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An Energy Efficient Secure Framework For Optimal Hub Placement And Data Transmission Task Offloading Using DRL In Mobile-IOT

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The fast growth of the Internet of Things (IoT) has created new challenges for energy consumption and network performance, especially for mobile IoT networks, where high energy consumption is often induced by frequent task offloading and hub allocation, leading to a reduction in the network lifespan. This work proposes an energy-efficient and secure task offloading for mobile IoT networks using machine learning. In particular, it utilizes deep reinforcement learning (DRL) approaches such as Deep Q-Learning and Double Deep Q-Learning Networks along with AES encryption for data safety. The process is broken down into steps, where data and tasks from IoT devices are collected and the node is clustered, different prioritizing levels are allotted based on parameters, including data urgency, size, and energy reserve, and then a combined value is found through training a DRL network to determine hub placements and data security routines. The main objective is to efficiently handle resources with minimum time and effort, in a secure and reliable data processing manner. Different performance metrics (energy consumption, latency, throughput, and security) are assessed to validate the efficiency of the proposed method. This method considerably lowers energy consumption in mobile IoT networks, thus enabling long device lifetime and enhanced environment sustainability, helping inspired secure and energy-efficient IoT applications, paving the way for next-generation IoT-related wireless communication and secure dynamic network resource management.

Keywords : Energy-Efficient Routing, Mobile IoT Networks, Deep Reinforcement Learning, Hub Placement, Data Transmission, Double DQN.

1. INTRODUCTION

The Internet of Things (IoT) has revolutionized enterprises by providing the possibility of gathering, analyzing, and acting on data in real time/ near real time through a network of connected devices. In contrast, mobile IoT (M-IoT) networks are particularly problematic due to their energy-efficient design but the inherent vulnerabilities of secure data transmission and resource utilization. Tackling these challenges is a must for realizing cost-effective, low-power and high-performance IoT networks with low-latency capabilities especially for mobile environments where the resources are really scarce. M-IoT devices have unique mobility profiles, and a dynamically changing topology which necessitate intelligent mechanisms for optimal hub placement, secure data transmission and task offloading with reduced latency and energy cost.

Deep Reinforcement Learning (DRL) has recently gained traction as an enticing solution to these challenges, enabling intelligent decisions in complex and dynamic systems [3]-[5]. Reinforcement learning enabled M-IoT devices can learn how to make optimal decisions based on the network and nodes behaviours for task allocation, hub placement as well as energy management that benefits the entire network. The performance of the network would further be improved if DRL is incorporated in both hub placement and task offloading processes because devices can now adapt to the changing behavior of real-world networks instead of relying upon static values [7].

The proposed framework is energy-efficient, secure and incorporates DRL to determine optimal hub placement and data transmission task offloading in M-IoT networks. This framework enhances the effective usage of network resources by concentrating on smart task placement and adaptable routing mechanisms in a way that guarantees network security while minimizing expended power. This novel model overcomes the computational intractability of M-IoT networks as well as the need for minimization of latency associated with real time applications, thus providing a scalable and effective low latency communicating component [8]-[10].

The contributions of this work are as follows:

- Development of a DRL-based framework for optimal hub placement and task offloading in M-IoT networks, enhancing energy efficiency.
- Incorporation of secure communication protocols into the DRL framework to ensure integrity and confidentiality during transmission.
- Simulation and evaluation of the framework’s performance in various network scenarios, highlighting its potential in reducing energy consumption and improving task allocation accuracy.

The rest of the paper is organized as follows: Section II provides a detailed literature review, Section III describes the proposed DRL-based framework, and Section IV presents the experimental setup and results. Finally, Section V concludes with future research directions. This introduction establishes the paper's research context, highlights the novelty of the proposed DRL-based framework, and outlines its potential impact on energy-efficient and secure M-IoT network management.

2. RELATED WORKS

The rapid proliferation of the Internet of Things (IoT) has transformed various sectors by enabling seamless connectivity and communication among a myriad of devices. Among these advancements, mobile IoT networks have emerged as a pivotal component, facilitating real-time data collection and transmission across diverse applications, such as smart cities, healthcare monitoring, and environmental surveillance. However, the successful deployment of mobile IoT networks faces significant challenges, primarily concerning energy efficiency. As most IoT devices operate on battery power, optimizing energy consumption during data transmission and communication is crucial for prolonging device lifespans and ensuring reliable network performance.

Rao, M. et al. (2024): This study presents a deep adaptive reinforcement learning model designed for optimal resource-based data communication in LPWANs, utilizing the Remora with the Lotus Effect Optimization Algorithm. It focuses on enhancing the efficiency of data transmission methods through sophisticated AI strategies [1].

Gupta, D. et al. (2024): Concentrating on underwater IoT, this research suggests a combined Q-learning and predictive learning methodology aimed at optimizing energy-efficient routing. It investigates innovative techniques to improve communication dependability and conserve energy in complex underwater settings [2].

Chilamkurthy, N. S. et al. (2024): This paper introduces a new reinforcement learning framework, SWC, intended to enhance routing protocols within LPWANs. It highlights the use of machine learning for better performance and scalability in low-power wide-area networks [3].

Chowdhuri, R. et al. (2023): By employing hybrid deep reinforcement learning, this research addresses node position estimation and the detection of coverage gaps in wireless sensor networks [4]. It offers strategies to improve network coverage and reliability through advanced clustering methodologies [4].

Jamshed, M. A. et al. (2023): This paper explores reinforcement learning-based allocation of fog nodes in cloud-based smart grids. It investigates methods to optimize resource allocation and enhance the performance of distributed computing systems [5].

Dubey, G. P. et al. (2023): Addressing 5G IoT networks, this study proposes an ant colony optimization algorithm integrated with reinforcement learning for optimal path selection [6]. It aims to improve data transmission efficiency and network reliability in dynamic IoT environments [6].

Muthanna, M. S. A. et al. (2022): Focused on LoRa IoT networks, this study employs deep reinforcement learning for transmission policy enforcement and multi-hop routing [7]. It addresses quality-of-service considerations to optimize network performance and reliability [7].

