Abstract—Sixth-generation wireless communication (6G) will be an integrated architecture of "space, air, ground and sea". One of the most difficult part of this architecture is the underwater information acquisition which need to transmit information across the interface between water and air. In this scenario, ocean of things (OoT) will play an important role, because it can serve as a hub connecting Internet of things (IoT) and Internet of underwater things (IoUT). OoT device not only can collect data through underwater methods, but also can utilize radio frequency over the air. For underwater communications, underwater acoustic communications (UWA COMMs) is the most effective way for OoT devices to exchange information, but it is always tormented by doppler shift and synchronization errors. In this paper, in order to overcome UWA tough conditions, a deep neural networks based receiver for underwater acoustic chirp communication, called C-DNN, is proposed. Moreover, to improve the performance of DL-model and solve the problem of model generalization, we also proposed a novel federated meta learning (FML) enhanced acoustic radio cooperative (ARC) framework, dubbed ARC/FML, to do transfer. Particularly, tractable expressions are derived for the convergence rate of FML in a wireless setting, accounting for effects from both scheduling ratio, local epoch and the data amount on a single node. From our analysis and simulation results, it is shown that, the proposed C-DNN can provide a better BER performance and lower complexity than classical matched filter (MF) in underwater acoustic communications scenario. The ARC/FML framework has good convergence under a variety of channels than federated learning (FL). In summary, the proposed ARC/FML for OoT is a promising scheme for information exchange across water and air.

Index Terms—Federated meta learning, underwater acoustic communication, deep learning, distributed system, convergence.

I. INTRODUCTION

With the continuous development of the blue economy, the communications for marine information gathering, transmission and fusion will become more and more important [1]. Moreover, sixth-generation (6G) agenda aims to connect the whole world together, which needs to ensure worldwide connectivity. The demand of communications will expand from space to air, ground, and sea environment in this era, dramatically [2] [3]. Hence, underwater information acquisition is becoming increasingly important. Underwater acoustic communication (UWA COMMs) as the most effective way of underwater information transmission has two challenges to face.

One challenge is underwater information need cross the water-air interface. Fortunately, using buoy node to exchange seabed observation information with satellite control information is a very typical and extremely important application for ocean observation [8]. The emerging ocean of things (OoT) based on low-cost floating devices [4] [5], will provide a feasible way for water and air information interaction. Therefore, OoT will be the hub of information interaction, linking IoT, which is for wireless devices and IoUT which is mainly focusing on underwater equipment [6].

Another challenge is that UWA COMMs need overcome many obstacles, such as strong noise interference, multipath effects, large scale Doppler effects and synchronization error [11]. The UWA COMMs can be divided into two research fields, high rate communication system and low rate robust communication system. Especially, the robust UWA COMMs play an important role in many underwater scenarios, such as control signaling transmission for unmanned underwater work system and information interaction in a high-noise environment. Recently, deep learning has shown amazing results in solving underwater acoustic signal recovery than classical signal processing method. However, the fatal problem is that devices are distributed and may have insufficient data in single node. Hence, there are two important problems that can’t be ignored. First, data is separated which lead to the marginalization and discretization of data acquisition. Second, single device may have insufficient data. The emerging federated learning (FL) can train deep learning (DL) models in distributed systems which is a good solution [7].

Motivated by above mentioned, we explore the power of deep learning and exploit the cooperation of acoustic and radio links to use distributed data to achieve robust UWA
COMMs and utilize distributed data. The surface relay buoy transmission system can utilize the cooperation of acoustic and radio. First, the system can realize information interaction with the subsea equipments through DL based UWA COMMs. Second, the sea surface relay buoy can do federated learning to share DL model parameters via radio frequency in order to improve single node performance. In this paper, the main contribution can be divided into three parts.

- We proposed an acoustic radio cooperative (ARC) training framework for deep learning based Ocean of Things, which can be used to DL-model training for surface equipment.
- To analyze the ARC performance, we take stability UWA COMMs for OoT device as an example. We propose a novel DL-based chirp communications receiver apply it over underwater acoustic channels, which can against doppler shift and symbol time offset. The bit error rate can be increased by an order of magnitude.
- To utilize the distributed data from multiple buoy nodes, we proposed an ARC enhanced federated meta learning (FML) based algorithm to train the DL-receiver in the context of random scheduling wireless networks, dubbed ARC/FML, which can achieve distributed transfer learning to adapt to a new dataset. Besides, we analysis the converges of FML with wireless communication. For any convergence target gap \( \epsilon \), the FML algorithm can acheive an gap after \( T \) rounds of communications.

The remainder of this paper is organized as follows. In section II, provides a brief survey on UWA COMMs, DL in physical layer and federated learning in wireless networks. Then, the system model is introduced in section III and the convergence of Federated Meta Learning in Wireless is analysed on section IV. In section V, the dataset is explained. In section VI simulation results are demonstrated. In last section, a conclusion is provided.

II. STATE OF ART

UWA COMMs: UWA characteristics are now known the disadvantages of severe transmission loss, time-varying multi-path propagation, severe Doppler spread, limited and distance-dependent bandwidth, and high propagation delay. These features will change as the communication scenario changes. Therefore, researchers usually divide underwater acoustic communication into two kinds according to application requirement. One is high-data-rate underwater acoustic communication for short- and medium-range communications. In this direction, in order to further improve the communication reliability, it is necessary to better overcome the complex multi-path fading of underwater acoustic channel. The joint equalization decoding method, which combines channel equalization and channel decoding, is a relatively advanced channel compensation technology at present and has high practical value and application prospect. Moreover, in order to meet the needs of more diversified applications with high data rate, new efficient modulation mode and multiple input multiple output technology are introduced into the medium and short range underwater acoustic communication, which significantly improves the rate of underwater acoustic communication and becomes a new research hotspot. The other is low-data-rate underwater acoustic communication for long-range communications. Many modulation techniques which have robust performance, such as frequency shift keying, chirp modulation and spread modulation, have been used for rapid timevarying channels. However, the most difficult aspect of UWA COMMs is lack of a accurate channel models the tractable mathematical descriptions of the underwater acoustic channel are elusive, because the signal propagation is very complicated. Hence, researchers pay more attention to data based deep learning method expecting to solve many problems that traditional methods cannot. With the improving computational resources and the quantity of data, deep learning brings a new era for communication system that many novel system architecture and algorithm are designed.

