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A Novel Algorithm for Wireless Marine Internet of Things

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Abstract. The increasing use of wireless iot devices and edge servers in maritime environments has sparked interest in distributed edge computing research. Federated Learning (FL) has become a key solution to address communication resource consumption and data privacy issues in distributed edge computing. Nevertheless, current FL frameworks might not fully consider resource limitations in challenging marine environments. In this paper, we introduce a novel FL algorithm for signal overlapping in marine scenarios, focusing on maritime communication environment modeling, Wireless Federated Learning Overlapping (FedOverlap) algorithm design, and resource allocation optimization. We create a detailed wireless signal propagation model for maritime environments and develop an iterative FL algorithm to tackle the challenge of slow model convergence due to signal overlapping. Moreover, we suggest a resource scheduling and allocation strategy for efficient bandwidth, energy, and computation usage. Comprehensive experiments validate our FedOverlap algorithm's properties and exhibit superior performance in accuracy, resource utilization, and convergence speed for practical network parameters and benchmark datasets in production-ready settings.

Index Terms. Signal overlapping, Federated learning, Channel model over marine, Resource allocated

1. Introduction

1.1. Background

Research in the field of sixth-generation communication technology has placed a significant emphasis on the integration of large-scale marine IoT devices and the potential benefits of AI capabilities for wireless networks [6]. The proliferation of IoT devices has led to a dramatic increase in data generated at the network edge, resulting in rapid consumption of storage space, substantial growth in communication bandwidth demands, increased latency, and reduced service quality [3]. In the context of 6G wireless network research, marine wireless IoT networks have emerged as a vital topic, with numerous studies on space-air-ground integrated network being published [12]. The

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exploration and development of Marine resources is crucial, especially in optimizing the wireless resource scheduling of Marine wireless IoT devices and edge server clusters.

In the study of marine IoT networking, wireless communication, resource management, and device heterogeneity are among the most critical issues. Federated Learning (FL) has been proven to address the problem of how to optimize communication and computational resources in large-scale IoT device networking scenarios, including joint optimization methods for bandwidth, energy, and computational resources, reducing communication overhead and improving model convergence rates [8]. Furthermore, the effective utilization of the computing power of these heterogeneous devices is essential for improving the performance of Federated Learning. Designing algorithms for device heterogeneity is an advantage of Federated Learning [11].

In marine IoT networking research, the main issues to be addressed generally include channel fading, channel interference, and spectrum selection. The unpredictable nature of marine channels, along with delayed feedback, is primarily due to the variable ocean environment, particularly the channel interference and channel fading caused by sea surface reflection and long-distance communication. To tackle these issues, researchers have proposed various solutions based on Federated Learning.

1.2. Main Contributed

As illustrated in Fig. 1, in real-world marine environments, a large number of surface or underwater IoT devices are distributed around islands and straits. These devices are often in working condition. Due to the varying degrees of salt water corrosion and other external environmental interference, they are challenging to maintain frequently, resulting in significant differences in the computing power and communication capabilities of different iot devices. Consequently, this research considers federated learning algorithms to be well-suited for such heterogeneous device scenarios. However, given the substantial differences between maritime environments and terrestrial environments, the surface channel model diverges considerably from the commonly used terrestrial channel model [5]. To account for these differences in fitting the marine channel modeling, we have studied the channel modeling characteristics in this scenario and reexamined the small-scale channel modeling for marine channels.

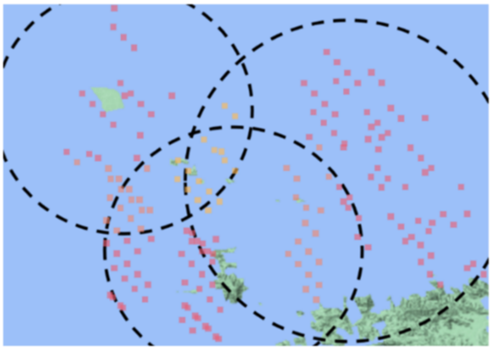


Figure 1. Signal Overlap Area

Furthermore, based on our research of the marine wireless IoT scenarios, a common situation is the occurrence of signal overlapping, where a single wireless IoT device may receive wireless signal transmissions from multiple base stations simultaneously. This phenomenon can lead to reduced communication performance and model convergence, as the client needs to process signals from multiple servers, potentially resulting in weakened signal strength, distortion, or errors, making model convergence difficult. To address this issue, we have developed a new federated learning strategy based on federated learning to optimize resource allocation, reduce interference, and improve communication efficiency. This approach aims to enhance the performance of IoT devices in marine environments, ensuring more reliable and efficient communication for various maritime applications.

