# Enabling Deep Learning-based Physical-layer Secret Key Generation for FDD-OFDM Systems in Multi-Environments

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Abstract-Deep learning-based physical-layer secret key generation (PKG) has been used to overcome the imperfect uplink/downlink channel reciprocity in frequency division duplexing (FDD) orthogonal frequency division multiplexing (OFDM) systems. However, existing efforts have focused on key generation for users in a specific environment where the training samples and test samples obey the same distribution, which is unrealistic for real world applications. This paper formulates the PKG problem in multiple environments as a learning-based problem by learning the knowledge such as data and models from known environments to generate keys quickly and efficiently in multiple new environments. Specifically, we propose deep transfer learning (DTL) and meta-learning-based channel feature mapping algorithms for key generation. The two algorithms use different training methods to pre-train the model in the known environments, and then quickly adapt and deploy the model to new environments. Simulation results show that compared with the methods without adaptation, the DTL and meta-learning algorithms both can improve the performance of generated keys. In addition, the complexity analysis shows that the metalearning algorithm can achieve better performance than the DTL algorithm with less time, lower CPU and GPU resources.

*Index Terms*—Physical-layer security, secret key generation, frequency division duplexing, deep learning, transfer learning, meta-learning.

## I. INTRODUCTION

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Xianbin Wang is with the Department of Electrical and Computer Engineering, Western University, London, ON N6A 5B9, Canada (e-mail: xianbin.wang@uwo.ca). **D** UE to the broadcast nature of radio signal propagation, wireless networks are vulnerable to various attacks such as eavesdropping, counterfeiting, and tampering [1]. Traditional security mechanisms, particularly public key cryptography, are facing many problems such as difficulty in key distribution and poor scalability in large-scale networks with limited resources, which make it difficult to meet the security needs of future wireless communications [2], [3]. In recent years, *physical-layer secret key generation (PKG)* has gradually become a research hotspot of wireless security. From the perspective of information theory, PKG provides a new security mechanism, which greatly simplifies the distribution and management of keys [2]–[4].

PKG techniques realize real-time sharing and coordination of random security keys by exploiting the channel reciprocity of uplink and downlink features [2], [5]. The channel features, such as received signal strength (RSS), channel state information (CSI), channel gain, etc., are widely used for PKG [2]. In time division duplexing (TDD) systems, the uplink and downlink transmissions operate in the same carrier frequency band, and the channel features observed by both communication parties is highly reciprocal. However, in frequency division duplexing (FDD) systems, due to the uplink and downlink works on different carrier frequency bands, most of reciprocal channel parameters may be completely different between the uplink and the downlink, thus can not be directly used for key generation. Therefore, the majority of the existing studies focus on PKG in TDD systems [3], [6], and the research on PKG in FDD systems is limited. Sine FDD mode is the primary duplexing strategy for cellular communications [7], [8], it has profound research value and practical significance to study the PKG method in FDD systems.

#### A. Related Work

In recent years, there has been some studied on the PKG in FDD systems, which can be categorized into model-based and deep learning-based approaches.

Model-based methods aim to extract frequency-independent channel features or construct a reciprocal feature. Specifically, the work in [9], [10] proposed to extract the frequencyindependent channel parameters (such as arriving angle, delay and covariance matrix eigenvalues). However, these methods have many limitations, such as large bandwidth or special configuration of the antenna array [11]. Besides, a reciprocal channel construction framework named SAR is proposed in [5], but it is difficult to separate the channel paths accurately in the complex multi-path environment. Some works proposed to construct reciprocal channels by additional reverse channel training and feedback, called the loopback-based methods [12]–[15]. However, these methods not only increase the complexity of channel detection but also has security risks [16].

Due to its excellent performance, deep learning has also been introduced into the field of PKG in TDD and FDD systems [17]-[22]. In FDD systems, deep learning-based approaches have been used to construct reciprocal feature for key generation with the help of the feature mapping function between uplink and downlink transmissions assisted deep learning. Since the uplink and downlink channels pass through the same propagation path and scattering clusters, it is experimentally shown in [11] that there is a transformation function that can map the channel to the underlying path. Furthermore, prior works have shown that it is possible to infer downlink channels from uplink channels [23]-[25]. These works inspire efforts for applying deep learning for FDDbased key generation by constructing reciprocal features via deep learning. In [22], it is proved that in a given environment, when the channel mapping function of possible user locations to antennas is bijective, there exists a feature mapping function that can map one frequency band features to another frequency band features, and the channel feature mapping function can be obtained by a simple deep learning model. This conclusion provides a theoretical basis for introducing deep learning into key generation for FDD-based OFDM systems [19]-[22]. A boundary equilibrium generative adversarial network (BEGAN) and an encoder-decoder based convolutional neural network were proposed to predict downlink CSI and key generation [20], [21]. Furthermore, a complex-valued neural network (CVNet) was proposed to improve the performance of generated keys [19].

Compared with conventional model-based PKG techniques (e.g. [5], [9], [10], [12]–[15]), deep learning-based key generation methods are not limited with channel models and can achieve excellent performance. However, existing deep learning-based approaches only consider a given wireless environment and the deep learning model only can learn the feature mapping function in this specific environment. In practice, users may experience different new environments. Existing machine learning techniques require data collection and model training for each communication environment, leading to a large amount of training resources and training data, which is difficult to be used in real-world applications. Therefore, how to quickly adapt the deep learning model to new environments for feature mapping and key generation with low cost is a new challenge that needs to be addressed.

Deep transfer learning (DTL) [26], [27] and meta-learning [28]–[30] are effective ways that can solve the problem of inapplicability of the deep learning model caused by environmental changes. DTL uses the knowledge of source tasks to improve the performance of target tasks and is a promising machine learning technology that can solve similar tasks with limited labelled data. Meta-learning aims to improve the ability

to adapt or generalize to new tasks and environments that have never been encountered during the training stage by training in multiple learning tasks. They have been widely used in many areas to solve the problem of performance degradation of deep learning models due to environmental changes, e.g., channel feedback [31], beam prediction [32], downlink channel prediction [33], resource allocation [34], etc.

## B. Main Contributions

Inspired by these works, this paper introduces DTL and meta-learning into the field of PKG to achieve fast and efficient key generation of FDD-OFDM systems in mult-environments. First, we formulate the key generation in multi-environments as a learning-based problem, i.e., using the knowledge from known (source) environments to learn the deep learning model in the new (target) environments more efficiently. Then we propose DTL-based and meta-learning-based feature mapping algorithms to achieve key generation for FDD systems in multi-environments. To the best knowledge of the authors, no work has ever focused on deep learning-based key generation for FDD-OFDM systems in multi-environments. Our major contributions are summarized as follows.

