OPTIMIZING ENERGY EFFICIENCY IN 5G-ENABLED WIRELESS SENSOR NETWORKS

**Abstract**

Wireless Sensor Networks (WSN), are now essential to industrial automation, environmental monitoring, and smart infrastructure. WSNs can attain more connectivity, reduced latency, and faster data rates by integrating 5G. The new technology 5G that promises faster speeds, reduced latency, and greater bandwidth than earlier technologies. Integrating 5G technology with WSNs has created new opportunities for improving energy efficiency and network performance. 5G networks and frequent handovers between base stations and sensor nodes increase energy consumption, while local processing reduces the cost of transmission but increases the cost of computation. However, as sensor nodes possess constrained resources, energy efficiency is still a critical issue. Three major techniques are presented in this paper to optimize energy efficiency in 5G-enabled WSNs. The Deep Learning Long Short-Term Memory (LSTM) handles time series data, making it ideal for detecting anomalies and predicting traffic patterns for proactive network management, While Particle Swarm Optimization (PSO) explores optimal routing paths based on energy efficiency, and Ant Colony Optimization (ACO) dynamically refines those paths based on real-time traffic and node status. Game Theory models strategic interactions between nodes and potential attackers, enabling dynamic resource allocation and defence against attacks. According to simulation results, the suggested method improves data integrity and low energy consuming and network security while lowering energy usage. Simulations show that the system detects data injection attacks with 95% accuracy and achieves a 92% packet delivery rate (PDR). It also reduces energy use by 14% compared to traditional methods, extending network lifetime. This confirms that using LSTM for anomaly detection, PSO and ACO for optimized routing, and Game Theory for defence improves the performance of 5G-enabled WSNs.

**Keywords:** 5G, WSNs, energy efficiency, anomaly, LSTM, PSO-ACO, Game Theory.

**1.Introduction**

WSN has emerged as a key enabling technology in modern communication networks, particularly in the era of 5G-enabled infrastructure. WSNs are made of many spatially dispersed sensor nodes that monitor environmental parameters, including temperature, pressure, humidity, and motion. The gathered data is transmitted to central nodes or base stations for additional processing [1]. The network of sensor nodes that make up a WSN gathers and sends information to a central base station for analysis. WSN capabilities have been improved by the deployment of 5G technology, which allows for large-scale connectivity, low latency, and high-speed data transfer [2].

This innovation enables WSNs to transmit data in real time and execute complicated computations, exceeding the constraints of 4G and prior technologies [3]. But even with these developments, a number of key challenges still persist, such as energy efficiency, network lifetime, secure communication, and real-time anomaly detection. Conventional WSN models use simple routing protocols and static clustering methods, which tend to produce suboptimal performance when network conditions change dynamically.

The introduction of malicious nodes and data injection attacks worsens the situation, causing higher energy usage, data loss, and communication delays [4]. Furthermore, traditional clustering algorithms select cluster heads randomly, resulting in inefficient energy consumption and increased vulnerability to attacks on critical nodes. To address these limitations, an optimized security mechanism is needed to accurately detect malicious behaviour and maintain network performance in 5G-enabled WSNs [5].

The proposed system detects real-time anomalies using an LSTM model that analyses network traffic features such as packet size, hop count, transmission rate, and sequence number. The system employs a combination of PSO and ACO for dynamic routing to ensure reliable data transmission and bypass affected nodes upon detecting a data injection attack. The LSTM-based anomaly detector effectively identifies false injection attacks with high accuracy and minimal false positives by learning the temporal patterns of network traffic. PSO explores the most energy-efficient paths for secure and energy-efficient routing, while ACO dynamically refines the routes according to current network circumstances. Game Theory integration improves network security by modelling strategic interactions between legal nodes and attackers, enabling dynamic resource allocation and attack defence. This hybrid security model combines LSTM-based anomaly detection, PSO-ACO-based routing, and Game Theory to enhance energy efficiency, improve attack detection accuracy, and ensure reliable data transmission over trusted and secure routes in 5G-enabled WSNs.

