Deep learning-based optimization techniques for network lifetime enhancement in wireless sensor networks

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ABSTRACT

Wireless sensor networks (WSNs) are integral to applications like environmental monitoring, healthcare, and surveillance, yet they face the critical challenge of limited energy resources, which shortens the network's operational lifespan. Addressing this issue, this paper explores deep learning-based optimization techniques as a solution to enhance network lifetime by efficiently managing energy consumption. We present a detailed review of the existing challenges in WSNs and examine various deep learning methods, including neural networks, deep reinforcement learning (DRL), and generative adversarial networks, specifically tailored for WSN optimization. In this study, we introduce a new reinforcement learning (RL) based optimization algorithm to prolong the network lifetime. The proposed technique is intended to smartly distribute the energy consumption among the network elements, leading to desirable performance with regard to the battery lifetime. The paper ends with a summary of design aspects and future research directions to improve the WSN performance further based on deep learning.

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1. INTRODUCTION

Wireless sensor networks (WSNs) consist of a number of distributed nodes, which gather data from the environment they are deployed in, and then send the data wirelessly. Such networks have progressively become critical in applications such as environmental monitoring, healthcare, industry automation and smart cities [1]. Whatever it is, but the system energy is always a limited resource, especially for WSNs in which the resources are scarce as the sensor nodes typically operate under limited battery power with the need to be operational for an extended time [2]. To circumvent these constraints, several optimization strategies were proposed in terms of managing the energy reserves of sensor nodes and prolonging network lifetime.

Recent progress in the field of machine learning, especially deep learning, has shown great promises to tame the complexities of WSNs management. Deep learning algorithms can be used to effectively adjust various network parameters and enhance energy efficiency and network lifetime [3]. In this paper, we survey existing deep learning-based optimization approaches toward WSNs, particularly to extend network lifetime. The most prominent challenge in WSNs is the scarcity of energy in sensor nodes that are generally deployed in environments that are not cost effective for manually replacing or recharging batteries. Conventional optimization approaches are not able to fully consider the complex relationship between network parameters and energy consumption. It may lead to inefficient energy consumption, pre-mature network reconfiguration and degraded overall performance [4]. Accordingly, the development of more effective techniques for energy consumption management is an open problem.

To solve these problems, we apply the deep learning techniques, especially the reinforcement learning (RL) in energy consumption optimization in WSNs. So, through the application of RL-based models, sensor nodes can adapt its actions dynamically on the fly according to real-time state of the network by learning into the environment to take the action as energy saving as possible. The solution not only extends network working length but also strengthens the data delivery ratio achieved by uniformly distributing energy consumption in the network. This paper also presents design issues for the deployment of such models in WSNs with limited resources. The novelty of this approach comes from its adaptation to the increasingly changing network conditions, where RL is applied to optimize the network management mechanism and network routing protocols. This deep learning influenced optimization architecture has the capability of prolonging the life of WSNs significantly, in order to keep pace with practical applications [5]-[10].

In the paper, the authors propose a novel deep learning-based RL model as an advanced energy optimization algorithm in WSNs compared to classical methods. RL is specifically suitable for the dynamic and unknown characteristics of WSNs since new nodes are added or existing nodes fail, leading to continuous variations in energy levels, topology, and traffic. RL learns online from agent interaction unlike static optimization methods, providing decisions for energy-efficient operation in the long term. Decentralization enables nodes to make independent choices and reduces computational overhang and networked it. RL also ensure balanced energy use among nodes, leading to increased network’s lifetime, and support for multi-objective optimization (energy, latency and reliability can be combined). This efficiency and adaptability are particularly beneficial in resource-constrained, large-scale WSNs.

The major contributions of this paper are as follows:

- We provide an extensive review of recent deep learning-based optimization techniques proposed from 2020 to 2024, with a particular focus on WSNs.
- The paper proposes a novel RL-based routing algorithm specifically designed to enhance network lifetime and improve packet delivery rates in WSNs.
- Our approach facilitates the balancing of energy consumption across sensor nodes, which helps to extend network lifespan and improve scalability.
- We also introduce mechanisms for incentivized data sharing within the WSN, evaluated using metrics such as hop count and remaining energy, ensuring efficient network operations.

The remainder of this paper is organized as follows: section 2 reviews related work on deep learning-based optimization techniques in WSNs, spanning from 2020 to 2024, and provides a comparative analysis. Section 3 provides an overview of several methods have been proposed in the literature that has explored of optimization of WSNs operation. The proposed RL based routing algorithm for network lifetime improvement in WSN is discussed in section 4. In section 5, the performance of the proposed method is presented and compared with classical optimization approaches. The challenges, constraints and future research directions are covered in section 6. Section 7 concludes the paper.

