

# Wireless Deep Mutual Learning: Challenges and Opportunities

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**Abstract**—The rapid proliferation of intelligent mobile devices has spurred the increasing interest in *collaborative learning* (CL). Existing CL methods rely on direct algebraic averaging of model parameters for knowledge transfer across devices, which faces communication bottlenecks, struggles to scale into distributed settings, and has difficulty in handling model and data heterogeneity. To address these challenges, building upon the single-device *deep mutual learning* (DML), we propose a novel communication framework that interconnects multiple devices to form a natively distributed DML system. Unlike the classic CL, multi-device DML utilizes a distillation loss term to enable models to mutually and indirectly influence each other, thereby sharing knowledge by identifying common optimum point across devices. This mechanism enhances the distributed scalability, fully leverages on-device communication and computation resources, and effectively addresses model and data heterogeneity. We explore the integration of our proposed multi-device DML into a wireless system, termed *wireless DML* (WDML). Since knowledge sharing is hampered by communication bottlenecks, we analyze the corresponding challenges and opportunities for enhancing learning efficiency. Through a case study on a device-to-device based synchronous peer-to-peer system, we validate the advantages of WDML in energy efficiency and generalization. We conclude by discussing open issues that guide future research towards a more efficient, lower latency, more flexible WDML system.

## I. INTRODUCTION

The past decade has witnessed two convergent trends: 1) mobile devices are becoming increasingly powerful, enabling on-device lightweight *deep neural network* (DNN) training; and 2) wireless technologies are advancing rapidly, achieving ultra-low latency, high reliability, as well as ubiquitous connectivity. This inevitably reflects the need of *collaborative learning* (CL), which is a key solution for wireless artificial intelligence applications. Central to CL is the knowledge sharing among multiple mobile devices. In a traffic management example as in Fig. 1, a fleet of unmanned aerial vehicles (UAVs) exchange local knowledge with one another to build

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a comprehensive understanding of traffic condition, enabling more efficient traffic flow optimization. As in [1], knowledge is a learned mapping from input to output, along with the rules of generalizing beyond the training data.

In general, knowledge sharing among multiple mobile devices confronts the following challenges: 1) workload orchestration for efficient utilization of computing and communication resources; 2) privacy preserving during wireless communications; 3) DNN heterogeneity due to divergent computing capabilities across devices; 4) data distribution heterogeneity from the prevalence of *non-independent and identically distributed* (non-IID) data; 5) timeliness of knowledge sharing for new real-time data generation; and 6) design optimization of communication mechanisms. In this context, wireless communications are tasked with delivering abstract knowledge representations, rather than raw data bits. This shift requires new performance evaluation metrics for communication efficiency, as well as novel scheduling and resource allocation mechanisms tailored to CL.

Traditional CL relies on a centralized architecture for knowledge sharing, where a central device trains a DNN using data collected from participating devices. It raises the concerns over computational efficiency and data privacy. *Federated learning* (FL) [2] addresses the privacy issue by distributing the training process and aggregating only model parameters at a central server [3]. FL retains centralized knowledge sharing, which becomes a bottleneck when participating devices need to share knowledge directly. Since all communication is routed through the server, it introduces latency and unnecessarily exposes local knowledge to all participants. Some efforts have extended FL to decentralized, as in [4]–[6]. [4] proposes a decentralized FL (DFL) framework based on a directed acyclic graph (DAG) to address dependencies on central coordinators and network asynchrony. However, the DAG structure requires users to maintain complete data history, substantially increasing communication overhead. To mitigate data heterogeneity, [5] designs a decoupling module that separates global and personalized information, thereby enhancing the global model’s focus on personalization. Nevertheless, [5] still relies on homogeneous model structures and fails to fundamentally eradicate the negative impact of non-IID dataset. Another alternative, *split learning* (SL) [7], protects data privacy by dividing a DNN between participating devices and a central device. As an integration of FL and SL, [6] introduces a dynamic tier scheduler to offload portions of the global model to a central server to mitigate resource limitations on slower clients. However, it is obvious that SL still needs a central coordinator as a bottleneck for clients to share knowledge.

