Rate-conforming Sub-band Allocation for In-factory Subnetworks: A Deep Neural Network Approach

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***Abstract*—This paper focuses on the critical challenge of sub-band allocation for dense 6G In-factory subnetworks. We introduce a deep learning (DL) framework explicitly designed to effectively address the inherent optimization problem in sub-band assignment to subnetworks. To enhance the model's training process, a novel strategy is implemented to handle integer optimization variables. The proposed approach aims at utilizing resources more efficiently by maximizing the number of rate-conforming subnetworks, serving as the key component of the loss function. Simulation results demonstrate that, across various classes of subnetworks, the proposed method achieves superior performance compared to State-of-the-Art (SoA) benchmarks with minimal computation time.**

***Index Terms*—deep learning, resource allocation, 6G, in-factory subnetworks**

I. Introduction

In the emerging era of 6G wireless communication, In-X subnetworks play a pivotal role by providing localized connectivity for diverse applications, ranging from in-robot and in-production module communication to in-vehicle, in-room, and even human-body communication [1]. These subnetworks are anticipated to support diverse services, possibly extreme requirements in terms of ultra-short control cycle time, reliability, and service availability, surpassing the capabilities of 5G and its evolution [2].

When In-X subnetworks coexist within the coverage area of a larger 6G network, such as an enterprise network in a factory, central radio resource management (RRM) becomes feasible. Various heuristic methods have been proposed in the literature, which have demonstrated satisfactory performance. One well-known approach involves representing the wireless network as a conflict graph, where cells are nodes, and edges represent interference relationships among these nodes; known methods utilize a graph coloring algorithm for sub-band assignment, e.g. coloring of the graph using a greedy algorithm [3]. An advanced frequency resource allocation scheme, known as sequential iterative subband allocation (SISA), has been designed recently to minimize the sum of interference-to-signal ratios across all subnetwork links [4]. While traditional optimization methods and heuristics have proven effective in certain contexts, the dynamic and complex nature of In-X subnetworks demands a more adaptive and data-driven approach, necessitating the adoption of advanced artificial intelligence (AI) solutions. The use of graph neural networks has gained considerable attention in addressing large-scale interference management challenges [5]. This category of machine learning (ML) approaches has been applied for power control for In-factory subnetworks (InF-S) [6]. Reinforcement learning approaches have been applied to various challenges, including sub-band allocation [7], power control [8], joint sub-band and transmit power selection [9], [10], and interference control [11]. For centralized resource allocation in multi-cell networks, supervised learning solutions based on Deep Neural Networks (DNN) have been presented in [12]. Furthermore, DNN methods have found application in various tasks such as user association, sub-band allocation, and power allocation within non-orthogonal multiple access systems, as outlined in [13]. Deep learning based sub-band allocation scheme aimed at minimizing overall co-channel interference is proposed in [14]. The effectiveness of treating signal processing problems as an unknown nonlinear mapping from input to output and employing deep neural networks to approximate it has been demonstrated in [15]. This approach was applied to approximate an interference management algorithm, showcasing its successful application in the realm of signal processing. Additionally, Deep power control to maximize either spectral efficiency (SE) or energy efficiency (EE), based on convolutional neural network (CNN), is proposed in [16]. Subnetworks may lead by nature to highly dense deployments (e.g., vehicles in a congested road, humans attending crowded events) and they can be mobile. A factor x10 densification with respect to 5G is indeed expected in 6G [17]. These characteristics may result in wide and rapidly fluctuating interference patterns, which make the problem of radio resource allocation more challenging than in traditional wireless setups, characterized by static base stations/access points and lower cell densities. InF-S is required to support different services, including Ultra-Reliable and Low Latency Communications (URLLC) and enhanced Mobile Broadband (eMBB), each with distinct requirements. While eMBB prioritizes high data rates, URLLC services demand low latency and high reliability. In this paper, we address the sub-band allocation problem for a dense InF-S by formulating and solving it with a focus on the efficient utilization of resources to meet the required data rates of various subnetworks. The contributions of our research can be summarized as follows.

- We consider heterogeneous subnetworks with varying required rates, defining the rate-conforming subnetworks (RCS) (i.e., count of subnetworks reaching the required rates) as the loss function and integrate a DNN to address the sub-band allocation optimization problem. Our approach diverges from simply maximizing the aggregate data rates of subnetworks, whether with or without Quality of Service (QoS) constraints.