2. RELATED WORK

This section gives a comprehensive overview of deep learning-based optimization methods for WSNs and clearly emphasizes energy efficient approaches towards improving network lifetime. The survey comprises deep reinforcement learning (DRL), clustering-based resource allocation, energy-efficient routing algorithms, and hybrid models for task scheduling and data aggregation. These strategies have been used to address the main WSN issues including power consumption, node localization, data transmission, and coverage optimization. These hybrid stitching methods overcome many power-related problems in WSNs, keeping the satisfactoriness of operation and guaranteeing the network reliability. Furthermore, we deeply review some other energy efficient WSNs protocols; deep Q-learning based strategies, adaptive transmission power control and energy harvesting prediction model. The second group of studies explore hybrid deep learning techniques where a combination of clustering, routing, and task scheduling techniques are utilized to minimize resource consumption and increase network lifetime in WSNs. In particular, we review techniques for intelligent energy control, sensor activation and energy-efficient communication protocol which are important to energy-limited environments. The reviewed works cover a wide range of applications such as environmental monitoring, healthcare, smart cities and precision agriculture, wherein energy efficiency is crucial for the effective and efficient operation of WSNs.

Godfrey *et al.* [6], also proposed a DRL based framework to optimize routing in WSNs for better energy efficiency. The DRL framework is proposed for nodes to learn how to route optimally through interactions with the environment, taking energy limitations and dynamical changes in the network into account. In the same line, a deep learning-enabled energy-efficient data aggregation than in to make data aggregation in WSNs aware of optimization to minimize energy consumption and maintain network performance and data accuracy [7]. A deep learning-based clustering was used to develop a resource allocation scheme that distributes the bandwidth and power of the nodes in WSNs in an efficient manner to enhance the network performance and energy efficiency [8].

Researchers presented a hybrid method of long short-term memory (LSTMs) and convolutional neural networks (CNNs) to extract features and locate node in packet traffic network, which led to significant improvement in node localization accuracy and energy consumption efficiency in WSNs [9]. An energy-efficient routing algorithm for WSNs based on deep Q-learning was developed by Kapileswar *et al.* [10] that enables the nodes to take routing decisions with minimum energy consumption while ensuring connectivity and data delivery [10]. Deep learning techniques were utilized in energy harvesting strategies to trade off data transmission performance and energy availability indicating dynamic behavior of the network to prolong its life time [11]. Chowdhury and De [12] proposed a hybrid optimization for DRL based coverage in WSN wherein the network adapts sensor deployment based on dynamic environment for energy efficient coverage by satisfying the operational energy requirements. An innovative method was also proposed for WSN energy consumption prediction based on deep learning, to facilitate communication protocol and resource allocation effectively [13]. Task scheduling in WSNs was optimized via deep learning models for minimizing the energy consumption while satisfying application demands towards network efficiency improvement [14]. Predictive energy harvesting models for task scheduling were also presented, which provide prediction of energy information for the network to make the optimum resource and scheduling decision based on predicted energy availability [15]. Deep learning-aided algorithms were used for actuation of the sensor, thus saving energy by adapting the sensor activations based on the environment while ensuring sufficient coverage [16]. Suresh *et al.* [17] investigated power control schemes with deep learning which adapted the transmission power in terms of minimizing the power consumption with ensuring the reliable communication.

Ávila *et al.* [18] proposed a deep learning based mobile sink routing scheme to enable energy-efficient data acquisition in WSNs. The network energy efficiency was extensively improved by suitably adjusting the movements of the sink and setting up the data collection strategies. Zhou *et al.* [19] introduced a deep learning-based energy harvesting prediction algorithm that tunes transmission schedules for increasing 5G network throughput. Hybrid machine learning approaches were also adopted in node deployment optimization in WSNs using DRL to enhance coverage and connectivity with reducing energy consumption [20]. Chen *et al.* [21] a hybrid deep learning scheme was proposed to optimize the data fusion procedures in WSNs and minimize the energy consumption, meanwhile satisfying the data accuracy and network performance. To address this problem, we have introduced a deep Q-learning-based optimal node selection in WSNs, where the nodes make decisions on the fly with respect to operating the nodes to sleep states, which both achieve tasks and energy saving [22]. Younus *et al.* [23] proposed a hybrid sleep scheduling method using deep learning for energy-efficient WSN operations, balancing energy usage with network performance. Underwater WSNs also benefitted from deep learning-based data transmission techniques, where energy-efficient transmission strategies were developed to minimize consumption while ensuring reliable data delivery [24]. Lastly, precision agriculture applications saw improvements through a deep learning-based energy-aware routing protocol, which optimized routing decisions in WSNs considering both energy constraints and environmental factors [25]. Table 1 presents the comparative analysis of all the proposed techniques in the literature.