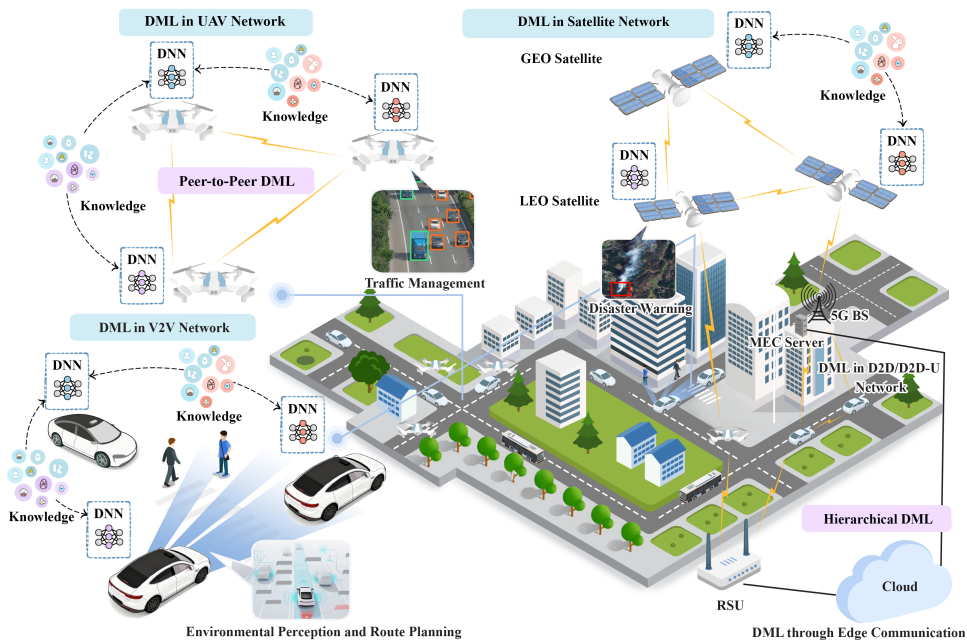


Fig. 1. Integration of *deep mutual learning* (DML) into wireless communication systems, such as traffic management by UAVs, disaster warning by satellites, as well as real-time environment perception in autonomous driving systems. (DNN: deep neural network; V2V: vehicle-to-vehicle; GEO: geostationary earth orbit; LEO: low earth orbit; MEC: multi-access edge computing; BS: base station; RSU: roadside unit.)

Existing CL methods still primarily rely on performing algebraic averaging of model parameters to transfer knowledge across devices. This approach, however, faces the difficulties in handling model heterogeneity, non-IID data, and significant communication overhead across rounds in distributed learning settings.

In line with the above discussions, we concentrate our focus on a novel framework that adapts *deep mutual learning* (DML) [8] for a fully decentralized setting. While originally designed for a single device, DML aims to train two compact DNN models cooperatively as equal partners on the same dataset to improve their generalization performance. We extend this principle from single device to multiple devices and derive a novel distributed DML framework, which we term *multi-device DML*. Our framework relies on bidirectional communication between devices, making it a natively distributed CL technique. By leveraging this framework at the communication layer, DML takes on a new objective of knowledge exchange across multiple mobile devices instead of a single device. Diverging from existing CL frameworks, multi-device DML eliminates the need for homogeneous models and data distributions while reducing communication overhead by avoiding inter-round transmissions.

The rest of this article is organized as follows. In the next section, we introduce our multi-device DML by extending the single-device DML principle. In Section III, we integrate our framework with conventional wireless technologies, including a peer-to-peer DML system based on *device-to-device* (D2D) [9]/*D2D unlicensed* (D2D-U) [10] or *ad hoc* [11], a hierarchical DML system leveraging edge communication, and a relay-assisted DML architecture. In Section IV, we present a case study on a peer-to-peer and synchronous system based on a D2D-U network to demonstrate the performance gains

from our proposed framework. We discuss the open issues in Section V. Finally, Section VI draws the conclusions.