DL Based COMMs: DL has been applied successfully in receiver design, channel estimation and signal detection over wireless channels. Unlike conventional receivers, DL can handle wireless channels in an end-to-end manner. It is widely acknowledged that the well-trained DL-receiver can not only reduce the receiver complexity, but also achieve perfect demodulation under unknown channels. The design of DL-receivers can be generally classified into two categories. One is the data driven method, such as the classical FC-DNN, which takes into account the characteristics of data and the ability of neural networks, aiming to achieve global optimality. Whereas, most existing works based on the data-driven method consider the communication system as a black box. The other category is the model driven method, such as the well-known ComNet, which combines DL and expert knowledge. In especial, some methods based on deep learning are also gradually being used in underwater acoustic communication.

FL: FL come into fashion because it can decouple the data acquisition and compute at the central unit. An analytical model is developed to characterize the performance of FL in wireless networks. Moreover, to ensure the DL based communications can work at a new environment. Meta-learning, which can train the network by alternating inner-task and across-task updates with a small number of labeled data to improve the transfer efficiency, has been used in wireless communications. Therefore, many researchers pay attention to federated meta learning. However, among many applications in federated learning based wireless network, deep learning (DL) based applications are actively and widely discussed on image classification task, such as MNIST, rather than DL based physical layer cases. Recently, in the ocean of things, with the increasing computational capacity of device, such as buoys, unmanned ships and offshore platform, as well as the increasing concerns about sharing private data. There is a precedent that the IoUOT device can realize federated learning (FL) computation.

III. FEDERATED META LEARNING BASED FRAMEWORK

In this section, we introduce the federated meta learning in wireless algorithm. For DL based applications, an important limitation of the approach is that training should be generally
that the model parameters of algorithm 1. The algorithm can be divided into two parts.

Fig. 2. Federated meta learning framework.

carried out from scratch for each new dataset. Aiming at improving the generalization of DL-receiver, we proposed FML based framework in random scheduling. Sequentially updating the network parameters from all edge nodes then do global aggregation which is very efficient than transmitted all data located on distributed node to the centre node. In many communication scenarios, the channel sources are precious. Hence, shuffling policy is used to allocate the limited channels to users. In [22], the federated learning in wireless network with three scheduling policies have been studied and the convergences are analyzed. However, existing federated learning as the framework for distributed model with random samples [24]. Hence, in this paper, we take federated meta learning as the framework for distributed model with random scheduling. In each communication rounds, the center node will uniformly pick $N$ users out of $K$ users and $G = N/K$ is the available channel ratio. Essentially, federated meta learning is used to do transfer learning in order to improve the generalization of DL-receiver. Here, we focus on applying FML in wireless networks. The procedure is description in algorithm 1. The algorithm can be divided into two parts.

- At edge node $i$, it first update using the training data $D_i^{train}$ stored on the device. For MAML algorithm, given that the model parameters of $i$ buoy node, the node can update its parameters by one step learning according gradient descent based on $D_i^{train}$,

$$\phi_i(\theta) = \theta - \alpha \nabla_\theta L(\theta, D_i^{train}),$$  

where $\alpha$ is the learning rate and then evaluates the loss $L(\phi_i, D_i^{train})$. Then, locally update $\theta_i$ using testing data $D_i^{test}$:

$$\theta_i^{t+1} = \theta_i^t - \beta \nabla_\theta L(\phi_i)$$

After that, if the node is chosen by AP, it will send $\theta_i^{t+1}$ to the AP. The framework can be seen in Fig.3.

**Algorithm 1** Federated Meta Learning Based on Random Scheduling

**Input:** Data set $\{D_i\}_{i=1}^K$ at each BN

1: for $t = 1 : T$ do
2: for each UE $k \in \{1, 2, \ldots, K\}$ in parallel do
3: Initialize $w_i^t = w^0$
4: for $t_{local} = 1$ to $T_0$ do
5: Sample $i \in D_k$ uniformly at random, and update the local parameter using $D_{train}$
6: $\phi_i^t = \theta_i^t - \alpha (\nabla_\theta L(\theta_i^t), D_{train})$
7: obtain $\theta_i^{t+1}$ based on $\theta_i^{t+1} = \theta_i^t - \beta (\nabla_\theta \phi_i^t, D_{test})$
8: end for
9: end for
10: Send parameter $w_i^t$ to the AP
11: end for
12: The AP collects all the parameters $\{\theta_i^t\}_{i=1}^K$, and updates
13: $\theta^{t+1} = \frac{1}{n} \sum_{i=1}^{K} w_i \theta_i^{t+1} u_i$

**Output:** $\theta^T$

- At the AP side, it selects part of BNs for collect parameters in order to the global aggregation. During a communication round $t$, the parameters can be uploaded and updated successfully which needs to meet two conditions, simultaneously. One is that the node $k$ should be selected and the other is that the transmitted data should be decoded without error. In this respect, we use indicator function $u_i \in \{0, 1\}$ to mark the node $i$ which will be used in federated learning process, which indicate whether the node $i$ be chosen at $t$-th round. Hence, the AP performs

$$\theta^{t+1} = \sum_{i \in S} w_i \theta_i^{t+1} u_i,$$

where $w_i$ can be calculated by the local data size according by $w_i = \frac{1}{|J_i|}$. Then, the new global parameters $\theta^{t+1}$ will be broadcast to all nodes in a reliable way.

