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RESEARCH ARTICLE

Improving the resource allocation with enhanced learning in wireless sensor networks

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Abstract

Efficient resource allocation is crucial for optimizing performance and extending the lifespan of wireless sensor networks (WSNs), which are often constrained by limited energy and bandwidth. This paper proposes an enhanced learning approach (ELA) for dynamic resource allocation in WSNs, leveraging augmented reinforcement learning to adaptively manage energy consumption, optimize routing, and schedule node activity. ELA integrates predictive feedback and real-time data from network states to refine policy decisions, enabling the network to maintain optimal performance under varying traffic loads and environmental conditions. Comparative analyses with existing methods, including deep neural networks (DNN), artificial neural networks (ANN), and support vector machines (SVM), demonstrate that ELA achieves superior results across multiple key metrics: energy consumption, network lifetime, packet delivery ratio, end-to-end delay, and throughput. Our findings indicate that ELA can sustain higher data reliability and throughput while minimizing latency and energy depletion, addressing fundamental challenges in WSNs. The proposed approach presents a scalable and adaptive solution that is well-suited for real-time and large-scale IoT applications, making it a valuable contribution to the advancement of intelligent resource management in WSNs.

Keywords: Wireless senor network, Reinforcement learning, Deep learning, Support vector machine, Artificial neural network.

Introduction

Wireless sensor networks (WSNs) represent a key advancement in communication and data collection technologies, offering a versatile platform for a wide range of applications, from environmental monitoring to industrial automation. Composed of spatially distributed autonomous sensor nodes, these networks are designed to monitor and collect data about physical or environmental conditions, such as temperature, humidity, pressure, motion, and chemical concentrations. The sensors communicate wirelessly, typically routing data through the network to a central processing node or gateway for analysis, Raja Basha, A. (2022), Jondhale, S. R., Maheswar, R., Lloret, J., Jondhale, S. R., Maheswar, R., & Lloret, J. (2022), Temene, N., Sergiou, C., Georgiou, C., & Vassiliou, V. (2022).

WSNs have become a crucial component in the Internet of Things (IoT), where they enable the connection of the physical world to the digital realm, facilitating intelligent decision-making, automation, and real-time monitoring. Their ability to function in harsh or remote environments, combined with advancements in energy-efficient protocols and hardware, has extended their utility in diverse fields such as agriculture, healthcare, defense, and smart cities, Nourildean, S. W., Hassib, M. D., & Mohammed, Y. A. (2022), Adday, G. H., Subramaniam, S. K., Zukarnain, Z. A., & Samian, N. (2022).

A WSN consists of a large number of sensor nodes, each with its own sensing, processing, and communication capabilities. The key components of a sensor node include Correia, F., Alencar, M., & Assis, K. (2023), Rahaman, M. M., & Azharuddin, M. (2022):

Sensors

The core elements responsible for detecting environmental or physical phenomena (e.g., temperature, light, pressure).

Microcontroller or Processor

The processing unit that handles data computation, management, and local decision-making.

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Communication Module

A transceiver that allows sensor nodes to communicate wirelessly with each other and a central base station or sink.

Power Source

Typically, sensor nodes are battery-powered, although some may include energy-harvesting capabilities to prolong their lifespan. The sensor nodes work collaboratively, forming an ad hoc network where data can hop between nodes before reaching a central base station. This decentralized structure allows WSNs to operate in challenging and large-scale environments without requiring pre-existing infrastructure, Kori, G. S., & Kakkasageri, M. S. (2023).

Resource Allocation

Resource allocation in WSNs is a critical factor that significantly impacts the overall performance, efficiency, and lifespan of the network. WSNs consist of a large number of sensor nodes that have limited resources, such as energy, bandwidth, processing power, and memory. Optimally managing and allocating these resources is essential to ensure that the network can perform its intended functions efficiently while maintaining sustainability over time, Ahmed, Q. W., Garg, S., Rai, A., Ramachandran, M., Jhanjhi, N. Z., Masud, M., & Baz, M. (2022), Velmurugadass, P., Dhanasekaran, S., Anand, S. S., & Vasudevan, V. (2023) [9,10].

The primary goal of resource allocation in WSNs is to optimize the use of limited resources while achieving the desired quality of service (QoS) and ensuring that sensor nodes perform their tasks efficiently. Due to the energy-constrained nature of sensor nodes and the dynamic topology of the network, poor resource management can lead to early depletion of node batteries, network partitioning, and reduced data quality. Effective resource allocation provides the following benefits. Mondal, A., Misra, S., Das, G., & Chakraborty, A. (2022), Mazloomi, N., Gholipour, M., & Zaretalab, A. (2022):

Energy Efficiency

By optimizing resource usage, particularly energy, resource allocation strategies can prolong the operational lifetime of the network.

