators of resource consumption. While user density is considered as an additional factor affecting client difficulty. Similarly, the client importance weights prioritize PRB utilization because it directly reflects radio resource occupation, while PRB variability, user density and traffic level provide complementary information about client behavior. For the event-aware score, higher contributions are assigned to client importance and PRB utilization to capture the operational relevance of clients under dynamic network conditions, while trend and locale performance information improve adaption capability. The aggregation coefficients were selected to provide a balance between statistical reliability and event-awareness. Therefore, the proposed strategy assigns 60% importance to local data contribution and 40% to event-aware relevance. To evaluate the robustness of these weighting choices, a controlled ablation study was performed by modifying one weighting component at a time while keeping the remaining ACE-FedAvg structure unchanged. The results are summarized in Table 3.

Table 3. Ablation study of weighting configuration in ACE-FedAvg.

Configuration	Modified Component	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)	Coefficient of Determination (R^2)	Correlation Coefficient
Proposed ACE-FedAvg	None	0.60459	0.39317	0.64092	0.39317
Curriculum-PRB	Curriculum	0.60459	0.39317	0.64092	0.39317
Importance-Users	Importance	0.60457	0.39234	0.64094	0.39234
Event-PRB	Event	0.60339	0.39399	0.64234	0.39399
Aggregation-Samples	Aggregation	0.60217	0.38848	0.64379	0.38848
Aggregation-Event	Aggregation	0.60859	0.40048	0.63615	0.40048

The results demonstrate that the proposed weighting strategy provides stable performance under different configurations. The variations in curriculum, importance and event-aware weights introduce only minor changes, confirming the robustness of the proposed design. For aggregation, increasing the contribution of local samples can slightly improve prediction accuracy, whereas excessive reliance on event information degrades the performance. Therefore, the selected coefficients provide a suitable compromise between learning stability and adaptation to dynamic 5G NSA conditions.

4. Experimental Results and Discussion

This section presents the experimental results of the proposed ACE-FedAvg framework using the real operational 5G NSA dataset. The proposed method is compared with the conventional FedAvg and FedProx algorithms and the AdaptiveFL on the unseen test day using multiple prediction performance metrics. Figure 2 presents the convergence behavior

of the evaluated federated learning models over the communication rounds by showing the validation RMSE during federated training.

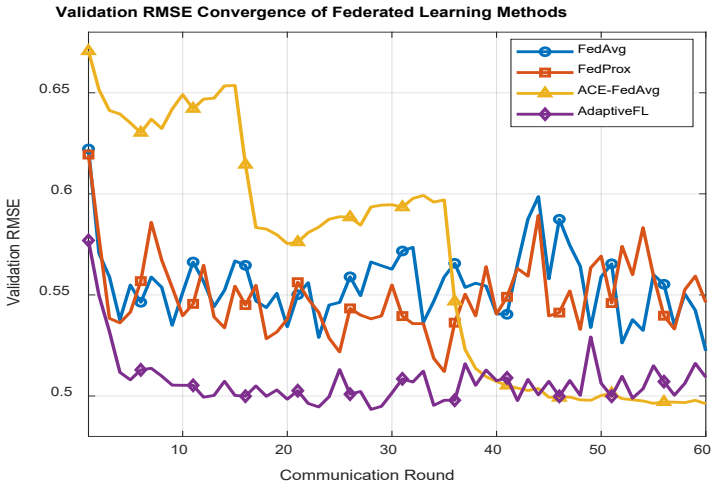


Figure 2. Training convergence of the federated learning models.

Although ACE-FedAvg starts with a higher error due to the curriculum learning strategy, its performance steadily improves as more informative clients are incorporated. It finally achieves the lowest validation RMSE, demonstrating effective convergence as the training progresses. The AdaptiveFL-based approach exhibits a different convergence behavior, reaching a relatively low validation RMSE during the early communication rounds and maintaining a comparatively stable error throughout the subsequent rounds. This behavior reflects the benefit of adapting client participation to the available communication conditions while considering client relevance. However, in the later communication, ACE-FedAvg achieves a lower validation RMSE than the three approaches, indicating that the curriculum and event-aware mechanisms provide a distinct convergence behavior for the considered resource-demand prediction task. To further assess the effectiveness of the converged models, Figure 3 compares the actual next-hour DL PRB utilization with predictions generated by FedAvg, FedProx, ACE-FedAvg and AdaptiveFL on the completely unseen day. All four models successfully capture the overall temporal evolution of the network demand. However, ACE-FedAvg follows the actual measurements more closely, particularly during sudden traffic surges and high-demand periods. The enlarged view further highlights that the proposed framework more accurately tracks rapid fluctuations while reducing both underestimation and delayed responses observed in the baseline federated learning models. AdaptiveFL also captures the general temporal dynamics of the DL PRB demand, providing an additional communication-aware reference for evaluating the proposed framework. These results indicate that incorporating adaptive client importance estimation and event-aware aggregation enables the global model to better capture dynamic demand patterns in real operational 5G NSA networks.