We first assume the distributed buoy $i \in S$ and $J_i$ represents its local dataset $(x_i^i, y_i^i), \ldots, (x_i^i, y_i^i), \ldots, (x_i^i, y_i^i)$, where $|J_i|$ means dataset and $(x_i, y_i)$ is the sample of this dataset. $x_i$ is the input of DL-based network which is the receive signal and $y_i$ is the output of DL-based network. The distribution of the dataset is unknown. The loss function can be defined as $l(\theta, (x_i, y_i)) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$. The receiver located on buoys can be trained by optimizing the loss function as

$$L_i(\theta, J_i) = \frac{1}{|J_i|} \sum_{(x_i^i, y_i^i) \in J_i} \left| x_i^i - \hat{x}_i^i \right|^2,$$

which can be simply denoted as $L_i(\theta)$.

IV. UWA CHIRP COMMUNICATIONS CASES

With the advance of deep learning, it has a very strong application in the physical layer. Hence, we take DL-based communications system as an example. In order to achieve the purpose of stable communication, each node selects chirp
communications for UWA COMMs, because of its characteristic of anti-noise and robustness to Doppler. The UWA stable communications adopt a pair of chirp signals in frequency band \([f_1 – f_2]\) Hz to transmit information which can be expressed as

\[
s_1(t) = \cos(2\pi f_1 t + \mu t^2/2 + \phi_0), 0 \leq t \leq T, \tag{5}
\]

\[
s_2(t) = \cos(2\pi f_2 t - \mu t^2/2 + \phi_0), 0 \leq t \leq T, \tag{6}
\]

where \(s_1\) means up chirp and \(s_2\) is down chirp where \(T\) is symbol duration, and \(\phi_0\) is arbitrary initial phase which is assumed to be zero without loss of generality, respectively. Moreover, the chirp signal is characterized by its start frequency \(f_1\), end frequency \(f_2\), and time duration \(T\) as

\[
\mu = \frac{|f_2 - f_1|}{T} = \frac{B}{T}, \tag{7}
\]

where \(B\) is the bandwidth of chirp signals. Usually, the chirp signal is defined as up-chirps with \(\mu > 0\) and down-chirps with \(\mu < 0\). After framed, the signal is transmitted over the channel which can be expressed as

\[
y(t) = \int_{-\infty}^{+\infty} h(\tau, t)s(t - \tau) d\tau + n(t), \tag{8}
\]

where \(h(t)\) means UWA channel impulse response.

### A. Matched Filter based Receiver

A classical method to implement the matched filter (correlator) receiver is convolution. Received signal \(y(t)\) is convolved with time-reversed versions of \(s_1(t)\) and \(s_2(t)\) to generate estimator \(c_1\) and \(c_2\), respectively. The receiver calculation process is as follows,

\[
c_i = \int y(\tau)s_i(T - \tau) d\tau, \quad i \in (1, 2), \tag{9}
\]

If \(c_1 \leq c_2\), the receiver estimates that \(s_1\) is transmitted. Otherwise, \(s_2\) is transmitted. However, to achieve the optimal detection, the matched filter needs to satisfy three conditions.

- Integral interval synchronization should be satisfied. That is to say, the received signals \(y(t)\) require precise synchronization.
- The noise \(n(t)\) should be Gaussian noise.
- The received signal \(y(t)\) must not be affected by Doppler shift.

Unfortunately, the abovementioned assumptions are impractical in UWA COMMs, because of the large delay, non-Gaussian noise and doppler shift characteristic. Hence, we proposed a novel DL-receiver solve those problems.

### B. DL based Receiver

We first introduce a specific DL based receiver, which depends on neural network architecture, called C-DNN, which can be employed for detection uses several fully connected NN layers. Hence, we assume that the DL-receiver can be denoted as \(f_\theta\) with parameters \(\theta \in \mathbb{R}^d\). In this paper, primitively, let us consider the simplest four-layer fully-connected neural network with one input layer, two hidden layers, and one output layer. Denote \(x_i\) and \(y_i\) as the estimated data and the network input of node \(i\), respectively. Therefore, the receiver \(f(\theta)\) which is a cascade of nonlinear transformation of input data can be expressed as

\[
\hat{x}_i = f(y_i, \theta) = f^{(L-1)}_{\text{sigmoid}}(f^{(L-2)}_{\text{Relu}}(...f^{(1)}_{\text{Relu}}(y_i))), \tag{10}
\]

where layer \(l\) contains a total of \(N_l\) neurons and each neuron in the layer \(l\) is connected to all neurons in the next layer \((l + 1)\) through the connection weights matrix. The output of hidden layer are activated by

\[
f_{\text{Relu}}(x_i) = \max(0, x_i), \tag{11}
\]

which is a non-linear function to provide a normalized output and keeps the output within the interval \([0, +\infty]\). The output of the final layer is the estimated bit. The output layer only consist one neuron, estimating the binary bits to be detected. Considering sigmoid activation function is applied to the output layer, which limits the output within the interval \([0, 1]\).

Thus, the task can be activated by

\[
f_{\text{sigmoid}}(x_i) = \frac{1}{1 + e^{-x_i}}. \tag{12}
\]

The input to the first layer is the received signal \(y_i(t)\) or the sampled feature factor \(y_i[k]\), which is selectively choosen from the observed signal through preprocessing. This dataset is then used to train a DL-based receiver that estimate the received signal \(y_i[k]\) to one of the transmission symbols in \([s_1, s_2]\).

