

Generalization of Deep Reinforcement Learning for Jammer-Resilient Frequency and Power Allocation

Swatantra Kafle, Jithin Jagannath, Zackary Kane, Noor Biswas, Prem Sagar Vasanth Kumar, Anu Jagannath

Abstract—We tackle the problem of joint frequency and power allocation while emphasizing the generalization capability of a deep reinforcement learning model. Most of the existing methods solve reinforcement learning-based wireless problems for a specific pre-determined wireless network scenario. The performance of a trained agent tends to be very specific to the network and deteriorates when used in a different network operating scenario (e.g., different in size, neighborhood, and mobility, among others). We demonstrate our approach to enhance training to enable a higher generalization capability during inference of the deployed model in a distributed multi-agent setting in a hostile jamming environment. With all these, we show the improved training and inference performance of the proposed methods when tested on previously unseen simulated wireless networks of different sizes and architectures. More importantly, to prove practical impact, the end-to-end solution was implemented on the embedded software-defined radio and validated using over-the-air evaluation.

Index Terms—Deep reinforcement learning, wireless network, power control, frequency selection, software-defined radio.

I. INTRODUCTION AND BACKGROUND

The dramatic increase in the number of connected wireless devices with demand for higher data rates has demanded increasingly efficient use of wireless resources, such as spectrum. In addition, the massive connectivity of wireless devices poses a daunting challenge to the conventional approach, i.e., developing detailed mathematical models for connectivity, systems, and channel for tractable analysis. Furthermore, as the number of devices, connectivity, and data rates increase with time, the conventional approach will fail to keep up with performance requirements. Hence, modeling complex wireless systems and the dynamic allocation of scarce resources demand data-driven methodologies such as powerful function approximation used by deep reinforcement learning.

In the last decade, several classes of machine learning algorithms were developed that have expedited research and development in science and engineering domains, with wireless systems no exception. Recent works in wireless technologies use supervised, semi-supervised, unsupervised, and reinforcement learning (RL) to tackle complex problems in wireless communication [1]–[9]. RL has been studied in the wireless community, especially for the problem of dynamic

resource management [10]–[15]. Power control and channel selection have been studied in both independent and joint settings. Authors in [14] developed a centralized deep Q-Network (DQN)-based algorithm for downlink power control. The work in [15] developed a deep distributed approach for multi-agent reinforcement learning (MARL) for power control to maximize the network weighted sum rate where each agent (transmitter) exchanges its instantaneous observation with its nearby transmitter. The work in [16] assumes Device-to-Device (D2D) networks and addresses the problem of joint power control and frequency allocation. In the problem setup, a macro base station (MBS) provides signaling for the synchronization of D2D pairs and assists in allocating pilots. In [17], a DRL-based joint power control and channel selection solution is developed in a cellular network setup. In contrast, [18] considers distributed multiple transmitter-receiver pairs (Tx-Rx pairs) setup making power control decisions but lacks the joint frequency selection considered in this work.

In most cases, these works are limited to simulation and do not take into account real-world conditions. Similarly, none of these works address the generalization capability of agent performance during inference in networks that have mismatches to the training environment. In real-world scenarios, the wireless network used for training and testing will most likely be different, resulting in a degradation of performance. So, trying to incorporate all the specifics of radio frequency (RF) environments and operating scenarios will lead to explosions of the solution space. This result in an exponential increase in sample complexity, demanding very high computational resource. We address these problems by proposing a novel training approach to the multi-agent problem in real-world wireless networks. To demonstrate the effectiveness of our approach, we consider a problem of joint power control and channel selection among the wireless nodes in an active jamming environment in a low probability of intercept and detection (LPI/D) networks due to its relevance to a tactical wireless network. To the best of our knowledge, there is no previous work that has designed and deployed DRL for joint power and channel selection in a hostile jamming environment on actual Software defined radio (SDR). We use direct-sequence code-division multiple access (DS-CDMA) to implement a robust LPI/D physical layer due to its advantages, such as easy frequency management, and low peak-to-average power ratio (PAPR), among others.

