Intelligent Energy Management System for Sustainable Smart Homes

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Abstract

Energy management in smart homes involves the use of technology to optimize energy consumption, reduce waste, and lower energy costs. Smart homes are equipped with various devices, sensors, and systems that are designed to monitor and control energy usage. We proposed a novel Energy Management System (EMS) that integrates Machine Learning (ML) techniques and IoT paradigms to optimize energy consumption and reduce energy costs for sustainable smart homes. In addition to the AI-based EMS, we propose integrating fog computing, a decentralized computing infrastructure, to improve the speed, accuracy, privacy, and security of the EMS. The fog nodes can collect data from the various sensors and devices in the smart home and process the data in real time, reducing latency and allowing for quicker decision-making. By processing data at the edge of the network, fog computing also reduces the amount of data that needs to be sent to the cloud, improving privacy and security. Experimental proof-of-concept simulations demonstrated the efficiency and effectiveness of our system in improving sustainability in smart homes.

Keywords: Smart Homes; Sustainability; Intelligent Energy Management; Fog Computing

1. Introduction

With the increasing demand for energy and the need to reduce carbon emissions, energy management in homes has become a crucial aspect. Smart homes, equipped with various technologies, have emerged as an effective solution to optimize energy consumption, reduce waste, and lower energy costs. The Energy Management System (EMS) in smart homes is an essential component of this solution, allowing for the efficient management of energy consumption. The EMS employs various technologies, including smart thermostats, energy-efficient lighting, smart appliances, renewable energy sources, and energy monitoring systems, to achieve energy efficiency. Smart thermostats automatically adjust the temperature of a home based on the occupants' behavior and preferences. Energy-efficient lighting can be dimmed or turned off when not in use, while smart appliances adjust their power consumption based on the user's behavior.

Renewable energy sources, such as solar panels, wind turbines, or geothermal systems, can be integrated into smart homes to generate electricity or heat. The excess energy can be stored in batteries or sold back to the grid. Energy monitoring systems track energy usage and provide real-time feedback to users to identify areas of energy waste and optimize energy consumption.

Machine Learning (ML) is an effective tool for optimizing energy consumption in smart homes through the EMS. The EMS can use ML algorithms to learn the energy usage patterns of a home's occupants and adjust energy consumption accordingly. ML algorithms can identify correlations between energy usage and other factors such as weather, time of day, and occupancy. This information can be used to create predictive models

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that adjust energy consumption based on expected usage patterns. ML algorithms can also be used to optimize energy consumption by identifying areas of energy waste and suggesting changes to energy usage patterns. By leveraging ML, the EMS can achieve greater energy efficiency and cost savings while maintaining occupant comfort and convenience.

Fog computing is a decentralized computing infrastructure that can enhance the Intelligent Energy Management System (IEMS) in smart homes by improving the speed, accuracy, privacy, and security of data processing. By deploying fog nodes closer to the sensors and devices generating data, fog computing can reduce latency and improve the real-time processing of data from various sensors and devices in the smart home. This allows for quicker decision-making and more efficient energy management. Furthermore, fog computing can improve the privacy and security of our IEMS by reducing the amount of data that needs to be sent to the cloud for processing. Overall, the integration of fog computing into the IEMS provides an effective solution for optimizing energy consumption, reducing waste, and lowering energy costs in smart homes.

In this context, we propose a novel EMS, employing AI and ML techniques, and integrating fog computing can further improve the efficiency and effectiveness of energy management in smart homes. With this system, energy management can be achieved with greater precision and speed, reducing energy consumption, carbon emissions, and energy costs, while ensuring the comfort and convenience of occupants.

The sections of this paper are as follows: An overview of related studies is presented in section 2. The methodology of our system is presented in section 3. The experiments analysis is given in section 4. Our conclusions are derived in section 5.

2. Literature Overview

In this section, we take a look at the various FL approaches that are currently available and discuss how to optimize FL performance over cellular IoT. It is possible that federated averaging, often called FedAvg, is the most widely used FL method [8]. FedAvg is an algorithm for synchronously decentralized optimization. Prior to actually aggregating the results of the local model updates at a centralized server, FedAvg performs many updates of stochastic gradient descent (SGD) concurrently on fog devices. In contrast to SGD, FedAvg conducts a greater number of local updates and a reduced number of global updates, which enhances the efficiency of communication. Through a series of experiments, it was demonstrated that FedAvg performs admirably on data that does not contain iid. On the other hand, conceptual convergence assurance in real-world conditions was not offered until only lately in [5]. In [7], a study was conducted on SGD-based FL for hetnets. In this study, an adaptable control scheme was suggested to obtain the required balance between local upgrades and comprehensive accumulation stages. The research presented in [8] suggested a FedAvg that would utilize a decentralized version of Adam optimization and encoding in order to cut down on the number of transmission cycles and the amount of data that would need to be uploaded. An asynchronous federated optimization technique was suggested in [9], and it has been demonstrated to exhibit near-linear convergence to an optimal solution. FedProx was introduced in [10], and it is a generalisation of FedAvg. FedProx works to enhance the speed of convergence by including the same proximal term in each of the local variables. Nevertheless, picking an adequate value for the penalty constant in the immediate period can be difficult, particularly when working with unbalanced and non-id data sets.

