Association in Dense Cell-Free mmWave Networks

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Abstract—We exploit a dense cell-free mmWave network where User Equipments (UEs) are served by multiple highly directional beams provided by multiple Base Stations (BSs) simultaneously. Such multi-beam scenarios can either offer high spectral efficiency when different information is transmitted through each beam or a diversity gain when each beam transmits the same information. However, this increased spectral efficiency or diversity gain costs a more complex network association phase. A UE requires finding multiple nearby serving BSs and determining the optimal beam pair for each one. Thus, an efficient association process is urgently needed. In this work, we propose a UE-initiated association method for dense cell-free mmWave networks. We design an efficient beam training mechanism with multiple BSs using hybrid beamforming. We evaluate the proposed association method under different network configurations. The simulation results show that compared to traditional solutions, our proposed association method can lead to maximally 100% faster beam training and reduce energy consumption by up to 77%. The proposed UE-initiated association method is also scalable to the number of RF chains and antennas at BSs and UEs, making it very suitable for dense cell-free networks.

Index Terms—Cell-free network, millimeter-wave (mmWave), association, beam training, hybrid beamforming.

I. Introduction

The millimeter-Wave (mmWave) frequency band has been exploited heavily to meet with the rapidly increasing demands on wireless capacity [1]. In mmWave networks, Base Stations (BSs) use multiple *highly directional beams* to serve the User Equipments (UEs). When each beam is used to transmit data, the mmWave networks can offer *high spectral efficiency*, being able to serve many UEs in a dense area. However, due to the high-frequency band, mmWave links can be easily affected by blockages, degrading the data rate significantly. To mitigate the impact of blockages and because of the small size of cells, mmWave BSs should be *densely deployed* in reality.

In this work, we apply the cell-free concept [2] to the dense deployment of mmWave BSs to create *dense cell-free mmWave networks*. In such networks, a large number of highly available and directional mmWave BS beams serve a smaller number of UEs simultaneously in the time and frequency domain. This inherits the advantages of cell-free networks: can increase the macro-diversity gain and reduce inter-cell interference, leading to a higher system spectral efficiency or diversity gain [3], [4].

Challenges. This increased spectral efficiency or diversity gain comes at the cost of a more complex network association phase, as a UE should now find multiple nearby BSs and determine the optimal beam for each one. An association process is needed to select the subset of serving BSs and

the best beam pairs between the BSs and the UE. The main challenge in designing an association algorithm for a cell-free mmWave network is to find an efficient beam training method that enables a UE and multiple BSs to find their best beam pair efficiently within a short period. The design of hybrid architecture, e.g., the number of RF chains and antenna element used by communicating stations, affects the duration and energy consumption during beam training. Another challenge faced during channel estimation in the association process is the increasing level of uplink interference due to the presence of a large number of users.

Our contributions. In this work, we propose an association method for dense cell-free mmWave networks that enables a UE to associate with multiple BSs using multiple orthogonal beams simultaneously. The association method enables parallel training packet transmission supported by multiple RF chains at UE and BS. The combination of hierarchical and sweep beam training methods with UE initiating the training makes the beam training process between a UE and multiple BSs faster. Our proposed beam training method requires the least number of time slots on the beam training for almost all the considered hybrid configuration. It is the fastest when compared to other existing single UE-BS association methods when implemented in a cell-free mmWave network. Besides evaluating the beam training duration, our proposed beam training method's energy consumption is also assessed. Our proposed beam training method's energy consumption is proportional to the number of beam training time slot. It can reduce the energy consumption of the fully-sweep method by up to 77%. We also observe the uplink interference resulting from beacon transmission by multiple UEs in our beam training method. To reduce the uplink interference, we can use more sectors, as validated by our simulation results, showing that having a large number of RF chains and antennas is fundamental for reducing the interference in dense cell-free mmWave networks.

II. BACKGROUND AND RELATED WORK

In mmWave networks, the beam training process is required to establish communication links by finding the best beam pair between the communicating nodes. In general, beam training methods can be categorized into *i) sweep or sequential beam training*, and *ii) hierarchical beam training* [5]. In sweep beam training, a node sweeps its beam exhaustively by transmitting training packets to the pairing node, and vice versa. The beam with the highest signal quality is selected. In hierarchical beam

training [6], low-resolution beams are first trained to estimate the direction of pairing nodes. Then higher-resolution beams are trained and the process repeats until a beam with targeted quality is found.