Contribution: In this work, we develop a new training approach to enhance the generalization of multi-agent DRL

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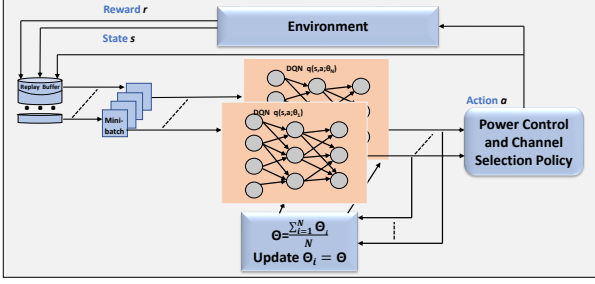


Fig. 1: Multi-agent Deep Reinforcement Learning for the joint power control and channel selection

problems in wireless networks. We demonstrate the effectiveness of the solution by addressing the problem of joint power control and frequency (channel) selection in an active jamming environment on actual radio hardware for the first time in literature (to the best of our knowledge). We provide extensive results of the proposed training method when the trained agent is deployed in simulated and actual wireless networks of different sizes and architectures. Furthermore, the solution is validated using OTA evaluation when the DRL agents are deployed at the edge on embedded SDRs. Finally, we provide a video demonstration of the solution operating in real-time in real-world outdoor deployment.

II. PROBLEM FORMULATION

Consider a wireless network consisting of several transceiver pairs using DS CDMA protocol. Assume that there are K wireless transceivers, each with spreading sequence matrix $\mathbf{S} \in \mathbb{C}^{L \times K}$, where L is the length of the spreading code. This forms $K/2$ transmit-receive pairs that can transmit at different power levels, $p_1 \dots, p_{n_p}$, and multiple frequencies f_1, \dots, f_{n_f} , where n_p and n_f are the number of power level and available frequencies, respectively. All agents learn policy to choose power level and channel by maximizing the same discounted sum of rewards. We assume each agent has partial observability, i.e., it cannot observe the entire underlying Markov state. Hence, we are interested in designing a reward function such that agents prefer to transmit at the lowest power and use available channels uniformly when maximized. We focus on the maximization of rewards through some form of centralized training. In this setup, each agent can share their learned model for aggregation.

We consider a problem of joint power control and channel selection so that multiple Tx-Rx pairs co-exist with each other while avoiding jammers. In this setup, each DRL agent optimizes its DQN based on the data it receives and the sampling from the replay buffer to optimize its policy.

1) *States:* Each Tx-Rx pair collects the local information and a few of the neighborhood information, which define the state of each node. The state of node i at the time slot t can be expressed as $\mathcal{S}_i^t = \{\mathbb{D}_i^t, B_i^t, I_c^t, S_i^t, SINR^t\}$, where $\mathbb{D}_i^t = \{d_{i,j}^t | j = 1, 2, \dots, K\}$ is the set of distances to the neighboring receivers, B_i^t is the number of packets in the

buffer, I_c^t is the interference caused by transmission from node i to the neighboring nodes, and S_i^t is the spectrum sensed by the transmitter node i . Note that the SINR is measured at the receiver and is communicated to the transmitter node i through an ACK message. If the transmission from node i is not received, it will not receive an ACK message, and the value for S_i^t is set to be -1 . Here, each agent maximizes its reward based on its state, which is a multi-agent reinforcement learning setup.

2) *Actions:* Let p_1, \dots, p_{n_p} be the power levels that agents can choose from and f_1, \dots, f_{n_f} be the number of frequencies that each agent can choose from. Then, the action of node i at time slot t is $\mathcal{A}_i^t = \{(p^i, f^i) | (p^i, f^i) \in \mathcal{A}\}$. Let \mathcal{P} be the set of all available power levels, and \mathcal{F} be the set of all available frequencies, then the action space is $\mathcal{A} = \{(p_i, f_i) | p_i \in \mathcal{P} \text{ and } f_i \in \mathcal{F}\}$.

3) *Rewards:* All the transmitters are required to transmit successfully while causing minimum interference to the neighboring node. Hence, it is desirable that each transmitter transmits successfully using the lowest power and choosing the available channels uniformly to minimize interference among nodes. To enforce all these constraints, we propose the following reward function for the given problem as

$$\begin{aligned} \mathcal{R} &= C1 + C2, & \text{successful transmission,} \\ &= C3, & \text{failure of the transmission,} \end{aligned} \quad (1)$$