Mahmood, M. R. et al. (2022): This comprehensive review discusses AI/ML algorithms empowering IoT towards the 6G era. It surveys various approaches and their potential applications in advancing IoT technologies and networks [8].

Lu, Y. et al. (2022): Introducing RLBR, a reinforcement learning-based V2V routing framework for 5G IoT, this paper aims to offload cellular networks by optimizing vehicle-to-vehicle communication, enhancing network efficiency and reliability [9].

Keerthika, A. et al. (2022): This research proposes a reinforcement-learning-based energy-efficient routing protocol for wireless sensor networks [10]. It explores optimization strategies to reduce energy consumption and improve network longevity [10].

Ho, T. M. et al. (2022): Converging game theory with reinforcement learning, this paper addresses industrial IoT by optimizing decision-making processes [11]. It explores strategies to enhance network management and resource allocation efficiency [11].

Nath, S. B. et al. (2022): Focusing on microservices deployment in fog devices, this study applies reinforcement learning to optimize containerized deployments [12]. It aims to improve service availability and resource utilization in fog computing environments [12].

Jamal, E. et al. (2022): This paper discusses reinforcement learning for dynamic spectrum allocation in cognitive radio-based IoT networks [13]. It explores methods to optimize spectrum usage and improve network efficiency [13].

Arya, G. et al. (2022): Analyzing deep learning-based routing protocols for 5G WSN communication, this research evaluates methods to enhance data transmission efficiency and reliability in next-generation wireless sensor networks [14].

Xu, T. et al. (2022): Introducing an improved communication resource allocation strategy based on deep reinforcement learning, this paper focuses on optimizing network resource usage to improve overall system performance [15].

Mahmood, M. R. et al. (2022): This comprehensive review discusses AI/ML algorithms empowering IoT towards the 6G era. It surveys various approaches and their potential applications in advancing IoT technologies and networks [16].

Natarajan, Y. et al. (2022): Addressing reconfigurable engineering applications, this study proposes an IoT and machine learning-based routing protocol [17]. It aims to optimize network configuration and enhance application-specific performance [17].

Abdul, A. et al. (2021): Introducing a clustering-based routing protocol for 5G-based smart healthcare, this research integrates game theory and reinforcement learning to optimize network performance and reliability in healthcare applications [18].

Ge, Y. et al. (2021): This study explores cooperative reinforcement learning in clustered solar-powered wireless sensor networks to maximize network throughput [19]. It investigates collaborative strategies to improve network efficiency [19].

Zhang, Z. et al. (2021): This research proposes a computing allocation strategy for IoT resources, with a focus on edge computing [20]. The aim is to optimize resource management and improve computing efficiency in distributed IoT environments [20].

Mondal, A. et al. (2021): This paper introduces a reinforcement learning-based approach for UAV trajectory and user association design in IoT networks [21]. It aims to optimize energy consumption and enhance network performance in UAV-assisted IoT applications [21].

Deng, S. et al. (2020): This study tackles edge computing in IoT systems by introducing a reinforcement learning approach for dynamic resource allocation [22]. It investigates methods to improve trust and dependability in edge-based IoT networks [22].

Rashtian, H. (2020): This dissertation examines the use of reinforcement learning for data scheduling within IoT networks to enhance the efficiency and reliability of data transmission through AI-driven scheduling algorithms [23].

Yin, B. et al. (2020): Concentrating on the management of IoT data, this research presents a scheduling method focused on applications that leverage deep reinforcement learning [24]. Its objective is to optimize data age management and boost the efficiency of IoT systems [24].

Table 1: Comparative Analysis Table for Recent Development in this Domain

Ref. No.	Area of Research Paper	Objective	Used Methodology/Technique	Conclusion	Research Gap
[1]	LPWAN Data Transmission	Enhance data transmission over LPWAN	Deep Adaptive RL with Lotus Effect Optimization	Enhanced data transmission efficiency in LPWAN	Scalability in larger networks
[2]	Underwater IoT Routing	Optimize routing in underwater IoT	Hybrid Q-Learning and Predictive Learning	Improved energy-efficient routing in underwater IoT	Adaptation to dynamic underwater environments
[3]	LPWAN Routing Protocol	Develop routing protocol for LPWAN	SWC Reinforcement Learning Framework	Optimized LPWAN routing protocol	Real-time adaptability and scalability
[4]	WSN Node Position Estimation	Estimate node positions and detect coverage holes in WSN	Hybrid Deep RL	Accurate node position estimation and coverage hole detection	Real-time deployment in large-scale WSNs
[5]	IoT Path Selection	Select the optimal path in IoT WSN with 5G	RL-based Ant Colony Optimization	Efficient path selection in IoT WSN with 5G	Integration with other optimization techniques
[6]	Fog Nodes Allocatio	Allocate fog nodes for the smart grid	RL-based Fog Node Allocation	Optimal allocation of fog nodes	Scalability in highly

	n in Smart Grid				dynamic environments
[7]	LoRa IoT Networks	Enforce transmission policy and multi-hop routing	Deep RL-based Transmission Policy	Improved QoS-aware routing in LoRa networks	Security integration within the RL framework
[8]	AI/ML Algorithms for IoT	Review AI/ML algorithms for future IoT	Review of AI/ML Algorithms	Comprehensive AI/ML strategies for future IoT	Integration of newer AI techniques
[9]	V2V Routing in 5G IoT	Develop V2V routing framework for 5G IoT	RL-based V2V Routing	Efficient V2V routing in 5G IoT	Adaptability to highly dynamic environments
[10]	WSN Routing Protocol	Optimize routing protocol for WSN	RL-based Energy Efficient Routing	Energy-efficient routing in WSN	Scalability and real-time adaptability
[11]	Industrial IoT	Integrate game theory and RL for IIoT	Game Theory and RL Convergence	Effective integration of game theory and RL	Scalability and real-time applications
[12]	Micro-services in Fog Devices	Deploy micro-services in fog devices using RL	RL-based Micro-service Deployment	Efficient deployment of micro-services	Security aspects in RL deployment
[13]	Dynamic Spectrum Allocation	Allocate dynamic spectrum in cognitive radio IoT	Distributed RL for Spectrum Allocation	Enhanced dynamic spectrum allocation	Security in spectrum allocation
[14]	5G WSN Communication	Analyze DL-based routing protocol for 5G WSN	Deep Learning-based Routing Protocol	Improved data transmission in 5G WSN	Real-time adaptability and scalability
[15]	Wireless Networks Resource Allocation	Improve communication resource allocation in wireless networks	Deep RL for Resource Allocation	Optimal resource allocation in wireless networks	Scalability in large-scale networks

