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Goal-Oriented Uplink Scheduling Requests in Wireless Networks via Graph Neural Networks

Lorenzo Mario Amorosa
Dept. of Electrical, Electronic and Information Engineering
University of Bologna
WiLab - National Wireless Commun. Laboratory (CNIT)
Bologna, Italy
lorenzomario.amorosa@unibo.it

Leonardo Spampinato
Dept. of Electrical, Electronic and Information Engineering
University of Bologna
WiLab - National Wireless Commun. Laboratory (CNIT)
Bologna, Italy
leonardo.spampinato@unibo.it

Chiara Buratti
Dept. of Electrical, Electronic and Information Engineering
University of Bologna
WiLab - National Wireless Commun. Laboratory (CNIT)
Bologna, Italy
c.buratti@unibo.it

Roberto Verdone
Dept. of Electrical, Electronic and Information Engineering
University of Bologna
WiLab - National Wireless Commun. Laboratory (CNIT)
Bologna, Italy
roberto.verdone@unibo.it

***Abstract*—In modern industrial internet of things (IIoT) networks, efficient management of communications resources is crucial to match stringent application requirements. Differently from traditional resource allocation policies, goal-oriented communications is an emerging paradigm that aims at better optimizing network resource usage by prioritizing the transmission of information that is most relevant to a given task. Moreover, recent trends show increasing interest in distributed machine learning-based optimization to enhance network performance while reducing the reliance on centralized control. In this context, graph neural networks (GNNs) have emerged as a powerful tool for learning distributed policies among nodes facilitating their cooperation. In this paper, we introduce a goal-oriented, distributed framework to optimize uplink scheduling requests for coordinated message transmission to a remote server, while minimizing communication overhead. Our approach employs GNN-based distributed unsupervised learning framework that does not require a centralized controller. Extensive simulations in a 3GPP-compliant industrial scenario demonstrate that the proposed solution effectively reduces redundant uplink scheduling requests while achieving efficient and scalable coordination across multiple networks. Our findings highlight the potential of GNNs for learning distributed policies that enhance communication efficiency in wireless industrial IoT systems.**

***Index Terms*—Graph neural networks, wireless networks, scheduling, goal-oriented communications, distributed learning**

I. Introduction

Industrial internet of things (IIoT) networks play a crucial role in modern smart factories and automation systems, where a large number of interconnected sensors and devices must communicate efficiently while operating under strict resource constraints [1], [2].

Traditionally, efficient resource allocation policies have been investigated to maximize radio key performance indicators (KPIs) [3], while recently goal-oriented communication is emerging as viable approach to better match application-oriented requirements rather than network KPIs [4]. Recently, machine learning (ML) techniques have emerged as promising approaches for resource allocation, allowing adaptive, distributed, and context-aware decision-making [5]. Moreover, the need for distributed resource allocation strategies is particularly relevant in IIoT scenarios where centralized control is impractical due to latency or scalability constraints, requiring nodes to autonomously allocate their communication resources based on local information [6].

These challenges motivate the need for distributed, goal-oriented, and learning-based solutions to address the management of wireless communication resources. As a relevant example, the authors in [7] proposed a novel problem in the context of distributed learning for medium access control (MAC) in IoT networks. In their work, a set of sensors needs to learn to communicate a shared message over shared orthogonal resource units (RUs). This message is shared by a random subset of nodes within the sensor network, which need to propagate it to a remote server that has to receive it at least once, regardless of the sender. To solve this coordination problem, they proposed a decentralized multi-armed bandit-based approach which proves to be effective for MAC in small-scale IoT networks.

In this work, we consider a setting similar to [7], where multiple nodes can simultaneously generate a shared message that must be successfully delivered to a remote server. While [7] focuses on learning which communication opportunities

