

DATA-DRIVEN TECHNIQUES FOR JOINT INFORMATION-POWER-TRANSFER AND JOINT COMMUNICATION-SENSING

BY

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A Thesis Presented to the
COLLEGE OF GRADUATE AND INTERDISCIPLINARY STUDIES
KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

ELECTRICAL ENGINEERING

May, 2024

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

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ACKNOWLEDGMENTS

First, I thank the almighty, the all-knowing, the only true god, Allah. This thesis would never have been possible if not for god's guidance and blessings. My thanks extend to my family. Their heartfelt support was always appreciated and their encouragement was a part of god's blessings. I am also grateful to my supervisor, Dr. Mudassir Ali Masood, and Dr. Ali Arshad Nasir for their continuous guidance and support for the past three years. It has been and it will always be - a pleasure working with you.

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THESIS ABSTRACT

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TITLE OF STUDY: Data-Driven Techniques for Joint Information-Power-Transfer and Joint Communication-Sensing Systems

MAJOR FIELD: Electrical Engineering

DATE OF DEGREE: March, 2024

This work explores the capabilities of machine learning tools to design system parameters and resource allocations for some next generation promising technologies in wireless networks. We consider co-located MIMO and cell-free MIMO wireless systems, where the corresponding base stations are required to perform two tasks. To that end, two types of base stations are considered; base stations that jointly perform communication and power transfer, and base stations that jointly perform communication and sensing. We propose a fully supervised training algorithm for deep learning models to predict allocation parameters for joint information and power transfer given a certain beamforming scheme. Also, we investigate unsupervised training paradigms to optimize beamforming vectors for integrated communication and sensing (ISAC) cell-free MIMO systems. Results show that the proposed supervised DL approach suc-

cessfully learns to generate power allocation parameters, for a joint information and power transfer MIMO system, that are close to the solution of the corresponding convex optimization solver tool, CVX, with a maximum mean square error (MSE) of -47.14 dB. On the other hand, the unsupervised DL approach successfully achieves a balanced, jointly-maximized, sensing and communication performance in cell-free ISAC systems. The main advantage of the DL approaches is to replace the time-consuming CVX solvers in real-time scenarios.

ملخص الرسالة

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عنوان الدراسة: طرق بيانية لتصميم أنظمة الاتصال اللاسلكي ونقل الطاقة، وأنظمة الاتصال اللاسلكي والاستشعار

التخصص: الهندسة الكهربائية

تاريخ الدرجة العلمية: مارس 2024

تستقصي هذه الأطروحة مدى قدرة الذكاء الصناعي وأدواته على تصميم أنظمة الاتصالات اللاسلكية الحديثة والمستقبلية الواعدة، وذلك عن طريق حساب بعض عوامل تلك الأنظمة التي تعين على توزيع الموارد اللاسلكية بشكل فعال. تركز هذه الأطروحة على دراسة نوعين من الأنظمة اللاسلكية متعددة المدخلات-متعددة المخرجات (م.م.م.م). محطات الإرسال في كلا النظامين تتطلب أداء مهمتين بشكل متناسق. النوع الأول من الأنظمة يعنى بالاتصالات مع توفير قدر من الطاقة للمستخدمين، والنوع الثاني من الأنظمة يقوم بدوري الاتصال والاستشعار معا. نقدم في الجزء الأول هذا البحث خوارزمية تدريب باستعمال قاعدة بيانات كاملة التصنيف لحساب معاملات نقل المعلومات والطاقة المشتركة في النظام الأول، كما نقوم في الجزء الثاني من هذا البحث بدراسة نماذج التدريب غير المراقبة (أي باستعمال قاعدة بيانات غير مصنفة) لحل مسألة تصميم المتجهات الشعاعية في أنظمة الاتصالات والاستشعار اللاحلوية. تفيد نتائج البحث بأن الطريقتين المقترحتين قادرتان على ما يلي: أولاً: حققت طريقة التدريب كاملة الرقابة نتائج متقاربة مع نتائج حل الأمثلية المحدبة. ثانياً: تثبت النتائج أن ما اقترحنه من طريقة التدريب غير المراقبة ناجع في تصميم الأنماط الإشعاعية المناسبة لتحري أداء متوازنا بين الاتصال والاستشعار. طرق الذكاء الصناعي التي نقدمها في هذا البحث واعدة من حيث قدرتها على العمل في الظروف الواقعية لقدرتها على حساب المطلوب في فترة زمنية أقصر بكثير مما قد تستغرقه خوارزميات الأمثلة التقليدية.

CHAPTER 1

INTRODUCTION

Fifth generation (5G) and sixth generation (6G) technologies are envisioned to accommodate denser networks, which meets the demands of the continuously increasing number of connected devices [3]. To maintain a reliable flow of information in such networks, an optimized resource allocation policy is required. Resource allocation (RA) problems aim to optimize a set of system parameters, such as beamforming patterns and transmit power [4], to achieve a certain objective, such as maximizing the sum-rate [5] or mutual information [6], or minimizing the radiated power [7] or interference [8]. Clearly, the allocation resources are limited by the available power and/or bandwidth. Also, threshold conditions may be applied to the RA problem in order to guarantee a certain quality of service (QoS) level or to avoid trivial solutions. Therefore, in general, resource allocation problems are constrained optimization problems. Typically, such optimization problems require solutions of high complexity [9], which can cause undesirable latency in the system.

To address the complexity problem, many researchers in the communication and

computer science fields focused on training deep learning (DL) models to predict the output parameters of the target resource allocation problem [10]. A feed forward DL model can replace the complex, iterative algorithms by direct matrix multiplication and element-by-element nonlinear functions, thus reducing the complexity significantly [10], [11]. Moreover, DL based solutions usually achieve highly accurate predictions, since such solutions provide universal approximation functions [12] that can be tuned offline [11] using appropriate datasets. In general, model architectures used for power allocation problems in literature are mostly fully connected neural networks (FCNNs), e.g., [10], [11], [13], with few hidden layers. Other works considered using different architectures such as convolutional neural networks (CNNs) [14], [15] and recurrent neural networks (RNNs) [16], [17]. In this work, we leverage such models to solve the resource allocation problem in multiple input multiple output (MIMO) wireless systems that employ some 5G/6G enabled technologies such as wireless information and power transfer (WIPT) [18] and integrated sensing and communication (ISAC) [19]. Specifically, we consider RA for massive-MIMO WIPT networks and beamforming for cell-free ISAC networks. Table 1.1 includes the abbreviations used in this work.

We pursue two publications from this work. The two publications and their current status are as follows.

1. A Deep Learning Model for Optimizing Downlink Parameters of Wireless Information and Power Transfer in Massive MIMO Networks. International Journal of Communication Systems. The paper is currently in the second review.

2. Unsupervised Learning Approach for Beamforming in Cell-Free Integrated Sensing and Communication. The paper is to be submitted.

Notation: We use boldface for vectors and matrices, where vectors are represented by lowercase letters ($\mathbf{v}$) and matrices are represented by uppercase letters ($\mathbf{V}$). We define $\mathbf{I}_N$ as the identity matrix of a size $N \times N$ and δ_n as a vector of zeros except for the n -th entry which has a value of 1. We use a format for sets such as $\mathcal{A}, \mathcal{B}$ and $\mathcal{C}$. $\mathbb{R}$ and $\mathbb{C}$ represent the sets of real and complex numbers, respectively. $\Re(\mathbf{v})$ and $\Im(\mathbf{v})$ represent the real and imaginary parts of the elements of the vector $\mathbf{v}$. The notation $\mathcal{CN}(m, n^2)$ represents the complex Gaussian distribution with a mean, m , and a variance, n^2 . The operator $\text{blk}[\mathbf{A}_1, \mathbf{A}_2]$ stacks the 2D matrices, $\mathbf{A}_1$ and $\mathbf{A}_2$, along a third dimension. The operators $\text{TR}(\cdot)$ and $\mathbb{E}[\cdot]$ represent the trace and mathematical expectation, respectively.

Table 1.1: List of key abbreviations.

Acronym	Definition	Acronym	Definition
1D-CNN	One-dimensional convolutional neural network	ISAC	Integrated sensing and communication
3GPP	3rd Generation Partnership Project	MC	Multi-carrier
5G	5th generation	MEC	Mobile edge computing
6G	6th generation	MIMO	Multiple-input multiple-output
ADMM	Alternating direction method of multipliers	MISO	Multiple-input single-output
AP	Access point	mMTC	Massive machine type communication
BN	Batch normalization	ML	Machine learning
BS	Base station	MSE	Mean squared error
CAE	Convolutional autoencoder	NOMA	Non-orthogonal multiple access
CLSTM	Convolutional long-short term memory	Pos-1	Position distribution configuration-1
CNN	Convolutional neural network	Pos-2	Position distribution configuration-2
CPU	Central processing unit	PS	Power splitting
CSI	Channel state information	QoS	Quality of service
CVX	Convex	RA	Resource allocation
DBN	Deep belief network	RBM	Restricted Boltzmann machine
DL	Deep learning	ReLU	Rectified linear unit
DNN	Deep neural network	RNN	Recurrent neural network
DRL	Deep reinforcement learning	SDP	Semidefinite programming
EE	Energy efficiency	SINR	Signal to interference plus noise ratio
EH	Energy harvesting learning	SSNR	Sensing signal to noise
ELU	Exponential linear unit	ST	Sensing target
FC	Fully connected	SWIPT	Simultaneous wireless information and power transfer
FCNN	Fully connected neural network	TS	Time switching
ID	Information decoding	UE	User equipment
IoT	Internet of things	ZFB	Zero forcing beamforming

CHAPTER 2

LITERATURE SURVEY AND CONTRIBUTIONS

The advancement of smart device technologies has resulted in an exploded number of diverse connected devices. Consequently, the data traffic is continuously increasing. The resulting tremendous demands necessitated the establishment of new communication standards, which are currently reformed as 5G and 6G technologies. Such technologies allow communication at high data rates, increase the capacity of cellular networks, and increase spectral efficiency (SE) [20]. 3rd Generation Partnership Project (3GPP) summarizes 5G requirements in four points [21]. One of which is Ultra Reliable and Low Latency Communications (URLLC), which is a highly required feature for real-time services such as unmanned aerial vehicle (UAV) networks [22], [23], vehicular networks [24], internet of things (IoT) [25], massive machine type communication (mMTC) [26], mobile edge computing (MEC) and cloud computing [27], [28]. Next generation technologies are expected not only to support the mentioned

services on an individual level, but also to support hybrid networks that are composed of two or more of the different services mentioned above (e.g., [29], [30], [31]). In both cases, a careful distribution of the limited resources is a must in order to maintain reliable communication channels while minimizing the expected trade-off effects on the communication speed. This process is represented by an RA problem. In this regard, a tremendous amount of research has been dedicated to RA problems in various wireless scenarios and applications [23], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51]. The algorithms used to solve the optimization problems proposed by the mentioned works, however, can be computationally demanding and time consuming, which is not desirable in real-time scenarios.

Recent works focusing on RA for wireless networks have explored machine learning tools as a potential solution that can replace the time-consuming optimization strategies. DL models have specifically attracted many researchers in the field due to their capabilities of representing complex relationships [12] and the possibility of fully training them offline [11]. Sanguinetti, Zappone and Debbah [11] proposed a generic FCNN design to allocate the available power to users in massive MIMO systems. The authors showed that the positions of the users with respect to the BS are sufficient for the network to learn the allocation process in a supervised fashion. Andrea *et al.* [13] trained a group of FCNNs with different numbers of neurons per layer to solve the RA problem for uplink cell-free massive MIMO systems. The authors reported that while pilot contamination does not affect the performance of the trained FCNNs,

shadowing causes noticeable degradation in the performance of the DL models. Xia *et al.* [14] fed the multiple-input-single-output (MISO) channel coefficients to a CNN to predict the optimum beamformer that maximizes the weighted sum rate. To ensure that the network learns the objective properly, a loss function based on the negative of the weighted sum rate was used for training instead of the standard mean square error (MSE) loss. Huang *et al.* [15] also proposed a different loss function, where the constraints were included in the loss as penalty terms. The authors trained a resource allocating CNN to maximize the sum data rate and energy efficiency in MIMO-non-orthogonal multiple access (NOMA) networks. Zhao, Niemegeers and De Groot [10] compared the performance of their proposed deep neural network (DNN) for predicting the power allocation in cell-free massive MIMO networks with the performance of the solver they proposed in terms of running time. They found that the solver spends on average 316 times the time needed by the DNN to evaluate the required power allocation.

The main objective of this work is to leverage DL to allocate resources in MIMO wireless networks, where a dual-function base station (BS) technology is deployed. Specifically, we are interested in two promising 5G/6G technologies, WIPT and ISAC. A BS that supports WIPT is responsible for data and power transmission to the users. WIPT receivers can be implemented using different architectures including time switching (TS) [52], power splitting (PS) [52], integrated receiver [52], and antenna switching (AS) [53]. A lot of work has been done on WIPT since it was first proposed. The main issue of this technique is the tradeoff imposed by data trans-

mission and power transmission on each other. For instance, Clerckx [54] focused on designing a WIPT transmitter model that considers the rectifier's nonlinearity. The author derived a mathematical expression for WIPT transmitted waveform as a function of the channel state information (CSI). As such, the author characterized the rate-energy region of the proposed system. Chen *et al.* [55] focused on some of WIPT issues such as rate-power tradeoff, security, and short distance limits, and aimed to enhance WIPT using multi-antenna architectures. In the domain of RA problems for WIPT systems, similar objective functions to the ones incorporated for RA problems in conventional communication systems are used. The difference, however, mostly lies within the constraints, where WIPT-based RA problems require additional constraints depending on the architecture adopted by the BS. For example, Jeong, Ju, and Chae [56] considered maximizing the end-to-end rate in WIPT-assisted two-hop relaying MIMO systems. They proposed a couple of algorithms to obtain the beamformer and assign the antennas to either perform information decoding (ID) or energy harvesting (EH) so that the end-to-end data rate is maximized. On the other hand, Wang *et al.* [57] proposed an energy efficiency (EE) maximization RA problem to design the downlink of multi-cell massive MIMO-NOMA networks featuring power transfer. The authors tackled the nonconvexity of the RA problem using nonlinear fraction programming and solved the resulting problem via a distributed alternating direction method of multipliers (ADMM), which was proposed in the same work. Lee *et al.* [58] formulated an optimization problem that seeks a time fraction for ID and a transmitter covariance matrix that maximize the sum rate variable for two users in wireless

MISO systems. Nasir *et al.* [7] used beamforming strategies to formulate a couple of optimization problems for PS and TS architectures. One problem adopted a min-max strategy for the power radiated from the BSs, whereas the other problem adopted the max-min data rate strategy. The output parameters of these problems included the beamforming vectors at each BS, the corresponding power splitting factors, and time fraction for EH. The work differentiated between two types of power allocation problems in WIPT systems, namely, the receive architecture and the transmit architecture. The receive architecture refers to the conventional simultaneous WIPT (SWIPT) design, where EH signals are identical to ID signals at the transmitter. The transmit architecture, on the other hand, assumes a distinct signal design for EH and ID at the transmitter. Nasir *et al.* [2] proposed the transmit-TS architecture. They formulated a max-min data rate strategy with conjugate and zero forcing beamforming to obtain the allocated ID and EH power and the corresponding ID and EH time fractions in WIPT-assisted massive-MIMO systems. Upper bound approximations are applied to the objective, logarithmic, function and the inequality constraints to decouple the optimization variables and convert the problem to a convex optimization problem. The resulting problem was solved iteratively using the CVX toolbox in MATLAB.

