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An Energy Efficient Routing Protocol based on Reinforcement Learning for WSN

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Abstract

Wireless Sensor Network (WSN) seems to be critical because they are responsible for maintaining network routes, packet forwarding, and higher multi-hop connectivity. Clustering nodes is still a powerful technique for modelling routing protocol for WSNs, as it increases the range of communication services with energy efficiency. This paper focuses on the energy efficiency and improved lifetime of the network based on the reinforcement learning protocols. The system can adapt to network changes, such as energy efficiency, mobility and make better routing decisions attributable to Reinforcement Learning (RL). The legal restrictions on sensor nodes are taken into consideration and an energy-balancing routing model based upon reinforcement learning has been provided. The results show that the enhanced protocol outperforms the state of energy savings and network lifetime when compared to Q-learning and LARCMS energy-efficient routing protocols. The proposed protocol's effectiveness is analysed by end to end delivery and packet delivery.

Keywords: Wireless sensor networks, routing algorithm, lifetime of the network and energy consumption

1. Introduction

In recent years, effective routing algorithms for wireless networks have been developed using Reinforcement Learning (RL) approaches. Wireless sensor Networks (WSNs) are made up of hundreds of nodes that are linked together. It has been reported that RL-based routes improve network lifetime and overall performance. Traditional routing protocols are predicated on the assumption of relatively uniform devices. The shortest pathway, absolute highest power, and least energy routes are examples of conventional strategies that might work in this situation. They will also lead to a limited lifetime of the

network and reduced energy efficiency in a network setting. Routing methods in WSNs that use RL can extend the life of the network and improve performance in general.

The problem of an agent acting in an unknowable environment and learning over time and make a sequence of trial-and-error responses to the environment, is resolved by the machine learning sub-field of reinforcement learning [1-3]. Nodes in a WSN use energy while accessing, sensing, transmitting, or receiving packets. The agent communicates with the surrounding by taking certain actions and receiving benefits, that also can be either highly dependent on whether the act done was correct. In comparison to static routing approaches, the above method brought the versatility on data routing and ability to adapt capability in network routing. The experiments demonstrate that interaction is the most energy-hungry source of consumption [12-16]. There are numerous ways to send available packets to the destination node in such a large network.

Nodes will start understanding and self-configure over period. There is no pre-requisite knowledge of topology needed. They will constantly start understanding and update their knowledge in order to make informed and timely decisions.

The below few are the two main constraints related to the energy efficient protocol architecture [17].

1.1 Network lifetime

It has three main elements: (1) the duration before the first death node emerges; (2) the duration before the first isolation node arises; and (3) the duration before the network is unable to send any more packets.

1.2 Energy efficiency

Equation below can be used to determine number of times packets are delivered for each unit of energy consumed.

$E=N/EC$

where, E-Energy consumed

N-Number of packets delivered.

EC- Total energy consumption.

Efficient energy utilisation is critical for maintaining a fully functional network as long as possible.

It is known that energy-efficient routing algorithms, in particular, can control how much of the available energy in WSNs is used to transmit sensed data [18-20]. Even with some of the limitations of network nodes and the harsh settings [4] under which the node in the network must operate, energy-efficient routing methods are known to aid in lengthening the lifespan of WSNs.

2. Related Works

As per a study, due to enormous nodes in many wireless sensor applications, it is not always practicable to provide each one a unique global identifier. However, sensor nodes typically operate at random dispersed environment. This technique makes it challenging to choose a few specific nodes and send them a specialised message commands or to communicate individually within the nodes. Routing can be used by protocols based on aggregated outcomes to enhance network efficiency and save energy [5].

In order to improve network and application performance, reinforcement learning [7] has been used in a variety of WSN schemes, including cooperative communication, routing, and rate control. This allows sensors and sinks nodes to observe and take the best possible actions in each operating environment.

Q-learning-depended data-aggregation-aware energy-efficient routing [8] algorithm, where each sensor network nodes reinforces to determine the optimum path, might maximise the benefits while taking into consideration the communication cost, residual energy, and sensor-type based data aggregation level of the neighbour node based on the distance and steps to the sink. This is how the sensor analysis the best next hop node can be determined by nodes utilising their according to the incentives, updated Q-values.

A routing for delay-tolerant networks is made possible through adaptive reinforcement-based routing. Nodes select the forwarding node in a cooperate system based on their combined knowledge, time metrics, and network latency. But this method is only meant to be used in a specific circumstance [6].

MRL-QRP [9] obeys the routing algorithm of PDR and power delay, employs each node to its full potential or learns enough about the network to make the best hop decision.

