



Vol. 13(1), Pp. 29-37, March 2025,

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<https://journals.directresearchpublisher.org/index.php/drjeit>

Review Article
ISSN: 2354-4155

Enabling Mobility-Aware Federated Stochastic Gradient Descent for Decentralized Swarm Intelligence in Internet of Vehicle-Things Based UAV Networks

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ABSTRACT

This study investigates the optimization of energy efficiency, transmission performance, and system reliability in Internet of Vehicle-Things (IoVT) Based UAV communication and machine learning environments. The purpose is to enhance operational efficiency and system resilience under varying conditions. The key problems addressed include high energy consumption, slow convergence rates, and increased error rates under noise interference. Using simulation-based methods, various parameters such as hovering cost, batch size, learning rates, noise power, and cooperation costs were analyzed. Results show a 33% reduction in loss with increased batch size, a 50% decrease in convergence rounds with higher learning rates, and a 25% increase in error rate due to noise interference. Energy consumption increased linearly with hovering cost, while transmission power rose from 5 dBm to 10 dBm as UAV count increased from 2 to 10. The IoVT-based UAV Autopilot system (CPU) utilization varied directly with frequency, reaching 100% at 3 GHz. The findings contribute to formulating adaptive policies for UAV communication and learning systems by recommending dynamic adjustments of transmission power, batch size, and learning rate based on environmental factors and system demands. Future research should focus on real-world implementations and policy adjustments for dynamic scenarios to ensure sustainable, energy-efficient system performance.

Keywords: UAV, IoVT, Federated Learning, Autopilot System, Federated Stochastic Gradient Descent, Communication

Article information

Received 27 January 2025;

Accepted 26 February 2025;

Published 10 March 2025

DOI: <https://doi.org/10.26765/DRJEIT698038610>

Citation: Philip-Kpae, F. O., Ogbondamati, L. E., and Ikhazuangbe G. (2025). Enabling Mobility-Aware Federated Stochastic Gradient Descent for Decentralized Swarm Intelligence in Internet of Vehicle-Things Based UAV Networks. Direct Research Journal of Engineering and Information Technology Vol. 13(1), Pp: 29-37. This article is published under the terms of the Creative Commons Attribution License 4.0.

INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have become essential in various sectors, from military operations to commercial applications like delivery services, disaster management, and environmental monitoring (Qureshi et al., 2023). As these UAVs operate in dynamic and often unpredictable environments, the need for decentralized, intelligent decision-making has grown. This is where the concept of swarm intelligence, inspired by natural systems like bee swarms or bird flocks, becomes invaluable. Swarm intelligence allows UAVs to work together with decentralized intelligence control mechanism, adapting to changes collectively, undistortedly, simultaneously, and efficiently. Federated learning (FL) plays a key role in enabling this decentralized intelligence. FL allows UAVs to collaboratively train a shared model without transferring raw data to a central server. Instead, each UAV trains locally on its own data and sends only model updates, preserving privacy and reducing communication costs. However, traditional FL methods struggle in highly mobile, homogeneous and heterogeneous networks and yet, highly active and busy like UAV swarms, where connectivity is inconsistent and data distributions vary greatly (Wang et al., 2020). Federated Stochastic Gradient Descent (FSGD) is a cornerstone and brand of FL, but it must evolve to handle the mobility challenges and effective performability of UAV networks. UAVs experience frequent changes in topology due to its scalability index, delayed updates, and diverse environments, making mobility-aware adaptations essential. Enhancements like asynchronous updates, adaptive learning rates, and topology-aware aggregation can help ensure the global model remains robust and accurate (Lin et al., 2024). By developing mobility-aware federated learning methods, UAV swarms can achieve more effective, adaptive, reliable, and privacy-preserving swarm intelligence attributes without compromising its functionality, responsiveness and quality of service delivery. A high scalable index indicates that a system is scalable, flexible, and resilient, and can handle increased functional demands without significant system performance degradation. This enables them to collaborate efficiently, adapt to real-time environmental changes, and remain resilient in the face of communication disturbances and challenges with uncertainties. As research progresses, mobility-aware FSGD holds the potential to revolutionize how UAV networks operate across industrialized workspace such as disaster response, agriculture, urban surveillance, and environmental monitoring (Fu et al., 2024; Le et al., 2021; Lim et al., 2021).