3. DEEP LEARNING-BASED OPTIMIZATION TECHNIQUES

3.1. Neural networks for energy prediction

Neural networks have been very popular in energy prediction for WSNs, as they can capture the nonlinear relationship between environmental variables and energy usage [6]. The feedforward neural networks (FNN), recurrent neural network (RNN), LSTM network, CNN are all used as models of brain and similarly investigated for SDB classification76. History sensor data, environmental conditions, and node properties are analyzed by neural networks that can accurately predict energy consumption [6].

To train the neural network to predict building energy, we preprocess the data so that it is compatible with our model training. Normalization, scaling, and feature engineering are the mean that are used standardize the data [7]. The models are trained with backpropagation or stochastic gradient descent learning algorithms using a loss function that measures the difference between the predicted and actual energy consumption [8]. When deployed on these resource-limited WSN nodes, so as to minimize the model complexity for energy-efficient inference, model compression techniques, such as quantization and pruning, need to be enabled [9].

Table 1. Comparative analysis of proposed techniques in the literature

Reference	Methodology	Results	Limitations
[6]	Reinforcement learning–based routing integrated with software-defined WSN architecture	Improved routing adaptability and reduced energy consumption compared to static SDWSN routing	Centralized SDN control introduces overhead and scalability constraints
[7]	Neural network–based data aggregation for energy efficiency	Reduced redundant transmissions and improved aggregation efficiency	Limited to aggregation; routing and clustering not jointly optimized
[8]	Cluster-based routing using fully recurrent deep learning with meta-heuristic optimization	Enhanced network lifetime and energy balance across clusters	High computational complexity limits real-time applicability
[9]	Secure deep learning–based routing with intrusion detection	Achieved energy-efficient and secure data transmission	Increased processing overhead due to integrated security mechanisms
[10]	Deep Q-learning combined with adaptive threshold-based clustering	Improved energy efficiency and stability period over classical clustering schemes	Evaluated on small-scale networks; scalability not fully analyzed
[11]	Deep reinforcement learning for throughput optimization in energy-harvesting WSNs	Improved throughput and energy utilization under harvesting constraints	Focuses on EH-WSNs; not applicable to battery-only networks
[12]	Voronoi–Glowworm Swarm Optimization with K-means clustering	Achieved better coverage efficiency and reduced energy consumption	Optimization complexity increases with network size
[13]	Deep learning–based energy prediction model	Accurate residual energy estimation for proactive energy management	Prediction-based approach does not include routing decisions
[14]	Analytical energy-efficient scheduling framework	Established optimal scheduling policies for energy conservation	Does not support adaptive or learning-based mechanisms
[15]	Deep learning–based grouping model for data transmission	Improved energy efficiency and balanced data forwarding	Grouping strategy lacks dynamic routing adaptation
[16]	Intelligent LEACH enhancement using deep belief networks	Improved cluster-head selection and extended network lifetime	Inherits LEACH-related overhead and periodic re-clustering cost
[17]	Federated deep reinforcement learning for distributed routing	Achieved scalable and privacy-preserving routing optimization	Communication overhead between federated agents
[18]	Systematic literature review on energy harvesting in WSNs	Comprehensive taxonomy and design insights for EH-WSNs	Does not propose or evaluate a concrete routing solution
[19]	Systematic mapping study on energy prediction in EH-WSNs	Identified trends and gaps in energy prediction techniques	No direct performance evaluation or algorithmic contribution
[20]	Machine learning–driven routing optimization for 6G-enabled WSNs	Demonstrated energy efficiency gains in next-generation WSN scenarios	Assumes advanced 6G infrastructure availability
[21]	Deep learning–based grouping model for energy-efficient transmission	Improved network lifetime through optimized node grouping	Duplicate of [15]; grouping-only focus
[22]	Q-learning–based delay-aware data fusion	Reduced delay and improved energy utilization	Limited to duty-cycled networks and fusion operations
[23]	Reinforcement learning–based routing in SDWSNs	Enhanced routing performance and adaptability	Dependence on centralized SDN controller
[24]	Deep learning–based data aggregation and fusion	Reduced communication overhead and improved energy efficiency	Does not address routing or clustering
[25]	Mobile sink–based intelligent routing scheme	Reduced hotspot energy depletion and improved lifetime	Sink mobility introduces additional system complexity
[26]	Survey of energy harvesting and optimization in WSNs	Comprehensive overview of EH techniques and challenges	No experimental validation or algorithmic proposal

3.2. Deep reinforcement learning for routing optimization

DRL has exhibited a strong potential in solving routing problems in WSNs, which can also make adaptive decisions according to the real-time state of the network. By formulating the WSN system as a Markov decision process (MDPs), DRL agents have been trained to acquire routing strategies that can reduce energy consumption and achieve better network performance [15].