Scalability

Efficient resource management ensures that the network can scale effectively, handling a large number of nodes without significant performance degradation.

Reliability

Proper resource allocation ensures reliable data communication, improving data quality and minimizing packet loss due to network congestion or node failures.

Network Longevity

By balancing resource consumption across nodes, resource allocation techniques can prevent premature failures of individual nodes and extend the overall network lifespan.

Challenges in Resource Allocation

Resource allocation in WSNs faces several challenges due to the inherent limitations of sensor nodes and the dynamic nature of WSNs, Osamy, W., Khedr, A. M., Salim, A., Al Ali, A. I., & El-Sawy, A. A. (2022), Mazhar, T., Malik, M. A., Mohsan, S. A. H., Li, Y., Haq, I., Ghorashi, S., ... & Mostafa, S. M. (2023):

Energy Constraints

Sensor nodes are typically powered by batteries with limited capacity, and energy replenishment is often impractical. As a result, energy-efficient resource allocation is a critical concern in WSNs.

Bandwidth Limitation

WSNs often operate in environments with limited bandwidth, leading to challenges in managing data transmission efficiently. Congestion and collisions in data communication can degrade network performance.

Node Heterogeneity

Sensor nodes in a WSN may have different capabilities in terms of energy, processing power, and communication range. This heterogeneity adds complexity to resource allocation since nodes with different capabilities must work together to achieve network goals.

Dynamic Topology

The topology of WSNs can change frequently due to factors like node mobility, node failure (e.g., due to energy depletion), and environmental conditions. Resource allocation strategies need to be adaptive to handle these changes.

Quality of Service (QoS) Requirements

Many WSN applications, such as real-time monitoring or surveillance, require guaranteed levels of QoS, including low latency, high reliability, and low packet loss. Achieving these QoS requirements while managing limited resources is challenging.

Environmental Interference

WSNs often operate in environments with physical obstructions, signal attenuation, and noise interference, which can affect the efficiency of resource allocation and data transmission.

Reinforcement Learning Approach

Reinforcement learning (RL) is a machine learning paradigm where an agent learns to make decisions by interacting with its environment to maximize cumulative rewards. In the context of WSNs, RL is employed to optimize resource allocation, such as energy management, routing, bandwidth allocation, and data transmission. RL-based approaches help nodes learn optimal policies over time based on feedback from the environment, allowing them to adapt dynamically to changing network conditions and constraints, Zhao, D., Zhou, Z., Wang, S., Liu, B., & Gaaloul, W. (2023), Okine, A. A., Adam, N., & Kaddoum, G. (2022, October).

The RL approach is particularly useful in WSNs because of the dynamic nature of sensor nodes (due to limited energy, varying data traffic, node failures, etc.) and the need for autonomous decision-making to prolong the network's lifetime while meeting quality of service (QoS) requirements.

Basic Concepts of Reinforcement Learning

In RL, the learning process revolves around the interaction between two key entities, Mahmood, T., Li, J., Pei, Y., Akhtar, F., Butt, S. A., Ditta, A., & Qureshi, S. (2022), Abadi, A. F. E., Asghari, S. A., Marvasti, M. B., Abaei, G., Nabavi, M., & Savaria, Y. (2022):

Agent

In WSNs, the agent can be a sensor node or a group of nodes. The agent takes actions to manage resources (e.g., adjusting transmission power, selecting routes, etc.).

Environment

The environment represents the overall network and its conditions, including node energy levels, traffic patterns, link quality, and network topology.

The RL process is modeled using the following components: State (s)

The current status of the environment. For a WSN, the state might include the remaining energy of the node, data buffer size, network congestion level, or distance to the base station.

Action (a)

The decision made by the agent. In WSNs, actions could include adjusting the transmission power, selecting a specific route, deciding whether to enter sleep mode, or choosing a data aggregation strategy.

Reward (r)

A numerical value provided as feedback to the agent based on the outcome of its action. A positive reward encourages actions that improve the network's performance (e.g., reducing energy consumption), while negative rewards penalize actions that degrade performance (e.g., causing network congestion).

Policy (π)

The strategy or decision-making process that the agent follows to determine the next action based on the current state. RL aims to learn an optimal policy that maximizes the cumulative reward over time.