## II. PRELIMINARIES AND MULTI-DEVICE DML

In this section, we introduce the basics of single-device DML and propose a multi-device DML framework.

### A. Single-Device DML

As illustrated in Fig. 2 a), single-device DML [8] cooperatively trains two compact models as equal partners on a dataset, involving the concept of *soft target* from KD [1], which is a model compression technique. Soft target is generated by applying a “temperature scaling” to the logits before the softmax layer, which contains richer information than hard labels. The training loss function for each network integrates a supervised learning loss with a Kullback–Leibler (KL) divergence term of soft targets, which serves as mimicry loss aligned with partner network’s soft distributions. This approach yields positive outcomes: each model in this peer-guided setting achieves better generalization than when trained alone. It remains effective even with different model architectures. [8]. Furthermore, the mutually enhanced model consistently outperform those trained through traditional distillation from a larger, pre-trained teacher model.

### B. Communication Framework of Multi-Device DML

In the original single-device DML framework, two DNN models are jointly trained on a dataset. During *stochastic gradient descent* (SGD), each model calculates different gradients. However, a mutual KL convergence term in both of their loss functions causes one model to directly influence the parameters of the other. This allows exchanging latest

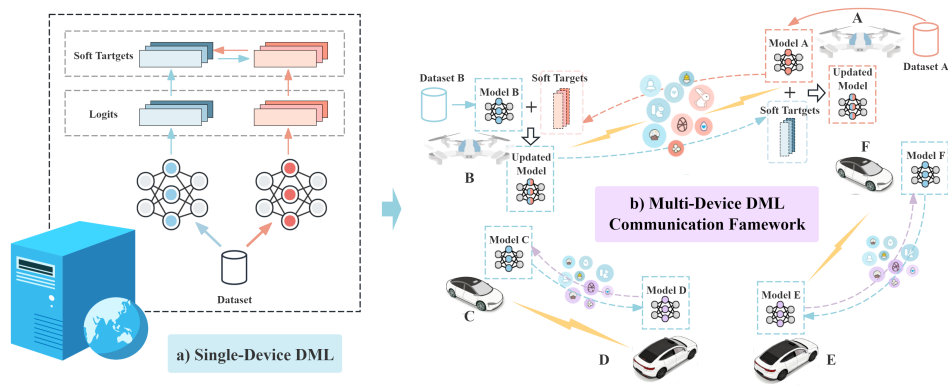


Fig. 2. a) The single-device DML originally aims to improve the generalization performance of the two compact models; b) We extend it to the multi-device natively distributed DML with bidirectional knowledge transmissions.

gradient information during model training. This phenomenon can be interpreted by that the resulting increase in the posterior entropy of soft targets promotes convergence toward more robust and flatter minima [12]. A two-way exchange of knowledge can be seen, where models learn from not only the training samples and labels, but the knowledge embedded in their parameters.

Consider a case in which two models originally co-trained on a single device are deployed on two separate devices, each with a local dataset. This raises a fundamental question regarding the feasibility of knowledge sharing between the two devices via wireless communications. In original single-device DML, both models usually start from the same untrained state with low generalization capability. In the multi-device case, however, each model can be first pre-trained independently on its local dataset, thereby acquiring local knowledge. As in Table I, the models from multi-device DML exhibit a substantial gain in generalization performance compared to the local pretraining alone. Model A and B is trained by using ResNet-32, ResNet-56, with parameters of 0.46M and 0.85M, respectively. The models exhibit different Top-1 accuracies after pretraining only, suggesting they have acquired distinct knowledge from their respective datasets. After DML, both models achieve similar and significantly improved Top-1 accuracies, indicating their comprehension of knowledge is aligned after knowledge exchange. It demonstrates that even under the conditions of model heterogeneity and non-IID data, the knowledge on both devices can still be effectively exchanged. A similar observation, which has been made in one of the results from [8], remains unanalyzed in prior works.