In this paper, we introduce a novel federated learning (FL) algorithm for marine wireless IoT communication, which addresses the distinct challenges associated with signal overlapping in ocean environments. Our contributions include:

- A comprehensive model of wireless signal propagation in marine environments, taking into account factors such as path loss, shadowing, and channel disturbances.
- A resource scheduling and allocation strategy that optimizes the utilization of bandwidth, energy, and computational resources to improve the performance of the federated reinforcement learning (FRL) framework in marine wireless IoT communication scenarios with signal overlap.
- An innovative marine wireless reinforcement learning framework that efficiently addresses the unique challenges of ocean surface communication, including overlapping regions and variable channel conditions.

By tackling these challenges and enhancing the performance of distributed learning in marine wireless communication environments, our proposed algorithm contributes to the progress of edge computing research and the effective implementation of IoT devices in maritime settings.

1.3. Related Work

Recent progress in federated learning and wireless communication research has tackled a variety of challenges, such as efficiency, privacy, and overall performance. However, the incorporation of federated learning within marine wireless communication remains largely unexplored, providing opportunities for innovative research and breakthroughs.

Federated learning typically divides data into smaller, manageable clusters and performs learning on these subsets rather than the entire dataset. This approach has been shown to increase efficiency by decreasing communication overhead and enhancing model update accuracy [7]. A recent study by Zhang et al. [13] proposes a personal cluster federated learning framework that employs wireless communication to reduce communication overhead and improve federated learning privacy. This method demonstrates increased accuracy and faster convergence compared to traditional federated learning techniques. The concept was initially introduced and its effectiveness was proven in healthcare settings [9].

Another study by Ahn et al. [10] investigates wireless communication in federated learning, proposing an innovative optimization algorithm to enhance federated learning communication efficiency. The authors show that this method significantly reduces data transmission volume over the network while maintaining high model accuracy. A comprehensive review of the current state of wireless federated learning is provided by Ahn et al. [1]. Joint optimization of communication and computation resources in federated learning is evaluated by Li et al. [9].

On the other hand, marine environments present unique challenges due to their dynamic nature, extensive coverage areas, and the requirement for robust communication systems to manage various IoT devices with limited network connectivity. Marine environment characteristics, such as water absorption, propagation delays, and the influence of weather conditions, can significantly impact wireless communication [4]. Research in marine wireless communication system modeling aims to understand these factors and develop strategies to mitigate their effect on communication quality and efficiency [2] .

Despite advances in both federated learning and marine wireless communication, their combination remains relatively uncharted. This may be due to the complexity of marine environments, the scarcity of available datasets, and the interdisciplinary nature of this research field. As a result, there is an opportunity for groundbreaking research that addresses the unique challenges and opportunities in this emerging field, such as balancing the trade-off between communication efficiency and privacy and managing communication overhead as the number of participating devices increases.

In conclusion, while significant progress has been made in federated learning and marine wireless communication, the application of federated learning in marine environments remains largely uncharted territory. This presents an opportunity for innovative research to address the unique challenges and opportunities in this emerging field. Our work aims to contribute to this area of research by investigating the potential of federated learning in marine wireless communication, acknowledging the limited available literature for reference and recognizing that our efforts represent a novel and pioneering direction in this domain.