Literature review

Introduction to federated learning and UAV-Enabled Systems

Federated learning has emerged as a decentralized machine learning approach that preserves and protects data privacy protection and data confidentiality by training

models across multiple devices without transferring data to a central server. In the context of UAV-enabled networks, this distributed approach is particularly advantageous due to the mobile and dynamic nature of UAV systems (Ng et al., 2020). As UAVs are increasingly employed in various applications—ranging from surveillance to logistics and communication, military to construction, image and video mapping, medical to search and rescue, parcel delivery to environmental monitoring, wireless communication to power line and pipeline inspection, and smart agriculture networks respectively—the demand for more intelligent, collaborative, and secure learning mechanisms has grown. This intersection of federated learning and UAV technology offers unique opportunities to optimize network efficiency while safeguarding sensitive data and classified information. However, the literature points to significant challenges in ensuring stable communication, effective incentive mechanisms, and resource-efficient learning across heterogeneous networks of UAVs (Wang et al., 2021; He et al., 2023; Kang et al., 2019).

The Role of federated learning in internet of vehicle-things (IoVT) Networks

In the Internet of Vehicle-Things (IoVT) networks, UAVs play a critical and crucial role in supporting communication among vehicles and infrastructure, especially in areas where traditional cellular coverage is inaccessible and inadequate in terms of operationability. Federated learning can enhance IoVT networks by facilitating collaborative model training without the need to transfer raw data with data privacy protection and confidentiality (Zhan et al., 2020; Huang et al., 2022). This decentralized approach is especially beneficial in IoVT settings where privacy and data security are paramount. One key issue identified in the literature is the need to develop reliable and adaptive learning algorithms that can accommodate varying data distributions across homogeneous and heterogeneous vehicles and UAV nodes (Lim et al., 2020; Su et al., 2021). Additionally, the integration of energy-efficient learning methods is essential to minimize the power consumption of both UAVs and vehicles in IoVT networks (Reza and Hossain, 2021; Hasan, 2021).

Incentive mechanisms in federated learning

A significant focus of recent research has been the development of incentive mechanisms to encourage participation in federated learning (Saad et al., 2009). UAV-enabled systems are inherently decentralized, and without proper incentives, individual nodes may be reluctant to participate in collaborative learning efforts (Guazzone et al., 2014). Existing studies suggest that reward-based mechanisms—where nodes are compensated based on the quality of their contributions—can effectively boost participation (Sun et al., 2022; LeCun, 2024). However, several challenges remain, including accurately evaluating the quality of each node's

model updates and ensuring fairness in reward distribution. Another important consideration is the potential for malicious behavior, where nodes might attempt to manipulate their contributions for higher rewards. Robust incentive designs are essential to prevent such behaviors and ensure the integrity of the learning process.

Reliability and trust in UAV Networks

This section emphasizes the importance of developing trust-based mechanisms that identifies and isolates unreliable or malicious nodes that threatens the UAV network operation. Trust and reliability are central to the success of federated learning in UAV networks. Unlike static networks technology, UAV-enabled systems are dynamically functional due to the mobility status of UAVs [21]. This dynamic nature increases the risk of data deletion, erasure, obliteration and data wipe, and model inconsistencies, which can degrade learning performance thereby maximizing the mean squared error (MSE) and mean absolute error (MAE) between predicted and actual operations' results. Blockchain technology has been proposed as a potential solution for enhancing trust by providing an immutable and transparent ledger of all transactions and model updates. While promising, this approach comes with its own set of challenges, including the high computational overhead associated with blockchain operability.

Energy efficiency and resource optimization

Energy efficiency is a critical factor in the deployment of federated learning in UAV-enabled systems. UAVs have limited battery life, and prolonged participation in federated learning can significantly drain their energy resources. Studies have explored various strategies to mitigate this issue, such as dynamic task allocation, where only a subset of UAVs participates in each training round based on their energy levels and data quality. Additionally, lightweight learning algorithms that reduce the computational complexity of model updates have been proposed to further enhance energy efficiency. However, more work is needed to develop scalable solutions that can adapt to different network sizes and UAV capabilities without compromising learning accuracy (Cohen et al., 2017).