TABLE I  
TOP-1 ACCURACY (%): COMPARISON OF PRETRAINING ONLY AND PRETRAINING + DML ON DEVICES A AND B.

	Pretrain Only	Pretrain + DML
Model A	46.40	52.08
Model B	40.48	52.34

<sup>1</sup> Devices A and B have different local datasets which has 10000 samples different from CIFAR-100 dataset. Model A is trained using ResNet-32, Model B is trained using ResNet-56.

As in Fig. 2 b), we illustrate the procedure of knowledge exchange between devices A and B, as in the following:

- 1) Device A and Device B first complete local model training on their respective local datasets.
- 2) Device A and Device B establish a communication link, formally constituting a knowledge exchange pair.
- 3) Device A sends the soft targets or model parameters to Device B.
- 4) Device B performs DML training using both its local model and the soft targets or the model parameters received from Device A. Then, the model on Device B incorporates new knowledge provided by Device A.
- 5) Device B sends the updated soft targets or model parameters back to Device A.
- 6) Device A performs DML training using both its local model and the soft targets or the model parameters received from Device B. Then, the model on Device A incorporates new knowledge provided by Device B.

In this framework, knowledge exchange between two devices does not require the transmission of their private datasets. Instead, it only involves the transmission of model parameters or soft targets. A general communication method is that the devices can directly share their locally trained model parameters. The receiving device uses these to initialize a DNN model, which along with its local model is then trained on the receiving device’s private dataset to generate soft targets as mutual supervision signals for DML training. Regarding the alternative method of transmitting soft targets, it is particularly suited for scenarios requiring a stricter of privacy protection, as it avoids the exposure of model parameters. In this approach, a transfer dataset must be constructed in advance—once and for all—containing proxy samples. These proxy samples must adequately represent the data distribution on the sending device. A feasible technique to achieve this is through the use of a *generating adversarial network* (GAN). One device inputs the transfer dataset into its local model to output soft targets, which are then transmitted to the other device. The receiving device uses these soft targets as additional supervision signals to train its local model on the transfer dataset and its private dataset.

WDML and existing CL methods differ fundamentally in their key mechanisms for inter-device knowledge transfer. Existing CL methods rely on direct algebraic averaging of

model parameters for inter-device knowledge transfer. In contrast, WDML utilizes a distillation loss term, enabling models to mutually and indirectly influence each other's training gradients, thereby sharing knowledge by identifying common optimum point across devices. This paradigm shift offers key advantages: 1) reduced inner-round communication overhead. 2) no requirement for model homogeneity. 3) improved performance on non-IID data. 4) no need for a central coordinator.

This framework requires for a consistent soft target layer across all devices to ensure the similarity of output semantics, even when the model architectures differ.

### III. WIRELESS COMMUNICATION FOR MULTI-DEVICE DML

The inherent distributed nature of multi-device DML enables the compatibility with diverse communication technologies. To investigate the consequent challenges and solutions, this section presents corresponding integrated system architectures.

#### A. Peer-to-Peer DML

It becomes natural to integrate multi-device DML into D2D/D2D-U and ad hoc networks, forming a peer-to-peer DML system architecture. In peer-to-peer DML systems, all devices are equal.

1) *D2D/D2D-U*: D2D communication is a cellular network-underlaid technology that enables direct communication between nearby user devices under the centralized control of base stations (BS). It aims to enhance local service capacity while minimizing interference to the primary cellular network. For further booming the network capacity, D2D-U has been developed, which extends D2D communication to unlicensed spectrum as an underlay of the cellular network. It enables coexistence among D2D users, LTE users, and Wi-Fi users through sensing-based sharing mechanisms.

In D2D/D2D-U, any pair of devices are capable of directly communicating in a fully connected topology. However, in wireless mobile environments, the effective distance between devices is dynamic. It expands beyond the physical separation to include the channel conditions, such as bandwidth, noise, and power gain, and most critically, the divergence in the knowledge distributions. The key challenge, therefore, lies in the selection of appropriate neighboring devices to maximize knowledge sharing efficiency to accelerate the convergence of multi-device DML.