One of the most widely used DRL algorithms is deep Q-learning, which uses deep neural networks to learn the Q-value function to estimate the expected cumulative reward for actions [16]. Policy gradient techniques which directly optimize policy parameters instead of estimating Q-values have also been investigated [18]. Additionally, DRL-based routing algorithms suffer from convergence stability, this shortcoming can be addressed by employing methods such as experience replay and target networks [21].

3.3. Generative adversarial networks for energy harvesting

Generative adversarial networks (GANs) have been recently studied for synthesizing the energy-harvested data to train the WSN energy harvesting model, thus accurately modeling the energy profiles in

WSNs [19]. GANs involve two networks, the generator and the discriminator; the generator generates synthetic energy profiles, while the discriminator differentiates between real and generated profiles [16].

The training of GANs is formulated as a min-max game, where the generator tries to generate synthetic energy profiles that are indistinguishable from real-world profiles and the discriminator tries to classify them correctly [20]. These are not real traces, but synthetic traces, which are useful to optimize energy management schemes in WSN, specially in transmission scheduling and network lifetime prolongation [21]. Nevertheless, issues such as guaranteeing the quality of synthetic data and accommodate GAN's computational requirements at resource constrained nodes should be addressed while deploying GANs [22].

4. PROPOSED METHOD

RL is a powerful discipline in machine learning that uses techniques to reinforce desired behavior and resistance undesired action. It lets agents do actions and query the resulting state, get rewards and learn a strategy to make decisions with. In the context of WSNs, RL provides to the possibility to make a dynamic adjustment of the routing decision, which greatly outperforms the traditional routing mechanism in the efficiency of data transmission. The approach considers the use of RL to yield energy conservation and network lifetime maximization base on search of optimal grounds for communication.

The proposed work can be broken down into two main parts: clustering (including cluster head select and clustering) and the use of reinforcement learning to improve the routing. Multiple clustering routing protocols have been found to be effective, which can improve the network stability and prolong its lifetime. In this paper we use a hybrid method, where clustering is integrated with RL to design an efficient routing algorithm for WSNs. Given the existing solutions being either too much on energy or more on hop, this approach balances both, because multi-hop is important just as energy efficiency.

The originality of this approach is to apply RL to take sequential decisions and thus, to perform decisions based on probabilities. This is a more solid and efficient method compared to deterministic ones employed in some WSN routing schemes. The RL network view treats every device in the network as an RL agent. The space for each device is the set of paths that it can take to go to the sink, and potential neighbor nodes to where it could send data. The objective of RL agent is to learn an optimal policy of selecting best next hop routing with in consideration to energy consumption and network lifetime. The proposed scheme can help devices to achieve better quality performance than traditional ones by sharing their local information with neighboring nodes to make the routing decision much better and save energy.

The RL model for energy optimization purpose in WSNs repeatedly unfolds indicates features such as state, action, and reward spaces define according to the network controller dynamics. Important metrics such as the residual energy, distance to the sink, link quality, and size of the queue are included in the state space, giving it much more information to make a decision. Actions include increasing or decreasing transmission power, deciding the next-hop neighbor (to route packets to), which affects energy consumption, and switching between active and sleep, which directly affects energy consumption. The reward function encourages energy efficiency, balanced energy depletion, and successful packet delivery and penalizes packet loss and high energy utilization. This can be further balanced by using the dynamic and distributed nature of WSN by energy efficient routing techniques that can enable adaptability, scalability and effective energy management in resource constrained and volatile environments.

Figure 1 illustrates the methodology for the RL-based approach aimed at extending the lifetime of the wireless sensor network. The key components are:

- Network setup: initialization of sensor nodes and network topology.
- Cluster formation: clustering of nodes, with the selection of cluster heads responsible for communication with neighboring clusters.
- Threshold criteria: establishing energy thresholds for node activity and routing decisions.
- Data transmission: optimized routing of data from nodes to the sink using the RL model.
- Network parameters comparison: evaluation of network performance based on metrics such as energy consumption, packet delivery ratio, and network lifetime.