- In order to solve the formulated problem which involves discrete optimization variables, we design an unsupervised learning based training methodology and incorporate a novel training strategy, which enables DNN to be trained without needing any labeled training data.
- The efficacy of the proposed scheme is assessed through computer simulations. Our findings validate that the proposed scheme outperforms SoAs in the same deployment scenario, achieving a higher number of RCS while requiring less computation time.

This paper is organized as follows: Section II introduces the problem statement. Section III presents the proposed DL-based sub-band allocation, including the DNN structure and training methodology. The performance evaluation is discussed in Section IV. Finally, the conclusion is presented at the end of the paper.

II. Problem Statement

In this section, we outline the problem statement, where we formulate the sub-band allocation problem under consideration.

We consider a manufacturing facility comprised of an entity equipped with RRM functionality. This entity harnesses its capabilities to effectively govern radio resources, serving the role of a centralized controller (CC). The factory incorporates numerous short-range cells deployed across robotic systems, production modules, conveyors, and other industrial machinery. Each of these cells, referred to as InF-S, encompasses a central communication node designated as an access point (AP), which functions as the edge processing resource for one or multiple devices within the respective subnetwork. Fig. 1 shows a simplified representation of a 2D layout of an InF-S deployment which contains different group of subnetworks with different required rates or equivalently SE. The representation shows a single uplink between a sensor and an AP in each subnetwork, and a signalling link from each subnetwork's AP to a CC. All the devices within a subnetwork are allocated orthogonal resources, therefore inter-cell interference is the main limitation to the subnetwork's SE. For simplicity, for the rest of the paper, we assume that each subnetwork serves a single device whose transmissions occupy the available bandwidth. We focus on the uplink transmission of N subnetworks which are indexed by $n \in \{1, \cdots, N\}$. In the considered system, there are K sub-bands, where $k \in \{1, \cdots, K\}$ denotes the set of sub-bands which devices use to transmit data to the AP. It is assumed that each subnetwork has the capability to operate exclusively over a single sub-band.

In this paper, the objective of resource allocation is to maximize the number of subnetworks which can achieve their required rates while ensuring the reliability of critical services. To achieve this goal, the selection of the sub-band, represented by $\boldsymbol{a_n}$, must be optimized based on current channel conditions. Instead of trying to find the solution of the mentioned variable optimization problem directly through numerical approaches, we transform it into a functional optimization problem. The aim is to find a function that maps the environment i.e., channel gains to optimal solutions, i.e., sub-band allocation. To address this functional optimization problem, unsupervised learning techniques are employed. Leveraging the universal approximation theorem [15], DNNs can approximate a wide range of functions. Therefore, they can be utilized to represent functions that approximate the optimal sub-band allocation strategy for various radio channel conditions. The achievable SE (bits/s/Hz) at subnetwork n in the k-th sub-band is approximated using the Shannon capacity equation as shown below

$$\mathrm{SE}_n^k = \log_2\left(1 + \frac{h_{n,n} f_n^k(\boldsymbol{H}) \mathrm{P}_m}{\gamma_{m,n}^2 + \sum_{m \in \mathbb{N} \setminus \{n\}} h_{m,n} f_m^k(\boldsymbol{H}) \mathrm{P}_m}\right), \tag{1}$$

where $h_{m,n}$ represents the channel state of the link from the interfering device in subnetwork m, and $f_n^k(.)$ denotes the approximation function for optimal sub-band selection, such that $a_n^k = f_n^k(\mathbf{H})$. The transmit power, denoted as P_m, is uniform across all subnetworks. The term $\gamma_{m,n}^2$ is the receiver noise power calculated as $\gamma_{m,n}^2 = 10^{(-174 + \mathbf{NF} + 10\log_{10}(W_k))}$ where W_k denotes the bandwidth of each sub-band and $\mathbf{NF}$ is the receiver noise figure. The proposed sub-band allocation scheme aims to find the optimal $f_n^k(.)$ to maximize the expected number of subnetworks conforming to the required SEs or, equivalently minimize the number of subnetworks that can not reach their target SEs or rates. Let $\mathrm{SE}_n^{\mathrm{req}}$ represent the required SE. The optimal sub-band allocation strategy can be found by solving the following optimization problem:

$$\begin{aligned} \underset{f_n^k \in \{0,1\}}{\text{minimize}} \quad & \sum_{n=1}^{N} \mathbb{1}(\mathrm{SE}_n(f_n^k(\boldsymbol{H}))) \\ \text{s.t.} \quad & \sum_{k=1}^{K} f_n^k(\boldsymbol{H}) = 1, \quad \forall n \in \mathbb{N}, \end{aligned} \tag{2}$$

where $\mathbb{1}(\mathrm{SE}_n)$ is a binary indicator function with a value of 1 if $\mathrm{SE}_n \leq \mathrm{SE}_n^{\mathrm{req}}$ and 0, otherwise. The optimization problem in (2) involves maximizing the number of RCS ($\sum_{n=1}^{N} \mathbf{1}(\mathrm{SE}_n \geq \mathrm{SE}_n^{\mathrm{req}})$) subject to a constraint that ensures only one sub-band is used by each subnetwork.

III. Deep Learning Framework for Sub-band Allocation

In this section, we present the structure of the adopted DNN model and describe the learning strategy employed for training the DNN model.

A. Structure of the DNN model

Fig. 2 illustrates the configuration of our proposed DNN, which is based on the fully connected neural network (FNN). The DNN takes the channel gain matrix $\boldsymbol{H}$ as input, estimates

