INTELLIGENT SENSOR NETWORK ALGORITHM BASED UPON Q-LEARNING

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ABSTRACT

Presently, Wireless Sensor Network is the key for various existing critical problems available in sensing domain like health monitoring, under water sensor network, volcano monitoring and precision agriculture. Machine learning is the key area of artificial intelligence. Q-learning is the part of reinforcement learning which is used to learn through experience and provide rewards to generate value function to finally update the results. The combination of Wireless sensor network and Q-learning create an intelligence to save energy consumption in wireless sensor network to achieve higher PDR and lower end to end packet delay. In this research study, we are proposing an intelligent sensor network algorithm to achieve the same based upon q-learning technique. We have compared the result with existing algorithms like RLLO (Wenjing et al., 2014) to better justify our research findings based upon various performance matrices like energy consumption, PDR and lower end to end delay.

Keywords: Wireless Sensor Network, Q-Learning, Reward, Value Function and PDR.

INTRODUCTION

Wireless Sensor Network works in very critical and challenging conditions where they constantly sense the changes from environment. To maintain complete correctness, a WSN operation needs to be smart enough to face on the spot challenges. Generally machine learning techniques are the answer for these kinds of requirements. Many scientists, researchers have already applied machine learning techniques in WSN for the recognition of activities, health care related issues, flight control and volcano monitoring. Machine learning algorithms are mainly divided into two categories: supervised and unsupervised. Q-learning (Christopher et al., 1992) which is derived from machine learning falls under reinforcement learning. The combinations of WSN and Q-learning (Christopher et al. 1992) have been applied in various wireless sensor network applications. In this research study, we are proposing an intelligent WSN algorithm to overcome various challenges using q-learning under certain performance matrices like PDR, end to end delay and energy consumption ratio (S.K. et al., 2011) (Ibrahim M. et al., 2017).

LITERATURE SURVEY

According to authors (Christopher et al., 1992) and (Kaelbling L.P. et al., 1996) the authors have described basics of q-learning techniques, RL Model, RL Behavior, Learning Automata, Delayed Awards, Policy iteration, and Model free methods which are very useful to implement in dynamic environments. According to authors (Yu-Han Chang et al., 2003), the authors focused to develop a rich new domain for multi agent reinforcement learning and establish several first results in this area. There was a need to make interplay between routing and movement. According to authors (Jamal N. et al., 2004), the author presented various routing challenges and design issues in wireless sensor network which are really very useful to understand problem areas in WSN. According to authors (Liu Z. et al., 2006), here author has given unique RL framework to develop energy efficient MAC protocol. Here the proposed framework can be used for cross-layer optimization in ad-hoc clusters of sensor nodes. According to authors (Nik. et al., 2006), here author explores how the nodes of a WSN can use policies for self-configuration. Depending on the state of a node's local environment, the policy determines how the node should configure. They showed how Machine Learning methods can be used in simulated networks to search for optimal policies for specific scenarios. According to authors (Wang P. et al., 2006), here author presented a novel routing scheme, AdaR which adaptively learns an optimal routing strategy, depending on multiple optimization goals. This paper does not used point-to-point routing, and not extended the technique to the case that multiple sensors cooperate with each other to facilitate routing. According to authors (Dyo V. et al., 2007), here author proposed an algorithm for energy efficient node discovery in sparsely connected mobile wireless sensor networks. The work takes advantage of the fact that nodes have temporal patterns of encounters and exploits these patterns to drive the duty cycling. Duty cycling is seen as a sampling process and is formulated as an optimization problem. Author (S.K. et al., 2011) (Ibrahim M. et al., 2017) have also used reinforcement learning techniques to detect and dynamically change the times at which a node should be awake as it is likely to encounter other nodes.

PROPOSED ALGORITHM

The q-learning algorithm (Christopher et al., 1992) used to learn from experience and create state and action to finally generate the updated policy function (Anna et al., 2007) (Mihil M. et al., 2009). The following algorithm works in suggested manner to provide efficiency (Zhang Y. et al., 2010) in WSN.