Figure 1 shows the system architecture that is an overview about the method proposed and how RL and clustering cooperate to contribute on the best network lifetime and optimal data transmission energy. It mainly addresses the problem of traffic optimization and energy management in the network.

Routing: is finding the best path for data to go between a source and a destination. The problems are complicated due to network topology, channel characteristics and performance metrics. These difficulties are addressed in the proposed approach by the RL model, which flexibly changes its routing decision according to the network status to achieve energy-efficient transmission.

Sleep scheduling: also, for further energy efficiency, we add a sleep scheduling phase to control the energy of the sensor nodes. Nodes turn on and off the activity to save power, while the sink always remains active to control the data flow within the cluster. To prevent premature energy exhaustion in cluster head, the cluster head function is rotated in round robin fashion by sharing energy equally on the nodes. Snooze scheduling can also significantly alleviate the useless packet transmissions by turning off the nodes that have been in idle state for a while.

Expected outcome: the proposed RL-based method we proposed in this paper has the potentials to remarkably improve the life period of networks by well organizing and controlling the sensor nodes. The overall goal is to reduce power consumption and prevent energy draining in sensor nodes, which would extend the lifetime of the network. The proposed method manages to make each member in the sensor nodes to work efficiently and it contributes the sustained performance of the WSN by adapting the trade of energy consumption and routing decisions intelligently.

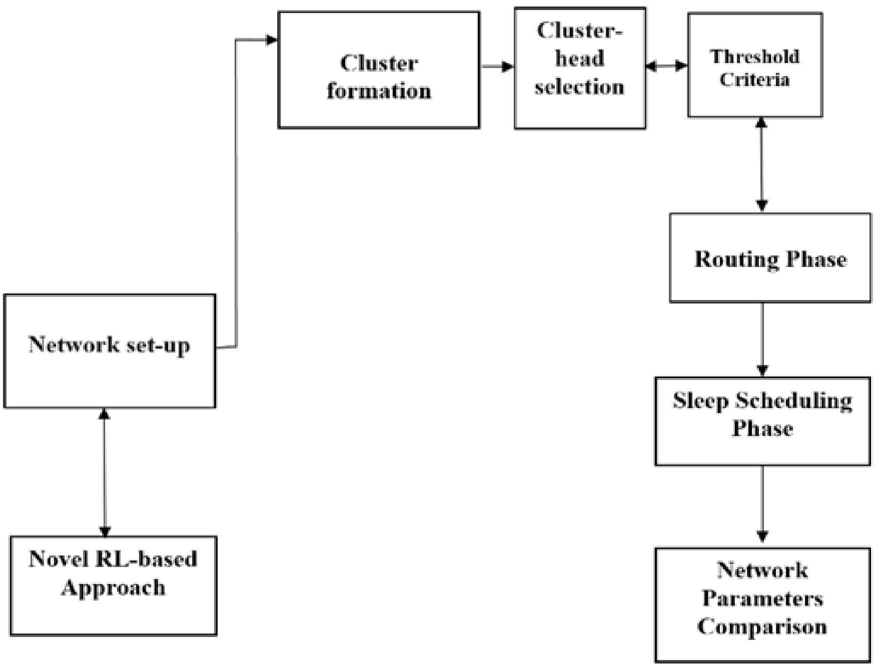

Figure 1. System architecture

5. PERFORMANCE EVALUATION

We initially developed the K-means algorithm in order to relay selection of the cluster head and tested its performance under the AODV protocol. In this paper, we evaluate our proposed scheme in terms of the following three performance indicators: packet delivery ratio (PDR), throughput and energy consumption. For future work, we will explore deep learning techniques for better optimization and compare with the proposed RL-based approach.

5.1. Experimental setup

Performance evaluation experiments were performed in a realistic simulation environment realized with network simulator 2 (NS-2). The K-means algorithm was implemented in the AODV protocol without any changes to the protocol, so that we could investigate the effect of clusters on the network performance. Table 2 describes the simulation configuration parameters employed for the evaluation. The simulation environment evaluates how the AODV protocol performs when integrated with the K-means cluster head selection algorithm. Three cases were simulated with different number of the cluster heads (3, 5, and 7) to investigate and analyze the effect of the cluster heads on the overall performance of the network.

