Deep Reinforcement Learning based Energy-Efficient Aggregation Model for Wireless Sensor Network*

Nada Alsalmi[1 [0009−0005−5185−8925]] and Keivan Navaie[1 [2222−−3333−4444−5555]]

Department of Computing and Communications, Lancaster University, UK, LA1 4WA.
{n.alsalmi,k.navaie@lancaster.ac.uk

Abstract. The proposed work discusses aggregation methods for Deep Reinforcement Learning (DRL) based wireless sensor networks. The aggregation algorithm plays a vital role in reducing overall energy consumption. The aggregation method aggregates the data samples, removes the redundant data, and reduces the number of overall packets, reducing overall energy consumption. We begin with the introduction, followed by the discussion on routing protocols with aggregation for MWSNs, which presents an overview of different routing protocols with aggregation. Optimized Link State Routing (OSLR) performance without aggregation is compared with the OLSR protocol with aggregation. Subsequently, routing protocols based on SOM concerning WSNs are elaborated. The SoM-OLSR with aggregation is reviewed and compared with the SoM-based routing protocol without aggregation for MWSNs.Similarly, the DRL with aggregation is reviewed and compared with the DRL-based routing protocol without aggregation for MWSNs.The result proves that DRL-OLSR 'with-aggregation' saves 50% of energy with respect to 'without-aggregation'.

Keywords: Aggregation · Deep Reinforcement Learning · Optimized Link State Routing · Wireless Sensor Network.

1 Introduction

A wireless sensor network (WSN) plays a vital role in various applications, e.g., border security application, agriculture application, forest monitoring application, etc. The small entity in WSN is the sensor node (SN). A typical SN includes a sensing unit, processing, and communication transceiver device. SNs transmit the collected data to a Base Station (BS) or a sink node directly or through multi-hop communication [1]. In most practical applications, sensor nodes may only have access to a limited energy supply, such as non-rechargeable batteries, e.g., [11], and [2]. Therefore, these nodes often operate within energy-constrained situations. To overcome the issue, the researchers have proposed various machine

* Supported by organization x.

learning (ML) methods for energy-efficient methods for data transmission. In MWSN, the sensor nodes can move within the network. They differ from traditional WSNs due to their mobility feature that improves network coverage, connectivity, scalability, and energy efficiency while prolonging the network's lifetime [3]. Therefore, the energy-efficient approach is more complex in MWSN with respect to static WSN.The proposed aggregation method is proposed for the energy-efficient data transmission and filtration of redundant data.

The remainder of the paper is organized as follows. Section 2 presents related work on aggregation-based MWSNs. Section 3 outlines the mathematical model of the proposed research work. Section 4 outlines the simulation results presented considering various scenarios and evaluating energy consumption metrics. Finally, Section 5 concludes the paper, summarizing the main findings and discussing future research directions.

2 Related Works

The research contribution of the researchers in the related field is analyzed for addressing challenges related to data transmission and data aggregation in Wireless Sensor Networks (WSNs) using machine learning and deep reinforcement learning techniques. The related works are explained in Table 1.

In [5], the author discusses the difficulty of data transmission in WSNs due to handling significant amounts of data. In [6], the author explores the potential of machine learning approaches to improve WSN performance and efficiency, particularly in dealing with the restricted interoperability of sensors. In [12], the authors propose an enhanced machine learning data aggregation model to overcome resource restrictions and efficiency problems in WSNs. In [9] and [13], the authors discuss deep reinforcement learning-based approaches for home energy management systems and energy trading in smart grids, respectively, to optimize power use and lower costs. The [14] addresses energy-efficient transmission in underwater acoustic communications using deep reinforcement learning. The [10] presents a privacy-preserving data aggregation game in crowdsensing using deep reinforcement learning. The [4] proposes a hybrid data aggregation algorithm to increase energy efficiency and extend the network lifetime in WSNs. The [7] studies energy-efficient data aggregation techniques and their impact on various aspects of WSNs. The [8] categorizes energy-efficient data aggregation algorithms based on their structure, search, and time-based techniques, with cluster-based protocols showing better energy efficiency and throughput rate performance. The detailed discussion is explained below in Table 1 regarding the objective, contribution, finding, and conclusion.