However, as discussed before, iterative and complex optimization algorithms for the RA problem may not be suitable for real-time applications. Nevertheless, only a few works focused on using DL algorithms for RA in WIPT systems. Both Luo *et al.* [59] and Tang *et al.* [60] proposed a deep belief network (DBN) to predict TS and PS-SWIPT parameters, respectively, in multi-carrier non-orthogonal multiple access

(MC-NOMA) networks. The DBN is composed of a series of restricted Boltzmann machines (RBMs), each of which is composed of a couple of fully connected layers. These layers were initiated via unsupervised training. Then, the entire DBN was trained in a supervised fashion using the data generated by solving the proposed optimization problem. Thien, Tuan and Koo [61], on the other hand, utilized a feed-forward FCNN with only two hidden layers to predict PS-SWIPT parameters in a single-input-single output (SISO) system that is vulnerable to eavesdropping. SISO PS-SWIPT channels were also considered in a previous work by the same authors [62], where FCNNs and three recurrent neural network (RNN) structures were used for predicting the system parameters. The model structures were compared in terms of performance and running speed. Lee *et al.* [63] designed a network that predicts the power policy and the splitting coefficient in SWIPT systems using two separate FCNNs.

The second technology considered in this work is ISAC. There are many promising applications of ISAC that have attracted a lot of researchers over the last decade. Unlike WIPT, for which the application mostly considered is relaying [64], [65], [66], [67], [68], ISAC is used for supporting various technologies in Beyond 5G and 6G such as radar [69], localization [70], vehicular networks [16], [71], [72], and UAV assisted networks [73]. On the other hand, like WIPT systems, ISAC system performance is affected by a tradeoff between the data rate and sensing accuracy. Dong *et al.* [74] studied such tradeoff after proposing a general scheme for RA in ISAC systems. The general scheme depended on the fairness of what the authors defined as sensing QoS.

Xu *et al.* [75] proposed an RA problem that emphasizes the security of the ISAC system. The system settings were centered around a single multi-antenna ISAC BS. The BS dedicated certain beams for scanning the surroundings, which results in the acquisition of multiple snapshots, each of which represents events within a certain time frame. The proposed RA problem aimed to maximize the sum secrecy rate for the system. The non-convex problem was constrained by a minimum data rate threshold and a maximum information leakage for a registered user. After handling the nonconvexity of the problem, the authors proposed an iterative algorithm based on block coordinate descent to obtain a suboptimal solution. Dong and Liu [76] allocated the communication power and the sensing bandwidth to minimize the Cramer-Rao bound for the estimated location error of the detected objects in a single cell MIMO system. The authors proposed an iterative solution that starts by assuming an evenly allocated bandwidth, and then updates the bandwidth and the power allocation to achieve a better value for the objective. The novelty of the objective functions used to optimize the parameters in an ISAC system, compared to the objectives of RA in conventional and WIPT systems, accounts for the different nature of the sensing task. Tang and Li [77] reported that the use of mutual information for ISAC system design had been extensively discussed in the literature. Such metric can also be used to propose an RA problem for ISAC-MIMO systems.

One system of interest, in which ISAC technology can be deployed, is cell-free wireless networks. Few recent works have considered such systems. Demirhan and Alkhateeb [1] proposed a joint sensing and communication beamforming optimiza-

tion problem, where the objective is to jointly maximize sensing signal-to-noise ratio (SSNR) and signal-to-interference plus noise ratio (SINR) subjected to the power budget constraint at each access point (AP). Their results show that the joint optimization problem outperforms other methods where sensing or communication beams are designed a priori. Liu *et al.* [78] considered the problem of AP selection (i.e., transmitting or receiving modes) to improve the degrees of freedom in cell-free ISAC networks. The authors formulated a sum-maximization problem to jointly optimize the AP selection mode, the beamformer vectors, and the receive filter vectors. On a related note, Xu *et al.* proposed an AP selection and user association framework for ISAC-assisted cellular network with multiple APs. Other works that studied the power allocation problem in cell-free ISAC-assisted networks include [79], [80], [81], [82].

The use of DL to allocate system parameters to design the downlink of general ISAC systems is abundant in literature [83]. For instance, Liu *et al.* [84] proposed a couple of DNNs to estimate sensing and communication channels for an ISAC system. Liu *et al.* [16] used a recurrent neural network (RNN) that is composed of convolutional long-short term memory (CLSTM) subunits. Such a network is expected to capture the spatial and temporal properties of the environment. The network was trained to predict the angles of the vehicles within the range of an ISAC multi-antenna BS. The predicted angles were used for designing a predictive beamformer for the BS. The training was done offline in a supervised fashion. A similar work was done by Liu *et al.* [17], where RNN with CLSTM subunits was used for direct beamforming

prediction in the same system considered by [16]. In [17], the authors first proposed a sum-rate maximization problem constrained by Cramer-Rao lower bound as a sensing error metric. Solving this problem provided means to both generate an unsupervised dataset and a baseline for comparison between the conventional CVX solver and the unsupervised learning scheme. Mu *et al.* [85] proposed an FCNN that predicts the beamformer and the angular parameters of the detected vehicles given the received signal at the ISAC-assisted roadside units. Liu *et al.* [86] proposed a DL network architecture to manage interference in ISAC systems by allocating power. To that end, the authors utilized unsupervised learning for training. They also used transfer learning to predict a proper beamforming scheme for interference management.

Since studies on ISAC-assisted cell-free MIMO systems are recent, solving the power allocation problem using DL techniques was not considered so far. The only exception is the recent work in [87], where the authors considered a deep reinforcement learning (DRL) solution to optimize power coefficients for the data and the pilot. However, this solution requires discretizing the optimization variables, since the action space is usually discrete.

It is worth mentioning that many works utilized DL solutions to allocate resources in cell-free MIMO and massive MIMO wireless non-dual systems (i.e., where ISAC is not deployed) [88]. In [89], for example, the author addressed three power allocation problems cell-free massive MIMO systems through deep supervised learning and DRL. Zaher *et al.* [90] formulated a centralized optimization problem for power allocation in cell-free networks. They then proposed a distributed DNN solution, highlighting

one advantage of using DL techniques in such systems by alleviating the need of using front-haul links for collecting information from different APs. Many works considered unsupervised learning for cell-free massive MIMO systems [91], [92], [93], [94]. Nikbakht, Jonsson and Lozano [91] reduced the dimension of the input to the DNN by using the effective gain vector instead of the concatenated large scale coefficients, which enabled them testing the performance on massive MIMO systems with large number of APs. However, such solution is not possible without collecting information from all APs at a central processing unit (CPU). In [92], two unsupervised training paradigms were studied, a decentralized paradigm (i.e., distributed) and a partially decentralized paradigm, to perform hybrid performing in free-cell massive MIMO systems. Zhang *et al.* [93] proposed unsupervised training schemes to solve the power allocation problem for the uplink and the downlink of cell-free massive MIMO systems. Rajapaksha *et al.* [94] considered hardware impairment in their problem design. Other works focusing on employing DL (supervised or unsupervised) or DRL for RA in MIMO or massive MIMO cell-free systems include [95], [96], [97].

The contributions of this work include the following.

1. We propose a supervised DL scheme to solve the resource allocation problem in cellular massive-MIMO transmit-TS WIPT systems.
2. The proposed supervised DL approach generates highly accurate predictions and yields more than 10,000 times computational efficiency compared to the existing CVX-based approach.
3. To alleviate the need for a time-consuming channel estimation algorithm, we

propose a training scheme that only requires the user distances, rather than channel information.

4. We propose an unsupervised DL scheme to solve the joint sensing and communication beamforming problem in cell-free ISAC systems.
5. The proposed unsupervised DL scheme provides a distributed solution to the beamforming problem, which reduces the computational load on the CPU.
6. Compared to an existing centralized CVX-based approach for the joint beamforming problem, the proposed unsupervised DL scheme is more computationally efficient, by at least 3 orders of magnitude, without compromising the quality of the predicted beamformers.

CHAPTER 3

BACKGROUND

This work requires integrating two fields, namely, DL and wireless communication. This chapter explains the necessary concepts pertaining both fields. The first section focuses on the concepts used from the field of DL, including the different architectures and training schemes that are related to the work. The second section explains the wireless communication aspects of this work, including the basic ingredients of such systems and the optimization problems used for benchmarking or for generating datasets.

3.1 Deep Learning

DL is deployed by training neural networks consisting of multiple layers, typically more than 3 layers. DL is viewed as a subset of a larger group of techniques known as machine learning (ML). Different architectures were proposed to increase the robustness or to alleviate issues concerning the preceding architectures. These architectures mainly include FCNNs, CNNs, RNNs and attention modules which are the building

blocks of the transformers. Depending on the task at hand, different schemes are designed to carefully train and fine-tune the parameters of the constructed DNN. Two common training schemes in the field of DL-based communication are the supervised and the unsupervised training. Since only FCNNs and CNNs are used throughout this work, we will narrow our discussion of the different architectures to these two models in Sec. 3.1.1. The differences between the supervised and the unsupervised training schemes are then discussed in Sec. 3.1.2.

3.1.1 Model Architectures

Owing to the expandable structures of DNNs, their capabilities of representing complex relationships were leveraged in different engineering and scientific fields. FCNNs, for instance, are comprised of multiple layers each of which is usually composed of several neurons that represent a certain level of the features of the provided data. For FCNNs, neurons of consequent layers are fully connected (FC). These connections are characterized by weight matrices, which are learned through the training process.

Figure 3.1 shows a descriptive illustration of a general FCNN during the training phase. The dimensions (i.e., the number of neurons) of the input and output layers should match the size of the input data and the size of the parameters targeted for inference, respectively. On the other hand, there is no strict rule for selecting the number of the hidden layers and the size of each one of them. Typically, the number of hidden layers in DL-based communication oriented works are 4-5 layers.

Due to the dense connections between layers in an FCNN, every neuron in the

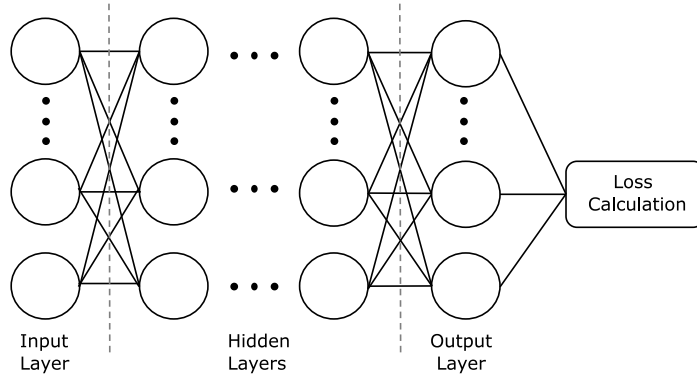


Figure 3.1: A generic FCNN scheme.

$(n + 1)$ -th layer retains information from all neurons in the n -th layer. Thus, FCNNs are oblivious to the spatial features of the input, since they require narrowing the scope of the information to a certain neighborhood. Therefore, when spatial features of the input data are considered, CNNs are usually used instead of FCNNs. CNNs utilize filters with trainable parameters that are convolved with the input data. There is no strict rule for selecting the filter size, the stride of the filter, padding, or the number of channels of a convolutional layer.

CNNs are mainly composed of convolutional layers, and they may also include pooling layers and batch normalization (BN) layers. Unlike convolutional layers, pooling layers do not include learnable parameters and do not change the number of input channels. Pooling layers represent every kernel in the feature maps by a single value, such as the maximum, the minimum or the average values of these kernels. BN layers are used to standardize the input feature maps in order to stabilize the training process of a CNN.

Figure 3.2 shows a sample CNN with a single convolutional layer, a single pooling layer, a flattening layer and FC layers leading to the output. It is a common practice to

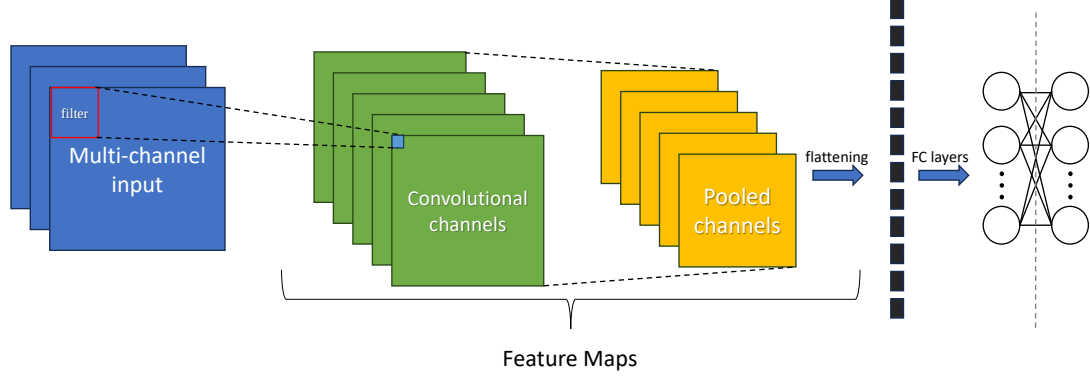


Figure 3.2: A simplified CNN scheme.

add more convolutional layers to increase the receptive field of the network. However, it should be noticed that a larger network is harder to train and is prone to overfitting. Therefore, sufficient training samples and BN layers are necessary to train such CNNs.

The input-output size relationship of a convolutional layer is given by

$$M_o = \left\lfloor \frac{M_i - (f - 1) + 2p}{s} + 1 \right\rfloor, \quad (3.1)$$

where M_i is the input size, M_o is the output size, f is the filter size, p is padding size and s is the stride.

Through padding size and stride, the convolution operation can be adjusted so that the input size and the output size are the same. On the other hand, some CNNs are meant to represent the input features in lower dimension than the original's, such as encoder CNNs. To eventually retrieve the original size of the reduced representation of the input, through a decoder CNN, it is necessary to inverse the convolution operation in terms of its effect on the size. Thus, another common layer in CNNs known as transposed convolutional layer is used for retrieving the size of a convolutional layer

given the same filter size, padding and stride.

One common practise in CNNs is to consider skip-connections. Skip-connections connect certain feature maps to non-adjacent convolutional layer. The connected feature maps can be concatenated, added, or multiplied with the non-adjacent feature maps. This step usually improves the performance of the CNN and facilitates the training process by creating alternative paths for the flowing gradients.

3.1.2 Training Schemes

In DL, supervision is a set of training schemes that vary according to the way they incorporate the labels of the dataset in the loss function. Supervised training completely depends on the labels in the dataset. Using MSE or cross entropy loss as loss functions indicates that the training scheme is supervised, since these functions require target values (i.e., a ground truth) for evaluation. Unsupervised training, on the other hand, does not require labels for evaluating the loss.

Most of the work done on deploying DL for wireless communication tasks used either supervised or unsupervised schemes. On the other hand, little work was done using other supervision schemes such as semi-supervised learning [98], [99], [100]. In this kind of learning, only a fraction of the dataset is labeled. The labeled data points are used to generate pseudo labels for the unlabeled data points and use these pseudo labels for further training the networks. Another promising, yet nearly not investigated in the field, supervision scheme is weakly supervised learning [101]. This scheme is useful when the dataset is completely labeled, but the label level is not at

the same level required by the target task [102].

One central training scheme to this work is the teacher-student architecture. This method can be deployed for non-supervised learning (e.g., semi-supervised or unsupervised learning). Generally, a teacher model is initially trained to generate weak labels from which the student model can learn. Different forms of teacher-student architectures were used in recent DL works for object detection tasks [103], [104], [105], [106], [107]. We use a novel version of the teacher-student training technique to solve the beamforming problem in cell-free ISAC systems. The detailed description of this technique is found in Sec. 5.4.

