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Original Article

An Iot-Integrated Federated Edge Computing Paradigm for Privacy-Preserving Smart Campus Infrastructure

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Abstract - *The rise in the use of the Internet of Things is resulting in extensive and varied data being generated on university campuses, especially in the domain of energy consumption and management in buildings. Conventional learning algorithms will fail in this scenario because they are restricted by privacy boundaries and communication cost considerations on edge devices. Against this background, we introduce a federated learning framework on campus. In which learning will occur at the edge nodes collaboratively. This scheme provides a resource-conscious multi-layer federating strategy that controls the number of devices taking part in the process as well as the frequency at which aggregation is done based on each device's capability. Contrary to existing federating designs that assume each edge node is similar in ability, this design considers the differences in each campus environment. The experiments conducted using the realistic smart campus test bed reveal that our approach ensures stronger convergence, reduced communication overhead, as well as more accurate predictions of energy consumption, when compared to traditional Federated Averaging as well as the fixed aggregation strategy. Moreover, the approach allows for simplicity in the preservation of privacy, without losing scalability, especially for the smart campus setting that has been projected to be rather large.*

Keywords - *Edge computing, Energy Management Systems, Federated Learning, Internet of Things (IoT), Machine Learning, Smart campus, Privacy-Preserving.*

1. Introduction

The growth of smart campuses has been stoutly obsessed the widespread espousal of Internet of Things (IoT) technologies that provide continuous monitoring of energy usage, environmental conditions, occupancy behavior and infrastructure health across diverse campus facilities. The various buildings in an organization, such as Academic buildings, research laboratories, residential hostels and administrative offices, increasingly depend on intense sensor networks that support intelligent decision making and resource management.

The availability of such fine-grained data presents momentous opportunities for data analytics and further provides additional challenges related to data privacy, system scalability and operation efficiency. Federated learning can be effectively employed to address these challenges. This federated learning offers a decentralized alternative by allowing machine learning models to be trained for addressing these challenges. This introduces federated learning models that are to be trained collaboratively across distributed nodes, keeping sensitive data localized. However, the direct application of federated learning to smart buildings remains problematic as campus edge nodes are inherently heterogeneous, exhibiting wide disparities with respect to power, memory availability, energy constraints and network reliability. To address these challenges, a new Context – Aware Resource Elastic Federated Edge Learning (CARE-FL) framework is proposed.

This framework integrates real-time contextual awareness into the federated learning process by vigorously adjusting the participation of the node, local training intensity and aggregated influence based on various operative indicators like energy stability, occupancy, volatility, computational readiness and network conditions rather than enforcing rigid participation. The proposed framework clearly states its ability to achieve rapid convergence, reduced communication overhead and predictive performance under heterogeneous and nonstationary conditions and further establishes a strong practical foundation for deployment of federated intelligence in real-world campus environments.

2. Related Work

Konečný et al. [1] provided the formal optimization framework of federated learning by tackling the problem of distributed learning over resource-constrained devices. This work presented with an objective of minimizing communication cost by maintaining integrity in data locality, which gives a theoretical foundation for decentralized learning. The Federated averaging using neural networks is given by H. B. McMahan in [2], which proves that neural networks can be effectively trained without sharing raw data. The extension of federated learning for multitasking scenarios is presented by V. Smith in [3]. This approach exactly fits smart campus environments where diverse IoT subsystems generate task-specific yet correlated data distributions.

Bonawitz et al. [4] addressed privacy risks in federated learning with the development of secure aggregation protocols. By making it impossible for the central server to infer updates from any individual client, this work strengthened the feasibility of federated learning in sensitive cyber-physical and campus-scale infrastructures. One of the earlier conceptual and application-oriented discussions related to federated machine learning was provided by Yang et al. [5]. The authors captured how the federated paradigms align with real-world IoT deployments at the level of smart cities and intelligent buildings.

Caldas et al. [6] proposed LEAF, a benchmark suite for studying federated learning algorithms under realistic systems and statistical heterogeneity. This represents one of the key validation instruments for federated approaches in edge and IoT contexts. Bonawitz et al tried for upscaling federated learning [7].

In the process of upscaling, it has been found that orchestration, fault tolerance, and client scheduling can be major hurdles in the deployment of smart campus-wide learning systems. The gulch between theoretical assumptions and real-world practicalities confronted by actual IoT and edge implementation has been highlighted by Q. Li in [8].