I/P=Initial Sensor Query, Define Possible Grid State(s, a) and Move Towards (L R U D)

O/P= Goal Achieved/Target Completed

Start of Algorithm

Begin

For (Every State Si: S) \\ Generates Action

Begin

Step1: Fetch the Start State Si

Step2: Find Possible Move or Search (L R U D) and Execute

Step3: Check for Goal Status

Step4: If (Yes: Goal=Start State)

Update Discount Rate DR1=DRγN1- i and i=i+1

Step5: Else

{

Goal ≠ Stat States

Store (s,a) value in look-up-table

}

Step6: Go to Step2

End

End. \\Target Achieved

where discount rate (DR1) (Ibrahim M. et al., 2017) is γ with range of ($0<\gamma<1$), which reduces effect of future expected rewards. (N1) is counted step and (i) is total step in the problem. Action or movement performed by agent is represented in the form of L: Left, R: Right, U: Up, D: Down

SIMULATION AND RESULT

We have simulated the proposed algorithm in MATLAB shown in figure 1 with following parameters specified in Table 1.

Table 1: Simulation Parameters	
No of Nodes	50
Learning Rate (α)	0.9,0.8,0.7
Discount factor (ϒ)	0.1,0.2,0.3
Initial Energy (in	500 mJ

jule)	
Range of transmission	100 m
Range of interference	50 m
Rate of Packet Generation	10 s
MAC protocol	CSMA
Physical layer protocol	IEEE 802.15.4
Dissemination of Data	0.5 s , 01 s and 01.5 s

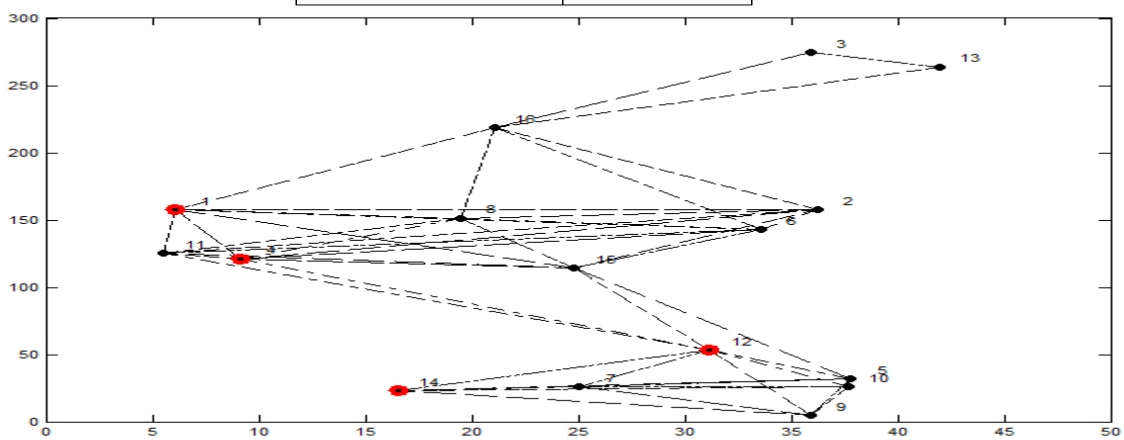

Figure 1: Proposed algorithm simulation in MATLAB

after successful simulation of proposed intelligent sensor network algorithm (figure 1) in MATLAB, we found that our algorithm performed better than existing RLLO (Wenjing et al., 2014) algorithm under various performance metrics like packet delivery ratio, average end to end delay, and throughput with energy consumption shown below.

(i) PDR:

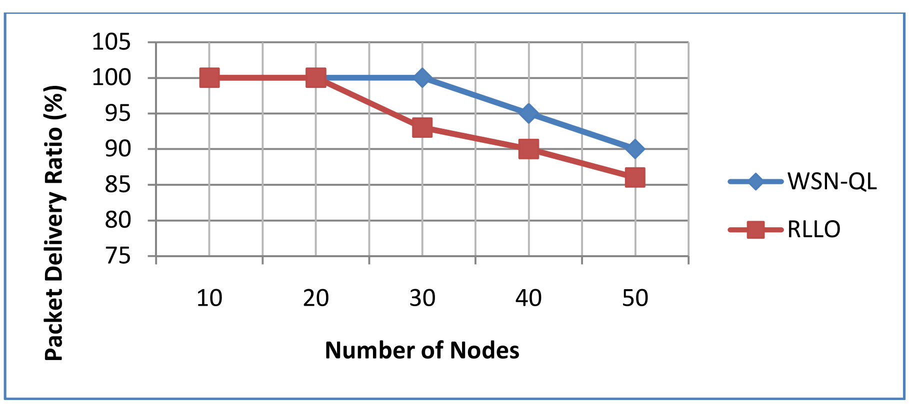

Figure 2: PDR Ratio

(ii) END TO END DELAY :