On a different path, many researchers have lately concentrated their attention on the dynamic provisioning of FL at the edge of wireless networks. Specifically, three distinct scheduling approaches were suggested in [11] as a means of hastening the convergence of FL algorithms while simultaneously taking into consideration the consequences of user planning and interruption. In [20], the optimal compromise between the amount of energy used by all fog devices and the amount of time needed for FL training is investigated. In this scenario, all fog devices are necessary to communicate their local updates in a synchronised fashion. This technique was expanded in [19], in which frequency-division multiple access (FDMA) is utilized to asynchronously send local changes. Nevertheless, the increased efficiency of these efforts is primarily dependent on already existing FL methods, and it calls for all fog devices to participate in the training process

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during each global round. This results in a solution that is less than optimum because of the restricted resources available.

3. Algorithmic Design of our system

We consider an FL system designed for smart homes comprising a single home device and a collection $\mathcal{K}_{tot} \triangleq \{1,2,\dots,K_{tot}\}$ of $K_{tot} = |\mathcal{K}_{tot}|$ fog devices. Both fog devices and home device are exploited to build a mutual model to forecast the functioning of EMS. In this setting, diversified computation capacities of fog devices could be enabled by different tools. For all $k \in \mathcal{K}_{tot}$, there is a local training set, $\mathcal{D}_k \triangleq \{\mathbf{x}_{k1}, \mathbf{x}_{k2}, \dots, \mathbf{x}_{kD_k}\}$, in which D_k represents the number of examples per training setting, while the example $\mathbf{x}_{ki} \in \mathbb{R}^d$ is shaped as input. The local training set of $k-th$ fog devices might be distinct from others, i.e., $\mathcal{D}_k \cap \mathcal{D}_{k'} = \emptyset \forall k \neq k'$. In this work, we take into consideration non-iid supplied data throughout the IoT, that are separate but not evenly allocated. Thereby, the overall size of the dataset could be specified as $D = \sum_{k\in\mathcal{K}_{tot}} D_k$. The conventional of DNN learning, every sample x_i has an output $y_i \in \mathbb{R}$.

For the $k-th$ fog devices, the cost function on the data D_k can be expressed as

$$F_k(\mathbf{w}) \triangleq \frac{1}{D_k}\sum_{i\in\mathcal{D}_k} f_i(\mathbf{w})\,. \tag{1}$$

The FL approaches seek to solve the decentralized optimization problem by minimizing the underlying global cost value:

$$\min_{\mathbf{w}\in\mathbb{R}^d} F(\mathbf{w}) = \sum_{k\in\mathcal{K}_{tot}} p_k F_k(\mathbf{w}) \tag{2}$$

whereas $p_k \triangleq \frac{D_k}{D}$ denote the weighting term for $k-th$ fog devices, which follow require $p_k \geq 0$ as well as $\sum_{k\in\mathcal{K}_{tot}} p_k = 1$.

Our system considers solving the local learning via stochastic gradient descent under the same learning rate equal number of *local updates* ≥ 1. In each round of FedAvg, the coordinator situated at home device transfers w_g to each user. Then, every user upgrades to the newest global update $\mathbf{w}_{g,0}^k := \mathbf{w}_g$, and later start local SGD to obtain L updates:

$$\mathbf{w}_{g,\ell+1}^k := \mathbf{w}_{g,\ell}^k - \lambda_{g,\ell}\nabla F_k\left(\mathbf{w}_{g,\ell}^k, \xi_{g,\ell}^k\right), \ell = 0,\dots,L-1 \tag{3}$$

Each round's (or iteration's) aggregation stage might involve either complete or partial user involvement. First, *Complete User Involvement, in whichever* fog devices direct its local update to home device for accumulation, and then download the accumulated global updates to be utilized to train the model in the $(g+1)^{th}$ round:

$$\mathbf{w}_{g+1} := \sum_{k\in\mathcal{K}_{tot}} p_k \mathbf{w}_{g,L}^k\,. \tag{4}$$