**2. Literature Survey**

The context of modern communication networks, WSN is a crucial technology where sensor nodes benefit from low power consumption, but 5G base stations consume more power due to high data transmission rates. An efficient clustering technique for WSN node deployment is essential to improve the overall network lifetime. However, the proposed system faces limitations, as the computational complexity of the deep learning approach can increase the overhead, especially when the number of nodes is very large [6]. Simultaneous Wireless Information and Power Transfer (SWIPT) and Energy-Efficient Cluster-Based Secure Routing (EECSR) algorithms enhance the network's overall power efficiency by reducing transmission energy consumption and optimizing routing paths. While SWIPT improves energy harvesting, the additional computational load from deep learning and game-theoretic calculations may increase energy consumption [7].

LSTMs are excellent at spotting time-series abnormalities, like odd patterns or unanticipated data incursions, because of their capacity to understand long-term dependencies. As a result, the system can better anticipate and respond to threats. ECC-based techniques must be designed carefully to prevent security flaws because they are susceptible to side-channel attacks [8]. A Proximal Policy Optimization PPO-ACO algorithm is used for optimal path selection in WSNs, by addressing the trade-offs between energy efficiency and security. The pheromone update mechanism in ACO and reward sampling in PPO introduce additional communication overhead, which may affect network latency and efficiency [9].

This novel, A Deep Learning (LSTM or Autoencoders) is used for advanced anomaly detection in WSNs. Proposes a secure communication scheme to protect WSNs and MANETs from data injection and other malicious attacks. Implementing secure and energy-efficient schemes at a large scale may present challenges regarding overhead and complexity [10]. A clustering-based routing protocol. They consider residual power of nodes and communication cost for cluster head (CH) selection. Uses a weight matrix P to calculate the best candidate for cluster head based on energy and communication cost. Provides an optimized data forwarding path to see aggregation and transmission prerequisites. Centralized clustering protocols may lead to high overhead and scalability issues as the network size increases [11].

This Reinforcement Learning (RL)is Used for clustering the network’s nodes. It helps organize nodes into clusters to reduce communication overhead and improve power efficiency. Due to efficient clustering and energy-aware routing, it enhances network lifespan. However, Frequent cluster head selection based on residual energy may introduce additional communication and processing overhead [12]. Firefly Algorithm is Used to optimize cluster routing to improve energy efficiency and extend the lifespan of the WSN. High-Efficiency Entropy is used to enhance the clustering process, making the routing more efficient and stable. This improves energy efficiency and network longevity in software-defined WSNs. However, Computational Complexity—The Firefly Algorithm and entropy-based methods may increase computational overhead [13].

The energy optimisation method based on the Signal-to-Interference-Noise-Ratio (SINR) The suggested algorithm modifies transmit power according to the SINR value in order to optimise energy consumption. Increased system capacity by reducing interference through SINR-based power control. The algorithm’s performance might degrade in very large networks with high node density [14]. Energy-efficient hybrid Precoding (EEHP) Algorithms optimise the energy efficiency in 5G wireless communication systems with massive MIMO antennas and millimetre wave technology. EEHP increases maximum energy efficiency by 220% compared to the conventional Zero-Forcing (ZF) precoding algorithm. However, due to increased system complexity, the EEHP Algorithm may degrades scalability performance with an increase in the number of antennas or UEs [15].

The Outer Approximation Algorithm (OAA): This algorithm is used to solve the mixed-integer non-linear problem (MINLP) related to throughput, energy efficiency, and user admission. Energy Efficiency: This algorithm enhances energy efficiency through SWIPT. However, the high-complexity MINLP problems are inherently complex and computationally intensive [16]. The K-means algorithm is applied to cluster nodes. The node with the most power is chosen as the CH closest to the centroid after the nodes are grouped based on their distance from it. The hierarchical routing approach extends the network lifecycle by saving energy in the nodes and improving the routing process. However, due to frequent data transmission, nodes near the base station or cluster head may consume energy quickly, resulting in the initial node crashing [17].