- We propose a DTL-based feature mapping algorithm for key generation in FDD-OFDM systems. This algorithm pre-trains the model using the datasets from source environments, and then fine-tunes the pre-trained model using a small number of samples from the new environment, after which this fine-tuned model can be used for key generation in the new environment.
- To better leverage knowledge from known environments, we propose a meta-learning-based feature mapping algorithm for key generation in FDD-OFDM systems. This algorithm performs intra-task and cross-task learning in multiple tasks (each task represents key generation in a given environment) to obtain the best model initialization parameters, allowing for fast model adaptation in new environments.
- We verify the proposed algorithms in an indoor corridor scenario using a ray tracing simulator Wireless InSite. The results show the DTL and meta-learning algorithms both can improve performance of generated keys in new environments. In addition, complexity analysis shows that the meta-learning algorithm can achieve better performance with less time, lower CPU and GPU resources, compared with the DTL algorithm.

The rest of this paper is structured as follows. The deep learning-based key generation for FDD-OFDM systems is introduced in Section II. In Section III, we formulate the PKG in multi-environments as a learning-based problem and give an overview. The DTL-based feature mapping for key generation is presented in Section IV. The meta-learning-based feature mapping for key generation is presented in Section V. The simulation results for evaluating the performance of the generated keys and the complexity analysis are provided in Section VI, which is followed by conclusions in Section VII.

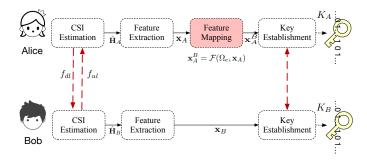


Fig. 1: Deep learning-based key generation for FDD-OFDM systems.

# II. PRELIMINARY: DEEP LEARNING-POWERED FDD-OFDM KEY GENERATION

#### A. Overview

We consider a FDD-OFDM system, where the BS (Alice) and user (Bob) are equipped with a single antenna and operate at the FDD mode. Alice and Bob simultaneously transmit signals on different carrier frequencies,  $f_{dl}$  and  $f_{ul}$ , respectively. The channel impulse response (CIR) can be defined as follows:

$$h(f,\tau) = \sum_{n=0}^{N-1} \alpha_n e^{-j2\pi f \tau_n + j\phi_n} \delta(\tau - \tau_n), \qquad (1)$$

where f is the carrier frequency, N is the total number of paths,  $\alpha_n$  is the magnitude of the  $n^{th}$  path, which is influenced by the distance  $d_n$  between Alice and Bob, the scattering environment and the carrier frequency f.  $\tau_n = \frac{d_n}{c}$  is the delay of the  $n^{th}$  path, where c is the speed of light.  $\phi_n$  is the phase shift of the  $n^{th}$  path, which is determined by the scatterer material and wave incident/impinging angles at the scatterer.

In FDD-OFDM systems, the channel frequency response (CFR) of the  $l^{th}$  sub-carrier can be expressed as

$$H(f,l) = \sum_{n=0}^{N-1} \alpha_n e^{-j2\pi f \tau_n + j\phi_n} e^{-j2\pi nl/L},$$
 (2)

where L is the number of subcarriers. The CFR of frequency f can be defined as the  $1 \times L$  channel vector  $\mathbf{H}(f) = \{H(f,0), ..., H(f,L-1)\}$ . As shown in (2), the amplitude and phase of wireless channel  $\mathbf{H}(f)$  are influenced by their frequencies. Therefore, extracting reciprocal channel features for key generation in FDD-OFDM systems is challenging.

Deep learning has been introduced for PKG in FDD-OFDM systems recently [19]–[22]. This type of method uses deep learning technology to map the uplink features to the downlink features, so that both parties can obtain the downlink features at the same time. As shown in Fig. 1, the deep learning-based key generation contains the following four steps.

## B. CSI Estimation

Alice and Bob simultaneously send OFDM pilot signals to each other at carrier frequencies  $f_{dl}$  and  $f_{ul}$ , and then independently estimate the channel CFR based on the received pilot signals, expressed as

$$\begin{cases} \hat{H}_A(f_{ul}, l) = H(f_{ul}, l) + E_1(f_{ul}, l) \\ \hat{H}_B(f_{dl}, l) = H(f_{dl}, l) + E_2(f_{dl}, l) \end{cases},$$
(3)

where  $E_1(f_{ul}, l)$  and  $E_2(f_{dl}, l)$  represent the channel estimation error, which can be modeled as additive white Gaussian noise (AWGN) with mean 0 and variance  $\sigma_E^2$ . After channel estimation, Alice and Bob get estimated CFRs  $\hat{\mathbf{H}}_A$  and  $\hat{\mathbf{H}}_B$ , respectively.

#### C. Feature Extraction

Alice and Bob perform feature extraction to extract realvalued channel features  $\mathbf{x}_A$  and  $\mathbf{x}_B$  that are suitable for training deep learning model and key generation. The real and imaginary parts are separated from **H** as

$$\mathbf{x}' \leftarrow (\mathfrak{R}(\mathbf{H}), \mathfrak{T}(\mathbf{H})),$$
 (4)

where  $\Re(\cdot)$  and  $\mathfrak{T}(\cdot)$  denote the real and imaginary parts of a matrix, vectors or scales, respectively.

The dataset is then normalized so that the range of the samples is between 0 and 1. The minimum and maximum values of the vectors in each dimension of the training dataset are saved and used for min-max normalization, i.e.,

$$\mathbf{x} = \frac{\mathbf{x}' - \min(\mathbf{x}'_{\text{train}})}{\max(\mathbf{x}'_{\text{train}}) - \min(\mathbf{x}'_{\text{train}})}, \quad \mathbf{x} \in [0, 1]^{n^d}, \qquad (5)$$

where  $\mathbf{x}$  is the normalized value of  $n^d$  dimensions. After feature extraction, Alice and bob get suitable channel features  $\mathbf{x}_A$  and  $\mathbf{x}_B$ , respectively.