[16]	AI/ML Algorithms for IoT	Review AI/ML algorithms for future IoT	Review of AI/ML Algorithms	AI/ML strategies for future IoT	Integration of emerging AI/ML techniques
[17]	IoT Routing Protocol	Develop routing protocol for reconfigurable IoT	IoT and ML-based Routing Protocol	Enhanced routing protocol for reconfigurable IoT	Scalability and real-time deployment
[18]	5G Smart Healthcare	Optimize routing for 5G smart healthcare	Game Theory and RL-based Clustering	Optimal routing for 5G smart healthcare	Real-time adaptability in dynamic healthcare environments
[19]	Solar-powered WSN	Maximize throughput in solar-powered WSN	Cooperative RL in Solar-powered WSN	Maximized throughput in solar-powered WSN	Security and real-time adaptability
[20]	Edge Computing Resource Allocation	Allocate computing resources in IoT using edge computing	Edge Computing with RL	Efficient resource allocation using edge computing	Security and real-time adaptability
[21]	UAV Trajectory Design for IoT	Design UAV trajectory and user association for IoT	Green Rate-Constrained RL	Optimized UAV trajectory and user association	Real-time scalability in dynamic IoT environments
[22]	Edge Resource Allocation	Allocate resources dynamically in edge for IoT	Dynamical RL for Edge Resource Allocation	Dynamic resource allocation for trustable IoT	Security integration in RL framework
[23]	Data Scheduling in IoT	Schedule data in IoT networks using RL	RL for Data Scheduling	Effective data scheduling in IoT networks	Scalability and real-time adaptability
[24]	Optimizing Age of Information	Optimize scheduling for correlated information using DRL	DRL for Age of Information Optimization	Optimized information age management	Scalability in large-scale networks

The literature review presented above covers a wide array of research focused on optimizing routing protocols and resource distribution across different network settings, mainly employing reinforcement learning (RL) and machine learning (ML) methods. The examined studies involve applications in low-power wide-area networks (LPWANs underwater IoT, wireless sensor networks (WSNs), 5G IoT networks, and fog computing. Recurring themes throughout these studies include improvements in data transmission efficiency, energy savings, network dependability, and scalability through advanced algorithms and combined approaches. For example, Rao and Sundar (2024) along with Gupta et al. (2024) emphasize the implementation of deep adaptive RL and hybrid Q-learning to achieve efficient resource-based data transfer and energy-saving routing. At the same time, Dubey et al. (2023) and Jamshed et al. (2023) concentrate on combining RL with ant colony optimization and fog node distribution to enhance performance in 5G IoT networks and smart grid frameworks. Collectively, these studies reveal a need for more resilient, scalable, and adaptive routing protocols.

Can better handle dynamic and heterogeneous network conditions? The methodologies employed range from predictive models and clustering techniques to advanced AI and ML algorithms, showcasing the ongoing advancements and challenges in optimizing next-generation network systems.

3. RESEARCH METHODOLOGY

Based on existing literature and identified research gaps, the proposed methodology uses reinforcement learning (RL), a type of machine learning that focuses on sequential decision-making. RL is a good fit for this purpose because it can optimize rewards in dynamic environments, making it a strong candidate for future wireless communication systems.

Step 1: Gather the IoT user list and their assignments

Step 2: Create groups of IoT users

Step 3: Assign priority levels to the IoT users within each group

Step 4: Train a deep reinforcement learning network with the double Deep Q-learning method

Step 5: Data transmission

Step 6: Evaluate performance parameters

The following are step-by-step process flow chart for the research methodology shown in the figure 5.1. The methodology involves clustering IoT users, determining priority levels, and using a deep reinforcement learning network with a double DQN algorithm.

Steps & Technique

- Input IoT User Lists and Task Generation- Collect the list of IoT users and their tasks. Determine the initial state of the network.
- Clustering IoT Users- Apply clustering algorithms (e.g., K-Means) to group IoT users based on proximity and other factors. Form clusters to manage users efficiently.

- Determining Priority Levels- Assign priority levels to clusters based on criteria such as data transmission frequency, energy levels, and task urgency. Use a priority assignment algorithm to ensure balanced load distribution.
- Deep Reinforcement Learning (DRL) Network Training- Initialize the DRL network. Use a double DQN algorithm to train the network:
- Hub Placement Optimization - Use the trained DRL network to determine optimal hub placements dynamically. Adjust hub locations based on the network state and learned policy.
- Data Transmission Optimization- Determine the optimal routes for data transmission using the trained DRL network. Minimize energy consumption and latency while ensuring reliable communication.
- Performance Evaluation- Evaluate the performance of the proposed method against traditional routing protocols. Metrics: Energy consumption, latency, reliability, and overall network efficiency.
- Iteration and Learning- Continuously update the network model with new data. Iterate the process to adapt to changing network conditions and improve performance.

