Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 46 No. 2 (2025)

Electrical Charge Station and Charge Detection Using QoS - aware Hybrid Learning routing protocol in Wireless sensor network for Electrical vehicle.

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Abstract

In this Abstract, In Electrical vehicle wireless sensor networks, an novel QoS -aware Hybrid Learning routing protocol(Qos-AHLRP) is very important to ensure that the key sensing data can be forwarded in a reliable path and solve the energy balance problem. In this paper, Electrical vehicle we classify the sensing data into three data types and set their priority, we present a novel QoS- aware Hybrid Learning routing protocol(Qos-AHLRP) to support high data rate for wireless multimedia sensor networks[6]. Hybrid learning that combines of Machine learning Techniques(Deep **learning and Reinforcement learning (RL))[26]** .The proposed (Qos-AHLRP)protocol works in a distributed manner to ensure bandwidth and end- to-end delay requirements of real-time data. And also Simulate average delay, average lifetime and network throughput. The results categorized in terms of the average amount of packet received and power conservation rate**[10]**. The QoS-aware Hybrid Learning routing protocol(Qos- AHLRP) model was determined, showed enhanced results regarding both parameters. In the end, they are comparing these results with (**Deep learning and Reinforcement learning (RL)).**

INTRODUCTION

Wireless Sensor Network (WSN) is a collection of small, self-contained electromagnetically devices that monitor the environmental conditions and be useful to employ in many applications such as medical, automotive safety, and space applications**[1][6]**. There are many essential priorities to build an architectural (WSN), such as deployment, mobility, infrastructure, network topology, network size and density, connectivity, lifetime, node address-ability, data aggregation, etc. Sensor nodes have several limitations, such as limited battery life, low computational capability, short radio transmission range, and small memory space. Still, the primary constraint of the nodes is their limited energy resource, which causes the disconnection of the network. Therefore, to reduce energy usage in wireless sensor networks, many cluster-based routing have been proposed[8].

Among those proposed, QoS-aware Hybrid Learning routing protocol(Qos-AHLRP)) architecture, which aims to distribute energy consumption evenly to every node in a given network. This Hybrid technique requires a predefined number of clusters and has been developed with an assumption that the sensor nodes are uniformly distributed throughout the network**[2]**.

Such limitations motivated the researcher to carry out this research. Numerous citations performed for the first paper released AHLRP. These studies based their work principles on AHLRP false assumptions, which in turn results in failure throughout their researches' works. Therefore, this research implemented and adopted a new model based on realistic values within the use of both Machine learning and deep learning represented in subsections respectively, to clarify AHLRP assumptions limitations[21].Therefore, this work will follow the below methodology Define the problem statement by implementing **Reinforcement learning (RL))** assumptions on real environments' parameters**[26]**.

Defining the scope of work by focusing on solving the formulated problems and issues of deep learning assumptions on real environments.

Proposing a new QoS- aware Hybrid Learning routing protocol algorithm. Divide the proposed technique into phases, to enhance its efficiency and ease the troubleshooting process**[3]**,**[6]**.

Evaluate the proposed technique by simulating it on the real environment's parameters using MATLAB

Besides this section, the next section reviewed some related works and current solutions for the problem under study. The proposed algorithm and its phases are discussed in the third section. The fourth section discussed the experiment and the scenarios that were implemented to prove the algorithm and the obtained results. Finally, yet importantly, the fifth section showed the conclusions and summarized the entire work

Related works

Still, **QoS- aware Hybrid Learning routing protocol** is the primary goal in WSN. Due to the composite real environment, an **QoS- aware Hybrid Learning routing protocol** is more challenging to depict in a heterogeneous WSN than in a homogeneous WSN. In a heterogeneous environment, the network dispenses with dissimilar sensors, turbulent links, and nearby interference. Luckily, there has been extensive work proposed in the last decade on Q-AHLRP

Mithra et al.[5] proposed an intelligent modified chain technique. The idea is to enhance network lifetime more than that achieved by PEGASIS by electing a cluster leader near the base station. In addition, information for BS is transmitted through members of the overlying chain technology

