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Research Article

Using Deep Learning Technology Based Energy-Saving For Software Defined Wireless Sensor Networks (SDWSN) Framework

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ABSTRACT

This paper discusses the significance of Wireless Sensor Networks (WSNs) in collecting critical data from various environments, highlighting the challenges presented by the limited resources of small, highly mobile sensors. The integration of WSNs into the Internet of Things (IoT) enables the collection and transmission of data to centralized locations. Especially in complex network topologies, efficient routing of packets is crucial for optimizing resource utilization in WSN nodes. Software-Defined Networks (SDNs), in which a centralized controller makes routing decisions based on network and packet data, are replacing traditional static routing. Nevertheless, due to the complexity of WSN topologies and cost-effectiveness concerns, Machine Learning (ML) techniques are currently being used to improve SDNWSN decision-making. This paper presents a technique that employs a neural network trained via Deep Reinforcement Learning (DRL) to extend the lifespan of WSNs by optimizing energy utilization via efficient routing. 2DCNN and 3DCNN neural networks are evaluated, with 3DCNN showing superior performance, resulting in an 18% increase in network lifespan. Additionally, the study emphasizes the significance of avoiding resource depletion in high-traffic nodes by considering alternative routing paths to guarantee the lifespan of the network.

1. INTRODUCTION

The WSNs or Wireless Sensor Networks have garnered considerable consideration across diverse fields, encompassing environmental monitoring, healthcare, industrial automation, and smart cities. These networks are comprised of numerous small sensor nodes that have limited resources and work together to gather and transmit data [1]. Nevertheless, a significant obstacle encountered by WSNs is to the constrained energy resources of the sensor nodes. The impracticality of replacing or recharging batteries in sensor nodes, primarily due to their remote and difficult deployment locations, underscores the need of energy saving as a crucial consideration [2-4].

The proliferation of internet connectivity in diverse formats has greatly enhanced network accessibility, hence enabling the formation of communication between devices located in distant areas. The enhanced availability of internet access has stimulated the usage of the fundamental infrastructure of the internet to connect a wide array of devices to the World Wide Web. This connection enables the transfer of data collected by these devices and the execution of commands issued from remote locations. These devices range from basic household appliances such as coffee makers to advanced entities like driverless vehicles, hence contributing to the emergence of the IoT [5, 6].

However, it is important to note that the architecture of the internet, including its communication protocols, was initially developed to cater to larger computers that possessed greater resources and exhibited generally stable features. This stands in contrast to the sometimes resource-limited and highly mobile nature of IoT devices. The inherent discrepancy has presented new and complex obstacles in maximizing the efficiency of these IoT devices [7, 8].

One significant issue pertaining to the functioning of IoT devices centers around the considerable energy utilization required for their execution of designated functions. In general, in order to address the issue of mobility associated with these devices, they depend on energy sources that possess a restricted energy capacity [9, 10]. Moreover, within expansive WSNs, these devices serve as essential nodes that are tasked with the responsibility of efficiently directing data traffic between hosts.

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These packets can be sent to the sink node, which collects data from the network and facilitates its transmission to the internet, or to any other node in the network. The sink node essentially serves as the gateway for the entire network.

Consequently, in a network, a node's use of energy is affected by more than just the volume of traffic passing through it. The node's influence is also determined by the traffic it is responsible for transmitting to other nodes, therefore playing a vital part in maintaining uninterrupted connections across the network [11, 12].

In the present scenario, the incorporation of SDN principles into WSNs has emerged as a highly promising technique. SDN facilitates the consolidation of network control, effective allocation of resources, and flexible reconfiguration, hence enabling enhanced intelligent and adaptable management of WSNs [13,14]. When combined with the capabilities of Deep Learning methods, SDN has the potential to greatly augment the energy efficiency of WSNs, resulting in extended network durations and enhanced sustainability [15].

2. RELATED WORK

The employment of Machine Learning techniques in SDN has become prevalent due to their ability to react dynamically to incoming data, rather than relying on inflexible and static rules [16]. The strategies gather information pertaining to the particular domain in which they are employed by utilizing datasets that have been obtained from said domain [17,18]. ML techniques can be classified into 3 main types as shown in Figure 1.

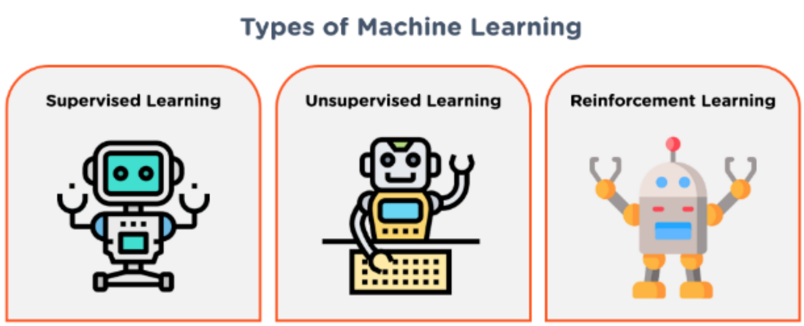

Fig. 1. Three main types of ML.