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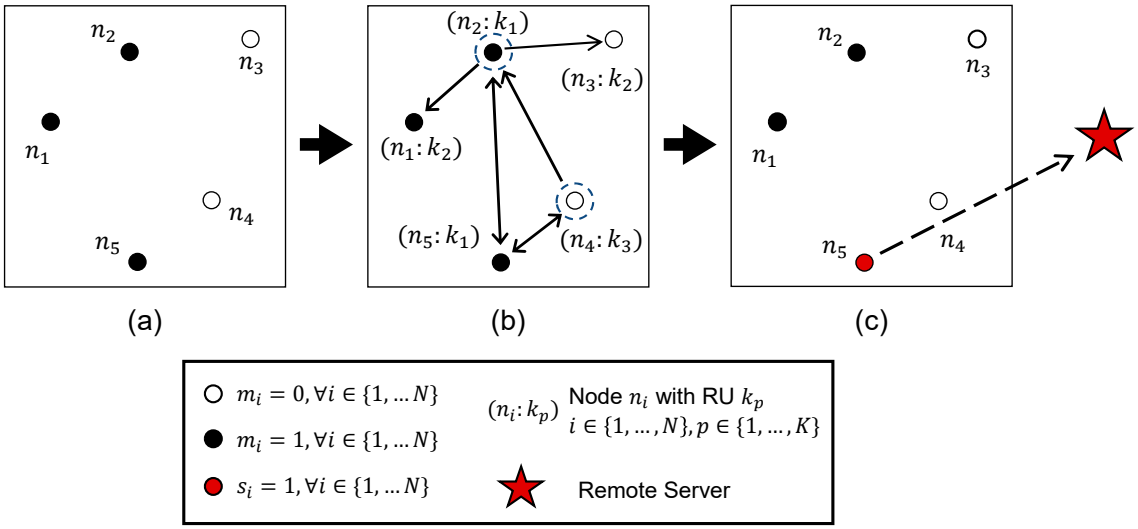


Fig. 1: Example of a network realization and coordination phase at time step t. (a) Initially, the shared message is available only for some nodes according to $\mathbf{m}_t$; (b) Secondly, each node randomly selects a RU to be used for local state exchange and the graph $\mathcal{G}_t$ is generated based on $\gamma_{i,j}^{(k)}$. For conciseness, only receiving and transmitting links for n_2 and n_4 are reported. (c) After L local state exchanges, the coordination phase ends and $\mathbf{s}_t$ is determined. In this example, only one node sends an uplink scheduling request to the remote server, representing an optimal outcome.

each sensor should utilize to ensure message delivery, our objective is to design a distributed resource allocation policy that guarantees the shared message is received at least once while minimizing redundant transmissions by sending the minimum number of uplink scheduling requests. This is particularly important when direct communication with the remote server is impractical and energy-intensive. However, if sensors within the network can communicate with each other at low cost, coordinated transmission strategies can significantly enhance efficiency by enabling nodes to cooperate in delivering the shared message leveraging a distributed policy.

Traditionally, a centralized controller coordinates and schedules uplink transmissions in a sensor network. While such methods can achieve optimal performance, they incur significant communication overhead, which may be prohibitive in energy-limited networks. To overcome these challenges, we investigate whether a distributed scheduling policy can be learned directly by the network itself, leveraging graph neural networks (GNNs) as a mechanism for decentralized decision-making [8]. GNNs provide an effective means for learning distributed policies due to their ability to model interactions among multiple nodes and facilitate cooperation. By incorporating multiple message-passing layers, GNNs allow nodes to iteratively refine resource allocation strategies within wireless networks [9], [10]. Overall, the key contributions of this work comprise:

- Development of a distributed and goal-oriented GNN-based framework to learn to efficiently send uplink scheduling requests that enable a shared message to be transmitted across the wireless network without requiring centralized coordination.
- Comprehensive evaluation of the proposed framework through simulations, including both small-scale and large-scale wireless networks.

The rest of the paper is organized as follows: Sec. II details the system model, Sec. III describes the proposed GNN-based distributed solution, Sec. IV reports numerical results obtained from extensive simulations, while in Sec. V conclusions are drawn.

II. System Model and Problem Formulation

A. Wireless Network Modeling

We consider a wireless network of N nodes $\mathcal{N} = \{n_1, \cdots, n_N\}$ operating at frequency f_c that have to transmit a shared message to a remote server within an industrial factory. Nodes are randomly distributed within an $D \times D$ area, with their fixed individual position defined as (x_i, y_i), for all $i \in \{1, \dots, N\}$. We represent with a binary vector $\mathbf{m}_t = [m_1, \dots, m_N]_t$ the availability of the shared message within the network at time step t, where $m_{i,t}$ is a binary random variable indicating whether the shared message is currently available at node n_i. Each $m_{i,t}$ is assumed to be Bernoulli distributed with probability π_i. An example of network deployment and message availability is represented in Fig. 1a. In this example, only nodes n_1, n_2, and n_5 have the shared message available. At each time step, nodes can send an uplink scheduling request to transmit the shared message to the remote server. However, uplink transmissions to the server are assumed to be costly - whether due to energy constraints caused by its remote location, traffic overhead,

potential interference, or other factors. To solve this issue, nodes can leverage their proximity, communicate with each other at a lower cost, and make coordinated decisions before transmitting to the server. To this end, at each time step each node n_i sends up to L times its local state to its neighboring nodes. After this initial *coordination phase*, each node that has the shared message available can autonomously decide whether to send an uplink scheduling request to the remote server.

