# A Survey of Reinforcement Learning Techniques In The Context Of Wireless Sensor Network

**Manish Shrivastava**

Assistant Professor
Department of CSE, Institute of Technology,
Guru Ghasidas University, Bilaspur, CG, India

***Abstract:*** **Currently wireless sensor network is the key figure for various existing and upcoming technologies like health care, IOT, monitoring, automation, home security and various critical care units. Wireless sensor network is facing challenges in the area of routing, clustering, energy efficiency and other issues. Machine learning offers supervised and unsupervised learning techniques. Reinforcement learning technique is unsupervised in nature which used to provide feedback based upon certain experiences. Later on these kinds of experiences generates reward which leads to create policy. Finally these policy based values saves the efforts and resources. In this research study, we are presenting different reinforcement techniques to solve the existing challenges of wireless sensor network.**

***IndexTerms*** **- Reinforcement Learning, Wireless Sensor Network, Q-Learning, Agent, State, Action and Reward.**

## I. INTRODUCTION

Presently Wireless Sensor Network is capable to work with different technologies in many research domains. That gives such technical solutions which are most applicable for critical applications. WSN have great potential of sensing various environmental variables. But WSN is also suffering from issues like energy consumption, routing, lifetime enhancement, PDR ratio, congestion of network with delay. Presently reinforcement learning algorithms provides great solution for energy consumption in wireless sensor nodes. The self learning has been used to generate new state by having the current state while working with the dynamic environment which is unknown in nature. This can be done by using the probability of changing the new state and the reward of changing. The mixture of WSN and reinforcement learning algorithm can be used to search the various policy based solution to overcome the existing issues of WSN. Here, we are presenting the available techniques of reinforcement learning (Christopher et al., 1992) to work with wireless sensor network for the optimization of WSN.

### 1.1 REINFORCEMENT LEARNING

Reinforcement Learning is unsupervised in nature. It enables machines and software agents to perform smartly, in order to increase the performance. To achieve the signal of reinforcement learning mostly feedback system for requiring reward is essential for learning agent to perform its best. Mainly, learning agent decides the exact action to represent its present state. When that process is repeated, the known issue is called Markov Decision Process. So, Reinforcement Learning has several components like state, action, reward and discount rate (Christopher et al., 1992) to achieve best optimum solution related to WSN issues.

### 1.2 Q-LEARNING (SELF LEARNING)

The Q-learning which is also known as self learning always work with learning agent whose observation is based upon the state, event, reward and policy which provides experience to work with changing environment. This learning creates the action by sensing certain parameters from available sensor through events which generally change the status of state. The Figure 1 shows the process of agent learning at particular time t. The Q-table records the feedback through rewards after successfully updating Q-value function to generate the final policy for research domain like WSN.

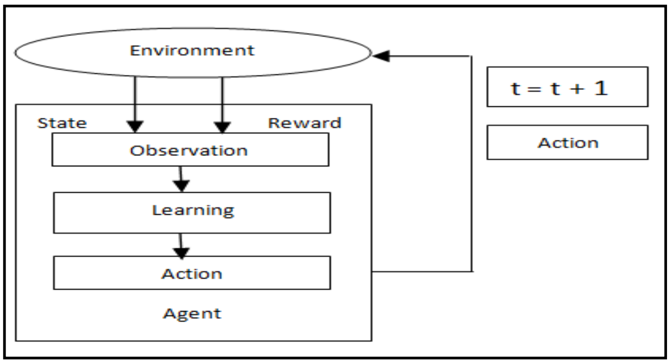


**Figure 1:** Working of RL Agent

### 1.3 Q-LEARNING (SELF LEARNING): APPROACH

Q-learning (Christopher et al., 1992) denotes mathematical expression in the form of state, event, action and reward in the form of s, e, a and r as with learning rate denoted by α and factor of discount by ϒ. The negative reward denotes cost. The Q-value works in below equation 01 (mathematically approach):

$Q_{t+1}\ S_t, e_t, a_t \longleftarrow (1\text{-}\alpha)\ Q_t\ (S_t, e_t, a_t)\ \alpha\ r_{t+1}\ (S_t, e_t, a_t)\ \gamma \max Q_t a\varepsilon A\ (S_{t+1}, e_{t+1}, a_1)$ (01)

Here, $0 \leq \alpha \leq 1$ with $0 \leq \gamma \leq 1$, learning agent ignore its last policy value, and update it by the new value. The highest value of achieved rewards updates policy value (Q) every time. Let we assume $\gamma = 1$, then discounted reward decreases the reward which had been received immediately. This is shown mathematically through equation 02:

$V^{\pi}(s, e) = \max a \in A\ Q_t(S_t, e_t, a)$ (02)

## II. REINFORCEMENT LEARNING (SELF LEARNING) TECHNIQUES FOR WIRELESS SENSOR NETWORK

From decay, Reinforcement Learning (Self learning) methods have been observed for different useful approaches in WSN to locate full lifetime of network with various performance enhancement parameters. This all techniques are described in below Table 1:

**Table 1:** Reinforcement Learning (Self learning) Techniques used for WSN

| **Author(s)** | **Brief details of proposed / implemented work** |
|---|---|
| (Christopher et al., 1992) | Provides basics of Q (Self) Learning. |
| (L.P.K. et al., 1996) | Provides general approach of Model with RL, Analysis of RL, Self Learning approach, Award based theory, policy iteration, and various RL methods. |
| (Yu-Han Chang et al., 2003) | That research study gives a vital domain related to multi agent RL with the publication of various observations in this domain. |
| (Jamal N. Al-Karaki et al., 2004) | That research study highlights the general routing issues with their various consequences in WSN. |
| (Aram Galstyan et al., 2004) | Here author elaborated game dynamics based upon RL methods. |
| (Z Liu et al., 2006) | This study has gives a very good RL-MAC protocol based upon RL framework to improve the efficiency of WSN. |
| (N i k l a s w i r s t r ö m et al., 2006) | This thesis shows the working of self node configuration based upon certain policies. |
| (Ping Wang et al., 2006) | That routing scheme firsts learns the optimal routing methods, mainly focused for several optimization goals useful to overcome various WSN issues. |
| (Vladimir Dyo et al., 2007) | Here, author developed self learning algorithm to improve the energy efficient of WSN node based upon discovery of nodes associated with sparsely jointed mobile wireless sensor networks based up on duty cycle. |
| (Anna Egorova et al., 2007) | This algorithm creates routing paths which are very cost effectives in the regard of energy efficiency with the help of exchanging information among WSN nodes. |
| (Anna Forster et al., 2007) | Here author worked with learning in MANET,WSN and Ad hoc network by using RL framework and self learning methods. |
| (Anna Forster et al., 2007) | This research study focuses to improve the routing efficiency for different mobile sinks to achieve energy efficiency. |
| (Anna Forster et al., 2007) | Here we can find the balanced methods of energy expenditure in wireless sensor Networks. |
| (Kunal Shah et al., 2008) | This research paper made the focus on self learning to develop Distributed Independent Reinforcement Learning (DIRL) based up on RL framework. |
| (Mihail Mihaylov et al., 2009) | Here research showed that latency can be decreased as well as energy saving can be done by q-learning methods. |
| (Anna Forster et al., 2009) | Here, author developed CLIQUE protocol, which provides freedom of wireless sensor node to be a cluster head or not based upon self learning techniques. |
| (Somayeh K. et al., 2011) | Here, author presents the dynamic power management technique to conserve the energy of wireless sensor nodes. |
| (Wenjing G. et al., 2014) | This research study provides the algorithm to enhance the network |

| | |
|---|---|
| | lifetime of WSNs, with the functionality of reinforcement learning (Self learning) and residual energy with hop count to better define the reward function. It distributes the energy uniformly. |
| (Ankit B. et al., 2015) | This paper contributes for energy efficient strategies using Q-routing algorithms and develops energy efficient shortest path based upon self learning. |
| (Ibrahim Mustapha et al., 2015) | This research study represents clustering algorithms for wireless sensor nodes. |
| (Gabriel M. et al.,2016) | This paper provides dynamic sampling rate adaptation scheme based on self learning to tune sensors sampling interval according to environmental conditions and application requirements. |

## III. CURRENT ISSUES IN WSN

There are various open challenges which are available for researcher:

Robustness of Reinforcement Learning Energy optimization

Mobile sink Mobile charger

Self Learning Algorithm for WSN.

Routing cost reduction in WSN using Reinforcement Learning.

Security issues of Reinforcement Learning.

Self replicate agent learning cost.

## IV. CONCLUSIONS AND FUTURE SCOPE

Self learning is very easy to adopt and deploy in wireless sensor network to completely improve the network lifetime through PDR ratio, energy efficiency, delay and throughput. This extensive survey provides various proposed protocols and different in co operated techniques to overcome the different issues and challenges of wireless sensor network from the past to the present scenario.

## REFERENCES

[1] Ankit B. Patel, Hitesh B. Shah (2015), Reinforcement Learning Framework For Energy Eficient Wireless Sensor Networks, *IRJET.NET*, 02, 1034-1040.

[2] Aram Galstyan, Bhaskar Krishnamachari, Kristina Lerman (2004). Resource Allocation and Emergent coordination in wireless sensor networks.

[3] Anna FOrster (2007). University Of Lugano, Switzerland, Machine Learning Techniques Applied To Wireless Ad-hoc Networks: *Guide And Survey*.

[4] Anna F Orstery, Amy L. Murphy (2007). FROMS: Feedback Routing For Optimizing Multiple Sinks In WSN with Reinforcement Learning.

[5] Anna F Orster, Amy L. Murphy (2008). Balancing Energy Expenditure In Wsns Through, Reinforcement Learning a study, *workshop on energy in wireless sensor networks.*

[6] Anna F Orster, Amy L. Murphy (2009). CLIQUE: Role-Free Clustering With Q-Learning For Wireless Sensor Networks, 1063-6927.