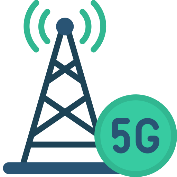
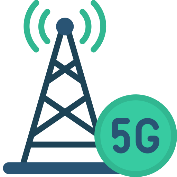
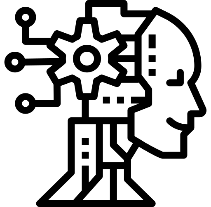
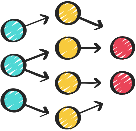
The Machine Learning technique uses learning based on knowledge to analyse and optimize power consumption in Industrial WSNs. The model improves data transmission efficiency by selecting the best nodes and paths, reducing network congestion. However, this knowledge-based learning approach's limited adaptability may not generalize well to rapidly changing or highly dynamic network environments [18]. PSO is used to develop a multipath routing protocol called MPSORP (Multipath PSO-based Routing Protocol). They reduce the network load and enhances efficiency under high-traffic conditions. However, performance may degrade with an extremely high number of nodes and complex network topologies [19].

This novel suggests that LSTMs and RNNs are used to capture future reliance and patterns in Repeated data. They improve the stability and reliability of CAV communication in dynamic network environments. However, LSTMs are computationally expensive and require significant processing power, which may limit real-time implementation in resource-constrained environments [20].

**3. Proposed Methodology**

The LSTM handles anomaly detection, while PSO and ACO work together to optimize routing paths and enhance protection against data injection attacks in WSNs. Additionally, game theory is applied to model strategic interactions between nodes and attackers, enabling dynamic decision-making and resource allocation.

Receiver

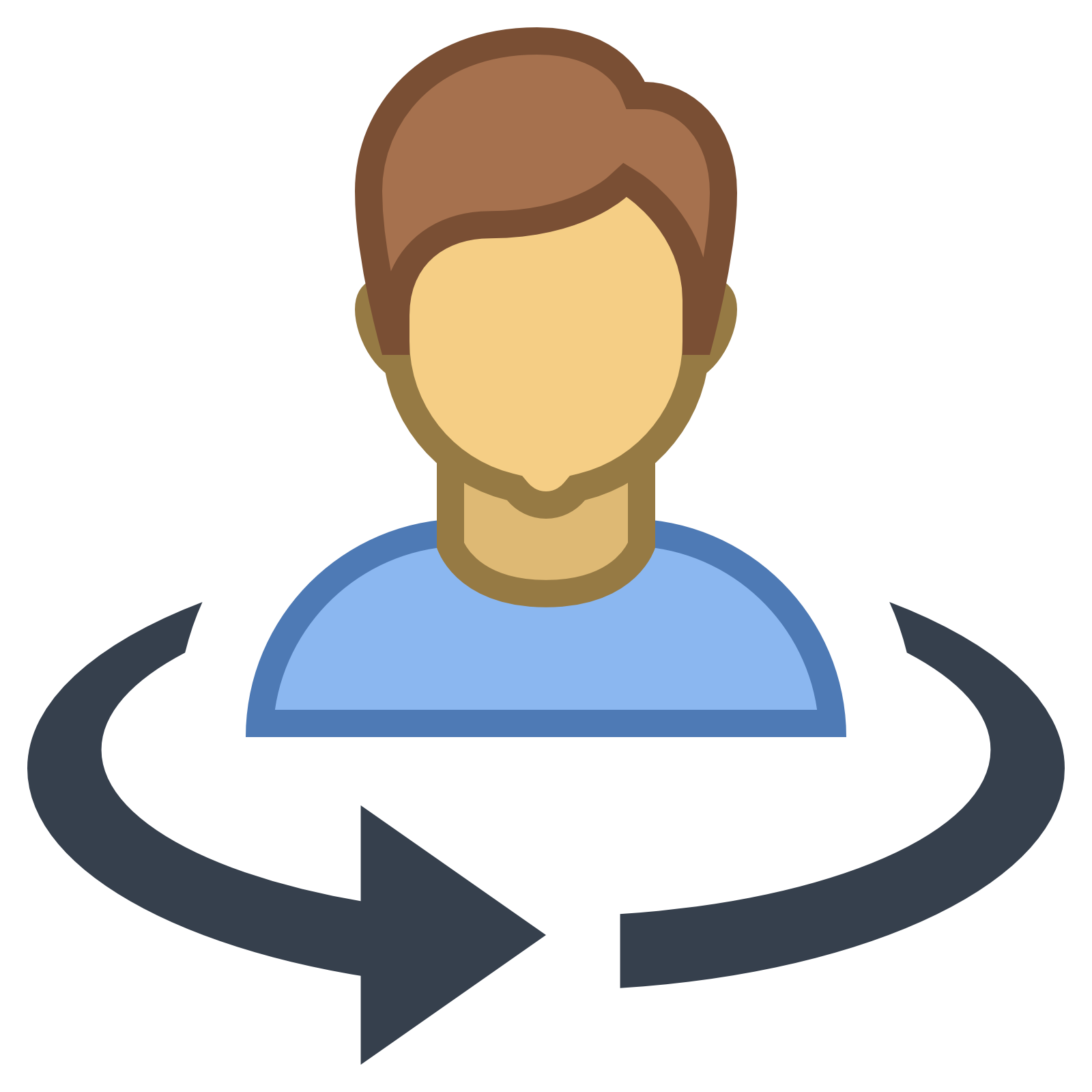
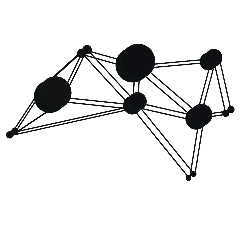