The IEEE 802.11ad standard provides beam training mechanism for single-user system using the exhaustive sector-level-sweep and beam refinement protocol [7]. Its successor, IEEE 802.11ay, adopts the same beam training method for multi-user systems [8]. There exists some works on improving the beam training for multi-user mmWave networks [9], [10]. However, they all discuss the scenario where a BS performs association to serve multiple users. *None of them discuss the beam training and association method between a user and multiple BSs, as for our proposed dense cell-free mmWave networks*. Although the performance of cell-free in mmWave networks have been studied in [11], [12], the beam training and association process for cell-free mmWave network have not been discussed.

III. SYSTEM MODEL

We consider a dense and cell-free mmWave network where a large number of distributed BSs are coordinated to serve a relatively smaller number of static UEs simultaneously, as illustrated in Fig. 1. The number of BSs and UEs are denoted as L and K, respectively. The BSs and UEs randomly distribute in an area-of-interest without obstacles. All BSs are connected to a Central Processing Unit (CPU) through reliable fronthaul links such as fiber links. The CPU determines the subset of BSs to serve a UE and also synchronizes the BSs during the process of association and data transmission. Each BS and UE has multiple RF chains. We use M_l and M_k to denote the number of RF chains at each BS and UE, respectively. Each RF chain has N antennas. As a result, a UE can be served by up to M_k BSs concurrently. Similarly, a BS can send data streams to several UEs simultaneously, and this capability is limited by the number of RF chains M_l .

Beamforming. We use hybrid beamforming where signal processing is split into analog domain and digital domain. Compared to pure analog beamforming, hybrid beamforming supports multi-stream and multi-user; compared to pure digital beamforming, hybrid beamforming consumes less energy [13].

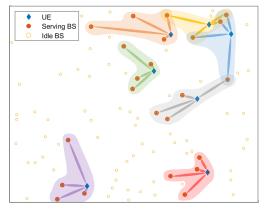


Fig. 1: The illustration of a dense cell-free mmWave network.

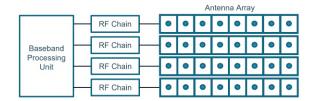


Fig. 2: The hybrid partially-connected architecture.

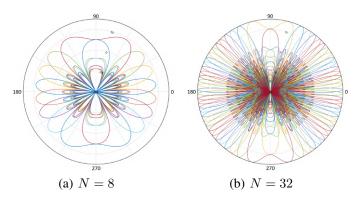


Fig. 3: The beam pattern of uniform linear array antennas.

Furthermore, we consider a partially-connected hybrid system architecture, where only a group of antenna elements is controllable by an RF chain [14]. It is more energy efficient when compared to the fully-connected architecture in which each antenna is connected to a dedicated RF chain [15]. An example of the partially-connected architecture with four RF chains is depicted in Fig. 2. The four RF chains can generate four orthogonal beams. Each RF chain independently controls a sub-array consisting of N=8 antenna elements. Baseband processing unit is used to perform precoding and combining in the digital domain.

We use Uniform Linear Array (ULA) antenna architecture to generate an analog beam in which every N antennas are controlled by an RF chain, enabling an independent data transmission with high beamforming gain. Fig. 3 shows the beam patterns of ULA with N=8 and N=32, respectively.

Channel model. The system works on 60 GHz environment with the carrier frequency of 60.48 GHz. We use Rician model approach in which Line-of-Sight (LOS) link is a dominant component that characterizes the channel between the BSs and the UEs. The large number of available BSs in cell-free networks ensures the availability of LOS paths between the BSs and a UE. Considering an uplink for example, the received signal $S_{k\to l}$ at the BS is calculated using Friis transmission formula as follows:

$$S_{k\to l} = \frac{PG(\theta_k)G(\theta_l)c^2}{(4\pi f d_{k,l})^2},\tag{1}$$

where P is the transmit power per sector, c is the speed of light constant, f is the carrier frequency, $d_{k,l}$ denotes the distance between the UE and the BS, $G(\theta_k)$ and $G(\theta_l)$ represent the UE's and the BS's beamforming gains at angle of θ_k and θ_l , respectively. Instantaneous channel estimation is

TABLE I: List of used notations in this work.