B. Local Coordination Phase

Assuming the availability of K orthogonal RUs, at the beginning of each coordination phase, i.e., at each time step t, nodes randomly select one RU $k \in \{k_1, \ldots, k_K\}$ according to a uniform sampling, possibly mitigating interference. Each node can receive signals over all the RUs. Moreover, we assume that each node operates in full duplex over its chosen RU k, thus it can both receive and transmit signals over k. We model MAC decisions made locally at each node with an indicator function $\delta_i(k) \in \{0, 1\}$, where $\delta_i(k) = 1$ only if node n_i selects the RU k to coordinate with the rest of the network. For each pair of nodes (i, j), we define signal to interference plus noise ratio (SINR) $\gamma_{i,j}^{(k)}$ perceived by the i-th node to the j-th node over RU k as

$$\gamma_{i,j}^{(k)} = \frac{P_{\text{tx},j}\ \mathbf{A}_{j,i}\ \delta_j(k)}{P_N + \sum\limits_{\substack{q=1 \\ q\neq i,\ q\neq j}}^{N} P_{\text{tx},q}\ \mathbf{A}_{q,i}\ \delta_q(k)}\ , \tag{1}$$

where $P_{\text{tx},j}$ is the transmit power of node j, $\mathbf{A}_{j,i}$ is the channel attenuation (or path gain) between j and i, and P_N is the noise power. We assume that each node is equipped with a single isotropic antenna. In order to have a successful transmission from j to i over RU k, it is required that $\gamma_{i,j}^{(k)} > \bar{\gamma}$, where $\bar{\gamma}$ is a target SINR. For each coordination phase, the set of communication links available in the sensor network is determined by SINR-based conditions, resulting in dynamic connectivity patterns. We model these connections via a directed graph among nodes $\mathcal{G}_t = (\mathcal{N}, \mathcal{E}_t)$, where $\mathbf{H}_t = [\mathbf{h}_1, \cdots, \mathbf{h}_N]_t$ are the node states and an edge $(i, j) \in \mathcal{E}_t$ is set at time t if there exists a k such that $\gamma_{i,j}^{(k)} > \bar{\gamma}$ and it represents that node i can receive the local state from node j. An example graph used during the local coordination phase is reported in Fig. 1b. In this example, n_2 is able to transmit its local state over k_1 to nodes $n_1, n_3,$ and n_5. However, while correctly receiving local states over k_1 and k_3, it is not able to receive the states from n_1 and n_3 due to the interference over k_2, as $\gamma_{2,1}^{(k_2)} < \bar{\gamma}$ and $\gamma_{2,3}^{(k_2)} < \bar{\gamma}$. Similarly, although node n_4 does not have the shared message, it still participates in the local coordination phase and it is able to transmit its local state to n_2 and n_5. However, it receives states only from n_5, as their proximity and weak interference from n_2 result in $\gamma_{4,5}^{(k_1)} > \bar{\gamma}$.

C. Uplink Scheduling Request Problem

At the end of a coordination phase, the binary vector $\mathbf{s}_t = [s_1, \cdots, s_N]_t$ represents the local network decision at time step t, with $s_{i,t} = 1$ if node n_i sends a scheduling request to the remote server for the uplink transmission of the shared message. In the optimal case, a single node $\bar{n} \in \mathcal{N}$ sends an uplink scheduling request, so that transmissions to the remote server are minimized and uplink resources to communicate the shared message are successfully obtained. An example of a coordination phase outcome is shown in Fig. 1c, where only node n_5 transmits an uplink scheduling request to the remote server. To evaluate the optimality of a decision variable $\mathbf{s}_t$, we model the uplink scheduling request cost function as

$$\mathcal{L}(\mathbf{s}_t) = c_1(1 - \lambda(\mathbf{s}_t)) + c_2\left(\sum_{i=1}^{N} s_{i,t} - 1\right)\ , \tag{2}$$

where c_1 is the penalty constant that ensures that at least one node is transmitting a scheduling request, while c_2 is the penalty constant penalizing redundant transmissions to the remote server. The term $1 - \lambda(\mathbf{s}_t)$ ensures that at least one scheduling request is sent to transmit the shared message, as