Wang et al. [9] Presented detailed discussion on adaptive federated learning mechanisms, stating that these mechanisms will often go beyond the feasibility of edge devices with limited resources, and there arises a necessity to maintain a delicate balance between communication and computation expenses. Xiaofei Wang et al. [10] introduced the term “in-edge AI”, which made federated learning take off in mobile edge computing, which is essential in the design of smart campuses, where inferences and learning are closer to the point of origin. The application of federated learning on wireless networks is presented by Nguyen H. Tran et al. [11]. This resulted in the creation of mathematical models that are very practical for the deployment of large-scale wireless IoT systems.

Li et al. [12] gave a broad analysis of the challenges in federated learning while inspecting the issues related to disparate data handling, confidentiality and communication efficiencies. This provided a detailed outlook on constructing robust and resilient learning smart architectures. FedProx, that enable flexible local updates by considering the heterogeneity of the system, is given by Li et al. [13].

This FedProx can handle devices with vast computing capabilities and thus secured a significant place in the world of IoT. SCAFFOLD is proposed by Karimireddy et al. [14] to sort out client drift due to the unlike nature of data received by different clients, and this mechanism brings stability to the convergence by leveraging a control variable, which is vital for the smart campus deployments to run over longer periods. Deep dug of FedAvg into its theoretical base was done by Li et al. [15], who looked at how convergence fares for the data of various clients not distributed identically. Aledhari et al. [16] have done a detailed survey on enabling applications of federated learning emphasizing IoT and Edge computing devices, and this consolidates interdisciplinary perception, which is relevant for building smart campus infrastructure. The hierarchical approach of extending federating learning into architectures known as Fog learning, which enabled aggregation of intermediate layers, is presented by Hosseinalipour in [17]. On similar lines, the investigation on the various applications of federated learning into the IoT ecosystem to make domain-specific changes, such as scalability, energy efficiency and intelligent infrastructure, has been carried out by Zhang et. al. [18]. A comprehensive survey of federated learning for mobile networks is presented by Yang in [19] that analyzes architectural designs and optimization strategies.

The extension of federated learning for health care domains is presented by J. Xu in [20], which provides privacy-preserving analytics. The decentralized network that copes with integrity issues in distributed infrastructure by combining blockchain and federated learning is given in [21]. Lin et al. [22] proposed semi-decentralized federated learning with device-to-device communication that mitigates server addiction and improves scalability in thick campus IoT deployments. N Shlezinger et al. [23] showed that decentralized federated learning enables repeated sharing of private users' data for local model updates, which consumes more bandwidth to mitigate this overhead universal vector quantization is proposed that can compress updates while maintaining low distortion by preserving accuracy and convergence. Wang et al. [24] proposed hierarchical aggregation for scalable federated learning, enabling multi-level coordination that benefits large smart campuses with network-layered structures. The framework of federated learning at the system level, insights to drive practical decisions using Fed-Scale, is proposed by Lai in [25]. C.Yu et al. [26] studied poisoning attacks in federated learning, and some security considerations were presented. T.Li et al. [13]

addressed robustness under system heterogeneity and identified ways that could stabilize training across edge devices with diverse resources. A comprehensive monograph on federated learning methods and applications was presented by Ludwig and Baracaldo [27]. On similar lines, the detailed survey on the applications of federated learning in IoT by addressing challenges like scalability and power consumption is given by T. Zhang in [28]. A detailed survey on system architectures, privacy, security mechanisms and resource management challenges by highlighting the research directions for building robust federated learning systems was presented by S Abdulrahman in [29]. Chai et al. [30] studied evaluation methodologies in federated learning and proposed standardized metrics that contributed to rigorous assessment of smart campus learning systems. An energy-efficient federated learning technique has been given by A. Salh in [31] that address sustainability issues in smart infrastructure.

Ma et al. [32] investigated resource-aware federated learning in IoT smart campus systems that aim at optimizing the learning performance under constrained resources. Privacy preserving energy management framework for multiple smart buildings using reinforcement learning is presented by Lee in [33]. Simulation results conclude that this approach provides optimal energy consumption while maintaining privacy under heterogeneous building environments. The review of communication-efficient FL Techniques that includes reducing communication complexity, efficient resource scheduling and over-the-air computation to improve training efficiency under limited wireless networks is presented by Ninghui Jia in [34]. The Resource aware hierarchical federated multitask learning framework is presented by Xingfu Yi in et. al. in [35]. This framework employs a dual optimization approach that enables a multi-tasking model without sharing raw data while balancing resource consumption and learning accuracy. Simulation results convey facts of improved convergence speed and learning performance compared to conventional FL techniques.