Moreover, Artificial Neural Networks (ANNs) are commonly utilized as a prominent approach for the approximation of complex functions. These networks have functional similarities to the manner in which actual neurons in the human brain transmit signals in order to influence an applicable judgment depending on inputs received as of many sensory sources. As a result, ANNs are specifically developed and trained to predict the outcome, sometimes denoted as a reward, of implementing a specific activity inside specified status. The training procedure encompasses the provision of environmental status information and the corresponding incentives acquired from the environment upon the execution of certain activities.

During practical implementation, the neural network receives input pertaining to the present condition of the surrounding environment. Afterwards, the neural network utilizes this knowledge to generate predictions concerning the expected rewards linked to every possible action that might be undertaken. The tool efficiently computes the anticipated benefits associated with several feasible courses of action. After conducting this evaluation, the agent responsible for performing the neural network algorithm chooses the action that is anticipated to have the largest reward. The objective of this methodology is to enhance the functioning of the environment by ensuring that the agent continually selects options that are anticipated to produce the most favorable results [19].

Neurons inside a neural network are organized in a layered structure, where the outputs of neurons in the layer above are added together to form the input of the layer below. The way these inputs are collected distinguishes between different varieties of neural networks. Each person has shown a rise in performance after being exposed to certain stimuli [20]. In order for the neurons in a convolutional neural network (CNN) to compute their outputs, they use multi-dimensional filters that are convolved with the input data. This particular category of neural networks has demonstrated notably improved efficacy in identifying localized, multi-dimensional characteristics within input data. Consequently, these networks have exhibited commendable performance in tasks involving image processing [21, 22]. Furthermore, it has been observed that this particular class of neural networks exhibits favorable outcomes in the realm of DRL when utilized for the controllers of SDNs. This can be attributed to their capability of identifying connections between neighboring nodes. Consequently, these networks can effectively identify nodes in close proximity to the one responsible for forwarding the packet, irrespective of the network's topology [23].

In light of the dynamic and ever-changing characteristics of IoT networks, several approaches have been developed to effectively handle packet routing in these networks by leveraging DL techniques [23,25]. Nevertheless, it is important to highlight that a significant aspect often disregarded by numerous methodologies is the energy usage within the network. The lack of attention to this issue has the potential to result in the exhaustion of energy supplies in particular nodes, contingent upon their respective locations within the network. The depletion of energy in the network can significantly affect its total lifespan. This is because the loss of these nodes affects communication between network nodes, which in turn hampers the timely delivery of data to their intended destinations.

One approach suggested in the study [23] is to tackle this issue through the implementation of a reward-based framework, wherein the network itself serves as the representation of the "environment." The computation of this incentive is contingent upon various parameters, encompassing packet latency, packet loss, and network throughput. In this methodology, the NN is utilized to prediction a maximum reward, which is hypothesized to align with the most efficient path for packet transmission. Nevertheless, it is crucial to acknowledge that this approach places emphasis on identifying the most efficient route without necessarily taking into account the equitable distribution of network traffic between nodes.

Moreover, the primary aim in [25] is to optimize the routing trajectory for individual packets in order to minimize the duration of their delivery. The primary objective of prioritizing the reduction of packet travel time is to enhance the efficiency of data transmission, hence enhancing the overall responsiveness of the network. In the meantime, a separate methodology is presented in [24], specifically designed for VANETs, with the primary objective of improving the probability of successfully delivering packets.

Fundamentally, although these deep learning-based routing algorithms for IoT networks display promising progress, it is imperative to acknowledge and tackle the issue of energy utilization to guarantee a durability as well as dependability of IoT network. Ensuring effective and resilient IoT connectivity necessitates the consideration of two crucial factors: balancing energy usage and optimizing routing paths.

3. METHODOLOGY

This section will concentrate on traffic management in Wireless Sensor Networks (WSNs) to effectively extend their operational lifespan. This approach relies on DQN to accomplish load balancing among network nodes. The central idea is to predict a reward value using DQN, which is directly related to the network's durability after sending a packet to any network node. This method chooses the next hop for each packet based on maximizing the network's lifespan, ensuring a balanced workload distribution among nodes to perpetuate the WSN. The method recognizes the significance of considering network constraints such as node transmission energy and packet delivery rates. Incorporating these constraints is essential for determining the efficacy of the approach. For the purpose of evaluating the strategy, numerous neural network architectures are analyzed, with exhaustive data on network nodes and transmitted packets. Deep DRL methods are used to train neural networks, with the duration of the WSN network being a crucial factor in the decision-making effectiveness. Negative reward values are incurred when decisions that exceed network limits incur penalties. Specifically, this methodology evaluates the 2DCNN and 3DCNN DQN algorithms. These algorithms play a crucial role in influencing decision-making in order to achieve a balance between workload distribution, network lifespan, and compliance with communication constraints.

a. Applied 2DCNN Algorithm.