3 Mathematical Model of Aggregation Protocol

The OLSR protocol transmits the data via various routing devices. The nodes aggregate the data at each fully function device (FFD) at an intermediate stage. Let us assume that the data samples collected for a particular sensor ID are

Table 1: Related works on data aggregation in WSN

Literature Study	
Objective [5]	This paper discusses the difficulty of data transmission in Wireless Sensor Networks (WSNs) while handling significant amounts of data.
Contribution	Examining numerous ML methods used in current DA research provides a thorough list of intelligent methods that have been applied to solve the data transmission problem.
Findings	The study discovers that when dealing with massive data quantities, data transmission in WSNs becomes difficult [1].
Conclusion	The evaluation and survey of the literature offer insightful information and establish the groundwork for future developments in WSN data transmission technology.
Objective [6]	Using machine learning (ML) approaches, this study discusses network problems in wireless sensor networks (WSNs) and provides solutions.
Contribution	By examining the potential of ML approaches in resolving network challenges, this study advances WSNs.
Findings	The use of ML methods in WSNs can make up for the constrained sensor interaction capabilities, improving the performance and efficiency of the entire network.
Conclusion	Overall, the thorough analysis of publications opens the door for more study and growth in this area by offering insightful information about the continuous improvements and uses of ML approaches in WSNs.
Objective [12]	This research proposes a unique Machine Learning Data Aggregation Model (EML-DA) to solve the resource restrictions and efficiency issues in Wireless Sensor Networks (WSNs).
Contribution	The emphasis on robust data aggregation with ICA and hybrid CH selection with ANN highlights the significance of intelligent methods to maximize energy consumption and data processing efficiency in WSNs.
Findings	When data is aggregated at CH nodes, the computational effectiveness of ICA and its use of differential entropy help reduce duplicated data and enhance energy usage.
Conclusion	In conclusion, the EML-DA model's use of ANN and ICA illustrates the potential of intelligent data-driven solutions to provide reliable and effective data transmission in WSNs.
Objective [9]	The purpose of this study is to discuss the difficulties in creating a Home Energy Management System (HEMS) that effectively manages home appliance power use in response to fluctuating electricity costs.
Contribution	The efficiency of the DRL-based HEMS in lowering power bills and optimizing appliance scheduling is shown by the simulation results used to validate the suggested technique.

Findings	For the development of a successful and practical HEMS in real-world circumstances, unpredictability in real-time power pricing and resident activities is essential.
Conclusion	Overall, the simulation results verify the usefulness of the proposed DRL-based HEMS in delivering effective DR scheduling without the requirement for thorough appliance models or familiarity with randomness distributions.
Objective [13]	The purpose of this study is to discuss the difficulties in creating effective energy trading in a smart grid with many users.
Contribution	The simulation findings show how the energy double auction trading strategy based on deep reinforcement learning is successful at lowering buyer expenses and raising seller profits as the learning process converges.
Findings	The study discovers that the deep reinforcement learning-based energy double auction trading technique successfully addresses the difficulties of energy trading in a smart grid with numerous players.
Conclusion	In order to accomplish successful energy trading in the smart grid, this research concludes by presenting an energy double auction trading technique based on deep reinforcement learning.
Objective [14]	Addressing the difficulties in producing energy-efficient transmission in Underwater Acoustic Communications (UACs) is the goal of this article.
Contribution	The emphasis on maximizing energy efficiency in UACs through dynamic transmit frequency and power adjustment emphasizes the significance of overcoming particular difficulties in underwater communication systems.
Findings	The study finds that using the TAS-DQN(two-action selection-based deep Q-network) algorithm enables the UAC system to dynamically modify transmit frequency and power without depending on previous environmental information, enabling the system to attain close to ideal energy efficiency.
Conclusion	Overall, the TAS-DQN algorithm outperforms conventional DRL techniques and achieves close to ideal energy efficiency for the network, offering a viable answer to the problems of energy-efficient transmission in UACs.
Objective [10]	To develop the best tactics for the dynamic payment-PPL game, the article uses reinforcement learning approaches to determine the game's Nash equilibrium point, especially Q-learning and deep Q network (DQN).
Contribution	The suggestion of using reinforcement learning strategies like Q-learning and DQN to figure out the payment-PPL strategy shows how effective dynamic learning methods are at dealing with the unidentified payment-PPL model.