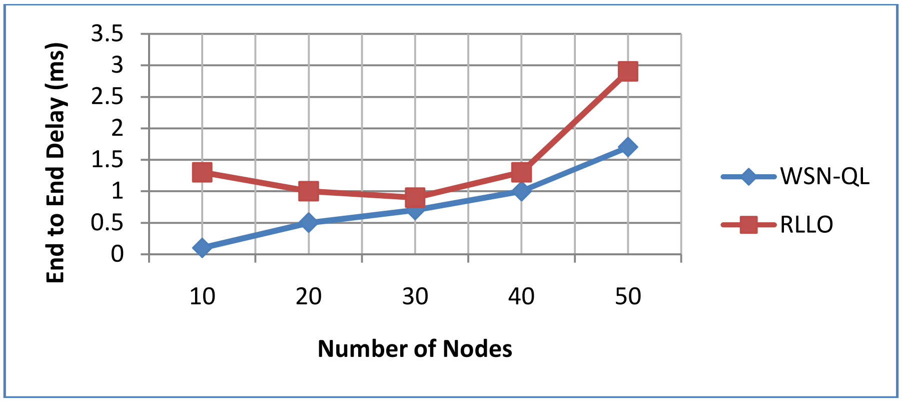

Figure 3: End to End Delay

(iii) THROUGHPUT

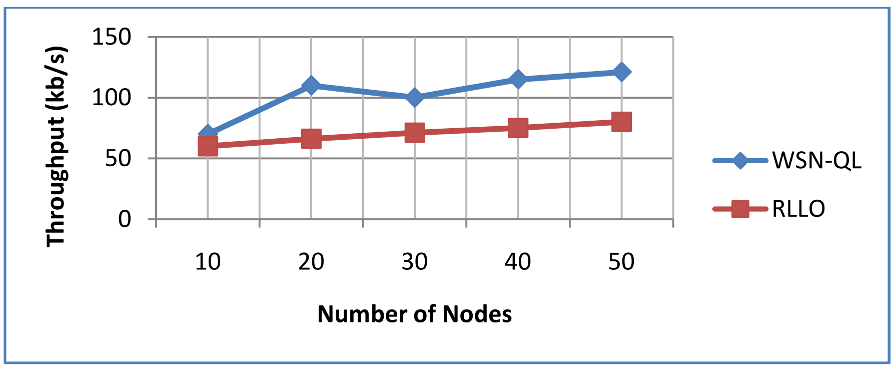

Figure 4: Throughput

(iv) ENERGY CONSUMPTION

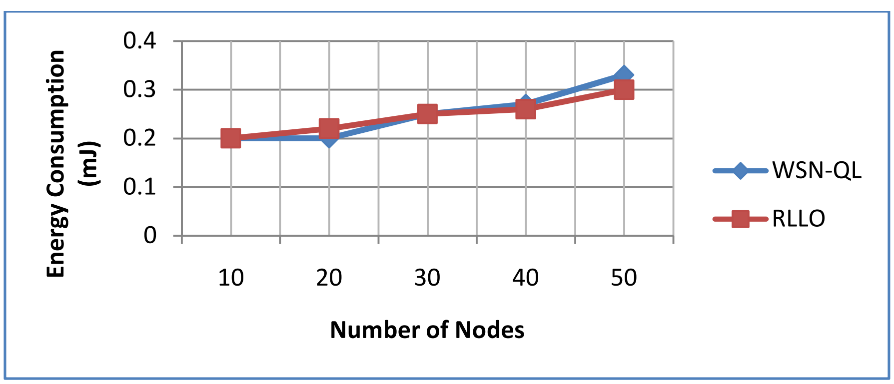

Figure 5: Energy Consumption

CONCLUSION AND FUTURE SCOPE

We have simulated the proposed algorithm (figure 1) in MATLAB with parameters specified in table 1 and also compared with existing algorithm RLLO (Wenjing et al., 2014). We found that our proposed algorithm (figure 1) performs better under various performance matrices like PDR ratio (figure 2), end to end delay (figure 3), throughput (figure 4) and energy consumption (figure 5). In future, we will try to implement this algorithm on real wireless sensor network.