Incomplete User Involvement, the coordinator selects a subgroup $\mathcal{K}_g \triangleq \{1,2,\dots,K_g\}$ of K_g fog devices with $K_g \leq K_{tot}$ at $g-th$ round, which is allowed to transmit their local updates, and later, the home device calculates:

$$\mathbf{w}_{g+1} := \frac{1}{K_g}\sum_{k\in\mathcal{K}_g} w_{g,L}^k\,. \tag{5}$$

$$f_i'(\mathrm{w}) \triangleq f_i(\mathrm{w}) + \frac{\mu p_k}{2}\|\mathrm{w} - \mathrm{w}_g\|^2 \forall i \in \mathcal{D}_k \tag{6}$$

Then, we can adjust the local updates in the following ways:

$$\begin{aligned} \mathrm{w}_{g,\ell+1}^k &:= \mathrm{w}_{g,\ell}^k - \lambda_{g,\ell}\nabla F_k'\left(\mathrm{w}_{g,\ell}^k, \xi_{g,\ell}^k\right) \\ &:= \mathrm{w}_{g,\ell}^k - \lambda_{g,\ell}\left(\nabla F_k\left(\mathrm{w}_{g,\ell}^k, \xi_{g,\ell}^k\right) + \mu p_k\left(\mathrm{w}_{g,\ell}^k - \mathrm{w}_g\right)\right). \end{aligned} \tag{7}$$

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To simplify the analysis, we first accept some hypotheses about the altered local objective, which are used extensively in [10-15].

$$F_k'(\mathrm{w}) \leq F_k'(\tilde{\mathrm{w}}) + \langle \nabla F_k'(\tilde{\mathrm{w}}), \mathrm{w} - \tilde{\mathrm{w}} \rangle + \frac{\Gamma}{2} \|\mathrm{w} - \tilde{\mathrm{w}}\|^2 \forall k. \quad (8)$$

When $F_k(\cdot)$ is curved, $F_k'(\cdot)$ turn out to be μ_k-greatly curved such that $\forall \mathrm{w}, \tilde{\mathrm{w}} \in \mathbb{R}^d$ and there is $\mu_k > 0$.

$$F_k'(\mathrm{w}) \geq F_k'(\tilde{\mathrm{w}}) + \langle \nabla F_k'(\tilde{\mathrm{w}}), \mathrm{w} - \tilde{\mathrm{w}} \rangle + \frac{\mu_k}{2} \|\mathrm{w} - \tilde{\mathrm{w}}\|^2 \forall k. \quad (9)$$

Then, we characterize the subsequent correlation to represent the dispassionate selection approach, which is relevant to how fog devices are selected throughout iterations. Next global updates of selected fog devices are expected to be equal to the mean of all fog devices updates

$$\mathbb{E}\{\frac{1}{K_g} \sum_{k \in \mathcal{K}_g} \mathrm{w}_{g+1}^k\} = \overline{\mathrm{w}}_{g+1}. \quad (10)$$

For $\mathrm{w}_{g+1} \triangleq (\frac{1}{K_g}) \sum_{k \in \mathcal{K}_g} \mathrm{w}_{g+1}^k$, the anticipated *divergence* between w_{g+1} and $\overline{\mathrm{w}}_{g+1}$ is described by the subsequent formulation. Given that $\{\lambda_g\}_{\forall g}$ is a nonincreasing order with decay as $\lambda_g \leq \left[\frac{\lambda_0}{1+ag}\right]$ for every no-negative factor $a > 0$, the anticipated upper limit of $\|\mathrm{w}_{g+1} - \overline{\mathrm{w}}_{g+1}\|^2$ could be formulated as:

$$\mathbb{E}\left\{\|\mathrm{w}_{g+1} - \overline{\mathrm{w}}_{g+1}\|^2 \middle| k \in \mathcal{K}_g\right\} \leq \frac{L^2 \lambda_0^2 \delta}{K_g(1+ag)^2}. \quad (11)$$