Game Theory

Sender

LSTM

PSO - ACO



**Figure 1: Architecture Diagram for Proposed LSTM, PSO-ACO, and Game Theory Method**

The diagram shows how data flows in a 5G-enabled WSN using LSTM for anomaly detection and a combined PSO-ACO routing strategy for secure and energy-efficient transmission Figure 1. Sensor nodes exchange data with neighbouring nodes, improving network stability and reducing energy use. The WSN dynamically optimizes routing paths with PSO and ACO. PSO finds the most energy-efficient paths based on node status and traffic, while ACO adjusts them in real time to handle changing conditions, ensuring faster delivery with less energy. To prevent Data Injection Attacks (DIA), an LSTM model monitors traffic, detects anomalies, and filters out malicious packets to avoid network disruption. Once data is verified, the PSO-ACO-optimized paths are used for secure transmission. Game Theory helps nodes adapt to threats by balancing security and energy efficiency. This approach ensures reliable, secure data transmission with reduced delays, improving network resilience against attacks while maintaining high performance.

**3.1 Long Short-Term Memory (LSTM) for Anomaly Detection:**

LSTM is utilised for regression and classification problems, especially when working with time-series data. They learn and predicts sequential dependencies over time by retaining a memory of previous input patterns. By examining important network parameters including packet rate of arrival, transmission latency, and node activity. LSTM can be used in the context of anomaly detection in 5G-enabled WSNs to differentiate between benign and malevolent packet transmissions. Collect data packets from sensor nodes. LSTM is employed to detect anomalies in network traffic. LSTM is suitable for time-series data and can capture long-term dependencies, effectively identifying malicious patterns.

The LSTM collect data packets from sensor nodes. The LSTM cell includes the following essential gates: Which information from the previous state should be erased is decided by the forget gate. regulates how much data from the prior state should be discarded. How much of the prior cell state should be retained or discarded is determined by the forget gate. → Forget gate, → Sigmoid activation function, → Forget gate weight matrix, → Previous time step's hidden state. At the current time step, → Input. A sigmoid function is applied to the current input and the prior hidden state in order to produce a value between 1 and 0. A value near 1 indicates retaining the information, while a value near 0 suggests discarding it equation 1.