In our proposed method, the input to the NN is a 3D-array with the dimensions 1001005. This input format consists of five discrete layers, each of which consists of 100100 values representing a specific characteristic:

1. Remaining Energy of Each Node: The energy that remains of every node in the network is represented by a single layer, which can be used to inform key decisions.
2. Source Host Position: Another layer contains values set to one at the position of the source host to assist the network in determining the origin of the packet.
3. Destination Host Position: Similarly, another layer contains values set to one for the location of the destination host, which aids in routing decisions.
4. Nodes Within Transmission Range: Nodes within range of the node receiving the packet have been assigned values of one in this layer.
5. Route Description: Last but not least, the layer describes the route taken by the packet, listing each host it visited before arriving at its current destination. In this layer, a value of zero indicates the original node and a value of one indicates the current host. Figure 2 shows the steps of neural network algorithm.

This input structure enables the neural network to make informed decisions regarding the next hop for each packet within the WSN. It optimizes routing decisions by utilizing the spatial arrangement of nodes, energy status, source and destination information, and network topology.

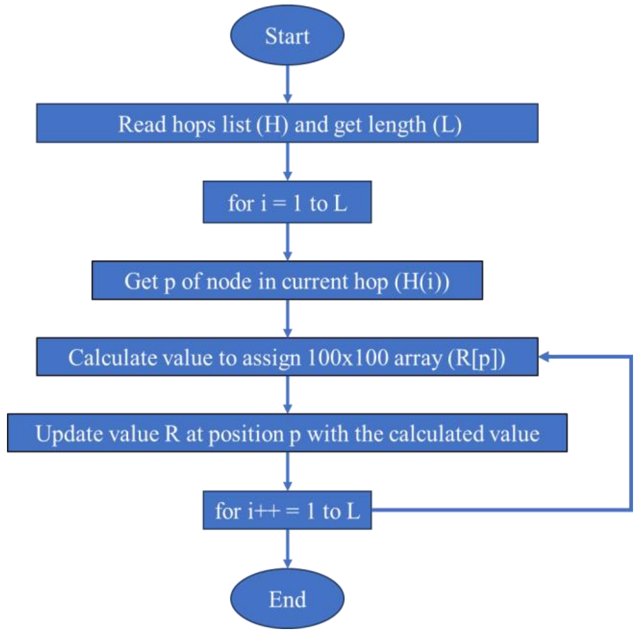

Fig. 2. Flowchart for Hops depiction of the neural network algorithm.

A 2D array is the CNN final output. Each node's reward is represented by a value in this array, as a result, the node with the largest reward is the one picked to forward the packet.

b. Applied 3DCNN Algorithm.

In contrast to 2DCNNs, which detect features predominantly across a single layer of the input array, 3DCNNs excel at identifying features that span multiple layers of the input. As our goal is to generate a single reward value for each node, resulting in a two-dimensional output, we employ an Average-Pooling layer. This layer is indispensable for aggregating the values associated with each node into a single representative value. Within the neural network's hidden layers, the Average-Pooling layer effectively combines the information garnered from various layers into a single value. This value is then utilized to predict the reward value associated with the selection of this particular node.

Within the 3DCNN model, the layers, the input values are consistent with the data gathered for the 2DCNN model. The filters in the Average-Pooling layer, on the other hand, are designed to combine the results of the original hidden layer's feature detection into a single metric. To be more precise, the filter size is (one, one, five), which means it can summarize features across all five levels. Adjusting the weight given to each feature value requires weight values to be present between the input and initial hidden layers. For example, the value generated by the Average-Pooling filters is modulated by factors such as remaining energy and route description. This modulation occurs in accordance with the network's learning process, adapting to the demands and needs of the network as determined during training.

c. Deep Q-Network Model Training

The neural network (NN) initially operates without knowledge of the rewards for actions, leading to somewhat arbitrary transmissions and routing decisions. The NN gains a greater understanding of the network environment and efficient packet transmission strategies as it gains knowledge from the feedback generated by these actions over multiple iterations. However, this acquired knowledge may not inherently prioritize the key objective of extending the network's lifespan.

A variable with an initial value of one is introduced to balance the exploration and exploitation of acquired knowledge. This variable is compared to random numbers between zero and one, and when the random number exceeds the variable's value, the NN's predictions determine the next course of action. When the random number is less than the variable's value, which decreases by 0.99 after each iteration, arbitrary actions are performed. This strategy guarantees a balance between informed decision-making and exploratory steps, optimizing routing decisions and network lifespan.