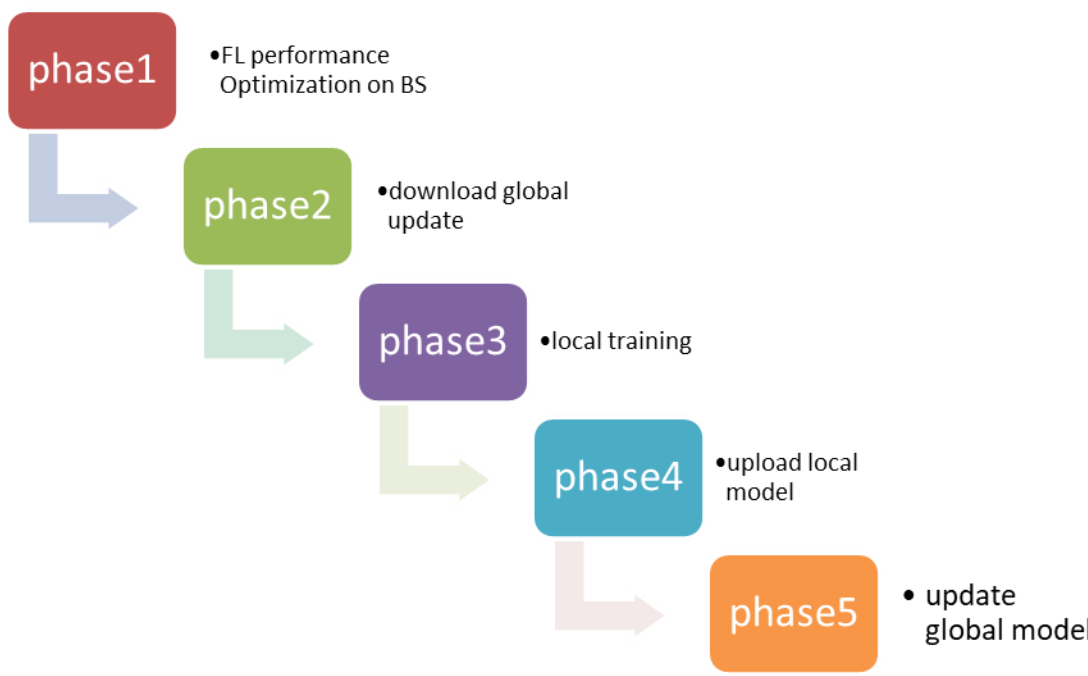

Figure 1: illustration of the main phases of proposed IEMS.

Regarding the previous Expectations, the global update w∗ , the learning rate $\lambda_g \leq \left[\frac{\lambda_0}{1+ag}\right]$ with $\lambda_0 \leq \left[\frac{2}{\mu+\Gamma}\right]$ and $\varepsilon_0 = \|\mathrm{w}_0 - \mathrm{w}^*\|^2$, the anticipated convergence upper limit for G rounds could be formulated as:

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$$\mathbb{E}\{F(\mathrm{w}_G)\} - F(\mathrm{w}^*) \leq \frac{\Gamma}{2}\left(\frac{L^2\lambda_0^2\delta}{K_G(1+aG)^2} + \prod_{i=0}^{G-1}\left(1 - \frac{2\lambda_0\mu\Gamma}{(\mu+\Gamma)(1+ia)}\right)\varepsilon_0\right). \quad (12)$$

On the other hand, by fixing the learning rate $\lambda_g = \left[\frac{2}{\mu+\Gamma}\right] \forall g$, the anticipated convergence upper limit for G rounds could be formulated as:

$$\mathbb{E}\{F(\mathrm{w}_G)\} - F(\mathrm{w}^*) \leq \frac{\Gamma}{2}\left(\frac{4L^2\delta}{K_G(\mu+\Gamma)^2} + \left(1 - \frac{4\mu\Gamma}{(\mu+\Gamma)^2}\right)^G\varepsilon_0\right). \quad (13)$$

Our IEMS consider two techniques, synchronous (Syn) and asynchronous (Asyn) transmission, to transmit local updates to home device over the uplink. In the former, each picked fog devices must finish the present phase before moving onto the subsequent [21], but in the latter, each chosen fog devices can interact with the home device asynchronously. At iteration g, the FL system's one communication round takes:

$$T_g^X = \begin{cases} \max_{k\in\mathcal{K}_g}\{t_{co,k}^{dl}\} + \max_{k\in\mathcal{K}_g}\{t_{cp,k}\} + \max_{k\in\mathcal{K}_g}\{t_{co,k}^{ul}\} & \text{if } X \text{ is Syn} \\ \max_{k\in\mathcal{K}_g}\{t_{co,k}^{dl} + t_{cp,k} + t_{co,k}^{ul}\}, & \text{if } X \text{ is Asyn.} \end{cases} \quad (14)$$

It is worth noting the functions $E_{co,k}$, $t_{co,k}^{dl}$, $t_{co,k}^{ul}$, SNR_k^{dl} , and $\mathrm{SNR}_k^{ul} \forall \mathrm{K}$ is neither curved nor bowl-shaped in $(\boldsymbol{\rho}, \boldsymbol{b})$, which could be validated by examining the Hessian matrix.