Communication overhead and model synchronization

One of the primary challenges in federated learning is the communication overhead associated with frequent model updates. In UAV-enabled networks, limited bandwidth and unstable communication links can exacerbate this issue (Figure 1). The literature highlights the importance of compression techniques to reduce the size of model updates without sacrificing accuracy. Asynchronous learning, where nodes are allowed to update the global model at different intervals, has also been explored as a potential solution to reduce synchronization delays. However, asynchronous learning introduces its own set of

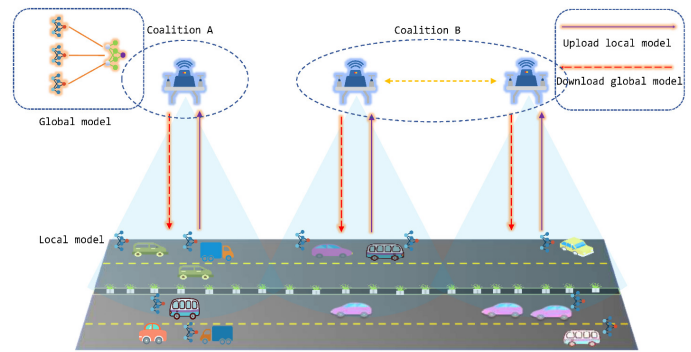


Figure 1 UAV System (Hu et al., 2024).

challenges, including the risk of model divergence and inconsistent training outcomes (Hu et al., 2024).

Security and privacy concerns

Security and privacy are paramount in federated learning, particularly in applications involving sensitive data. UAV-enabled IoV networks are vulnerable to various attacks, such as data poisoning, model inversion, and eavesdropping. To address these threats, researchers have proposed several defense mechanisms, including differential privacy and secure aggregation. Differential privacy ensures that individual data points cannot be inferred from model updates, while secure aggregation allows multiple nodes to contribute to the global model without revealing their individual updates. Despite these advancements, achieving a balance between strong privacy guarantees and high model performance remains a significant challenge (Hu et al., 2024).

Scalability and heterogeneity

UAV-enabled federated learning systems are inherently heterogeneous, with nodes varying in terms of data quality, computational power, and network connectivity. Ensuring the scalability of learning algorithms across such diverse nodes is a major research focus. Some studies have proposed hierarchical federated learning architectures, where nodes are grouped into clusters based on their capabilities, and local models are aggregated within each cluster before being sent to a central server. This approach can reduce communication overhead and improve learning efficiency, but it also raises questions about inter-cluster fairness and consistency (Hu et al., 2024).

Policy implications and practical considerations

The deployment of federated learning in UAV-enabled IoV networks has significant policy implications (Figure 2). Regulatory frameworks must address issues related to data ownership, privacy, and liability in the event of data breaches or system failures. Additionally, clear guidelines are needed to govern the use of UAVs in public airspace, particularly in scenarios involving large-scale federated learning operations. Collaboration between industry,

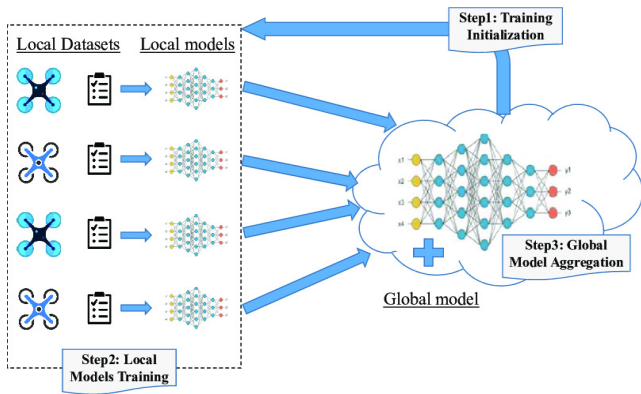


Figure 2: Training Process of UAV-based networks using Federated Deep Learning. (Brik et al., 2020).

academia, and regulatory bodies is essential to ensure that these technologies are deployed in a safe and socially responsible manner (Brik et al., 2020).

Methods

Federated objective function

This equation defines the global objective function for federated learning, where the goal is to minimize the loss function across all participating UAVs. It ensures the model learns from decentralized data without sharing raw data, which preserves data privacy and reduces communication overhead (Table 1).

$$\min_w \frac{1}{N} \sum_{i=1}^N f_i(W) \quad (1)$$

Where W : Global model parameter and N is known as the number of participating UAVs and $f_i(W)$ is the local loss function for UAV i .