Findings	Even in situations where the payment-PPL model is unclear, the use of reinforcement learning techniques, particularly Q-learning and DQN, makes it easier to determine the best payment-PPL strategies.
Conclusion	DQN, in particular, outperforms standard Q-learning in terms of performance overall, resulting in better platform and participant utilities and improved data aggregation accuracy in the crowd sensing environment.
Objective [4]	To acquire data from many types of sensors for applications like agriculture and security, wireless sensor networks (WSNs) face an issue of redundancy. This research aims to solve this problem.
Contribution	By eliminating redundant data in the collected data, data aggregation techniques strive to increase the accuracy and dependability of data processing in real-time applications.
Findings	An energy-efficient data aggregation procedure is produced by the clustering method, and cluster heads are chosen based on sensor rankings.
Conclusion	Overall, the proposed HDAA shows improved performance in cutting down on energy use and communication delays, resulting in a longer network lifetime.
Objective [7]	To save costs and manage energy effectively, this research aims to emphasize the value of data aggregation in Wireless Sensor Networks (WSNs).
Contribution	Data aggregation's function in effective data forwarding to the base station, which results in increased energy efficiency, is highlighted by the focus on the process of condensing data from source nodes and eliminating duplicate information.
Findings	In the context of WSNs, the introduction of aggregation protocols solves several issues, including the elimination of redundancy, energy efficiency, network longevity, privacy protection, and communication efficiency.
Conclusion	In comparison to traditional algorithms, the suggested data aggregation algorithms show higher performance in privacy protection and communication efficiency, resulting in a longer network lifetime and reduced energy usage.
Objective [8]	This article's goal is to draw attention to the value of data aggregation protocols in Wireless Sensor Networks (WSNs) for effectively organizing data and sparing node energy to extend the network's lifespan.
Contribution	A thorough study of the various protocol types is provided by suggesting a unique method for categorizing data aggregation methods based on their structure, search-based, and time-based techniques.
Findings	According to the research, cluster-based data aggregation protocols outperform structure-less, time-based, or search-based protocols in terms of energy efficiency and throughput rate.
Conclusion	The simulation findings show that in terms of energy consumption and throughput rate, cluster-based data aggregation protocols perform better than structure-free, time-based, and search-based protocols.

$d_1, d_2, d_3 .... d_n$. The aggregation of all data samples depends upon the aggregation function. The data packets are aggregated using the average value function in the present work. However, the aggregated average value is transmitted only if the deviation is smaller than the deviation threshold (D_{Th}).

$$D_{Agg} = \begin{cases} (1/n) \cdot \sum_{i=1}^{n} d_i, & \text{if } \frac{\sum_{i=1}^{n} \left(d_i - (1/n) \cdot \sum_{i=1}^{n} d_i\right)^2}{(1/n) \cdot \sum_{i=1}^{n} d_i)} \leq D_{Th} \\ d_1, d_2, d_3 ...., d_n, & \text{otherwise} \end{cases} \tag{1}$$

To develop an aggregation method for OLSR with deep learning, a state space model is developed for the proposed OLSR protocol. The aggregation method is analyzed with DRL and SOM. The state space at time step t includes information about the link qualities and queue lengths for each node i. The state of node i is represented at time t as a vector $\mathbf{s}_t^i$:

$$\mathbf{s}_t^i = [qu_t^i, L_Q^i] \tag{2}$$

Where qu_t^i is the queue length, L_Q^i is the link quality at node i at time t.

As already discussed, the action space and reward function are The action space includes possible actions that the deep reinforcement learning agent can take at each node i at time step t. The action taken by node i at time t is represented as $\mathbf{a}_t^i$ as given below:

$$\mathbf{a}_t^i = [a_t^i, N_H^i] \tag{3}$$

Where a_t^i represents the local action taken at node i, and N_H^i is a next hop for i_{th} node representing the actions related to next-hop node selection or transmission power adjustments.