5.2. Results and discussion

K-means clustering was adopted in order for data to route more by optimizing routing paths and reducing the load on individual nodes. This resulted in a significant energy saving and an extended network life. The analysis included the following critical performance measures:

- PDR: the ratio of packets correctly received at the destination to the packets transmitted. As shown in Figure 2, the introduction of clusters increased the PDR, indicating better data transmission reliability as the network becomes more organized.
- Throughput: this refers to the total number of successfully transmitted bits per second. Figure 3 illustrates that throughput increased with the deployment of clusters, as more efficient routes and balanced traffic loads were established across the network.
- Energy consumption: energy consumption was measured as the percentage of energy utilized by the sensor nodes during data transmission and reception. As depicted in Figure 4, the network with three clusters exhibited lower energy consumption compared to networks with fewer or no clusters, which indicates better energy management and prolonged network lifetime.

The results demonstrate that clustering using the K-means algorithm improves network efficiency by enhancing packet delivery, increasing throughput, and reducing energy consumption. These improvements lay the foundation for further optimization using deep learning-based approaches, which we plan to implement in future work for comparison.

Table 2. Simulation configuration parameters

Parameters	Values
Channel type	Wireless
Propagation model	Two ray ground
MAC type	802.11
Link layer type	LL
Interface queue type	DropTail/ PriQueue
Number of nodes	100
Cluster heads	3, 5, 7
Simulation time (s)	10
Initiator routing protocol	AODV
Topology dimensions (X, Y)	1000, 1000
Traffic type	TCP