### V. Convergence Analysis of Federated Meta Learning

In this section, we focus on the convergence of the federated meta-learning method. We first define \(G_i(\theta) = L_i(\phi_i(\theta))\) and \(G(\theta) = \sum_{i \in S} w_i G_i(\theta)\). For simplicity, we assume \(T = NT_0\) and do four assumptions for all objective functions.

**TABLE I**

| Notations | Definition |
|-----------|------------|
| \(T_0\)   | number of local update steps |
| \(v_i^n\) | parameters for global aggregation at each iteration within the interval \([n – 1]T_0, nT_0]\) |
| \(\theta_i; \theta^t\) | local parameters; weighted average of local parameters which is synchronized with \(v_i^n\) |
| \(\alpha; \beta\) | learning rate during meta training (local adaptation); learning rate during meta training (update initialization) |
| \(L_i; G_i; G\) | objective function |
| \(D_{\text{train}}, D_{\text{test}}\) | dataset for training and dataset for testing |
Assumption 1. Each $L(\theta)$ is $\mu$-strongly convex, i.e., for all $\theta, \theta' \in \mathbb{R}^n$,
\[ ||\nabla L_i(\theta) - \nabla L_i(\theta')|| \geq \mu ||\theta - \theta'||. \tag{13} \]

Assumption 2. Each $L(\theta)$ is $H$-smooth, i.e., for all $\theta, \theta' \in \mathbb{R}^n$,
\[ ||\nabla L_i(\theta) - \nabla L_i(\theta')|| \leq H ||\theta - \theta'||. \tag{14} \]
and there exists constant $B$ such that for all $\theta' \in \mathbb{R}^n$,
\[ ||\nabla L_i(\theta)|| \leq B. \tag{15} \]

Assumption 3. The hessian of each $L_i(\theta)$ is $\rho$-Lipschitz, i.e., for all $\theta, \theta' \in \mathbb{R}^n$,
\[ ||\nabla^2 L_i(\theta) - \nabla^2 L_w(\theta)|| \leq \rho ||\theta - \theta'||. \tag{16} \]

Assumption 4. There exists $\delta$ and $\sigma$ such that for all $\theta \in \mathbb{R}^n$,
\[ ||\nabla L_i(\theta) - \nabla L_w(\theta)|| \leq \delta_i \tag{17} \]
\[ ||\nabla^2 L_i(\theta) - \nabla^2 L_w(\theta)|| \leq \sigma_i \tag{18} \]

Assumption 1 and 2 are standard in standard and hold in many deep learning algorithms. Assumption 3 illustrates that the local loss function is second-order smooth which is possible to analyse local meta learning loss function. Assumption 4 describes the node similarity, whose gap between an implementation and the sample average can be measured by $||\nabla L_i(\theta) - \nabla L_w(\theta)||$.

Next, to analysis the convergence characteristic of FML based on random scheduling, we first characteristic the global loss function $G(\theta)$. Here, we first show that $G(\theta)$ is $\mu''$-strongly convex and $H''$-smooth.

Lemma 1. Suppose assumption 1-3 hold, $G(\theta)$ is $\mu''$-strongly convex and $H''$-smooth, where $\mu'' = N \mu'$, $H'' = NH'$, $\mu' = \mu(1 - \alpha H')^2 - \alpha_0 G$ and $H' = H(1 - \alpha H)^2 + \alpha_0 G$.

Lemma 1 tells us that the total loss function $G(\theta)$ is also a convex function as $L(\theta)$.

Proof: To establish the smooth, we should show $||\nabla G(\theta) - \nabla G(\theta')|| \leq H'' ||\theta - \theta'||$. By the definition of $H$-smooth, we have
\[ G_i(\theta) \leq G_i(\theta') + \nabla G_i(\theta')(\theta - \theta') + \frac{H'}{2} ||\theta - \theta'||^2, \tag{19} \]
which is equivalent to
\[ ||\nabla G_i(\theta) - \nabla G_i(\theta')|| \leq H' ||\theta - \theta'||, \tag{20} \]
where $i \in S$. Because $G(\theta) = \sum_{i \in S} w_i G_i(\theta)$, by summing we can get
\[ \sum_{i \in S} G_i(\theta) \leq \sum_{i \in S} G_i(\theta') + \sum_{i \in S} \nabla G_i(\theta')(\theta - \theta') + \frac{\sum_{i = 1}^N H'}{2} ||x - y||^2. \tag{21} \]
That is to say,
\[ G(\theta) \leq G(\theta') + \nabla G(\theta')(\theta - \theta') + \frac{NH'}{2} ||\theta - \theta'||^2, \tag{22} \]
which is equivalent to
\[ ||\nabla G(\theta) - \nabla G(\theta')|| \leq H'' ||\theta - \theta'||, \tag{23} \]
where $H'' = NH'$.

In the same way, we can establish the convex,
\[ ||\nabla G(\theta) - \nabla G(\theta')|| \geq N\mu'' ||\theta - \theta'||. \tag{24} \]

From abovementioned, we can have
\[ N\mu'' ||\theta - \theta'|| \leq ||\nabla G(\theta) - \nabla G(\theta')|| \leq NH'' ||\theta - \theta'||. \tag{25} \]

Thereby we complete the proof.

Next, we analysis the influence of the similarity between local learning tasks. Based on Lemma 1, we can get the convergence target gap of the FML based method.

Theorem 1. For any convergence target gap $\epsilon$, the FML algorithm can achieve the gap after $T_z$ rounds of communications, i.e.,
\[ \mathbb{E}[G(\theta^*) - G(\theta^T)] \leq \epsilon \tag{26} \]
if $T_z$ satisfies the following
\[ T_z \geq \frac{\log(\frac{1}{\beta}(e + Km(T)))}{\log(\xi)}, \tag{27} \]
where $K = \frac{\mu''}{1 - \epsilon}, \xi = 1 - 2H'' \beta (1 + \frac{\mu''}{2})$ and $m(T) = \alpha T - \frac{\alpha'}{\eta_T} [1 - (1 - \beta H')^T]$.