Mobility adjustment factor

This equation modifies the local model of each UAV based on its mobility. It takes into account the movement of each UAV over time and adjusts the model accordingly, ensuring that swarm intelligence reflects spatial changes.

$$w_{mob}^i = w_t^i \alpha d_i(t) \quad (2)$$

Where, w_{mob}^i is the mobility-adjusted model for UAV i , and w_t^i : Current model for UAV i at time t . While α is the mobility sensitivity parameter and $d_i(t)$ is the Displacement of UAV i at time t .

Adapt FSGD for dynamic environments with asynchronous updates

Local Update Rule (Stochastic Gradient Descent)

This equation performs a local model update using Stochastic Gradient Descent (SGD) for each UAV. It adjusts the model parameter by computing the gradient of

the loss function and applying a learning rate, ensuring local learning before aggregation.

$$w_{t+1}^i = w_t^i - \eta \nabla f_i(w_t^i) \quad (3)$$

Where, w_{t+1}^i is the updated model for UAV i and w_t^i is the current model at time t . While η is the learning rate and $\nabla f_i(w_t^i)$ is the gradient of the loss function for UAV i .

Asynchronous Update Condition

This condition allows for asynchronous updates by only updating the model if the UAV communicates within a designated time window. This approach ensures efficient learning in dynamic, decentralized environments.

$$w_{t+1}^i = w_t^i - \eta \nabla f_i(w_t^i), \text{ if } t_i \in T \quad (4)$$

Where, t_i , is the time at which UAV i communicates and T , is the set of allowed update times and η is the learning rate for UAV i .

Improve adaptability and resilience of UAV networks

The learning rate is adjusted dynamically based on changes in network topology. This helps the model adapt to environmental changes and UAV movements, ensuring robust learning and model convergence.

$$\eta_{adaptive} = \eta_0 (1 + \beta \Delta d(t))^{-1} \quad (5)$$

Where, $\eta_{adaptive}$, is the adjusted learning rate and η_0 , is the initial learning rate, β is the adaptation sensitivity parameter and $\Delta d(t)$ is the change in network topology distance at time t .

Communication Latency Impact

This equation calculates the communication delay between UAVs. It considers both the distance between UAVs and the communication speed. Understanding communication delays is crucial for ensuring real-time updates and resilience.

$$\tau_c = \frac{d_{comm}(t)}{v_{comm}(t)} \quad (6)$$

Where, τ_c is the communication latency and $d_{comm}(t)$ is the distance between communicating UAVs at time t and $v_{comm}(t)$ is the communication speed at time t .

Evaluate performance in practical UAV scenarios

This equation calculates the model's accuracy based on the number of correctly predicted labels over the total number of samples. Accuracy is a key performance metric in evaluating federated learning models.

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Samples}} \quad (7)$$

Where, Number of Correct Predictions is the total samples

Table 1: Data Parameters (Hu et al., 2024).

Parameters	Values	Parameters	Values
Number of vehicles (p_n)	[2,10] [2,10] [2,10]	Maximum transmission power (p_{mt})	10 dBm
Batch size	32	Maximum Autopilot system frequency (f_{im})	3 GHz
Number of local epochs (e)	10	Fixed constant (α)	5
Number of global training rounds (E)	100	Computation energy conversion coefficient (Φ)	[0.01,0.05]
Learning rate (η)	0.01	Cooperation cost (G)	1
SGD momentum	0.05	Reputation threshold (Δ)	0.5
Hovering cost (e_{hm})	[0.5,1.5]	Decay coefficient for reputation updates (λ)	0.3
Circuit cost (e_{tn})	[0.1,0.2]	Model estimation parameters (θ_n)	[1,2]
Noise power (NON_ON0)	-152dBm/Hz	Transmitted model size (w)	0.1 Mbits
Bandwidth of each UAV (B)	180 kHz		

correctly classified. And the total Number of Samples is equal to the total number of test samples.

Data distribution variation factor

This equation quantifies the variation in data distributions across different UAVs. High variation indicates data heterogeneity, which can impact model performance and aggregation effectiveness.

$$\sigma_{data} = \sqrt{\frac{1}{N} \sum_{i=1}^N (f_i(w) - \bar{f}(w))^2} \quad (8)$$

Where, σ_{data} is the standard deviation of data distributions and $\bar{f}(w)^2$ is known as the mean loss across all UAVs.