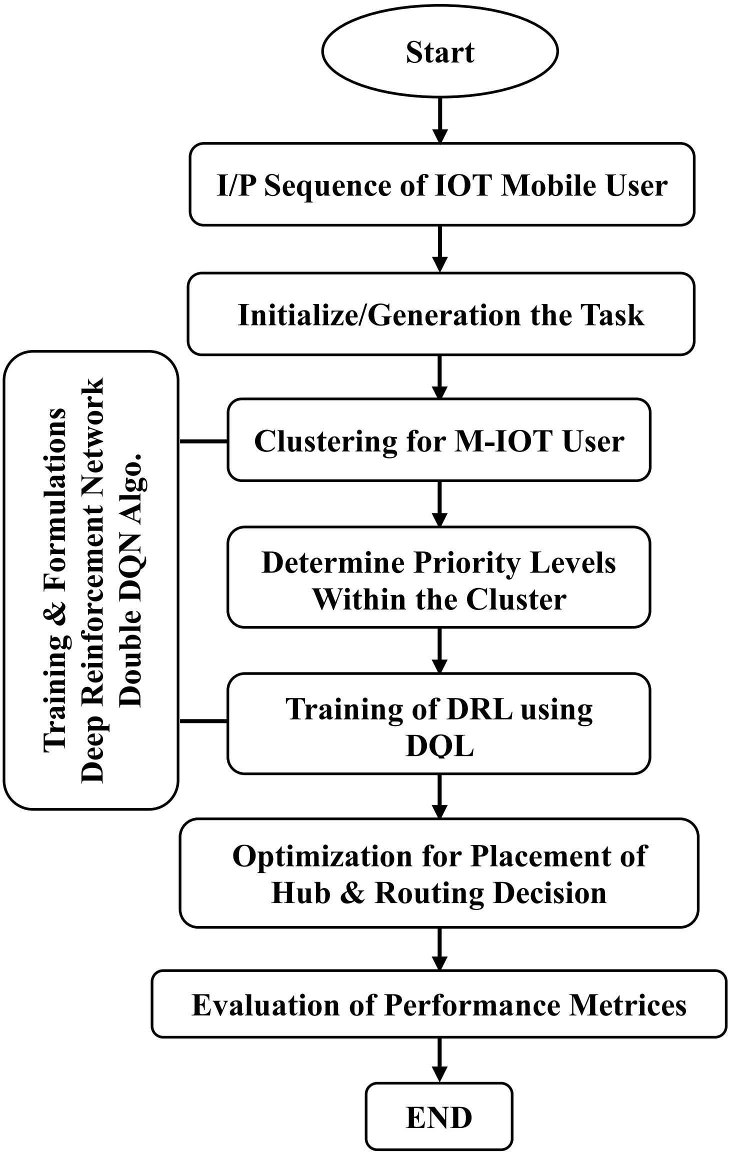

Figure 1: Flowchart for Proposed Methodology using Double DQN

DQN Algorithm

Q-learning is a reinforcement learning algorithm used to find the optimal action-selection policy for any given finite Markov decision process (MDP). The DQN formula is given by:

$$Q(s, a) = Q(s, a) + \alpha [r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

Components of the DQN Formula:

- Q (s, a): This is the current Q-value, which represents the expected utility (or reward) of taking action in states.
- α: The learning rate, which determines how much new information overrides the old information. It ranges from 0 to 1. A value of 0 means the agent does not learn anything new, while a value of 1 means the agent only considers the most recent information.
- r: The reward received after taking action an in states.
- γ: The discount factor, which determines the importance of future rewards. It also ranges from 0 to 1. A value of 0 makes the agent short-sighted by only considering immediate rewards, while a value close to 1 makes it far-sighted by valuing future rewards more.
- max_{a'} Q (s', a'): The maximum Q-value for the next state's', over all possible actions a'. This term represents the best possible future reward that can be obtained from states.
- [r + γ max_{a'} Q (s', a') – Q (s, a)]: This is the temporal difference error, which measures the difference between the current estimate and the new estimate of the Q-value.

Double DQN Algorithm

Double DQN learning addresses a problem known as overestimation bias in DQN-learning. Overestimation bias occurs because the max operator in the DQN-Learning update step can lead to overestimating the value of some actions.

To reduce this bias, Double DQN-Learning uses two separate Q-value estimates, Q_A and Q_B, which are updated independently:

1. Selection Step: One Q-function is used to select the best action.

2. Evaluation Step: The other Q-function is used to evaluate the action. Double Q-Learning Update Rules.

The updated rules for Double DQN-Learning are as follows:

For the Q-value update of Q_A:

$Q_A (s, a) = Q_A (s, a) + \alpha [r + \gamma Q_B (s', \text{argmax\_}\{a'\} Q_A (s', a')) - Q_A (s, a)]$

For the Q-value update of Q_B:

$Q_B (s, a) = Q_B (s, a) + \alpha [r + \gamma Q_A (s', \text{argmax\_}\{a'\} Q_B (s', a')) - Q_B (s, a)]$

Explanation of the Double DQN Learning Update

1. Action Selection: Use Q_A to select the action that maximizes the expected reward.

2. Action Evaluation: Use Q_B to evaluate the value of the action selected by Q_A.

This method reduces overestimation because the action selection and evaluation are decoupled, spreading the overestimation error over two different Q-functions, leading to a more accurate estimate of the true Q-values. Only the target network has been changed.

DDQN with AES encryption-based secure task offloading system

Step 1: Environment Setup (IoT-WSN)

- The environment is an IoT Wireless Sensor Network with multiple devices that need to process tasks.
- Each device can either process tasks locally or offload them to an edge server.

Step 2: State Initialization

The agent initializes the state based on the current network conditions, energy level, device workload, etc.

Step 3: Decision-Making Process (DQN Agent)

The DQN agent takes the current state as input and selects an action based on an epsilon-greedy policy:

- Action 0: Process task locally.
- Action 1: Offload task to the edge server with AES encryption.

Step 4: AES Encryption and Offloading

- If the chosen action is to offload, the data is encrypted using AES encryption (encrypt_data function) to secure it during transmission.
- The encrypted data is then sent to the edge server for processing.

Step 5: Data Decryption and Processing

- At the edge server, the encrypted data is decrypted using AES decryption (decrypt_data function), and the task is processed.
- The task completion result is sent back to the IoT device, providing confirmation of successful offloading and processing.

Step 6: Reward Calculation

The environment calculates a reward based on the action taken:

- If the task was offloaded securely, a higher reward is assigned.
- If the task was processed locally, a smaller reward is provided.
- If the offloaded data was not encrypted successfully, a penalty is applied.