#### D. Feature Mapping (only Alice)

Based on [22], there is a feature mapping function  $\mathcal{F}$  in each given environment. Alice can use  $\mathcal{F}$  to predict the estimated downlink features  $\mathbf{x}_{A}^{B}$  from  $\mathbf{x}_{A}$ , which can be expressed as

$$\mathbf{x}_A^B = \mathcal{F}(\mathbf{\Omega}, \mathbf{x}_A),\tag{6}$$

where  $\Omega$  is the parameters for feature mapping, which can be obtained by deep learning techniques. Through this step, Alice and Bob are considered to have obtained highly similar features  $\mathbf{x}_A^B$  and  $\mathbf{x}_B$ , respectively. How to get the optimal value of parameters to minimize the gap between  $\mathbf{x}_A^B$  and  $\mathbf{x}_B$  is essential to generating highly similar features.

#### E. Key Establishment

Alice and Bob use obtained features to generate keys, including quantization, information reconciliation and privacy amplification [35]. We use a Gaussian distribution-based quantization method with guard-band proposed in [22] to get the initial keys  $\mathbf{Q}_A$  and  $\mathbf{Q}_B$ . Denote the probability of the channel features  $\mathbf{x}$  as a definite Gaussian distribution  $\mathcal{N}_Q = \mathcal{N}(\mu, \sigma^2)$ , where  $\mu$  is the mean of vector  $\mathbf{x}$ ,  $\sigma$  is the standard deviation of vector  $\mathbf{x}$ , and  $F^{-1}$  as the inverse of the cumulative distribution function (CDF) of  $\mathcal{N}_Q$ . The values between 0 and  $F^{-1}(0.5-\varepsilon)$ are quantized as 0, and the values between  $F^{-1}(0.5+\varepsilon)$ 

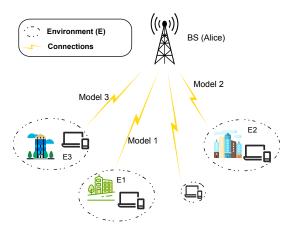


Fig. 2: Deep learning-based PKG problem in multienvironments.

and 1 are quantized as 1. The  $\varepsilon \in (0, 0.5)$  is defined as the quantization factor, and the values between  $F^{-1}(0.5 - \varepsilon)$  and  $F^{-1}(0.5 + \varepsilon)$  are discarded.

Information reconciliation and privacy amplification methods adopted by most key generation methods are mostly common [36], [37]. In addition, the research purpose of this paper is to improve the channel reciprocity in the FDD system, thus this paper only compares the performance of the initial keys after quantization and does not carry out the steps of information reconciliation and privacy amplification.

## **III. SYSTEM OVERVIEW**

Among the four steps introduced in Section II, feature mapping is the crucial step for key generation between Alice and Bob. Therefore, this paper focuses on how to use deep learning techniques to quickly and efficiently obtain feature mapping functions  $\mathcal{F}$  in multiple environments.

#### A. Problem Statement

It is clear that the good performance of generated keys depends on the performance of the deep learning model. The existing works have verified the good fitting and generalization performance of the deep learning model to obtain the feature mapping function  $\mathcal{F}$  in a certain environment [19]–[22]. However, when the environment changes, the parameters of  $\mathcal{F}$  are also affected by the environment, and the training samples and the actual samples of the deep learning model no longer obey a uniform distribution, which will lead to poor performance of the parameters in the new environment and even invalidate the effect of feature mapping.

As shown in Fig. 2, suppose a user is in the environment(E)1, a deep learning model 1 can be trained to get the parameters  $\Omega$  for feature mapping and key generation between the BS and the user in this given environment. However, when the user moves to other environments, such as E2 and E3, the training samples of model 1 and actual samples in the new environment no longer obey the same distribution, resulting in the performance of pre-trained deep learning model being degraded or even invalid. A simple way to solve this problem is to re-collect the data and re-train the model for each new environment. However, training a model requires a lot of training data and training resources, which is unacceptable for practical applications. Therefore, this paper aims to address this problem and formulates it as a learning-based problem to more efficiently learn feature mapping functions in new environments using known knowledge in the source environment.

# B. Learning-based Problem for PKG

Assume that there are data in E wireless scenarios, and the uplink and downlink channel characteristics in the  $e^{th}$ environment are defined as  $\mathbf{x}_A^e$  and  $\mathbf{x}_B^e$  respectively. The "domain" and "task" in the  $e^{th}$  environment are defined as following:

**Definition** 1 (Domain): The domain  $\mathcal{D}(e)$  is composed of the feture space  $\mathcal{X}^e$  and the marginal probability distribution  $P(\mathbf{x}_A^e)$ , i.e.,  $\mathcal{D}(e) = \{\mathcal{X}^e, P(\mathbf{x}_A^e)\}$ . And the symbol  $\mathcal{X}^e$ denotes an instance set, which is defined as all possible uplink channel features  $\mathbf{x}_A^e$ , i.e.,  $\mathbf{x}_A^e \in \mathcal{X}^e$ .

**Definition** 2 (Task): The task  $\mathcal{T}(e)$  is composed of the label space  $\mathcal{Y}^e$  and a decision function  $f^e$ , i.e.,  $\mathcal{T}(e) = \{\mathcal{Y}^e, f^e\}$ . And the symbol  $\mathcal{Y}^e$  denotes an instance set, which is defined as all possible uplink channel features  $\mathbf{x}_B^e$ , i.e.,  $\mathbf{x}_B^e \in \mathcal{Y}^e$ .

In a certain environment (domain  $\mathcal{D}_{SE}$  and task  $\mathcal{T}_{SE}$ ), the decision function  $f^e$  can be obtained by model training. According to [22], the decision function  $f^e$  can be considered as the feature mapping function  $\mathcal{F}^e$  in the  $e^{th}$  environment. Trained networks can act as the feature mapping function to achieve the feature mapping for key generation. However, when in a new environment (domain  $\mathcal{D}_{TE}$  and task  $\mathcal{T}_{TE}$ ), the feature mapping function  $\mathcal{F}$  will change, and the performance of the trained model will be greatly reduced and cannot be used continuously.