NN training continues until one of the network nodes runs out of energy at the conclusion of each iteration. This network lifespan is used to independently update reward values for each packet, as the delivery of packets is regarded as parallel rather than serial. Based on prior research indicating enhanced performance with this value, a discount factor (Gamma) with a value of 0.90 is used to reduce the reward value associated with the final packet action. This optimizes the learning procedure and routing decisions. The predictions made by the NN are updated by plugging the current value of Q into Equation 1. After the packet has been forwarded to the next hop, the agent is in a new state s', and the agent's maximum expected reward in this state is max-Q', while the actual reward amount, R, is what the agent receives from the environment.

$$New.Q(b,c) = Q(b,c) + \propto (R(b,c) + x \max Q'(b',c') - Q(b,c)) \quad (1)$$

The computed value obtained from this formula solely indicates the value of reward associated with the node to which the packet is passed. The values of reward for the remaining nodes are preserved according to the predictions made by the NN. By employing this methodology, the retention of any pre-existing knowledge is ensured, allowing for the ongoing extraction of information even in the presence of randomly selected actions. To expose the necessary learning to the neural network (NN) as well as prevent the forwarding of packets to positions lacking nodes, negative reward values of -1, referred to as penalties, are assigned to such vacant positions. The training technique is performed subsequent to the depletion of the initial node in the network. Instant training is triggered when any of the following conditions are met:

1. If the destination node is beyond the current node's range of transmission, the packet is forwarded to it.
2. The packet is sent to a node other than the destination node that lacks the capability to either obtain or packet forward.
3. To prevent infinite recurrence, the packet is only sent to the next hop in the list of hops it has already traversed.
4. The packet takes more than 10 times as many hops as there are nodes in the network.

4. RESULTS AND DISCUSSION

The methodology under consideration involves the utilization of diverse neural networks specifically developed for the Deep Q-Network. In order to facilitate the training process of artificial neural networks, a dataset including 100 WSNs that have been randomly constructed is utilized. The WSNs exhibit variations in the number of nodes, which range from 8 to 32. These nodes are uniformly dispersed throughout a square area measuring 1000×1000 square meters. In order to achieve uniform network development across all investigated approaches, random seeds with comparable values are utilized. This practice guarantees the generation of identical random integers for each trial.

At the outset, every node is assigned an initial energy level of 1 joule. The process of transmitting or receiving a packet result in an energy utilization of 5×10-9 joule. The packets have been configured with a size of 1025 bytes and a transmission rate of 2Mbps. The maximum transmission range of a node is specified as 300 meters. Hence, in the event that a packet is transferred to a node situated beyond this specified range, it is regarded as an unsuccessful transmission. It is noteworthy to acknowledge that every node consumes energy at a rate of 10-10 joule per second in its idle state, wherein no packets are being broadcast or received.

The training procedure encompasses the utilization of designated training data with Programming Language (Python), Neural Network Framework Keras with TensorFlow backend, and the generation of network traffic occurs randomly, with randomly selected source and destination hosts, until a node exhausts its energy supply. Figure 3 presents a graphical depiction of the randomly generated WSNs along with sample traffic, in addition, Table 1 shows the details of the parameters used in the experiments.

TABLE I. PARAMETERS USED IN THE EXPERIMENTS

WSN Network	Specifications
Training Data	100 randomly generated WSNs

Evaluation Data	Separate set of 10 networks
Traffic Generation	Random packet production

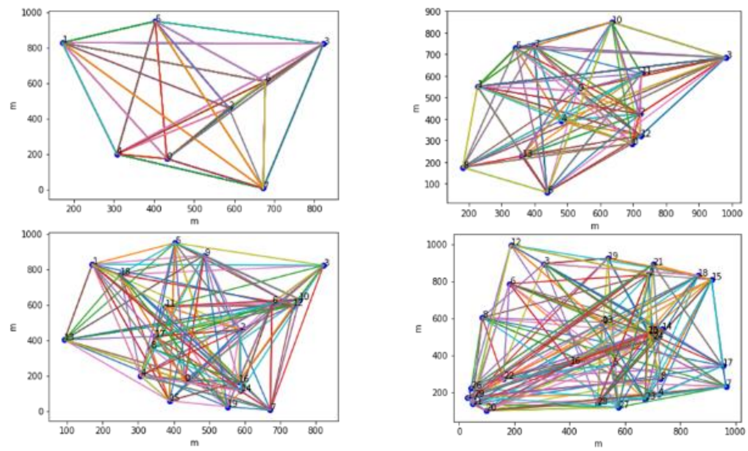

Fig. 3. Randomly generated WSN and traffic samples.

a. Performance of the 2D-CNN

In a manner akin to the preceding experiment, the 2D-CNN model undergoes training using an identical collection of 100 WSNs, followed by evaluation using an additional set of 10 networks. The networks under consideration exhibit an Avg. duration of 638169 seconds. The experimental results indicate that, on Avg., the number of hops per packet is 12.37, resulting in a PDR of 83.3%. Additionally, the Avg. prediction time is measured to be 316.03 µs.

Additionally, the research entails the observation and analysis of the mean minimum remaining energy in the nodes throughout their operational period. The data presented in Figure 4 demonstrates a correlation between the decline in available energy and the use of measures by the 2D-CNN algorithm to restrict packet forwarding through nodes with diminishing energy levels. The observed behavior is distinguished by a declining pattern in the Avg. minimum energy quantity as time develops.