The impact of the communication process on model performance is further analyzed in Figure 4. The results show that ACE-FedAvg achieves competitive and consistently strong performance across a broad range of communication rounds, with its most favorable results observed at 20 and 50 rounds. At 20 rounds, ACE-FedAvg attains an RMSE of 0.6511 and R^2 of 0.7087, corresponding to a 4.58% RMSE reduction relative to FedAvg. At 50 rounds, the proposed method maintains a similar RMSE of 0.6513 while achieving the largest relative improvement over FedAvg, reaching 8.82%. Although some performance fluctuations are observed at specific communication levels, particularly at 3 and 30 rounds, ACE-FedAvg recovers at subsequent rounds and maintains an R^2 above 0.70 at 20, 50 and 60 rounds. These results indicate that the proposed adaptive aggregation strategy can

effectively exploit iterative communication while maintaining robust resource-demand prediction performance across different communication budgets.

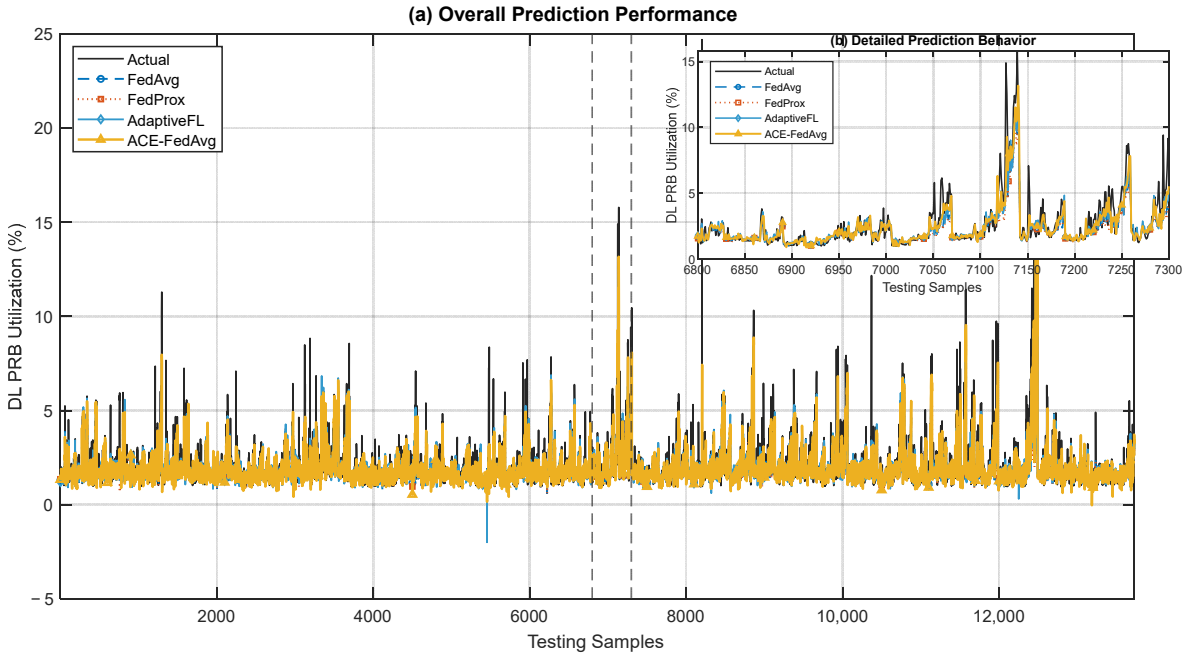


Figure 3. Next-hour DL PRB utilization prediction comparison on the unseen 5G NSA test day.

