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Maximizing Throughput of Decentralized Wireless Sensor Network Using Reinforcement Learning

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Abstract— A reinforcement learning algorithm with the aim to increase the throughput of a Wireless Sensor Network (WSN) and decrease latency in a decentralized manner. WSNs are collections of sensor nodes that gather environmental data, where the main challenges are the limited power supply of nodes and the need for decentralized control. A distributed resource allocation algorithm for cellular MIMO networks by adopting a Reinforcement Learning (RL) approach. We use RL methods which employ Growing Self Organizing Maps to deal with the huge and continuous problem space. The goal of the algorithm is to maximize the network throughput in a fair manner. Indeed, the algorithm maximizes the throughput until fairness violation does not exceed an adjustable threshold.

***Key Terms** – Throughput, Reinforcement Learning (RL), Wireless Sensor Network*

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I.INTRODUCTION

An increasingly popular approach for environmental and habitat monitoring is the use of Wireless Sensor Networks (WSNs). The nodes in such a WSN are limited in power, processing and communication capabilities, which require that they optimize their activities, in order to maximize the throughput of the network and minimize latency. A complicating factor is communication, because some nodes can fall outside the transmission range of the base station, or can belong to different stakeholders, serving various purposes, thus rendering the common centralized approach inapplicable for large networks. [1]

*A.*BACKGROUND

In this section we describe the basics of a Wireless Sensor Network and the Learning Methods. Subsection elaborates on WSNs and explains MIMO and the Learning Method.

*B.*WIRELESS SENSOR NETWORKS

A Wireless Sensor Network is a collection of densely deployed autonomous devices, called sensor nodes that gather environmental data with the help of sensors. The un tethered nodes use radio communication to transmit sensor measurements to a terminal node, called the sink. [1]

*C.*WSN ARCHITECTURE

The sinks the access point of the observer, who is able to process the distributed measurements and obtain useful information about the monitored environment. Sensor nodes communicate over a wireless medium, by using a multi-hop communication protocol that allows data packets to be forwarded by neighboring nodes to the sink. This concept is illustrated in Figure 1. [1]

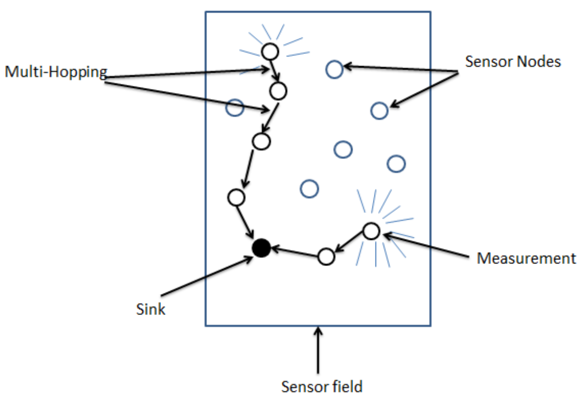

Figure 1: WSN architecture [1]

The WSN can vary in size and topology, according to the purpose it serves. The sensor network is assumed to

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be homogeneous where nodes share a common communication medium (e.g. air, water, etc.).[1]

II.MIMO

The considerable interest in multiple antenna systems during the last few years is due to the remarkable increase in Shannon capacity in wireless systems, which deploy multiple antennas at the transmitter and the receiver.

MIMO system can obtain larger capacity via the potential de-correlation between the coefficients of the MIMO channel. These coefficients are exploited to create several sub-channels .The capacity gain depends highly on the multipath richness, because a fully de-correlated coefficients provides multiple sub-channels. [4]

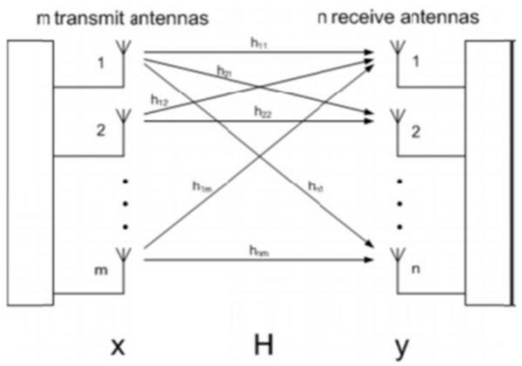


Figure 2: MIMO system architecture [4]

$$Y=Hx + n \text{ ----------------------------------- (1)}$$

Y: receive vector

x : transmit vector

n:noise

For a single input single output system SISO the capacity is given by Shannon theorem is as (2)

$$C=Wld(1+\frac{P}{WN_0})\text{----------------------------(2)}$$

W is the Bandwidth, p is the average power, N0/2 is power spectral density od additive noise.