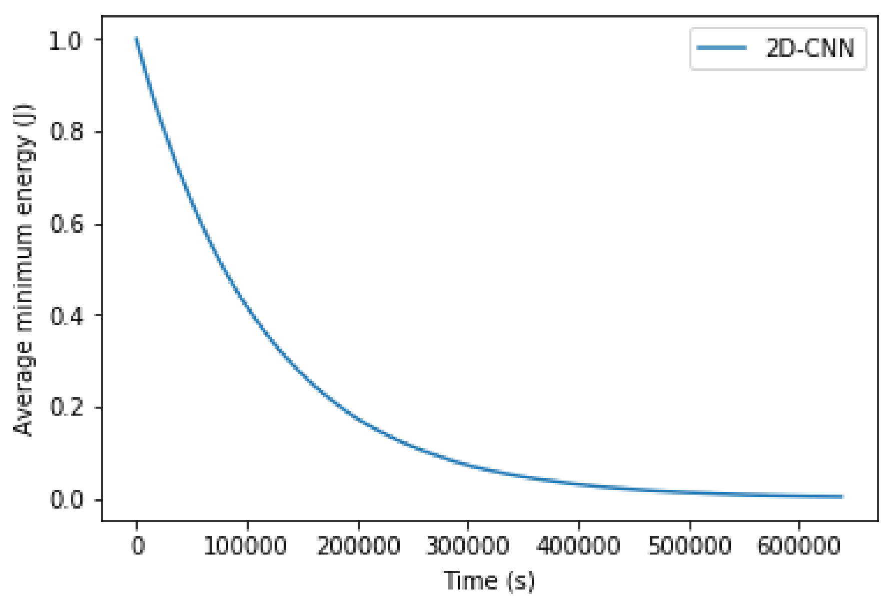

Fig. 4. Avg. energy of WSNs calculated using the 2DCNN algorithm.

In addition, the proposed methodology serves as a traffic flow manager by monitoring the mean number of hops throughout the operation of WSNs. In order to improve clarity, the values are grouped into periods of 1000 seconds and then Avg. d to obtain mean values. A notable pattern arises wherein the mean quantity of hops exhibits a noticeable rise after surpassing the 400,000-second threshold, which aligns with the commencement of critical energy levels within the nodes.

As the network approaches its terminal phase, this specific model exhibits a tendency towards favoring shorter pathways. The change in preference can be ascribed to the declining energy levels observed in a significant number of nodes, hence presenting a greater difficulty for the network to circumvent them. The behavior is visually depicted in Figure 5.

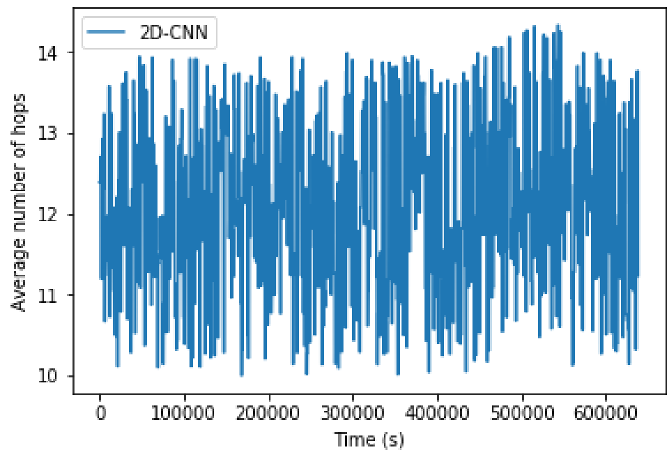

Fig. 5. 2DCNN algorithm Avg. number of steps vs. time.

Furthermore, the ongoing monitoring of the Avg. PDR has been a consistent practice during the operation of WSNs. The measure is evaluated at regular intervals of 1000 seconds in order to provide a more thorough viewpoint. As illustrated in Figure 6, we notable the ability to sustain a high PDR despite the decrease in energy levels of the nodes and the necessity for packets to traverse longer paths.

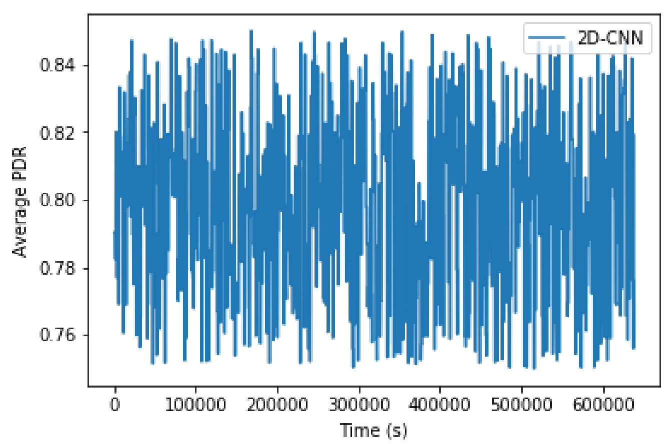

Fig. 6. Avg. packet delivery rate across time by 2DCNN algorithm.

b. 3DCNN Algorithm Performance

After being trained on a dataset containing data from 100 WSNs, the 3DCNN used in the Deep Q-Network to evaluating. The evaluation phase employed the identical set of 10 WSNs as utilized in the preceding trials. The observed networks displayed a mean lifespan of 678251.62 seconds. Furthermore, the study revealed that the mean number of hops per packet was calculated to be 9.81, while the PDR was observed to be 85.1%. It is noteworthy to mention that each prediction within this particular context was executed with an Avg. time utilization of 351.71 µs.