Algorithm 1 Generalized Training for DRL

- 1: **Initialize:** DQN network parameters $\theta_i^0 = \theta^0, \forall i \in [1 : N]$, learning rate α , Experience replay buffer \mathcal{R} , and mini-batch \mathcal{B}
- 2: **for** Each Network configuration **do**
- 3: **for** each episode = 1, \dots , N **do**
- 4: Observe an initial system state s
- 5: **for** each time step $t = 0, \dots, T$ **do**
- 6: Select action a_t at random with probability ϵ
- 7: Otherwise select a_t as: $a_t = \arg \max_{a_t \in \mathcal{A}} q(s_t, a_t; \theta_t)$
- 8: Execute action a_t , receive reward r_t and state s_{t+1}
- 9: Store the experience $e_t = (s_t, a_t, r_t, s_{t+1})$
- 10: **end for**
- 11: Update DQN parameter θ using gradient-descent update
- 12: Model Aggregation: $\bar{\theta} = \frac{1}{N} \sum_{i=1}^N \theta_i$, and update $\theta_i = \bar{\theta}, \forall i$
- 13: **end for**
- 14: Use Model Aggregation: $\bar{\theta} = \frac{1}{N} \sum_{i=1}^N \theta_i$, and update $\theta_i = \bar{\theta}, \forall i$.
- 15: **end for**
- 16: **Return**

where $C1$ refers to the cost of using power by an agent, $C2$ refers to the cost of using different frequencies, and $C3$ refers to the cost of failed transmission. The cost could be functions such as normalized SINR and normalized interference or constants. We choose $C1$ as -0.05 , -5 , and -10 for using preset transmission power of P_{low} dBm, P_{med} dBm, and P_{high} dBm, respectively. In this work, we consider two frequencies available to each agent. To promote uniform distribution of choice of frequencies among agents, we create preference of channel uniformly among agents. We choose $C2$ as -0.05 and -2 for transmitting at the assigned channel and at a different

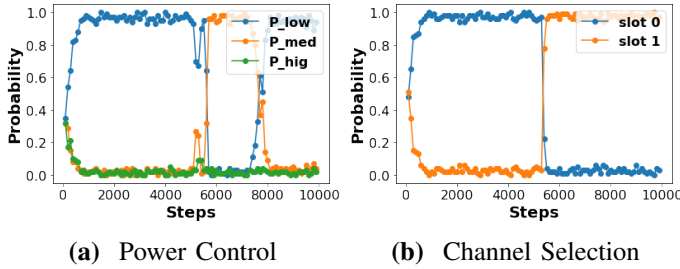


Fig. 2: Probabilities of Agent 1 as a function of steps (a) Power Control Probabilities (b) Channel Selection Probabilities.

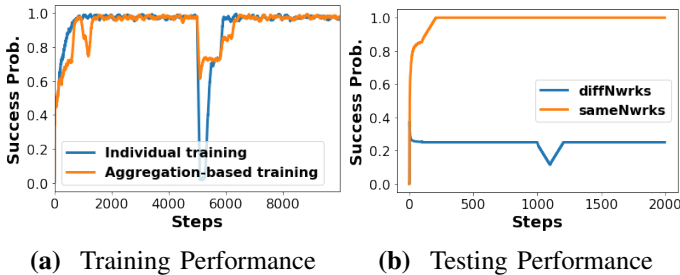


Fig. 3: Performance comparison of Node-level Aggregation-based approach (with individual training approach) in (a) training and (b) testing (when deployed in a different network), respectively.

channel so that agents prefer transmitting at a different channel to transmitting at higher power. Finally, we choose $C3$ as -10. These values are hyper-parameters and are chosen after numerous experiments.

4) *Training Strategies:* The training should focus on the generalization of performance over wireless networks of different sizes and operational scenarios. Next, we enlist steps in the proposed training strategy,

States Uniformity: For this consideration, we have fixed the size of the state vector. The size of input for DQN for all the networks of different sizes will be the same and hence is the first step towards the generalization. In the state vector, the dimension of \mathbb{D} depends on the size of the network. Instead, we fix the number K and choose the K most significant distances, i.e., the distances of the closest neighboring receivers where the interference caused by the agent is the most significant.

Node-level Aggregation: The RF environment that each agent experience is limited. If the agents are trained individually, the policy learned by each agent is limited to the data seen by each agent. When deployed, any of these agents will have worse performance as the training and testing scenario is going to be different. The problem is solved by node-level model aggregation. In the algorithm, we first train agents individually for a certain number of steps. We then aggregate the models and repeat the training. When the training converges, all the agents learn the policy corresponding to the RF scenario that all agents face in the network.

Network-level Aggregation: Further, we should emphasize that creating all possible RF scenarios within a network is difficult. First, the network grows very large, and second, creating individual RF scenarios across each node in a bigger network is difficult compared to a small network. We further extend the ideas of model aggregation across nodes to aggregation over networks. Here, we design several smaller networks, where each network has specific network scenarios. Next, we train the agents of each network until convergence individually and save the DQN parameters. We aggregate all these DQN parameters from each network scenario and use the average DQN as the starting network in each node. Starting with the averaged model, we iterate over each network with model aggregation in between until convergence in all network scenarios. This approach ensures each agent learns a policy that can accommodate all wireless environments seen by agents in all networks.