3.1.3 Related DL Notions

Some technical and common notions in the field of DL are explained here, namely, activation functions, overfitting and early stopping. The first common notion is the activation functions. It can be noticed that the operations discussed in Sec. 3.1.1 for FCNNs and CNNs are linear. However, many complex relationships in fields where DL is applied cannot be described by linear models. Thus, extra layers are added, typically one layer after each convolutional or FC layer, where non-linear functions are applied to the output of the previous layer. These non-linear functions are known as activation functions and the corresponding layers are known as activation layers. The activation functions that will be used in this work are the leaky rectified linear unit (LeakyReLU) and exponential linear unit (ELU), which are respectively defined as follows

$$\text{LeakyReLU}(x) = \begin{cases} x, & \text{if } x > 0 \\ mx, & \text{if } x \leq 0 \end{cases} \quad (3.2)$$

and

$$\text{ELU}(x) = \begin{cases} x, & \text{if } x > 0 \\ \alpha(\exp(x) - 1), & \text{if } x \leq 0 \end{cases}, \quad (3.3)$$

where m and α are the activation function constant parameters.

During the training phase of the model, the dataset is usually divided into training points and validation points. Model parameters (weights) are updated according to its performance on the training set. However, the generality of the model may be compromised, since it is trained on a limited number of data points. Thus, the model is evaluated on the validation set to track its performance on unseen data points. If the model's performance on the training set is much better than its performance on the validation set, the model is said to be overfitting the training samples.

One common sign of overfitting is the decline in the validation performance curve after a certain number of training epochs. Since the model's performance on the validation set indicates its generality, an early stopping criteria is usually followed to terminate the training if no improvement in the validation set is observed for a certain number of epochs.

3.2 Wireless Networks

Chapter 1 discussed the potential of futuristic wireless networks in supporting various applications. Chapter 2, on the other hand, shows the tremendous amount of work done to design efficient and robust wireless systems to perform different tasks. This section describes some of the underlying technologies that support such systems.

3.2.1 Multiple Antenna Technology

The main advantage of using multiple antenna technology over a single antenna is increasing the data rate [108], [109] by providing more diversity to the system [110]. Multiple antenna arrays enable focusing and steering electromagnetic wave into a desired direction, which is known as beamforming. Beamforming is achieved by controlling the gains and phase shifts of the received or transmitted signals at each antenna. These gains and phase shifts are arranged into a complex-valued vector whose length equals the number of antennas. This vector is known as the transmit/receive beamforming vector.

When multiple single antenna users are served by a BS equipped with multiple antenna, the corresponding channels are modeled as in typical MIMO wireless systems. Therefore, the mentioned setting is usually considered a MIMO system. If the number of BS antennas is much larger than the number of users, the resulting system is known as massive MIMO [111]. Massive MIMO increases beamforming capabilities by narrowing the beamwidth and, consequently, reduces power consumption over the channels and further increases the data rate and spectral efficiency [112], [113]. Finally,

if the entire network is served by a single BS equipped with multiple antennas, the system is usually referred to as co-located MIMO or co-located massive-MIMO to differentiate between it and the case of cell-free networks, which is discussed in the following subsection.

3.2.2 Cell-free Networks

In conventional MIMO cellular networks, users within every cell are served by a single BS that is assigned to that specific cell. In cell-free networks, however, users are served by a group of low-cost and low-power APs simultaneously. These APs are distributed over a geographical area and are connected to a CPU that arranges the tasks of every AP. APs also cooperate with each other for information relaying and synchronization, unlike conventional cellular networks that only depend on the fronthaul connections to the CPU. If the number of APs is large, the resulting system is usually called cell-free massive MIMO even if each AP is equipped with a single antenna [114].

Cell-free systems are promising in terms of meeting the demands of the next generation technologies, such as energy and spectral efficiency, low latency and reliability [115]. It was found that cell-free schemes outperform conventional small-cell networks tremendously in terms of 95%-likely per-user throughput, energy efficiency and spectral efficiency [116], [117], [118], [119].

Despite the theoretical gains cell-free networks promise, the required amount of fronthaul signaling and the complexity of the tasks (e.g., channel estimation and RA) performed by the CPU hinders the practical implementation of such systems even

with cooperation between the APs [120]. One way of reducing the fronthaul signaling burden is by considering decentralized or semi-decentralized alternative schemes, where an AP performs a part of the tasks without relying on external information. We consider a DL-RA scheme, for cell-free ISAC setup, with centralized offline training and online distributed deployment.

3.2.3 Information and Power Transfer

Out of the different WIPT receiver architectures mentioned in Chapter 2, we consider the transmit-TS massive MIMO system [2]. A schematic of the transmitter and the n -th user receiver of such system is shown in Figure 3.3. The transmit-TS system is featured by distinct design of the energy symbols, which is used for EH by the receiver, and the information symbols, which is used for ID by the receiver. Considering a massive MIMO setting reduces the effects of fading channels on WIPT systems and, hence, allows a longer EH distance [55].

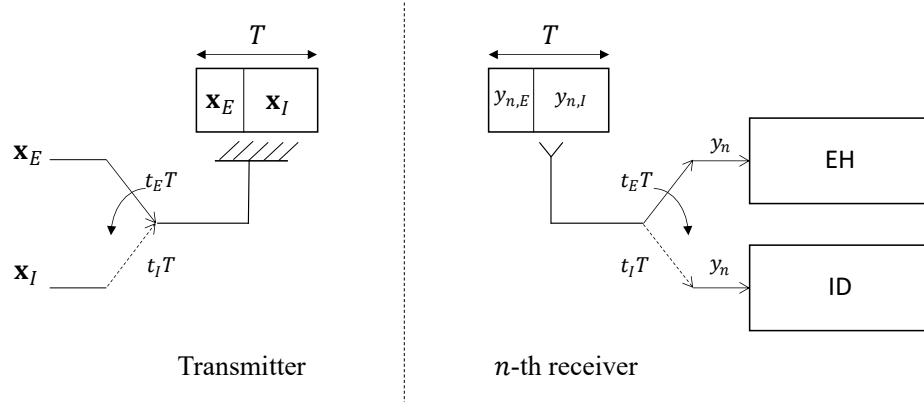


Figure 3.3: Transmit-TS architecture. Adapted from [2].

Given receive beamforming schemes, e.g., zero forcing beamforming (ZFB) and conjugate beamforming (CB), for ID and EH, the problem formulated in [2] targets

maximizing the minimum data rate while maintaining an energy threshold for EH and ensuring a power budget constraint. Since the considered architecture is TS, the optimization parameters include allocated power coefficients and ID/EH time fractions (i.e., t_E and t_I in Figure 3.3). Additional constraints include the positivity of the optimization variables and the completeness of the time fractions (i.e., they add up to 1).

The non-convexity of the resulting problem was addressed by replacing the data rate function with a concave lower bound function, and replacing the budget power constraint by an approximation. The authors also reduced the complexity of the problem by optimizing the ID power for only one user, where the allocated ID power for the rest of the users is calculated based on the balanced rates between the users at the optimum solution (Refer to Appendix A in [2] for the proof).

3.2.4 Communication and Sensing

An efficient ISAC system is expected to perform the two functionalities, communication and sensing, simultaneously with minimal tradeoff between them. The target balance between the two functionalities is usually pursued by optimization problems that aim to maximize or minimize metrics that evaluate the performance of communication and sensing. Such metrics include SINR, throughput, and detection error for communication; and SSNR, mutual information and localization error for sensing. Notice that some works consider a single sensing target (ST) in their analysis [1], [79]. In particular, [1] considered a single path sensing model, where clutter and non-line

of sight sources are neglected.

We aim to jointly maximize SSNR and minimum user SINR to design the beamformer vectors in cell-free ISAC networks. One way to solve this problem was presented in [1], where SINR is first maximized after projecting the sensing beamformer to the null space of the communication channels. The resulting SINR is then used as a minimum threshold for the joint problem. To that end, the resulting joint problem is converted to a constrained problem where the SSNR objective is maximized while keeping the minimum user SINR above the threshold.

In other words, the described solution requires solving two optimization problems using CVX. The first problem was solved using the bisection algorithm, which requires solving the underlying optimization problem repeatedly. The second problem was solved by a change of variables to convert it into a semi-definite program (SDP) with a rank-1 constraint. The SDP problem was relaxed by removing the rank-1 constraint. The resulting variable is then projected into a feasible set of communication and sensing beamforming vectors. Such solution can undoubtedly inflict delays upon the system operations due to its complexity.

CHAPTER 4

WIRELESS INFORMATION AND POWER TRANSFER

4.1 System Model

Consider N users served by co-located antennas whose number is M . While all users can perform ID, only a fraction of nearby users, $N_1 < N$, are enabled to perform EH for a fraction of a time-slot, T . The index set for all users is denoted by $\mathcal{N}$. The nearby user index set is denoted by $\mathcal{N}_1$, whereas the far user index set is defined by $\mathcal{N}_2 = \mathcal{N} \setminus \mathcal{N}_1$. Figure 4.1 illustrates the stated configuration.

The channel state information (CSI) matrix is denoted by $\mathbf{H} \triangleq [\sqrt{\beta_1}\mathbf{h}_1, \dots, \sqrt{\beta_N}\mathbf{h}_N]$, where $\mathbf{h}_n \in \mathbb{C}^{M \times 1}$, $\forall n \in \mathcal{N}$, is the small scale fading channel vector for each user and β_n is the large scale fading. The small scale fading is assumed to be complex circular Gaussian random variable with zero-mean and unit variance. The large scale fading coefficient for the n -th user is modeled by $\beta_n \triangleq -30 - 10\gamma_n \log_{10}(d_n)$ (in dB), where

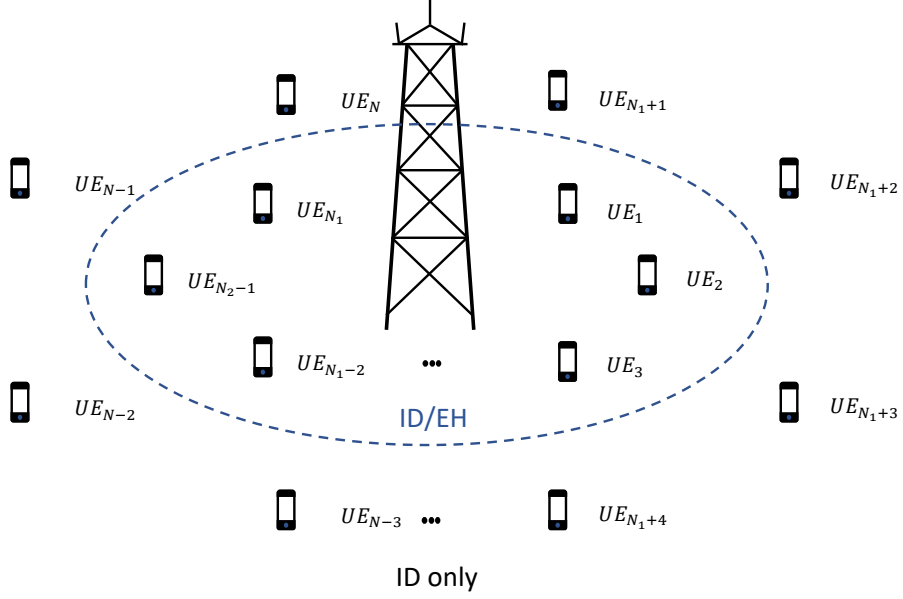


Figure 4.1: Massive-MIMO WIPT system considered in this chapter. The BS transmits ID signals for all users for a time duration of $t_I T$ and transmits EH signals for the nearby users (within the dotted circle) for a time duration of $t_E T$.

d_n is the distance between the n -th user and the BS and γ is the path-loss exponent.

It is assumed that CSI is available at the transmitter via standard channel estimation techniques.

ZFB and CB are utilized for information and energy transfer, respectively. Define $\mathbf{W} \triangleq [\mathbf{w}_1, \dots, \mathbf{w}_N] = \mathbf{H}(\mathbf{H}^H \mathbf{H})^{-1}$ as the ZFB matrix. Thus, the transmitted signals for ID and EH are given by $\mathbf{x}_I = \mathbf{W} \text{diag}(\sqrt{\mathbf{p}_I}) \mathbf{s}_I$ and $\mathbf{x}_E = \mathbf{H}_{N_1} \text{diag}(\sqrt{\mathbf{p}_E}) \mathbf{s}_E$, respectively, where $\mathbf{p}_I \triangleq [p_{I,1}, \dots, p_{I,N}]$ is the power allocation vector for ID, $\mathbf{H}_{N_1} \triangleq [\sqrt{\beta_1} \mathbf{h}_1, \dots, \sqrt{\beta_{N_1}} \mathbf{h}_{N_1}]$, and both $\mathbf{s}_I$ and $\mathbf{s}_E$ are the symbols designed to convey information and energy, respectively, such that $\mathbb{E}[|s_{E,n}|^2] = \mathbb{E}[|s_{I,n}|^2] = 1$.

The received signal at the n -th user is defined as

$$y_{S,n} = \sqrt{\beta_n} \mathbf{h}_n^H \mathbf{x}_{S,n} + v_n, \quad (4.1)$$

where $\mathcal{S} \in \{I, E\}$ and v_n is an additive i.i.d. Gaussian noise with zero-mean and a variance σ^2 . Equation (4.1) does not hold if the number of users is comparable to the number of transmit antennas [121]. As long as (4.1) holds, interference from other channels is mitigated by incorporating ZFB if $\mathcal{S} = I$, and CB if $\mathcal{S} = E$ [2]. As such, the total energy harvested by the n -th user, $E_n(\mathbf{p}_E)$, is given by

$$E_n(\mathbf{p}_E) \triangleq \eta \beta_n \sum_{n'=1}^{N_1} p_{E,n'} |\mathbf{h}_n^H \mathbf{h}_{n'}|^2, \quad (4.2)$$

where $\mathbf{p}_E \triangleq [p_{E,1}, \dots, p_{E,N_1}]$ is the power allocation vector for EH, $0 < \eta < 1$ is the energy conversion efficiency and both subscripts n and n' refer to the near user indices. Notice that (4.2) assumes a linear EH model.

Finally, the maximum attainable data rate for the n -th user is given by

$$r_n(t_I, p_{I,n}) = t_I \ln(1 + p_{I,n} |\mathbf{h}_n^H \mathbf{w}_n|^2 \beta_n / \sigma^2), \quad \forall n \in \mathcal{N}. \quad (4.3)$$

4.2 Information-Power Transfer RA Problem

The optimization problem proposed in [2] for RA in transmit-TS massive MIMO systems is given by

$$\max_{\mathcal{V}} r_1(t_I, p_{I,1}) \quad (4.4a)$$

$$\text{s.t. } E_n(\mathbf{p}_E) \geq e_n^{\min}/t_E, n \in \mathcal{N}_1, \quad (4.4b)$$

$$\xi t_I p_{I,1} + t_E \varphi_E(\mathbf{p}_E) \leq P_T, \quad (4.4c)$$

$$0 < t_I, 0 < t_E, t_I + t_E = 1, \quad (4.4d)$$

$$p_{I,1} \geq 0, \mathbf{p}_E \geq 0, \quad (4.4e)$$

where $\mathcal{V} \triangleq \{p_{I,1}, \mathbf{p}_E, t_I, t_E\}$ is the set of optimization variables, $e_n^{\min}$ is the energy harvesting threshold and P_T is the power budget at the BS. ξ and $\varphi_E(\mathbf{p}_E)$ are given by

$$\xi \triangleq \sum_{n=1}^N \frac{\beta_1 |\mathbf{h}_1^H \mathbf{w}_1|^2}{\beta_n |\mathbf{h}_n^H \mathbf{w}_n|^2} \|\mathbf{w}_n\|^2 \quad (4.5)$$

and

$$\varphi_E(\mathbf{p}_E) \triangleq \sum_{n=1}^{N_1} \|\mathbf{h}_n\|^2 p_{E,n}, \quad (4.6)$$

respectively.