$$\lambda(\mathbf{s}_t) = \frac{\sum\limits_{i=1}^{N} s_{i,t}\ e^{s_{i,t}/\tau}}{\sum\limits_{i=1}^{N} e^{s_{i,t}/\tau}}\ , \tag{3}$$

is softmax-based differentiable function to approximate the maximum function which is unsuitable for gradient-based optimization. Here, τ is a temperature parameter controlling the sharpness of the approximation. As τ approaches 0, the expression converges to the standard maximum function. Consequently, the final optimization problem is given by

$$\min_{\mathbf{s}_t} \mathcal{L}(\mathbf{s}_t)\ . \tag{4}$$

This problem has global minimum in $\mathcal{L}(\mathbf{s}_t^*) = 0$ for any $\mathbf{s}_t^*$ such that $\sum_{i=1}^{N} s_{i,t}^* = 1$ and it is trivially solved when a centralized controller has access to global information. However, it is complicated to solve it in a distributed manner as consensus has to emerge in the sensor network so that a single node transmits an uplink scheduling request to successfully send to the remote server the shared message.

III. GNN-based Unsupervised Learning

A. Graph Neural Network Parameterization

In pursuit of a distributed solution, we propose an unsupervised GNN-based framework to solve the uplink scheduling request problem in Eq. (4). Our proposed GNN provides node-level decisions for transmitting uplink scheduling requests needed to send the shared message to the remote server. Our approach operates over $\mathcal{G}_t$, which is the directed graph connecting nodes $\mathcal{N}$ at time t to locally exchange node states for coordinated remote transmissions. This GNN consists of L layers, allowing each node to exchange L times its local state over $\mathcal{G}_t$. Equivalently, repeating the exchange L times allows a deeper propagation of information inside the network,

with nodes reaching neighbors up to the L-th order, possibly mitigating the limited connectivity of some nodes. To better allow coordination, we consider that each node selects the same orthogonal RU for the L local transmissions within the same time step t, resulting in a static $\mathcal{G}_t$. Each layer $l \in [1, \cdots, L]$ updates the local states as

$$\mathbf{h}_{i,t}^{(l+1)} = f_i^{(l+1)} \left(\mathbf{h}_{i,t}^{(l)},\ g_i^{(l+1)} \left(\left\{ \mathbf{h}_{j,t}^{(l)} : (j,i) \in \mathcal{E}_t \right\} \right) \right) , \quad (5)$$

where $f_i^{(l+1)}$ and $g_i^{(l+1)}$ are the transformation and aggregation functions for node n_i at layer l, respectively. The initial state for node n_i is $\mathbf{h}_{i,t}^{(0)} = \mathbf{m}_{i,t}$ and the final state $\mathbf{h}_{i,t}^{(L)} = s_{i,t}$. Nodes perform local state exchanges as discussed in Sec. II and aggregation functions locally concatenate the available states to perform each layer update. Aggregated states are then processed by transformation functions, which are parameterized using a multilayer perceptron (MLP) with rectified linear unit (ReLU) activations. However, each final layer $f_i^{(L)}$ employs a sigmoid activation to produce $s_{i,t}$. This ensures that $s_{i,t}$ takes values in the continuous range $[0, 1]$, which is essential for gradient-based optimization algorithms to function effectively. Discretizing $s_{i,t}$ would prevent gradient updates and hinder the optimization process.

B. Unsupervised Learning Framework

We consider centralized training and decentralized execution settings to operate the proposed GNN solution, leaving it unconstrained to apply parameter sharing. Therefore, we both consider *shared* GNN models, allowing for shared transformation functions across nodes, and *individual* GNN models, defining specific transformation functions at each node. While the former require the fitting of a smaller number of MLPs, the latter enables increased decentralization as each MLP does not need to be shared and transmitted across nodes at training time, reducing communication overhead. At each training step t, all nodes receive $\mathcal{L}(\mathbf{s}_t)$ from the remote server to update their models according to the decision variable $\mathbf{s}_t$. At inference time, the execution is fully local and distributed, as nodes are only involved in local state exchanges and there is no feedback from the remote server.