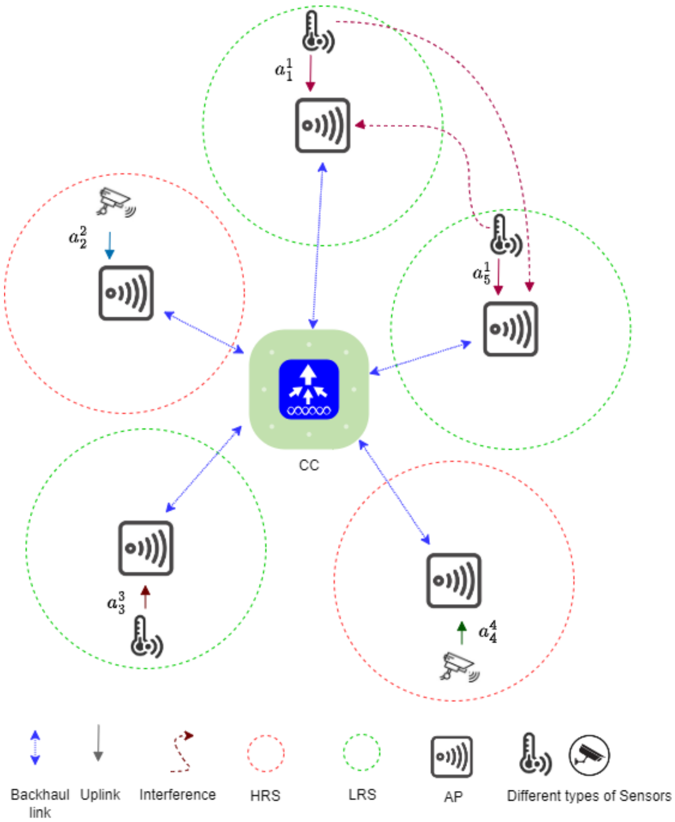


Fig. 1: In-factory subnetworks with different rate requirement

the function f_n^k, and generates the sub-band allocation vector $\boldsymbol{a_n}$ as the output. In the preprocessing stage, the channel gains undergoes reshaping into a one-dimensional vector, a crucial step for integration within the FNN [16]. Subsequently, the values are transformed to the dB scale to restrict the range of possible channel gains. Following this, normalization ensures a zero mean and unit variance. The model then processes the normalized channel gain through the FNN. The FNN structure consists of M_L layers, each including a fully connected unit, batch normalization, and a rectified linear unit (ReLU). After the last ReLU, dropout is applied for regularization [14]. The number of hidden nodes for a fully connected unit is set to M_H, with ReLU acting as the activation function. Batch normalization and dropout are employed to mitigate overfitting of the DNN. The output of the final layer connects to the last fully connected unit, resulting in NK outputs. These outputs are then reshaped into $N \times K$ and fed into N softmax modules. Each softmax module corresponds to the sub-band assignment for a specific subnetwork, executing the softmax operation. This yields K outputs indicating the probability that a sub-band is utilized by the respective subnetwork. The constraint on the sub-band allocation problem (2) is consistently satisfied, as the softmax outputs sum to one. As illustrated in Fig. 2, the sub-band allocation process differs between training and inference. Specifically, during training, the output of the softmax module, a_n^k, directly represents the selected sub-band. However, during inference, a_n^k is set to 1 for $k' = \arg\max_k a_n^k$, and a_n^k is set to 0 for all other k to adhere to the binary constraint in the implementation. This binarization introduces a difference between the resource allocation strategy used in training and that employed during inference, leading to performance degradation. To address the binary constraint, as outlined in the optimization problem in (2), a soft binarization technique is implemented. This technique progressively guides continuous output values towards binary representations during the training steps. Parameterized softmax modules are leveraged for this purpose, where the n-th softmax layer block's k-th output ($\phi_\delta(z_n^k)$) is defined as:

$$\phi_\delta(z_n^k) = \frac{e^{z_n^k/\delta}}{\sum_{k=1}^{K} e^{z_n^k/\delta}}. \tag{3}$$

Here, z_n^k represents the input to the n-th softmax layer block, and $\delta \in (0, 1]$ is a parameter controlling the sharpness of the probability distribution generated by the softmax. A higher δ value results in a softer, more uniform distribution, while a lower δ value leads to a sharper distribution. For a moderate regime of δ, the parameterized softmax function maintains a non-zero gradient, facilitating efficient training via the stochastic gradient descent algorithm. To mitigate the vanishing gradient problem associated with a small value of δ, an adaptive scaling approach is employed. The scaling factor is decreased at predefined intervals by a reduction factor, ensuring effective training convergence without encountering the vanishing gradient issue.

B. *Loss function and training of the DNN model*

The decision to adopt unsupervised learning is driven by the significant time investment required to obtain labeled data for supervised training, especially when dealing with a substantial number of subnetworks. Unlike supervised learning, where input data $\boldsymbol{H}$ is labeled by the output data (optimal sub-band allocation $\boldsymbol{a_n}$), our approach leverages unsupervised learning. This allows our DNN to be effectively trained using a carefully designed loss function, eliminating the need for labeled data. Directly using the objective of (2) as the loss function can impact the efficiency of back-propagation-based training. This is due to the non-differentiability of a step function, as in the objective of (2), at specific points. To address this challenge, we employ a modified version of the objective function in (2) to ensure differentiability throughout the optimization process. By replacing the binary indicator function with sigmoid function as a differntiable alternative, We construct the loss function as

$$L = \frac{\sigma(SE_n^{req} - SE_n)}{SE_n^{req}}, \tag{4}$$

where $\sigma(\cdot)$ denotes the sigmoid function defined as $\sigma(z) = \frac{1}{1+e^{-z}}$. The denominator is used to weight different required SEs, reflecting practical scenarios where low-rate subnetworks (LRS), such as those involved in robot control applications, are usually critical and should be more reliable. In contrast, high-rate subnetworks (HRS), like those in visual inspection