ID power allocation for the rest of the users is given by

$$p_{I,n} = \frac{\beta_1 |\mathbf{h}_1^H \mathbf{w}_1|^2}{\beta_n |\mathbf{h}_n^H \mathbf{w}_n|^2} p_{I,1}, \quad n = 2, \dots, N. \quad (4.7)$$

While (4.4a) prioritizes increasing t_I and $p_{I,1}$, the threshold constraint (4.4b) is

the main factor that prevents t_E and $\mathbf{p}_E$ from being set to zero.

To solve problem (4.4), convex bounds and approximations are used to replace the objective and the threshold constraint, respectively. The resulting convex problem can be solved by off-the-shelf solvers, such as CVX. The computational complexity of the algorithm applied to solve problem (4.4) is $\mathcal{O}((N_1 + 3)^3(2N_1 + 5))$ [2].

4.3 Model Architecture

To enable a real-time computationally efficient solution to replace the complex CVX-based one, DL can be utilized. Specifically, a 3-stage DNN is proposed to facilitate predicting the optimization set, $\mathcal{V}$. Every DNN is trained to predict a subset of $\mathcal{V}$. This way, every DNN can focus on learning its own specialized task. Also, a 3-stage DNN allows using different predictions from the early two stages to predict the final subset in the last stage.

To that end, the set $\mathcal{V}$ is divided into three subsets, $\mathcal{V}_1 \triangleq \{\mathbf{p}_E\}$, $\mathcal{V}_2 \triangleq \{t_I, t_E\}$, and $\mathcal{V}_3 \triangleq \{p_{I,1}\}$. The DNNs assigned to predicting each subset are termed as Net-1, Net-2 and Net-3, respectively, for ease of discussion. Every network is an FCNN (c.f., Figure 3.1) that takes a distinct input that facilitates its learning. The input to Net-1 is the nearby user distances. The input to Net-2 is the distances of all users. The input to Net-3 is the predictions of Net-1 and Net-2. Also, the three FCNNs differ in terms of their depths and activation layers. While Net-1 includes 5 hidden layers, Net-2 and Net-3 are composed of 10 hidden layers in addition to the input and output layers. Also, LeakyReLU is incorporated in Net-1 and Net-2, whereas Net-3 utilizes

Table 4.1: Network architecture details.

	Net-1	Net-2	Net-3
Input layer size	N_1	N	$N_1 + 2$
Output layer size	N_1	2	1
Number of hidden layers	4	10	10
Prediction task	$\mathbf{p}_E$	t_E, t_I	$p_{I,1}$

ELU activation function to provide an element-wise non-linearity to the FCNNs. The mentioned details are summarized in Table 4.1.

4.4 Supervised Training Scheme

After generating a fully labeled dataset by solving problem (4.4) using CVX repeatedly, the input and output pairs are separated according to Sec. 4.3 to train every Net independently. The loss function used is the well-known MSE loss, formerly defined as

$$L_s = \frac{1}{B} \sum_{b \in \mathcal{B}} (\mathbf{x}_b - \hat{\mathbf{x}}_b)^\top (\mathbf{x}_b - \hat{\mathbf{x}}_b), \quad (4.8)$$

where the real vectors $\hat{\mathbf{x}}_b$ and $\mathbf{x}_b$ represent the prediction and the ground truth of the b -th batch, respectively, B is the mini-batch size and $\mathcal{B}$ is the mini-batch index set.

The three networks are initialized and trained for a certain number of epochs, N_{ep} . Through each epoch, the batched training set is shuffled and passed into the networks. The predictions at each batch is assisted by calculating the loss and applying an optimizer to update the network through backpropagation. After each epoch, the model is evaluated on the validation set, without backpropagation, to track the model's

performance on a foreign (unseen) data. After the training, the model that achieved the lowest loss on the validation set is selected for online deployment.

A schematic of the offline training paradigm is shown in Figure 4.2. The online deployment is implemented by first applying Net-1 and Net-2 to the input distances, then Net-3 is applied to the outputs of Net-1 and Net-2. Such system is expected to achieve a comparable performance to the original CVX solution and at a much higher speed than CVX. Figure 4.3 illustrates the mentioned online deployment of the 3-stage DNN.

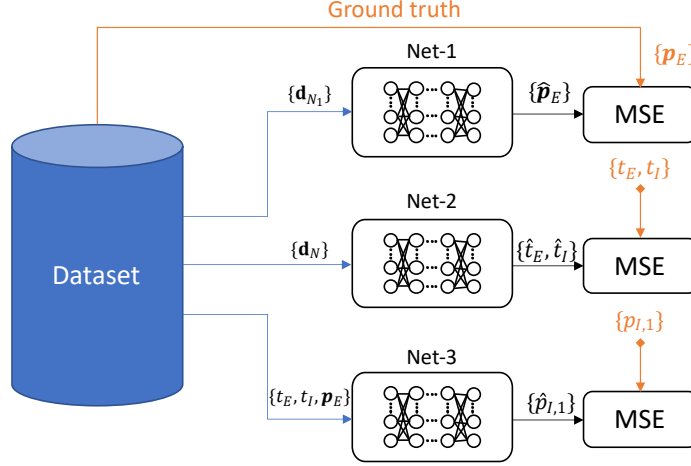


Figure 4.2: Offline training paradigm. Blue and orange arrows are non-backpropagation paths.

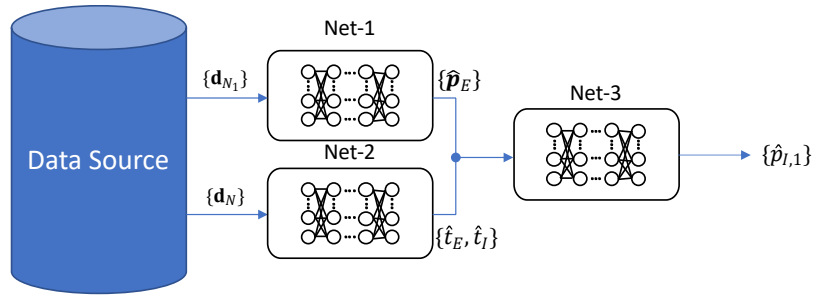


Figure 4.3: Online deployment of the proposed 3-stage DNN.

Table 4.2: System parameters.

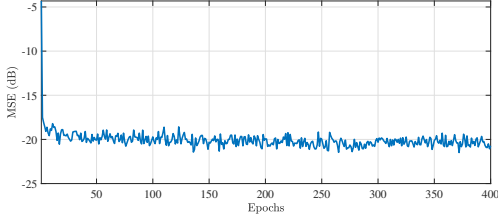
Param.	M	N	N_1	e_n^{min}	η	P_T	Band-width	Noise spectral density
Value	100	20	5	-20 dBm	0.5	-16 dBW	20 MHz	-174 dBm/Hz

4.5 Results and Discussion

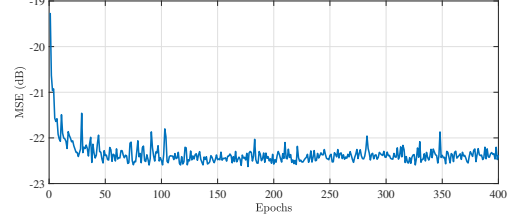
To evaluate the performance of the proposed DL framework for transmit-TS WIPT architecture, we first generate 50,000 data points using CVX. 5,000 data points are reserved for the final assessment (i.e., test dataset), whereas 80% of the rest are used for training and 20% are used for validation. The user distances are randomly generated within a radius of $300m$. The maximum distance allowed for the nearby users is $50m$. Also, $\gamma_n = 3$ for $n \in \mathcal{N}_1$ and $\gamma_n = 3.76$ for $n \in \mathcal{N}_2$. The rest of the system parameters at which the dataset was generated are detailed in Table 4.2.

The three Nets are trained for several epochs using standard mini-batch training, where the batch size is 64. The learning rate at which Net-1 and Net-2 are optimized is 10^{-4} . Net-3 is trained at a learning rate of 10^{-5} . ADAM optimizer is used for all three Nets. Every Net is trained for a different number of epochs. The activation function parameters in equations (3.2) and (3.3) are set to $m = 0.01$ and $\alpha = 1.0$. No batch normalization or dropout layers are used for any of the three Nets. The training and validation curves for Net-1, Net-2 and Net-3 are respectively shown in Figure 4.4, Figure 4.5 and Figure 4.6.

Before training, the input-output pairs in the dataset were standardized. The ground truth for the three DNNs were normalized. On the other hand, only the inputs to Net-1 and Net-2 were normalized, whereas the input to Net-3 was not nor-

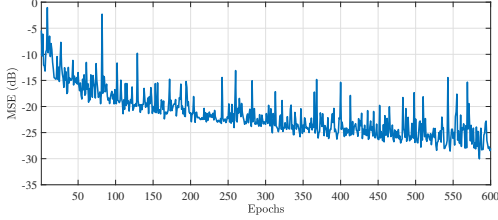


(a) Training curve

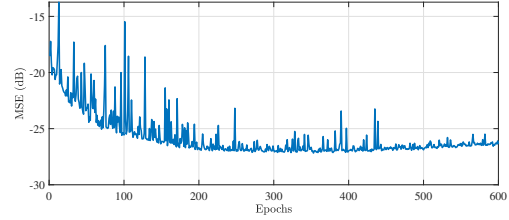


(b) Validation curve

Figure 4.4: Net-1 training (a) and validation (b) plots for 400 epochs.

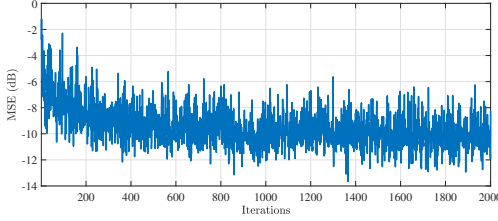


(a) Training curve

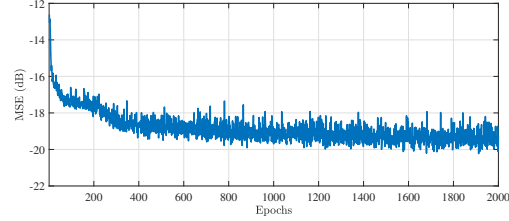


(b) Validation curve

Figure 4.5: Net-2 training (a) and validation (b) plots for 600 epochs.



(a) Training curve



(b) Validation curve

Figure 4.6: Net-3 training (a) and validation (b) plots for 2000 epochs.

malized. Also, for Net-2, the nearby user distances and the distant user distances are normalized separately. To that end, the three networks learn to generate zero-mean and unit variance predictions given normalized inputs as described. The predictions are converted to their original scales for assessment and online deployment using the statistics of the training set. Thus, it is crucial that the training set is diverse and large enough so that its statistics can be generalized to any unseen points. Table 4.3 shows the statistics of the training pairs. Notice that the statistics of the output

Table 4.3: Mean and standard deviation (STD) of the training set.

Param.	$\mathbf{p}_E$ (W)	$p_{I,1}$ (W)	t_E	t_I	$\mathbf{d}_{N_1}$ (m)	$\mathbf{d}_{N_2}$ (m)
Mean	0.0063	0.0391	0.0180	0.9820	35.02	174.93
STD	0.0072	0.0311	0.009	0.009	8.66	72.10

Table 4.4: Average MSE, in dB, across training and validation dataset.

	Net-1	Net-2		Net-3
Parameter	$\mathbf{p}_E$	t_E	t_I	$p_{I,1}$
Training set	-66.10	-70.82	-70.82	-50.14
Validation set	-65.46	-68.22	-68.22	-49.93

predictions are relatively small. Such scales will result in misleadingly small MSE values, which in turn results in negligible updates to the network’s initial parameters. Additionally, the networks may learn to produce constant predictions regardless of the input. Therefore, the training is performed using completely normalized ground truth. The MSE curves in Figure 4.4, Figure 4.5 and Figure 4.6 express the error in the normalized predictions, not for the predictions in their original scales.

After training, representative models are selected based on their performance on the validation set during training. We report the average MSE achieved by the three selected models on the training set and validation set in Table 4.4. The MSE is evaluated after converting the predictions to their original scales.

Next, the online deployment scheme is evaluated using the reserved 5,000 data points (i.e., the test set). The results shown in Table 4.5 are for real scale predictions. Table 4.6 compares the CPU running time needed by the proposed 3-stage DNN and the CVX-based solver proposed in [2]. Every cell in the table represents the running time for 50 data points. The total time required to process all 500 data points is 0.401 seconds by the 3-stage DNN and 6130 seconds by the CVX solver.

Table 4.5: Average MSE of the 3-stage DNN on the test set. All values are reported in dB.

	Net-1	Net-2		Net-3
Parameter	$\mathbf{p}_E$	t_E	t_I	$p_{I,1}$
Test set	-65.43	-68.14	-68.16	-47.14

Table 4.6: CPU running time in seconds for 10 experiments, 500 data points each.

DL model	0.0481	0.0322	0.0481	0.0425	0.0321	0.0329	0.0499	0.0321	0.0486	0.0341
[2]	654.27	579.88	624.76	609.78	609.81	623.83	603.44	576.61	635.46	612.03

The results shown in Table 4.4, Table 4.5 and Table 4.6 indicate that the proposed 3-stage DNN achieves the goals intended for this part of the thesis. That is, we successfully devised a methodology that achieves almost the same performance as the benchmark with an immense reduction in the complexity. Additionally, notice that the proposed DL solution requires only the distances of the users. Unlike typical CVX solutions for RA problems in wireless systems, including the considered system in this chapter, the proposed DNN does not require CSI estimation. This is particularly beneficial in massive MIMO systems, where large number of channels are required for estimation to solve the underlying RA problem using convex optimization.

The reason why the proposed DL scheme can achieve similar performance to the convex optimization scheme is the supervised learning. One crucial requirement for achieving such accuracy in supervised regression problems is to ensure that the relation between the input-output pairs is one-to-one. In case of unsupervised learning, however, the input needs to be involved in the unsupervised loss itself. Otherwise, the DNN will not learn. From the problem formulation in Sec. 4.1, it is indicated that the distances correspond to different CSI through large scale fading, and CSI is heavily involved in calculating the optimization parameters using CVX. Therefore, in

general, user distances satisfy the one-to-one condition to a high degree.

It can be seen from Figure 4.4 that Net-1 is easily trained compared to Net-2 and Net-3 in Figure 4.5 and Figure 4.6, respectively. Since Net-1 is smaller than Net-2 and Net-3 in terms of the number of hidden layers, it is expected that the reason for the mentioned difference is the network architecture. A larger network is generally harder to train. Thus, it is expected that reducing the number of hidden layers for Net-2 and Net-3 or training them with a larger number of data points may result in faster and less confused training.

Although Net-2 and Net-3 are identical in terms of the number of hidden layers and the number of neurons, Net-3's training curve in Figure 4.6a is noisier than the training curve of Net-2. This is most likely attributed to the fact that Net-2's input size is larger than Net-3's input size by $N_2 - 2$.