A WSN can be commonly defined as a structure of nodes that collectively feel and may restraint the surrounding permissive communication between people or computers and the surrounding habitat (Verdone, et al., 2008). On the one hand, WSNs empower new operations and hence enables new probable retails; on the other hand, its structure is disturbed by many restraints that hail for new criteria. The movement of sensing, preparing, and broadcasting under the finite amount of power, inflames a cross-layer structure access that demands the joint application of scattered signal/data transmission, medium ingress control, and broadcasting protocols[25]

Kumar et al. [12] consider the benefit of node energy heterogeneity in WSN through the design of an EEHC (Energy-Efficient Heterogeneous Clustered) protocol for a trilevel network. It elects a cluster head based on sensor node residual energy through a probability threshold function. As a heterogeneous technique, EEHC is more successful than LEACH in terms of network lifetime improvement. Similarly, Sharma et al. [12] developed an energy paradigm and proposed a traffic and energy-aware routing (TEAR) to refine the stability interval, while assuming sensor nodes with arbitrary initial energies and discrepancies in traffic origination rate beneficial to prevail over the limitation of system complexity[9].

On the other hand, QAHLP proposes an energy forecasting scheme to conserve node energy and improve network lifetime. However, real network conditions are dynamic and complex, so, it is not easy to accurately assess network lifespan[11].

Hong et al. [15] developed a clustering-tree topology control based on the energy forecast (CTEF) for network load balance and saving energy while considering multiple factors (e.g., PLR and link reliability) into consideration. In addition to a conventional CH selection mechanism and cluster formation, both central theorem and log normal distribution procedures are applied for accurately forecasting the mean energy of the network in respect of the differentiation between the actual and ideal average residual energy.

Priority-based application-specific congestion control clustering (PASCCC) [16] is another clustering approach to ensure QoS in WSNs. PASCCC minimizes congestion through the efficient scheduling mechanism of CH. The packets of distant nodes are given higher priority by the CH than the packets of nearby nodes. This routing approach integrates the mobility feature of a sensing node. PASCCC also considers the heterogeneity of a network. However, the main limitation of PASCCC is that it does not address the delay for non-real-time traffic. Non-real-time packets suffer more in this routing approach, and thus the overall network throughput is affected

The energy-efficient and QoS-aware routing protocol addresses both issues (energy efficiency and QoS). In the EEQR protocol, network traffic is prioritized on the basis of traffic content. A combination of static and mobile sink is devised to provide multi-paths for real-time traffic. The end-to-end delay is minimized by prioritizing network traffic[21]. This approach enhances the network lifetime and stability of homogeneous WSNs. However, the EEQR protocol is limited by the fact that it does not address the heterogeneity of a network. Its performance usually drops when a heterogeneous network environment is used to ensure the QoS in WSNs

The QoS-based adaptive route optimization and load balancing ROL [6] routing approach addresses the QoS-related applications of WSNs. ROL protocol employs the link metrics that can be modified according to the network traffic priority. It enhances network robustness and network lifetime. Nutrient-flow-based distributed clustering (NDC) is an optimization criteria used by the ROL to achieve load balancing in hierarchical routing protocols. The use of various link metrics and NDC incurs an overhead on network traffic. The excessive congestion of ROL protocol affects real-time traffic and does not minimize the end-to-end delay

Machine Learning –

In networking and services – can contribute to Adaptive and effective pattern mining ,Learning as the data or patterns change (traffic, users/tenants requests, network conditions, etc.) ,Scaling with network and services data,General characteristics are (ML) (subset of AI).Traditional programming Input Data, Rules (function) ,Computing Machine,Output data, ML: The rules are not known in advance, but discovered by a machine, ML idea: “Optimizing a performance criterion using example data and past experience” “A computer program is said to learn from experience E with some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E “ Tom Mitchell. Machine Learning 1997 The experience E comes usually in the form of data A learning algorithm is used to discover and learn knowledge or properties from the data In some cases, algorithms learn by rewards and/or punishments[7]. The data set quality or quantity affect the learning and prediction performance. After first learning, the ML can provide results, for new input unknown data .Wide variety of architectures, methods and algorithms based on Unsupervised (UML), Supervised (SML), Semi-supervised (SSML),Reinforcement (RL) machine learning ,Deep learning (DL), , etc. Adaptive and automation capabilities Autonomic Network Management ,Cognitive management[9].