IV. Experimental Results

A. Simulation Setup

We simulate a wireless network considering 3rd generation partnership project (3GPP)-complaint setup for indoor factory with dense clutter and low node height (InF-DL) [11] as reference scenario for channel models. The simulation parameters modeling the wireless network are reported in Table I, where default parameters values used in simulations when not specified otherwise are highlighted in bold. Each node position is sampled from a 2D uniform distribution as $(x_i, y_i) \sim \mathcal{U}([0, D] \times [0, D])$, while node height is fixed at 1.5 m. Transmit power at each node i is set to $P_{\text{tx},i} = P_{\text{tx}}$. Each probability π_i parameterizes a Bernoulli distribution that governs the availability of shared messages at each node and is drawn from $\pi_i \sim \mathcal{U}(0, 1)$. The uplink scheduling request cost function is set using $c_1 = 1$, $c_2 = 0.1$, and $\tau = 0.1$. Each training process lasts for a total of 250 epochs. The employed GNN models feature L MLP layers each with a shallow network of 128 neurons and are trained using Adam optimizers with a learning rate of 10^{-4}.

Parameter	Description	Value
N	N. of nodes	$\{16, 32, 64, 128\}$
K	N. of RUs	$\{N/2, \mathbf{N}, 2N\}$
K/N	RU to nodes ratio	$\{0.5, \mathbf{1}, 2\}$
L	N. of local exchanges	$\{1, \mathbf{3}, 5\}$
P_{tx}	Transmit power	$\{0, \mathbf{-5}, -10\}$ dBm
f_c	Carrier frequency	15 GHz
$\bar{\gamma}$	Target SINR	8 dB
P_N	Noise figure	10^{-12} W
D	Factory side	500 m

TABLE I: Simulation parameters used for modeling the wireless network according to 3GPP InF-DL scenario.

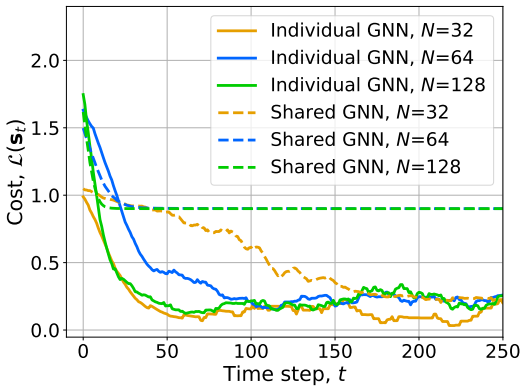


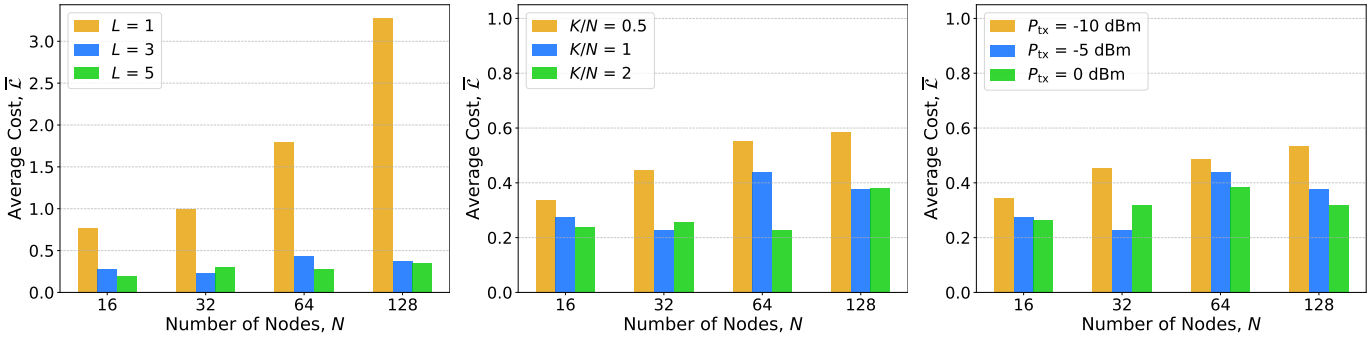
Fig. 2: Cost over training time step t for different number of nodes N and distributed learning scheme.

B. Local Graph Connectivity Analysis

The graph connectivity across nodes highly depends on the simulation parameters used for the considered wireless networks. In Tab. II, we discuss connectivity of graphs $\mathcal{G}_t$ during the training processes when fixing some simulation parameters. It is worth noting that within 3 hops each node can reach all the rest when considering $K/N = 1$ and $P_{\text{tx}} = -5$ dBm. Although setting $L = 3$ during trainings allows for reaching all nodes, training with larger $L > 3$ can potentially benefit of better performance, as it exposes the model to a wider range of multi-hop interactions. As expected, increasing K leads to a larger set of first order neighbors for each setting. Interestingly, also higher P_{tx} results in a denser graph, as the increased transmission power extends the communication range, enabling more direct connections between nodes.