$$\min_{\boldsymbol{\rho},\mathbf{f},\mathbf{b},\boldsymbol{\vartheta},\mathbf{t}} \eta E_g(\boldsymbol{\rho}^{ul}, \mathbf{f}, \boldsymbol{\vartheta}^{ul}) + (1-\eta)T_g^X(\mathbf{t}) \text{ s.t. } r_k^x \geq \vartheta_k^x \forall k \in \mathcal{K}_g, x \in \{dl, ul\} \quad (15)$$

$$E_g(\boldsymbol{\rho}^{ul}, \mathbf{f}, \boldsymbol{\vartheta}^{ul}) = \sum_{k\in\mathcal{K}_g} E_k(\rho_k^{ul}, \mathrm{f}_k, \vartheta_k^{ul}) \quad (16)$$

and $\mathbf{t} \triangleq \{t_{cp}, t_{co}^{ul}, t_{co}^{dl}, t\}$, and $\boldsymbol{\vartheta} \triangleq \{\boldsymbol{\vartheta}^{ul}, \boldsymbol{\vartheta}^{dl}\}$ with $\boldsymbol{\vartheta}^{ul} \triangleq \{\vartheta_k^{ul}\}_{k\in\mathcal{K}_g}$, and $\boldsymbol{\vartheta}^{ul} \triangleq \{\vartheta_k^{ul}\}_{k\in\mathcal{K}_g}$, and $\boldsymbol{\vartheta}^{dl} \triangleq \{\vartheta_k^{dl}\}_{k\in\mathcal{K}_g}$ are recently created variables to disentangle the cost function.

4. Empirical Results

To evaluate the efficacy of the proposed FL method in a diverse environment, we train it on 100 fog devices s using both Fashion-MNIST and CIFAR-10 datasets. The number of samples across fog devices s follows a power law, in which every fog device only has access to two classes of data. Artificial datasets are created for each of the above datasets by following the mechanism given [3].

for guaranteeing the convergence of the proposed FL scheme, the experiments set the $\lambda_g = \left[\frac{\lambda_0}{1+0.01g}\right]$ as a fixed learning rate, in which the initial value λ_0 is thoroughly selected from the following group of values {0.1,0.03,0.01}. Moreover, He initialization is used to define initial parameters $\boldsymbol{w}_0 = 0$. For both datasets, the batch size is set to 64 and 16 for both realistic and artificial samples, correspondingly. To validate the effectiveness of the proposed FL scheme, fair comparisons are performed against FedAvg, FedProx, and FL. In these comparisons, the number of chosen fog devices per round is set fixed for all deemed FL approaches.

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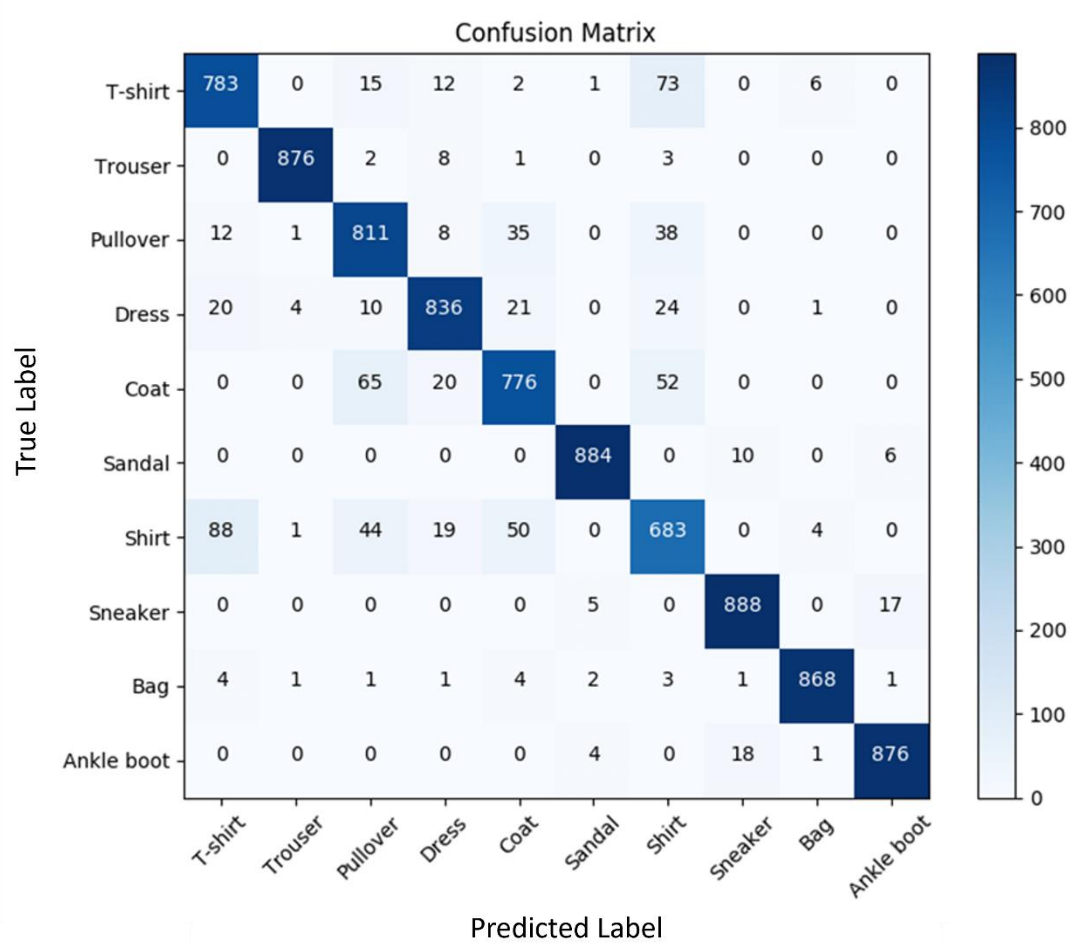