Supervised learning (SML)-predicting one or more dependent variables based on (initially) labeled data use cases examples: classification and regression

semi-supervised learning (SSML): not all data is labeled

active learning: the algorithm has to ask for some labels with a limited budget

Unsupervised learning (UML)-look for structure in (unlabelled) data sets

Reinforcement learning (RL) -using feedback to an agent actions in a dynamic Environment use cases examples: self driving cars, learning games, ...no feedback exists on individual actions, just win or lose information Neural net[13].

Deep learning (DL) - use a cascade of multiple layer of non liner processive.

units for feature extraction and transformation **Qos- AHLRP:** Deep learning (DL)+ Reinforcement learning (RL) RL defines the objective; DL gives the mechanism[14].

Machine Learning Model and Algorithms

In a wireless network, group of nodes communicate with each other and forward others packet to the destination[18]. Herse web consister multiple source single destination communication scénario. Each node in the network needs to identify a neighbour node to forward its packets to final destination. The selection of neighbors is an important factor that affects the performance of the network[23]. The proposed learning algorithm gives a method to rank the neighbors of a node and generate best topology for communication by interacting with the environment. The traditional routing protocols could not adapt quickly to the changes in the network due to mobility of nodes or link failures. To capture the dynamism of the network and incorporate in the routing decisions, self learning capabilities are very effective. As the wireless environment is changing over time, it is very difficult to provide supervision to the learning agent[4]. Also unguided learning is difficult in this scenario. So we use a reinforcement learning model to interact with the environment and take actions based on the feedback signal. Reinforcement learning (RL) which is semi-supervised learning where there is no teacher but a critic who tells whether an action chosen was good or bad. RL technique is suited for solving optimal control problems such as routing problem because of its inherent advantages such as less memory and computational requirements. Also, it is highly flexible to the topology changes and produces optimal results[19].

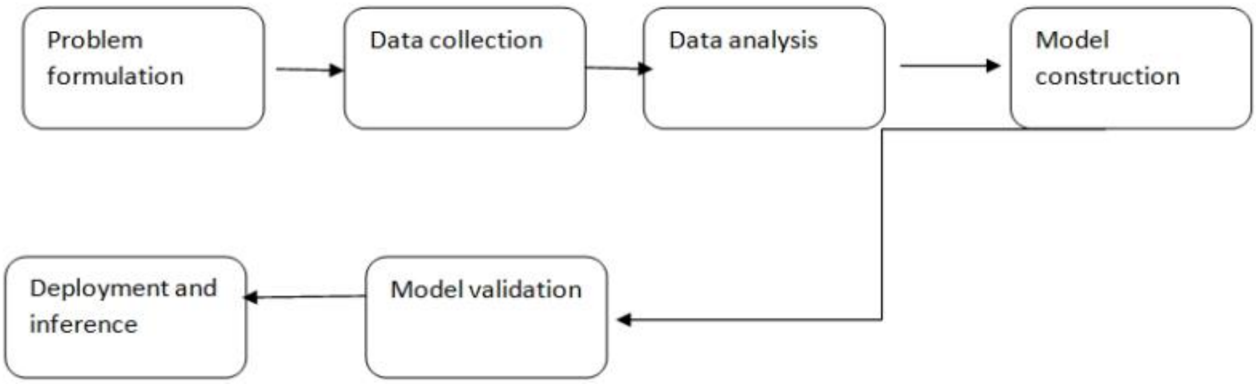

Fig1 Block Diagram

Deep-learning algorithm

D- learning is a model-free reinforcement technique as the probabilities of transition from state to state and the reward function is unknown. Learning is based on the real-time experience technically known as the D-values we gain using the D update rule mentioned in Eqn. 1 where R(s, a) is the immediate reward or the feedback received from the environment[20].

Algorithm 1: Deep-learning algorithm for learning data flow rate for selection of packet forwarder.

Step 1 Input: States S = (Nodes in the network). ctions A = (SUCCESS, FAILURE}, Reward R= (Mean throughput of the node}. y= 0.5, a-4.6.