	$K/N = 1,\ P_{\text{tx}} = -5$ dBm			Varying K/N, with P_{tx} = -5 dBm			Varying P_{tx}, with $K/N = 1$		
N	1st order	3rd order	5th order	0.5	1	2	-10 dBm	-5 dBm	0 dBm
16	4.63	12.53	13.44	2.52	4.63	6.45	2.66	4.63	6.59
32	9.35	28.88	30.05	4.96	9.35	13.14	5.46	9.35	12.68
64	18.72	61.84	62.73	9.86	18.72	26.31	10.87	18.72	25.53
128	37.23	126.76	127.21	19.46	37.23	52.64	21.60	37.23	51.14

TABLE II: Average number of neighboring nodes in graphs $\mathcal{G}_t$ at training time considering all values of N. The first three columns show the numbers of neighbors of 1st, 3rd, and 5th order having fixed K/N and P_{tx}. Columns from forth to sixth show first order neighbors when varying K/N and having fixed P_{tx}, while columns from the seventh to the ninth show first order neighbors when varying P_{tx} and having fixed K/N.



(a) (b) (c)

Fig. 3: Average cost $\bar{\mathcal{L}}$ over training (a) as a function of local exchanges L, with P_{tx}=-5 dBm, N/K=1; (b) as a function of resource ratio K/N, with P_{tx}=-5 dBm, L=3; (c) as a function of transmit power P_{tx}, with K/N=1, L=3.

C. Numerical Results

The training trends of both shared GNN models and individual GNN models are presented in Fig. 2. Given the multiple set of simulation parameters available, we conducted several training sessions. In this figure it is assumed a scenario with default parameters as defined in Sec.IV-A, since this set of parameters provides a good balance for graph connectivity and node transmitting power. For smaller networks comprising $N = 32$ nodes, both approaches reach competitive performance producing limited overhead for uplink transmissions to the server as $\mathcal{L}$ approaches the global minimum. However, in larger scenarios with $N = 64$ and $N = 128$, only GNN models without parameter sharing reach competitive performance. Indeed, optimal solutions to this coordination problem require nodes to learn distinct policies. However, parameter sharing often results in homogeneous behavior across nodes, as they rely on shared neural network weights to determine node-level decisions. Results that follow are shown assuming individual GNN models deployed at each node, given their better ability to efficiently scale with increased N.

In Fig. 3, we present the average cost $\bar{\mathcal{L}}$ at training time when varying L, K/N, and P_{tx}. Similarly to the previous case, while a variable changes the others are kept fixed with their default value. In Fig. 3a the trends with varying L are reported. Results show that good performances is achieved for $L \geq 3$ local exchanges, as local information propagates deeper within the connected graph, enabling nodes to coordinate more effectively. On the contrary, when L=1 the average cost remains high, indicating insufficient level of coordination among nodes. Moreover, setting L=3 reduces the communication overhead with respect to setting L=5. Fig. 3b shows the performance when varying the RUs to nodes ratio K/N. Generally, a higher number of channels reduces the probability of nodes interfering with each other, allowing more connected graph and faster training. Finally, Fig. 3c shows the influence on the P_{tx} to training performance. Higher transmitting power reduces the average cost, however, nodes will need a higher amount of energy to sustain their local communication, potentially reducing the benefit of distributed scheduling policies. Interestingly, both Fig. 2 and Fig. 3 shows that the proposed approach scale well with respect to larger networks, as good performance are reached for all tested values of N.

V. Conclusion

In this paper, we proposed a distributed GNN-based approach for a goal-oriented wireless communication scenario, where nodes in a sensor network are tasked to learn a coordination policy to send uplink scheduling requests to a remote server for transmitting a shared message while minimizing communication overhead. The developed methodology leverages distributed unsupervised learning, where a GNN model deployed over the sensor network can learn to solve distribu-

tively this goal-oriented challenge. Extensive simulations are conducted in 3GPP-complaint scenarios, considering multiple wireless network parameters and GNN architectures. Numerical results show that the proposed GNN-based framework can successfully achieve distributed coordination to solve the considered problem in wireless networks comprising up to 128 nodes while reducing communication overhead and limiting interactions with the remote server.

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