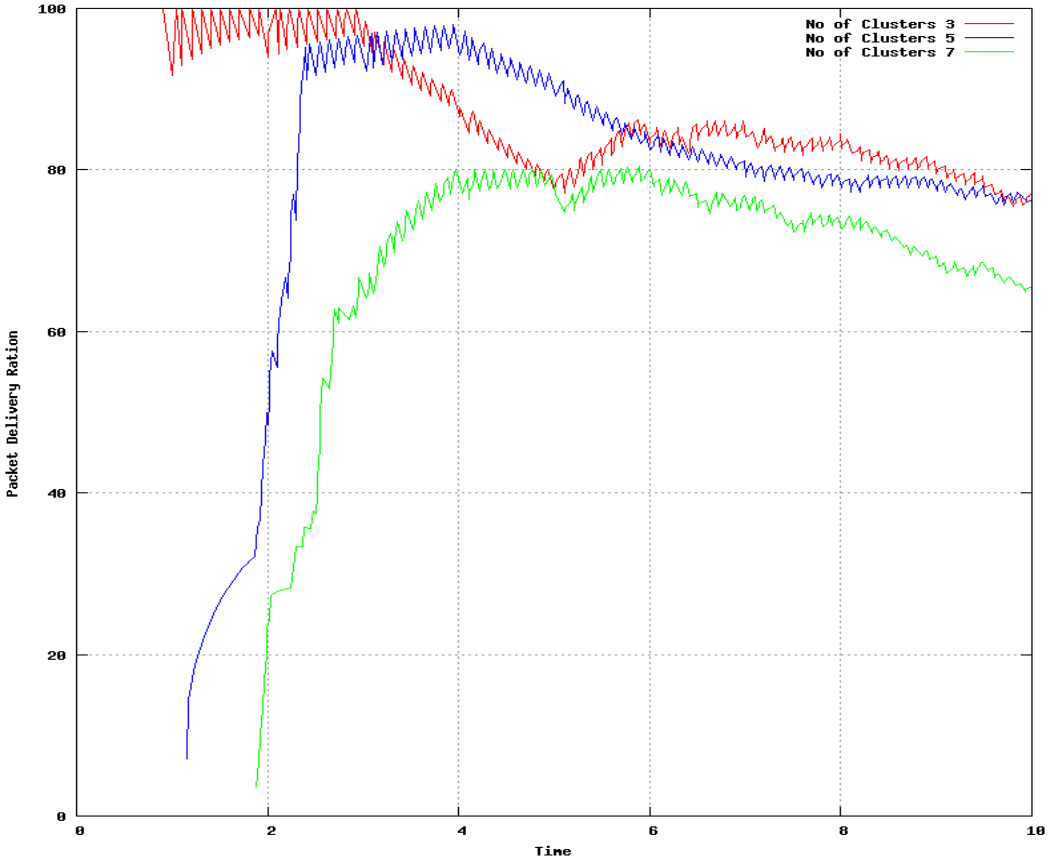

Figure 2. Packet delivery ration

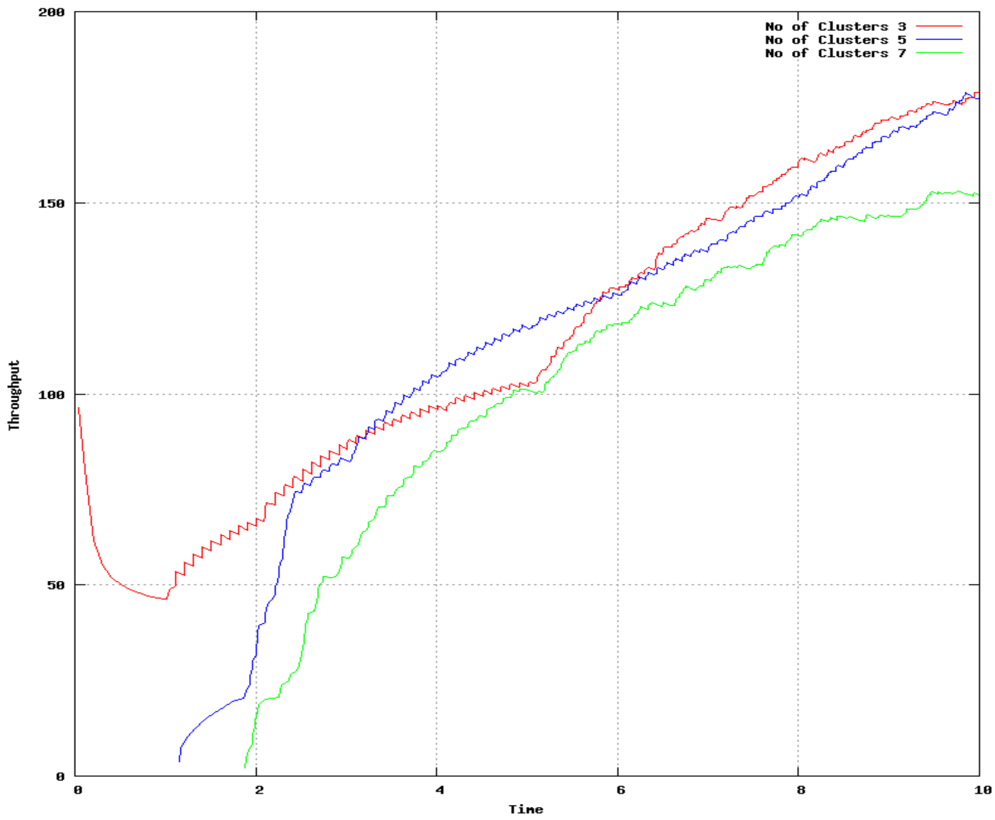

Figure 3. Throughput

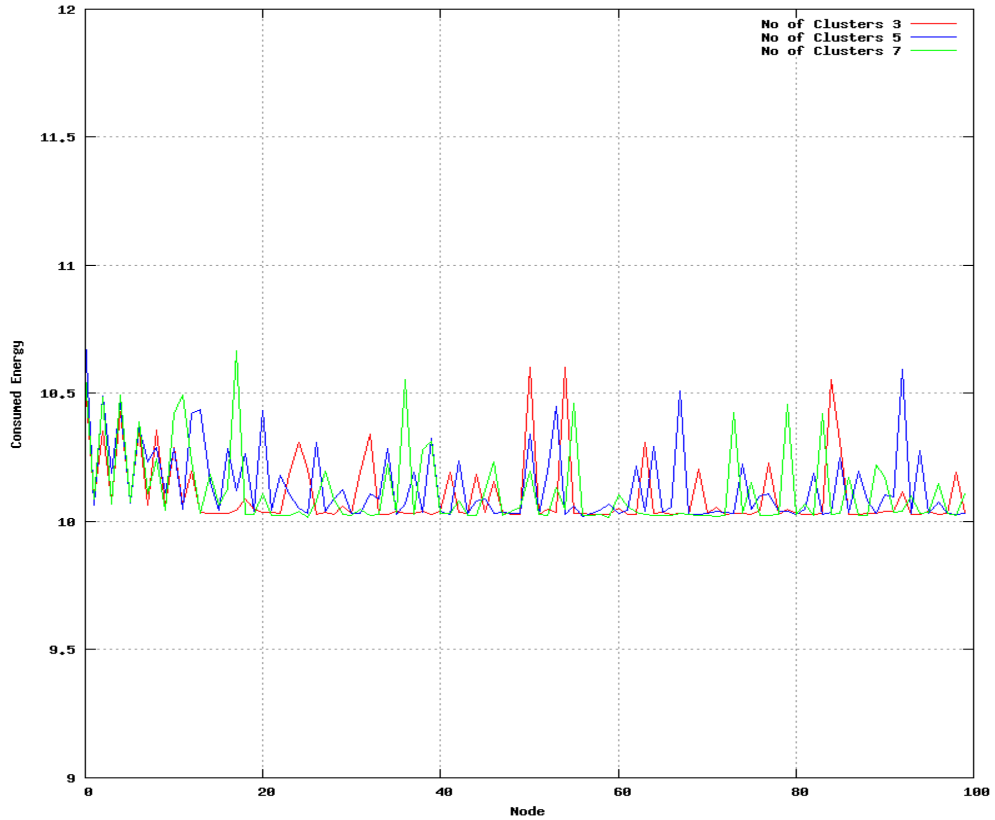

Figure 4. Energy consumption

6. CHALLENGES AND FUTURE DIRECTIONS

6.1. Scalability and real-time performance

One of the major problems for WSNs in using deep learning is scalable and real-time processing, particularly in big data and dense sensor networks. The majority of sensor nodes are resource-constrained with respect to processing power, memory and energy. On-device processing allows deep learning models to be scaled, whilst being reactive on such devices is a big challenge. The future work should pay attention to design lightweight and efficient deep learning models tailored for WSNs, especially in the aspects of model compression (e.g., pruning, quantization), and deployment of energy-efficient solutions that offer acceptable performance on limited resources. Recent optimization-based clustering and routing frameworks have demonstrated improved scalability in dense WSN deployments by employing advanced meta-heuristic strategies for cluster-head selection and coverage balancing [27]-[29].

6.2. Security and privacy concerns

Since deep learning models are being used with WSNs, it is of great importance to secure and preserve the confidentiality of the data. WSNs generally deal with sensitive information and potentially vulnerable to attacks, such as adversarial attack or data leakage, when deep learning models are deployed. Thus, it is necessary to devise strong security measures and privacy preserving techniques, such as those based on differential privacy or homomorphic encryption, to prevent sensitive information from leakage over training and inference. Further studies need to handle these shortcomings such that the safe and secure deployment of deep learning in WSNs can be guaranteed.

6.3. Hardware implementation challenges

Another issue is that deploying deep learning models into sensor nodes in a hardware form. However, the computational capability of sensor nodes is very limited and their power supplies have severe energy constraints, so executing deep learning models at the edge are not realistic unless specialized hardware accelerators or energy-efficient architectures can be provided. Future work will focus on hardware-software co-design: energy-efficient processor and hardware accelerator (e.g., tensor processing units (TPUs), field-programmable gate arrays (FPGAs)) designs tailored for deep learning tasks in sensor networks. There is a need for optimizing the training and inference to work within the constraints of WSN nodes, in order to achieve full potential of the deep learning-based optimization methods.