The calculation of the Avg. remaining minimum energy in the nodes was performed during their operation and is depicted in Figure 7. The presented data demonstrates that the current model has a diminished gradient in comparison to prior experiments, suggesting that it has accomplished a more equitable allocation of energy usage among the network's nodes.

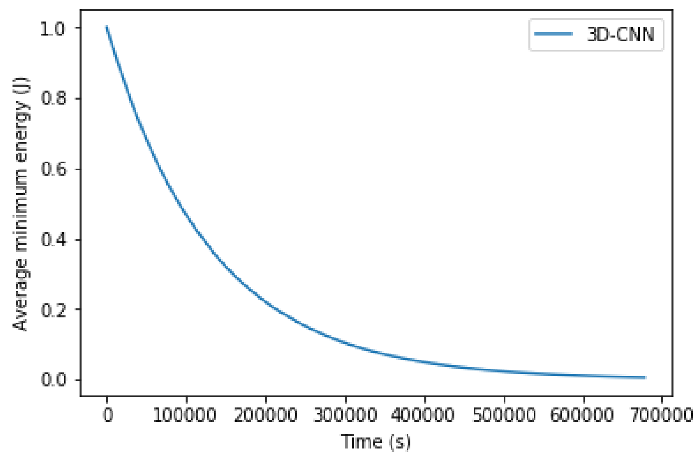

Fig. 7. Avg. energy of WSNs calculated by 3DCNN algorithm.

Furthermore, the approach under consideration operates as a traffic flow manager by consistently monitoring the mean number of hops throughout the functioning of WSNs. In order to enhance precision, the data points are gathered at regular intervals of 1000 seconds, leading to the computation of mean values that are subsequently subjected to further averaging. Throughout the entire lifespan of the network, there is a lack of observable variation in the Avg. number of hops. The trend, in conjunction with the comparatively lower mean number of hops per packet in the 3DCNN model relative to the 2DCNN model, implies that the 3DCNN model has implemented measures to distribute the workload more evenly at an earlier phase, notably prior to the depletion of the nodes' energy levels as shows in Figure 8.

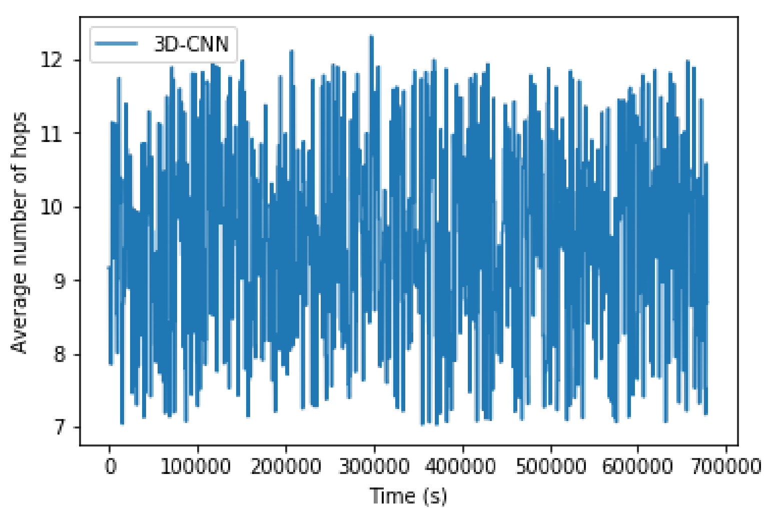

Fig. 8. Number of Avg. of steps throughout time by 3DCNN algorithm.

Furthermore, an ongoing monitoring of the Avg. PDR has been a consistent practice during the operation of WSNs. The measure is evaluated at regular intervals of 1000 seconds in order to provide a more detailed depiction. According to the findings presented in Figure 9, the suggested methodology has consistently demonstrated its capacity to sustain a high PDR across the whole duration of the wireless sensor network lifespan.

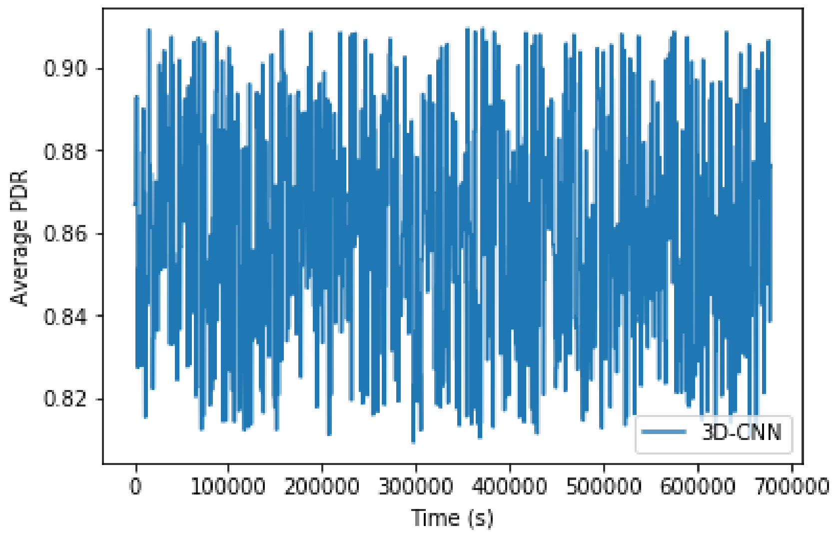

Fig. 9. Avg. packet delivery rate across time by 3DCNN algorithm.