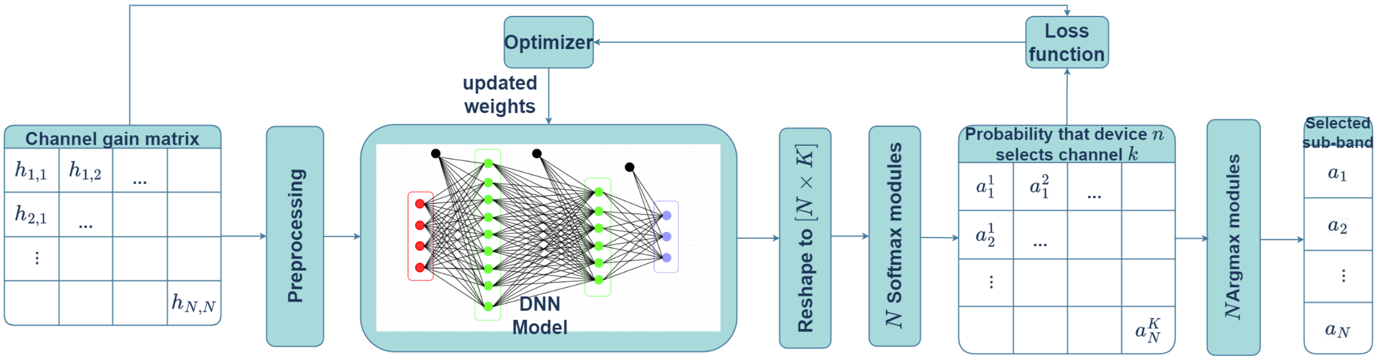


Fig. 2: Structure of the proposed DNN model

applications, despite high data rate requirement allow for acceptable degradation in instantaneous performance. In the proposed DNN-aided sub-band allocation, the trained model approximates the sub-band allocation for any channel realization, allowing the scheme to adapt to various channel conditions without requiring retraining. While the DNN's structure is influenced by the deployment configuration, including the number of subnetworks and sub-bands, the training phase may require significant computation time. However, this training process is conducted offline, prior to operations. This offline training approach significantly reduces time complexity compared to iterative algorithms. In the upcoming section, we evaluate both the performance and complexity of the proposed model.

IV. Performance Evaluation

In this section, we present the performance of the proposed DNN sub-band allocation scheme and compare it with SoA algorithms serving as benchmarks. We consider N InF-S deployed in an $L \times L\left(m^2\right)$ factory area. At each InF-S, AP positioned at the center of a circular coverage area with radius R, and a device located at a distance d from the AP, ensuring a minimum proximity of d_{min}. We consider two groups of subnetworks: LRS and HRS, aligning with robot control and visual inspection use cases. The selected values for SE_L^{req} and SE_H^{req}, taking into account the bandwidth of 10 MHz per sub-band, yield rate requirements of 4 Mbps and 80 Mbps for LRS and HRS, respectively [1].

The wireless communication channel model that we consider for the connection of the devices and AP is based on the model that the 3rd Generation Partnership Project (3GPP) released for InF scenarios [18]. The channel gain in the link between the sensor at subnetwork m and the AP in subnetwork n is expressed as

$$h_{m,n} = \left|g_{m,n}\right|^2 \cdot \Gamma_{m,n} \cdot \psi_{m,n}, \tag{5}$$

where $g_{m,n}$, $\Gamma_{n,m}$ and $\psi_{m,n}$ are complex small-scale fading, path loss and correlated shadowing respectively. The small scale fading, g, is assumed to be Rayleigh distributed and for the path loss model we consider dense clutter and low base station height InF (DL) scenario. The specific details regarding the calculation of losses can be found in [18]. Subnetwork links are assumed to have correlated shadowing [19], meaning a source of shadowing will affect several links simultaneously. First part of the Table I shows the simulation parameters for system model. Regarding the DNN structure, we set the hyperparameters according to the second part of the Table I. The performance evaluations were conducted in a

TABLE I: Simulation parameters

Parameter	Value
Deployment and System Parameters	
Factory area, $L \times L$	20 m×20 m
Number of subnetworks, N	20
Number of sub-bands, K	4
Subnetwork radius, R	1 m
Number of devices per subnetwork, J	1
Minimum distance between APs	2 m
device to APs minimum distance, d_{min}	0.8
Shadowing standard deviation, λ	7.2 dB
DL clutter density, r, clutter size, d_s	0.6, 2
De-correlation distance, d_c	5 m
Transmit power, P_m	0 dBm
Bandwidth, B	40 MHz
Center frequency, f_c	10 GHz
Noise figure, NF	5 dB
LRS required SE, SE_L^{req}	0.4
HRS required SE, SE_H^{req}	8
DNN Parameters	
Number of hidden nodes, M_H	1000
Number of hidden layers, M_L	4
Learning rate, α	$1e^{-5}$
Dropout rate	0.1
Batch size, M_B	1024
Training epochs	200
Training samples	$1e^5$
Validation samples	$1e^4$