Value Function (V)

A function that estimates how good a particular state or action is in terms of the expected long-term rewards. The value function helps the agent evaluate the potential benefits of being in a certain state or taking a particular action.

Q-learning

Q-Learning is one of the most widely used RL algorithms in WSNs due to its simplicity and effectiveness in learning optimal policies without requiring a model of the environment, Keum, D., & Ko, Y. B. (2022), Su, X., Ren, Y., Cai, Z., Liang, Y., & Guo, L. (2022).

Q-Function

In Q-Learning, the agent learns a Q-function, $Q(s,a)$, which estimates the expected cumulative reward of taking action a in state s. Over time, the agent updates its Q-values based on feedback from the environment, allowing it to learn the best actions to take in each state.

Update Rule

The Q-value is updated using the following formula: where $s \text{ and } s'$ are the current and next states, respectively. $a \text{ and } a'$ are the current and future actions. r is the reward received after taking action a. α is the learning rate, and γ is the discount factor, which determines how much future rewards are taken into account.

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left(r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right)$$

Proposed Enhanced Learning Approach For Resource Allocation In Wsn

The proposed augmented learning approach for resource allocation in WSNs integrates reinforcement learning with predictive feedback and neighboring node information. The approach ensures energy efficiency, low latency, and optimized resource utilization by dynamically adjusting the network's resources based on real-time feedback.

Stage 1: Initialization Phase

In this phase, we define the key components of the reinforcement learning problem, including the action space, state space, and reward function. This sets up the foundation for the learning process.

Step 1.1: Define the Action Space (A)

The action space defines the set of actions that the RL agent (sensor node) can take to manage resources in the network. Actions include:

- *Transmission Power Control*

Adjust the node's transmission power to save energy while maintaining communication quality.

- *Routing Path Selection*

Choose the next hop for data forwarding based on link quality, energy level, and congestion.

- *Sleep Cycle Scheduling*

Decide whether the node should stay active or enter a low-power sleep mode to conserve energy.

Thus, the action space A can be represented as:

$A = \{Adjust\ Transmission\ Power, Select\ Routing\ Path, Schedule\ Sleep\ Cycle\}$

Step 1.2: Define the State Space (S)

The state space captures the current condition of the network, providing context for the RL agent to make decisions. Key states include where S represents the set. Energy Set (E_i) The remaining energy at node i. Traffic Load (T_i), Latency Metrics (L_i) End-to-end delay between source and destination. Link Quality (Q_{ij}) Quality of the communication link between nodes I and j.

$S = \{E_i, T_i, L_i, Q_{ij}\}$

Step 1.3: Set the Reward Function (R)

The reward function is critical for guiding the RL agent towards optimal decisions. The reward is computed based on factors such as energy efficiency, network latency, and packet delivery success. The goal is to maximize rewards by reducing energy consumption and ensuring network reliability. A composite reward function R can be defined as: where E_i is the remaining energy at node i (the penalty for high energy consumption). L_i is the latency experienced by the network (the penalty for high latency). P_s is the packet delivery success rate (positive reward for a higher success rate) and α, β, γ are weighting factors for energy, latency, and packet delivery, respectively.

$$R(s,a) = \alpha.\frac{1}{E_i} + \beta.\frac{1}{L_i} + \gamma.P_s$$

Stage 2: Augmented Learning Process

Once the RL framework is initialized, the learning process begins. The agent (sensor node) interacts with the environment by observing the network state, taking actions, and receiving feedback. Augmented feedback enhances standard reinforcement learning by incorporating predictive models and neighboring node information.

Step 2.1: State Observation

At each time step t, the RL agent observes the current state of the network S_t which includes:

$$S_t = \{E_i(t), T_i(t), L_i(t), Q_{ij}(t)\}$$

Step 2.2: Action Selection

The RL agent selects an action $a_i \in A$ based on the current state S_t sing its current policy π. The action can be selected using either an epsilon-greedy policy or other exploration-exploitation techniques.

$$a_t = \pi(S_t)$$

Step 2.3: Standard Feedback

After taking action a_t, the agent receives standard feedback from the environment, including:

- Energy Consumption (E_{Cons}): Energy used during data transmission.
- Network Latency (L_t): Delay between sending and receiving packets.
- Packet Success Rate (P_s): Fraction of successfully transmitted packets.

Step 2.4: Augmented Feedback

Augmented feedback is generated by incorporating predictive models (e.g., for energy consumption and traffic estimation) and information from neighboring nodes (e.g., congestion and route conditions). This augmented feedback enhances the agent's understanding of future outcomes based on its current actions.