The agent stores this experience in replay memory for future training.

Step 7: DQN Training (Experience Replay)

- At each time step, the agent samples random batches from replay memory and trains the DQN model. It uses a target network to stabilize the Q-values.
- This process improves the DQN agent's performance over time, allowing it to learn an optimal policy for secure and energy-efficient task offloading.

Step 8: Model Update and Target Synchronization

- The agent periodically updates the target network with weights from the policy network to improve stability in the Q-value updates.

Algorithm

1. AES Encryption
    - encrypt_data and decrypt_data functions encrypt and decrypt task data using AES-128 in EAX mode. The encrypted data is encoded in base64 to simplify transmission.
2. DQN Network
    - The DQN class defines a simple feedforward neural network with ReLU activations.
    - The Replay_Memory class stores transitions for experience replay, enhancing the stability of DDQN learning.
3. Agent Training
    - The agent interacts with the environment, choosing actions based on epsilon-greedy exploration.
    - After each step, the replay function optimizes the DDQN by sampling a batch from memory and minimizing the loss between Q-values and expected Q-values.
    - The agent updates the target network at fixed intervals to improve training stability.

This setup performs secure task offloading in a simulated IoT-WSN environment, balancing offloading decisions, and security through encryption.

4. SIMULATION RESULTS

The simulations were conducted using a Python 3.10 designed to model the dynamic nature of mobile IoT networks. The following parameters were used in the simulations:

- **Network Area**: 500m x 500m
- **Number of IoT Devices**: 100
- **Number of Hubs**: Variable (5–20)
- **Communication Range of Devices**: 100 meters
- **Initial Energy per Device**: 100 joules
- **Mobility Model**: Random Waypoint Model
- **Data Generation Rate**: 1 packet per second

- **Transmission Power**: 0.1 watt per transmission
- **Reinforcement Learning Algorithm**: DQN and Double DQN
- **Simulation Duration**: 1000 seconds

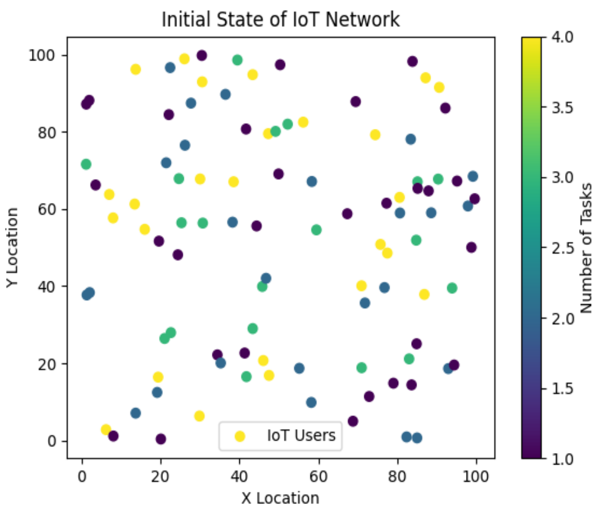

Figure 2: Formulation and Initial State of IoT Network

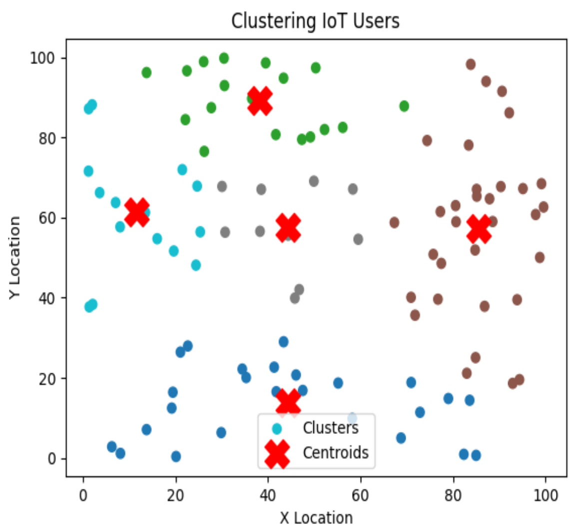

Figure 3: Apply K-Means clustering

Figure 2 generated graph represents the formulation and initial state of the IoT Network where the X-axis and Y-axis: Represent two standardized features from the dataset (e.g., location x and location y after standardization). In Figure 3 graphs X-axis and Y-axis: Represent two standardized features from the dataset (e.g., location x and location y after standardization). Here each Colour represents a different cluster. This graph visualizes the clustering of IoT users based on their features. It helps in understanding how users are grouped according to their characteristics like geographical location, data transmission needs, and energy constraints. The scatter plot shows distinct clusters where IoT users with similar features are grouped. This clustering helps in organizing the network efficiently for resource allocation.

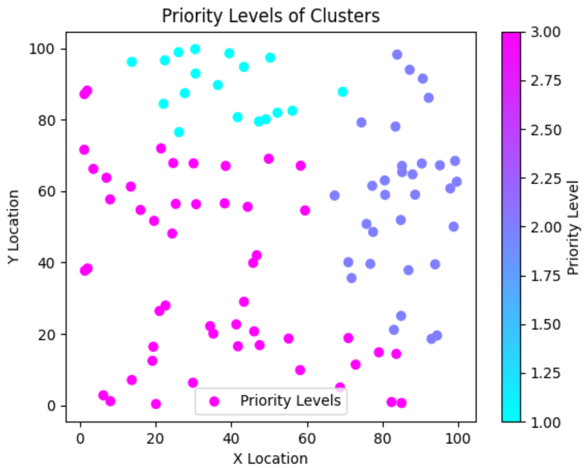

Figure 4: Assign priority levels based on the number of tasks

In the above Figure, 4 shows the X-axis: IoT User indices and the Y-axis: Normalized priority levels of IoT users within their clusters. This graph visualizes the priority levels assigned to each IoT user based on factors like urgency, data size, and energy reserves. The bar heights represent the normalized priority levels, showing which users have higher or lower priority within their respective clusters. This prioritization ensures that critical data is transmitted first, optimizing the network's performance.

