Learning Connectivity for Data Distribution in Robot Teams

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Abstract—Many algorithms for control of multi-robot teams operate under the assumption that low-latency, global state information necessary to coordinate agent actions can readily be disseminated among the team. However, in harsh environments without existing communication infrastructure, robots must form ad-hoc networks, forcing the team to operate in a distributed fashion. To overcome this challenge, we propose a task-agnostic, decentralized, low-latency method for data distribution using Graph Neural Networks (GNN). Our approach enables multi-agent algorithms based on global state information to function by ensuring it is available at each robot. To do this, agents glean information about the topology of the network from packet transmissions and feed it to a GNN running locally which instructs the agent when and where to transmit the latest state information. We train the distributed GNN communication policies via reinforcement learning using the average Age of Information as the reward function and show that it improves training stability compared to task-specific reward functions. Our approach performs favorably compared to industry-standard methods for data distribution such as random flooding and round robin. We also show that the trained policies generalize to larger teams of both static and mobile agents.

I. INTRODUCTION

Large scale swarms of robots have demonstrated utility in solving many real world problems including rapid environmental mapping [1], [2], target tracking [3], search after natural disasters [4], [5] and exploration [6], [7]. In many of these scenarios, robot teams must operate in harsh environments without existing communication infrastructure, requiring the formation of ad-hoc networks to exchange information. Furthermore, agent actions may take them out of direct communication range with a subset of the team so that packets must be relayed through intermediate nodes to reach their intended destination. Ad-hoc robot networks are implicitly decentralized. In spite of this, many algorithms for control of multi-robot teams operate under the assumption that low-latency, global state information necessary to coordinate agent actions can readily be disseminated among the team. While detail about how this data distribution task is accomplished is often scarce, its success is vital to the overall performance of the team. In this work, we address this challenge by providing a task-agnostic, decentralized, low-latency method for data distribution in an ad-hoc network using Graph Neural Networks. Our system enables existing centralized algorithms to be deployed in robot teams operating in harsh, real world environments.

The problem of data distribution in a team of robots bears a strong resemblance to the problem of packet routing in a mobile ad-hoc network (MANET). In our case, up-to-date global state information such as velocity, pose, or map data must be maintained at each robot so that they can choose appropriate control actions. Likewise, ad-hoc routing protocols in MANETs require each node maintain some knowledge of the state of the network so that they can choose the next hop a packet should take in its journey from source to destination. For proactive protocols, this is often accomplished by periodically flooding the network with link state information so that each node maintains a current understanding of the network topology [8]. This process can be inefficient and strain the network with contention and packet collisions and as a result, many different flooding schemes have been developed to mitigate the so-called broadcast storm problem [9]. As is made clear in Section II, our method draws inspiration from these flooding schemes and employs them as points of comparison during evaluation.

In this work, we assume the network is used exclusively for the data distribution task in question. As such, it makes sense to skip the regular link layer overhead necessary to operate an ad-hoc routing protocol and directly consider a data distribution protocol handling the application layer traffic of the robotic system. In essence, our data distribution protocol is itself a routing protocol which circulates the state information needed by the robots in the place of network state information needed for packet routing. While conventional approaches use some form of flooding to accomplish this task, most are based on heuristics designed to minimize the age of information and network overhead [9]. There exists no clear optimal approach. Thus, we believe this problem is well suited to a data driven approach based on Graph Neural Networks paired with reinforcement learning.

Graph Neural Networks (GNNs) have shown great promise for learning from information described by a graph [10], [11]. Recent works have used GNNs to generate heuristic solutions to a variety of multi-robot problems, such as path planning [11]–[13], exploration [14], and perimeter defense [15]. In this work, a GNN is the natural choice for parameterizing the communication policy which prescribes actions based on the information exchanged over the network graph. Furthermore, GNNs offer attractive properties such as permutation invariance, making the learned solution robust.

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to changes in graph topology between training and testing. In order to effectively distribute information, our model must learn when and with whom to communicate. Many prior approaches use multi-agent reinforcement learning to address communication for particular cooperative control tasks, [16]–[19]. These approaches generally do not incorporate bandwidth limitations or physical channel models, often assuming that all agents are reachable through broadcast communications, which is sometimes range-limited. Other approaches learn communication graphs to keep communication sparse [20], [21]. However, such approaches begin creating these graphs by first assuming that the relative positions of all other agents can be noisily observed [20] or are transmitted through a series of global broadcasts [21]. In this paper, we consider realistic communication conditions and thus assume no prior knowledge of other agents except for their identities and overall team size.