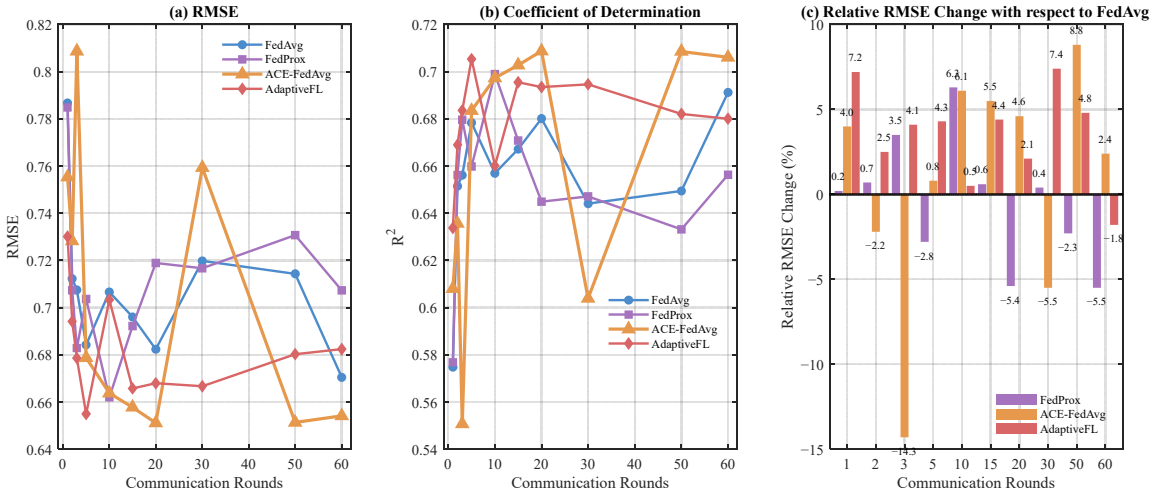


Figure 4. Impact of communication rounds on prediction performance.

To explain the improved convergence Figure 5 illustrates the distribution of normalized event-aware scores for all participation federated clients. The proposed client selection strategy prioritizes clients with higher event-aware scores while lower-ranked clients are excluded from the current communication round.

This adaptive selection mechanism enables the global model to focus on the most informative clients, improving learning efficiency and reducing unnecessary communication overhead.

After examining the proposed client selection mechanism, the influence of different client participation rates is evaluated in Figure 6. The results show that prediction performance varies across participation rates, with ACE-FedAvg achieving its lowest RMSE and highest R^2 at a client fraction 20%, while AdaptiveFL attains its best results at 30%. The relative RMSE reduction further shows improvements over FedAvg across all evaluated

participation rates, reaching 3.97% for ACE-FedAvg at 30% and 4.88% for AdaptiveFL at 10%. Based on this sensitivity analysis, a client fraction of 20% is selected for the main experiments, as it provides the most favorable RMSE and R^2 values for the proposed ACE-FedAvg framework. These results indicate that the choice of client participation rate influences the effectiveness of the federated aggregation and client selection strategies.

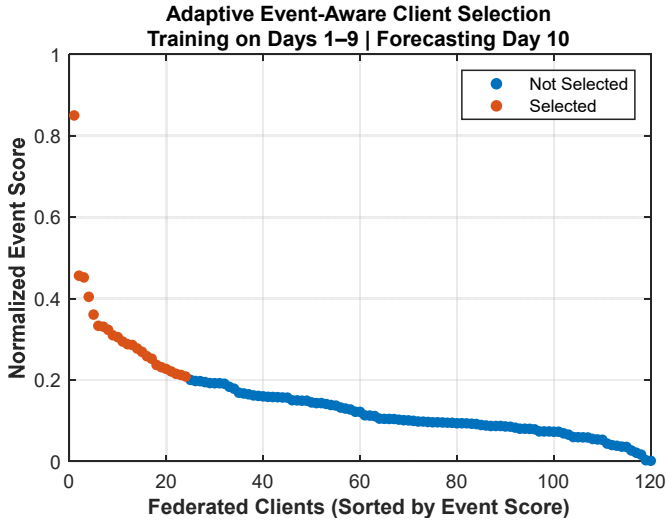


Figure 5. Distribution of event-aware scores assigned to the participating federated clients.