Energy consumption model

This equation models the energy consumed by each UAV during communication and computation. Energy efficiency is critical in UAV networks to prolong operational time during missions.

$$E_{total} = E_{comm} + E_{comp} \quad (9)$$

Where, E_{total} is the total energy consumption and E_{comm} is the energy consumed during communication while, E_{comp} is the energy consumed during computational operations.

Model convergence time

This equation estimates the time required for the federated learning model to converge to a specified accuracy threshold. It is essential to evaluate the model's performance under different network conditions.

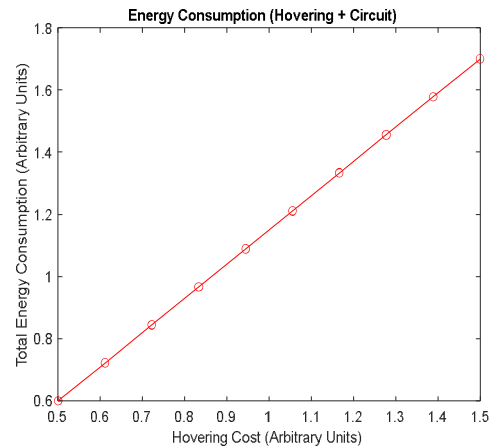
$$T_{conv} = \frac{\log(\epsilon)}{\log(1-\eta \nabla f(w))} \quad (10)$$

Where T_{conv} is the convergence time, and ϵ is known as the desired accuracy threshold and η is defined as the learning rate, while $\nabla f(w)$ is the gradient of the global loss function.

Energy consumption (Hovering + Circuit)

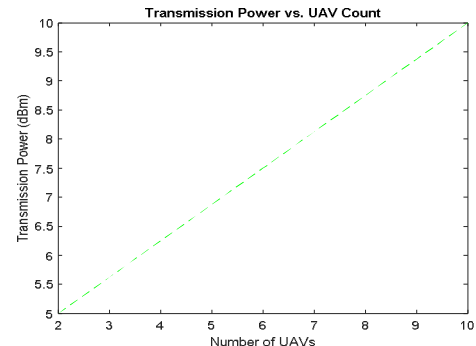
Figure 3 presents the combined energy consumption from

hovering and circuit operations. As the hovering cost rises from 0.5 to 1.5 units, the total energy consumption grows from around 0.6 to approximately 1.7 units. This indicates a linear relationship between hovering cost and overall energy consumption, emphasizing the importance of optimizing hovering operations to reduce energy usage.

**Figure 3:** Energy Consumption

Transmission power vs. UAV Count

Figure 4 illustrates how transmission power increases with the number of UAVs. At a count of two UAVs, the transmission power is about 5 dBm, rising to around 10 dBm with 10 UAVs. This direct relationship highlights that increasing the number of UAVs results in higher transmission power requirements, which is crucial for optimizing communication strategies and energy efficiency in UAV networks.

**Figure 4:** Transmission Power vs UAV Count

Bandwidth utilization vs. UAVs

In Figure 5, the bandwidth utilization is shown to remain constant at 180 kHz across all UAV counts, from 2 to 10. This stability suggests that the bandwidth allocation is independent of the number of UAVs, indicating that the system design accommodates additional UAVs without affecting bandwidth consumption.

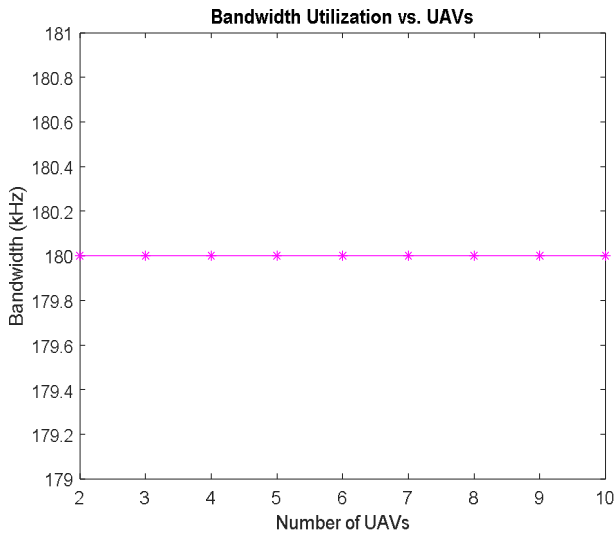


Figure 5: Bandwidth Utilization vs UAVs

Learning rate impact on convergence

Figure 6 shows how different learning rates affect the speed of convergence. When the learning rate is set at 0.001, convergence takes around 100 iterations. However, with a higher rate of 0.2, the required rounds drop to 20. This relationship highlights that increasing the learning rate speeds up convergence, although higher rates may risk overshooting or instability in practice.