Theoretically, the capacity C of a MIMO system increases linearly with the number of streams M:

$$C=MWld(1+\frac{P}{WN0})\text{--------------------------------(3)}$$

M is the number of streams.

*A.*LEARNING METHOD

*B.*INTRODUCTION

Learning takes place as a result of interaction between an agent and the world, the idea behind learning is that, Percepts received by an agent should be used not only for acting, but also for improving the agent's ability to behave optimally in the future to achieve the goal. [1]

*C.*LEARNING TYPES:

Supervised learning: A situation in which sample (input, output) pairs of the function to be learned can be perceived or are given.

Reinforcement learning: In the case of the agent acts on its environment, it receives some evaluation of its action (reinforcement), but is not told of which action is the correct one to achieve its goal. [2]

*D.*REINFORCEMENT LEARNING

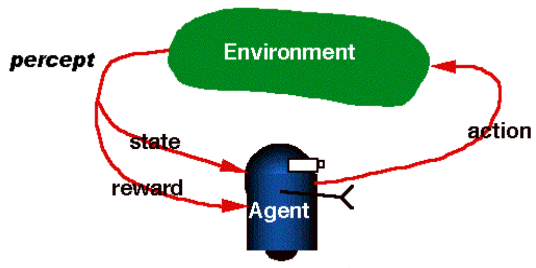


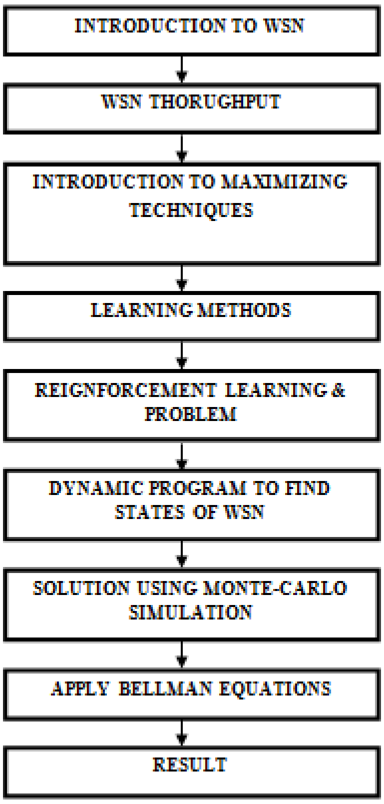
Figure 3: Reinforcement block diagram

Reinforcement Learning is about to learn how to behave successfully to achieve a goal while interacting with an external environment. It is learn via experiences. RL concerns interactions between an agent and its environment, through discrete state-action-reward-state cycles. RL gives a value to states or state-action pairs in order to and the optimal strategy that gathers the maximum of reward on the long-term (return).Reinforcement is a strengthening of a specific behavior due to its association with a stimulus. Reinforcement is an important part of operant or instrumental conditioning. [2]

A reinforce is the stimulus that strengthens the behavior, in contrast to punishment that weakens the behavior. The effect of reinforcement may be measured as an increase in the frequency of its expression (e.g., pulling a lever more frequently), duration (e.g., pulling a lever for longer periods of time), magnitude (e.g., pulling a lever with greater force), or decrease in latency (e.g., pulling a lever more quickly following the onset of an environmental event).

In RL problem, an agent attempts to control a dynamic system, often referred to as the environment, by choosing actions in a sequential fashion. The agent receives a scalar signal or reward in response to the selected actions. The ultimate goal of the agent is to learn a policy for selecting actions such that the expected sum of discounted rewards called return is maximized. Usually, the RL problem is studied under the assumption that the state of the system contains all the information required to predict the future state of the system given agent's actions.[2]

III.PROPOSED ALGORITHM



IV.SIMULATION

(Calculating the number of all possible states)

The purpose of this simulation is to calculate the total number of all possible states in 4X4 virtual MIMO system, because these states will be included in the second simulation in order to apply dynamic programming method in contrast to Monte Carlo method which can be used with unknown number of states.

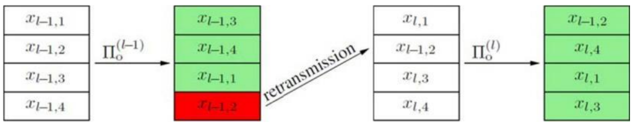


Figure4:Re transmission of the non-decodable signals

Using the first simulation the total number f state sin this 4X4 virtual MIMO system with buffer limit = 11is:**(45873**states). [3]

V.CONCLUSION AND FUTURE WORK

From this, as per the application of wireless sensor network are used and from review of Reinforcement learning, it is more beneficial for the sensor network when nodes learn what actions to take, rather than follow a pre-defined schedule. Furthermore, maximize the throughput of wireless sensor network by Reinforcement learning.

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