The proof is as follows. From formula (27), we can find that the term $K$ is influenced by the difference of meta task and the multiple local update using the function $m(T_0)$. According to the $m(T_0)$, we can find that the local step $T_0$ impacts the convergence time $T_z$. With the increasing of $T_0$, the $T_z$ decrease. Hence, we can adjust the $T_0$ to balance transmission cost and local calculation cost.

Proof: Considering the same ways of [25, 26], we define virtual sequence $v_{i}^{(n)}$ for global aggregation at each iteration for $t \in [(n - 1)T_0, nT_0]$, the internal $(n - 1)T_0, nT_0$ is regarded as $[n]$. In general, we have
\[ v_{i}^{(n+1)} = v_{i}^{(n)} - \beta \nabla G(v_{i}^{(n)}), \tag{28} \]
where $v_{i}^{(n)}$ is assumed to be "synchronized" with $\theta^t$ at the beginning of interval $[n]$, i.e., $v_{i}^{(n)} = \theta^{(n-1)T_0}$, where $\theta^{(n-1)T_0}$ is the global averaging model parameters $\theta$.

To show the convergence, we first analyze the gap between $v_{i}^{(n)}$ and $\theta^t$,
\[ ||\theta^t - v_{i}^{(n)}|| = ||\theta^t - \beta \nabla G_i(\theta^t) - v_{i}^{(n)} + \beta \nabla G(v_{i}^{(n)})|| \leq ||\theta^t - v_{i}^{(n)}|| + \beta ||\nabla G(v_{i}^{(n)}) - \nabla G_i(\theta^t)|| \leq ||\theta^t - v_{i}^{(n)}|| + \beta ||\nabla G_i(\theta^t) - \nabla G_i(v_{i}^{(n)})|| + \beta ||\nabla G(v_{i}^{(n)}) - \nabla G_i(v_{i}^{(n)})|| \leq (1 + \beta H') ||\theta^t - v_{i}^{(n)}|| + \beta \delta_i + \alpha C(H \delta_i + B \sigma_i + \tau) \tag{29} \]
where the upper bound of $||\theta^t - v_{i}^{(n)}|| \leq \delta_i + \alpha C(H \delta_i + B \sigma_i + \tau)$ can be found from [26].
Next, we denote \( g(x) \triangleq \delta + \alpha C(H \delta + B \sigma + \tau) \), and we can have \( ||\theta_i^t - v_{i[t]}|| \leq g(t - (n - 1)T_0) \). According to this, we can get
\[
||\theta^{t+1} - v_{i[t+1]}||
\]
\[
= ||\sum w_i \theta_i^{t+1} u_i - v_{i[t+1]}||
\]
\[
= ||\theta^t - \sum w_i \nabla G_i(\theta_i^t)u_i - v_{i[t]} + \beta \nabla G_i(v_{i[t]})||
\]
\[
\geq ||\theta^t - v_{i[t]}|| - \beta ||\sum w_i (\nabla G_i(\theta_i^t) - \nabla G_i(v_{i[t]})) u_i||
\]
\[
\geq ||\theta^t - v_{i[t]}|| - \beta H' ||\sum w_i |\theta_i^t - v_{i[t]}|| u_i
\]
\[
\geq ||\theta^t - v_{i[t]}|| - \beta H' ||\sum w_i |\theta_i^t - v_{i[t]}||
\]
\[
\geq ||\theta^t - v_{i[t]}|| - \beta H' \sum w_i g(t - (n - 1)T_0)
\]
\[
= ||\theta^t - v_{i[t]}|| + \alpha'[1 - (1 + \beta H')^{t-(n-1)T_0}]
\]  
(30)

where \( \alpha' = \beta [\delta + \alpha C(H \delta + B \sigma + \tau)] \). Iteratively, we have
\[
||\theta_t - v_{i[t]}|| \geq \sum_{j=1}^{j=t-(n-1)T_0} \alpha'[1 - (1 + \beta H')^j]
\]
\[
= \alpha'[t - (n - 1)T_0] - \frac{\alpha'}{\beta H'}[1 - (1 - \beta H')^{t-(n-1)T_0}]
\]
\[
= m(t - (n - 1)T_0)
\]  
(31)

Then, we analyse the gap between virtual sequence \( v_{i[t]} \) and \( v_{i[t+1]} \) within the interval \([n]\) at \( t \in [(n - 1)T_0, nT_0] \). Because \( G(.) \) is \( H'' \)-smooth, we have
\[
G(v_{i[t+1]}^n) - G(v_{i[t]}^n)
\]
\[
\leq \nabla G(v_{i[t]}^n)(v_{i[t+1]}^n - v_{i[t]}^n) + \frac{H''}{2} ||v_{i[t+1]}^n - v_{i[t]}^n||^2
\]  
(32)

Assumption 3 told us that \( G(.) \) is \( H'' \)-smooth and \( \theta^* \) is the minimum point, we have
\[
G(\theta^*) = \min_{\theta} G(\theta)
\]
\[
\leq \min_{\theta} [G(v_{i[t]}^n) + \nabla G(\theta)^n(\theta - v_{i[t]}^n) + \frac{H''}{2} ||\theta - v_{i[t]}^n||^2]
\]
\[
= G(v_{i[t]}^n) + \min_{||y||=1} \min_{t \geq 0} \nabla G(v_{i[t]}^n)yt + \frac{H''}{2} t^2
\]
\[
= G(v_{i[t]}^n) + \min_{||y||=1} \left[ \frac{||G(v_{i[t]}^n)||^2}{2H''} \right]
\]
\[
= G(v_{i[t]}^n) - \frac{||G(v_{i[t]}^n)||^2}{2H''},
\]  
(33)

where \( t = \theta - v_{i[t]} \). Therefore, we can get
\[
\frac{1}{2H''} ||G(v_{i[t]}^n)||^2 \leq G(v_{i[t]}^n) - G(\theta^*)
\]  
(34)