5. SUMMARY RESULTS AND DISCUSSION

Table 2 presents an evaluation of several approaches employed for the management of traffic flow inside WSNs. The method known as "3DCNN" exhibits a notably prolonged Avg. lifespan of WSNs, reaching roughly 678,252 seconds. This duration surpasses that of alternative methods, suggesting its efficacy in sustaining network activities over lengthy timeframes. Although the "2DCNN" approach has a slightly lower Avg. prediction time (351.7 µs) compared to the method under consideration, it is justifiable to accept this discrepancy due to the longer network lifespan associated with the latter. Furthermore, the "3DCNN" approach demonstrates the lowest mean number of hops per packet (9.81), indicating its inclination towards shorter transmission pathways. Notably, it attains a PDR of 85.07%, indicating its outstanding ability to deliver packets, even over extended periods of network operation. On the contrary, [25] demonstrates the lowest PDR at 64.71%, suggesting comparatively elevated rates of packet loss. In light of the findings presented, it is evident that the "3DCNN" technique demonstrates superior performance in terms of network lifespan and efficacy in delivering packets. However, it is important to acknowledge that additional considerations, such as computational complexity, should be taken into account when determining the most appropriate approach for specific WSN applications.

TABLE II. PERFORMANCE MEASUREMENT FOR THE CURRENT AND PROPOSED METHODS.

Methods	Lifespan	Time of Prediction	Avg. H	PDR
2DCNN	638169	316 uS	12.37	83.3 %
3DCNN	678252	351.7 uS	9.81	85.1 %
[24]	541840	341.9 uS	10.53	72.5 %
[25]	520364	283.1 uS	8.76	65.7 %

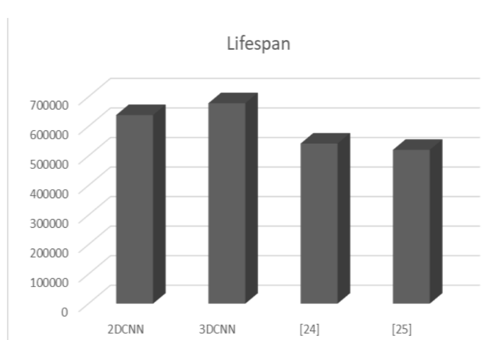

Fig. 10. Avg. lifespan for our method and current methods.

3D-Convolutional Neural Network (3DCNN) model has demonstrated a notable increase of 17% in the duration of the network's operational lifespan when compared to the previously documented maximum. Furthermore, this particular model has successfully enhanced the PDR of the network while simultaneously preserving a comparable Avg. number of hops needed for data transmission. The results of this study are consistent with the primary hypothesis, indicating that incorporating the lifespan of the network as a reward metric can successfully enhance the general network performance. Moreover, the explanation advised in this study demonstrates the highest hop count, as shown in Figure 11 expected outcome can be attributed to the requirement of the SDN controller to construct extended data transmission routes in order to mitigate the risk of resource exhaustion in some nodes.

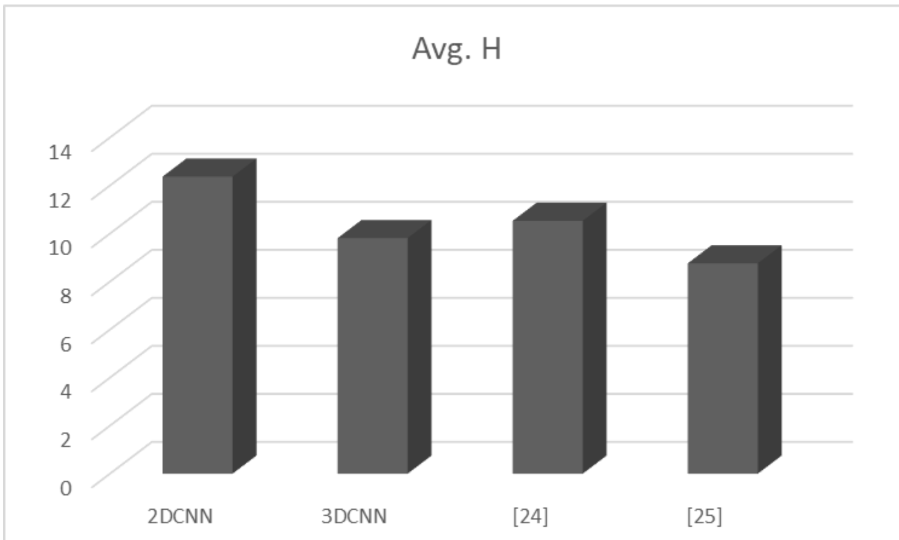

Fig. 11. Avg. number of hops for our method and current methods.