Introducing Randomness: It is a common approach in RL to train and test the learned agent in the same environment. However, wireless networks tend to be different from the training network during deployment. While network-level aggregation helps to address some of the variations in the wireless environments, introducing stochasticity in the environment itself, such as by using a random walk-based mobility model, improves the generalization capacity of the policy of DRL agents to small variations in wireless networks.

The generalized training algorithm is summarized in 1.

III. EXPERIMENT RESULTS

For the experiments, we use MR-iNet Gym [19] that uses ns3-gym [20]. This includes our custom DS-CDMA module for ns-3 to simulate a distributed LPI/D wireless network controlled by RL running in an OpenAI-Gym.

A. Simulation-based Performance

In the first experiment, we compare the training performance of the node-level aggregation-based training approach with individual training. Each Tx-Rx pair can communicate using three power levels in two different channels. Jammers disrupt communication between radios by changing their jamming frequency in the middle of the training. In Fig. 2, we plot Agent-1's power and channel selection probabilities, where we can see agents deciding to choose minimum power and avoid jamming frequency to get successful transmission. In Fig. 3, we can see that while the node-level aggregation-based approach learns almost as good as the individual training approach, the node-level aggregation-based approach has better performance when there is a change in network dynamics, i.e., jamming frequency. However, from Fig. 3, we can see that the test performance of the node-level aggregation-based approach in an unseen network deteriorates, which motivates the need for the next part of our approach.

In the second experiment, we consider the proposed training approach, which also included network-level aggregation. In

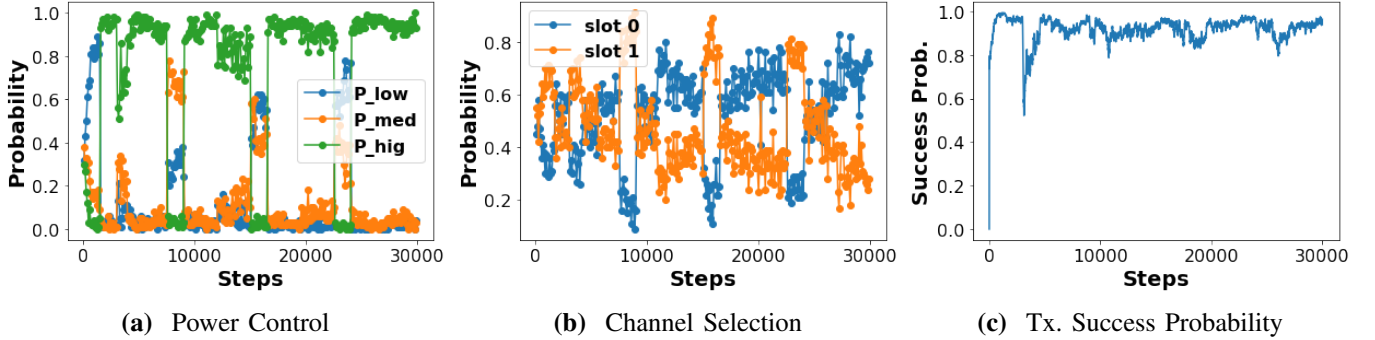


Fig. 4: Training performance of the proposed generalized training approach as a function of steps: (a) Power Control Probabilities, (b) Channel Selection Probabilities, and (c) Transmission Success Probability with aggregation among networks, respectively.

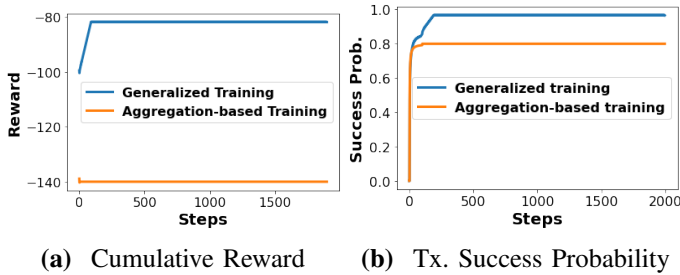


Fig. 5: Performance comparison of agents when tested on an unseen network of size 10 using aggregation-based training and with proposed training approach: (a) Cumulative Reward; and (b) Network Transmission Success Probability.