Step 2: Output: Nodes with learned data flow rates

Step 3: procedure **DEEP LEARNING**

Step 4: Initialize Q(s; a) to zero for all s: a: s cS: a cA

Step 5: for each packet at a node do

Step 6: s intermittente node pack-et redises

Step 7: if (On a'— SUCCESS) then

Step 8: Observe resultant state C and reward R

Step 9: Update Q value as follows:

Step 10: Q(s, a) = Q(s, a) + a[R(s, a) + y maxds Q (s' , a') — Q(5, a)]

Step 11: end if

Step 12: Choose next hop having highest Q value

Step 13: end for

Step 14: end procedure

Q(s, a) = Q(s,a) + a[R(s,a) +y Q(s',a') — Q(s,a)]

The states are defined as the nodes at which the packet resides. Actions are defined as success and failure based on packet acknowledgement received. Each time a packet is transmitted successfully at an intermediate node, the Q-value gets updated based on above equation. Next time when a packet has to be forwarded, the intermediate hop having the best Q-value indicating the data flow rate that it can support is selected for routing. Thus we develop a routing strategy based on the learned data flow rates in the network nodes to yield improved network performance in terms of the throughput, packet loss and packet delay

Hybrid algorithm

A network can be structured into different levels based on their geographical distance to the sink node as illustrated in Fig. 1. After independent D-learning has been executed, the nodes at each level have its own view of the wireless environment. hybrid occurs at each level whereby the nodes share information with each other. hybrid employed in based on D values which is a function of success probability and delay. The node having the highest D-value will be selected as the expert node. The expert node in each level keeps account of other node's D values which will be propagated to the expert node in the previous level in the hierarchy. This is repeated at each level and accordingly the D-table gets updated. The nodes in the network then make use of this D-table for packet forwarding. Thus learning among the nodes is made easier and more accurate by considering the view of each node in the network

Algorithm 2: QoS-aware Hybrid Learning routing protocol algorithm[17][11].

1: Input: States S = (Nodes in the network), Actions A = {SUCCESS; FAILURE}, Reward R= (Mean throughput of the node), y = 0.5, a=0.6. Qt, = (Q values associated with backward exploration source. sink) Qi= {Q values associated with forward exploration source sink) Direction = initially set as source . Sink

2: Output: Nodes with lucarne data flow rates

3: procedure : **QoS-aware Hybrid Learning routing protocol**

4: for each packet at a node do

5: inter node packet

6: if (On a 4—SUCCESS) then

7: Observe resultant state: C and reward R

8: Update Q value,Q)as follows: Q(s,a) = Q(s,a)+ a[R(s,a)+ y max., Q(s',a') — Q(s,a)]

9: Calculate change in Q value AQ =1%e._ Qadl

10: Choose node with highest Q value in a layer as the expert node

II: if (AQ > 0) then

12: Set Direction = source .—sink

13: Propagate this change AQ to expert node in previous level which is used to update the Q-value of last hop as follows: AQ

14: end if

15. end if

16. end for

17: end procedure

PERFORMANCE EVALUATION OF THE QoS-aware Hybrid Learning routing protocol

In this section, we have evaluated the performance of the proposed QHLR protocol. The extensive simulations are performed using MATLAB to validate the results. In our simulations, we use 100 sensor nodes with various energy levels. Out of these 100 nodes, 35 are hybrid , 28 are high, 20 are medium, and 17 are low energy nodes. The network area of 400m 400m is used for the sensing operation. Different simulation parameters are given in Table 2. The larger area with 100 nodes is used to ensure the sensing operation for larger areas as in the case of larger industrial units. We compare the performance of the Qos-AHLR protocol with those of the **Deep learning and Reinforcement learning(DLRL) and neural network(NN)** protocols. Network lifetime, stability period, throughput, energy consumption, and end-to-end delay are used in the comparative analysis.

