Proposal

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Motivation

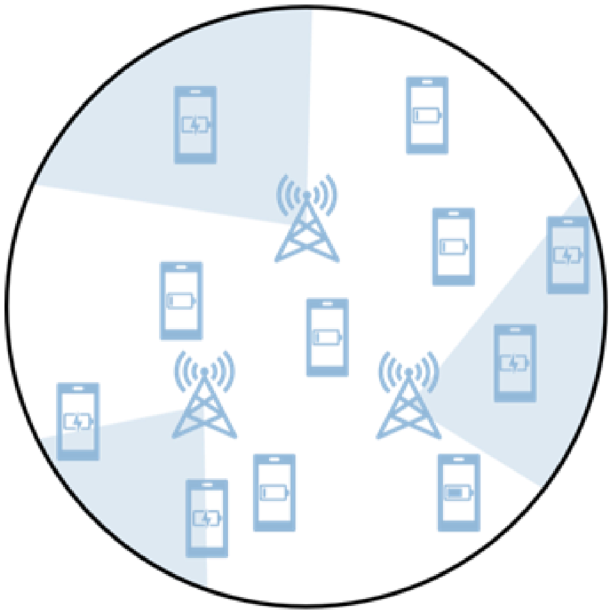
In recent years, the Internet of Things (IoT) technology has been applied in numerous industrial systems. Sensors with monitoring and computing capabilities are interconnected through networks. However, during data transmission, these devices inevitably consume battery power. In most cases, replacing sensor batteries is impractical and costly. Consequently, using Radio Frequency Energy to maintain sensor operation has become a common solution. Charging stations for sensors are generally categorized into omnidirectional and directional antennas. Although directional antennas have a limited transmission range, their energy emission is more concentrated, resulting in higher energy utilization efficiency. Therefore, this study focuses on directional antennas.

Energy harvesting refers to the technology of collecting and converting small amounts of energy from the surrounding environment to power sensors. These energy sources can include solar power, thermal energy, kinetic energy, and radio waves. This technology plays a crucial role in reducing dependence on traditional batteries and achieving sustainable operation of wireless sensor networks and IoT devices.

Considering the deployment of multiple charging stations, the phase of frequencies between them affects the power received by the devices. For instance, destructive interference can reduce power. Additionally, the distance from the sensors is another factor affecting charging efficiency, known as path loss. The greater the distance between the transmitter and the sensor, the less energy the sensor can harvest.

In summary, the process of wireless sensor network charging involves numerous factors, making it challenging for charging stations to determine the optimal direction for energy emission. Moreover, the stations can interfere with each other, leading to inefficient energy utilization. Therefore, this study aims to utilize Multi-Agent Reinforcement Learning (MARL) algorithms to train a reliable and efficient decentralized control system in a simulated environment. This system will operate multiple charging stations with directional antennas, making optimal decisions on charging directions for sensors distributed over a given area.

MARL



- **Full-Cooperative Dec-POMDP**

  As described above, multiple charging stations need to collaborate to charge sensors distributed within the environment, sharing a common goal. Furthermore, these charging stations are spaced apart and must control the direction of their directional antennas to emit radio frequency energy under limited communication conditions, requiring decentralized execution capabilities. Therefore, this environmental model can be framed as a Full-Cooperative Decentralized Partially Observable Markov Decision Process (Dec-POMDP).

- **Mullti-Agent Reinforcement Learning (MARL)**

  Multi-Agent Reinforcement Learning (MARL) has demonstrated significant success in solving Full-Cooperative Dec-POMDP problems. In MARL, each agent learns optimal strategies through interactions with the environment and other agents to achieve a common goal. In the context of wireless charging, each charging station acts as an agent that must learn how to cooperate with limited communication to maximize the energy harvested by the sensors.

- **Centralized Training& Decentralized Execution (CTDE)**

  Centralized Training & Decentralized Execution (CTDE) is a widely used framework within MARL. CTDE allows for the collection of all agents' state and action information during the training process to more efficiently learn cooperative strategies. During execution, each agent independently makes decisions based on its local observations. This approach is particularly effective in systems requiring decentralized control and is applicable to the problem of multi-station control in wireless sensor networks.

Expected Result

Under the CTDE (Centralized Training & Decentralized Execution) framework, we expect to train a reinforcement learning model capable of decentralized execution, autonomously adjusting antenna directions. This model is anticipated to enhance the energy transmission efficiency of multi-station systems in wireless sensor networks. Through experiments in a simulated environment, we will compare this model's energy utilization efficiency and sensor charging effectiveness against other methods.