# Novel Algorithm Based Upon Reinforcement Learning to Better Improve Energy Consumption in WSN

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*Abstract*- Nowadays, Wireless sensor network is highly potential area in various sectors like industry, research, medical, education and IOT. Sensor nodes are generally equipped with tiny battery to perform various operations. The key area is to save energy consumption of WSN node. In this research study, we have proposed a novel algorithm to better improve the energy optimization using reinforcement learning. The reinforcement learning technique is based upon state, action, policy and certain learning and discount factors. We have simulated the proposed algorithm in mat lab and compared the findings with state of the art algorithm like RL-CRC [26] to better improve energy consumption and other performance parameters.

Keywords: Wireless Sensor Network, Reinforcement Learning, State, Action, Policy, Learning and Discount factor.

### I. INTRODUCTION

Wireless Sensor Network plays role of sensing information from challenging conditions where situation is harsh but they continuously sense the data from current environment. To provide error free domain, WSN operation must learn to overcome hurdles. Presently machine learning techniques represent the best algorithms for such types of challenges. Various researches show that machine learning techniques are easy to adopt and error free in nature and can be used in WSN for the learning and training purpose under various iterations. These techniques are generally falls under two branches: supervised and unsupervised. Reinforcement learning [01] which is derived from machine learning falls under self learning. The joint of WSN and Reinforcement Learning [01] has already produced certain solutions to overcome the WSN challenges. In this research paper, mainly we are presenting a novel WSN algorithm to save energy consumption using Reinforcement Learning algorithm along with other WSN performance parameters [20-23]. The organization of this paper is below mentioned:

Introduction	Related work
Proposed Novel Algorithm	Simulation and Findings
Conclusion & Future Scope	

### II. RELATED WORK

According to Reference [01] [02], the authors presented basics of reinforcement learning and applications.

According to Reference [03], the authors joint between routing, sensing and certain progress of learning automata.

According to Reference [04] [06], the author has given routing data challenges along with designing topology in WSN.

According to Reference [07], here author has presented framework to make energy efficient MAC protocol based upon learning.

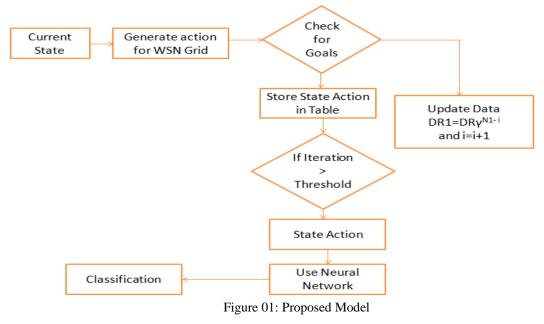
According to Reference [08], here author showed where Machine Learning methods can be used while searching for optimal techniques to certain scenarios.

According to Reference [09], here author performs a novel routing scheme, ADAR which performs learning of routing tricks, based on management.

According to Reference [10], here author presents duty cycling techniques to overcome optimization issue related to energy consumption. This research paper has used reinforcement learning techniques to find and performs dynamic change to perform intercommunication among various sensors nodes.

#### III. PROPOSED NOVEL ALGORITHM

The Reinforcement Learning algorithm used to perform learning through experience and generate state, action and function to mainly create the policy [11 - 18] based upon figure 01. The following proposed model and novel algorithm performs better to provide energy efficiency [19] in WSN.



The below algorithm performs step by step iterations using q-learning in WSN to achieve better throughput and saving energy among wireless sensor node.

**Step 01** Set initial Q-values for each node **Step 02** Get the first packet from the packet queue of node x **Step 03** Choose the best neighbor node  $\hat{y}$  and forward the packet to node  $\hat{y}$  by  $\hat{y} = \arg \min_{y \in N(x)} \{Q_x(y, d_y)\}$ 

**Step 04** Get the estimated value  $(T_{\hat{y}}(d) + q_{\hat{y}})$  from node **Step 05** Update  $Q_x(\hat{y}, d) \leftarrow Q_x(\hat{y}, d) + \eta [t_{x\hat{y}} + q_{\hat{y}} + T_{\hat{y}}(d) - Q_x(\hat{y}, d)]$ **Step 06** Go to (Step 02)

### Where

### IV. SIMULATION AND FINDINGS

We have implemented proposed model (figure 01) in MATLAB [25] and simulated above mentioned novel algorithm under certain parameters mentioned in table 01.