Notation	Parameter
K	Number of UEs
L	Number of BSs
M_k, M_l	Number of RF chains at UE, BS
N_k, N_l	Number of antennas per RF chain at UE, BS
α_k, α_l	Sector used by UE, BS
β_k, β_l	Beam used by UE, BS
θ_k, θ_l	Transmit/receive angle at UE, BS

performed at the BSs by calculating instantaneous the Signal-to-Interference-plus-Noise-Ratio (SINR) as shown below:

$$SINR = \frac{S_k}{\sum_{i=1, i \neq k}^K S_i + n},$$
 (2)

where S_k represents signal power of UE_k received by BS_l , S_i is the received interference power from other UEs, while n is the additive white Gaussian noise variables at the receiver.

IV. PROPOSED ASSOCIATION METHOD FOR CELL-FREE MMWAVE NETWORKS

Before being served by multiple BSs in a cell-free mmWave network, a UE needs to join the network through an association process. Our proposed association method uses three principles to enable effective association in a cell-free mmWave network:

- Parallel beam training. The advantage of having multiple RF chains enables the communicating stations to transmit and receive beam training frame using different sectors/beams simultaneously. Hence, the beam training process is faster than when a single RF chain is used.
- 2) *UE-initiated*. This approach enables a UE to introduce it's presence while transmitting a training packet simultaneously. It is more efficient compared to a BS-initiated approach as in UE-initiated approach, the beacon and the first training frame are sent simultaneously by the UE.
- 3) Combined hierarchical-sweep method. Fully hierarchical beam training only requires a few steps to achieve the best beam pair between a UE and a BS; the fully sweep beam training works effectively with multiple BSs. The combination of these two makes the association faster as less beam training slots are required during the process.

Association in cell-free mmWave networks includes the processes of 1) beacon transmission, including the BS candidates selection, and 2) beam training. A beacon sent by a UE to introduce its presence is also used by the CPU to select serving BSs. Following that, beam training process is performed to find the best beam pair between the UE and all the assigned BSs.

A. Beacon Transmission and BS Candidate Selection

To begin the association process, a UE transmits a beacon signal broadcasting its presence in the network. This beacon transmission is applied for all beam training methods. When using UE-initiated approach, the beacon transmission becomes part of the beam training process as the beacon contains a training frame indicating UE's identity and its sector ID. It