Combined formula (32) and (34), we can have
\[
G(v_{i[t]}^n) - G(v_{i[t]+1}^n) \leq 2H'' \beta (1 + \frac{H'' \beta}{2}) [G(v_{i[t]}^n) - G(\theta^*)]
\]  
(35)

Hence, we can get
\[
G(\theta^*) - G(v_{i[t]+1}^n) \leq [1 - 2H'' \beta (1 + \frac{H'' \beta}{2})] [G(\theta^*) - G(v_{i[t]}^n)]
\]  
(36)

Here we denote \( \xi = 1 - 2H'' \beta (1 + \frac{H'' \beta}{2}) \). That is to say,
\[
G(\theta^*) - G(v_{i[t]+1}^n) \leq \xi [G(\theta^*) - G(v_{i[t]}^n)].
\]  
(37)

Iteratively, we can have
\[
G(\theta^*) - G(v_{i[T_0]}^{N_{T_0}}) \leq \xi^{T_0} [G(\theta^*) - G(v_{i[n-1]T_0]}^{N_{(n-1)T_0}}]
\]
\[
= \xi^{T_0} [G(\theta^*) - G(v_{i[n-1]T_0]}^{N_{(n-1)T_0}}] + \xi^{T_0} [G(v_{i[n-1]T_0]}^{N_{(n-1)T_0}} - G(v_{i[n-1]T_0]}^{N_{nT_0}})]
\]  
(38)

Because \( G(.) \) is \( \mu'' \)-strong convex, we can get that \( ||G(\theta) - G(\theta^*)|| \geq \mu'' ||\theta - \theta^*|| \). Hence, the lower bound \( G(v_{i[n-1]T_0]}^{N_{(n-1)T_0}} - G(v_{i[n-1]T_0]}^{N_{nT_0}}) \) is shown as follow
\[
\mathbb{E}[G(v_{i[(n-1)T_0]}^{N_{(n-1)T_0}})] - G(v_{i[n-1]T_0]}^{N_{(n-1)T_0}})
\]
\[
= \mathbb{E}[G(\theta^{(n-1)T_0}) - G(v_{i[n-1]T_0]}^{N_{(n-1)T_0}})
\]
\[
\geq \mathbb{E}[\mu''] ||\theta^{(n-1)T_0} - v_{i[n-1]T_0]}^{N_{(n-1)T_0}}||
\]
\[
\geq \mu'' m(T_0).
\]  
(39)

Iteratively and incrementally, we can get
\[
\mathbb{E}[G(\theta^*) - G(v_{i[N_{T_0}]}^n)]
\]
\[
\leq \xi^{T_0} \mathbb{E}[G(\theta^*) - G(v_{i[n-1]T_0]}^{N_{(n-1)T_0}})] - \xi^{T_0} \mu'' m(T_0)
\]  
(40)

After receiving updates from \( T \)-th rounds, the convergence gap of objective function can be expressed as
\[
\mathbb{E}[G(\theta^*) - G(\theta^T)]
\]
\[
= \mathbb{E}[G(\theta^*) - G(v_{i[N_T]}^n)] + \mathbb{E}[G(v_{i[T]}^n) - G(v_{i[T]}^n)]
\]
\[
\leq \xi^T \mathbb{E}[G(\theta^*) - G(\theta^0)] - \sum_{j=1}^{N-1} \xi^T m(T_0) - \mu'' m(T_0)
\]
\[
\leq \xi^T \mathbb{E}[G(\theta^*) - G(\theta^0)] - \frac{\mu'' m(T_0)}{1 - \xi^T},
\]  
(41)

The upper bound of is \( \epsilon \) and we have \( \mathbb{E}[G(\theta^*) - G(\theta^0)] \leq n \) \([27]\). Thereby we complete the proof.

VI. DATASET

In addition, massive data is critical for deep learning. In radio frequency (RF) communication system, the required data sets can be found online, such as DeepSig dataset \([28]\) and RF channel dataset \([18]\). But open source underwater acoustic communication dataset for learning algorithm is still blank. What’s more, acoustic channel models and open-source software are foreseen as some of the key elements in the next generation of UWA COMMs research practices \([29]\). The approximate channel models can be implemented by the tapped delay line. We assume the signal is bandlimited within
TABLE II
PARAMETERS OF CHANNEL DATASET

| Parameters   | SIM-P | SIM-B | NOF   | NCS   | CWR   |
|--------------|-------|-------|-------|-------|-------|
| Environment  | Rayleigh | Default | Fjord | Shelf | Reservoir |
| Range        | -     | 500m~8000m | 750m   | 540m   | 1100m, 2100m, 6000m |
| Water depth  | -     | 100m | 10m   | 80m   | 50m   |
| Transmitter depl | -   | Suspended | Bottom | Bottom | Suspended |
| Receiver depl | -     | Suspended | Bottom | Bottom | Suspended |
| Doppler coverage | 30Hz | Uncalculated | 7.8Hz | 31.4Hz | Uncalculated |

Fig. 4. A snapshot of CIR dataset.

bandwidth B which can be described by discrete samples. Hence, formula (8) can be expressed as

\[ r[k] = \sum_{k=0}^{K} g_k(t)x(t - kT_s) \] (42)

where \( T_s \) is the sampling interval and \( T_s = \frac{1}{B} \). The tap gain can be calculated by

\[ g_k(t) = \int_{-\infty}^{+\infty} h(\tau, t) \text{sinc}\left( \frac{\tau - kT_s}{T_s} \right) d\tau. \] (43)

where \( \text{sinc} \) is sample function. Formula (42) shows that \( y(t) \) can be generated by passing \( x(t) \) through a tapped delay line or FIR-filter with taps spaced \( T_s \). Next, we use three methods to get \( h(\tau, t) \) for our dataset.