Figure 2: confusion matrix of the proposed FL scheme on the Fashion-MNIST dataset.

For each fog device, the local data is divided into 80% for training and 20% for evaluation. The implementation of FL solutions is done with TensorFlow, running on a python 3.9 environment.

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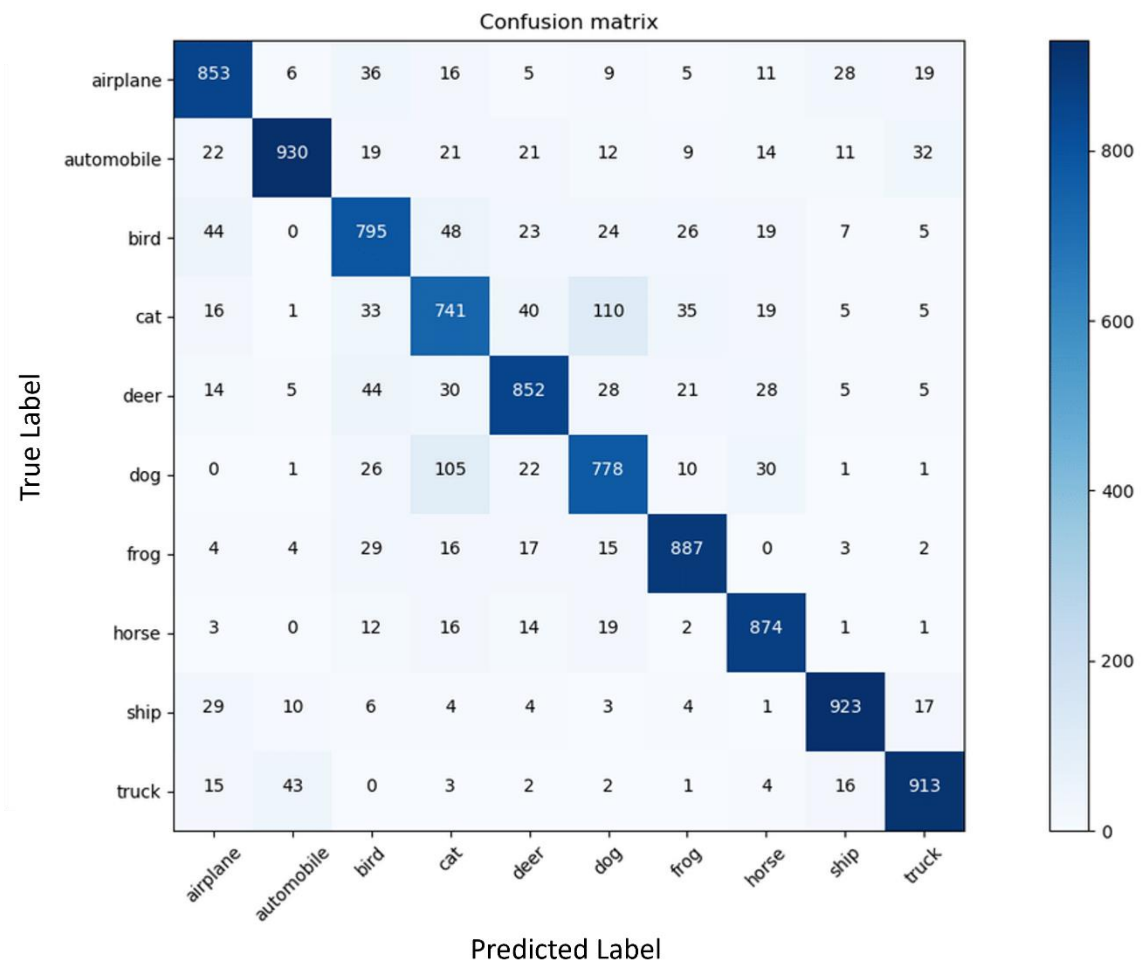