We formulate this problem as a learning-based problem, i.e., learning from the known environments enables fast key generation in multiple new environments using a small amount of data and limited resources, formally defined as follows. Given the number of source tasks  $E_S$ , the source domains  $\{\mathcal{D}_{SE}(e)\}_{e=1}^{E_S}$ , the source tasks  $\{\mathcal{T}_{SE}(e)\}_{e=1}^{E_T}$ , the number of source tasks  $\{\mathcal{T}_{SE}(e)\}_{e=1}^{E_T}$ , the number of source tasks  $\{\mathcal{T}_{TE}(e)\}_{e=1}^{E_T}$ , the number of source tasks  $\{\mathcal{T}_{TE}(e)\}_{e=1}^{E_T}$ , the target domains  $\{\mathcal{D}_{TE}(e)\}_{e=1}^{E_T}$  and the target tasks  $\{\mathcal{T}_{TE}(e)\}_{e=1}^{E_T}$  and the target tasks  $\{\mathcal{T}_{TE}(e)\}_{e=1}^{E_T}$  and  $\{\mathcal{T}_{SE}(e)\}_{e=1}^{E_S}$  to learn new tasks  $\{\mathcal{T}_{TE}(e)\}_{e=1}^{E_T}$  with a small amount of data and limited resource, where  $\{\mathcal{T}_{TE}(e)\}_{e=1}^{E_T} \neq \{\mathcal{T}_{SE}(e)\}_{e=1}^{E_S}$  and  $\{\mathcal{D}_{TE}(e)\}_{e=1}^{E_T} \neq \{\mathcal{D}_{SE}(e)\}_{e=1}^{E_S}$ .

#### C. Algorithm Overview

This paper proposes DTL-based and meta-learning-based feature mapping algorithms for key generation in multienvironments, elaborated in Section IV and Section V, respectively. DTL and meta-learning aim to learn from source tasks to increase the generalization ability of the model under multi-task, and thus are two promising techniques for solving learning-based problems. Unlike learning functions  $\mathcal{F}$  directly training the deep learning model in a given environment, these

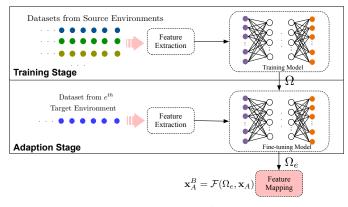


Fig. 3: The proposed learning-based feature mapping scheme.

two algorithms include the training and adaptation stages, as shown in Fig. 3.

- Training stage: The two algorithms use datasets from known environments to train the model. DTL and meta-learning use different training methods, called pre-training and meta-training, respectively.
- Adaptation stage: The two algorithms fine-tune the model using the datasets from the new environments, and then the fine-tuned model can be used for feature mapping and key generation.

This paper considers a simple FNN as the basic network structure to learn the feature mapping function  $\mathcal{F}$  in the proposed algorithms, as shown in Fig. 3. The input of the network is the uplink channel feature vector  $\mathbf{x}_A$  obtained by Alice, and the output of the network is the result of the cascade of  $\mathbf{x}_A$  through nonlinear transformation. The network is used to map the features of the uplink and downlink, so the output of the network is considered to be the estimated vector  $\mathbf{x}_A^B$ of the downlink channel feature vector  $\mathbf{x}_B$ , which also can be expressed as (6), i.e.,  $\mathbf{x}_A^B = \mathcal{F}(\mathbf{\Omega}, \mathbf{x}_A)$ , where  $\mathbf{\Omega}$  is all parameters in this network to be trained for feature mapping. The FNN consists of M layers, including one input layer, M - 2 hidden layers and one output layer. The output  $f_m(\mathbf{x})$ of the  $m^{th}$  layer is a nonlinear transformation of the output of  $m - 1^{th}$  layer, which can be written as:

$$f_m(\mathbf{x}) = F_{A,m}(\mathbf{W}_m \mathbf{x} + \mathbf{b}_m), 2 \le m \le M, \tag{7}$$

where  $F_{A,m}$ ,  $\mathbf{W}_m$  and  $\mathbf{b}_m$  are the activation function of  $m^{th}$  layer, weight vector between  $(m-1)^{th}$  and  $m^{th}$  layers and bias vector of  $m^{th}$  layer, respectively. The rectified linear unit (ReLU) function commonly used in regression problems is selected as the activation function  $F_{A,m}$  of the hidden layers, and the sigmoid function is selected as the activation function  $F_{A,m}$  of the output layer.

The purpose of the network is to learn the band feature mapping, so we could train network to minimize the difference between network output  $\mathbf{x}_{A}^{B}$  and  $\mathbf{x}_{B}$ . Obviously, a vector regression problem is considered in this paper, we consider to use the mean squared error (MSE) as the loss function of the neural network. The loss function is defined as:

$$\mathcal{L}_{\mathbb{D}}(\mathbf{\Omega}) = \frac{1}{N_{batch}} \sum_{i=0}^{N_{batch}-1} \|\mathbf{x}_{A}^{B}(i) - \mathbf{x}_{B}(i)\|_{2}^{2}, \qquad (8)$$

where  $\mathbb{D} = \{(\mathbf{x}_A, \mathbf{x}_B)\}_{i=0}^{N_{batch}-1}$  is a batch-sized training dataset,  $N_{batch}$  is the batch size.

## IV. DTL-BASED FEATURE MAPPING

Based on the learning-based problem formulated in Section III-B, this section proposes a DTL-based feature mapping to achieve key generation in new environments for FDD-OFDM systems. DTL transfers knowledge from the source environment to the target environment, so that the network in target environment can achieves a better learning effect. In general, datasets in the source environments are abundant, while datasets in the target domains are small, so most DTL algorithms use datasets from source tasks to pre-train the model and then fine-tunes it under a new task [27]. Like these works, in our proposed DTL-based feature mapping, we use the datasets from the source environments to pre-trained a model and then use a small number of samples to fine-tune the pre-trained model to obtain a model with good performance in the new environment.

## A. Definition of Dataset

Assume that the source datasets  $\{\mathbb{D}_S(e)\}_{e=1}^{E_S}$  is collected from  $E_S$  source environments, where the dataset  $\mathbb{D}_S(e) = \{(\mathbf{x}_A^{(n)}(e), \mathbf{x}_B^{(n)}(e))\}_{n=1}^{N_S}$  includes  $N_S$  samples in the  $e^{th}$  environment. Furthermore, it is necessary to collect dataset in multiple target environments to evaluate the performance of the algorithm. Assume that the target datasets  $\{\mathbb{D}_T(e)\}_{e=1}^{E_T}$ from  $E_T$  target environments, where the dataset in the  $e^{th}$ environment  $\mathbb{D}_T(e) = \{(\mathbf{x}_A^{(n)}(e), \mathbf{x}_B^{(n)}(e))\}_{n=1}^{N_T}$  includes  $N_T$ data samples.

In DTL algorithm, the datasets  $\{\mathbb{D}_{S}(e)\}_{e=1}^{E_{S}}$  from all source environments are considered as a whole as the training dataset. The dataset  $\mathbb{D}_{T}(e)$  in the target  $e^{th}$  environment divides into adaption dataset  $\mathbb{D}_{Ad}(e) = \{(\mathbf{H}_{A}^{(n)}(e), \mathbf{H}_{B}^{(n)}(e))\}_{n=1}^{N_{Ad}}$  and testing dataset  $\mathbb{D}_{Te}(e) = \{(\mathbf{H}_{A}^{(n)}(e), \mathbf{H}_{B}^{(n)}(e))\}_{n=1}^{N_{Te}}$ , where  $N_{Ad} + N_{Te} = N_{T}$ .