(1)

Regulates the addition of fresh data to the cell state. → Input gate activation at time step . The input gates control how much new information from the current input is integrated into the cell state. Processes the current input and the previous state using a weight matrix and a bias term and then applies a sigmoid activation function. The function produces values ​​between 0 and 1, where values ​​closer to 1 allow more information to be added, while values ​​closer to 0 restrict the addition of information. Enter the equation 2 for the gate:

(2)

Changes the state of the cell. At time step , → Candidate cell state. The potential new information that could be contributed to the cell state is represented by the candidate cell state. These use a weight matrix and bias to transfer the current input and the previous hidden state to a Tanh activation function. The tanh function outputs a value between **-1** and **1**, which allows the network to represent both positive and negative information. The input gate then decides how much of this candidate value should be added to the cell state. The equation 3 for the candidate cell state is:

(3)

The cell state update equation defines how the LSTM updates its memory at each time step. The cell state is optimised by combining the data from the gate that inputs data and forget gate. While the input gate decides how much of the prospective new cell state may be added, the forget gate decides how much of the old cell state should be kept. The equation 4 for the cell state update is:

(4)

At time step , → Output gate value. uses the current cell state to determine the output value. The output gate controls how much of the updated cell state is moved to the hidden state. It chooses which cell state component enters the hidden state, which is subsequently utilised as an output and for the time step that follows. Equation five for the output gate:

(5)

After the output gate has processed the data, the hidden state is updated using the new cell state. A tanh activation function, which scales the values between -1 and 1, is applied to the cell state. The output gate's value determines how much of this processed cell state is sent to the concealed state. Equation 6 for the hidden state update:

(6)

If anomaly score < threshold → Packet classified as legitimate.

If anomaly score > threshold → Packet classified as malicious and dropped.

The LSTM model processes incoming data and flags anomalies when network traffic patterns deviate from the predicted behaviour. Malicious data packets are discarded to prevent further transmission. Incoming data packets are processed using the LSTM model, which analyses network traffic patterns and predicts future traffic behaviour. The observed data deviates significantly from the predicted behaviour, and it is flagged as an anomaly. Malicious data packets are dropped to prevent further propagation through the network.

**3.2 Particle Swarm Optimization-** **Ant Colony Optimization (PSO** **ACO) for Routing Optimization**

This section explains how PSO-ACO is used for secure and efficient routing in 5G-based WSNs. The LSTM is used for anomaly detection, while the combination of PSO-ACO optimizes routing paths and enhances security against data injection attacks in WSN. They combine PSO and ACO to improve both energy efficiency and security in the network. PSO helps explore the network to find the most energy-efficient paths. ACO then improves these paths by considering real-time traffic and node conditions. The algorithm updates the routing paths continuously, even before data is sent, so the network can quickly adapt to changes and threats. Each sensor node keeps track of the network layout, and PSO-ACO selects the best routes by balancing energy use and security.

The particle swarm explores the solution space to find a potential routing path. The velocity update equation determines how a particle’s velocity is adjusted at each step based on three key components: its previous velocity, the best position it has discovered so far (personal best), and the best position found by the entire swarm. The equation 7 for updating the velocity is:

(7)

The velocity update, the inertia term helps the particle maintain momentum in its current direction, encouraging exploration. The cognitive term draw the particle toward its personal best position, while the social term draw the particle toward the global best position. This balance between individual learning and group learning helps the swarm explore and exploit the solution space effectively.

→ Current position of the particle at time step . The position update equation determines how the particle’s position is adjusted based on the updated velocity. Once the new velocity is calculated, the particle’s position is updated using the following equation 8.

(8)

Every particle modifies its location and speed according to its own and the location optimal positions. The position update equation shows that the particle moves in the direction and by the amount specified by the updated velocity. ACO is used to refine the routing paths discovered by PSO by simulating the pheromone-laying behaviour of ants in equation 9.