3. Materials and Methods

The system architecture of the proposed framework is given in Figure 1, which is designed for a realistic smart campus, encompassing academic buildings, research labs, hostels, libraries, and administrative offices. Within these facilities, IoT sensors continuously monitor energy consumption, equipment status, indoor environmental conditions, and occupancy patterns. In this methodology, the edge nodes process the data locally and provide support to the on-site model.

The learning is harmonized through a federated paradigm where a central orchestrator aggregates and synchronizes model updates without accessing raw sensor data. This provides a heterogeneous and vibrant nature of campus environments, in which data across different nodes are non-identical and non-independent and operational conditions such as network availability, network quality, and energy conditions will oscillate.

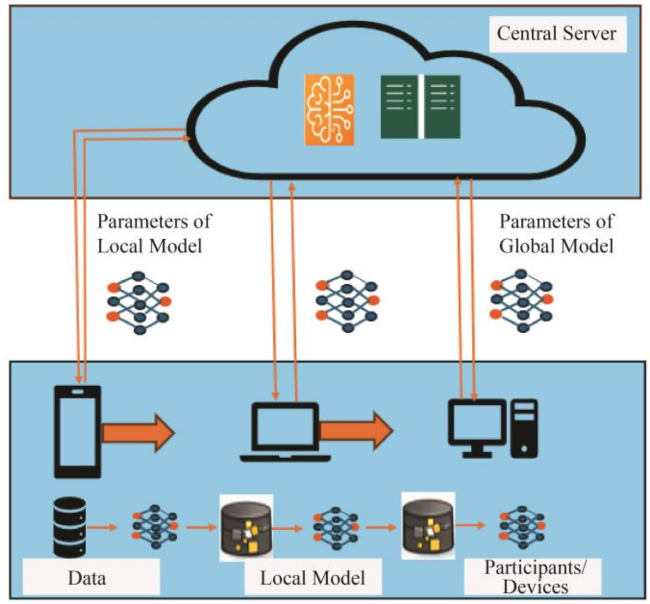

Fig. 1 Architecture of proposed CARE-FL

Here, the edge node maintains a log of local operational profile, such as capturing energy trends, occupancy variability, computational capacity and network conditions. And further, these indicators are normalized and combined into a unified complex vector to guide decision-making without exposing sensitive information. This local training adopts nodes with abundant resources vigorously while setting back constrained nodes to avoid interference with the critical campus services. This strategy balances computational load and mitigates divergence from uneven local updates. The participation of different nodes in federated rounds is context-aware. These nodes compute the participation score based on resource availability. The nodes that meet a particular dynamic threshold only will participate in learning rounds. This selective participation will reduce synchronization delays, the straggler effect, and ensure reliable contributions. Further, the communication overhead can be minimized through this adaptive partial update strategy. This makes the model more sensitive as the core layers are prioritized under energy strell as compared to static compression methods.

At the orchestrator, all the updates are aggregated using context-weighted aggregation and these contributions are scaled according to data inferred in reliability and representativeness derived from participation history. This ensures the nodes with active workloads will greatly influence the global model to produce a balanced representation of campus-wide dynamics as compared to a simple average of heterogeneous updates. The privacy is preserved throughout the process as raw sensor readings remain at the edge nodes and only exchanged model updates are clipped and normalized to ensure that locally sensitive operational patterns are not leaked. Further, no contextual attributes are explicitly shared, achieving privacy without heavy cryptographic overhead.

Across successive cycles of context sensing, adaptive training, selective participation, partial updates, and context-aware aggregation, the global model converges progressively, learning long-term energy consumption and occupancy patterns across the campus while avoiding uniform computational and communication overheads. This framework can be successfully deployed on existing campus infrastructure using commercial embedded platforms. Its modular architecture enables scalability and long-term evolution, allowing individual components, such as context modeling, participation policies, and aggregation logic, can be updated independently based on the operational requirements.