In reinforcement learning, the reward function is used to evaluate the performance of the corresponding action in a given state. It typically considers energy consumption, data delivery latency, and data aggregation efficiency. Let R_t^i denote the reward obtained by node i at time t as given below:

$$R_t^i = \text{Reward}(s_t^i, a_t^i) \tag{4}$$

The OLSR protocol is used with data aggregation to remove redundant data and energy-efficient data transmission. The reinforcement learning algorithm is integrated with OLSR to optimize the cumulative reward over time by learning a policy π that maps states to actions. One common approach is using Deep Q-Learning, which uses a deep neural network with aggregation function D_{Agg} to represent the Q-function, denoted as $Q(s_t^i, a_t^i; D_{Agg})$. The Q-function estimates the expected total reward when taking action a_t^i in state s_t^i and following the policy afterward.

The Q-learning update rule can be represented as follows:

$$\begin{aligned} Q(s_t^i, a_t^i; D_{Agg}) \leftarrow\ & Q(s_t^i, a_t^i; D_{Agg}) + \\ & \alpha \left[R_t^i + \gamma \max_{a'} Q(s_{t+1}^i, a'; D_{Agg}) - Q(s_t^i, a_t^i; D_{Agg}) \right] \end{aligned} \tag{5}$$

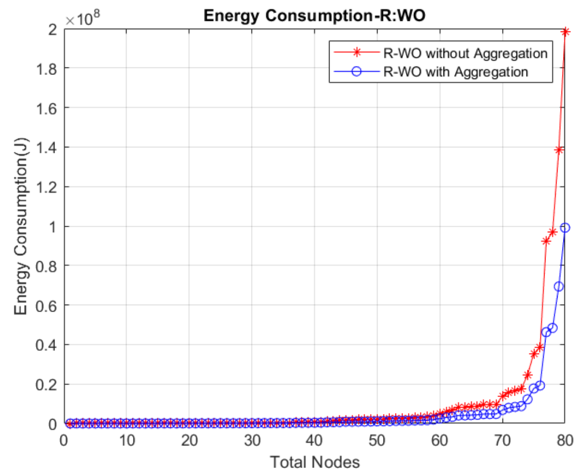

Fig. 1: Energy Consumption of OLSR with and without aggregation

Where:

- α is the learning rate, determining the step size of the updates.
- γ is the discount factor, representing the importance of future rewards.

The deep neural network is trained by minimizing the Mean Squared Error (MSE) loss between the target Q-values and the predicted Q-values.

4 Result Analysis and Discussion

The results are analyzed for three scenarios. The results are analyzed for OLSR (with and without data aggregation) in the first scenario. In scenario 2, the results are analyzed for SOM-OLSR for aggregation condition. Similarly, scenario 3 analyzes DRL-OLSR for aggregation conditions.

4.1 Scenario-1

On comparison of the energy consumption without reinforcement learning & data aggregation (WO-RL-WO-DA) with without reinforcement learning & with data aggregation (WO-RL-W-DA), the reduction in Energy consumption can be noticed from the graph. The energy consumption starts when total nodes reach 60 and beyond. We can observe, particularly when there are 70 total nodes, the consumption of energy of WO-RL-WO-DA is higher when compared to WO-RL-W-DA. The same can be implied as the number of nodes is increasing, and the power consumption is exponentially increasing at a high rate when there is no Data aggregation. The maximum difference can be observed when there are a total of 80 nodes. With Data aggregation, the consumed energy is 10^8 J.

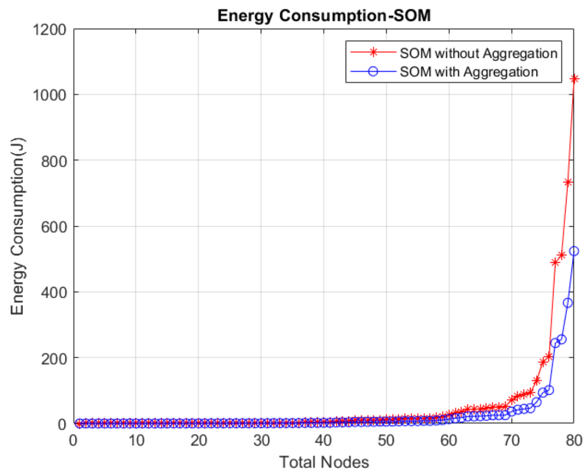

Fig. 2: Energy Consumption of SOM-OLSR with and without aggregation

This equals half of 2×10^8 J consumed Without data aggregation. The higher energy consumption results in lesser efficiency. Here, statistically proving that WO-RL-W-DA is preferred over WO-RL-WO-DA.