# B. Training (Pre-training) Stage

The pre-training stage trains the model using dataset  $\{\mathbb{D}_{S}(e)\}_{e=1}^{E_{S}}$  from the source environments to minimize the loss function  $\mathcal{L}_{\mathbb{D}_{Tr}}(\mathbf{\Omega})$ .

In each batch,  $N_{batch}$  samples are randomly selected from  $\mathbb{D}_{Tr}$  to construct a batch training dataset and then ADAM [38] optimizer is used to optimize the parameters of the model. When the performance of the model tends to be constant or the number of iterations reaches the upper limit, the parameters  $\Omega$  of the pre-trained model is obtained.

# C. Adaption Stage

For the  $e^{th}$  target environment, the parameters  $\Omega$  of the pre-trained model are used to initialize the network model parameter  $\Omega_e$  in the target environment. Then the parameter  $\Omega_e$  is optimized using the adaption dataset  $\mathbb{D}_{Ad}(e)$  in the target environment to minimize  $\mathcal{L}_{\mathbb{D}_{Ad}}(\Omega)$ . When the performance of the model tends to be constant or the number of iterations

reaches the upper limit, the parameters  $\Omega_e$  of the model in a new environment is obtained.

After repeating the adaption stage in  $E_T$  target environments, we can obtain the parameter  $\{\Omega_e\}_{e=1}^{E_T}$  in the target environments. After this, the network parameter  $\Omega_e$  is fixed, and the network can be directly used in the feature mapping step in the target environment. Two users, Alice and Bob, follow the steps in Section II for key generation, where Alice uses the deep learning model with parameter  $\Omega_e$  for feature mapping.

We also calculate the average values of Normalized Mean Square Error (NMSE), Key Error Rate (KER) and Key Generation Ratio (KGR) using the testing dataset  $\{\mathbb{D}_{Te}(e)\}_{e=1}^{E_T}$  in target environments to evaluate the performance of the proposed algorithm.

#### V. META-LEARNING-BASED FEATURE MAPPING

To better leverage knowledge from the source environments, this section proposes a meta-learning-based feature mapping. Most existing meta-learning algorithms are problem-specific. In order to eliminate the limitation of the model architecture on the application of meta-learning, a model-agnostic metalearning (MAML) algorithm was proposed in [39]. The goal of the algorithm is to achieve adaptation by alternately learning the parameter initialization of the model between the intra-task process and the cross-task process [28]. Different from the DTL algorithm, the meta-learning algorithm requires training the model from multiple source tasks and aims to learn the best model initialization parameters through intra-task and crosstask updates. More importantly, unlike the DTL algorithm that emphasizes performance on current tasks, the meta-learning algorithm focuses more on performance of new tasks.

## A. Definition of Dataset

In meta-learning, the training dataset is the datasets from the source environments  $\{\mathbb{D}_{S}(e)\}_{e=1}^{E_{S}}$ , and the training dataset in each task is the dataset in each source environment. The training dataset  $\mathbb{D}_{S}(e)$  in  $e^{th}$  task needs to be divided into support dataset  $\mathbb{D}_{Su}(e)$  and query dataset  $\mathbb{D}_{Qu}(e)$ , and must satisfy  $\mathbb{D}_{Su}(e) \cap \mathbb{D}_{Qu}(e) = \emptyset$ . The dataset  $\mathbb{D}_{T}(e)$ in the target environment is to be divided into adaptation dataset  $\mathbb{D}_{Ad}(e) = \{(\mathbf{x}_{A}^{(n)}(e), \mathbf{x}_{B}^{(n)}(e))\}_{n=1}^{N_{Ad}}$  and testing dataset  $\mathbb{D}_{Te}(e) = \{(\mathbf{x}_{A}^{(n)}(e), \mathbf{x}_{B}^{(n)}(e))\}_{n=1}^{N_{Te}}$ , where  $N_{Ad} + N_{Te} = N_{T}$ .

## B. Training (Meta-training) Stage

During the meta-training phase, the goal of the metalearning algorithm is to learn a network initialization that can effectively adapt to new tasks. The underlying network architecture used here is the same as used in DTL. First, the parameters  $\Omega$  are randomly initialized, and then updated through two iterative processes, namely intra-task update and cross-task update. The network parameters of each source task are optimized within the intra-task update, and the global neural network is optimized within the cross-task update. 1) Intra-task Update: A batch of  $E_{batch}$  tasks is randomly selected from  $E_S$  environments in a batch. The goal of each task is to optimize its own neural network parameters on its support dataset  $\mathbb{D}_{Su}(e)$ . The objective of each task is achieved by minimizing the loss function based on supervised learning. The objective function of each task can be expressed as:

$$\mathbf{\Omega}_{S,e} = \arg\min_{\mathbf{\Omega}_{S,e}} \mathcal{L}_{\mathbb{D}_{Su}(e)} \left( \mathbf{\Omega}_{S,e} \right), \quad e = 1, \dots, E_B, \qquad (9)$$

where  $\Omega_{S,e}$  is the network parameter of the  $e^{th}$  task in the source task set. In each task,  $\Omega_{S,e}$  is initialized to  $\Omega$ , and is then updated with  $G_{Tr}$  times of gradient descent, i.e.,

$$\mathbf{\Omega}_{S,e} \leftarrow \mathbf{\Omega}_{S,e} - \alpha \nabla_{\mathbf{\Omega}_{S,e}} \operatorname{Loss}_{\mathbb{D}_{Su}(e)} \left( \mathbf{\Omega}_{S,e} \right), \qquad (10)$$

where  $\alpha$  is the learning rate between tasks. The  $\Omega_{S,e}$  also can be updated by ADAM optimizer [38].

The intra-task update only performs once. In the original MAML algorithm [39], intra-task updates were made also only once, but some literature proposed to increase the times of intra-task update to improve the performance [32]. This paper analyzes the impact of task update times on performance in Section VI-D. The results show that the increase of  $G_{tr}$  has no obvious effect on performance, but will increase the training cost, thus we set  $G_{tr}$  to 1.