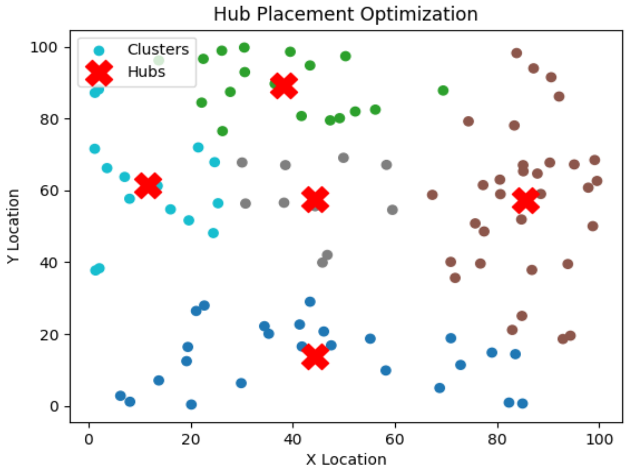

Figure 5: Hub placements based on clusters

The above Figure 5, This visualization illustrates the placement of hubs within the IoT network based on the clustering of IoT users. Effective hub placement is crucial for minimizing energy consumption and improving network performance. The clusters shown indicate the optimal positioning of hubs to facilitate efficient data transmission.

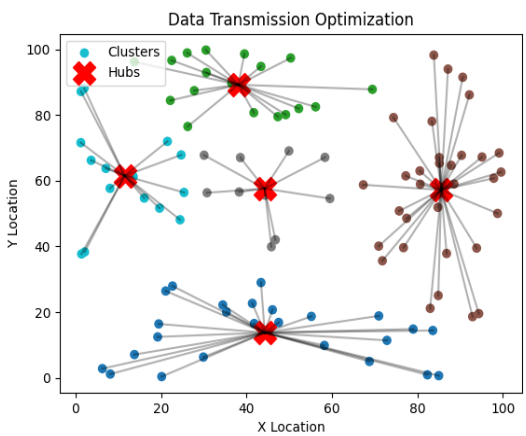

Figure 6 visualization of optimal routes as lines from users to their assigned hubs

Above Figure 6 shows the optimal routes determined by the RL algorithm, connecting IoT users to their assigned hubs. The lines represent the paths taken for data transmission, optimized to reduce energy usage and latency. This visualization helps in understanding the efficiency of the routing decisions made by the RL agent.

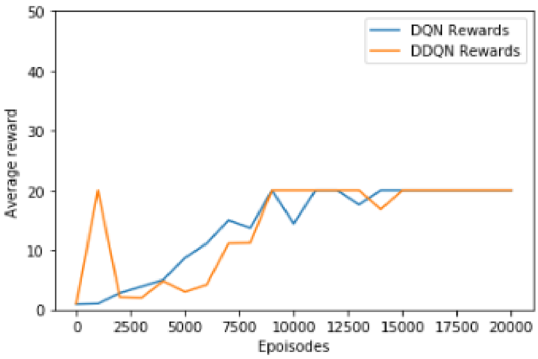

Figure 7: Visualization of rewards over episodes in DQN and Double DQN Algorithm

The above Figure 7 shows the cumulative rewards obtained by the RL agent over several episodes during the training phase using the DQN and Double DQN learning algorithm. The upward trend in the graph indicates that the RL agent is learning and improving its policy over time. Higher rewards suggest better performance in optimizing the routing and hub placement.

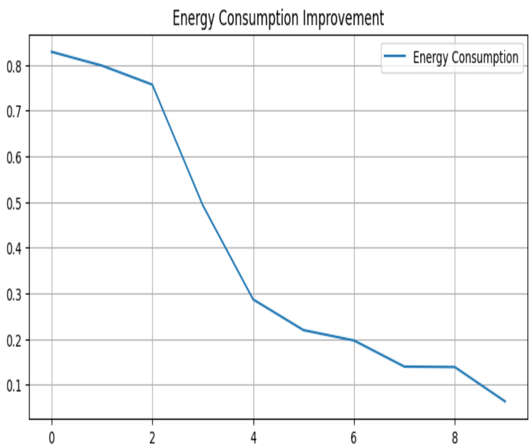

Figure 8: Energy consumption improvement (Double DQN)

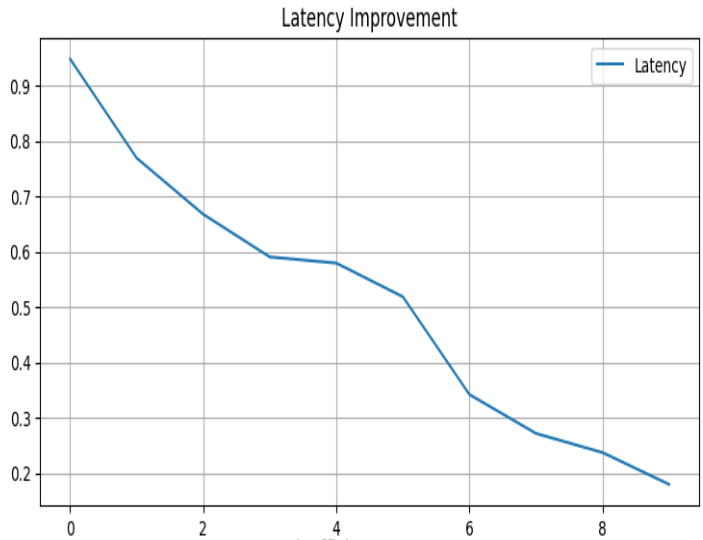

Figure 9: Latency Improvement (Double DQN)