3.1. Proposed Context-Aware Resource Elastic Federated Edge Learning (CARE-FL)

Input:

- Set of edge nodes E={e1,e2,…,eN}
- Initial global model parameters W^0
- Maximum federated rounds T
- Participation threshold function τ(t)
- Learning rate η

Output:

Trained global model: W^T

Step 1: Initialize round counter t←0

Step 2: Initialize the global model W^0 at the federated orchestrator

Step 3: Broadcast W^0 to all edge nodes

Step 4: While t < T do

Step 4.1: Initialize participating node set $S^t \leftarrow \emptyset$

Step 4.2: For each edge node $e_i \in$ E do

Step 4.2.1: Sense local operational context

- Energy load variation E_i^t
- Occupancy volatility O_i^t
- Available computational resources R_i^t
- Network condition indicator N_i^t

Step 4.2.2: Construct normalized context vector

C_i^t = Normalize (E_i^t, O_i^t, R_i^t, N_i^t)

Step 4.2.3: Determine resource-elastic training parameters

$Epochs_i^t$= f(R_i^t, E_i^t, O_i^t)

$BatchSize_i^t$=g (R_i^t,N_i^t)

Step 4.2.4: Compute participation score

$PS_i^t = \alpha R_i^t + \beta(1-E_i^t) + \gamma(1-N_i^t)$

Step 4.2.5: If $PS_i^t \geq \tau$ (t), then

Add e^i to the participating set. S^t

End For

Step 4.3: For each participating node $e^i \in S^t$ do

Step 4.3.1: Initialize local model

$W_i^t \leftarrow W^t$

Step 4.3.2: Perform local training

For epoch =1 to $Epochs_i^t$ do

$W_i^t \leftarrow W_i^t - \eta \nabla L_i W_i^t$

End For

Step 4.3.3: Select partial model updates

ΔW_i^t = Select Critical Updates $W_i^t - W^T$

Step 4.3.4: Transmit ΔW_i^t to orchestrator

End For

Step 4.4: Initialize aggregated model

$W^{t+1} \leftarrow W^T$

Step 4.5: For each $e^i \in S^t$ do

Step 4.5.1: Compute aggregation weight

$W_i^t = \lambda_1 R_i^t + \lambda_2 O_i^t + \lambda_3(1- E_i^t)$

Step 4.5.2: Update global model

$W^{t+1} = W^T + \omega_i^t \,.\, \Delta W_i^t$

End For

Step 4.6: Broadcast updated global model W^{t+1} to all edge nodes

Step 4.7: Increment round counter t←t+1

End While

Step 5: Return the final global model W^T

The Context-Aware Resource Elastic Federated Edge Learning (CARE-FL) presented above provides shared learning across edge nodes, adapting to their real-time operational conditions. This makes it suitable for smart dynamic campus environments, in contrast to enforcing uniform participation of each node. Training starts with initializing the orchestrator global model and distributing it to all nodes, and this creates a harmonized starting point.

Further, learning proceeds in rounds that consist of local optimization and are then followed by global optimization. Here, the nodes assess their context and validate training parameters accordingly. The more capable nodes use more batch sizes while constrained nodes opt for lighter configurations to ensure efficient learning without overloading less constrained nodes.

The participation of each node is selective based on the resources available with nodes. Each node computes scores based on the available resources. The node participates in the next round only if the resource score exceeds a certain specific threshold. This local training also preserves data privacy, as only the most significant updates are shared by reducing communication overhead.