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Algorithm 1 Beacon transmission and BS candidate selection
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Input: UE<sub>k</sub> transmits TRN_{k,m} beacons through all \alpha_{k,m}
Output: Best \alpha_{k,m} and \alpha_{l,m}
 1: \mathrm{BS}_l receive \mathrm{TRN}_{k,m} beacons using \alpha_{l,m}
 2: for each \alpha_{l,m} do
         for each TRN_{k,m} beacons do
 3:
              Calculate SINR_{k,l} (cf. Eq. (2))
 4:
              Identify \alpha_{k,m}
 5:
 6:
         end for
 7:
         Rank the UE according to SINR_{k,l}
         Identify the best \alpha_{l,m} and \alpha_{k,m}
 8:
 9: end for
10: for each UE_k do
         Assign M_k candidates of serving BS
11:
         Send FB containing the best \alpha_{k,m}
12:
13: end for
```

makes UE-initiated approach becomes more efficient compared to BS-initiated as the beacon and the first training frame are sent simultaneously within one training time slot.

Instead of exchanging the beacon in an omni-directional way, the UE and the BS utilize their M_k and M_l RF chains to transmit and receive the beacon signals in parallel through their available sectors. Each RF chain uses small number of N antennas focusing transmission and reception in sector α_k and α_l , respectively.

All BSs in standby mode listen to the beacon transmission, measure the instantaneous SINR and report the information of SINR and UE's sector ID to the CPU. The CPU ranks the list of serving BS candidates according to SINR information. Following that, the BS with highest SINR sends a feedback to UE containing list of serving BS candidates and information of best UE's sector to train at the next stage. Algorithm 1 explains the beacon transmission and the BS candidate selection.

B. UE-initiated hierarchical-sweep Beam Training

Our proposed association method is shown in Fig. 4, in which a UE performs beam training with 4 BSs using $M_k = M_l = 4$ RF chains and $N_k = N_l = 32$ antennas. The remark of TRN and FB timeslot on the bottom left of each step indicates the number of required training (TRN) and feedback (FB) time slots to complete the beam training. The whole process is detailed as follows:

- 1) The UE initiates the transmission of a beacon, that also becomes the first TRN, using M_k sectors while surrounding BSs receive it using M_l sectors, as explained in Sec. IV-A. The training process is illustrated in the Step 1 of Fig. 4. At the end, best UE's transmit sector (α_k) and best BS's receive sector (α_l) are obtained.
- 2) UE_k divides the best $\alpha_k = \beta_{k,m,s-1}$ into M_k narrower beam $\beta_{k,m,s}$ in a hierarchical way, according to the beam code book. The training packet $TRN_{k,m,s}$ are sent by sequentially sweeping their beams in parallel until all beams finish transmitting the TRNs while all BSs listen using best $\alpha_l = \beta_{l,m,s-1}$ obtained in previous stage, as

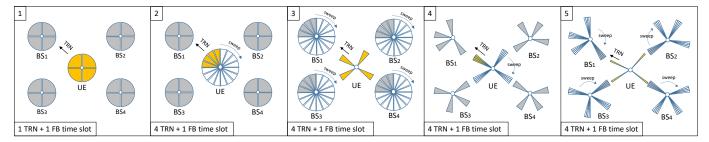


Fig. 4: Proposed UE-initiated parallel hierarchical-sweep beam training (TRN: training; FB: feedback).

depicted in Step 2 of Fig. 4. FB is sent by a BS with highest SINR informing the list of UE_k's best $\beta_{k,m,s}$.

- 3) UE_k transmits $TRN_{k,m,s}$ using its best $\beta_{k,m,s}$ while all BSs sweep their receive beams ($\beta_{l,m,s}$) in parallel to find their own best receive beam as shown in Step 3 of Fig. 4.
- 4) The processes of 2) and 3) are repeated until beam pair with intended resolution are found, as illustrated in the Step 4 and Step 5 in Fig. 4, respectively.
- 5) In the final stage, the duplicates of UE's beam obtained in beam training process (if any) will be removed to avoid multiple BSs communicate with one UE's beam.

The Pseudocode of this beam training process is presented in Algorithm 2.

C. Realization of other beam training methods in cell-free mmWave networks

In this section, we discuss the realization of other two beam training methods: parallel fully-sweep and parallel fullyhierarchical when implemented in cell-free networks.

Parallel fully-sweep beam training: This method uses concept of exhaustive beam searching in which a station sweeps its beam for transmitting/receiving TRN while the pairing stations receive/transmit the TRN using omni-directional mode. A station transmits and receives using multiple beams simultaneously thanks to multiple RF chains used at both UE and BS. In Fig. 5, UE sends series of TRNs by sweeping its 4 out of 64 available narrow beams at a time, indicated by yellow colored beams in Step 1, while all BSs listen to the TRN transmitted by the UE using omni-directional mode. UE performs $[2N_k/M_k]$ times sweep until all UE's beams complete transmitting the TRN. Similar step is taken to train AP's beam, in which UE transmits TRN in omni-directional mode while all BSs sweep their receive beams $\lceil 2N_l/M_l \rceil$ times as illustrated in Step 2. In this method, the number of required beam training time slot remains the same regardless who transmits the TRN, as long as the transmit sweep of all BSs are synchronized in case of BS-initiated training.

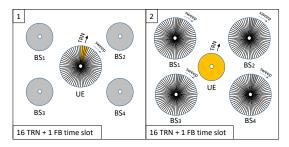
Parallel fully-hierarchical beam training: This beam training concept is used in Parallel-Adaptive Beam Training [5] in which higher beam resolution is trained based on the lower beam resolution selected at previous stage with BS initiating the beam training process. Fig. 6 depicts beam training process between UE and BS₁ only. BS₁ initiates the beam training

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Algorithm 2 Hierarchical-Sweep Beam Training
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Input: \beta_{k,m,s-1} = best \alpha_{k,m} and \beta_{l,m,s-1} = best \alpha_{l,m}
Output: Best \beta_{k,m} and \beta_{l,m}
 1: while \beta_{k,m,s-1} \beta_{l,m,s-1} \neq \text{best } \beta_{k,m} \beta_{l,m} do
 2:
         \beta_{k,m,s-1} is split into M_k of \beta_{k,m,s}
 3:
         for each UE_k's transmit sweep do
              UE_k transmits TRN_{k,m,s} through all \beta_{k,m,s}
 4:
 5:
              BS<sub>l</sub> receive TRN<sub>k,m,s</sub> using \beta_{l,m,s-1}
              for each TRN_{k,m,s} do
 6:
                   Calculate SINR<sub>k,l,s</sub>
                                                       # cf. Equation (2)
 7:
              end for
 8:
              Select the highest SINR_{k,l,s}
 9:
10:
              Identify the best \beta_{k,m,s}
11:
              Send FB containing best \beta_{k,m,s}
         end for
12:
         for each BS<sub>l</sub>'s receive sweep do
13:
              UE_k transmits TRN_{k,m,s} using its best \beta_{k,m,s}
14:
              BS<sub>l</sub> receives TRN_{k,m,s} using M_l of \beta_{l,m,s}
15:
              for each TRN_{k,m,s} do
16:
                   Calculate SINR_{k,l,s}
                                                        # cf. Equation(2)
17:
              end for
18:
              Select the highest SINR_{k,l,s}
19:
20:
              Identify the best \beta_{l,m,s}
         end for
21:
22: end while
23: if \beta_{k,m} duplication = True then
         Remove \beta_{k,m} duplicate
24:
25: end if
```