Let $\hat{f}(S_t, a_t)$ represent the predictive model for energy and traffic. The augmented feedback is given as: where $\hat{f}(S_t, a_t)$ is the predicted future impact of action a_t on energy and traffic conditions and δ is the augmentation factor that balances the standard and augmented feedback.

$$R_{avg}(s_t, a_t) = R(s_t, a_t) + \delta.\hat{f}(S_t, a_t)$$

Step 2.5: Policy Update

The RL agent updates its policy based on the augmented reward $R_{avg}(s_t, a_t)$. If using Q-Learning, the Q-values are updated as follows: Where α is the learning rate. γ is the discount factor for future rewards. $Q(s_{t+1}, a')$ is the maximum expected future reward for the next state s_{t+1}.

$$Q(S_t, a_t) \leftarrow Q(S_t, a_t) + \alpha\left(R_{avg}(s_t, a_t) + \gamma \max_{a} Q(s_{t+1}, a') - Q(S_t, a_t)\right)$$

Stage 3: Optimization Phase

The RL algorithm (e.g., Q-learning or Deep Q-Networks (DQN)) optimizes the agent's policy using augmented rewards. The learning continues over time as real-time data from the network allows the agent to adapt to changes in topology, traffic patterns, and node failures.

Step 3.1: Real-Time Model Updates

To ensure that the agent adapts to dynamic network conditions, the policy is periodically updated using real-time feedback. For example:

- If a node's energy drops below a threshold, the agent may prioritize energy-saving actions.
- If network traffic increases, the agent may optimize routing paths to reduce congestion.

Stage 4: Resource Allocation Decision

Based on the learned policy, the agent dynamically adjusts its resource allocation decisions. At each time step, the agent selects actions that minimize energy consumption and maximize network throughput.

Step 4.1: Transmission Power Adjustment

The agent decides whether to increase or decrease the node's transmission power based on its current energy and link quality: where P_{tx} is the transmission power, E_i is the remaining energy, and Q_{ij} is the link quality.

$$P_{tx} = f(E_i, Q_{ij})$$

Step 4.2: Routing Path Selection

The agent selects the optimal route for data transmission based on its learned policy. The selected path minimizes latency and avoids congested nodes: Where L_{path} is the path latency and Q_{path} is the link quality along the path.

$$Route = arg\min_{path}\left(\frac{L_{path}}{Q_{path}}\right)$$

Step 4.3: Sleep Cycle Scheduling

The agent determines the sleep schedule for the node to maximize energy savings while maintaining data transmission requirements. The decision is based on the node's traffic load and energy level:

$$Sleep\ Cycle = f(T_i, E_i)$$

Result And Discussion

The performance of the proposed enhanced learning approach (ELA) with the existing deep neural network (DNN), artificial neural network (ANN), and support vector machine (SVM) for the resource allocation in WSN.

Table 1 depicts the energy consumption (in Joules) obtained by the proposed ELA, DNN, ANN, and SVM for the resource allocation in WSN. From Table 1, ELA consistently shows lower energy consumption across the range of nodes, demonstrating its ability to efficiently allocate resources as the network scales. DNN, ANN, and SVM consume more energy due to less optimized resource management, especially in larger networks. Energy consumption increases with the number of nodes for all approaches, but the rate of increase is lower for ELA, showing its scalability and adaptability to larger networks.

Table 2 depicts the network lifetime (in Hours) obtained by the Proposed ELA, DNN, ANN, and SVM for the resource allocation in WSN. From Table 2, ELA consistently achieves a longer network lifetime across various node counts, highlighting its ability to efficiently manage energy and prolong network operation. DNN, ANN, and SVM show shorter network lifetimes due to less efficient energy optimization, particularly as the network size grows. Network lifetime decreases with an increase in node count for all approaches, but ELA maintains a slower rate of decrease, showing its scalability and adaptability to larger networks.

Table 3 depicts the packet delivery ratio (PDF) obtained by the proposed ELA, DNN, ANN and SVM. From Table 3, ELA consistently achieves a higher PDR across all node counts, indicating better data reliability and network performance. DNN, ANN, and SVM show lower PDRs due to less effective resource allocation, especially as the number of nodes grows. PDR slightly decreases as the number of nodes increases for all approaches, but ELA shows a smaller reduction rate, demonstrating its scalability and reliability in larger networks.