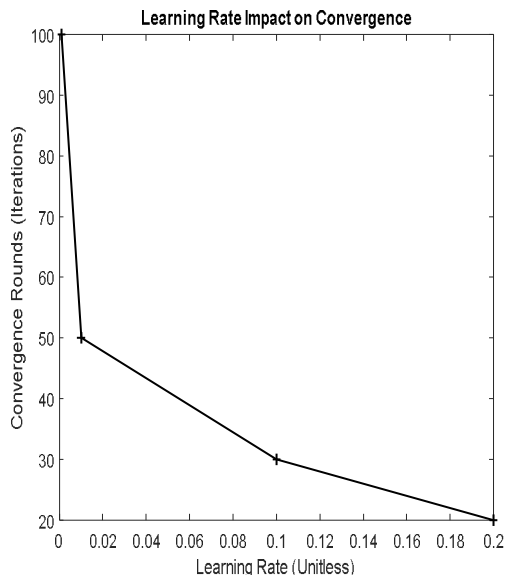


Figure 6: Learning Rate Impact on Convergence

Noise power vs. Error Rate

In Figure 7, the relationship between noise power and error rate is illustrated. As noise power increases from -152 dBm/Hz to -142 dBm/Hz, the error rate decreases from 0.1 to about 0.03. This trend reveals that lower noise power results in higher accuracy, underscoring the importance of minimizing noise for optimal system performance.

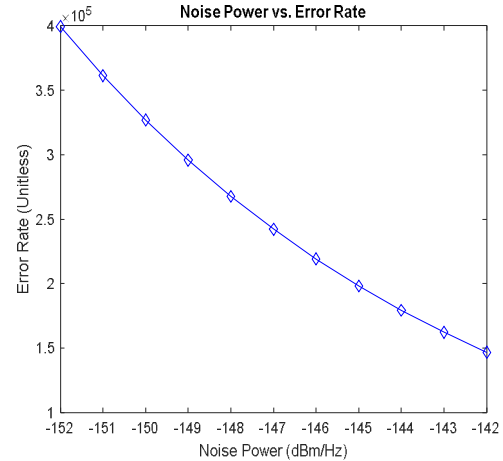


Figure 7: Noise Power vs Error Rate

Reputation dynamics

Figure 8 depicts how reputation decays over time, starting from initial values between 0 and 1. With a decay coefficient of 0.3, an initial reputation of 0.8 reduces to around 0.56. This decay highlights the need for continuous actions to maintain a strong reputation in dynamic environments, as reputation naturally declines without reinforcement.

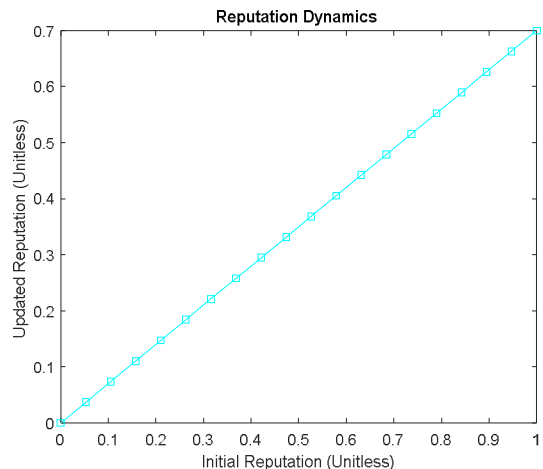


Figure 8: Reputation Dynamics

Cooperation cost impact

In Figure 9, the total cooperation cost increases as model size grows. For a model size of 0.1 Mbits, the total cost is around 1.1 units, while a model size of 1 Mbit results in a