REFERENCES

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

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

Chang Y., Tracey Ho, Kaelbling L. K. (2003). Mobilized Ad-Hoc Networks: *A Reinforcement Learning approach*, Massachusetts Institute Of Technology -Computer Science And Artificial Intelligence.

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*.

Galstyan A., Krishnamachari B. and Lerman K. (2004). Resource Allocation And Emergent coordination in wireless sensor networks.

Al-Karaki J. N. and Kamal A. E. (2004). Routing Techniques In Wireless Sensor Networks: A Survey, In *IEEE* wireless communications, 11(6), 6-28.

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

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 .

Wang P. and Wang T. (2006), Adaptive Routing For Sensor Networks Using Reinforcement Learning, *Proceedings of The Sixth IEEE International Conference On Computer And Information Technology*.

Dyo V. and Mascolo C. (2007). Efficient Node Discovery In Mobile Wireless Sensor Networks.

Anna Egorova-F¨Orster Amy L. Murphy (2007). Exploiting Reinforcement Learning For Multiple Sink Routing In WSN.

Anna F¨Orster (2007). University Of Lugano, Switzerland, Machine Learning Techniques Applied To Wireless Ad-hoc Networks: *Guide And Survey*.

Anna F¨Orstery And Amy L. Murphy (2007). FROMS: Feedback Routing For Optimizing Multiple Sinks In WSN with Reinforcement Learning.

Fasolo E., Rossi M., Widmer J. and Zorzi M. (2007). In-Network Aggregation Techniques For Wireless Sensor networks: A Survey, In *IEEE Wireless Communications*, 14(2), 70-87.

Shah K. and Kumar M. (2007). Sensorlogic Inc., Addison TX 75001, Distributed Independent reinforcement learning (DIRL) Approach To Resource Management In Wireless Sensor Networks.

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

Mihaylov M., Tuyls K. and Nowé A. (2009), Decentralized Learning In Wireless Sensor Networks, Proc. Of The adaptive And Learning Agents Workshop (ALA 2009), *Taylor And Tuyls (Eds.),* Budapest.

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

Zhang Y., Meratnia N. and Havinga P. (2010). Outlier Detection Techniques For Wireless Sensor Networks: survey, In *IEEE Communications Surveys & Tutorials*, 12(2), 159-170.

Kianpisheh S. and Charkari N. M. (2011), A New Approach For Power Management In sensor node Based On Reinforcement Learning.

Nauman Ahad, Junaid Qadir, Nasir Ahsan (2016), Neural Networks In Wireless Networks: Techniques, applicationsand guidelines, *Journal Of Network And Computer Applications*, 68, (1-27).

Zhou Q., Li D., Kar S., Huie L. M., Poor H. V. and Cui S. (2017), Learning-Based Distributed Detection-estimation In Sensor Networks With Unknown Sensor Defects, In *IEEE Transactions On Signal processing*, 65(1), 130-145.

Ibrahim M. , Borhanuddin M. Ali, Sali A.,. Rasid M.F.A and Mohamad H. (2017). An Energy Efficient reinforcement Learning Based Cooperative Channel Sensing For Cognitive Radio Sensor Networks, p*ervasive and mobile computing*, 35,165-184.

Russell, S, Norvig, P.: Artificial Intelligent: A Mordern Approach, Third Edition. Prentice Hall.

Wenjing Guo1,A *, Cairong Yan2,B. , Yanglan Gan 3,C. and Ting Lu4 (2014). An Intelligent Routing Algorithm in wireless sensor networks based on reinforcement learning.