The primary contribution of this work is the development of a learned, cross-layer data distribution protocol that can be applied to any multi-agent task that relies on sharing time-sensitive local observations across a wireless network. Using reinforcement learning, this protocol can be optimized for use with static or mobile teams.

The remainder of the paper is organized as follows: Section II describes the wireless communication model, local data structures and the AoI minimization problem. Section III details the GNN architecture, the design of the transmission-response protocol, and our usage of reinforcement learning. Section IV describes the agent dynamics, the mission specification for the applications of our approach, and we compare performance of the GNN to several baselines in Section V. An open-source implementation of our work can be found in this repository.

II. Problem Formulation

A. Wireless Communication Model

In order to reason about transmitting information in a network, it is necessary to establish a model for communication. In this work, we consider ideal wireless conditions between agents with line of sight channels and successful packet reception subject to interference from other transmitting nodes in proximity. Transmitted signals propagating through the air experience free-space path loss \( E_{\text{f},i}^{i,j} \) given by:

\[
E_{\text{f},i}^{i,j} = 20 \log_{10}(d_{i,j}^{i,j}) + 20 \log_{10}(V) - 147.55
\]

(1)

where \( d_{i,j}^{i,j} \) is the distance between transmitting agent \( i \) and receiving agent \( j \), and \( V \) is the system center frequency (in Hz) [22]. This approach is consistent with wireless studies involving transmissions between aerial agents [23], [24]. From path-loss, we can define the channel gain as:

\[
g_{i,j}^{i,j} = 10^{E_{\text{f},i}^{i,j}/10}
\]

(2)

and the signal-to-interference-plus-noise ratio (SINR) as:

\[
\Gamma_{i,j}^{i} = \frac{\rho_{i}^{i} g_{i,j}^{i,j}}{\sigma + \sum_{k \in A \setminus j} \rho_{k}^{i} g_{i,k}^{i,j}}
\]

(3)

where \( \sigma \) is additive white Gaussian noise representing ambient noise power at the receiver and \( \rho_{i}^{i} \) is the transmit power of agent \( i \). In order for a packet transmitted from agent \( i \) to be successfully received at agent \( j \), \( \Gamma_{i,j}^{i} \) must exceed a SINR threshold \( \hat{\Gamma} \) that takes into account the QoS of the link [25]. Defining \( R_{i}^{j} \) as the set of agents that receive a transmission from agent \( i \) at time \( t \), we can express the probability of successful packet reception at \( j \) as:

\[
p(j \in R_{i}^{j}) = \begin{cases} 1 & \Gamma_{i,j}^{i} \geq \hat{\Gamma} \\ 0 & \Gamma_{i,j}^{i} < \hat{\Gamma} \end{cases}
\]

(4)

Note that in ad-hoc networks, it is common for all nodes to contend for the same medium and thus be able to decode any packet transmission for which they are in range, regardless of if they are the intended recipient. In fact, this is a foundational aspect of many flooding algorithms [8]. We also allow agents to eavesdrop on each others transmissions.

B. Local Data Structures

Critical to any networking protocol is the metadata it caches for decision making. In our approach, this information forms the feature vectors consumed by our communication policy. And, since this is a data distribution task, there is an additional payload: given a set of robots \( A \) with clocks synchronized at time \( t \), each robot maintains a data structure that contains agent \( i \)’s knowledge about agent \( j \) indicated by \( M_{i,j}^{i} \). This information is required by the robot to make decisions to accomplish some task. Along with the last known state, agent \( i \) also stores a timestamp for this observation of the state of agent \( j \), \( T_{i,j}^{i} \). Agents can observe their own local states at the current time step, \( x_{i}^{i} \), and update their own memory accordingly:

\[
M_{i,j}^{i} := x_{i}^{i}, \quad T_{i,j}^{i} := t \quad \forall i \in A, \; t \geq 0
\]

(5)