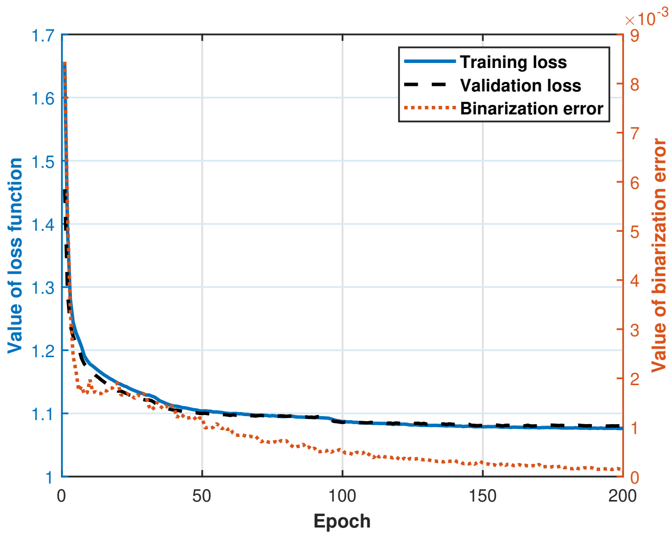


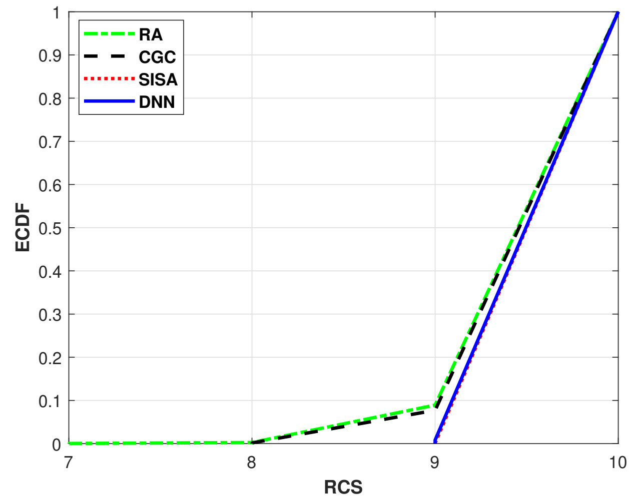
Fig. 3: Training metrics of DNN

cloud computing environment using resources equipped with an AMD EPYC-Rome Processor(40 cores, 40 threads at 2.9 GHz) and an NVIDIA A40 GPU, with 64GB of RAM. The proposed scheme is compared with three baseline schemes:

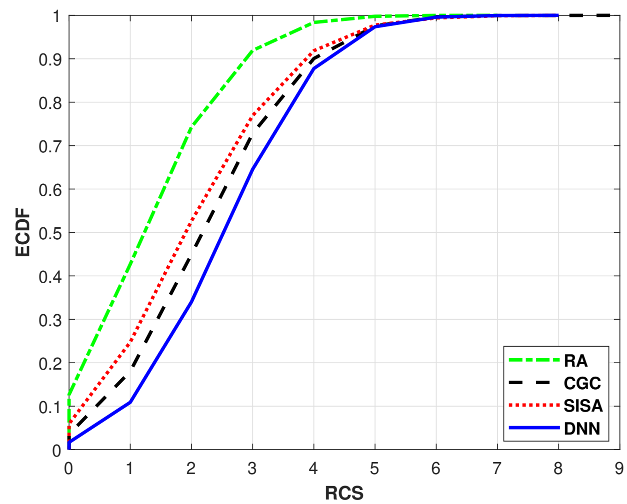
- Centralized Graph coloring (CGC): Utilizes a graph coloring algorithm for color assignment, ensuring that nearest $K-1$ neighbors generating the strongest interference do not share a common sub-band [3].
- Sequential Iterative Sub-band Allocation (SISA): A centralized iterative algorithm that minimizes the sum of weighted interference [4].
- Random Allocation (RA): A distributed scheme where one sub-band is randomly selected from the available K options for each subnetwork.

To validate the efficacy of the loss function in handling the binary constraint, the evolution of the loss functions and the binarization error is assessed. The binarization error is defined as $\mathbb{E}|\boldsymbol{a_n} - \mathrm{round}(\boldsymbol{a_n})|$. Fig. 3 illustrates the values of the loss functions for both training and validation data, along with the binarization error. Considering that optimization variables $\boldsymbol{a_n}$ fall within the range of 0 to 1, the maximum value of the binarization error is 0.5. Post-convergence, the binarization error becomes exceedingly small, confirming that our DNN model proficiently generates binary values.