2. System Model

2.1. Federated Learning

Consider a federated learning system consisting of K devices, denoted as K= 1,2,...,K , and a central server. Each device k∈K has a local dataset D k of size n_k, with a total of $N = \sum_{k=1}^{K} n_k$ data points across all devices. The devices collaborate to learn a shared model parameterized by a weight vector W, while keeping their local data private. The goal of federate learning is to solve the optimization problme:

$$\min_{\mathbf{w}} F(\mathbf{w}) = \min_{\mathbf{w}} \sum_{k=1}^{K} \frac{n_k}{n} F_k(\mathbf{w}) \tag{1}$$

We assume that the devices communicate with the central server over a wireless network, where the communication links may be subject to delays and losses. The central server. coordinates the federated learning process and aggregates the local model updates. The federated learning process involves the following steps, Initialization: The central server initializes the global model with random weights W^0 and broadcasts it to all devices. Local Training: Each device k trains its local model on its data D_k for E epochs using mini-batch stochastic gradient descent (SGD) or any other optimization algorithm. For each mini-batch $B \subseteq D_k$, the device computes the gradient of the local loss function $L_k(W)$ with respect to the model weights: $\nabla L_k(W) = (1/|B|) \sum_{x_i, y_i \in B} \nabla l(W; x_i, y_i)$ where $l(W; x_i, y_i)$ is the per-example loss function for data point (x_i, y_i). The local model weights are updated according to the optimization algorithm, e.g., for SGD:

$$W_k^t + 1 = W_k^t - \eta \nabla L_k(W_k^t) \tag{2}$$

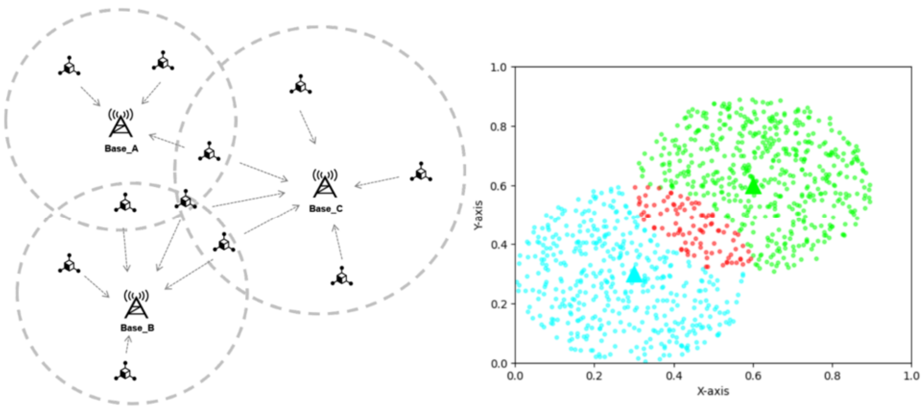
where η is the learning rate, and t is the current iteration. Model Aggregation: After local training, each device k sends its local model updates $\Delta W_k = W_k^t + 1 - W_k^t$ to the central server. The server aggregates the updates by taking a weighted average: $\Delta W_{global} = \left(1/_N\right) \sum_{k=1}^{K} n_k \, \Delta W_k$.Global Model Update: The central server updates the global model using the aggregated updates: $W_{global} + 1 = W_{global}^t + \Delta W_{global}$ Model Dissemination: The updated global model is sent back to the devices, and the process repeats for T communication rounds or until a predetermined convergence criterion is met. After every processing, the federated learning process allows devices to collaboratively learn a shared model while preserving data privacy. The performance of this federated learning system can be further enhanced by incorporating techniques such as adaptive learning rates, model compression, and secure aggregation.

2.2. Communication Over Marine

In actual mobile communication network planning, channels can be classified into three categories according to their conditions: Line of Sight (LoS), Non-Line of Sight (NLoS), and broad Line of Sight (b-LoS), with different path loss models being applied for different channel models. The LoS channel model occurs when there are no obstructions between two base stations or between a mobile terminal and a base station. As the attenuation is lower, the LoS channel model offers better signal quality and higher throughput compared to NLoS channels. In NLoS channel models, multipath effects are common due to obstructions such as buildings and vegetation, causing reflection, diffraction, and penetration losses in addition to attenuation. Lastly, in high humidity coastal areas, ducting is more likely to form, and in such cases, ducted channel b-LoS communication can connect distances of 500-1000 kilometers in maritime environments.

Research on maritime communication models mainly focuses on statistical average characteristics such as path loss. Large-scale channel fading refers to channel parameters that change slowly over time, such as path loss and angle of arrival. Small-scale channel fading, on the other hand, is dynamically affected by factors such as sea surface reflection, refraction, and scattering, reflecting the complex randomness of maritime wireless channels.