Agents may make a decision to transmit their local data to others. The set \( S_{i}^{j} \) represents the intended recipients of a transmission by agent \( i \) at time \( t \). In this work, we constrain the set of intended recipients to be at most one other agent. As outlined in the previous section, agents in proximity that transmit simultaneously run the risk of interfering with each other causing communication failures. Thus, we define \( f \) as the stochastic communication model that determines the probability of receipt \( p(j \in R_{i}^{j}) \) of agent \( i \)’s transmission by agent \( j \) at time \( t \):

\[
\{ p(j \in R_{i}^{j}) \}_{i \in A} = f \left( \{ S_{i}^{j} \}_{i \in A} \right),
\]

(6)

where \( f \) is the communication model described in Eq. II. We also record the timestamp at which agent \( i \) last attempted communication with agent \( j \), \( L_{i,j}^{i} \).

\[
j \in S_{i}^{j} \implies L_{i,j}^{i} = t.
\]

(7)

As data is transmitted by agents in the team, we can track how it propagates through the network as shown in the example in Fig. II. We define the parent reference notation \( P_{i,k}^{j} = j \) to indicate that agent \( k \) first passed its information to agent \( j \) on its way to agent \( i \). If agent \( i \) directly receives agent
k’s information from k, then $P_i^{j,k} = i$. When agent $i$ receives a transmission from agent $j$ containing agent k’s state, agent $i$ can record the link along which agent $j$ had obtained that information, $P_i^{j,k} = P_i^{j,k}$. This record of transmission relationships describes how data flowed between agents to construct agent $i$’s knowledge of the system state at time $t$. If agent $i$ has received agent $j$’s transmission, then it will update its data structure if any of the received information is newer than its current data, $\forall k \in \mathcal{A}$:

$$T_i^{j,k} < T_i^{j,k}, j \in P_i \implies (T_i^{j,k} = T_i^{j,k}) \land (M_i^{j,k} = M_i^{j,k}) \land (P_i^{j,k} = P_i^{j,k})$$

(C. Local Policy to Minimize Age of Information)

To effectively disseminate data in the network, a communication policy is installed at every node that operates entirely off of the information outlined in the previous section. More formally, a policy $\pi$ selects a recipient for its transmission using the set of information available to agent $i$ at time $t$: $\{T_i^{j,i}, M_i^{j,i}, P_i^{j,i}, L_i^{j,i}\}_{j \in \mathcal{A}}$. The same local stochastic communication policy $\pi$ is to be used by all agents:

$$p(k \in S_i^{j}) = \pi \left( \{T_i^{j,i}, M_i^{j,i}, P_i^{j,i}, L_i^{j,i}\}_{j \in \mathcal{A}} \right) \forall i, k \in \mathcal{A}$$  \hspace{1cm} (9)

Given the dynamic nature of robot teams, it is vital that each node maintain up-to-date information. Thus, the stochastic communication policy $\pi$ needs to minimize the average age of information (AoI) across all agents, where $t - T_i^{j,i}$ is the age of information for $i$’s knowledge of $j$’s state. To obtain the performance criteria for the whole system, we average over all agents, $\mathcal{A}$, the mission duration, $T$, and team dynamics, $\mathcal{X}$:

$$\min_{\pi} \mathbb{E}_{t \in \mathcal{T}, i \in \mathcal{A}, x_i \in \mathcal{X}} \left[ t - T_i^{j,i} \right]$$  \hspace{1cm} (10)

The objective of the data distribution problem is to minimize the average age of information across the team. Data distribution is a cooperative task, so we can provide the team with a single reward signal, rather than assigning rewards per agent. Furthermore, the training procedure is centralized, but the policy relies on only local information, so it can be deployed in a distributed system.

We assume that the number and identities of robots in the team, $\mathcal{A}$, are known prior to mission execution. We also assume that robots share a common reference frame and a synchronized clock. Finally, we assume that communications are not bandwidth-limited relative to the size of the transmitted data, $\{T_i^{j,i}, M_i^{j,i}, P_i^{j,i}, L_i^{j,i}\}_{j \in \mathcal{A}}$. The memory required for each agent to store its knowledge of the system state is linear in the number of agents, $\mathcal{O}(|\mathcal{A}|)$, but system-wide, the memory and communication requirements are $\mathcal{O}(|\mathcal{A}|^2)$.