S.no	Parameter	value
1	Transmit power	20mW
2	Receive Power	15mW
3	power	10mW
4	Transmission range	24mW

5	Max buffer size	256 k-bytes
6	Number of nodes	100
7	Area of Network	400m x 400m

Table 1 Evaluation Of The Qos-Aware Hybrid Learning Routing Protocol

NETWORK LIFE TIME

Network lifetime can be defined as the time period between the installation of the first node to the death of the last node. At the start of each round, energy of every node is calculated and based on that energy, the sensing nodes are grouped into different energy levels. Therefore, if the energy of any node decreases, then at the next round of CH election, that node will be a part of low energy level than its present energy level. In this way, when a node dies, that node will ultimately not be considered for the election of the CHs in the next round. And through the CHs advertisements, the information of dead node is also deleted from the database of the other Fig. , the Qos-AHLRP has a more improved network lifetime than the Deep learning and neural network protocols This improvement in network lifetime is due to the efficient energy conservation approach employed by the Qos-AHLRP [22].

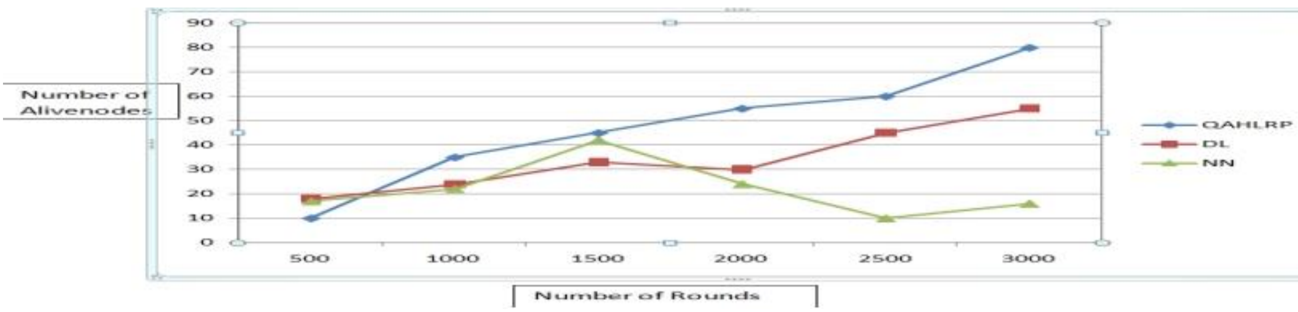

Fig 2 **Network Life Time**

THROUGHPUT

Throughput performances are presented in Fig.. Through- put is defined as the number of packets sent to the BS. Improvements in the throughput are achieved by the QOS-AHLRP protocol but not by the **(DLRL)**, and NN protocols. . This improvement is due to the minimization of end-to-end delay and the availability of multi paths. The avail- ability of multipart enables more numbers of packets to be transmitted to the BS. The increased in the throughput is also due to the smooth transmission of the real-time and non-real- time traffic on the dedicated links by avoiding any bottlenecks in the networks.