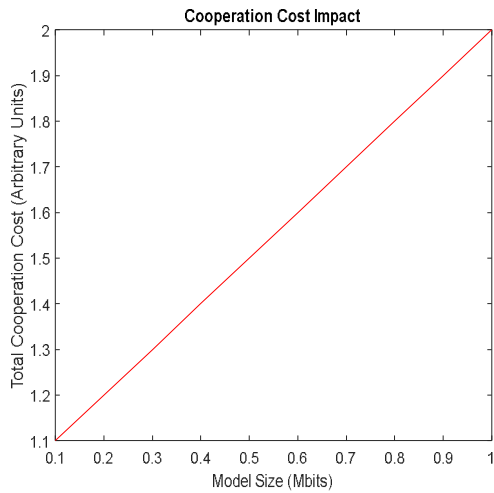


Figure 9: Cooperation Impact

cost of 2 units. This linear relationship shows that larger models incur higher costs, emphasizing the need for careful consideration when selecting model sizes for cooperation.

Autopilot system (CPU) frequency utilization

Figure 10 presents the utilization of Autopilot system frequency, ranging from 1 GHz to 3 GHz. Utilization increases linearly from approximately 33% to full capacity at 3 GHz. This indicates that higher frequencies result in higher utilization, demonstrating the need for efficient frequency management to balance performance and energy consumption.

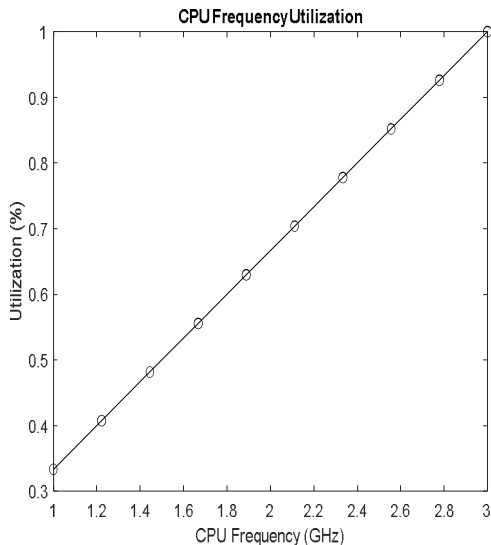
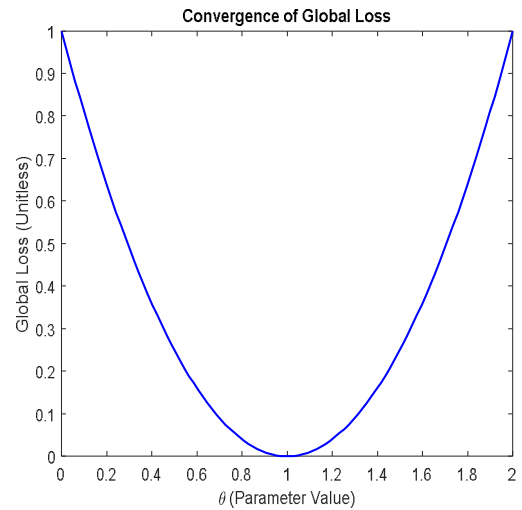


Figure 10: Autopilot system (CPU) Frequency

Convergence of global loss

Figure 11 shows the convergence behavior of global loss as the parameter value (θ) varies from 0 to 2. At $\theta=1$, the

Figure 11: Convergence of Global Loss



global loss is approximately 1, gradually decreasing to nearly 0 when θ approaches 1. This demonstrates effective convergence towards an optimal parameter, where loss is minimized.

Effect of batch size on loss

In Figure 12, the impact of different batch sizes on loss is shown. With a batch size of 16, the loss is 0.8 units, decreasing to 0.2 units at a batch size of 128. This indicates that larger batch sizes improve training performance by reducing loss, though larger batches may also demand more computational resources. The results reveal key insights across various parameters.