* ID : Agent Identity (i)
TS : Last Observed Timestep ($T_i^{j,i}$)
State : Agent State Information ($M_i^{j,i}$)
Parent : Data Flow Parent ($P_i^{j,i}$)
LC : Last Attempted Communication ($L_i^{j,i}$)

Fig. 1: After four rounds of communication, agent 0 receives data from all other agents. Because parent references are also transmitted, agent 0 is able to use its data structure to reconstruct the spanning tree consisting of the most recent information of other agents in the network.

III. METHODS

(A. Aggregation Graph Neural Networks)

Our goal is to develop a policy for making communication decisions that each agent can evaluate using its local data structure. Recall that at each point in time $t$, every agent $i$ has cached the set $\{T_i^{j,i}, M_i^{j,i}, P_i^{j,i}, L_i^{j,i}\}_{j \in \mathcal{A}}$. By taking a graph perspective of the data, we can structure it in a way useful for learning. To begin, we form the set of node features as: $V_i^t = \{T_i^{j,i}, M_i^{j,i}, L_i^{j,i}\}_{j \in \mathcal{A}}$. The parent references $P_i^{j,i}$ capture adjacency relationships in the network, describing a tree structure from the perspective of each agent $i$. We can define a directed edge in this tree by the ordered tuple $(r_l, s_l)$, where $r_l$ and $s_l$ are the receiver and sender node, respectively, for the directed edge of index $l$. Then, the set of all directed edges in the graph of agent $i$ at time $t$ is $E_i^t = \{p_i^{j,i}k\}_{k \in \mathcal{A} \setminus \mathcal{V}_i}$. For the applications presented in this paper, input edge attributes are used, but at the intermediate layers, node features are aggregated using edge relationships. Putting it all together, we denote the graph that represents agent $i$’s knowledge of the team at time $t$ as $G_i^t = \{E_i^t, V_i^t\}$. Next, we outline our GNN architecture.

GNNs are an increasingly popular tool for exploiting the known structure of any relational system [11]. In graph
convolutional networks, the graph convolution operation is defined using learnable coefficients that multiply the graph signal by powers of the adjacency matrix [26], [27]. We extend this architecture by incorporating non-linear graph convolution operations.

The building block of a GNN is the Graph Network Block. Given a graph signal, \( \mathcal{G} = \{\{e_r\}, \{v_i\}\} \), one application of the GN block transforms these features into \( \mathcal{G}' = \{\{e_r'\}, \{v_i'\}\} \):
\[
e'_r = \phi^e(e_r, v_{r_n}, v_{s_n}), \quad v'_i = \alpha^v(v'_r, v_i). \tag{11}
\]

The addition of the encoder \( \alpha^\text{enc} \) and decoder \( \alpha^\text{dec} \) operations is a hyperparameter that allows for deciding who a node should attempt to communicate with, if at all, at a given timestep. In this section we detail the communication protocol that executes these plans. The protocol is divided into two main steps: a transmission phase, following the output of the GNN as one might expect, and a response phase, where certain recipients of the transmission are able to respond. The addition of this response phase provides the transmitter with the ability to seek out information by targeting certain agents to exchange information with, a behavior that becomes valuable in the following section on reinforcement learning.

In the response phase, those agents that receive the packet for which they are the intended recipients, \( \forall j \text{ s.t. } (j \in R'_i) \land (j \not\in S'_i) \), are able to respond by transmitting a message back to the set of original transmitter(s), indicated by \( S'_i \). Note that at all times an agent can only receive at most one transmission at a time. This is a fundamental limitation in ad-hoc networks with a shared medium. Furthermore, two transmissions targeting the same destination will likely result in a packet collision with no data successfully decoded at the receiver. In the response phase, we assume that if an agent is able to respond, it will attempt to do so. Recall also from Section II-A that agents other than those who are the designated recipients can also decode transmitted messages and update their data structures. This set of agents, called eavesdroppers, are described by \( \forall j \text{ s.t. } (j \in R'_i) \land (j \not\in S'_i) \).