In general, DNN solutions can be always enhanced by trial and error. The network size, input type and its pre-processing schemes, learning parameters such as the learning rate and the batch size, optimizers and loss functions are different parameters that can be used to enhance the results. Since the presented scheme is powerful enough as indicated by the results, we focus on the next topic of this thesis, which involves an unsupervised learning scheme.

CHAPTER 5

INTEGRATED SENSING AND COMMUNICATION

5.1 System Model

Consider a cell-free ISAC system with L APs, N UEs and a single ST. Every AP is equipped with M antennas and is capable of transmission and reception simultaneously. All APs are connected to a CPU through fronthaul links for administration and synchronization. Figure 5.1 depicts an example of the described system. Let the AP index set be denoted by $\mathcal{L}$. Define the set of beamforming vectors, $\mathcal{W} \triangleq \{\mathbf{w}_q\}_{q=1}^{N+1}$, where $\mathbf{w}_q \triangleq [\mathbf{w}_{1q}^\top, \dots, \mathbf{w}_{Lq}^\top]^\top$ is the stacked q -th beam from all APs and $\mathbf{w}_{lq} \in \mathbb{C}^{M \times 1}$ is the beam dedicated by the l -th AP to the q -th agent (i.e., a UE or an ST). Notice that $q \in [1, N+1]$ is reserved for the agent index. We define $\mathcal{Q}$ as the agent index set. We also define the subsets $\mathcal{N}$ and $\mathcal{S}$ to respectively denote the stacked communication beam indices and the stacked sensing beam indices (one in our case

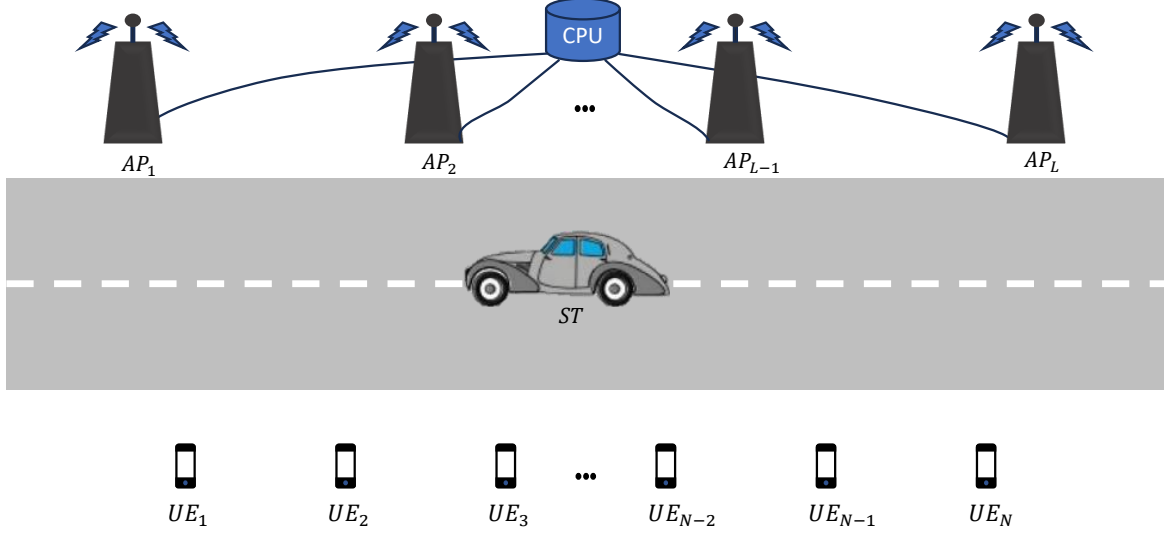


Figure 5.1: Cell-free ISAC example setup.

as the number of considered sensing target is one) in the set $\mathcal{Q}$. The first N beam indices in $\mathcal{Q}$ are reserved for the UEs, whereas the $(N + 1)$ -th index is reserved for the ST. Moreover, define the stacked communication channel vector for the n -th UE as $\mathbf{h}_n \triangleq [\mathbf{h}_{1n}^\top, \dots, \mathbf{h}_{Ln}^\top]^\top$, where $n \in \mathcal{N}$ and $\mathbf{h}_{ln} \in \mathbb{C}^{M \times 1}$ represents the channel between the l th AP and the n th UE.

User assignment is not considered in this model, meaning that all APs serve all users and sense the targets. Consequently, the received signal at the n -th UE is given by

$$y_n = \sum_{q \in \mathcal{Q}} \mathbf{h}_n^H \mathbf{w}_q x_q + n_n, \quad (5.1)$$

where $n_n \sim \mathcal{CN}(0, \sigma_n^2)$ is the UE's receiver noise and x_q is the symbol sent for the q -th agent. Notice that all APs transmit the same message to each agent, which explains why x_q is not a function of the AP index, l .

The expression in (5.1) is composed of the desired signal at $q = n$, communication interference at $q \in \mathcal{N} \setminus \{n\}$, sensing interference at $q \in \mathcal{S}$, and noise. Assuming a unit power symbol-based design (i.e., $\mathbb{E}[|x_q|^2] = 1 \ \forall q$), the SINR at which the n -th UE decodes the received signal is given by

$$\text{SINR}_n = \frac{|\mathbf{h}_n^H \mathbf{w}_n|^2}{\sum_{n' \in \mathcal{N} \setminus \{n\}} |\mathbf{h}_n^H \mathbf{w}_{n'}|^2 + \sum_{s \in \mathcal{S}} |\mathbf{h}_n^H \mathbf{w}_s|^2 + \sigma_n^2}, \quad (5.2)$$

where the subscripts n, n' and s indicate the target user, the other users and the sensing target, respectively.

While characterizing the communication metric, SINR, requires signal analysis at the user's end, characterizing the sensing metric requires signal analysis at the receiver AP. The received signal at the r -th AP is given by

$$\mathbf{y}_r = \sum_{l \in \mathcal{L}} \alpha_{lr} \mathbf{a}(\theta_r) \mathbf{a}^H(\theta_l) \mathbf{x}_l + \mathbf{n}_r, \quad (5.3)$$

where $\alpha_{lr} \sim \mathcal{CN}(0, \sigma_{s_{lr}}^2)$ is the effective sensing channel gain, $\mathbf{a}(\theta_r) \in \mathbb{C}^{M \times 1}$ is the steering vector given by

$$\mathbf{a}(\phi) = [1, e^{j2\pi\lambda\cos(\phi)}, \dots, e^{j2\pi\lambda(M-1)\cos(\phi)}], \quad (5.4)$$

where λ is the wavelength-antenna spacing ratio, θ_l is the angle of departure from the l -th AP, θ_r is the angle of arrival at the r -th AP, $\phi \in \{\theta_l, \theta_r\}$, $\mathbf{n}_r \sim \mathcal{CN}(0, \sigma_{a_r}^2)$ is the receiver antenna noise vector at the r -th AP, and $\mathbf{x}_l \in \mathbb{C}^{M \times 1}$ is the transmitted signal from the l -th AP which is defined as

$$\mathbf{x}_l = \sum_{q \in \mathcal{Q}} \mathbf{w}_{lq} x_q. \quad (5.5)$$

To assist the sensing quality, we define the SSNR as follows

$$\text{SSNR} = \frac{\sum_{r \in \mathcal{L}} \sum_{l \in \mathcal{L}} \sigma_{s_{lr}}^2 \|\mathbf{a}^H(\theta_l) \bar{\mathbf{W}}_l\|^2}{\sum_{r \in \mathcal{L}} \sigma_{a_r}^2}, \quad (5.6)$$

where $\bar{\mathbf{W}}_l \triangleq [\mathbf{w}_{l1}, \dots, \mathbf{w}_{l(N+1)}]$. Notice that all beams contribute to sensing rather than considering them as interference. This can be justified by the fact that the sensing functionality requires analyzing the incident signal to track its reflection pattern and does not require decoding the information content within the received signal.

5.2 Joint Sensing-Communication Beamforming

The joint cell-free ISAC optimization problem is given by

$$\max_{\{\mathbf{w}_{lq}\}_{q=1}^{N+1} \forall l} \{g_1, g_2\} \quad (5.7a)$$

$$\text{s.t.} \quad \sum_{q \in \mathcal{Q}} \|\mathbf{w}_{lq}\|^2 \leq P_l, \quad \forall l \in \mathcal{L}, \quad (5.7b)$$

where $g_1 \triangleq \text{SSNR}$, $g_2 \triangleq \min\{\text{SINR}_n\}_{n=1}^N$ and P_l is the power budget at the l -th AP.

One way to solve (5.7) is found in [1]. Instead of jointly optimizing for two functions, only one function is optimized while the other is converted into an additional constraint. The resulting problem is given by

$$\max_{\{\mathbf{w}_{lq}\}_{q=1}^{N+1}} g_1 \quad \forall l \quad (5.8a)$$

$$\text{s.t. } g_2 \geq \gamma_{high} \quad (5.8b)$$

$$\sum_{q \in \mathcal{Q}} \|\mathbf{w}_{lq}\|^2 \leq P_l, \quad \forall l \in \mathcal{L}. \quad (5.8c)$$

γ_{high} is the output of another optimization problem, where sensing beams are defined a priori. For instance, the sensing beams can be projected to the null-space of the communication channels and solve the following feasibility problem

$$\begin{aligned} & \text{find} \quad \{\mathbf{w}_{ln}\}_{n \in \mathcal{N}} \quad \forall l \\ & \text{s.t.} \quad \text{SINR}_n \geq \gamma, \quad \forall n \in \mathcal{N} \\ & \sum_{n \in \mathcal{N}} \|\mathbf{w}_{ln}\|^2 \leq \rho P_l, \quad \forall l \in \mathcal{L}, \end{aligned} \quad (5.9)$$

where $0 \leq \rho \leq 1$ is the communication power ratio, which dedicates a portion of the power budget to communication beams.

The optimal solution to the problem (5.9) is found at the maximum possible γ where the problem is feasible. To find such value for γ , the problem was solved repeatedly in [1] using the bisection algorithm. The resulting value of the threshold, namely γ_{high} , is substituted in the joint optimization problem (5.8). Solving (5.8) by following the described method has achieved higher performance than the performance of cell-free ISAC beamformer design given communication or sensing beams a priori.

However, the mentioned solution requires solving two optimization problems. The first optimization problem, i.e., the solution to (5.9), is solved multiple times until

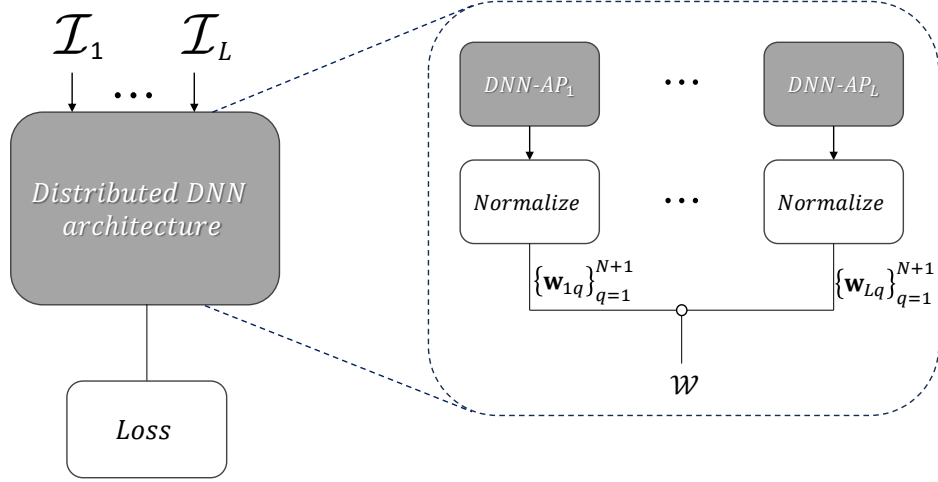


Figure 5.2: General (left) and detailed (right) scheme of the proposed training unit for cell-free ISAC beamforming. The shaded boxes in the detailed scheme are trainable parameters.

the bisection algorithm converges. The second optimization problem is to jointly find communication and sensing beamformers by semidefinite programming (SDP). Such complex solution is impractical for the system depicted in Figure 5.1, since the sensing target is not moving slowly. Alternatively, we introduce in the remaining sections of this chapter an unsupervised DL-based solution to (5.7) that can be deployed in real time.

5.3 The Unsupervised Loss

Refer to the unsupervised training scheme depicted in Figure 5.2. We train L DNNs so that the l -th DNN evaluates the l -th AP's beamforming vectors, $\{\mathbf{w}_{lq}\}_{q=1}^{N+1}$, independently (i.e., without requiring information from the othe APs). Thus, the proposed training scheme is distributed. Also, we denote the input of the l -th DNN by $\mathcal{I}_l$. Detailed description of the training unit in Figure 5.2 in relation to the teacher-student

technique is found in Sec. 5.4. The DNN architectures and the input-output expressions are detailed in Sec. 5.5. This section's main focus is explaining the loss block in Figure 5.2.

Different losses are used to train the teacher models and the student model. Given the concatenated prediction, $\mathcal{W}$, two unsupervised losses are utilized to evaluate and update the L DNNs. The first loss is called the teacher loss, and is given by

$$L_t^{(\beta)} = -[(1 - \beta)g_1 + \beta g_2], \quad (5.10)$$

where $0 \leq \beta \leq 1$ is a normalization parameter that controls the balance between g_1 and g_2 . Specifically, when $\beta \rightarrow 0$, the model tends to maximize g_1 and ignores g_2 . In other words, the model becomes biased towards sensing. On the other hand, when $\beta \rightarrow 1$, the model tends to maximize g_2 and ignores g_1 , preferring communication over sensing. Since fine-tuning β so that the model equally focuses on maximizing both SSNR and SINR is difficult, we exploit the described behavior of the teacher loss to train two biased models. One model is biased towards sensing, namely the SSNR teacher, and the other model is biased towards communication, namely the SINR teacher.

The second loss is called the student loss, which is defined as follows

$$L_s^{(\lambda)} = - \left[(1 - \lambda) \frac{g_1}{\mathbb{E} [g_1^{(max)}]} + \lambda \frac{g_2}{\mathbb{E} [g_2^{(max)}]} \right], \quad (5.11)$$

where $g_1^{(max)}$ and $g_2^{(max)}$ are respectively the maximum possible SSNR and the maxi-

mum possible minimum SINR values that can be attained by a certain model architecture, and $0 \leq \lambda \leq 1$ is a normalization parameter that is adapted according to the gap between the prediction scores (i.e., g_1 and g_2) and the maximum attainable scores (i.e., $g_1^{(max)}$ and $g_2^{(max)}$).

While the behavior of the student loss with respect to λ is similar to the teacher loss behavior with respect to β , which is detailed above, there is a difference between the two losses. That is, the student loss is bounded between 0 and -1 unlike the teacher loss, whose lower bound is dependent on the SSNR and SINR.

The maximum attainable scores, $g_1^{(max)}$ and $g_2^{(max)}$, are obtained from the trained SSNR teacher and the SINR teacher, respectively. Instead of evaluating $g_1^{(max)}$ and $g_2^{(max)}$ at every iteration, the trained teacher models are evaluated on the training set once before the student training, and the mean value of the teacher scores is taken, hence the expected value operator in the denominator of (5.11).

5.4 Training Scheme

We propose a distributed unsupervised training scheme that jointly maximizes g_1 and g_2 . Specifically, L DNNs are trained to predict suitable beamforming vectors for the L APs. The generated L predictions are normalized, concatenated, and fed to the loss function as shown in Figure 5.2. The evaluated loss is used to update the parameters of the L DNNs through backpropagation. Notice that the training loss is the only way through which the different DNNs collaborate. After the training, every DNN evaluates its own beamforming vectors without collaboration with the other

DNNs. The mentioned training process will be referred to as a training unit hereafter.