A feasible solution leverages the D2D/D2D-U communication under control cellular spectrum sharing. The BS obtains a global view of all devices, including signal-to-interference-plus-noise ratio (SINR), model size, and computational capacity. With this information, we can design optimal DML pairing strategies that work over the direct D2D links. The goal is to minimize the energy consumption by communication and computation per unit of knowledge exchanged between devices.

2) *Ad Hoc*: Ad hoc [11] networks are characterized by their self-organizing and self-managing capabilities, allowing devices to autonomously form networks without relying on a fixed infrastructure. DML based on ad hoc network allows devices spontaneously to establish connections with nearby peers to facilitate knowledge exchange. The advantages exist in not only enhancing the robustness of the network but also allowing for more efficient use of communication resources.

A major challenge in ad hoc networks stems from their fully distributed resource allocation. Besides conventional methods include competition-based channel access like carrier sensing and random backoff, novel knowledge-oriented resource allocation mechanisms are needed to dynamically and fairly allocate communication resources in real-time. A promising approach utilizes the self-organizing properties of ad hoc networks through *online convex optimization* based on *game theory* for dynamic resource allocation. Incentive mechanisms can be designed to promote device participation in resource competition based on channel state and knowledge contributions, minimizing the regret between actual decisions and posterior optimal solutions to achieve real-time allocation.

#### B. Hierarchical DML

In practical wireless environments, peer-to-peer connectivity is often unattainable because of excessive device distance or large scale deployments. In such cases, edge communication can be leveraged to construct a hierarchical DML system, where devices are grouped into clusters based on physical distance or functional similarity [13]. Each cluster has one or more edge devices that serve as intermediaries for knowledge exchange between devices within the cluster and with other clusters. Typically, devices in a cluster communicate with each other directly, acting as a peer-to-peer DML system. Devices within the cluster usually has access to global cluster information. Edge devices of different clusters may lack direct links and possess only local information. The target of each device is to learn all intra-cluster knowledge, while edge devices accumulate maximal inter-cluster knowledge.

Nevertheless, an edge DML network faces several challenges. First, the selection of cluster head devices should not be based on not only on computational capability but also knowledge they possess. Devices with rare knowledge and strong generalization capabilities should be prioritized as edge devices. Furthermore, given the hierarchical nature of edge communication networks, we need to carefully address: 1) how to cluster devices based on knowledge disparity and channel conditions to maximize communication efficiency per unit of knowledge exchanged; and 2) how to design a multi-layer asynchronous collaborative DML mechanism to fully utilize the computing and storage resources across different layers.

One promising solution involves using *graph neural networks* (GNN) or *online reinforcement learning* to group devices into clusters according to their data distribution and channel conditions. By maximizing intra-cluster knowledge similarity and channel quality while minimizing inter-cluster interference, overall knowledge exchange efficiency can be enhanced. Additionally, a multi-layer asynchronous DML mechanism can be designed, allowing devices at different layers

to perform knowledge exchange on respective time scales. For instance, edge devices may frequently conduct DML with directly connected devices, while higher-layer devices can aggregate and distribute knowledge at a larger time-scale. Furthermore, efficient resource allocation is critical. Implementing a hierarchical DML system requires formulating an optimization problem, which defines thresholds that manage the trade-off between device states (i.e., waiting or working) and resource types (i.e., communication and computation).

### C. Relay in DML Transmission

Relay technology is essential for facilitating indirect knowledge exchange. Within DML systems, we define the following two relay modes.

- 1) **Raw Data Relay:** The relay device is only responsible for forwarding received soft targets or model parameters without performing any processing. Note that in the context of DML, “data” refers to soft targets or model parameters, rather than private datasets of devices.
- 2) **Knowledge Relay:** After receiving soft targets or model parameters from a sender, the relay performs local DML training to comprehend the new knowledge, generates updated soft targets or model parameters as new carriers of knowledge, and forwards them to the next device, which can be another relay or the destination device.