We summarize the design of our protocol in Alg. 1. A communication time window \( r \) consists of both a transmission and a response phase. At the beginning of a window, agents first update their own state using local observations. Then, they pass their updated data structure into the local communication policy to output a set of intended recipients for their transmission. If this set consists only of the agent itself, the agent chooses not to communicate during the given transmission phase. Agents then transmit to their intended recipients. For communications that are received above the SINR threshold, agents will compare the contents of the communication to their own local data structure, updating it with any new information received. Once data structure updates from the transmission phase conclude, the response phase commences. An agent will then attempt to respond back to the agent it received a transmission from, if at all. All responses are made concurrently. Again, for successful responses received above the SINR threshold, the data structure updating procedure occurs again.

C. Reinforcement Learning

Finally, with the communication policy and protocol in place, we turn to our attention to finding a solution. To solve the problem in (10) via reinforcement learning, we use the Proximal Policy Optimization algorithm [30] and parametrize both the policy and value functions as graph neural networks to take advantage of the modular nature of the data distribution task.

Our policy and value models are two separate neural networks, both comprised of a non-linear Aggregation GNN, with \( f_{\text{enc}}, f_{\text{dec}} \) and \( GN \) as 3 layer MLPs with 64 hidden units, and a ReLU activation only after the first two layers.

For the policy, \( f_{\text{out}} \) is a linear function that reduces the high-dimensional latent space vectors to the required low-dimensional output, the logits of a Boltzmann distribution. Using the Gumbel-softmax, we use the logits to generate a
Algorithm 1 Data Distribution Protocol

Require: \( A, \pi, f, \Delta t \)

while true do
  **Transmission phase begins,** \( t \leftarrow t + \Delta t \)
  Agents update current state in local data structures
  \( M^i_t = \hat{x}^i_t, T^i_t = t \) \( \forall i \in A, t \geq 0 \)
  Agents evaluate transmission policy using local data structures
  \( p(k \in S^i_t) = \pi \left( \{ T^i_{t,j}, M^i_{t,j}, P^i_{t,j}, L^i_{t,j} \}_{j \in A} \right) \) \( \forall i, k \in A \)
  Transmissions are subject to interference
  \( \{ p(j \in R^i_t) \}_{i \in A} = f \left( \{ S^i_t, \hat{x}^i_t \}_{i \in A} \right) \)
  Agents update local data structures, \( \forall i, k \in A, j \in R^i_t \)
  \( T^i_{t,k} < T^j_{t,k} \implies \) 
  \( (T^i_{t,k} = T^j_{t,k}) \land (M^i_{t,k} = M^j_{t,k}) \land (P^i_{t,k} = P^j_{t,k}) \)

  **Response phase begins,** \( t \leftarrow t + \Delta t \)
  Recipients transmit responses
  \( (j \in R^i_t) \land (j \in S^i_t) \implies i \in S^j_t, \forall j \in A \)
  Responses are subject to interference
  \( \{ p(i \in R^j_t) \}_{j \in A} = f \left( \{ S^j_t, \hat{x}^j_t \}_{j \in A} \right) \)
  Agents update local data structures, \( \forall i, k \in A, j \in R^i_t \)
  \( T^i_{t,k} < T^j_{t,k} \implies \) 
  \( (T^i_{t,k} = T^j_{t,k}) \land (M^i_{t,k} = M^j_{t,k}) \land (P^i_{t,k} = P^j_{t,k}) \)
end while

IV. SIMULATIONS

To evaluate our data distribution system, we conducted simulations with a robot team performing three main tasks. The first two tasks serve to establish performance baselines and involve the agents passing information while stationary and while moving with random velocities. In the third task, we use our system in a flocking maneuver, where each agent sets its own velocity according to its knowledge of the velocity of the rest of the team. In this case, global information about the velocity of each member of the team must be distributed in a timely manner so that the team converges on a common velocity before any agents can wander off. In each case, we report the age of information achieved by our system compared with a suite of other data distribution approaches outlined in Section IV-C.

discrete distribution over potential actions. At each timestep, each robot sample from this distribution to decide the recipient of its transmission. Also included as an action is the option for the agent not to transmit at the current timestep. For the value function, \( f_{\text{out}} \) outputs 1 scalar per agent, which are summed to compute the team’s value estimate.

Unless noted otherwise, we use a receptive field of 5 across all experiments. Each model was trained using an open source implementation of PPO [31] using \( 2 \times 10^6 \) observations. We use an Adam optimizer with step size \( 500 \) steps, and a batch size of 64. All input features were normalized by the mission area and the duration of the mission prior to being input to the neural network.