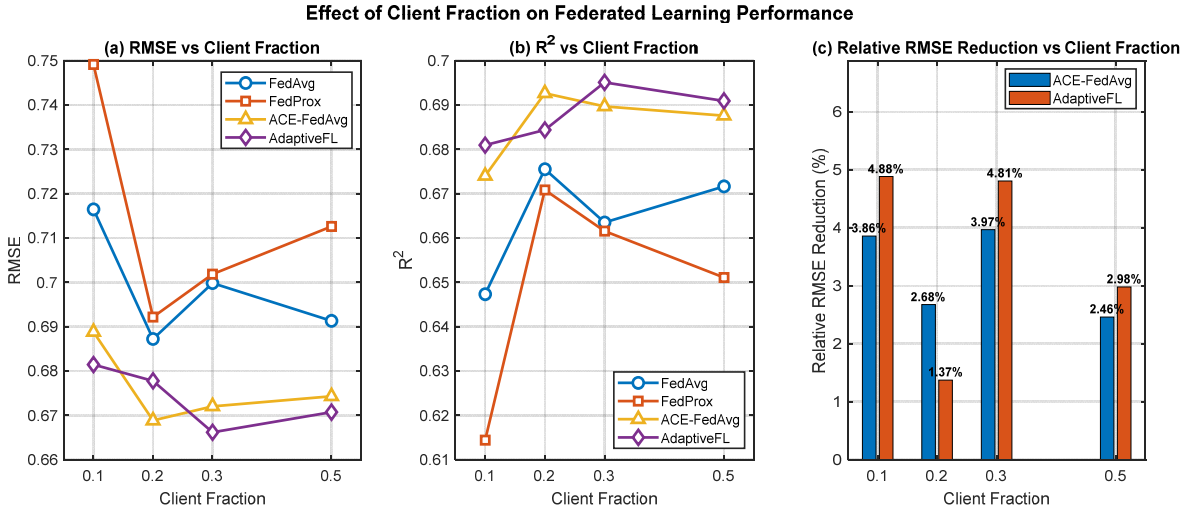


Figure 6. Impact of client participation rate on prediction performance.

Finally, the overall prediction performance of the evaluated models is summarized in Figure 7 using multiple evaluation metrics. ACE-FedAvg achieves the lowest RMSE, peak RMSE, top 5% error and weighted RMSE, while obtaining the highest coefficient of determination (R^2). In contrast, FedAvg achieves a marginally higher Pearson correlation than ACE-FedAvg. These results demonstrate the effectiveness of the proposed framework in improving prediction accuracy and capturing high-demand behavior under realistic 5G NSA network conditions.