Compared to the raw relay, the knowledge relay on one hand enhances the efficiency of each transmission by concurrently delivering both the source and the relay knowledge, while on the other hand introduces increased computational load and latency at the relay.

Effective relay transmission requires an appropriate routing mechanism to improve the efficiency and reliability of knowledge delivery. To this end, two primary types of routing mechanisms exist: pro-active and reactive. The former maintains a global routing table, offering low latency and rapid response, which makes it well-suited for knowledge relay. Yet, for a highly dynamic network, maintaining a global routing table seems impractical. In contrast, the reactive mechanism establishes routes on-demand, making it more suitable for raw relay, though it may introduce higher latency.

Beyond traditional metrics such as channel state and computational power, DML routing should consider inter-device knowledge divergence. One of the potential solutions is to select relays with knowledge that substantially diverges from both the sender and receiver, aiming to maximize the knowledge richness in each hop. This requires incorporating a regularization term in the loss function of the optimization problem to describe knowledge divergence, often leading to a complex mixed-integer programming problem.

In relay transmissions, another critical challenge is the suppression of learning noise due to the inherent stochasticity of wireless channels, which is progressively amplified through multi-hop relaying. This amplification manifests as a distinctive form of learning noise within the SGD process. This “learning noise” not only degrades the performance of individual devices, but also propagates hallucinations and

artifacts across the entire network. Two strategies can mitigate the adverse effects of such learning noise: multipath redundant transmission and incorporation of a channel-aware regularization term in the loss function. The principle behind multipath redundant transmission is to transmit identical soft targets or model parameters through multiple independent paths, averaging out effects of channel perturbations. The channel-aware regularization term involves introducing a regularization term in the DML loss function that correlates with the statistical characteristics of the channel, thereby enhancing the model’s robustness against channel-induced distortions. It is feasible to adaptively estimate the statistical characteristics of these channel effects using DNNs.

## IV. CASE STUDY: A D2D-U BASED SYNCHRONOUS PEER-TO-PEER DML SYSTEM

In this section, we present a case study on a synchronous peer-to-peer DML system based on D2D-U communication, which consists of 6 wireless devices with an index set  $\{A, B, C, D, E, F\}$ , and a BS. The system uses the 5.8 GHz unlicensed band with totally 10 MHz bandwidth. Devices transmit at up to 24 dBm power with 1 s latency constraints. The channel model for the urban line-of-sight (LOS) scenario assumes a noise spectral density of -174 dBm/Hz and follows a free-space path loss model given by  $PL(d) = PL(d_0) - 10\nu \log_{10}(d/d_0)$ , where the path loss exponent  $\nu$  is 2.2. A log-normal shadow fading with a standard deviation of 6 dB is also incorporated. Without loss of generality, the devices are randomly located on the ground or at low altitude within a circular area of radius 200 m, with inter-device distances between 50 and 150 m. BS uses *carrier sense multiple access with collision avoidance* (CSMA/CA) [14] and *frequency division multiple access* (FDMA) [15] to prevent collisions and allocate spectrum. The devices employ heterogeneous model architectures: ResNet-32, ResNet-56, ResNet-44, ResNet-110, ResNet-32, and ResNet-44. We partition the CIFAR-100 training dataset into 10 subsets of 5,000 samples each, with a knowledge label set of  $\{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$ . Each device uses the union of two randomly chosen subsets as its local private dataset. Here we assume that each data subset corresponds to a unit of knowledge and use the knowledge label set of the data subset of each device as a proxy metric to quantify knowledge disparity. With the goal of minimizing the communication energy consumed per unit of knowledge exchanged in each round, devices are paired and allocated transmission power and the *duty-cycle-muting* (DCM) time fraction of on-period sub-frames.