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Table 01: Simulation Parameters				
No of Nodes	100			
Learning Rate (a)	0.8,0.7,0.6,0.5			
Discount factor $(\Upsilon)$	0.1,0.2,0.3,0.4,0.5			
Initial Energy (in jule)	1000 mJ			
Range of transmission	200 m			
Range of interference	60 m			
Rate of Packet Generation	10 s			
MAC protocol	CSMA			
Physical layer protocol	IEEE 802.15.4			
Dissemination of Data	0.7 s , 02 s and 02.5 s			

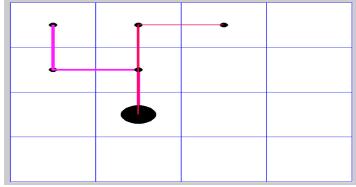


Figure 02 Learning Agent Path 1

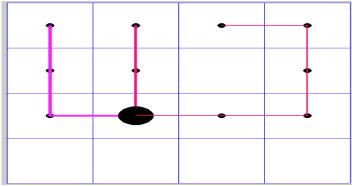


Figure 03 Learning Agent Path 2

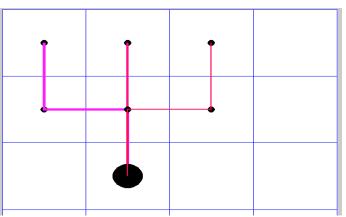


Figure 04 Learning Agent Path 3

state_action <16x4 double>						
	1	2	з	4		
1	0	31.3811	0	20.5891		
2	0	22.8768	18.5302	16.6772		
з	0	18.5302	16.6772	8.8629		
4	0	8.8629	9.8477	0		
5	28.2430	47.8297	0	90		
6	15.0095	100	43.0467	25.4187		
7	12.1577	25.4187	28.2430	8.8629		
8	7.1790	9.8477	9.8477	0		
9	81	53.1441	0	43.0467		
10	0	0	0	0		
11	12.1577	81	100	59.0490		
12	3.4337	72.9000	72.9000	0		
13	72.9000	0	0	59.0490		
14	100	0	65.6100	65.6100		
15	90	0	90	72.9000		
16	65.6100	0	81	0		
17						
-						

### 4.1 RESULT

The proposed model implementation has taken place in MATLAB [25], we observed that our proposed novel algorithm has shown better improvement over RL-CRC [26] algorithm. The improvement has been recorded and compared; finally results can be depicted under various performance parameters like packet delivery ratio, average end to end delay, and throughput along with energy consumption ratio.

Figure 05 Learning Agent State Action Values

• Packet Delivery Ratio :

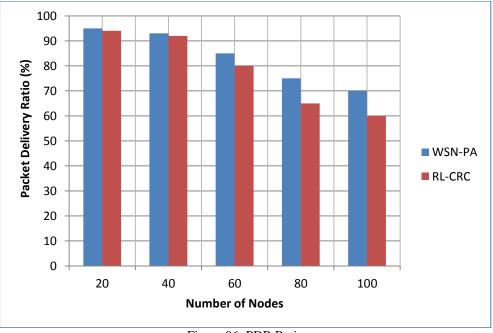


Figure 06: PDR Ratio

• End To End Delay :

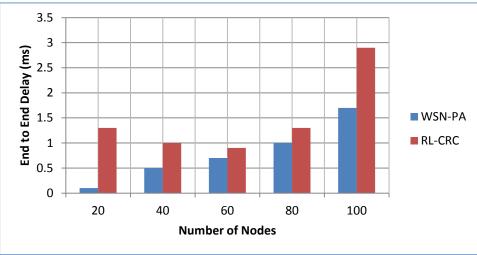


Figure 07: End to End Delay



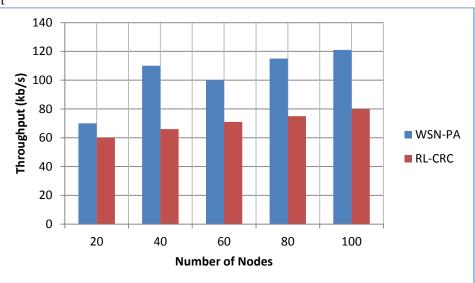


Figure 08: Throughput

• Energy Consumption

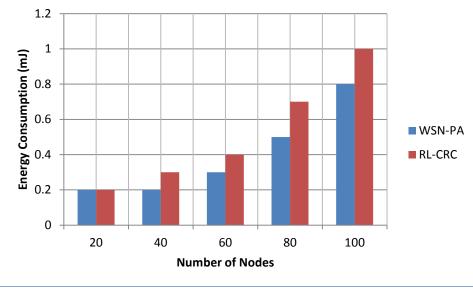


Figure 09: Energy Consumption

#### V. CONCLUSION & FUTURE SCOPE

In this research paper, we have presented proposed model and a novel algorithm to save the energy consumption among wireless sensor nodes which is simulated in MATLAB [25] with certain parameters given in table 01. The results are compared with state of the art algorithm like RL-CRC [26]. The comparison shows that our proposed novel algorithm has given better results on the basis of PDR ratio (figure 06), End to End delay (figure 07), Throughput (figure 08) and Energy consumption (figure 09). In future we will extend our work with large number of wireless sensor node.

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