Large-scale Channel Model: Taking into account the influence of sea surface reflection signals, antenna height, wave fluctuation height, and tidal height, a continuously modified two-path model can generally better fit experimental data. The various modified two-path models can achieve good fitting results in certain scenarios but are only applicable to relatively short-distance maritime communication. Special atmospheric refractivity structures in the marine atmosphere easily form evaporation ducts, providing conditions for longdistance communication. Previous work has measured the nearshore maritime channel in line-of-sight scenarios, and the analysis results indicate that the presence of evaporation ducts affects the path loss model when the distance between the transmitting and receiving ends exceeds a certain threshold (related to the height of the transmitting and receiving antennas). Based on this, a three-path path loss model has been proposed, which is closely related to the evaporation duct height and the height of the transmitting and receiving antennas. The effect of evaporation duct height on signal attenuation and diversity has also been simulated and analyzed. The measured results show that the evaporation duct three-path model can provide significant communication performance gains compared to the two-path model. Small-scale Channel Model: In addition to path loss, maritime channel models also need to consider small-scale fading caused by factors such as sea surface fluctuations and atmospheric scattering. Maritime channel models are not only related to signal frequency, transmission distance, antenna height, and moving speed but are also affected by marine meteorological and hydrological environments. Depending on the direct link and multipath reflection link conditions, Rician fading and Rayleigh fading are typically used to represent channel fading. However, when Rician and Rayleigh distributions do not fit the experimental data well, a more general channel fading distribution, the Nakagami-m fading, has been proposed.



(a) (b)

Figure 2. (a) Defined the signal overlapping problem (b) Iot device distribution map drawn from data

In our research, as the Fig.1 shown, we can observe that most of the maritime IoT devices are located near the sea surface, within a Line of Sight (LoS) range. Therefore, we will focus more on the small-scale channel models in this context. In the case of LoS communication scenarios, Rician fading is often used to model small-scale fading effects. Rician fading accounts for the presence of a dominant direct path between the transmitter and receiver, along with the multipath components that result from reflections, scattering, and refraction.

$$P_{Rayleigh}(r) = \begin{cases} \frac{r}{\sigma^2} exp\left(-\frac{r^2}{2\sigma^2}\right), & r \geq 0 \\ 0, & r < 0 \end{cases} \tag{3}$$

The Rician fading model is defined by the Rician K-factor, which is the ratio of the power in the direct path to the power in the multipath components. A higher K-factor

indicates a stronger direct path and less fading, leading to better communication performance. In maritime environments, the K-factor can vary depending on factors such as the distance between devices, the height of the antennas, and the sea state.

$$P_{\text{Rice}}(r) = \begin{cases} \frac{r}{\sigma^2} \exp\left(-\frac{r^2+A^2}{2\sigma^2}\right) I_0\left(\frac{Ar}{\sigma^2}\right), & r \geq 0 \\ 0, & r < 0 \end{cases} \tag{4}$$

The Rician random variable h can be modeled as:

$h = Directpathcomponent + Rayleighrandomvariable$ hi, First, determine the K-factor, which is the ratio of the power of the direct path component (a constant) to the power of the Rayleigh random variable, i.e., $K = Directpathcomponentpower/Rayleighpower$. According to the channel normalization requirement $E\,|h|^2 = 1$,h can be normalized as follows: $K = sqrt\left({}^{K}/_{(K+1)}\right) + sqrt\left({}^{1}/_{(K+1)}\right) * Rayleigh_{random}$

The Nakagami-m fading channel model can better fit a wider range of experimental data:

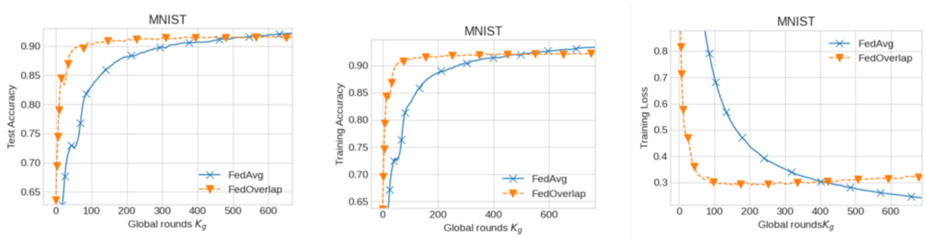
$$pZ(z) = \frac{2m^m z^{2m-1}}{\Gamma(m) P_r^m} \exp\left[-\frac{-mz^2}{P_r}\right] \tag{5}$$

where P_r represents the average power, $\Gamma(m)$ is the gamma function, and m is the fading parameter. When m = 1, the equation reduces to the Rayleigh fading model. If we set $m = (K+1)2/(2K+1)$, the equation approximates the Rician fading model with a K-factor of K. When $m = \infty$, it represents no fading. By changing the value of m, the Nakagami fading model can be transformed into various fading models.

To better understand and model maritime communication channels, researchers should continue to focus on the statistical average characteristics of these channels, such as path loss and large-scale fading, while also considering small-scale fading effects due to environmental factors like sea surface fluctuations and atmospheric scattering. By developing more accurate and robust channel models, it is possible to optimize the design and deployment of maritime communication systems to meet the growing demand for high-speed data transmission in coastal and offshore environments.

3. Problem Formulation and Algorithm Design

Based on Fig. 1, the problem is abstracted as depicted in Fig. 2, where the signal overlapping issue can be regarded as a federated multi-cluster resource allocation challenge. Assuming there are L clusters, each has its respective IoT devices and Base Stations (BS). Contrasting with traditional cloud-based FL systems with a central cloud



(a) The test accuracy of FedOverlap (b) The training accuracy of FedOverlap (c) The Training Loss of FedOverlap

Figure 3. Algorithm iteration result

Algorithm 1: Federate learning over signal overlapping

Initialization: Number of device K, Channel model parameters B, System parameters f, Larger weight $\triangle\delta$
Output: Optimal resource allocation R^*; User selection vector $\triangle\delta$; Transmit power vector P^*
1: Calculate uplink and downlink capacities for different channel models
For each device from 1 to n :
if $m \in Rayleigh$:
$p = p_{ray}\ from\ 3$
if $m \in Rician$:
$p = p_{Rician}\ from\ eq. 4$
if $m \in Nakagami$:
$p = p_{Nakagami}\ from\ eq. 5$
output the User weight vector $\triangle\delta$
2: Optimize the signal overlapping and resource allocated
For $t = 1$ to round do:
For each Iot device $k = \{1,2,3,\ldots,K\}$ do:
$W_k^t + 1 \leftarrow W_k^t - \eta \nabla L_k(W_k^t)$// local model update
Else: (Iot i randomly selects $S(i)t + 1$ to receive the updated models from other area)
For each Iot device $k \subseteq U_i \& E_i$ do:
$$\mathbf{w}_k(t) = \frac{1}{\sum_{k\in S_t^{(i)}} n_k + \sum_{k\in S_t^{(j)}} n_k} \times \left(\sum_{k\in S_t^{(i)}} n_k \mathbf{w}^{(i)}(t) + \sum_{k\in S_t^{(j)}} n_k \mathbf{w}^{(j)}(t)\right) + \triangle\delta \quad //$$
Average of two edge aggregations
Transmission: UE n sends w_n^t and $\nabla F_n(w_n^t)$ for all n to the edge server
Aggregation and Responses: The server updates model w^t and ∇F^t ,respectively, and subsequently provides feedback to all UEs.
3:Evaluate system performance

server covering all clients, this paper considers L Edge Servers (ESs), each covering its local area. These local coverage areas are referred to as cells. In marine overlapping area, dense deployment of ESs often results in multiple ESs within a specific user's communication range. We term the region where a client can reliably communicate with multiple ESs as the overlapping cell area. Let C_i represent the set of indices for users in cell $i \in 1,2,\ldots,L$. We define U_i as the set of user indices for the non-overlapped region of cell i, a subset of C_i . Additionally, we define $E_{i,j}$ as the set of user indices for the overlapping area between cell i and cell j $\left(i \neq j\ and\ E_{i,j} = E_{j,i}\right)$, also a subset of C_i. Clients in $E_{i,j}$ can communicate with both ES i and ES j during model download or upload. For simplicity, we only consider cases where the coverage of at most two ESs overlaps. Thus, the coverage of cell i , or C_i , can be expressed as: $C_i = U_i \cup (\cup_{j\in[L]/i} E_{i,j})$. for all $i \in 1,2,\ldots,L$. It is important to note that each ES can only communicate with clients in its covered area. In this research, we aim to solve the 1 problem, and we can transfer the 2 to:

$$\mathbf{w}_k(t) = \frac{1}{\sum_{k\in S_t^{(i)}} n_k + \sum_{k\in S_t^{(j)}} n_k} \times \left(\sum_{k\in S_t^{(i)}} n_k \mathbf{w}^{(i)}(t) + \sum_{k\in S_t^{(j)}} n_k \mathbf{w}^{(j)}(t)\right) + \triangle\delta \tag{6}$$

At the onset of step t, clients in cell i obtain the current model $w^i(t)$ from ES i. If a client is situated in the non-overlapped region, $i.e.$, $k \in U_i$, they set $w^k(t) = w^i(t)$. For clients in the overlapping region, $k \in E_{i,j}$, they download $w^j(t)$ from ES j and combine both received models as follows: $w^k(t) = (1-\lambda) * w^i(t) + \lambda * w^j(t)$ Here, $S_t^{(i)}$ and $S_t^{(j)}$ represent the client sets that sent their results to ES i and ES j, respectively, during the prior aggregation step. A larger weight ($\triangle\ \delta$) is assigned to the aggregated model of the ES that depend on the communication resource allocation from hybrid derivation of 3,4,5. Consequently, clients $k \in E_{i,j}$ should obtain the value of $\sum_{k \in S_t^{(j)}} n_k$ from ES i and $\sum_{k \in S_t^{(j)}} n_k$ from ES j.

4. Experiment Evaluation

The applications under consideration include ship guidance and cloud computing services in a strait of islands, as well as edge computing services like convolutional neural networks (CNN) and deep neural networks (DNN). Since the communication environment is at the land edge and involves near-coastal communication, we utilize high-frequency (HF) communication paradigms, with a focus on the very highfrequency (VHF) range of 30 MHz to 300 MHz. Mobile services' golden channels fall between 156 MHz and 152 MHz, yielding a wavelength range of 1m to 10m. Both onshore and offshore base stations serve as fixed stations for communication nodes, eliminating the need for mobility consideration. These stations are defined as fixed edge IoT communication nodes in this context. With fixed nodes, shadowing attenuation is set to 0 dB, and the antenna gain is 11 dB. The VHF transmission power is 25 W, and the frequency is set at 1.5 GHz with a 2-meter wavelength. Ten edge IoT devices are involved in communication.

As shown in Figure.3, the Fedovlap algorithm has a slight edge in convergence speed over the traditional FedAvg algorithm. This is due to the optimization of communication and computational energy after integrating realistic oceanic conditions, enabling the algorithm to attain higher accuracy in a shorter time. The performance after 200 rounds essentially demonstrates the FedOverlap algorithm's convergence. Although the FedOverlap algorithm's accuracy after convergence, around 92%, is not as high as that of the FedAvg algorithm, it is because of the strict trade-off between communication and computational energy employed. Nonetheless, this is consistent with the rapid convergence and reasonable accuracy scenario, which is more suited to harsh and highly variable environments like maritime communications. This further validates the practical applicability and value of our Fedovlap algorithm in real-world maritime communication settings.

5. Conclusion

In this study, we re-model the marine channel based on actual sea surface conditions, using Rayleigh fading, Rician fading, and Nakagami fading to redefine the channel transmission characteristics. We innovatively propose the FedOverlap algorithm, leveraging the gradient aggregation properties of federated learning to apply weights to IoT nodes within the overlap area. This ensures that all devices within the signal coverage range can receive signals with sufficient strength, guaranteeing the accuracy of federated learning. At the same time, we incorporate communication weight factors to minimize interference with other base stations. In the future, we will consider more complex overlap environments to make the algorithm as close as possible to real-world maritime wireless scenarios. We will also explore various resource optimization methods, such as channel allocation selection, dynamic power control, scheduling slot allocation, and federated learning collaborative filtering, for algorithm scheduling under signal overlapping conditions.

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