2) Cross-task Update: The global network parameters  $\Omega$  are optimized based on the sum of the loss functions of all tasks in one batch. After intra-task update, the loss function for all tasks in the batch can be estimated based on the related tasks and their query datasets  $\{\mathbb{D}_{Qu}(e)\}_{e=1}^{E_{batch}}$ . These loss functions can be added together to form the loss function used to optimize the global network parameters, i.e.

$$\mathcal{L}_{total}(\mathbf{\Omega}) = \sum_{e=1}^{E_{batch}} \mathcal{L}_{\mathbb{D}_{Qu}(e)}(\mathbf{\Omega}_{S,e}).$$
(11)

This loss function can also be minimized by optimizing  $\Omega$  by gradient descent or ADAM algorithm (learning rate  $\gamma$ ).

After the cross-task update is over, assign the updated  $\Omega$  to  $\Omega_{S,e}$ , and then repeat the intra-task update and cross-task update until  $\mathcal{L}_{total}(\Omega)$  does not converge. At this time, the parameter initialization of network learning is obtained, so that only a small number of samples can be adapted to the new environment.

It is clear that the training methods of the DTL algorithm and the meta-learning algorithm are almost completely different. In the DTL algorithm, the DTL algorithm minimizes the loss of the current model (only one) on all tasks, so the DTL algorithm hopes to find an initialization parameter that performs better on all current tasks. The Meta-learning algorithm first uses the support dataset to minimize the loss function in each task, then uses the query dataset to minimize the loss sum of all tasks, and finally updates all model parameters with the model parameters obtained by minimizing the sum of loss functions of all tasks, which means that the performance of the model obtained after training to convergence under each task using the final initialization parameters obtained by meta-learning should still be as good as possible. Therefore, compared to the DTL algorithm, meta-learning algorithm makes better use of knowledge in multiple environments, and the resulting model

TABLE I: Default Parameters of Proposed Algorithms

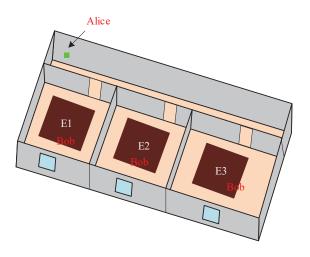


Fig. 4: A overview of the ray-tracing indoor scenario.

initialization parameters have better generalization, which is also proved in the results in Section VI.

# C. Adaption Stage

This step is the same as the Section IV-C. We also use the fixed parameters  $\{\Omega_e\}_{e=1}^{E_T}$  for feature mapping and key generation to calculate evaluation metrics that can evaluate the performance of the proposed algorithm using the testing datasets  $\{\mathbb{D}_{Te}(e)\}_{e=1}^{E_T}$  in the target environments.

# VI. SIMULATION EVALUATION

In this section, we will first present the data generation and simulation setup. Then, we give the benchmarks, metrics and compare the performance of all algorithms.

#### A. Simulation Setup and Dataset Generation

In the simulation, we consider an indoor corridor scenario, which is constructed based on the accurate 3D ray tracing simulator Wireless InSite [40]. The overview of the ray-tracing indoor scenario is illustrated in Fig. 4. The antenna of the base station (Alice) is located in a small green box on the ceiling of the indoor corridor. The three maroon rectangles represent the possible positions of the user (Bob), and each room represents an environment. As Alice is in the corridor and Bob is located in the room, all channels are Non-line-of-sight (NLOS). The uplink and downlink frequencies are 2.4 GHz and 2.5 GHz, respectively. The number of OFDM subcarriers is 64 and the bandwidth is 20 MHz.

Assuming that E1 is the source task scenario, a total of 40,000 locations are collected, while E2 and E3 are target task environments, and 5,000 locations are collected in each environment. Due to different environments in different rooms, the environment information learned by the model is different, so the model trained in E1 is not suitable for new environments (E2 and E3). In response to this problem, this paper proposes two algorithms to use the collected data in E1 to obtain some

	Parameter	Value		
For All Algorithms	Number of neurons in hidden	(512,1024,1024,512)		
	layers			
	Batch size	128		
	Optimization	ADAM [38]		
	Exponential decay rates for	(0.9,0.999)		
	ADAM: $(\rho_1, \rho_2)$			
For Meta-learning	Inner-task and across-task	(1e-3,1e-3)		
	learning rate: $(\alpha, \beta)$			
	The number of gradient update	1		
	for inner-task training			
	the number of the gradient	300		
	update in fine-tuning and			
	meta-adaption stages			
	The number of source task in	400		
	meta-learning			
	The number of samples in	100		
	each source task			

prior knowledge, so that pre-trained model can quickly adapt to new environments (E2 and E3).

A workstation with an Nvidia GeForce GTX 1660Ti GPU and an Intel Core I7-9700 CPU was used. This paper used Tensorflow 2.1 as the underlying framework of deep learning to build the network. The network parameters and some parameters in the training stage are shown in Table I.

# B. Benchmarks

For comparison, we introduce two benchmarks, namely the direct algorithm and the joint dataset algorithm. All algorithms are explained below.

- (1) Direct algorithm directly uses the model trained in E1 and tests the performance in E2 and E3.
- (2) Joint dataset algorithm combines all the data in E1 and part of the data in E2 or E3 to form a joint training dataset and then uses the model trained by the joint training dataset to test the performance in E2 and E3, respectively [32].
- (3) DTL algorithm uses the proposed DTL-based feature mapping in Section IV for key generation to test the performances.
- (4) Meta-learning algorithm uses the proposed metalearning-based feature mapping in Section V for key generation to test the performances.

For fair comparison, some default training parameters adopted in all algorithms are consistent. Furthermore, the datasets used for training and adaptation in transfer learning and meta-learning algorithms are of the same size. The 40,000 total training dataset used in the DTL algorithm is divided into 400 datasets with a sample size of 100 in the metalearning algorithm to represent the data under multiple tasks. The training dataset used by the joint dataset algorithm is the combination of the training dataset and the adaptation dataset in the transfer learning and meta-learning algorithms.

# C. Evaluation Metrics

We use the following metrics for performance evaluation.

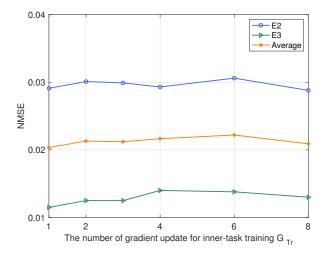


Fig. 5: The NMSE performance comparison for different numbers of iterations  $G_{Tr}$ .