Table 1: Energy consumption (in Joules) obtained by the proposed ELA, DNN, ANN and SVM

Number of nodes	*Energy consumption (in Joules)*			
	ELA	*DNN*	*ANN*	*SVM*
80	50.4	65.2	68.9	70.3
100	52.7	69.8	72.5	74.1
120	56.3	75.1	78.3	80.7
140	58.9	80.4	83.6	86.2
160	61.5	85.9	88.1	91.5
180	64.1	91.3	92.7	96.8
200	66.7	96.8	97.3	102.1

Table 2: Network lifetime (in Hours) obtained by the proposed ELA, DNN, ANN and SVM

Number of nodes	*Network lifetime (in Hours)*			
	ELA	*DNN*	*ANN*	*SVM*
80	420	360	345	335
100	410	350	340	330
120	400	340	330	320
140	390	330	325	310
160	380	320	315	300
180	370	310	305	290
200	360	300	295	280

Table 3: Packet delivery ratio (PDF) obtained by the proposed ELA, DNN, ANN and SVM

Number of nodes	*Packet delivery ratio (PDF in %)*			
	ELA	*DNN*	*ANN*	*SVM*
80	98.5	96.2	95.8	94.3
100	97.8	95.7	94.9	93.4
120	97.3	95.2	94.5	92.8
140	96.8	94.7	93.9	92.1
160	96.4	94.3	93.4	91.6
180	95.9	93.8	92.8	91
200	95.5	93.3	92.4	90.5

Table 4: End-to-end delay (in Milliseconds) obtained by the proposed ELA, DNN, ANN and SVM

Number of nodes	*End-to-end delay (in Milliseconds)*			
	ELA	*DNN*	*ANN*	*SVM*
80	10.3	12.6	13.2	13.9
100	10.8	13.1	13.7	14.4
120	11.4	13.7	14.3	15.1
140	11.9	14.3	14.9	15.7
160	12.5	14.9	15.5	16.3
180	13.1	15.5	16.1	17
200	13.7	16.1	16.7	17.6

Table 5: Throughput (in kbps) obtained by the proposed ELA, DNN, ANN and SVM

Number of nodes	*Throughput (in kbps)*			
	ELA	*DNN*	*ANN*	*SVM*
80	180.2	160.5	155.3	150.6
100	178.9	158.2	153.8	148.9
120	176.3	156	151.4	146.5
140	174.8	154.3	149.8	144.1
160	172.5	152.7	148.1	142.8
180	170.2	151	146.5	141.3
200	168.4	149.5	144.9	139.8

Table 4 depicts the end-to-end delay (in Milliseconds) obtained by the proposed ELA, DNN, ANN and SVM. From Table 4, ELA consistently achieves a higher PDR across all node counts, indicating better data reliability and network performance. DNN, ANN, and SVM show lower PDRs due to less effective resource allocation, especially as the number of nodes grows. PDR slightly decreases as the number of nodes increases for all approaches, but ELA shows a smaller reduction rate, demonstrating its scalability and reliability in larger networks.

Table 5 depicts the throughput (in kbps) obtained by the proposed ELA, DNN, ANN and SVM. From Table 5, ELA consistently achieves higher throughput across different numbers of nodes, indicating better data transmission capacity and network performance. DNN, ANN, and SVM yield lower throughput as network size increases due to less efficient resource management and congestion control. Throughput decreases slightly as the number of nodes increases for all approaches, but the decrease is less significant for ELA, showcasing its ability to handle larger network sizes while maintaining effective data transmission.

Conclusion

Efficient resource allocation in wireless sensor networks (WSNs) is critical for maximizing network performance and longevity, especially given the energy constraints and communication demands of these networks. The proposed enhanced learning approach (ELA) demonstrates significant improvements in energy efficiency, network lifetime, packet delivery ratio, end-to-end delay, and throughput when compared to existing methods like deep neural networks (DNN), artificial neural networks (ANN), and support vector machines (SVM). By leveraging augmented learning, ELA can dynamically adapt to changing network conditions, enabling more precise control over resource usage, such as node transmission power, routing path selection, and node scheduling.

The enhanced performance of ELA in maintaining high data transmission rates, low latency, and balanced energy consumption highlights its suitability for scalable and real-time WSN applications. These advantages not only reduce the frequency of node replacements due to battery depletion but also ensure reliable communication for applications requiring timely data transmission, such as environmental monitoring, industrial automation, and smart infrastructure. Future research can focus on further refining ELA by incorporating advanced optimization techniques and exploring its applicability in diverse, large-scale IoT ecosystems. Overall, ELA offers a robust solution for resource management challenges in WSNs, supporting both current and evolving needs in the field.

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