As shown in Fig. 3, the system operates over 4 rounds. Initially, each of the 6 devices possesses a distinct model architecture and knowledge label set:  $\{0, 1\}$ ,  $\{2, 3\}$ ,  $\{3, 4\}$ ,  $\{5, 6\}$ ,  $\{4, 8\}$ ,  $\{7, 9\}$ . For instance, in the first round, an optimal pairing scheme is formed between Devices A and E, B and D, and C and F. Initially, Device A holds knowledge labels  $\{0, 1\}$  and Device E holds  $\{4, 8\}$ . After the first round of knowledge exchange, both devices obtain the unified label set  $\{0, 1, 4, 8\}$ . As shown in Fig. 4, initial pre-training on local datasets yields Top-1 accuracy of 47.18%, 45.83%, 46.25%, 41.89%,

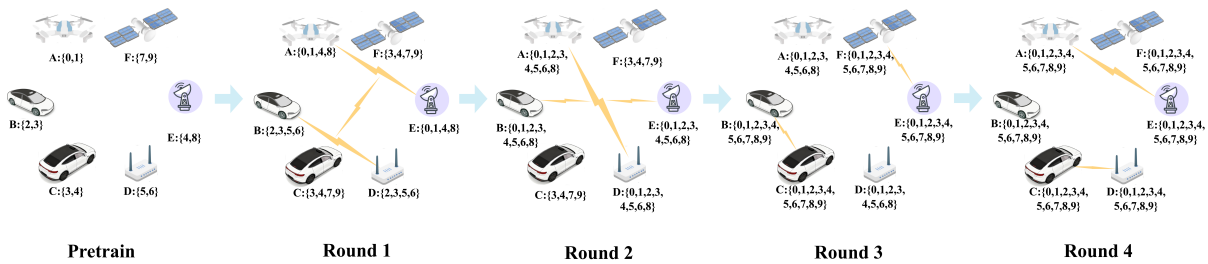


Fig. 3. Communication pairing and knowledge evolution per device during 4 knowledge exchange rounds. Round 1: A–E, B–D, C–F; Round 2: A–D, B–E, C and F waiting; Round 3: B–C, E–F, A and D waiting; Round 4: A–E, C–D, B and F waiting.

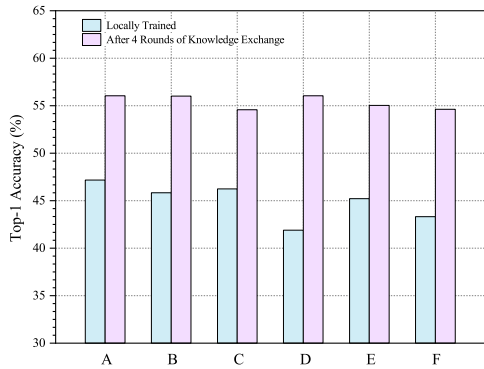


Fig. 4. Comparison of Top-1 accuracy on the test dataset between locally trained models and models after 4 rounds of knowledge exchange in Devices A, B, C, D, E, and F.

45.22%, and 43.32% on the test set. After 4 rounds of knowledge exchange, their Top-1 accuracy increases to 56.05%, 56.02%, 54.58%, 56.05%, 55.04%, and 54.63%, showing improved generalization across all models after 4 operational rounds despite their architectural differences. Fig. 5 depicts the convergence process of communication resource allocation, including the energy consumption per unit of knowledge and the communication time between devices. Without loss of generality, the curves show the convergence process within Round 1. The pairing schemes adopted are simply denoted as A–E, B–D, and C–F, which minimizes the energy consumption per unit of knowledge exchange in Round 1. It is worth noting that each DML pair consists of two unidirectional transmission links, for example, we have links  $A \rightarrow E$  and  $E \rightarrow A$  for the A–E DML pair. Due to channel symmetry, their energy consumption and communication time converge to identical values, which is consistent with theoretical analysis.

In the proposed multi-device DML system, knowledge exchange across devices proceeds distributedly, even with non-IID data and heterogeneous models. The communication strategy also minimizes energy consumed per unit of knowledge exchange.

## V. OPEN ISSUES

The development of WDML systems presents numerous unresolved issues, highlighting key research directions for future investigation.