• *NMSE* is used to evaluate the predictive accuracy of the network, which is defined as

$$\text{NMSE} = E\left[\frac{\parallel \mathbf{x}_A^B - \mathbf{x}_B \parallel_2^2}{\parallel \mathbf{x}_B \parallel_2^2}\right], \quad (12)$$

where  $E[\cdot]$  represents the expectation operation.

- *KER* is defined as the number of error bits divided by the number of total key bits.
- *KGR* is defined as the number of initial key bits divided by the number of subcarriers.
- *Randomness* reveals the distribution of bit streams. The National Institute of Standards and Technology (NIST) statistical test [41] is used for the randomness test for the generated keys.

## D. The Impact of Hyper-parameters in Meta-learning

The selection of the number of iterations  $G_{Tr}$  in the task and the batch size  $E_{batch}$  in the training phase are very important to the meta-learning algorithm. These two parameters are analyzed below.

For some tasks, the increase of  $G_{Tr}$  can greatly improve the performance. For example, the work in [32] sets  $G_{Tr}$  to 3, which improves the downlink channel prediction accuracy in massive MIMO systems. At the same time, as  $G_{Tr}$  increases, more memory and time resources are required for meta-learning training. Therefore, the value of  $G_{Tr}$  should be determined comprehensively by weighing the consumed resources and performance. In this paper,  $G_{Tr}$  is set as  $\{1, 2, 3, 4, 6, 8\}$  for learning, and tests are carried out in the indoor corridor environment respectively. The results are shown in Fig. 5. The results show that with the increase of  $G_{Tr}$ , the performance of the meta-learning algorithm does not improve, but basically stabilizes around a certain range. Therefore, in order to guarantee the minimum resource consumption, the  $G_{Tr}$  is set to 1.

Reasonable selection of the batch size  $E_{batch}$  in the training phase is also very important for the training effect. Since

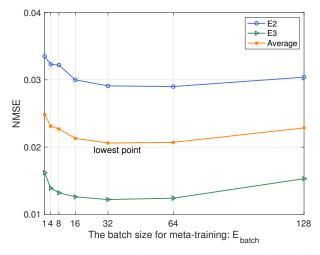


Fig. 6: The NMSE performance comparison for different numbers of the batch size  $E_{batch}$ .

the choice of batch size  $E_{batch}$  has nothing to do with the resource consumption of training, it is only necessary to focus on the training performance under different batch sizes. Fig. 6 compares the NMSE performance under different batch sizes  $E_{batch}$ . The results show that the tested NMSE performance is getting better with the increase of  $E_{batch}$  and reaches optimal when  $E_{batch} = 32$ . Therefore, in order to achieve optimal performance, the  $E_{batch}$  is set to 32.

## E. Performance of Reciprocal Features

Fig. 7 compares the NMSE performance of the four algorithms during adaption stage in E2. Since the direct algorithm has no adaptation phase, it is set as a fixed value for its test results. The results show that the algorithms based on transfer learning and meta-learning are better than the direct and joint dataset algorithms. The NMSE of the joint dataset algorithm increases with the number of iterations  $G_{Ad}$ . This is due to the fact that in the joint dataset, the number of data samples in E2 is much larger than that in E1, so the over-fitting occurs during the training process, and its test performance is still better than that of the direct algorithm. This result shows that it is necessary to add datasets under new scenarios to the test dataset to improve the performance of the model in new scenarios. In addition, the meta-learning algorithm is significantly better than the DTL algorithm.

Fig. 8 compares the influence of the number of adaptation dataset samples  $N_{Ad}$  on the performance of the four algorithms. Since the direct algorithm does not use the adaptation dataset in the new environments, it is assumed that the performance of the algorithm under different sample numbers is consistent. When the number of samples  $N_{Ad} = 1000$ , since the data in the new environment in the joint dataset only accounts for 1000/41000 of the total data, the resulting over fitting reaction makes the performance of the direct algorithm. Overall, the meta-learning and DTL algorithms can achieve better performance than the two benchmarks with a smaller

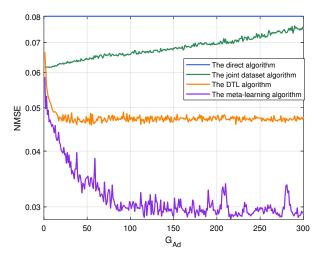


Fig. 7: The NMSE performance during adaption stage.

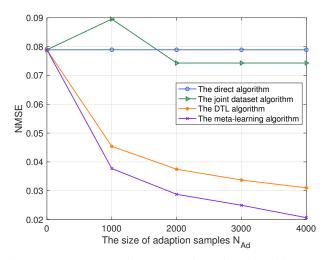


Fig. 8: The NMSE performance of the four algorithm versus the size of adaption samples  $N_{Ad}$ .

number of samples, and the performance of the meta-learning algorithm is better than that of the DTL algorithm.

In this paper, testing datasets at SNRs of {0, 10, 20, 30, 40} dB are generated to analyze the generalization performance of the four algorithms. Fig. 9 compares the performance of the four algorithms tested under different SNRs. The results show that the DTL and meta-learning algorithms can achieve better performance than the direct and joint dataset algorithms. However, at SNRs less than 10 dB, the DTL algorithm achieves worse performance than the direct and joint dataset algorithms. By this time, the meta-learning algorithm can still effectively improve the reciprocity of features obtained by Alice and Bob.

Fig. 10 compares the features obtained by Alice and Bob before and after using the four algorithms at the SNR of 20 dB. As shown in Fig. 10(a), the original channel features obtained by Alice and Bob are influenced by the frequency and are almost completely different. After using the four algorithms proposed in this paper, the channel features obtained between

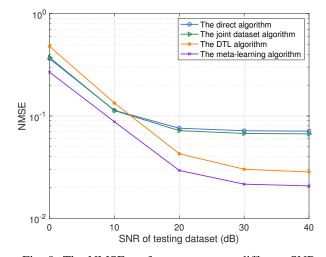


Fig. 9: The NMSE performance versus different SNRs.

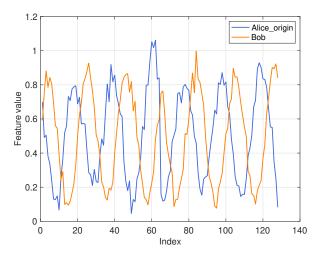
Alice and Bob are shown in Fig. 10(b). The results show that the reciprocity of the features obtained by Alice and Bob is significantly enhanced when using the meta-learning and DTL algorithms, while the reciprocity of the other two benchmark algorithms is still poor. Overall, the meta-learning and DTL algorithms can achieve better fitting performance and generalization under multiple SNRs, with the meta-learning algorithm achieving better performance than the DTL algorithm.