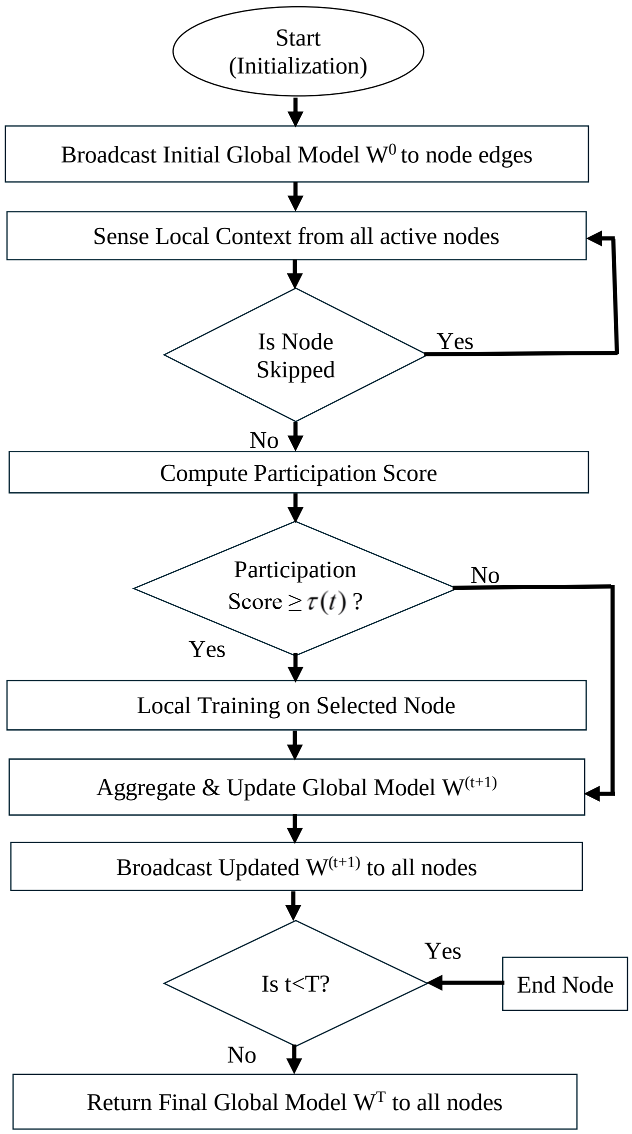

Fig. 2 Implementation of proposed CARE-FL

At the end of each round orchestrator collects the updates and weights them according to the reliability and operating context of each node. This ensures that the well-resourced nodes have greater influence on the global model and hence the global model can accurately reflect campus-wide patterns. This modified model is sent to all local nodes, including non-participant nodes, to spread the knowledge across the network. This process continues until the resulting global model captures long-term energy and occupancy dynamics that adopt to various nodes with varying resources.

The selected nodes now attain local training using their private datasets. In the training, the nodes identify critical updates (ΔW_i^t) that are selectively transmitted to the orchestrator. This selective sharing will aid in reducing network overhead, ensuring privacy preservation by limiting the exposure of local model information. The orchestrator performs aggregation of weights (ω_i^t) based on the node reliability, computational capacity, and context stability, thus making sure that the nodes provide high-quality updates to influence the global model.

The updated global model (W^{t+1}) is now sent to all edge nodes so that the updates of the global model are communicated to all nodes in the network, including the nodes that did not participated in the current federated round. This completes a single federated round, and the same process is repeated for other federated learning rounds to increase the efficiency and accuracy of the model. This emphasizes the iterative nature of federated learning that continues until predefined numbers of federated rounds (T) are reached. By clear modeling of real-time variables, adaptive training parameters, participation thresholds and weighted aggregation, the Context-Aware Resource Elastic Federated Edge Learning (CARE-FL) can be effectively applied for real-time smart campus deployments.

4. Experimental Setup

The experiment is steered on the smart campus of the administrative office, Hostels, Academic blocks and various laboratories in which dense IoT sensor networks continuously monitor energy consumption, environmental conditions, and occupancy patterns, capturing both spatial and temporal visibility. All data pertaining to local nodes is processed in line with the privacy principles, ensuring raw measurements and sensitive information are never transmitted externally. This design reflects realistic deployment constraints and institutional data fortification requirements.

The edge computing devices handled local preprocessing of data, model training and context-aware decision making. All the nodes are provided with heterogeneous hardware to reflect differences in processing power, memory and energy availability. The network conditions of the federated orchestrator are well varied to various parameters such as latency, bandwidth and reliability differences. The orchestrator is well designed to manage synchronization and aggregation without storing local datasets, ensuring data privacy. This experimental setup aims to learn predictive models of building energy behaviour, focusing on short-term energy consumption and forecasting anomaly detection to support proactive energy management.

The training begins with a global model to ensure consistency across federated rounds. Local optimization follows Context-Aware Resource Elastic Federated Edge Learning (CARE-FL), adjusting training intensity according to node capacity and the number of federated rounds is selected to guarantee convergence under non-independent and identical distributed data. The performance is measured against various baselines, including centralized and decentralized methods with static and dynamic client participation. This framework is done in a modular federated learning environment to support configurable client behaviour, ensuring aggregation strategies. Each configuration is executed across multiple independent trials with varied random initializations to ensure reproducibility.

5. Results and Discussion

The results pertaining to various buildings, such as administrative office, Hostels, Academic blocks and various laboratories with dense tailored sensors were depicted in Table 1. The academic blocks deploy 15 sensors for monitoring power, occupancy and HVAC systems every 5 minutes. The laboratories employed 20 sensors for energy and equipment load at one-minute intervals. Hostels had 10 sensors for energy and occupancy being sampled every 10 minutes. The administrative building employed 12 sensors for power and environmental monitoring every 5 minutes. The edge nodes are employed to process this data locally for tasks such as predictive modelling, anomaly detection, demand forecasting and control optimization.