**Metric of Knowledge Disparity:** Knowledge is an abstract property embedded in raw datasets. Currently, there are few

metrics to quantify the abstract differences between data samples of a device, which may constitute a generalized inequality relation. Furthermore, as a dataset comprises numerous samples, there are also few established approaches for measuring the divergence between two datasets. Experimental observations indicate that the improvement in generalization capability through DML is influenced by multiple factors, such as the quantity and distribution of data samples of a DML pair. The relationship between generalization improvement and the number of learned samples is nonlinear.

### Global Optimization for Asynchronous and Hierarchical DML System:

The case study considers a synchronous and peer-to-peer system which is of low temporal utilization. While an asynchronous system boosts the efficiency by overlapping device workflows, the design is highly complex. Establishing criteria for idle devices for local optimization is feasible, but constructing a global optimization framework remains challenging. Furthermore, beyond peer-to-peer networks, hierarchical communication structures indicate a viable alternative. Key challenges include not only how to cluster devices effectively but also how to select appropriate cluster heads.

### Quantitative Analysis of the Impact of Channel Noise:

Errors in uplink and downlink transmissions impact DML system performance. A quantitative question is whether a DML system can mitigate these negative effects when the SINR is controlled within an mathematical upper bound relative to the number of communication rounds. A promising research direction involves formulating a rigorous mathematical model of the noise propagation mechanism throughout the global learning process of DML system. Another interesting direction is the joint optimization of spectrum, computing, and power allocation under given latency constraints to minimize model error and enhance training performance.

### Strategy Based on Local Information in Dynamic Networks:

The common assumption in the DML literature of full connectivity in communication networks is unrealistic for large scale deployments. From a practical viewpoint, devices have limited and local views of the surrounding and operate within a topology that changes dynamically. This poses a key research question, namely, how to design a strategy enabling individual devices can collectively achieve global knowledge spread using only local neighbor information.

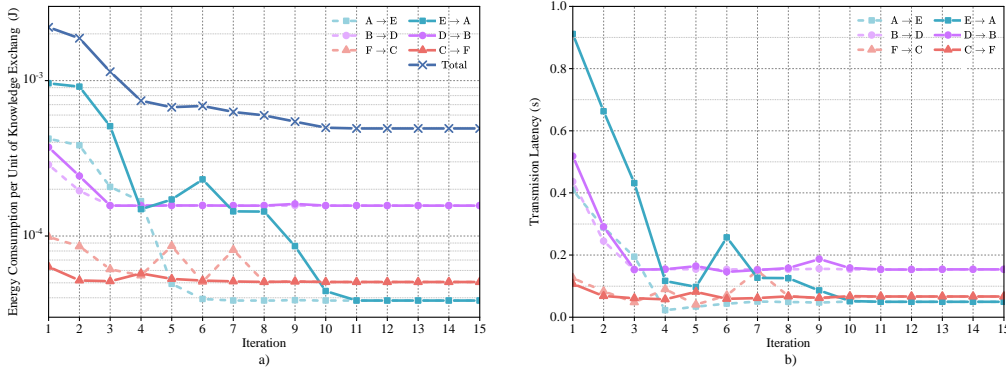


Fig. 5. Energy consumption per unit knowledge exchange and communication time of each link between devices in Round 1: a) Energy consumption per unit knowledge exchange; b) Communication time. The pairing schemes adopted are simply denoted as A–E, B–D, and C–F.

## VI. CONCLUSION

This article presents a novel communication framework that extends single-device DML to multi-device DML. By interconnecting multiple devices, the framework overcomes the key limitations of existing CL techniques. It enables full utilization of computational resources, eliminates central device bottlenecks, ensure data privacy, and supports heterogeneity in both model architecture and data distribution. We introduce system architectures that leverage conventional wireless technologies. While our proposed framework shows promise, several open issues remain for future investigation, including developing knowledge sharing disparity metrics, designing asynchronous strategies, analyzing noise propagation, and optimizing decision-making strategies with limited local information.

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