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[Poster Presentation]
Reinforcement Learning Aided Orthogonal Frequency Allocation in LoRaWAN

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Abstract

Recently, massive wireless terminals are deployed to harvest environment information such as temperature, humidity. For massive connectivity, low power wide area (LPWA) systems, including LoRaWAN, have been developed. However, these protocols can adopt simple functions due to the limited capability of wireless terminals. For example, distributed asynchronous medium access control (MAC) protocol (e.g., pure ALOHA, CSMA/CA) is implemented. Packet collision happens due to mutual interference among wireless terminals. There have been extensive research works on resource allocation to avoid or mitigate mutual interference. However, the conventional works only consider spreading factor (SF) allocation, which is a modulation parameter of the physical layer, and a random-hopping is applied so that each node changes frequency channel at the start of packet transmission. In this research, we propose frequency channel allocation using reinforcement learning. In the proposed system, a fusion center (FC) calculates Q-rewards for each wireless terminal based on the number of successfully received packets, which the FC can observe. Moreover, FC allocates different frequency channels to wireless terminals that may collide. The computer simulation results under the LoRaWAN environment elucidate the effectiveness of the proposed method.

Keywords Frequency Sharing, Machine Learning, Reinforcement Learning, LoRaWAN, Wireless Resource Allocation

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Background

- Dense distribution of wireless terminals in IoT network
  - LoRaWAN [1] is one of communication protocols that can accommodate large number of terminals
  - ✓ In LoRaWAN, packet collision and PDR degradation frequently happens
- Related research
  - Spreading Factor allocation [2]: Optimal modulation parameter allocation can improve packet delivery performance under massive connectivity
  - There is no research of frequency channel allocation in LoRaWAN environment

→ Effective utilization of frequency resources is necessary to further massive connectivity for LoRaWAN

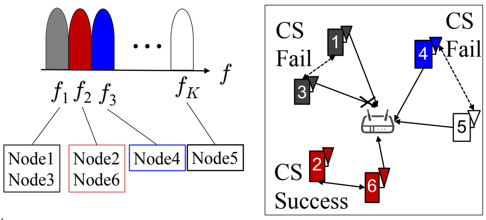


Fig. 1. LoRaWAN system model

Proposed Method: Resource allocation using DQN[3]

- **Learning Model**
  - State $\mathcal{S}$: Resource indices of each terminal
  - Act $\mathcal{A}$: allocated resource index to terminal n at epoch t+1
  - Reward $Q_{n,k_n,t+1}$: Weighted sum of the number of received packets
- Orthogonal resource allocation in Fusion Center (FC)
  1. Observe resource indices of each terminal
  2. Estimate Q-reward of each resource index of terminal n
  3. Allocate resources to each terminal based on ε-greedy
  4. Observe the number of received packets during one epoch
  5. Calculate Q-reward for each terminals from the number of received packets
  6. Execute Back-Propagation of FC's Neural Network (NN)

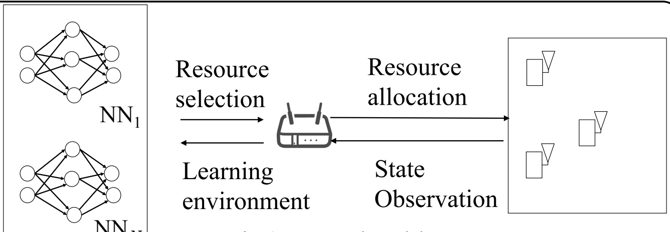


Fig. 2. Proposed Model

$$Q_{n,k_n,t+1} = \underbrace{D_{n,t+1}}_{\text{From interested node n}} + \nu \times \underbrace{\frac{\sum_{n' \in \mathcal{N} \backslash n} D_{n',t+1}}{N-1}}_{\text{From all nodes excluding n}}$$

$$\nu = \tanh\left(\frac{D_{n,t+1}}{\min_{n' \in \mathcal{N} \backslash n} D_{n',t+1}}\right)$$

Numerical Simulation

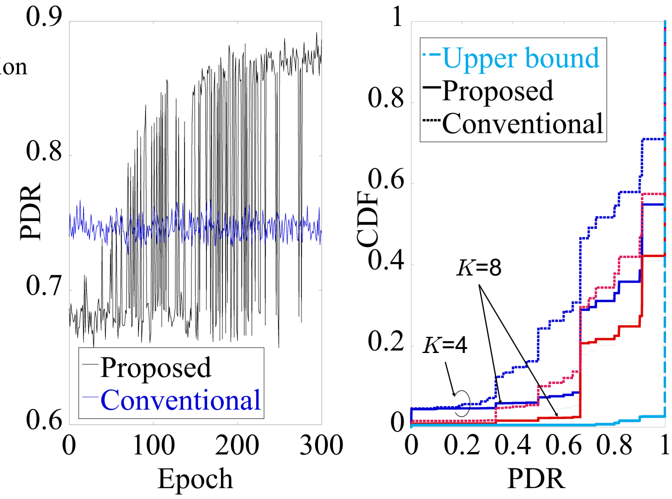
- Channel Model: Pathloss + spatially correlated shadowing [4]
- Two packet traffics model is assumed [5]: Regular + Event detection
  - Regular traffic: 2 application types
    - Packets occur with intervals {0.5,5}[min/packet]
  - Event traffic: Event occurs every 5 minutes
- Compared method
  - Conventional: Each node hops frequency at start of transmission
  - Upper bound: In case of no mutual interference i.e. $K\to\infty$

Table 1. Wireless parameters

Communication area	3000×3000[m^2]	Carrier frequency	923 [MHz]
No. of terminals N	3000	Shadowing deviation	3.48 [dB]
Transmit power	13 [dBm]	CS threshold	-80.0 [dBm]
Noise power density	-174 [dBm/Hz]	No. of resources K	{4,8}
Bandwidth	125 [kHz]		

Table 2. Learning parameters

Epoch Length	600 [sec]	Number of NN layers	4
Number of Epochs	1000	Number of neuron of hidden layer	(10,5)
Q-learning rate	0.4	NN learning rate	10^{-3}



(a) Learning process (K=4)

(b) PDR performance

Fig. 4. Performance

Performance is improved with learning proceeds

✓ 13% average PDR improvement
✓ PDR's 10% point is 40% improved

Conclusion

- Reinforcement learning based resource allocation
  - ✓ Q-reward calculation without additional overhead
  - ✓ Proposed method can improve average PDR 13%
  - ✓ lower PDR point is also improved

Acknowledgement

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