Table 1. Building-wise sensor deployment and local edge processing metrics for smart campus operations

Building Type	Sensors Deployed	Number of Sensors	Sampling Interval (in Minutes)	Estimated Data Volume per Interval (KB)	Edge Node Role
Academic Blocks	Power, Occupancy, HVAC	15	5	45	Local Training
Laboratories	Energy, Equipment Load	20	1	60	Anomaly Detection
Hostels	Energy, Occupancy	10	10	30	Demand Prediction
Administrative	Power, Environment	12	5	36	Control Optimization

Figure 3 gives a pictorial description of the number of sensors consumed by different buildings, along with the sampling interval and estimated data per interval. This clearly states that the laboratories consumed more sensors and thereby the estimated data is more compared to the other building, and the sampling interval here is 1 minute, which is less compared to all other blocks that are taken for experimental purposes.

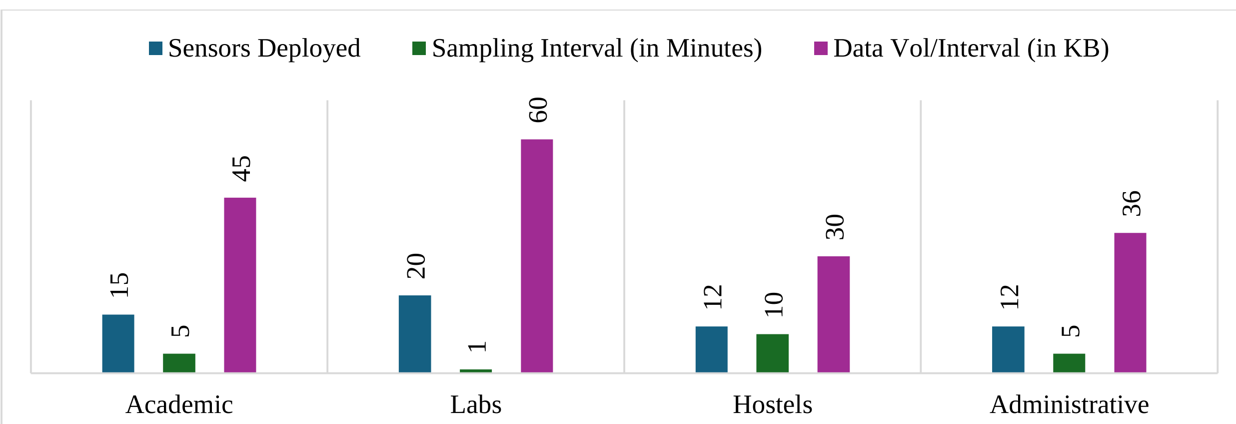

Fig. 3 Illustration of number sensors, interval and estimation of data volume across different blocks of interest of proposed CARE-FL

Table 2 depicts information about the different nodes used in the experimental setup. The nodes were categorized into three different categories, namely High Capacity, Medium Capacity, and Low Capacity. The High-Capacity nodes were featured with a quad-core with 8 GB RAM, having a power constraint of 10 W and providing a latency of 5 milliseconds. The Medium Capacity nodes were featured with Dual core with 4 GB RAM, having a power constraint of 25 W, and providing a latency of 20 milliseconds. On similar lines, The Low-Capacity nodes were featured with a single core with 2 GB RAM, having a power constraint of 50 W and providing a latency of 50 to 100 milliseconds.

Table 2. Edge node resource profiles and network conditions

Node Category	CPU Class	Memory	Energy Constraint	Network Latency
High-Capacity	Quad-core	8 GB	10 W	5 ms
Medium-Capacity	Dual-core	4 GB	25 W	20 ms
Low-Capacity	Single-core	2 GB	50 W	50–100 ms

The Figure 4 gives a diagrammatic representation of resources consumed by the various nodes. It in conventionally well-known fact that low-capacity nodes consume less memory as compared to medium and high-capacity nodes, and conversely, the low-capacity nodes suffer with more network latency and energy as compared to high-capacity and medium-capacity nodes.