6.4. Integration with edge computing and IoT platforms

Deep learning- powered optimization paradigms integrated on edge computing and IoT platforms offer the ability to improve the intelligence and autonomy of WSNs. Edge computing can be used to push more intensive computations to an edge location, helping to alleviate processing at sensor nodes. Collaborative learning models such as federated learning and edge intelligence have also been proposed for the distributed optimization and cooperative decision-making in decentralized WSNs. Further research is also warranted to investigate how commodity edge computing and IoT platforms of deep learning could be touchlessly integrated into the era of WSNs, in order to achieve more intelligent, scalable, and efficient WSN functioning.

7. CONCLUSION

In this paper, we have presented a RL based method to optimize the routing in WSNs and so improve the lifespan of network and the energy utilization. We conducted an extensive study which poses these deep learning-based optimization solutions: neural networks for predicting energy, DRL for routing, generative adversarial networks for harvesting. The K-means clustering process selection of cluster head and the AODV routing protocol had been combined to result into remarkable increase in packet delivery ratio, throughput, and energy efficiency. The results of our performance analysis prove that deep learning using techniques provide a potential and effective solution for WSNs in overcoming some of the latter's main challenges in decoupling the energy power and the routing decisions. Our proposed reinforcement learning based approach allows for the dynamic and adaptive routing, leading to longer network lifetime with lower energy consumption. The experiment showed pronounced prolonged network, energy efficient and system performance compared to traditional routing protocols. Our study insights highlight the benefits of integration of deep learning into clustering and routing policies in WSNs. Taking advantages of the powerful deep learning-based proactive data-driven decision-making, we are able to adjust the WSNs in a timely manner so as to achieve the real-time performance for the scalability, robustness, and efficiency in resource-constrained environments. In our future work, we will implement and compare advanced deep learning techniques to enhance these algorithms and verify their feasibility in large-scale WSN.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to animal use has complied with all the relevant national regulations and institutional policies for the care and use of animals.

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