According to node mobility and wireless channel conditions, sensor nodes alter the likelihood of the environment. It is sufficient to have profoundly optimal performance across the network's local information, including knowledge about nearby nodes.

By utilizing a routing strategy for energy balancing in multi-hop WSNs [10], the system increases the usage and lifetime of the network. It is included in combining satellite and WSN technologies in space, designed and deployed for plenary exploration scenarios.

Location Aware Routing for Controlled Mobile Sinks (LARCMS), [21] demonstrated low reporting delay using two controlled portable sinks, and the suggested sink location updating method has been discussed. Choosing the shortest route possible and utilising the most energy compared to current routing, and increased network lifetime protocols have been performed.

The RLBR routing framework, which is based on reinforcement learning was suggested in [11]. To determine who will move ahead next, RLBR takes into account distance, remaining energy, and hop count. RLBR has some limitations even though it produces results that are superior to those of Q-routing and BEER. Nodes with more hops or a larger distance than that of the current node are not taken into account by RLBR when choosing the next forwarder. This limitation does not, however, permit maximum of LT, but only minimization of energy use.

3. Proposed Protocol

RL gathers information by interacting with the environment consistently and enhancing performance of the system by reaching ideal outcomes by carrying out all necessary tasks required to reach conclusions. Q-learning RL scheme class generates a series of observations regarding the reward point. The flow diagram of the proposed algorithm is as shown in figure 1.

There are two steps in this phase:

3.1 Initialize Q value

Devices can use local data to estimate the first Q-value due to the network configuration. A heartbeat message, which includes the base station's location coordinates, is the first message it sends out. Each device notes the position of the base station after acquiring a packet from

it, then utilises formulae to determine the effective Q-value with the first source of intensity and the number of hops.
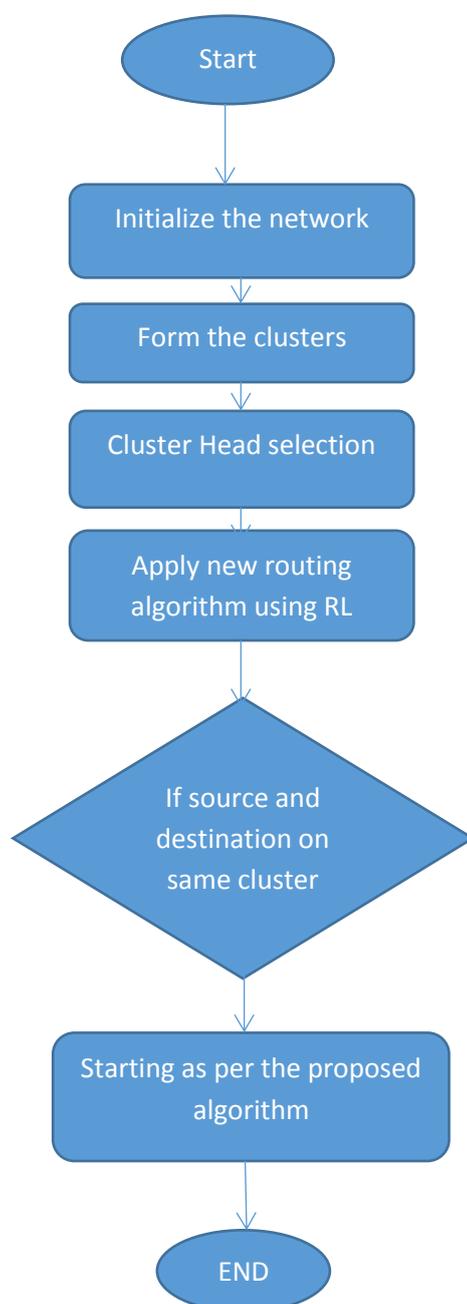

Figure 1. Flow chart of the proposed protocol

In order to reduce network overhead and make it easier for sensors located far from base stations to locate a Cluster Head (CH), a distance threshold is additionally specified among CHs and the BS (Base Station). All devices have different energy levels. A CH cannot be near the network's edge, since doing so could waste energy due to the lengthening of the

communication distance, which would cause links to deviate to the BS rather than converging.

$$Q \text{ value} = \begin{cases} \dfrac{1}{NH} \\ e * \left(Er - \dfrac{Ef}{ES} - EF \right) if \ EF \neq ES \end{cases}$$

where, NH=Dlink / Range of Tx

3.2 Divide area into clusters

The network as a whole is separated into several cluster groups, and the node with the most energy acts as a CH. If a network area is split with a dimension of 1800 X 1800 and a cluster size of 300 x 300, the network area is divided into 36 clusters.