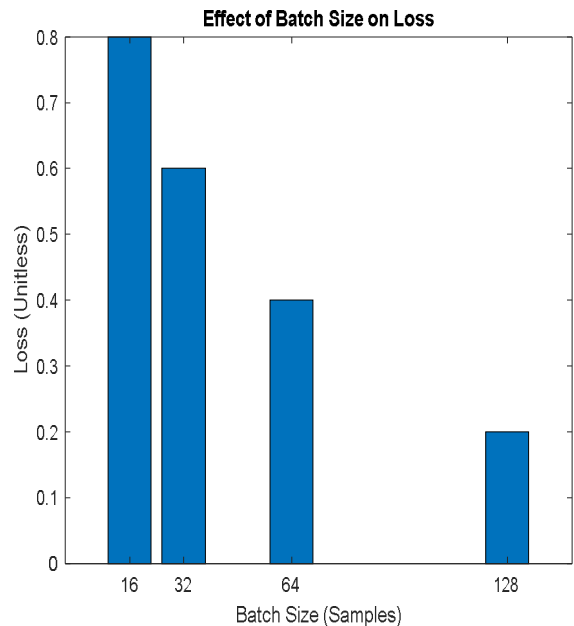


Figure 12: Effect of Bath Size on Loss

Table 2 Simulation Results.

Parameter	Values/Range	Observations
Hovering Cost	0.5 - 1.5 units	Total energy consumption increases linearly with hovering cost.
Total Energy Consumption	0.6 - 1.7 units	
UAV Count	10-Feb	Transmission power increases as the number of UAVs increases.
Transmission Power	5 - 10 dBm	
UAV Count	10-Feb	Bandwidth utilization remains constant regardless of UAV count.
Bandwidth Utilization	180 kHz	
Learning Rate	0.001 - 0.2	Higher learning rates reduce convergence rounds.
Convergence Rounds	100 - 20 iterations	
Noise Power	-152 to -142 dBm/Hz	Error rate decreases as noise power increases.
Error Rate	0.1 - 0.03	
Initial Reputation	0 - 1	Reputation decays with a decay coefficient of 0.3.
Updated Reputation	0.56 (for an initial reputation of 0.8)	
Model Size	0.1 - 1 Mbits	Total cost increases as model size increases.
Total Cooperation Cost	1.1 - 2 units	
Autopilot system (CPU) Frequency	1 - 3 GHz	Utilization increases linearly with autopilot system (CPU) frequency.
Utilization	33% - 100%	
Parameter (θ)	0 - 2	Loss decreases as parameter approaches 1.
Global Loss	Jan-00	
Batch Size	16 - 128	Larger batch sizes result in reduced loss.
Loss	0.8 - 0.2	

Conclusion

This study provides a comprehensive analysis of various performance metrics related to energy consumption, transmission efficiency, learning optimization, and system reliability in UAV communication and machine learning applications. The findings highlight the linear relationship between hovering cost and energy consumption, the impact of UAV count on transmission power, and the positive influence of learning rate and batch size on loss reduction. Additionally, insights into the effects of noise power on error rates and Autopilot system frequency on utilization were established, contributing to improved decision-making in system design. The study's contribution to knowledge lies in its detailed exploration of system behaviors under varying conditions, offering practical guidelines for optimizing energy and transmission efficiency, convergence rates in machine learning, and overall system utilization. It also provides a solid framework for understanding the trade-offs between reputation decay, cooperation cost, and computational resources in real-time, data-driven environments. However, knowledge gaps remain in real-world validation under complex dynamic conditions. Future research should focus on integrating environmental factors, real-time interference modeling, and multi-UAV coordination dynamics to further enhance the robustness of the proposed models. Additionally, investigating adaptive learning techniques and advanced optimization algorithms could yield even more efficient outcomes. To address these gaps, it is recommended that further experimentation be conducted using real-world data, adaptive parameter tuning mechanisms be implemented, and hybrid learning strategies be explored to account for dynamic system behavior. This will ensure that both machine learning systems and UAV communication networks continue to evolve in response to complex, unpredictable scenarios.

Author contributions

Friday O. Philip-Kpae: Writing – original draft, Methodology, Investigation and optimization analysis, Technical and integrated Analysis, results interpretation, proof-editing and proofreading final work formatting.

Lloyd E. Ogbondamati: Writing – Programming and Simulation results editing and final result analysis, interpretation and editing.

Godson Ikhazuangbe: Writing – Drafting, Methodology, System modelling and also final editing.

Funding

The authors received no funding from both internal and external source. All authors are solely contributory to the completion of this research.

Competing interest

All authors hereby declare that there is no conflict of interest associated to this study.

Acknowledgements

Rivers State University Port Harcourt Nigeria, University of Port Harcourt Rivers State Nigeria and University of Nottingham United Kingdom are highly appreciative for providing the authors the platform for which they gained research experience that necessitated the completion of this study. We are indeed grateful after all.

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