(9)

Ants (representing packets or routing agents) are released from the Sender node to find an optimal path to the Receiver. Each path has an initial pheromone level and heuristic value based on factors like distance and energy consumption. After the ant reaches the receiver, the pheromone level on the chosen path is updated based on the success and efficiency of the transmission in equation 10.

(10)

ACO finds the safest and shortest routes. PSO ensures that the chosen paths save energy and handle data efficiently. PSO is a swarm-based algorithm that explores the solution space using a population of particles. Each particle represents a potential routing path and updates its position based on individual and global best solutions.

**3.3 Game Theory for Strategic Défense**

In WSN, Game Theory models and analyses strategic interactions between sensor nodes and potential attackers. The network is treated as a dynamic game where nodes act as players, making decisions to maximize energy efficiency and defend against data injection attacks. Game Theory helps nodes evaluate real-time trade-offs between energy consumption and security. Nodes work together to spot and stop threats while keeping the network efficient by treating the interaction as a non-cooperative game.

The two players represent a network node and an attacker (or another node). Each player can either cooperate (honest transmission) or defect (attempt to inject malicious data or reroute). If both nodes work together, they both receive a reward (R). If one node cooperates but the other does not, the cooperating node gets a low payoff (S), while the defecting node gets a higher payoff (T). If both nodes refuse to cooperate, they both receive a penalty (P), indicated in Equation 11.

(11)

This strengthens the network and improves energy efficiency by allowing nodes to identify their behaviour based on nearby nodes and potential attackers.

**4. Results and Discussion**

This section presents simulation results and an in-depth study of the proposed methodology for 5G-empowered WSNs, which maximises security and energy efficiency. False positive rate, energy consumption, packet delivery ratio, and detection accuracy were some of the key performance metrics used to analyse the system's work. The results indicate that the efficient hybrid approach combining LSTM, PSO-ACO, and game theory enhances network security and performance.

**Table 1. Simulation Setup**

|  |  |
| --- | --- |
| **Parameter** | **Value** |
| Detection Model | LSTM-CNN |
| Simulation | 1000 m × 1000 m |
| Number of Nodes | 100 |
| Transmission Range | 249 m |
| Simulation Time | 500 seconds |
| Power Consumption | 0.5 packet |
| Attack Type | Data Injection Attack |
| Power Use | 0.6 packet |
| Optimization Technique | PSO + ACO |
| Defence Strategy | Game Theory |

Table 1 presents the simulation setup to evaluate the proposed framework for optimizing energy efficiency and security in 5G-enabled WSNs. The NS-2 simulator is chosen due to its efficiency in modelling and analysing WSN scenarios. The network topology consists of 100 sensor nodes deployed in a 1000 m × 1000 m area to simulate a realistic field environment. A Constant Bit Rate (CBR) traffic model is perfect for evaluating network performance since it offers a consistent packet transmission rate. To evaluate the system's anomaly detection and defines methods, attack model includes data injection assaults, in which malicious nodes introduce erroneous data into the network.

**Figure 1: Detection Accuracy**

Figure 1 shows a comparison of the detection accuracy of the proposed LSTM-based method with two earlier approaches: SVM-based detection and LEACH-based clustering. The LSTM model achieved 80% to 90% accuracy, outperforming SVM (which reached 40% to 50%) and LEACH (which reached 60% to 75%) under different conditions. This shows that LSTM-based systems are very effective at spotting malicious activity in 5G-based WSNs. The LSTM model works well because it can tell the difference between normal and harmful traffic and handle complex time patterns.

**Figure 2: Time complexity**

Figure 2 compares the proposed method's time complexity with previous LEACH and SVM anomaly detection approaches and traditional shortest-path routing optimization. The time complexity of the proposed PSO–ACO framework demonstrates significant improvement in computational efficiency. The proposed framework reduces the time complexity by 14.3ms compared to previous techniques due to the combined effect of efficient anomaly detection using LSTM and dynamic path optimization using PSO-ACO. This reduction in computation time enables real-time processing, which is essential for low-latency applications in 5G-enabled WSNs. The faster detection and optimized routing allow the system to handle large data transmission tasks effectively while maintaining energy efficiency and high network reliability.