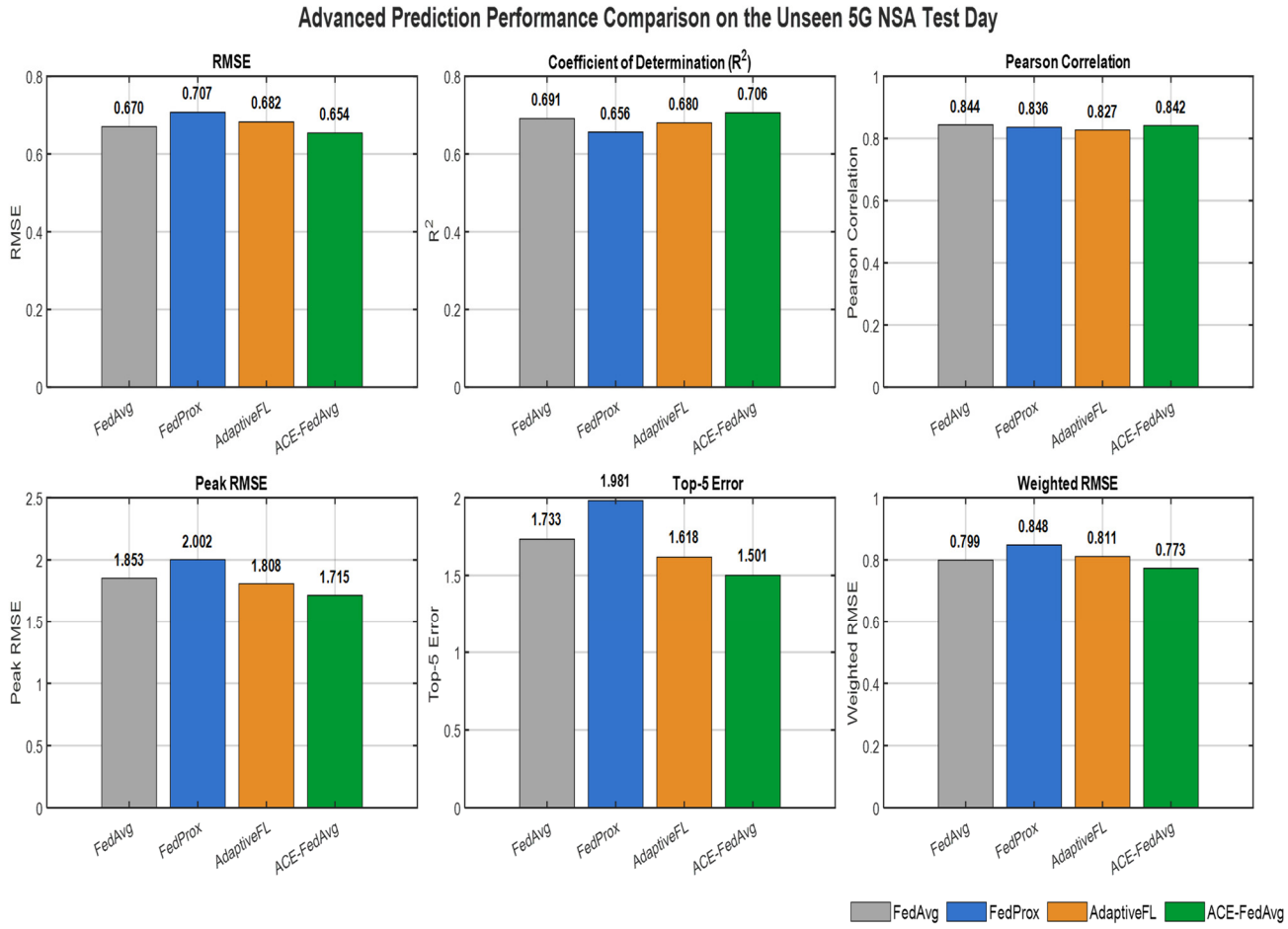


Figure 7. Overall prediction performance comparison on the unseen 5G NSA test day.

5. Conclusions

This paper presented ACE-FedAvg, an Adaptive Curriculum Event-Aware Federated Averaging framework for short-term DL PRB utilization prediction in operational 5G NSA networks. The proposed framework integrates curriculum-based client selection, adaptive client importance estimation and an event-aware aggregation strategy into a unified federated learning architecture. Unlike conventional federated learning approaches, ACE-FedAvg prioritizes informative clients according to their traffic characteristics and event-aware scores, enabling more effective collaborative model training while preserving data privacy. The proposed framework was evaluated using a real operational 5G NSA dataset collected from a commercial mobile network. Experimental results demonstrated that ACE-FedAvg achieved competitive and, under several experimental settings, improved prediction performance compared with the conventional FedAvg and FedProx approaches, as well as the communication-adaptive AdaptiveFL approach, in terms of RMSE, coefficient of determination, Pearson correlation, peak RMSE, top-5 error and weighted RMSE. The analysis of different traffic-demand levels, communication rounds and client participation rates further demonstrated the robustness of the proposed framework. In particular, ACE-FedAvg maintained strong prediction performance across a broad range of communication budgets, achieving favorable results at 20 and 50 communication rounds, while the comparison with AdaptiveFL provided an additional assessment against communication-adaptive client participation under varying network conditions. Overall, the results demonstrate the potential of ACE-FedAvg for federated resource-demand prediction in operational 5G NSA networks. Future work will investigate more advanced adaptive aggregation strategies, extend the framework to multi-cell and multi-operational scenarios, evaluate its real-time

operation for periodic resource-demand prediction under operational network conditions and explore its integration with emerging AI-native RAN architecture for next-generation wireless networks.

Author Contributions: Conceptualization, R.K., A.B., A.L. and P.L.; methodology, R.K., A.B. and A.L.; software, R.K. and A.B.; validation, R.K., A.B. and A.Z.; formal analysis, A.B., A.L. and A.Z.; investigation, R.K., A.B. and A.Z.; data curation, R.K. and A.B.; writing—original draft preparation, R.K., A.B. and A.L.; writing—review and editing, A.L., A.Z. and P.L.; visualization, R.K. and A.B.; supervision, A.L. and P.L.; project administration, A.L. and P.L.; funding acquisition, P.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to the ethical and institutional requirements stipulated under the agreements between the participating institutions.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

5G	Fifth Generation
FL	Federated Learning
IoT	Internet of things
Qos	Quality of Service
KPI	Key Performance Indicator
AI	Intelligence Artificial
RAN	Radio Access Network
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
gNodeB	Next Generation (5G) Node Base station
NSA	Non-Standalone
DL PRB	Downlink Physical Resource Block

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