Fig. 4 presents the empirical cumulative distribution curve (ECDF), which serves as a statistical tool to illustrate the proportion of subnetworks achieving a given level of SE or better, across all evaluated scenarios. In Fig. 4(a), it is evident that RA and CGC cannot guarantee the required rates for all LRS. For approximately 10 percent of the subnetworks, these methods fail to reach the specified rate. In contrast, both SISA and DNN perform exceptionally well for LRS. The majority of the time, employing either of these algorithms enables LRS to meet their required rates. Fig. 4(b) illustrates RCS for HRS, showcasing the superiority of the proposed DNN-based sub-band allocation over other benchmarks. On average, three subnetworks of HRS can achieve the required rates, while this number is two for SISA. It is important to emphasize that the data traffic of subnetworks may vary at each time interval, necessitating effective data transmission management through a scheduler within the InF-S. In high-load scenarios, where resources are limited and not all subnetworks can attain their target rates, those falling short of the target may need to adjust their functionality to a lower rate. This adaptation is particularly relevant in use-cases such as vision inspection, where sensors can still operate effectively with lower resolution. Despite the evident advantages of our proposed scheme, it is essential to acknowledge that, in the current landscape of hyper-dense deployment and constrained resources like bandwidth, relying solely on sub-band allocation may not guarantee meeting the expected rate requirements for all subnetworks simultaneously. Therefore, it becomes crucial to consider implementing power control mechanisms or exploring alternative approaches to further enhance the number of subnetworks meeting their rate requirements.



(a) Low rate subnetworks



(b) High rate subnetworks

Fig. 4: Rate-conforming InF-Ss

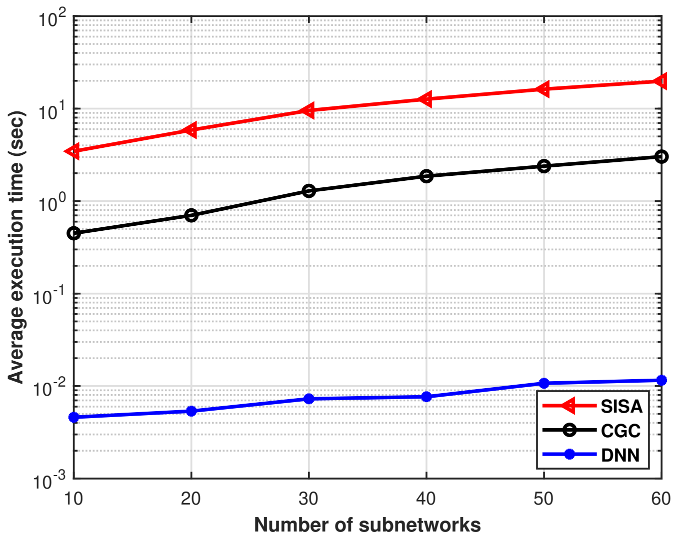


Fig. 5: Computational runtime for different algorithms

The trained DNN network consists of simple linear and nonlinear transform units in the forward path, enabling the potential for parallel computation. This design choice facilitates efficient execution and results in low computation time. In contrast, benchmarks like CGC and SISA rely on iterative algorithms, introducing challenges in parallel implementation and limiting their computational efficiency. The computational runtime for different algorithms is shown in Fig. 5. The significantly lower time required by DNN compared to the benchmarks highlights the efficiency of the DNN-based approach in the context of sub-band allocation, particularly in scenarios involving large-scale computations.

V. Conclusion

This paper has introduced an unsupervised DNN-based sub-band allocation algorithm specifically tailored for 6G In-F subnetworks, considering heterogeneous data rate requirements. Our primary objective was to maximize the number of subnetworks achieving their target data rates, utilizing a formulation that incorporates discrete optimization variables. Through computer simulations, we demonstrated the superiority of our proposed scheme over heuristic benchmarks, showcasing enhanced performance accompanied by reduced computation time. While the DNN-based sub-band allocation exhibits comparable performance to SISA for low rate subnetworks, it has enhanced the likelihood of achieving specific RCS targets by approximately 20% for high rate subnetworks. Future research endeavors will delve into extending the DNN approach to address other radio resource management challenges, such as power control, with the aim of ensuring that all subnetworks simultaneously reach their target rates, even in extremely dense and dynamic factory environments.

Acknowledgements

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