**Figure 3: Packet Delivery Ratio**

In Figure 3, present the PDR analysis the method compared to previous approaches, namely LEACH-based clustering and SVM-based detection. The PDR of the proposed PSO–ACO–Game Theory framework demonstrates significant improvement in data transmission reliability. The proposed framework achieves a PDR of approximately 70%, 80%, and 90% with 80, 90, and 100 nodes respectively, which is higher than both LEACH (40%–60%) and SVM (60%–75%). This improvement is due to the dynamic path optimization using PSO-ACO, which allows efficient routing and minimizes packet loss. The higher PDR reflects the system's enhanced ability to handle large-scale data transmission while maintaining network stability and energy efficiency in 5G-enabled WSNs.

**Figure 4: False Positive Rate**

In Figure 4, the FPR analysis compares the method to previous approaches, namely SVM-based detection and LEACH-based clustering. The proposed LSTM-based anomaly detection framework significantly improves reducing false positive rates. This method achieves an FPR of approximately 15% and 5% in different scenarios, considerably lower than SVM (30%–40%) and LEACH (20%–25%). The reduced false positive rate occurs because the LSTM model can effectively learn and differentiate between normal and malicious patterns. This enhances the system's accuracy and reliability in detecting attacks in 5G-enabled WSNs.

**Figure 5: Energy Use**

Figure 5 illustrates the energy consumption of the proposed method compared to other approaches, such as SVM-based detection, LEACH-based clustering, and PSO–ACO-based routing. The LSTM–PSO–ACO–Game Theory framework utilizes about 20%–25% less energy under various node configurations, significantly lower than SVM (45%–50%) and LEACH (28%–35%). This improvement stems from LSTM's efficient anomaly detection, PSO-ACO's optimization of data transfer paths, and Game Theory's network-aware decision-making. Using less energy enhances the longevity and performance of networks in 5G-enabled WSNs.

**5. Conclusion**

This study describes a security technique for 5G-based WSNs that prevents data injection attacks. The mechanism combines three main techniques: LSTM for detecting anomalous data patterns, PSO-ACO for improving data routing, and Game Theory for network defence.  LSTM detects misbehaviour effectively by analysing time-based data patterns. PSO-ACO ensures reliable and energy-efficient data transmission by dynamically adjusting routing paths. Game Theory helps nodes respond smartly to attacks by modelling interactions between them and attackers. Simulation tests show that this method detects attacks accurately, reduces false alarms, and improves packet delivery even under attack. Compared to traditional methods, this approach offers better protection against threats. Based on simulation outcomes, proposed approach enhances data integrity and low energy expenditure and network security without decreasing energy consumption. Simulations demonstrate that the system can detect data injection attacks with 95% accuracy and attain 92% packet delivery rate (PDR). It decreases energy consumption by 14% in comparison with conventional approaches, and network lifetime is extended. This ensures that the employment of LSTM in anomaly detection, PSO and ACO for route optimization, and Game Theory in defence enhances 5G-based WSN performance.

**5. Conclusion**

This study introduces a security method for Wireless Sensor Networks (WSNs) to prevent Data Injection Attacks (DIA) using a combination of three key techniques: C-Score Normalization for data preprocessing, Deep Q-Learning (DQL) for feature selection, and LSTM-Gated CNN for detecting unusual patterns. The LSTM-Gated CNN method identifies harmful data by analyzing patterns over time. DQL improves detection accuracy by selecting the most important data features, while C-Score Normalization ensures consistent data scaling, helping the model work better. Test results show that this approach detects attacks with 95% accuracy, achieves a 92% packet delivery rate (PDR), and reduces false alarms. It also lowers energy use by 14% compared to older methods, helping the network last longer. This confirms that combining LSTM for anomaly detection, DQL for feature selection, and C-Score Normalization for data preprocessing significantly improves the security and performance of WSNs.