A. Channel Impulse Response

1) Probability Model: Deep learning requires massive underwater acoustic channel impulse response to trained our net. There are many ways to simulate underwater acoustic channel impulse response. For generate massive CIR for learning, the probability model is selected to model and analyze the underwater acoustic channel. In this article, we summarize the experience of our predecessors, built a simulation underwater acoustic Rayleigh channel dataset for shallow water horizontal communication. The UWA multipath distribution can be assumed as a Rayleigh-distributed [30]. In this model, maximum excess delay is set to 12ms, exponentially decaying is designed and the power attenuation coefficient is 0.66 dB per tap [31]. And the UWA channel Doppler spread is considered by a bell-shaped function with \( a \) equals 9 as the formula (12).

\[ S(f) = \frac{\sqrt{a}}{\pi f_d \left( 1 + a \left( \frac{f}{f_d} \right)^2 \right)} |f| \leq f_d \] (44)

2) Propagation Model: BELLHOP (SIM-B) is a widely-known UWA channel simulation method. Taking it into account, we create a part of data by [32]. The horizontal distance between the receiving end and the transmitting end varies between 500m and 8000m, randomly. The vertical distance varies from 10m to 90m, randomly.

3) Measured CIR: In this subsection, we provide a multi-scene validation dataset, containing simulation and measured CIRs with multi-communication environments, and multi-communication ranges. In addition, the CIRs measured under different environments are considered. The raw CIRs were measured at Norway-Oslofjord (NOF), Norway-Continental Shelf (NCS) [33] and China-Wanlu Reservoir (CWR). It is worth noting that, in CWR, CIRs from different distances were collected. Both receiver and receiver terminals were located on two ships for long-distance communication test, with distances of 1100m, 2100m, and 6000m, respectively. After this, we consider two specific condition as data augmentation.

B. Data Augmentation

1) Symbol Time Offset: If the synchronization error or loss of synchronization occurs in the communication system, the performance of the communication system will be reduced or the communication failure will occur. In order to ensure that the system can reliably detect the synchronous signal, it is more difficult to detect the synchronous signal of underwater communication system due to the complexity of the above-mentioned conditions of underwater acoustic signal transmission

\[ \hat{r}'(t) = r(t + \delta), \] (45)

where \( \delta \) means the deviation caused by inaccuracy synchronization.

2) Doppler Shift: In UWA channel, the effect of platform motion on a wideband signal is more accurately modeled as a complete time scaling (expansion or compression) of the
signal waveform. We assume that the mean Doppler shift cannot be removed from the sounding data before the correlation. The signal can be expressed as

\[ r(t) = s((1 + \alpha)t), \]

where \( s(t) \) and \( r(t) \) are the source and Doppler-shifted received signals, respectively. The relative Doppler shift \( \alpha \) is defined as the ratio of the relative platform speed to the sound speed, which can be calculated by

\[ \alpha = \frac{\delta f}{f_c} = \frac{v}{c}, \]

where \( c \) means the speed of sound in the water and \( v \) denotes the relative speed of the transmitter and receiver.

VII. SIMULATION RESULTS

In this section, in order to evaluate the effect of proposed system. The results are divided into two parts. One is focus on amazing performance of DL based chirp receiver. The other is the convergence performance of FML enhanced communications. Specially, we first introduce the parameters we used in our simulations. Then, we start with the performance of single node to illustrate how great deep learning is for physical layer, especially for complex UWA COMMUs.

A. Parameters

In our experiments, Pytorch and Matlab are used as development framework. Each chirp frame contains 200 symbols and each symbol duration is 10ms. The input contains real parts. Every symbol is predicted independently. The parameters of receiver DNN scheme are shown in table I. In the following experiment, if there is no special explanation, the local adaptation rate \( \alpha \) is 0.001 and the update rate \( \beta \) is 0.0001. The parameters the available ratio, the number of access users and local epoch are configured with \( G = 0.3, N = 10 \) and \( T = T_0 \). For buoy node, each local dataset contains 1000 symbols for training.

B. Performance of Single-node

1) Under different down-sampling factors: Figure 5 shows BER curves of DNN and MF under different downsample factor and different channel conditions. From the results, we can discover a distinct characteristic that the smaller sample factor we get, the lower bit error rate can be obtained. This is due to the smaller sample factor means the more sample points which influence signal-to-noise ratio of the used signal in detection. Besides, we can find that the C-DNN receiver can reach the almost ideal bit error rate performance.
2) Under different STO and DOP: The accuracy vs SNR performance of C-DNN and matched filter is presented in Fig.4. Through observation, we can see For deep learning based receiver, not only BER is the key characteristic to depict communication system performance, but also needs the comparison of train loss and the valid loss to reflect the generalization capability of the receiver. Fig.3 The DNN receiver BER performance can be There is a fact that the receiver is easy to overfit as shown in Fig.4. When receiver is trained online, the loss of model on training set is better than that on validate set. Even so, when the receiver is deployed offline, the receiver performance can better than traditional minimum meansquare error algorithm based receiver . If the generalization ability of the model can be further improved, the receiver performance will be further improved. Deep learning based receiver has great potential.