Figure 3: confusion matrix of the proposed FL scheme on the CIFAR-10 dataset.

A. Numerical Results

To evaluate how well a set of categorization models performs on test data, statisticians use a matrix called the confusion matrix. Only if the actual values of the test data are provided, it can be computed. The matrix itself can be simply comprehended, but the accompanying terminologies may be difficult. It is also called an error matrix since it displays the model's execution defects in a matrix form. Thus, the detailed performance of the proposed framework on fashion-MNIST is given in Figure 2. As noted, the proposed FL scheme can effectively recognize the data class with almost zero confusion. Similarly, the detailed performance of the proposed framework on CIFAR-10 is given in Figure 3. As noted, the proposed FL scheme can effectively recognize the data class with low confusion.

Figure. 4 indicates the convergence of our system for both actual and artificial data from fashion-most. The learning rate of the competing methods is decayed in the same way as with the proposed FL scheme. The findings prove that the proposed FL scheme can significantly surpass the competing methods on both actual

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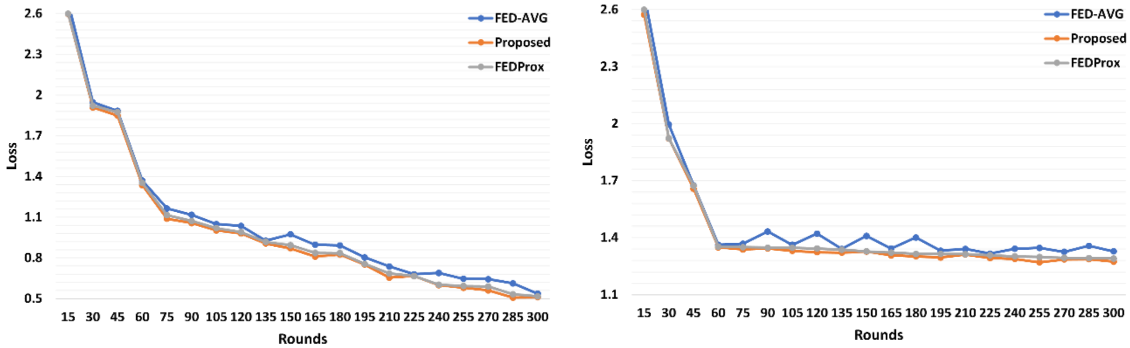

Figure 4. performance vs versus the number of communication rounds lobal rounds on actual (left) and artificial (right) data from Fashion-MNIST.

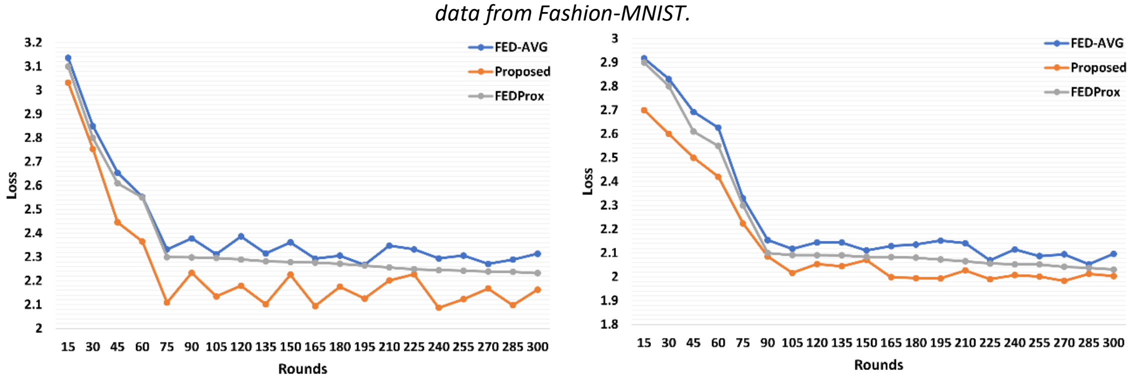

Figure 5: performance vs versus the number of communication rounds lobal rounds on actual (left) and artificial (right) data from CIFAR-10.

and artificial data sets. The proposed system is shown to be more stable and to converge faster than competing methods, in addition to having high results. Further evidence is that a weighted proximate term is an efficient tool for mitigating the unfavorable consequences of the arbitrary selection method for choosing client involvement in a multi-faceted environment.