by transmitting TRN using its M_l sectors while UE receives using its M_k sectors in parallel. FB is required to exchange information of UE's best transmit and BS's best receive sector. The best sector indicated in the FB is then divided into M narrower beams according to beam code book. The process is repeated until the beam pair with intended resolution achieved. By this method, best beam pair between a UE and a BS can be obtained within small number of training steps. However, a UE needs to repeat the process M_k times in order to establish connection with other BSs.

The time slots on beam training under our proposed beam training method and the above two methods is a function of M and N, and can be expressed by the functions shown in Table II.



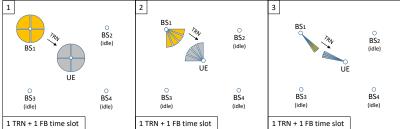


Fig. 5: Parallel fully-sweep beam training.

Fig. 6: Parallel BS-initiated fully-hierarchical beam training.

TABLE II: Required number of slots on beam training.

Beam training method	Maximally required time slots
Fully-sweep BT	$2 + \left\lceil \frac{2N_k}{M_k} \right\rceil + \left\lceil \frac{2N_l}{M_l} \right\rceil$
Fully-hierarchical BT	$2M_k \max \left[\lceil \log_{M_k}(2N_k) \rceil, \lceil \log_{M_l}(2N_l) \rceil \right]$
Our proposed BT	$\lceil (M_k + 1) \log_{M_k} (2N_k) \rceil - M_k + $ $\lceil (M_l + 1) \log_{M_l} (2N_l) \rceil - M_l$

V. PERFORMANCE EVALUATION

In this section, we calculate the performance of our proposed association method for dense cell-free mmWave networks, in terms of beam training duration and energy consumption.

In the association process, the channel estimation by calculating the instantaneous SINR is crucial for allocating multiple BSs to a UE. However, when multiple UEs attempt to associate with the network simultaneously, higher uplink interference will be caused, reducing the SINR. Therefore, before evaluating the performance of our association method, it is important to study how this interference affects the association process.

A. Uplink interference during beacon transmission

During the beacon transmission, a UE transmits low resolution beams generated by small number of sub-array antennas, causing the signal power spreads in a wide direction. This beacon signal is received by all BSs using their low resolution sectors that have a wide reception angle. When multiple UEs transmitting beacon signals simultaneously, BS will experience higher level of interference.

This uplink interference is indicated by the reduced SINR level measured at each BS sector. Fig. 7 shows the average SINR measured by all BSs during beacon transmission process for various number of sectors used for exchanging the beacons. Each UE and BS use the same number of sectors to send and receive beacons. We can observe that the presence of more UEs (i.e., larger K) in the network reduces the average SINR.