3) Complexity Analysis: From Table III it is obvious that, DL-receiver has lower complexity. The computations of matched filter are all from correlation calculation. The total number of additions (ADD) used by matched filter is \( N_1 + N_2 - 1 \) and multiplications (MUL) is \( N_1(N_1 + N_2 - 1) \), where \( N_1 = N_2 = \frac{\lambda}{4} \). The total number of additions used by matched filter is \( C_{ADD}^{MF} = 2N_1 - 1 \). The total number of multiplications is \( C_{MUL}^{MF} = 2N_1^2 - 2N_1 \). The total number of computations are presented in terms of the elementary operations is \( C_{TOTAL}^{MF} = C_{ADD}^{MF} + C_{MUL}^{MF} = 2N_1^2 - 1 \). The total number of additions used by DNN is \( C_{ADD}^{DNN} = \sum_{l=1}^{L_1} N_l = \frac{15}{8}N_1 + 1 \). The total number of multiplications is \( C_{MUL}^{DNN} = N_1^2 + \sum_{l=2}^{L_2} N_lN_l - 1 = \frac{53}{32}N_1^2 + \frac{31}{8}N_1 + 1 \). The total number of non-linear activations, amount to \( C_{NAV}^{DNN} = \sum_{l=1}^{L_1} N_l = \frac{15}{8}N_1 + 1 \). The total number of computations are presented in terms of the elementary operations is \( C_{TOTAL}^{DNN} = C_{ADD}^{DNN} + C_{MUL}^{DNN} + C_{NAV}^{DNN} = \frac{53}{32}N_1^2 + \frac{31}{8}N_1 + 2 \). It can be concluded from the above, the \( C_{TOTAL}^{DNN} \leq C_{TOTAL}^{MF} \), because \( N_1 \) always is a large number.

C. Generalization of C-DNN

Figure 8 shows that C-DNN can achieve similar performance under channels that have never appeared in the training dataset. We use simulation data to train our C-DNN and test its performance under simulated and measured dataset. We test C-DNN under different scenarios, where NCS, NOF and CWR have diverse communication environments. It is worth mentioning that a variety of distance are employed in CWR. Hence, we can believe the C-DNN receiver can handle multiple scenarios with only a small loss of accuracy. That is to say, C-DNN is robust can deal with different channels. Moreover, we also test C-DNN performance under emergency conditions (EC) that the data augmentation cannot cover all Doppler shift and symbol timing offset cases. Unfortunately, under EC condition, the C-DNN encounter performance degradation because the DL-model meet something it had never seen before.

D. Performance of FML

1) With federated learning: From Fig 9 we can find that FL and FML have the similar convergence performance under training dataset. But for test stage, test dataset considered, FL accuracy will decrease because the insufficient generalization of the model. FML utilize the then fine-tune the network with the labeled data in the target dataset. In genearl, if the source dataset and target dataset are highly related, a FL algorithm would perform well, without the need for fine-tuning the DL-receivers according to the target environment, which owes to generalization of it. However, most of the time, it’s hard to make source and target dataset equally distributed. Hence, FML has wider application scenarios.

2) With different local epochs: Performance of accuracy vs communication rounds with different local epoch is shown in Fig 10. From the results we can find that as \( T_0 \) increase, so does the accuracy of DL-receiver. The case with local epoch \( T = 5T_0 \) converges more than 10 communication rounds faster than that with \( T = T_0 \). However, as the number of local training epoch increases, this advantage will decrease. The case with local epoch \( T = 5T_0 \) and that with \( T = 10T_0 \) have the similar convergence rate. Formula (27) tell us that \( K \) and \( m(T) \) are increments of \( T_0 \). Hence, the simulation results verify the Theorem 2 that the convergency gap increase with \( T_0 \) under a fixed communication rounds \( T \). This result can guide us to balance the consume of communication rounds and local computations in the real system.

3) With different data volumes: Figure 12 shows the variation of accuracy compared and communication rounds under different data volumes on a single node. From the results, we can find that with the number of users increasing, the convergence of the whole system becomes faster. It is easy to see that the larger data volume used for training, the better
system performance can be got. But in a real system we can’t overdo the amount of local data, because of the distributed data storage, especially in the ocean. Most importantly, we compare three kind of data volume to understand the influence of data volume to single node.

4) With different number of channels: Figure 11 and Fig. 13 indicate the effect of the number of users and the impact of the number of channels available. We can draw the following conclusions. At a certain number of accessible channels, with the increasing of access users, the higher accuracy of DL-receiver we can get. Meanwhile, at a certain number of access users, the higher access rate, the slower the convergence rate. We can explain it qualitatively and quantitatively. For quantitative analysis, with the increasing of users, the convergence rate $T_z$ will become slower. Formula (27) tell us $N$ and $G$ affect the convergence rate which is inversely proportional relationship. From qualitative aspect that as the number of users increases, leading to riching the differences of training data, it slows down the convergence.

VIII. CONCLUSIONS

Deep learning have great potential in underwater acoustic communication system but the disadvantage is sensitive to the distribution of training data. Therefore, considering the generalization of DL-based applications, we utilize the acoustic radio cooperation characteristic of OoT, we proposed a federated Meta Learning Enhanced Acoustic Radio Cooperative Framework for Ocean of Things, which take advantage of the data distributed on surface nodes. Through this method, we can achieve transfer learning. We take UW A chirp communications as an example, which can provide stable UW A COMMs for Ocean of Things. In order to overcome UW A doppler shift and symbol time offset, we proposed C-DNN receiver based on data driven deep learning. Besides, to understand its performance, a comprehensive convergence analysis framework for FML with random schedule in wireless is developed. This work represents the first attempt to combine FML and DL in physical layer. For future work, we will consider the framework of the current work to sea trial. As another interesting direction, the proposed design only for OoT device can be extended to the IoUT scenario by