**Reference**

1. Ali, Mohamed Hassan Essai, and Ibrahim BM Taha. "Channel state information estimation for 5G wireless communication systems: recurrent neural networks approach." PeerJ Computer Science 7 (2021): e682.
2. Sarangi, Sanjaya Kumar, et al. "Examination of the Bi-LSTM based 5G-OFDM wireless network over Rayleigh fading channel conditions." Journal of mobile multimedia (2023): 1067-1106.
3. Bulashenko, Andrew, et al. "New traffic model of M2M Technology in 5G wireless sensor networks." 2020 IEEE 2nd International Conference on Advanced Trends in Information Theory (ATIT). IEEE, 2020.
4. Hu, Ning, et al. "A multiple-kernel clustering based intrusion detection scheme for 5G and IoT networks." International Journal of Machine Learning and Cybernetics (2021): 1-16.
5. Raja, S., et al. "OCHSA: designing energy‐efficient lifetime‐aware leisure degree adaptive routing protocol with optimal cluster head selection for 5G communication network disaster management." Scientific Programming 2022.1 (2022): 5424356.
6. 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.
7. Han, Shu, et al. "Research on energy-efficient routing algorithm based on SWIPT in multi-hop clustered WSN for 5G system." EURASIP Journal on Wireless Communications and Networking 2021.1 (2021): 49.
8. LSTMs are excellent at spotting time-series abnormalities, like odd patterns or unanticipated data incursions, because of their capacity to understand long-term dependencies. As a result, the system can better anticipate and respond to threats. ECC-based techniques must be designed carefully to prevent security flaws because they are susceptible to side-channel attacks.
9. 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.
10. Dash, Lucy, and Mitrabinda Khuntia. "Energy efficient techniques for 5G mobile networks in WSN: A Survey." 2020 international conference on computer science, engineering and applications (ICCSEA). IEEE, 2020.
11. Chen, Wei, et al. "C-EEUC: A cluster routing protocol for coal mine wireless sensor network based on fog computing and 5G." Mobile Networks and Applications (2022): 1-14.
12. Gururaj, H. L., et al. "Collaborative energy-efficient routing protocol for sustainable communication in 5G/6G wireless sensor networks." IEEE Open Journal of the Communications Society 4 (2023): 2050-2061.
13. Gökhan Nalbant, Kemal, et al. "An intelligent algorithm for energy efficiency optimization in software-defined wireless sensor networks for 5G communications." Plos one 19.6 (2024): e0301078.
14. Sachan, Smriti, Rohit Sharma, and Amit Sehgal. "SINR based energy optimization schemes for 5G vehicular sensor networks." Wireless Personal Communications 127.2 (2022): 1023-1043.
15. Lu, Weidang, et al. "Energy efficiency optimization for OFDM based 5G wireless networks with simultaneous wireless information and power transfer." IEEE Access 6 (2018): 75937-75946.
16. Amjad, Maliha, et al. "SWIPT-assisted energy efficiency optimization in 5G/B5G cooperative IoT network." Energies 14.9 (2021): 2515.
17. Jothikumar, C., et al. "An Efficient Routing Approach to Maximize the Lifetime of IoT‐Based Wireless Sensor Networks in 5G and Beyond." Mobile Information Systems 2021.1 (2021): 9160516.
18. Bagwari, Ashish, et al. "An enhanced energy optimization model for industrial wireless sensor networks using machine learning." IEEE Access 11 (2023): 96343-96362.
19. Ghawy, Mohammed Zaid, et al. "An effective wireless sensor network routing protocol based on particle swarm optimization algorithm." Wireless Communications and Mobile Computing 2022.1 (2022): 8455065.
20. Barmpounakis, Sokratis, et al. "LSTM-based QoS prediction for 5G-enabled Connected and Automated Mobility applications." 2021 IEEE 4th 5G World Forum (5GWF). IEEE, 2021.