In both (2D and 3D) convolutional neural networks (CNNs), the neural network architecture stays invariant with respect to the total amount of nodes and the size of the network's environment. The assignment of values to a fixed-size array is determined by their relative positions inside the chosen region, hence guaranteeing a consistent computational time for various methods. In Figure 12, the PDR attained by the proposed and existing approaches is presented. Figure 13 illustrates the Avg. prediction time duration measured by both the proposed and existing methodologies.

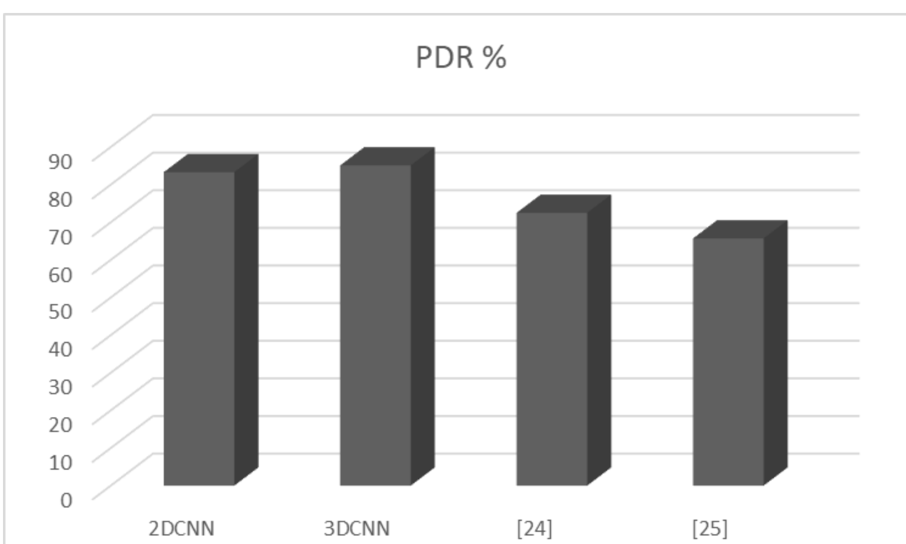

Figure 12: summary of the packet delivery ratio for our method and current methods

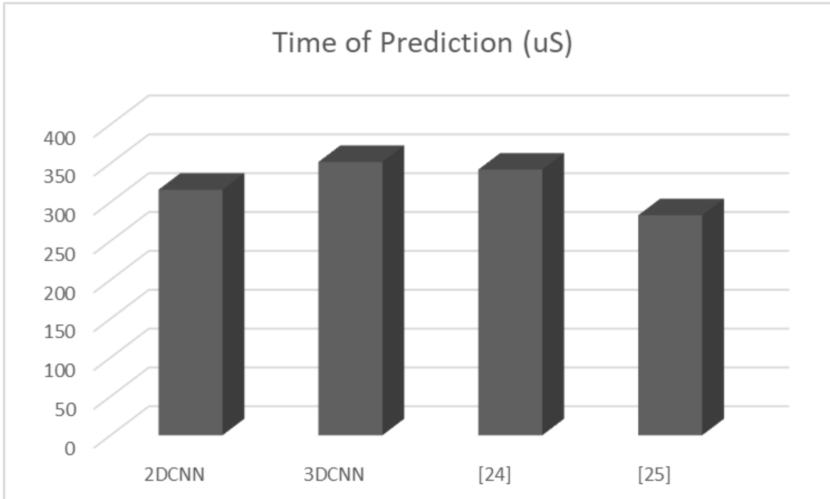

Figure 13: Avg. prediction time needed using our method and current methods.

6. CONCLUSION

In conclusion, the IoT has given rise to tiny, resource-constrained devices designed for remote data collection and control. Optimizing data flow and communication in WSN is essential for the viability of the Internet of Things. SDN has emerged as a promising solution, employing a dedicated controller to manage data packet routing and enhance network efficiency. This study introduces a novel method for improving SDN management by utilizing DQN to forecast the rewards associated with packet forwarding to various network nodes. By providing relevant data to the DQN about packets and network nodes, informed decisions can be made to extend the WSN's lifespan. This study employs the network's lifespan as the reward criterion in an effort to improve DQN training by balancing overall WSN functionality and optimizing resource utilization on an individual node level. Several DQN models, such as 2DCNN and 3DCNN, are examined. CNN-based models efficiently process and analyze input data, thereby augmenting SDN packet forwarding decision-making. Future research will enhance the DRL model to include packet discard decisions, allowing for the efficient removal of packets destined for inaccessible nodes. PDR must be incorporated into reward calculations. By reducing congestion and optimizing resource allocation, this augmented reinforcement learning model has the potential to substantially increase WSN network lifespan. Further investigation of alternative methods will continue to improve the efficacy and optimization of network control systems.

Conflicts Of Interest

The author's paper explicitly states that there are no conflicts of interest to be disclosed.

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