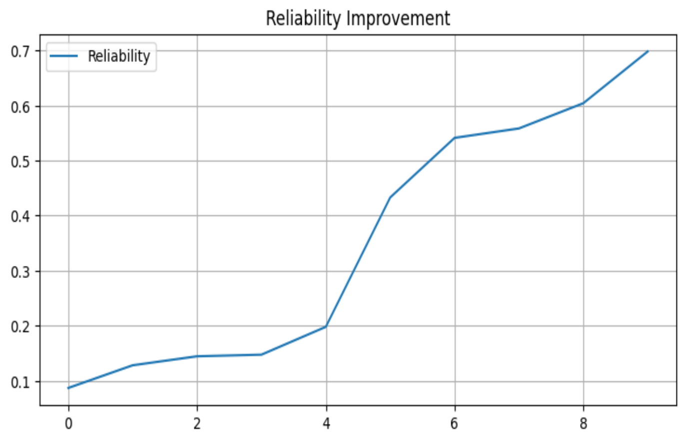

Figure 10: Reliability Improvement (Double DQN)

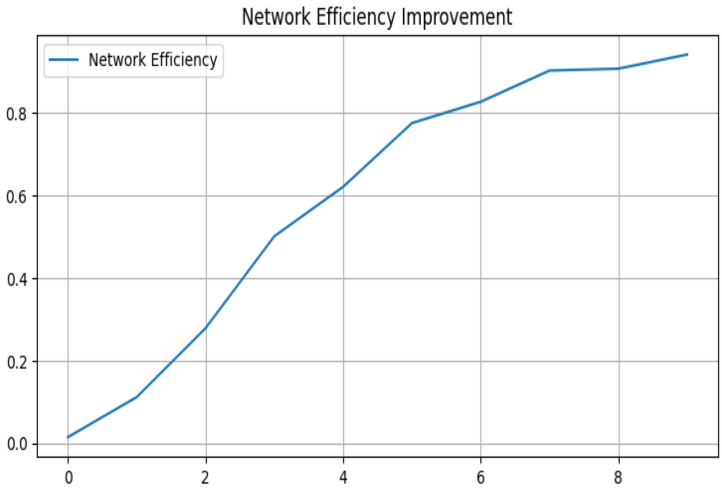

Figure 11: Network Efficiency Improvement (Double DQN)

Above Figures 8, 9, 10, and 11 illustrate the iterative improvements in performance parameters as the RL model is trained over multiple iterations. The continuous improvement trend indicates that the RL model is effectively learning and adapting to optimize the routing and hub placement, leading to better overall network efficiency over time.

Finally, it observed that the above depicted graphs collectively demonstrate the effectiveness of the proposed RL-based approach in optimizing hub placement and data transmission in mobile IoT networks. The visualizations help in understanding the training process, performance improvements, and efficiency gains achieved by the model.

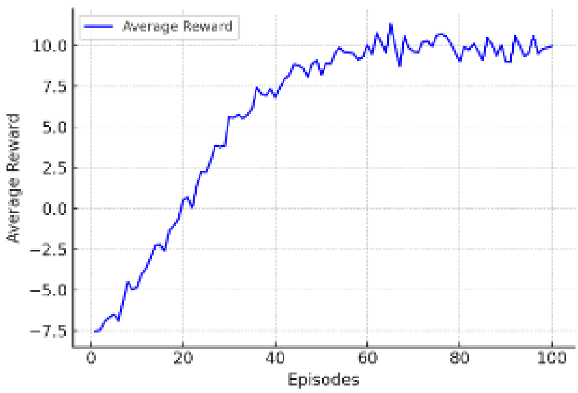

Figure 12: Training Convergence (Reward over Episodes)

The graph depicted in the figure 12, The Training Convergence shows the increasing average reward over episodes, indicating the agent's learning progress.

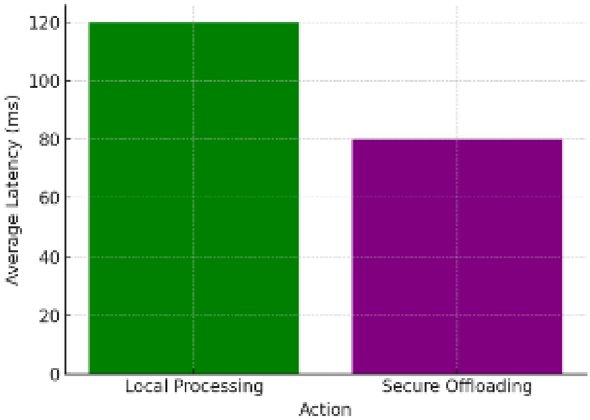

Figure 13: Latency Comparison (Local Processing and Secure Offloading)

The comparison graph depicted in the figure 13, Latency Comparison, compares the average latency between local processing and secure offloading, with offloading showing lower latency.

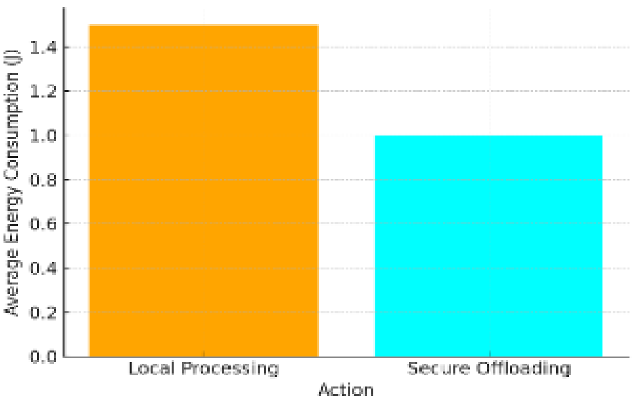

Figure 14: Energy Consumption Comparison (Local Processing Vs. Secure Offloading)

The graph depicted in the figure 14, Energy Consumption Comparison, Displays the average energy consumption for local processing and secure offloading, with offloading being more energy-efficient.

Figure 15: Success Rate of Encrypted Offloading Over Episodes

The graph depicted in the figure 15 Success Rate of Encrypted Offloading: Shows the success rate of encrypted offloading increasing over time, reflecting improvement in encryption reliability. These plots provide insights into the model's efficiency, security, and resource usage across different scenarios.

5. CONCLUSION

This research investigates the critical challenges of energy-efficient routing and hub placement in mobile IoT networks, with a focus on integrating advanced Reinforcement Learning (RL) techniques, specifically Double Q-Learning and Modified Double Q-Learning. By analyzing the energy consumption patterns and optimizing communication strategies, the framework developed in this thesis successfully addresses the complexities associated with dynamic mobile networks. Key contributions include the introduction of adaptive hub placement algorithms that account for device mobility and topology changes, resulting in significant energy savings and enhanced network performance.