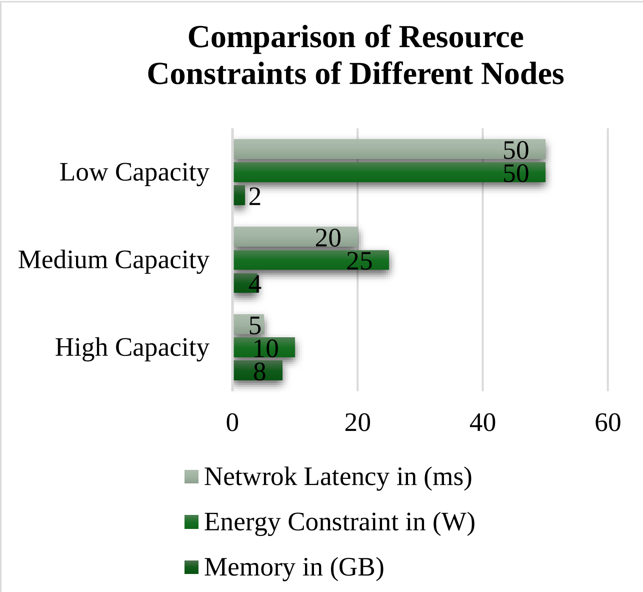

Fig. 4 Resource constraints of different nodes of experimental interest

The learning configuration that balances predictive capability and computational feasibility is given in Table 3. Here, the lightweight neural network is trained for 50 federated rounds with an initial learning rate of 0.001. Here, the Context-Aware Resource Elastic Federated Edge Learning (CARE-FL) stabilizes faster than static baselines by selectively including capable nodes and suppressing low-quality updates.

Table 3. Edge node resource profiles and network conditions

Parameter	Value
Model Type	Lightweight Neural Network
Optimizer	Adaptive Gradient Descent
Initial Learning Rate	0.001
Federated Rounds	50
Local Epochs	Adaptive

The robustness and scalability are evaluated by increasing the node participation is presented in Table 4. The proposed CARE-FL's has achieved a maximum efficiency of 95% with 10 nodes having a communication overhead growth of 120 MB and a Resilience Score of 0.9. The minimum efficiency 91% is attained for 50 nodes having a communication growth of 500MB and a resilience score of 0.95. From the table 4, it is very clear that the various parameters, such as accuracy, Communication overhead and Resilience score drops down with the increase in the number of nodes.

Table 4. Impact of network scale on CARE-FL accuracy, communication, and resilience

Number of Nodes	Accuracy (%)	Communication Growth (MB)	Resilience Score
10	95	120	0.9
25	94	250	0.92
50	91	500	0.95

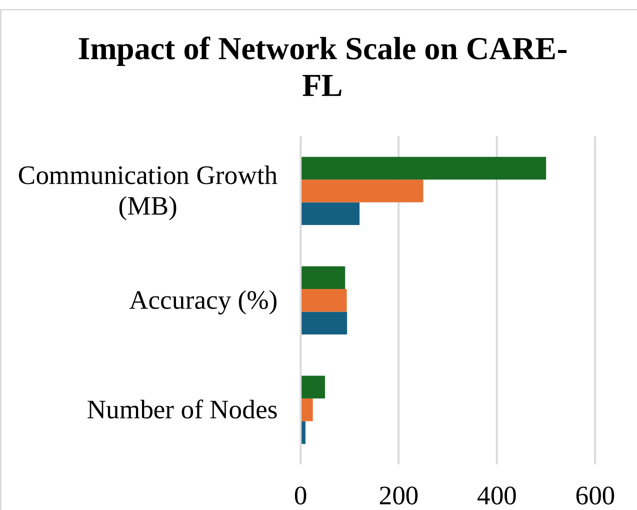

Fig. 5 Performance of proposed CARE-FL with respect to the number of nodes, accuracy and communication overhead

The pictorial representation of performance efficiency is given in Figure 5 with respect to the accuracy of the Resilience score and the accuracy of the proposed CARE-FL. This clearly states the fact that with the increase in the number of nodes, the accuracy, communication growth and Resilience score increased.

The proposed CARE-FL, in which nodes will compute a participation score based on resource availability and the nodes that meet a particular dynamic threshold only will participate in the next upcoming federated learning rounds. This selective participation of nodes has clearly provided significant improvement in the performance of CARE-FL with respect to other existing techniques that are presented in Table 5. The results clearly indicate that the proposed CARE-FL achieves superior performance across all key performance metrics. The CARE-FL achieves a low prediction error of 0.15 kWh, whereas the other techniques, Fed. Avg [2], Fed. Prox [13], Hierarchical FL [24] and Energy Aware FL [34] achieve prediction error of 0.25, 0.22, 0.23 and 0.24 respectively. These results clearly indicate that the proposed CARE FL achieves an improvement of 10%, 7%, 8% and 9% superior performance with respect to prediction error as compared to Fed. Avg [2], Fed.Prox [13], Hierarchical FL [24] and Energy Aware FL [34] respectively. On similar lines, CARE-FL converges for 15 rounds, whereas the other techniques, Fed. Avg [2], Fed. Prox [13], Hierarchical FL [24] and Energy Aware FL [34] converge in 35, 25, 22 and 30 rounds, respectively. This shows the proposed CARE FL achieves 20%, 10%, 7% and 15% faster convergence as compared to Fed. Avg [2], Fed.Prox [13], Hierarchical FL [24] and Energy Aware FL [34] respectively. The communication cost of the proposed CARE-FL is found to be 120, whereas the communication cost of Fed. Avg [2], Fed. Prox [13], and Hierarchical FL [24] are found to be 250, 200, and 150, respectively. This provides an improvement of 85%, 80%, and 30% with respect to communication cost as compared to Fed. Avg [2], Fed.Prox [13], and Hierarchical FL [24], respectively.