3.3 Cluster head selection

$$S = \frac{\sqrt{\sum_{I=1}^{n} Dn - sink \ X \ln(I) \ X \ area}}{\Omega}$$

where, $\Omega = \begin{cases} 2 \ if \ \dfrac{N}{totalarea} < 0.1 \ and \ N > 50 \\ 1 \ elsewhere \end{cases}$

3.4 Routing protocol

The following is the proposed routing protocol algorithm. The parameters and the notifications are,

N- Number of nodes

EC-energy consumption

CA-Coverage area

DS-Distance from sink.

CHO-Cluster head optimized.

A-Active Q learning function

1) Start
2) Calculate threshold
3) Apply RL for CH selection
4) for i=1 to n do
5) If A(i)>0 then
6) Max T=max(T(i))

7) If A(i).e<Tx

8) If A(*i*) is next-hop, then

9) *Aggregate data*

10) *Send data to sink*

11) Else

12) *Send data to sink*

13) End if

14) If *CH* within TX$_{range,}$

15) then

16) *Send data to CH*

17) Else

18) *Find closest neighbour in the cluster*

19) *Send data to closest neighbour*

20) End if

21) End if

22) Determine reward

23) Update A value

24) End if

25) End for

The simulation parameters for the proposed algorithm are listed as below:

Table 1. Simulation parameters

Parameters	Values
Number of nodes	200
Number of destination node	1
Area of the network	1400X1400
Initial energy	1J
Packet size	125 bits
Learning rate	.75
Distance threshold	4m

At first, 200 node positions are generated. Different ways use the same configuration. The same event with a constant seed value is created. These events could include motion events, for instance, which node in a monitoring device would notice. Each node's communication range is limited to 15 metres. As part of the third definition of LT, the simulator for each of the protocols is executed until no more packets can be delivered to the sink. The results are obtained with the range 15 m.

Table 2. Validated output results

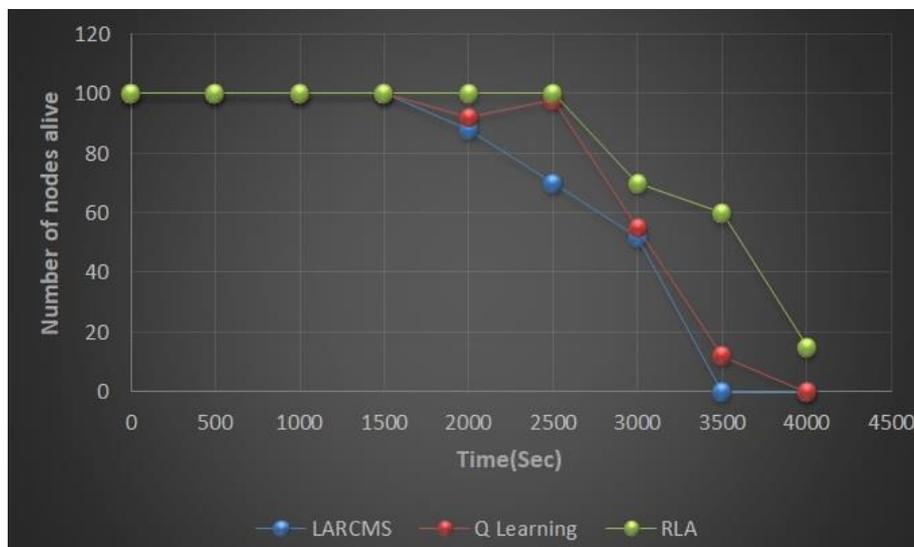| Approach	Lifetime	Consumed energy	Node	Energy efficiency
RLA	2379	21,135	3724	17,5241
Q- learning	2215	25,478	2971	13,6497
LARCMS	1724	36,785	2465	89,174

Figure 2. Comparative results on lifetime of the network

Overall, these findings from table 2 show that the proposed method outperforms Q-Routing and LARCMS in a variety of learning topologies and energy-efficiency metrics. This method proposes an efficient routing mechanism using simulations and analytics. To investigate the hardware needs of various nodes, such as memory and processing time, a real-world implementation of these protocols is necessary.

4. Conclusion

WSN has been created for a variety of specialised applications, including military, agricultural, and rescue operations, each of which calls for a unique set of features. Every situation on a network, calls for new communication protocols. To attain the desired performance, considerations for network design must also be made. In terms of the percentage of living nodes, lifetime distinct definitions based on number of packets delivered, and energy efficiency, proposed RLA overcomes Q-learning and LARCMS. This protocol can be used with a real time application wireless sensor network in the future.

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