# F. Performance of Initial Keys

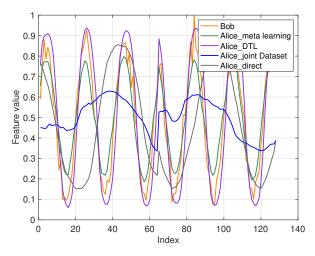
Based on the above analysis of the performance of the feature reciprocity generated by the algorithms, this section analyzes the performance of the initial keys, which includes KER, KGR, and key randomness. The quantization factor  $\varepsilon = 0.1$ , which means that 20% of the features near the isolation zone are removed in the quantization.

Fig. 11(a) and Fig. 11(b) compare the performance of the keys generated by the four algorithms tested under different SNRs. As shown in Fig. 11(a), the KERs of the keys generated by the direct and joint dataset algorithms are as high as 50%. This indicates that the model trained in the source environments is invalid in the new environment. This is due to the fact that in this scenario, each room represents an environment and there is no similar or common channel environment between each environment. The DTL and meta-learning algorithms can significantly reduce the KERs of generating keys in these new environments, where the DTL algorithm generates keys at the SNR of 20 dB with the KER of 30%, which is 38.8% lower compared to the direct algorithm. The KER of the metalearning algorithm is 23.4% when the SNR is 20 dB, which is 52.9% lower than that of the direct algorithm. As shown in Fig. 11(b), the KGRs of the keys generated by the DTL and meta-learning algorithms are also higher than that of the keys generated by the two benchmarks. It is important to emphasize that although the KER is still high, we can reduce it at the expense of KGR by adjusting the quantization factor  $\varepsilon$ .

The NIST test is used to test the randomness of the generated keys. We generate a total of 718 sets of 128-bit keys



(a) The obtained features between Alice and Bob without using the proposed two algorithms.



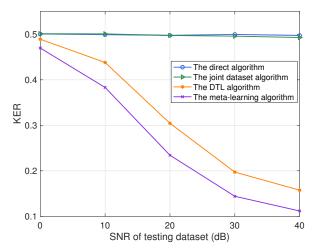
(b) The obtained features between Alice and Bob using the four algorithms.

Fig. 10: Comparison of the features obtained by Alice and Bob before and after using the four algorithms .

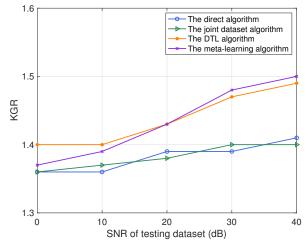
TABLE II: NIST Statistical Test Pass Ratio.

Test	Pass Ratio		
Approximate Entropy	0.9545		
Block Frequency	0.9931		
Cumulative Sums	1		
Discrete Fourier Transform	1		
Frequency	0.9311		
Ranking	0.9105		
Runs	0.9835		
Serial	0.9504		

at the SNR of 20 dB. A serial test is composed of two types of serial tests. When both tests pass, the serial test is considered to be passed. Table II gives the pass rate of the generated keys in several tests that can be tested, i.e., the ratio of the number of key sets that pass the test to the total number of key sets. The results show that the pass rates in several randomness tests are over 90%.



(a) The KER performance versus different testing SNRs.



(b) The KGR performance versus different testing SNRs.

Fig. 11: KER and KGR versus SNR.

## G. Complexity Analysis

As shown in Table III, We analyze the complexity of the four algorithms in terms of the time cost, the CPU average load, and the GPU memory utilization.

In the training stage, since the training process of metalearning includes multiple intra-task and cross-task updates, meta-learning consumes significantly more resources than DTL. However, it was found experimentally that the training process of meta-learning requires only 10 iterations before the loss function stops decreasing, which takes about 110 seconds. The CPU average load and GPU memory utilization consumed are also less in meta-learning than the DTL. Besides, the trained model only requires 25.6 MB of memory to save on the device, so it can be deployed on resource-constrained embedded systems. In the adaption stage, the DTL and metalearning algorithms increase the consumption required for the adaptation stage on top of the direct algorithm and the joint training algorithm, however, the improved performance shows that the consumption is worth it. In our experiments, the DTL

	Training Stage Adaptation Stage			age	Key Generation		
Algorithm	Time Cost	CPU Average Load	GPU Memory Utilization	Time Cost	CPU Average Load	GPU Memory Utilization	Stage Time Cost
The direct algorithm	183s	15.82%	5.1 / 9.9 GB	-	-	-	0.95e-4s
The joint training algorithm	253s	18.22%	5.1 / 9.9 GB	-	-	-	0.95e-4s
The DTL algorithm	183s	15.82%	5.1 / 9.9 GB	37s	10.2%	5.1 / 9.9 GB	0.95e-4s
The meta-learning algorithm	110s	12%	1 / 9.9 GB	38s	10.2%	5.1 / 9.9 GB	0.95e-4s

TABLE III: Complexity analysis of four algorithms

and meta-learning algorithms only take about 37 seconds to complete the adaptation to the new environment, which is an acceptable cost. In the key generation stage, the time cost of each feature mapping is around 0.95e-4 seconds, which can be done in almost real-time.

In summary, it takes about 148 seconds to train and adapt the network in total, and only 0.95e-4 seconds to use the network for feature mapping in the key generation stage. Furthermore, the training stage only needs to be performed once for all environments, and the adaptation stage is performed only once for each environment. Compared with the training consumption of networks used in other areas, the proposed algorithms can achieve fast key generation in FDD-OFDM systems.

# VII. CONCLUSION

In this paper, aiming at the problem of inapplicability of deep learning model caused by environment changes, we formulated this problem as a learning-based problem, i.e., using knowledge from source environments to learn the feature mapping in the new environments, and proposed a DTL algorithm and a meta-learning algorithm to achieve fast key generation in multi-environment for FDD-OFDM systems. Simulation results showed that both algorithms can effectively improve the performance of generated keys in new environments. When the SNR=20 dB, the KERs of the keys generated by the DTL and meta-learning algorithms were reduced by 38.8% and 52.9%, respectively, compared with the method without adaptation (the direct algorithm) in the new environments. In addition, the complexity analysis showed that the meta-learning algorithm consumed less time and lower CPU and GPU resources for training than the DTL algorithm. Furthermore, the complexity analysis showed that the meta-learning algorithm consumed less time and less CPU and GPU resources than the DTL algorithm in the training stage, and these costs were acceptable in real-world applications.

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