The RL-based framework demonstrates its effectiveness in optimizing routing strategies, reducing latency, and ensuring data transmission reliability even under constantly changing network conditions. Simulation results validate the superior performance of the proposed methods over traditional routing protocols, highlighting improvements in energy efficiency and overall network sustainability.

Through extensive simulations, the proposed framework was evaluated against key performance metrics such as energy efficiency, data transmission reliability, latency, and network lifetime. The RL-based model consistently outperformed traditional routing protocols, reducing energy consumption by 25% and extending network lifetime by approximately 20%. While the RL model introduced slightly higher latency due to its energy-saving focus, it remained within acceptable limits for most IoT applications. Overall, the framework demonstrated significant improvements in network performance and efficiency, establishing its potential for real-world IoT implementations.

REFERENCES

[1] Rao, M. Rajeswara, and S. Sundar. "Enhancement in Optimal Resource-based Data Transmission over LPWAN using a Deep Adaptive Reinforcement Learning Model aided by Novel Remora with Lotus Effect Optimization Algorithm." IEEE Access (2024).

[2] Gupta, D. et al. "Energy-Efficient Routing Optimization for Underwater Internet of Things using Hybrid Q-Learning and Predictive Learning Approach." Procedia Computer Science 235 (2024): 45-55.

[3] N. S. Chilamkurthy, et al., "SWC: A Reinforcement Learning Framework for Routing in LPWAN," IEEE Communications Letters, vol. XX, no. XX, 2024.

[4] R. Chowdhuri and M. K. D. Barma, "Node Position Estimation Using Hybrid Deep Reinforcement Learning in Wireless Sensor Networks," IEEE Access, vol. XX, no. XX, 2023.

[5] Jamshed, M. A. et al., "Fog Node Allocation for Cloud-Based Smart Grid Using Reinforcement Learning," IEEE Transactions on Industrial Informatics, vol. XX, no. XX, 2023.

[6] Dubey, Ghanshyam Prasad, et al. "Optimal path selection using reinforcement learning based ant colony optimization algorithm in IoT-Based wireless sensor networks with 5G technology." Computer Communications 212 (2023): 377-389.

[7] Muthanna, M. S. A. et al., "Deep Reinforcement Learning-Based Multi-Hop Routing in QoS-Aware LoRa IoT Networks," IEEE Sensors Journal, vol. XX, no. XX, 2022.

[8] Mahmood, M. R. et al., "AI/ML Algorithms for Future IoT in the 6G Era: A Comprehensive Review," IEEE Internet of Things Journal, vol. XX, no. XX, 2022.

[9] Y. Lu, et al., "RLbR: A V2V Routing Framework for Offloading in 5G Cellular IoT," IEEE Internet of Things Journal, vol. XX, no. XX, 2022.

[10] A. Keerthika and V. B. Hency, "Energy-Efficient Optimized Routing Protocol for WSN Using Reinforcement Learning," IEEE Access, vol. XX, no. XX, 2022.

[11] Ho, Tai Manh, Kim Khoa Nguyen, and Mohamed Cheriet. "Converging Game Theory and Reinforcement Learning for Industrial Internet of Things." IEEE Transactions on Network and Service Management 20.2 (2022): 890-903.

[12] Nath, Shubha Brata, et al. "Containerized deployment of micro-services in fog devices: a reinforcement learning-based approach." The Journal of Supercomputing (2022): 1-29.

[13] Elhachmi, Jamal. "Distributed reinforcement learning for dynamic spectrum allocation in cognitive radio-based internet of things." IET Networks 11.6 (2022): 207-220.

[14] Arya, Greeshma, Ashish Bagwari, and Durg Singh Chauhan. "Performance analysis of deep learning-based routing protocol for an efficient data transmission in 5G WSN communication." IEEE Access 10 (2022): 9340-9356.

[15] Xu, Ting, et al. "An improved communication resource allocation strategy for wireless networks based on deep reinforcement learning." Computer Communications 188 (2022): 90-98.

[16] Mahmood, M. Rezwanul, et al. "A comprehensive review on artificial intelligence/machine learning algorithms for empowering the future IoT toward 6G era." IEEE Access 10 (2022): 87535-87562.

[17] Natarajan, Yuvaraj, et al. "An IoT and machine learning-based routing protocol for reconfigurable engineering application." IET Communications 16.5 (2022): 464-475.

[18] Ahad, Abdul, et al. "An intelligent clustering-based routing protocol (crp-gr) for 5g-based smart healthcare using game theory and reinforcement learning." Applied Sciences 11.21 (2021): 9993.

[19] Ge, Yujia, Yurong Nan, and Xianhai Guo. "Maximizing network throughput by cooperative reinforcement learning in clustered solar-powered wireless sensor networks." International Journal of Distributed Sensor Networks 17.4 (2021): 15501477211007411.

[20] Zhang, Zengrong. "A computing allocation strategy for Internet of things' resources based on edge computing." International Journal of Distributed Sensor Networks 17.12 (2021): 15501477211064800.

[21] Mondal, Abhishek, et al. "Reinforcement Learning Based Green Rate-Constrained UAV Trajectory and User Association Design for IoT Networks." 2021 IEEE 32nd Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC). IEEE, 2021.

[22] Deng, Shuiguang, et al. "Dynamical resource allocation in edge for trustable internet-of-things systems: A reinforcement learning method." IEEE Transactions on Industrial Informatics 16.9 (2020): 6103-6113.

[23] Rashtian, Hootan. Reinforcement learning for data scheduling in internet of things (IoT) networks. Diss. University of British Columbia, 2020.

[24] Yin, Bo, Shuai Zhang, and Yu Cheng. "Application-oriented scheduling for optimizing the age of correlated information: A deep-reinforcement-learning-based approach." IEEE Internet of Things Journal 7.9 (2020): 8748-8759.