To reduce the interference, we can use more sectors, as validated by the results shown in Fig. 7. The use of more sectors focuses the beam transmission/reception to a narrower direction, increasing the channel sparsity and thus reducing the interference from other UEs. Therefore, having a large number of RF chains and antennas is fundamental for the association process in dense cell-free mmWave networks.

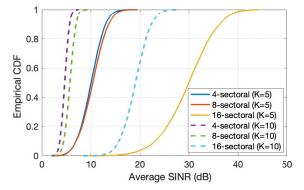


Fig. 7: The SINR during beacon transmissions.

B. Beam training duration

The beam training duration depends on how many training steps required by the BS and UE to find their best beam pair. The higher the achievable beam resolution, the more beam training time slots required, that is, the longer beam training duration will be. Fig. 8 shows the comparison of beam training time slots required by each method presented in Sec. IV, with the same number of RF chains and antennas used at UE and BS sides.

In all configuration scenarios, our proposed beam training method outperforms the fully-hierarchical method in terms of the required time on beam training. Our proposed method can reduce the time spent on beam training by up to 56% when compared with the fully-hierarchical method. For a larger M, the fully-hierarchical method requires more time on beam training. This is because a UE must repeat the beam training process M_k times with the BS candidates, making the method not feasible for networks with a large number of BSs such as a dense cell-free mmWave network considered in this work.

On the other hand, increasing the number of RF chains can accelerate the beam training process in both fully-sweep and our proposed methods. A higher M enables more parallel TRN exchanges with multiple BSs at once, thus reducing the number of sweep in beam training. Under a large ratio of N/M, our proposed method can perform 100% faster than the fully-sweep method. Thus, our proposed method is scalable to the increasing number of antennas. In cell-free mmWave networks, the use of large M and N is necessary to increase the system's spectral efficiency. From Fig. 8, our proposed association method requires the least amount of time on beam

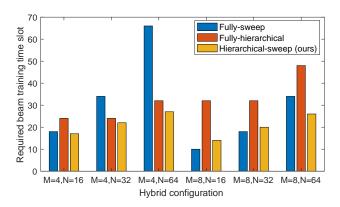


Fig. 8: Required time slots on beam training.

training compared to other methods, especially when M and N are large. This demonstrates that our method is very suitable for dense cell-free mmWave networks.

C. Energy consumption

The energy consumption on beam training depends on the number of exchanged training packets during the training process. In the hybrid architecture, the analog power consumption is affected by the number of RF chains and antenna elements used at the BS and UE. Following the power consumption per analog component such as phased-locked loop, local oscillator, splitter/combiner, phase shifter and mixer provided in [15], we calculate the energy consumption by a UE and the multiple involved BSs during the association process for different beam training methods.

The results are shown in Fig. 9. In general, the increasing of M and N leads to large system energy consumption. For all configurations, fully-hierarchical and our proposed method consume approximately similar amount of energy. Fully-sweep method consumes large amount of energy because high resolution beam generated by large number of antennas is always used for beam training. With a large ratio of N/M, fully-hierarchical and our proposed method reduce the energy consumption of fully-sweep method by up to 77%.

VI. CONCLUSION

In cell-free mmWave networks, the UE association is essential to determine the optimal selection of multiple serving BSs to provide data streams for the UE. The association process has to be performed in an efficient way to minimize the overhead. Our proposed association method can accelerate the beam training process by up to 100% compared to the fully-hierarchical method. It can achieve up to 77% less energy consumption compared to the fully-sweep method. Its scalability with many RF chains and antennas makes our proposed association method feasible for the practical implementation in dense cell-free mmWave networks. We also showed that using many RF chains and antennas in channel estimation contributes to reducing the interference during association process. For future work, we will investigate the performance of cell-free mmWave networks under dynamic environment.

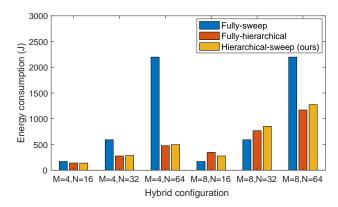


Fig. 9: Energy consumption during beam training process.

ACKNOWLEDGMENT

This work has received funding from the European Union's Framework Programme for Research and Innovation Horizon 2020 under Grant Agreement No. 861222 (MINTS project).

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