[7] Anna Egorova, FOrster Amy, L. Murphy (2007). Exploiting Reinforcement Learning For Multiple Sink Routing In wsn.

[8] Christopher J.C.H. Watkins (1992). Technical Note Q-Learning, Kluwer Academic Publishers, Boston *Machine learning*, 8, 279-292.

[9] Emilio Ancillotti, Carlo Vallati, Raffaele Bruno and Enzo Mingozzi (2017). A reinforcement learning- based link quality estimation strategy for RPL and its impact on topology management, *Computer Communications*, 112, 1-13.

[10] Gabriel Martins Dias, Maddalena Nurchis And Boris Bellalta (2016). Adapting Sampling Interval of Sensor Networks Using On-Line Reinforcement Learning.

[11] Habib Mostafaei, Antonio Montieri, Valerio Persico and Antonio Pescapé (2017). A sleep scheduling approach Based on learning automata for WSN partial coverage, *Journal of Network and Computer Applications*, 80, 67-78.

[12] Hedde HWJ Bosman, Giovanni Iacca , Arturo Tejada , Heinrich J. Wörtche and Antonio Liotta (2017). Spatial anomaly detection in sensor networks using neighborhood information, *Information Fusion*, 33, 41-56.

[13] Ibrahim Mustapha Borhanuddin M. Ali, A. Sali, M.F.A. Rasid, H. Mohamad (2015). An Energy Efficient Reinforcement Learning Based Cooperative Channel Sensing For Cognitive Radio Sensor Networks, *Pervasive and mobile computing*, 35,165-184.

[14] Jamal N. Al-Karaki, The Hashemite University Ahmed E. Kamal (2004). Iowa State University, Routing techniques in Wireless Sensor Networks: A Survey, *IEEE Wireless Communications*.

[15] J. N. Al-Karaki And A. E. K amal (2004). Routing Techniques In Wireless Sensor Networks: *A Survey, In IEEE wireless communications*, 11, 6-28.

[16] Kunal Shah, Mohan Kumar (2007). Sensor logic Inc., Addison TX 75001, Distributed Independent Reinforcement learning (DIRL) Approach To Resource Management In Wireless Sensor Networks.

[17] Leslie Pack Kaelbling, Michael L. Littman (1996). Andrew W. Moore, Reinforcement Learning: A Survey, *Journal of Artificial Intelligence Research*, 4, 237-285.

[18] Mihail Mihaylov, Karl Tuyls,Ann Nowé (2009). Decentralized Learning In Wireless Sensor Networks, *Proc. of The adaptive And Learning Agents Workshop* , Taylor And Tuyls (Eds.), Budapest.

[19] N i k l a s w i r s t r ö m (2006). Optimization of Wireless Sensor Networks Using Machine Learning, *MS Thesis kth CS* And Foundation.

[20] Palvinder Singh Mann and Satvir Singh (2017). Energy efficient clustering protocol based on improved metaheuristic in wireless sensor networks, *Journal of Network and Computer Applications*, 83, 40-52

[21] Ping Wang, Ting Wang (2006). Adaptive Routing for Sensor Networks Using Reinforcement Learning, *Proceedings of The Sixth IEEE International Conference On Computer And Information Technology*.

[22] S. Gheisari and M.R. Meybodi (2017). A new reasoning and learning model for Cognitive Wireless Sensor Networks based on Bayesian networks and learning automata cooperation, *Computer Networks*, 124, 11-26.

[23] Shah Jahan Miah, John Gammack and Najmul Hasan (2017). Extending the framework for mobile health Information systems Research: A content analysis, *Information Systems*, 69, 1-24.

[24] Somayeh Kianpisheh, Nasrolah Moghadam Charkari (2011). A New Approach for Power Management In Sensor node Based On Reinforcement Learning.

[25] Soo-Hoon Moon , Sunju Park and Seung-jae Han (2017). Energy efficient data collection in sink- centric Wireless sensor networks: A cluster-ring approach, *Computer Communications*, 101, 12-25.

[26] Vladimir Dyo, Cecilia Mascolo (2007). Efficient Node Discovery In Mobile Wireless Sensor Networks.

[27] Yu-Han Chang, Tracey Ho, Leslie Pack Kaelbling (2003). Mobilized Ad-Hoc Networks: A Reinforcement Learning approach, Massachusetts Institute Of Technology — *Computer Science And Artificial Intelligence*.

[28] Z Liu, I Elhanany (2006). RL-MAC A Qos Aware Reinforcement Learning Based Mac Protocol For WSN, 1-4244-0065.

[29] Wenjing Guo, A , Cairong Yan, B , Yanglan Gan , C And Ting Lu (2014). An Intelligent Routing Algorithm In wireless sensor networks based on reinforcement learning.

[30] Zhenchun Wei, Yan Zhang, Xiangwei Xu, Lei Shi and Lin Feng (2017). A task scheduling algorithm based on Q-learning and shared value functions for WSNs, *Computer Networks*, 126,141-149.