4.2 Scenario-2

Self-Organizing Maps Based-Optimized Link State Routing (SOM-OLSR) without data aggregation and SOM-OLSR with data aggregation are compared regarding energy usage. The graph shows how energy use has decreased. When there are 60 or more total nodes, energy consumption begins. We can see that SOM-OLSR without Aggregation consumes more energy than SOM-OLSR with Aggregation, especially when there are 70 total nodes. When there is no data aggregation, it may be inferred that as the number of nodes grows, so does the power consumption exponentially and rapidly. The most significant difference may be seen when there are 80 total nodes and 510 J of energy is used for data aggregation. This is equivalent to using half the 1020 J Without data aggregation. Less efficiency is produced by using more energy. The SOM-OLSR with Aggregation is preferable here statistically compared to the SOM-OLSR without Aggregation.

4.3 Scenario-3

After implementing the Deep Reinforcement Learning Based-Optimized Link State Routing (DRL-OLSR), There are 2 sets of data collected with Data aggregation and without it. In both cases, we can see that the consumption of energy starts when the nodes are above 10. With the increase in no. of nodes, the DRL-OLSR with data aggregation slowly rises at a similar rate as that of DRL-OLSR

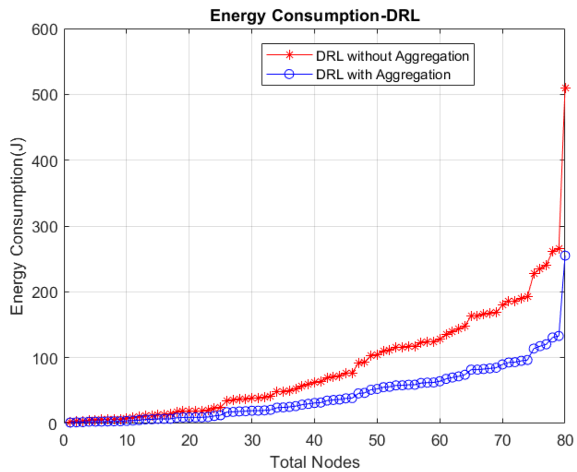

Fig. 3: Energy Consumption of DRL-OLSR with and without aggregation

without data aggregation. The rise in energy consumption is noticeable at the point after which the number of nodes is increased by more than 30.

5 Conclusion

The presented analysis involves three distinct routing scenarios aimed at evaluating energy consumption patterns. In the first scenario, a comparison is drawn between Optimized Link State Routing (OLSR) implementations without reinforcement learning and without data aggregation (WO-RL-WO-DA) and with data aggregation (WO-RL-W-DA). Notably, energy consumption becomes significant at around 60 nodes, and a pronounced increase occurs as the node count rises. Particularly, the energy consumption of WO-RL-WO-DA surpasses that of WO-RL-W-DA at 70 nodes, with the divergence becoming most pronounced at 80 nodes, where data aggregation reduces energy consumption by half. In the case of SOM, a similar trend is observed, where energy consumption becomes noticeable at approximately 60 nodes, and the energy-efficient advantage of data aggregation becomes evident at 70 nodes, with the disparity becoming most pronounced at 80 nodes. Finally, in the third scenario involving Deep Reinforcement Learning Based-Optimized Link State Routing (DRL-OLSR), energy consumption commences after surpassing 10 nodes, and as node count rises, DRL-OLSR with data aggregation consistently outperforms its non-aggregated counterpart in terms of energy efficiency. These findings collectively highlight the advantageous impact of data aggregation on reducing energy consumption across different routing scenarios and the potential of DRL-OLSR with data aggregation to optimize energy usage as the network size grows.

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