Different training units are characterized by the different losses mentioned in Sec. 5.3.

To avoid looking for suitable β in (5.10) that achieves a balanced maximization for g_1 and g_2 through a time-consuming grid search, a teacher-student scheme is adapted instead (See Sec. 3.1.2). Specifically, two teacher models, namely the SSNR teacher and the SINR teacher, are trained and used for training a student model. The three models are identical (See Sec. 5.5 for the exact model architectures considered), take the same inputs, and generate the same output, but they are trained using different losses as mentioned in Sec. 5.3. Specifically, the SSNR teacher is trained by $L_t^{(0)}$ and the SINR teacher is trained by $L_t^{(1)}$, according to (5.10). Next, we apply the two teachers to the training dataset to obtain $\hat{g}_1^{(max)} \approx \mathbb{E} \left[g_1^{(max)} \right]$ and $\hat{g}_2^{(max)} \approx \mathbb{E} \left[g_2^{(max)} \right]$ by taking the sample means of the trained teachers' prediction scores across the training points. The student model is then trained by substituting the maximum attainable scores, $\hat{g}_1^{(max)}$ and $\hat{g}_2^{(max)}$, into the denominators of (5.11). To maintain a sensing-communication balance throughout the student training stage, the normalization parameter (λ) is adapted according to the following rule

$$\lambda^{(i)} = \begin{cases} \lambda^{(i-1)} + \epsilon \mathbb{E} \left[\frac{\hat{g}_2^{(max)} - g_2}{\hat{g}_2^{(max)}} \right] & \text{if } \mathbb{E} \left[\frac{\hat{g}_2^{(max)} - g_2}{\hat{g}_2^{(max)}} \right] \geq \mathbb{E} \left[\frac{\hat{g}_1^{(max)} - g_1}{\hat{g}_1^{(max)}} \right] \\ \lambda^{(i-1)} - \epsilon \mathbb{E} \left[\frac{\hat{g}_1^{(max)} - g_1}{\hat{g}_1^{(max)}} \right] & \text{otherwise,} \end{cases} \quad (5.12)$$

where ϵ is a step size and i is the training iteration. The update equation (5.12) is applied as long as $\lambda^{(i)} \in [0, 1]$. If $\lambda^{(i)}$ is out of the range, it is forcibly set to the closest

value in the range (i.e., 0 if $\lambda^{(i)} < 0$ or 1 if $\lambda^{(i)} > 1$).

Equation (5.12) basically monitors the gap between the prediction scores, g_1 and g_2 , and the maximum attainable scores, $\hat{g}_1^{(max)}$ and $\hat{g}_2^{(max)}$. If the SSNR gap is larger than the SINR's, λ is decreased. According to (5.11), decreasing λ biases the training towards sensing, reducing the SSNR gap in the process. Once the SSNR gap becomes smaller than the SINR gap, λ is increased to focus more on communication. This process continues until SSNR and SINR are balanced.

Notice that the gaps in (5.12) are normalized by the maximum attainable scores to stabilize λ and to avoid biasing the training towards the higher attainable score. For example, if $\hat{g}_2^{(max)} \gg \hat{g}_1^{(max)}$, then the SINR gap will always be larger than the SSNR gap, and λ will keep increasing through the training and the model will not get the chance to maximize the SSNR. As such, it is crucial to normalize the score gaps in the conditions of (5.12).

The CSI, which includes communication and sensing channels, is fed as input to the DNNs. The output is the set of beamforming vectors for all agents q from all APs l , $\{\mathbf{w}_{lq}\}_{q=1}^{N+1} \forall l$. The output of every network is normalized to guarantee the power constraints (5.8c). Predicting $\{\mathbf{w}_{lq}\}_{q=1}^{N+1}$ given the CSI of the l -th AP enables distributing the trained L networks among the APs. In other words, the proposed DL solution is decentralized, where every AP deploys a network to evaluate its own beamforming vectors.

5.5 Test Network Architectures

Three CNN architectures are used to test the performance of the proposed training scheme as described below.

1. One-dimensional CNN (1D-CNN): The first architecture is composed of three 1D convolutional layers, c_1, c_2 and c_3 , and two fully connected (FC) layers, $fc1$ and $fc2$, as shown in Figure 5.3. Every convolutional layer is followed by a BN layer and a LeakyReLU activation layer. Every FC layer is followed by a LeakyReLU activation layer.
2. Convolutional Autoencoder (CAE): The second architecture is a convolutional autoencoder (CAE) with skip connections. The general layout of the CAE is shown in Figure 5.4. In our experiments, the encoder and the decoder parts consist of four convolutional layers each. The skip connections are established after the second convolutional layer for all convolutional layers of the encoder. They are established by concatenating the encoder feature maps of the encoder to their counter feature maps of the decoder.
3. U-net: The third model is an off-the-shelf model known as U-net. The detailed architecture of the original U-net is found in [122]. U-net was originally used for medical image segmentation. Images are usually large in size and consist of non-negative values. However, negative values are required for the output beamforming vectors and the input size is limited by the number of users and the number of antennas. Consequently, a number of modifications are made to the

original U-net architecture. These modifications include dropping the pooling layers, using LeakyReLU activation function instead of ReLU, and applying zero padding to preserve the size of the input. It is worth noticing that U-net utilizes skip-connections just like the CAE.

The 1D-CNN model input is given by

$$\mathcal{I}_l^{(1D)} = [\Re(\mathbf{h}_{l1}^\top), \dots, \Re(\mathbf{h}_{lN}^\top), \Re(\mathbf{a}(\theta_l)^\top), \Im(\mathbf{h}_{l1}^\top), \dots, \Im(\mathbf{h}_{lN}^\top), \Im(\mathbf{a}(\theta_l)^\top)]^\top, \quad \forall l. \quad (5.13)$$

On the other hand, the inputs to both the CAE and the U-net models are identical.

The 2D input is given by

$$\mathcal{I}_l^{(\text{CAE})} = \text{blk} [\Re(\mathcal{H}_l), \Im(\mathcal{H}_l)], \quad \forall l, \quad (5.14)$$

where $\mathcal{H}_l \triangleq [\mathbf{h}_{l1}, \dots, \mathbf{h}_{lN}, \mathbf{a}(\theta_l)]$ is the CSI of the l -th AP. The information required by the input layers is assumed to be available to the APs.

The direct outputs of the l -th network for the 1D-CNN and the CAE (U-net) cases are given by

$$\boldsymbol{\omega}_l = [\Re(\boldsymbol{\omega}_l^{(r)\top}), \Im(\boldsymbol{\omega}_l^{(i)\top})]^\top, \quad \forall l, \quad (5.15)$$

and

$$\boldsymbol{\Omega}_l = \text{blk} [\Re(\boldsymbol{\Omega}_l^{(r)}), \Im(\boldsymbol{\Omega}_l^{(i)})], \quad \forall l, \quad (5.16)$$

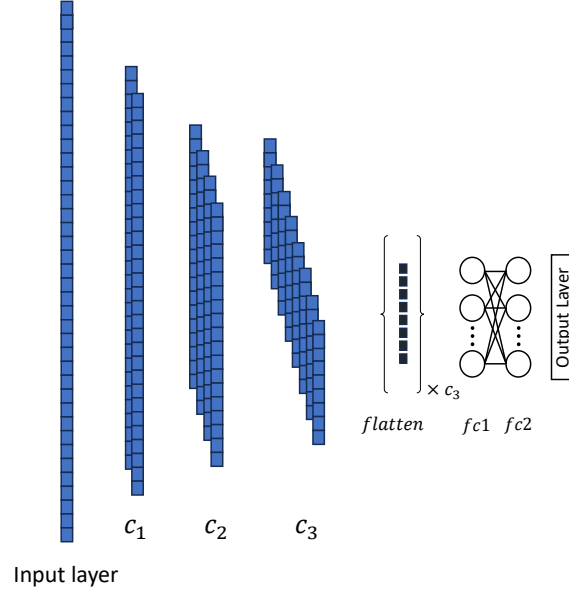


Figure 5.3: A 3-layer 1D-CNN.

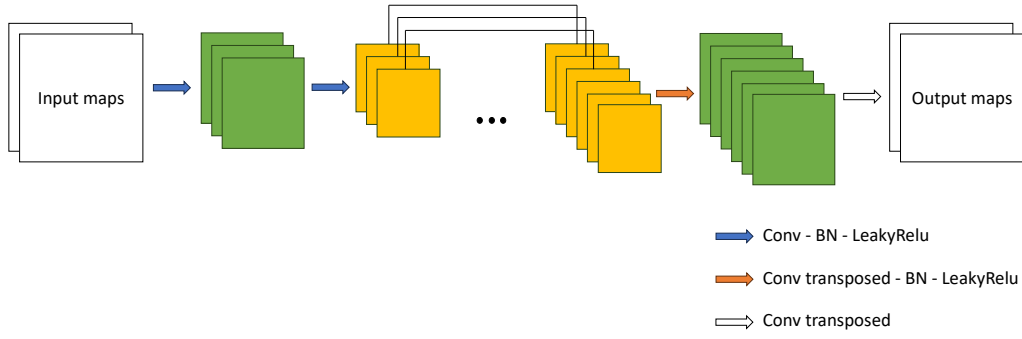


Figure 5.4: A convolutional autoencoder with skip-connections.

respectively.

To enforce the power constraints, the direct output of each network is normalized as follows

$$\bar{\omega}_l = \sqrt{P_l} \frac{\omega_l^{(r)} + j\omega_l^{(i)}}{\|\omega_l^{(r)} + j\omega_l^{(i)}\|}, \quad \forall l. \quad (5.17)$$

or

$$\bar{\Omega}_l = \sqrt{P_l} \frac{\Omega_l^{(r)} + j\Omega_l^{(i)}}{\|\Omega_l^{(r)} + j\Omega_l^{(i)}\|}, \quad \forall l. \quad (5.18)$$

The post-processed outputs are defined as $\bar{\omega}_l \triangleq [\mathbf{w}_{l1}^\top, \dots, \mathbf{w}_{l(N+T)}^\top]^\top$ and $\bar{\Omega}_l \triangleq [\mathbf{w}_{l1}, \dots, \mathbf{w}_{l(N+T)}]^\top$. As this is an unsupervised approach, a ground truth for $\bar{\omega}_l$ or $\bar{\Omega}_l$ is not present. Instead, the SSNR and SINR are calculated to evaluate the loss.

5.6 Dataset Generation

The system parameters, at which the unsupervised datasets are generated, follow in general the system parameters used to evaluate the joint beamforming performance in [1]. That is, we consider 2 APs, 16 antennas per AP, a power budget of 1W per AP, a noise power of 1W for both the UEs and the receiver, and a sensing channel gain power of 0.1. Depending on the orientation of the target with respect to the APs, the sensing channel is generated according to (5.4). Equation (5.4) is also used to generate the communication channels given the orientation of UEs with respect to the APs. Similar ISAC channel models were considered in [1], [123], [124]. Only line of sight is considered for the channel model.

Figure 5.5 shows two position distribution configurations for the UEs and the target. Specifically, Figure 5.5a shows an example of the distribution scheme followed by [1] at $L = 2$ and $N = 5$, where the y -coordinate for all agents is fixed at 50m whereas the x -coordinates for the agents are randomized between $x = 0$ and $x = 100$ m. The scheme in Figure 5.5b is more closely related to the realistic scenario depicted in Figure 5.1, where a two-lane road with a total width of 20m is considered. While the UE

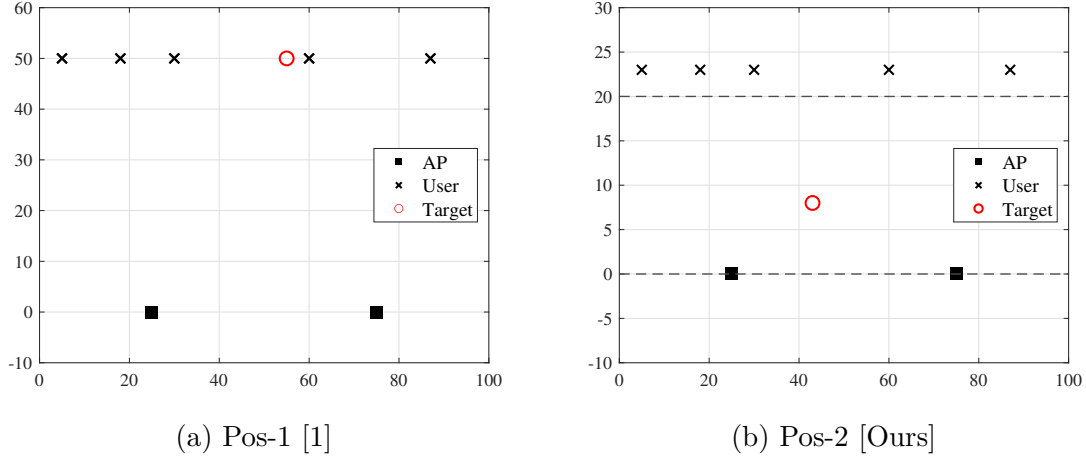


Figure 5.5: Different position distribution schemes used for dataset generation at $L = 2$ and $N = 5$. The area enclosed by the dashed line is the road, which indicates the possible locations of the ST.

positions are fixed at $y = 23\text{m}$ (3m away from the traffic) and randomized along the x -axis between 0 and 100m, both x and y coordinates are randomized for the target between $x = 0$ and $x = 100\text{m}$, and $y = 0$ and $y = 20\text{m}$. In both configurations, the 2 APs are positioned at $(25, 0)\text{m}$ and $(75, 0)\text{m}$. To avoid confusion, we refer to the position distribution configuration of the benchmark (i.e., Figure 5.5a) by Pos-1. Our position distribution configuration (i.e., Figure 5.5b) is referred to by Pos-2. Furthermore, we specify at each experiment which position distribution configuration is used for the corresponding dataset generation. All random positions are drawn from uniform distributions.

After generating the agent positions, the communication and sensing channels are both calculated according to (5.4) as mentioned earlier. Once the channels are generated, the unsupervised dataset generation is accomplished. On the other hand, following a supervised training scheme requires evaluating the beamforming vectors of

all generated data points, which consumes a tremendous amount of time to generate sufficient number of data points for training.

Unless mentioned otherwise, 20,000 point-datasets are generated, where 97% is used for training and the remaining points are used to validate the model’s performance after every training epoch.

5.7 Results and Discussion

This section investigates the performance of the proposed DL unsupervised scheme. First, the performance of the algorithm at different networks is investigated by observing how training and validation SINR and SSNR evolve throughout the training process, and comparing the resulting curves to the mean performance of the CVX-based solution [1]. Next, a sensitivity assessment is conducted to study the effect of the parameters β and λ on the training performance. Then, the effects of changing the number of UEs on the algorithm’s performance is studied. We conclude the experiments by a comparison between the proposed DL algorithm and the CVX-based solution of [1] in terms of running time.

We use a single 2GB GPU NVIDIA Quadro P600 to train the models. The run time experiment is conducted using an 11th generation Intel CPU with an i5 core running at 2.40 GHz. The Pytorch library is used to conduct all experiments. Both SINR teacher and student models are trained for a maximum of 1000 epochs, and the training is terminated if no improvement in the validation metrics occurs for 100 epochs (i.e., patience is set to 100). SSNR teachers are trained for 100 epochs without

Table 5.1: Parameter summary for the three test CNNs.