The convergence of our system is shown for both real and simulated CIFAR-10 data in Figure. 5. The proposed FL scheme's decline of the learning rate is similar to that of the competing approaches. Results show the suggested FL approach can greatly outperform the alternatives on real and synthetic data sets. It is demonstrated that the proposed system is superior to alternative approaches, both in terms of stability and convergence speed. More proof that the weighted proximate term is a useful instrument for reducing the drawbacks of the arbitrary tasting technique when choosing client membership in a complex setting.

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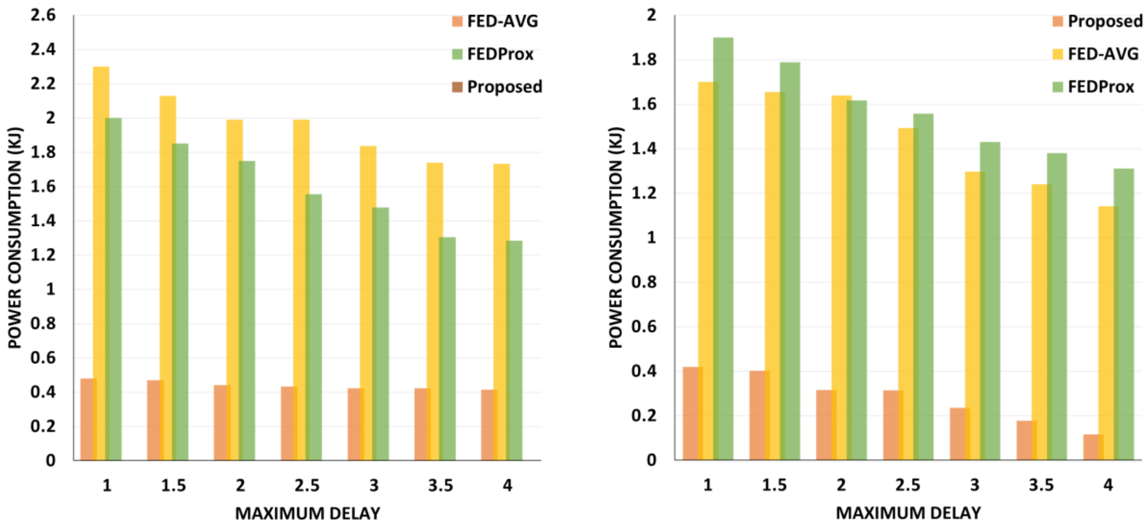

Figure 6: power consumption vs maximum Delay on actual (left) and artificial (right) data from CIFAR-10..

B. *Energy Consumption Minimization*

The relation between the consumed powered and maximal delay required to carry out one communication round is depicted in Figure. 6. This is what we can deduct from looking at the diagram. The suggested FL offers a significant improvement in overall power usage contrasted with complete user engagement throughout a wide range of maximum delay values, as is immediately apparent. A larger K_g can marginally hasten FL convergence, but at the expense of significantly increased energy usage across the board. Furthermore, a smaller number of fog devices s participating in the training process will more effectively utilize scarce resources (i.e., bandwidth). In addition, the effective energy usage decreases noticeably as the maximum delay increases. This makes sense, as the ideal value of energy usage and CPU frequency may be attained while still obeying the restriction, and the total delay need decreases, resulting in energy savings. Third, when the delay requirement is stricter, performance improves thanks to the combined optimization of bandwidth.

5. Conclusion

In this work, we proposed an Intelligent Energy Management System (IEMS) that take the advantage of fog computing and Machine Learning to provide an effective solution for optimizing energy consumption, reducing waste, and lowering energy costs while ensuring the comfort and convenience of occupants. By using predictive models to learn energy usage patterns, the EMS can adjust energy consumption based on expected usage patterns and identify areas of energy waste to optimize energy usage. The integration of fog computing can improve the speed and accuracy of data processing and reduce latency, leading to quicker decision-making and more efficient energy management. Our solution can lead to reduced carbon emissions, improved energy efficiency, and cost savings.

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