Table 5. Quantitative comparison of centralized, FedAvg, and CARE-FL learning strategies

S.No.	Method	Principle	Error Prediction	Convergence Rounds	Communication Cost
1	Proposed CARE-FL	Context Aware Participation+Weighted Aggregation	0.15	15	120
2	Fed.Avg [2]	Uniform Averaging +Full Participation	0.25	35	250
3	Fed.Prox[13]	Proximal Term for handling Heterogeneity	0.22	25	200
4	Hierarchical FL [24]	Multi-level Aggregation	0.23	22	150
5	Energy Aware FL [34]	Reinforcement Learning+ Federated Learning	0.24	30	120

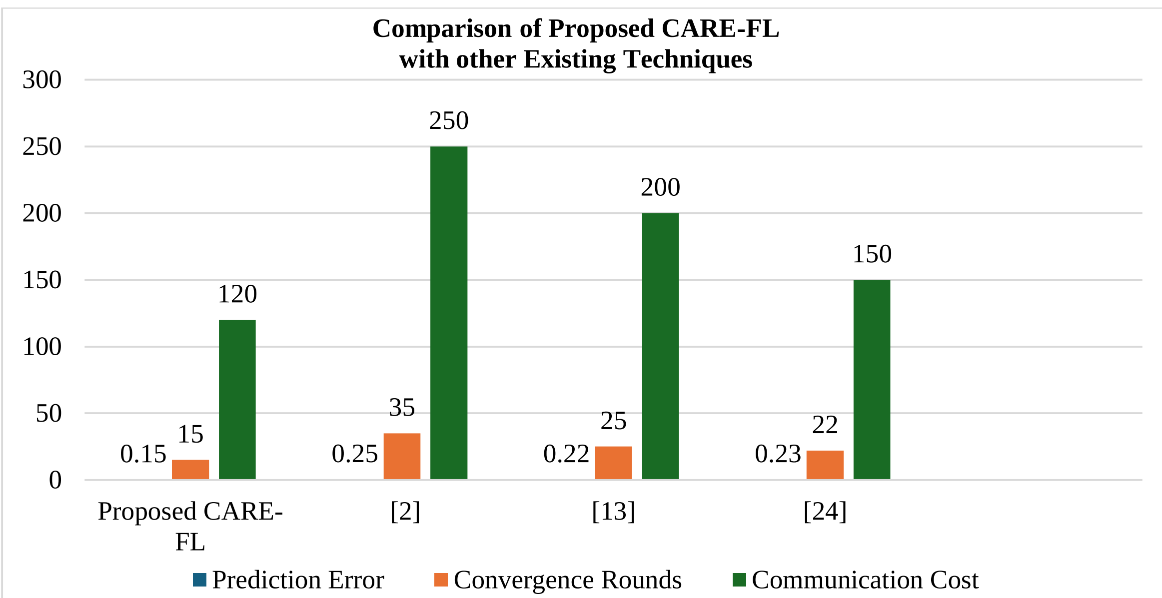

Fig. 6 Comparison of Prediction Error, Convergence Rounds and Communication Cost

The graphical representation of the performance improvements of the proposed CARE-FL in comparison with the other existing techniques is presented in Figure 6.

6. Conclusion

The experimental results clearly convey the fact that the CARE-FL not only achieves a low prediction error rate of 0.14KWH but also converges very quickly within 15 federated rounds while keeping a low communication overhead of 120 MB as compared to centralized federated learning and FedAvg. This minimum overhead is achieved by selectively leveraging nodes based on their available resources and operational conditions. Further, the CARE-FL is also very successful in maintaining high predictive accuracy and controlled communication growth with the increase in the network size. This highlights CARE-FL robustness in the real-world smart deployments. Overall, CARE-FL provides privacy conscious and resource-efficient approach for energy prediction management systems.

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