1D-CNN			
Conv layers	Channels	Filter size	Padding
c_1	2	(11,1)	(0,0)
c_2	4	(11,1)	(0,0)
c_3	8	(11,1)	(0,0)
FC layers	Number of neurons		
$fc1$	90		
$fc2$	90		
CAE			
Parameter	Encoder	Decoder	
Channels	16, 32, 64 and 128	32, 64,128 and 256	
Filter size	(3,5), (2,5), (1,3), (1,3)	(3,5), (2,5), (1,3), (1,3)	
Padding	0	0	
U-net			
Parameter	Encoder	Decoder	
Channels	16, 32, 64 and 128	32, 64,128 and 256	
Filter size	(3,3)	(3,3)	
Padding	(1,1)	(1,1)	

early stopping. For student training, the initial value of the normalization parameter, $\lambda^{(0)}$, is set to 0.5. Also, the step size, ϵ , in (5.12) is set to 0.01. A mini-batch size of 500 is used for all training processes. ADAM optimizer is used for training all models at an initial learning rate of 0.01. The learning rate is reduced by a factor of 10 if no improvement in the average unsupervised loss through the epoch is observed for 10 consecutive epochs (i.e., ReduceLROnPlateau learning rate scheduling module in Pytorch library). The specifications for the three models used to assist the algorithm at $N = 5$ UEs and $M = 16$ antennas per AP are detailed in Table 5.1.

The benchmark performance is obtained by solving problem (5.9) at $\rho = 0.5$, where the sensing beam is designed by projecting its vector to the null space of the communication channel. The obtained γ_{high} from the bisection algorithm is used for solving problem (5.8). The problem is solved for 200 points randomly selected from

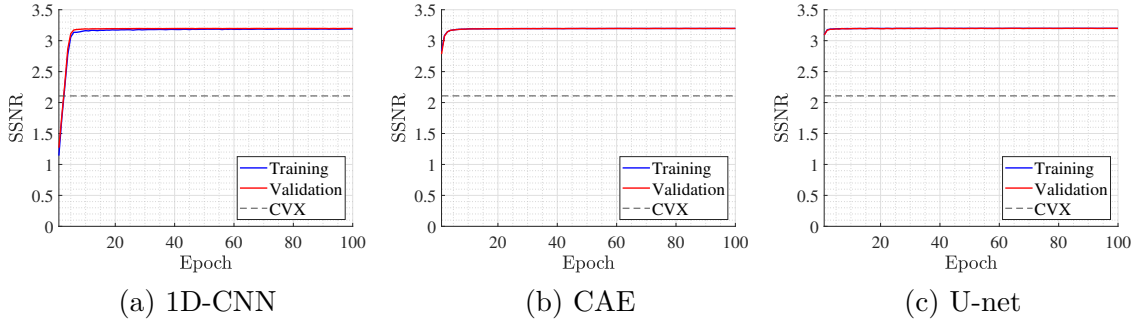


Figure 5.6: SSNR teacher performance.

the corresponding dataset, whereas the average SSNR and SINR of these points are the benchmark for our method.

5.7.1 Benchmark comparison with teacher-student scheme

All results in this section are based on datasets generated via Pos-1 configuration (Refer to Figure 5.5a). Figure 5.6 shows SSNR teacher performance through training and validation using the three networks. It can be seen from both Figure 5.6 and equation (5.6) that maximizing the SSNR alone is relatively simple. All networks attain the same level of SSNR within 100 epochs of training. This level surpasses the CVX-based solution (i.e., the dashed line in Figure 5.6) by a considerable margin. The only difference between the three networks in terms of the SSNR curves is the speed at which the maximum SSNR is attained, where U-net is the fastest to converge and the 1D-CNN is the slowest. Notice that the initial points of the three training curves in Figure 5.6 are different, since the first training point is always recorded at the end of the first epoch.

Unlike the concave quadratic nature of the objective that SSNR teachers are ex-

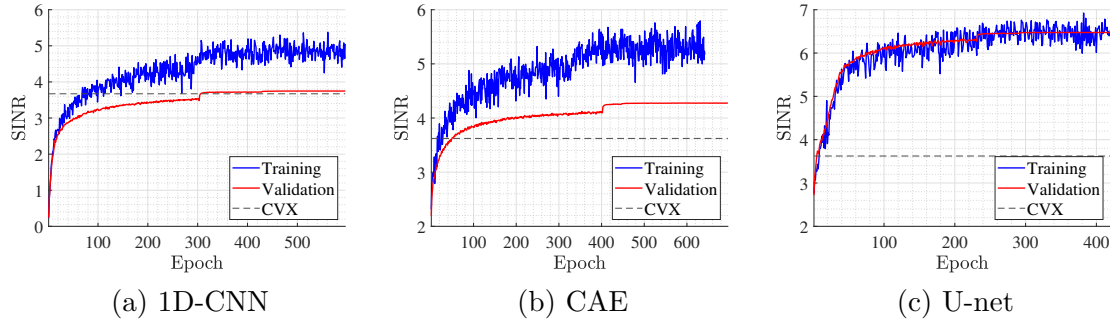


Figure 5.7: SINR teacher performance.

pected to optimize, maximizing the minimum SINR is a more difficult task due to its non-convex nature. Figure 5.7 shows clear distinctions between the three test networks in terms of effectiveness in maximizing the minimum SINR. While both CAE and U-net are capable of achieving higher SINR than the CVX-based algorithm (represented by the dashed lines in Figure 5.7) in terms of both training and validation, 1D-CNN validation curve barely attains the CVX-based algorithm performance as shown in Figure 5.7a. Consequently, the student's performance of the 1D-CNN will not be able to jointly maximize SSNR and SINR properly, since its maximum performance is bounded by the teachers' performance.

The training-validation curves of the CAE in Figure 5.7b exhibit an overfitting issue -due to the considerable gap between the training and validation curves- which reflects poorly on the student's performance depicted in Figure 5.8c. U-net does not suffer from any of the issues exhibited by the CAE and the 1D-CNN.

Figure 5.6c and Figure 5.7c show that the training-validation curves of the U-net teacher models converge to considerably higher SSNR and SINR than the CVX-based algorithm performance. Thus, it is expected that the U-net student can achieve

promising results. Said results are shown in Figure 5.9c and Figure 5.9d. It is expected that the student’s final performance should be at least slightly lower than the CVX-based solution, since the CVX-based solution is near-optimal whereas DNNs are general approximators. The trained student models, however, can evaluate the beamforming vectors at every AP in real time given CSI. However, the CVX-based solution burdens the CPU with calculating the beamforming vectors using a time consuming iterative algorithm, and sending the evaluated beamforming vectors to their respective APs. On the other hand, the trained student models only require the corresponding AP’s CSI, which can be estimated either using a centralized or a distributed method [125], [126], [127], to evaluate good quality beamforming vectors in real-time compared to the CVX-based solution.

5.7.2 Sensitivity assessment

All results in this section are based on datasets generated via Pos-1 configuration (Refer to Figure 5.5a). One possible solution to the joint optimization problem using unsupervised learning is to directly select a fixed β in (5.10) using a grid search. Figure 5.10 shows the expected behavior of U-net models trained using L_1 directly at a fixed β through the entire training process. It can be seen from Figure 5.10 that only a narrow range of β values can achieve similar performance to the CVX-based algorithm (represented by dashed lines in the figure). In other words, the performance is highly sensitive to β , thus it is difficult to find a value for β that guarantees the best joint beamforming solution for the underlying network. Furthermore, a considerably

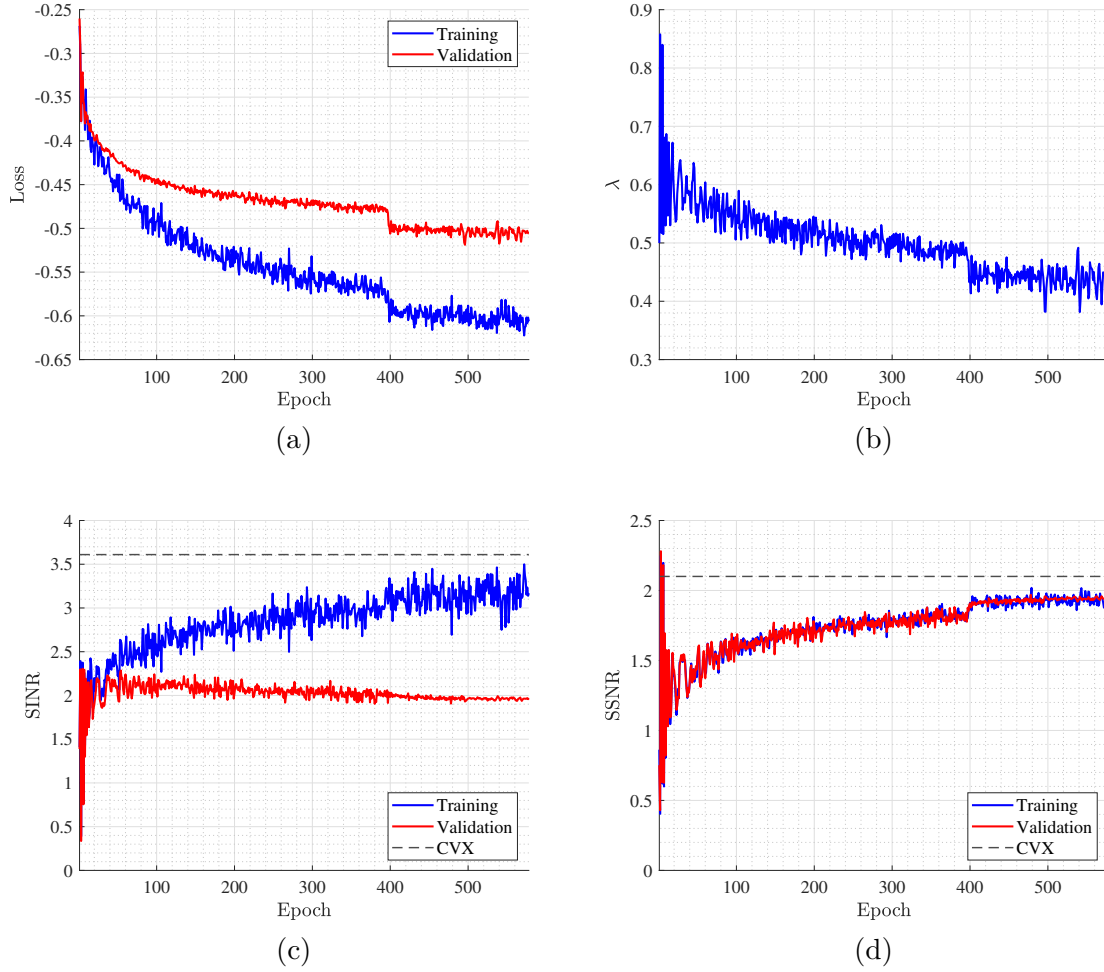


Figure 5.8: Student performance of the CAE.

large range of β results in a biased performance towards SINR or SSNR (i.e., either sensing or communication is completely ignored at this range of β). This is not equivalent to the parameter ρ , which gradually controls the tradeoff between sensing and communication [1]. Additionally, it is expected that the curves in Figure 5.10 are susceptible to uncontrollable changes caused by changes in the system model, network architecture, training parameters, or training data points. Such susceptibility to minor changes renders the fixed β training practise impractical. A similar argument can be stated about the impracticality of fixing λ throughout the training process, whose

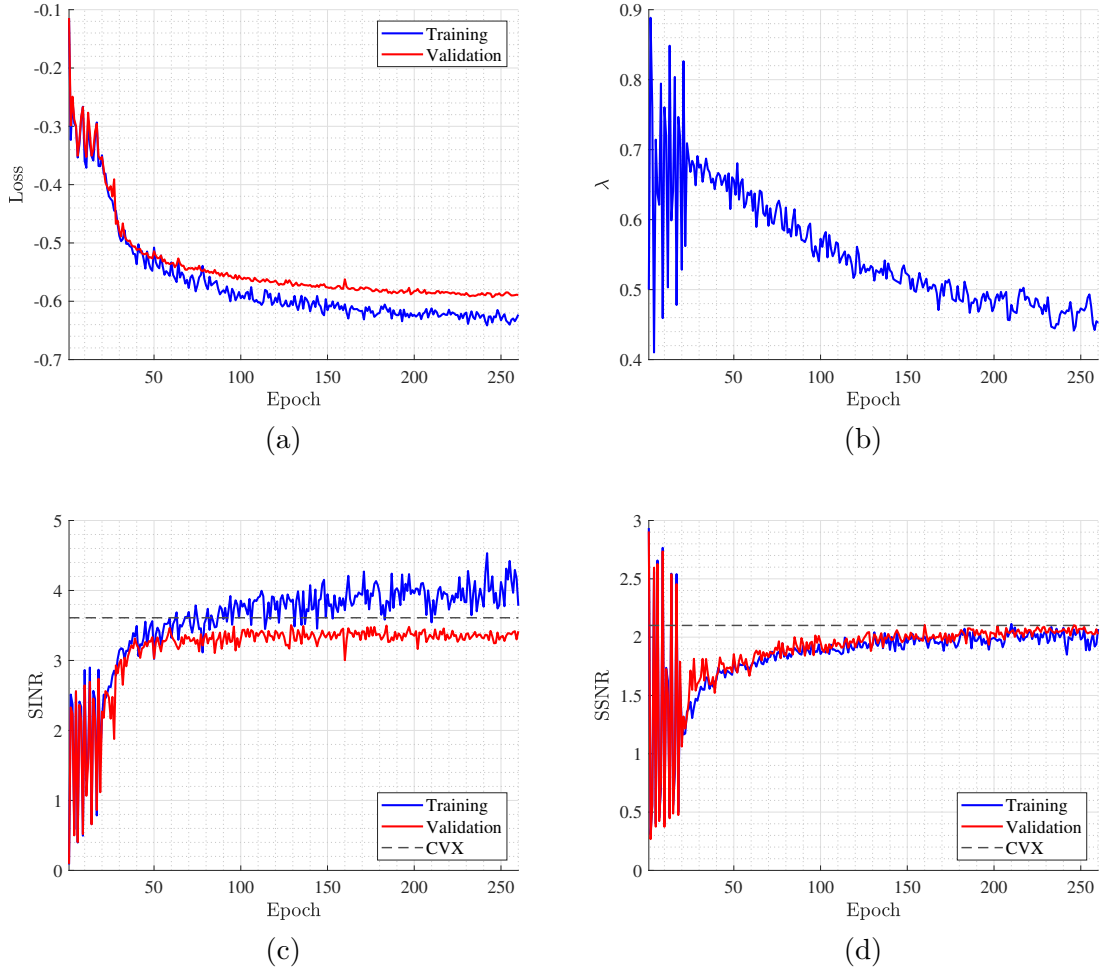


Figure 5.9: Student performance of U-net.

behavior is depicted in Figure 5.11.

5.7.3 Changing agent position distribution scheme and the number of UEs

We use U-net to evaluate the teacher-student scheme performance for different number of users. In this experiment, the datasets are generated using Pos-2 configuration (Refer to Figure 5.5b). To this end, the validation curves for SINR and SSNR at

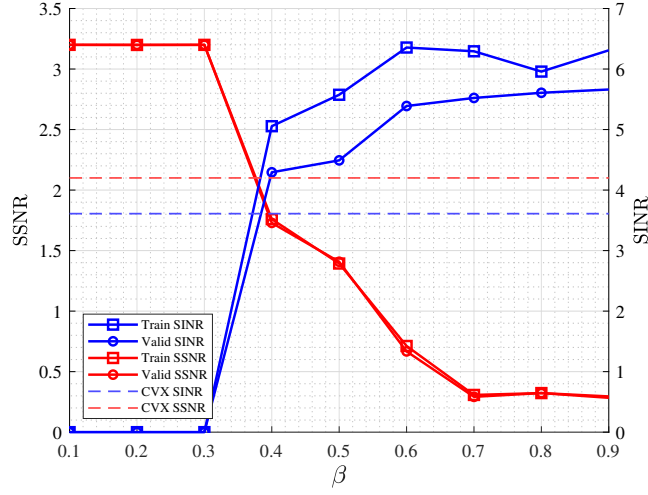


Figure 5.10: SINR and SSNR at fixed β .