Fig. 6: In-lab Testbed

this setup, we consider five networks so that each agent learns a policy for different wireless scenarios. Agents are trained separately for each network, and the DQN model is saved. We then aggregate all these saved models and retrain agents with node-level aggregation for each network sequentially until we exhaust all networks. We repeat this training until convergence. Next, we plot the training results of this experiment in Fig. 4. We can see that the agent is changing power and frequencies with time depending on which network is being switched on. We should note that the network transmission success

Nwk	Parameters	PA	Rd	Gd
Nwk 1	PDR	89.88	45.33	75.71
	SE	3.17	0.48	3.01
Nwk 2	PDR	91.23	48.88	72.45
	SE	3.15	0.51	3.02
Nwk 3	PDR	90.63	47.69	76.13
	SE	3.15	0.48	3.01

TABLE I: PDR and SE of the proposed algorithms (PA), Greedy (Gd), and Random (Rd) in three different network scenarios.

probability is approaching unity with increasing training steps. This suggests that each node is converging to a policy that can address all possible scenarios encountered by all agents in different networks. Next, we used this trained agent in an *unseen network* of size 10. The results of these tests are shown in Fig. 5. From the results, we can see from the inference that the proposed method outperforms the node-level aggregation-based approach in both cumulative rewards and network transmission success probability, demonstrating the proposed approach's *effectiveness in an unseen network*.

B. Over-the-air Hardware Experiments and Demonstration

In the final experiment, we conduct an OTA experiment where we deploy the inference engine obtained through the generalized training approach in the MR-iNet Gym environment. The DRL inference engine is now compressed using TensorRT, which not only reduces the model size of the inference engine but also reduces its processing time. In this experiment, we take two pairs of SDRs acting as two Tx-Rx pairs in an active jamming environment. The jammer changes the transmission frequency at random to disrupt the communication between the Tx-Rx pairs. In this setup, the Tx-Rx pairs are set to transmit within ISM band (S-Band). The transmitters are set to transmit at three different power levels. We transmit video packets over the SDRs, measure packet delivery rate (PDR) and spectral efficiency (SE), and compare the performance of the proposed algorithm to two different algorithms. The first algorithm selects each of the available

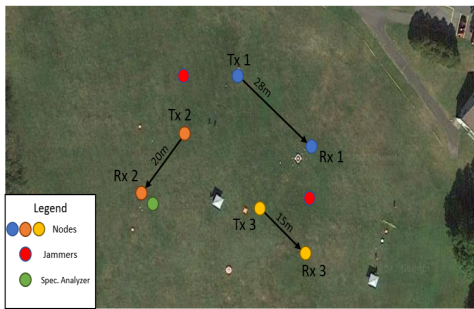


Fig. 7: Outdoor Test Scenario: Three pairs with two jammers

frequencies and power options available to the transmitter at random. We refer to this approach as *Random*, which is similar to the baseline used in [17]. This serves as the lower baseline for the proposed algorithm. The second algorithm scans the available channel and transmits it on the channel with the least interference with the maximum power, which is referred to as *Greedy*. A single topology of the in-lab hardware testbed is shown in Fig. 6. The results in Table I shows that the PDR and SE of the proposed algorithm are consistently better than the other approaches in all networks. The proposed algorithm makes better power control and channel selection decisions than other algorithms such that most packets are transmitted successfully in all the radios. In addition, all the networks considered for OTA evaluation *were different from the networks used for training*, which shows that the inference engines obtained through the proposed training approach in the ns3-gym environment generalize over the unseen wireless networks.

Finally, we deployed the DRL engine on three pairs of radios with two jammers in an outdoor real-world environment. The deployment setup is shown in Fig. 7 with the demonstration video of the real-time operation of the DRL inference engine available in [21] with a voice-over description.

IV. CONCLUSION

We investigated the problem of joint power control and channel selection among multiple Tx-Rx pairs in a hostile jamming environment with the goal of hardware deployment. Striving for the real-world operating scenarios of the trained agent in unseen networks, we presented our generalized algorithmic approach to training agents for DRL problems in wireless networks. Unlike prior works that presented results on a specific network architecture, the proposed approach showed improved training and testing performance across seen and unseen networks for the problem of joint power control and channel selection in both simulated and actual wireless networks. Finally, we demonstrated the video streaming operation of the agent in an outdoor hostile jamming environment to prove the impact of the proposed solutions. We hope the proposed approach can accelerate the deployment of DRLs for real-world wireless networks.

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