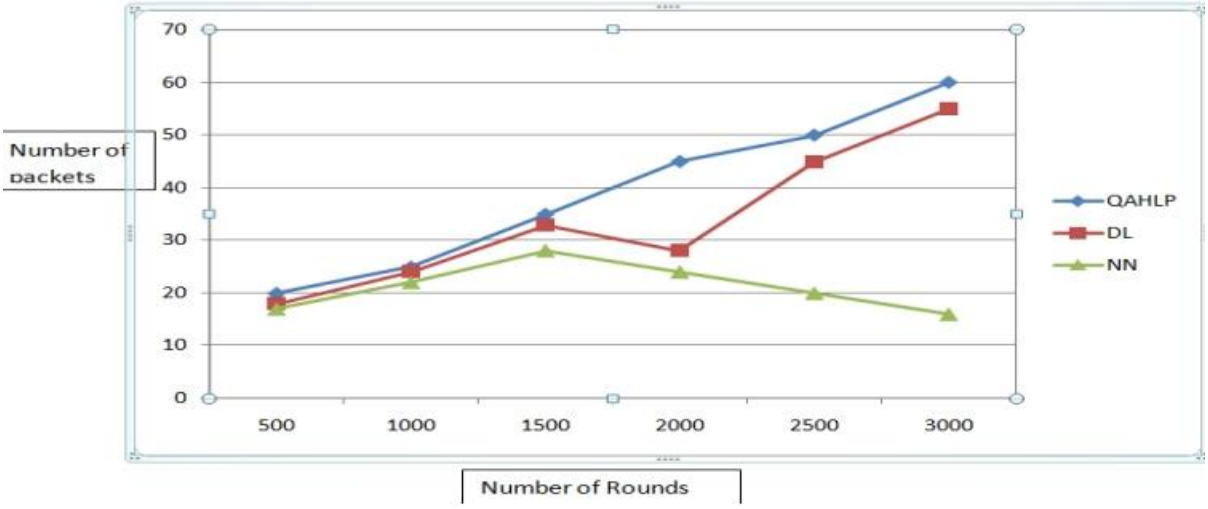

Fig 3 QOS-AHLRP protocol

AVERAGE ENERGY CONSUMPTIONS

The average energy consumption in the QOS-AHLRP protocol is illustrated in Fig. The QOS-AHLRP protocol has better energy efficiency than the other routing protocols of WSNs under consideration. This energy conservation is due to the optimal clustering of heterogeneous networks. The C_v metrics for CH election and the P_{metric} for the minimization of

Dis- tance makes QOS- AHLRP protocol more energy efficient than the **(DLRL)**, and NN protocols[24].

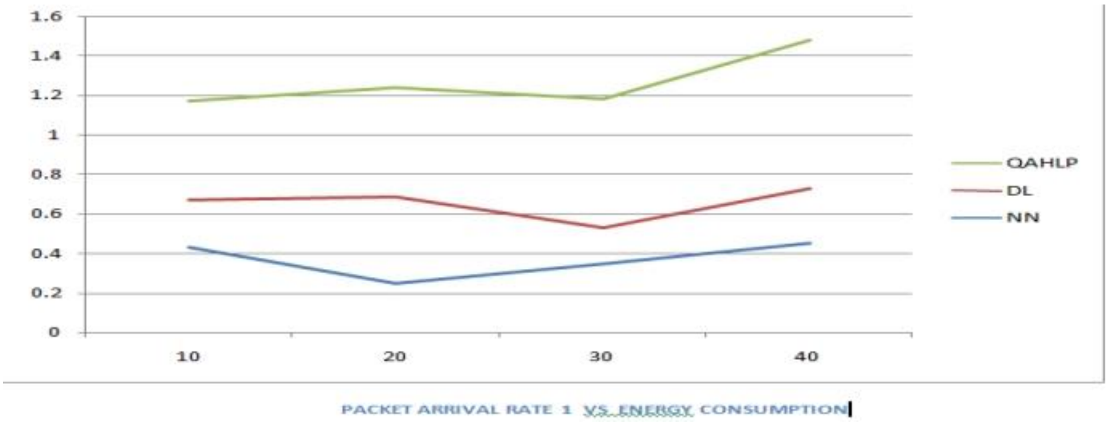

Fig 4 Average Energy Consumptions

CONCLUSION

In this paper, we have proposed a novel quality-of- service (QoS)-based routing approach for heterogeneously clustered wireless sensor networks (WSNs). The real-time traffic is transmitted with less delay by dedicated paths. To achieve the QoS in heterogeneous network, nodes of four energy levels with different initial energies are used. A cost value (C_v) is employed to achieve the optimum clustering in each energy level. In our proposed QoS-aware Hybrid Learning routing protocol(Qos-AHLRP)) protocol, sensing nodes which are at longer distance from cluster head (CH) used other sensing nodes as an intermediate nodes to transmit the packets. Multiple paths are provided with the help of path metric (P_{metric}). This P_{metric} used initial energy of sensing nodes from different energy levels, expected transmission count (ETX), inverse expected transmission count ($InvETX$), and minimum loss (ML). The real-time and non-real-time traffic is then transmitted over different paths with less delay. Qos-AHLRP protocol minimizes the end-to-end delay, transmission delay and congestion. It also provides load balancing, fault tolerance, flexibility and reliability in a heterogeneous WSNs. Simulations results shows an improvement in network life time, stability, throughput and minimization in end-to- end delay.

Acknowledgement:

The authors extend their due thanks to the Thiagarajar College of Engineering management, Madurai, India for their extensive research facilities and the financial backing from Thiagarajar Research Fellowship

(TRF) scheme (File.no: **TCE/RD/TRF/5** dated 08-01- 2024_) is gratefully acknowledged.

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