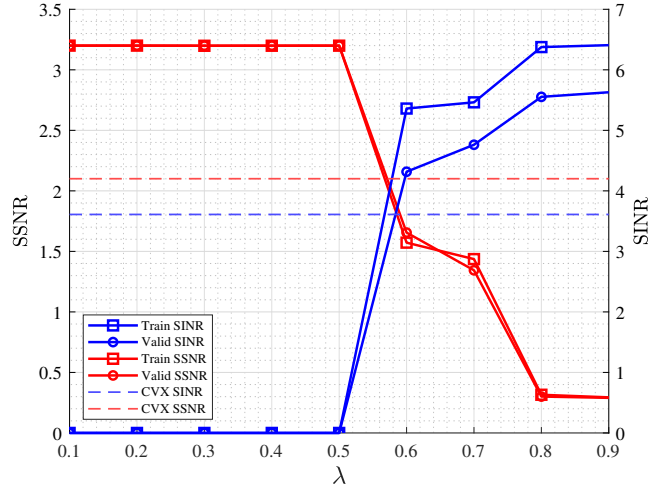


Figure 5.11: SINR and SSNR at fixed λ .

$N = 2, 5, 8$ are shown in Figure 5.12.

It is expected that SINR would increase as N decreases, since the multi-antenna equipped APs are required to serve less number of users by the same power budget. This explains the differences between the three curves in Figure 5.12a. On the other hand, the maximum attainable SSNR is expected to remain the same under the same power budget and sensing channel model regardless of the number of users, since it

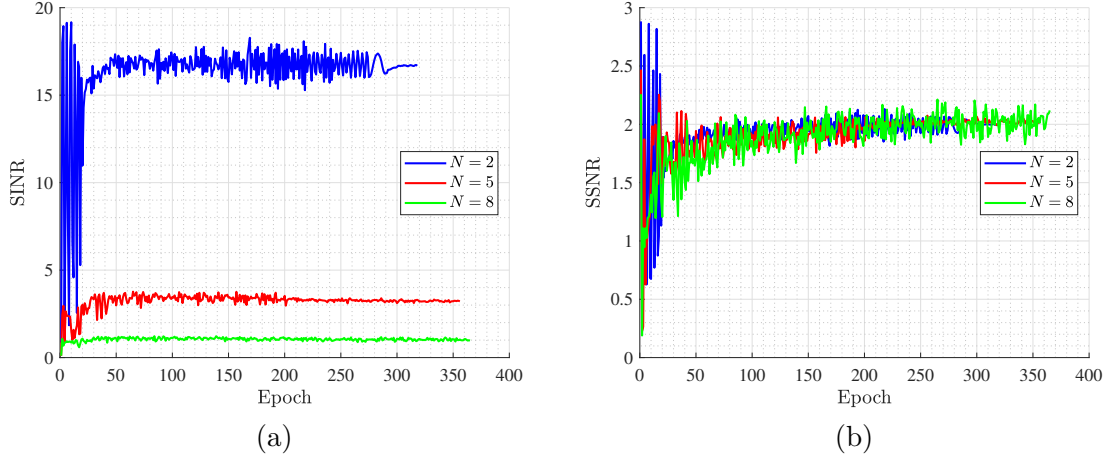


Figure 5.12: Student performance of U-net at different number of UEs: (a) SINR and (b) SSNR validation curves.

is dedicating all beams (i.e., the entire power budget) to detecting the target. This explains the similarity between the curves in Figure 5.12b.

Figure 5.13 compares the student performance on two datasets. One dataset is generated using Pos-1 configuration and the other one is generated using Pos-2 configuration. Since the channel model depends solely on the orientation, only minor changes are expected. Said changes can be observed in Figure 5.13a, where the SINR curve starts to decline after around 200 epochs, suggesting a slight overfitting during the training process.

To address the results shown by Figure 5.14, we use the notation, F_n , to indicate a filter size of (n, n) and an appropriate padding that will conserve the output size. For instance, all past U-net experiments used a filter size of $(3, 3)$ and a padding of $(1, 1)$. This filtering configuration is referred to as F3 in Figure 5.14. Consequently, F5 refers to a filter size of $(5, 5)$ and a padding of $(2, 2)$. Finally, F7 refers to a filter size of $(7, 7)$ and a padding of $(3, 3)$.

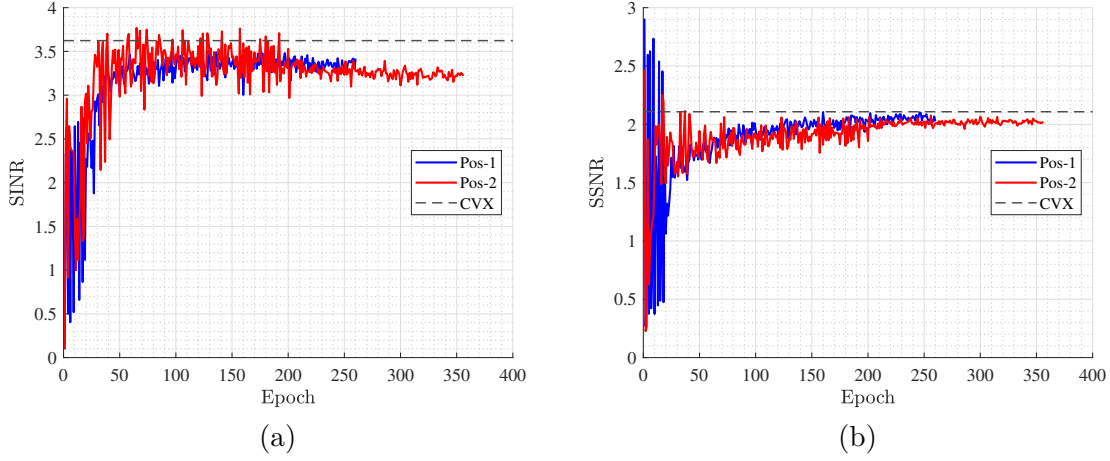


Figure 5.13: Student performance at $N = 5$ for different agent position distribution schemes: (a) SINR and (b) SSNR validation curves.

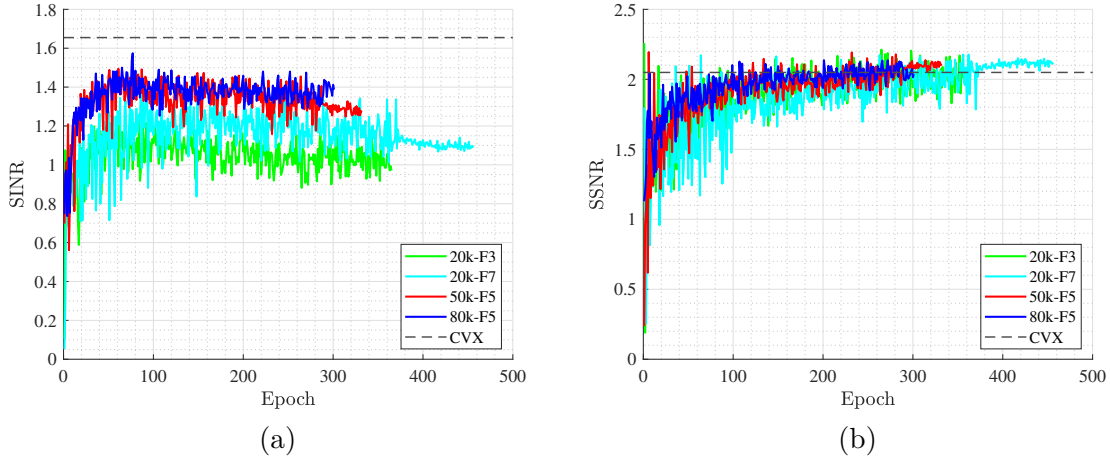


Figure 5.14: Student performance at $N = 8$ for different training and network setups: (a) SINR and (b) SSNR validation curves.

The observed slight overfitting in Figure 5.13a becomes more severe as the number of users increases as shown in Figure 5.14a. This problem can be alleviated by changing the filter size of the U-net and, more importantly, by increasing the training size. The blue curve in Figure 5.14a shows that F5 configuration with a dataset size of 80,000 points considerably enhances the SINR performance of the student model. In all cases, the overfitting issue does not affect the SSNR performance as shown in Figure

5.13b and Figure 5.14b. Judging by the similar performance of the blue and red curve corresponding schemes in Figure 5.14a, further increase in the dataset size may not contribute to the performance anymore.

After offline training, one model needs to be selected for deployment in real time. That is, we need to determine the epoch at which the model achieved the best combination of SSNR and SINR. Due to the aforementioned overfitting problem, the model state at the end of the training process may not correspond to the best sensing-communication tradeoff. Thus, a proper select-criterion should be followed to find the best student model throughout the training. A simple strategy is followed to find such model. Specifically, we look for the highest SSNR achieved within a certain range of epochs for which the achieved SINR is within a certain percentage of the maximum SINR performance. For instance, the maximum SINR of the blue curve in Figure 5.14a is 1.5743. We search for the best SSNR within the epochs that correspond to an SINR of at least 1.4798 (i.e., 94% of the maximum SINR). As such, out of ten epochs that satisfy the 94% condition, the maximum SSNR is achieved at epoch number 222. The corresponding SINR and SSNR achieved by the model at epoch 222 are 1.4802 and 1.9338, respectively. The corresponding model parameters at this epoch can be selected for deployment in real-time.

Applying the aforementioned strategy on the validation curves of $N = 2, 5$ and 8, where the percentage threshold for the SINR is 94%, yields the results shown in Figure 5.15. While the DL method outperforms the CVX-based solution in terms of average SINR at low number of users, the corresponding average SSNR is lower

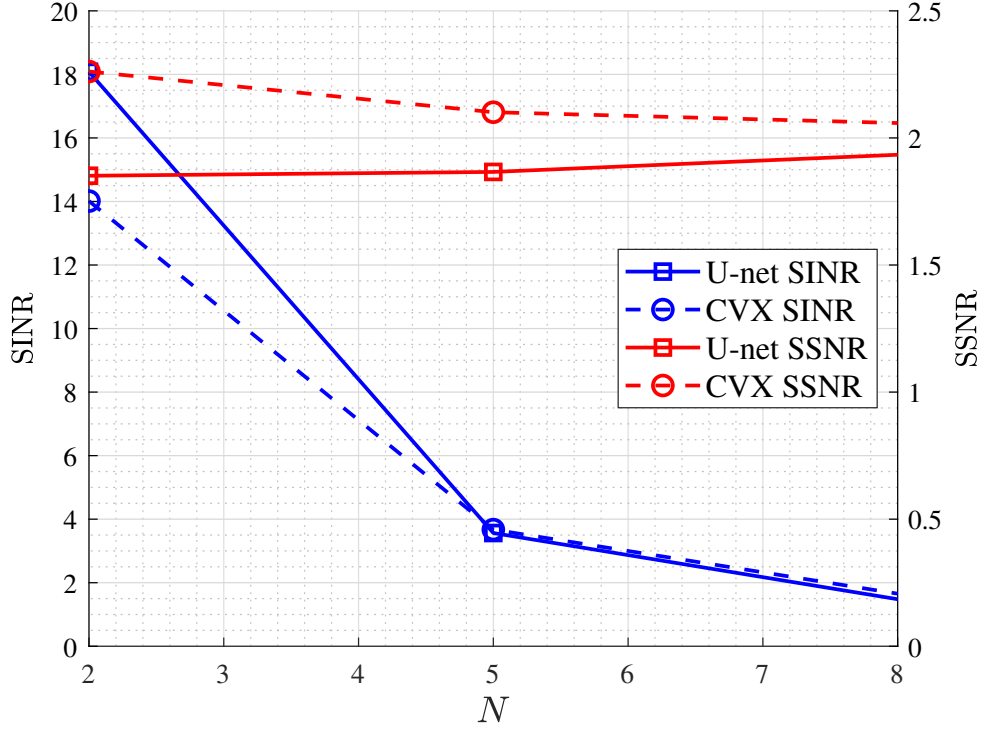


Figure 5.15: Selection strategy results at 94% threshold percentage of SINR for different users.

than the CVX-based solution. As the number of users increases, the gap between the DL and the CVX-based outputs is reduced. The SINR achieved by the proposed DL method at higher number of users is slightly lower than the CVX-based algorithm.

5.7.4 Time complexity

While the performance comparison between the DL and the CVX algorithms varies depending on the architecture and the number of users, the running time of the proposed DL scheme is consistently much lower than the running time of the CVX algorithm.

To assist the running time of both methods, we consider the same settings as the previous section (i.e., 2 APs, 16 antennas per AP and different number of users). As

Table 5.2: Average run-time for the proposed algorithm using U-net and the CVX-based algorithm proposed by [1] for different number of users.

Number of users	2	5	8
DL run-time	0.0049	0.0078	0.0200
CVX run-time	11.46	14.19	17.89

such, the proposed DL scheme associates two U-nets to the system. We apply the two U-nets to 100 data points for a certain number of users, N . Every U-net reports its own running time. As the proposed method is distributed, we consider the maximum running time of the two reported time values rather than adding them. The CVX-based algorithm proposed in [1] consists of two steps; the bisection algorithm, where problem (5.9) is solved repeatedly until the algorithm converges, and SDP to solve problem (5.8). We report the total running time of both steps. We apply the CVX-solution to the same 100 data points at a certain number of users, N . The numerical values of the described experiments at $N = 2, 5$ and 8 are shown in Table 5.2. For the 8 user case, we consider a filter size of 5×5 throughout the U-net layers. Recall that the filter size of the U-net for $N = 2$ and $N = 5$ cases is 3×3 .

The time complexity of a general CNN is given by $\mathcal{O}\left(\sum_{d=1}^D (M_d N_d) f_d^2 C_{d-1} C_d\right)$ [128], where D is the number of convolutional layers, M_d and N_d are the dimensions of the output size, f_d is the filter size (assuming square filters) and C_d is the number of channels. In Table 5.2, the DL run-time for 5 users is slightly longer than the run-time for 2 users due to the difference in only one dimension of the feature map sizes. On the other hand, the filter size used for the 8 user case is responsible for the large running time gap between the 8 user case and the other two user cases.

CHAPTER 6

CONCLUSION

This work consists of two parts. The first part addresses the resource allocation problem in WIPT massive MIMO systems where a TS-transmit scheme is considered. The proposed supervised learning method used FCNNs to learn solving the resource allocation problem associated with the mentioned system given the distances of the UEs. The results show that the proposed learning method can create models that predict allocation parameters that are close to the expected solution of CVX.

The second part addresses the beamforming problem in cell-free ISAC systems. Three CNNs are utilized to validate the performance of the unsupervised, distributed, teacher-student-based learning method to predict the beamformers that jointly optimize SSNR and SINR of the system. It was found that U-net achieves the best performance out of the mentioned three networks. Further improvement in the performance for higher number of UEs is possible through increasing the filter size and/or increasing the dataset size.

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