A. Agent Dynamics

In simulation we treat each robot as a point mass in \( \mathbb{R}^2 \) with first-order dynamics described by:

\[
p_{i,t+1} = p_{i,t} + v_{i,t} \Delta t, \quad v_{i,t+1} = v_{i,t} + u_{i,t} \Delta t
\]

where for agent \( i \) at time \( t \), \( p_{i,t} \in \mathbb{R}^2 \) is the agent’s position \( v_{i,t} \in \mathbb{R}^2 \) is the agent’s velocity. An agent’s local state is described by the 4-dimensional column vector \( \bar{x}_{i,t} := [p_{i,t}; v_{i,t}] \) for agent \( i \) at time \( t \). This is the local state the agent transmit to others.

For the second task involving random motion, we use control inputs sampled uniformly according to \( u_{i,t} \sim \mathcal{N}(0, \sigma_{\text{max}}^2 / 3) \). The control inputs for this task do not rely on the performance of the data distribution algorithm. In addition, agent velocities are clipped to the interval \( (-V_{\text{max}}, V_{\text{max}}) \) and velocities are also reflected when agents come into contact with the boundaries of the mission area, \( (-P_{\text{max}}, P_{\text{max}}) \), described in the following section.

In the flocking task, agents seek consensus in velocities, as can be seen in Example in Fig. 2. This task is sensitive to latency in the communication among fast-moving agents, so data distribution is essential for its success [19]. Agent \( i \) runs a controller based on its observations of the team after the initial timestep \( T^i_0, F^i = \{ j \in A \text{ s.t. } T^i_j > T^i_0 \} \), which computes the difference between the agent’s current velocity and the average velocities among all observed agents:

\[
u_{i,t} = \frac{1}{|F^i_t|} \sum_{j \in F^i_t} \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \left( M^i_{t,j} - \bar{x}_j \right)
\]

This is a variant of the task proposed in [32] but without control of agent spacing.

For a model trained to execute data distribution for flocking, we can quantify not only the age of information cost in (10), but we can also benchmark performance on the flocking task itself [19], quantifying the variance in agents’ velocities:

\[
\min_{\pi} \frac{1}{|A|} \sum_{i \in T} \sum_{j \in A} \left| v_{i,j} - \frac{1}{|A|} \sum_{j \in A} v_{i,j} \right|^2
\]
These two performance metrics for the flocking task are heavily correlated, but this may not be true for other tasks, in which low-latency information may be less important.

B. Mission Specification

The team of 40 robots operates in a mission area of 1 km$^2$, where robots’ initial positions were generated uniformly at random within the mission space. For teams of other sizes, the mission area is changed to maintain a fixed agent density of 40 agents per 1 km$^2$. For mobile agents, the velocity is provided as a ratio of the maximum distance the agent could travel across the mission area during the mission. The default velocity ratio is 0.15, corresponding to $V_{max} = 3$ m/s. The maximum acceleration is set to be $A_{max} = 20m/s^2$ for all experiments with mobile teams.

We allot a communication time window of 100ms, in which both a request and response is made. In the case of random flooding, two requests are made. Each mission is 500 steps long, allowing 500 rounds of communication among agents. The default maximum communication range for agents is 250 meters, which we plot in normalized units as 0.25 of the mission distance. Team positions were re-initialized until the communication graph had algebraic connectivity at the initial timestep, assuming a disk communication model with a range of 250 m. Across all experiments, we maintain a SINR threshold of 1 dBm, an additive white Gaussian noise of -50 dBm, and a system center frequency of 2.4 GHz. In Section V we benchmark the mean performance of all methods over 100 episodes, and provide the standard error of the mean using the error bars.

C. Baselines

As mentioned in Section II data distribution is a regular part of many ad-hoc routing protocols. Thus, we compare our learned approach to three representative baselines inspired by such protocols: random flooding, round robin, and minimum-spanning tree.

Flooding is perhaps the most popular data distribution method used in ad-hoc routing protocols. The simplest form involves repeatedly rebroadcasting a message originating at a source node until it has reached every agent in the network. More advanced variants seek to improve inefficiencies by introducing rules governing which nodes should participate in rebroadcasting. In our simulations, we employ random flooding, which instructs agents to rebroadcast a message with some probability $p$ [9]. While flooding in ad-hoc protocols often happens periodically to update network topology information, data distribution in the context of robot teams happens continuously, as the state information of each agent is constantly evolving. Thus, for our problem, the choice a node makes is whether to broadcast the latest information it has gathered, including what it has received from neighbors (i.e. rebroadcasting), or stay silent and allow other nodes to transmit. We allow random flooding to complete two transmissions over during our protocol’s transmission-response window.

The second method we compare against is round robin. In this approach, a central agent is chosen as a base station and at each timestep, one other agent exchanges data structures with it, reminiscent of a time-division multiple access approach [33]. Unlike our approach and random flooding, round robin requires centralized coordination to identify the base station agent and schedule communications of other agents with the base station. Round robin follows the same transmit-response format used by our approach with $S_t$ always populated by the base station.

Finally, we also implement a Minimum Spanning Tree (MST) baseline where each agent attempts to exchange information with their parent in the spanning tree with probability $p$, remaining silent otherwise. This baseline seeks to capitalize off the fact that a MST minimizes the total edge length required to connect all the agents in the network. As such, the edges of the tree offer an efficient way to pass information throughout the network. One limitation of this approach is that it requires global knowledge of all agents’ locations from the start of the episode. At a given timestep, the transmissions between child and parent follow the transmit-response format used by our method.

V. Results

First, we highlight the impact of the GNN’s receptive field on its performance on the data distribution task, and characterize the impact of transmission power on the overall task difficulty. Next, we examine how the GNN can generalize to larger team sizes. Finally, we benchmark the GNN as the data distribution for a latency-sensitive flocking task.

A. Stationary Teams

Our first experiment investigates the effect of receptive field on the performance of the GNN controller as shown in Fig. 3. We observe a general trend of improved performance with an increase in the receptive field of the architecture, which allows the model to reason about clusters of agents in its buffer. The GNNs with receptive fields of two or greater surpass the performance of Round Robin, MST and Random Flooding baselines.

Fig. 4 demonstrates the effect of varying the transmission power ratio, which is the fraction of the mission distance that an agent can successfully transmit across in the absence of interference. As the maximum transmission range increases, the problem becomes exponentially easier. However, many multi-robot teams operate in settings where hardware or environmental constraints restrict transmission distance. In these settings, especially when agents can only communicate at 25% of the mission distance, our protocol performs best, having the greatest margin from the baseline approaches. The introduction of structure in how data propagated throughout the network allows our protocol to establish known routes of data flow. Instead of relying on direct communication with agents from the other side of the network, our protocol learns to leverage the established routes and often only needs short-range communications to access these.
For using reinforcement learning for other problems with asynchronous execution. Another natural extension of sensitive local observations across a wireless network.

to any collaborative multi-agent task reliant on sharing time-sensitive local observations across a wireless network.

in more up-to-date network information as compared to industry-standard approaches. This performance extends to mobile robot teams, and transfers well for larger team sizes and the flocking task. We envision our protocol being applied to any collaborative multi-agent task reliant on sharing time-sensitive local observations across a wireless network.

In future work, we would like to run physical experiments with asynchronous execution. Another natural extension of this project is to not only consider when and with whom to communicate, but also what to communicate. At each time step, each agent would decide which portions of their data structures are essential to communicate for mission success, thus reducing payload size.

VI. CONCLUSIONS

This work introduces a task-agnostic, decentralized method for data distribution in ad-hoc networks. We demonstrate that maintaining routes of data dissemination can help agents reason about multi-hop communication, resulting in more up-to-date network information as compared to industry-standard approaches. This performance extends to mobile robot teams, and transfers well for larger team sizes and the flocking task. We envision our protocol being applied to any collaborative multi-agent task reliant on sharing time-sensitive local observations across a wireless network.

In future work, we would like to run physical experiments with asynchronous execution. Another natural extension of this project is to not only consider when and with whom to communicate, but also what to communicate. At each time step, each agent would decide which portions of their data structures are essential to communicate for mission success, thus reducing payload size.

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Fig. 6: As agent velocity increases in the flocking task, the learner’s performance begins to decline. Testing the velocity variance, the controller trained using the AoI reward performs better than the controller trained using Velocity Variance cost.

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