International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

A Systematic Review of Intelligent Energy-Efficient AODV Routing Protocols in Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) are widely used in applications such as environmental monitoring, healthcare systems, military surveillance, and Internet of Things (IoT) environments. Due to limited battery power and dynamic network topology, designing energy-efficient routing protocols remains a critical challenge. The Ad hoc On-Demand Distance Vector (AODV) routing protocol is a widely adopted reactive routing protocol; however, it presents certain challenges related to control overhead, route stability, and efficient energy utilization in dynamic environments. Recent studies (2023–2026) have introduced various enhancements to AODV using fuzzy logic, machine learning, reinforcement learning, and hybrid optimization techniques to improve energy efficiency, routing stability, and Quality of Service (QoS). This paper presents a comprehensive literature review of these approaches, analysing their working mechanisms, performance improvements, and design considerations. Despite these advancements, several research challenges remain, including the need for more unified multi-metric decision-making frameworks, improved integration of predictive energy modelling, enhanced real-time adaptability, and reduced computational complexity in intelligent routing approaches. Addressing these aspects can contribute to the development of more efficient, lightweight, and adaptive routing strategies for next-generation Wireless Sensor Networks.

Keywords— AODV, Wireless Sensor Networks, Energy Efficiency, Routing Protocols, Machine Learning, Fuzzy Logic, Reinforcement Learning, QoS

I. Introduction

Wireless Sensor Networks (WSNs) are widely deployed in applications such as environmental monitoring, healthcare systems, military surveillance, and Internet of Things (IoT) environments. These networks consist of resource-constrained sensor nodes with limited battery power, processing capability, and memory. Due to energy constraints and dynamic topology changes, designing efficient and reliable routing protocols remains an important challenge for ensuring prolonged network lifetime and stable communication.

The Ad hoc On-Demand Distance Vector (AODV) routing protocol is a widely adopted reactive routing protocol in WSNs and Mobile Ad hoc Networks (MANETs) due to its simplicity and on-demand route discovery mechanism. However, in practical deployments, AODV presents certain challenges related to control overhead associated with flooding-based route discovery, route stability in dynamic environments, and energy utilization efficiency, which can influence overall network performance.

To address these aspects, recent advancements (2023–2026) have explored enhanced AODV variants incorporating techniques such as fuzzy logic, machine learning, reinforcement learning, and hybrid optimization methods. These approaches aim to improve energy efficiency, enhance Quality of Service (QoS), reduce end-to-end delay, and support more stable routing decisions. While these methods demonstrate notable improvements over conventional AODV, they also introduce considerations such as computational complexity, adaptability in highly dynamic environments, and the integration of multiple decision parameters within routing frameworks.

This paper presents a comprehensive literature review of these enhanced AODV protocols. It systematically examines their working principles, performance characteristics, and design considerations using commonly adopted performance metrics and energy consumption models. The study also identifies key trends and observations in recent research, providing insights into the evolving landscape of intelligent routing techniques for Wireless Sensor Networks.

With the rapid growth of IoT-enabled Wireless Sensor Networks, traditional routing protocols face increasing challenges in supporting adaptive, scalable, and energy-aware communication. This has motivated recent research toward intelligent routing approaches integrating fuzzy logic, machine learning, and reinforcement learning techniques.

II. AODV Routing Mechanism

The Ad hoc On-Demand Distance Vector (AODV) routing protocol is a reactive routing protocol designed for Wireless Sensor Networks (WSNs) and Mobile Ad hoc Networks (MANETs), where routes are established only when required. This on-demand nature helps in reducing unnecessary routing overhead and improving bandwidth utilization.

AODV operates using three primary control messages: Route Request (RREQ), Route Reply (RREP), and Route Error (RERR). The routing process begins when a source node intends to communicate with a destination node for which it does not have an existing route. In such cases, the source node initiates route discovery by broadcasting an RREQ packet to its neighbouring nodes. Each intermediate node that receives the RREQ processes and forwards it further until the packet reaches either the destination node or an intermediate node that has a valid and fresh route to the destination.

Upon receiving the RREQ, the destination node (or an intermediate node with a valid route) generates a Route Reply (RREP) message. This RREP is unicast back to the source node along the reverse path established during the RREQ propagation. Once the RREP reaches the source node, a route is established, and data transmission can begin.

During active communication, if a link break or node failure is detected, a Route Error (RERR) message is generated and propagated to inform the affected nodes about the invalid route. This mechanism enables timely route maintenance and triggers route rediscovery when necessary.

AODV employs sequence numbers to ensure loop-free routing and to maintain the freshness of routing information. By always selecting routes with the most recent sequence numbers, AODV avoids routing loops and ensures reliable data delivery in dynamic network environments.

III. AODV Architecture

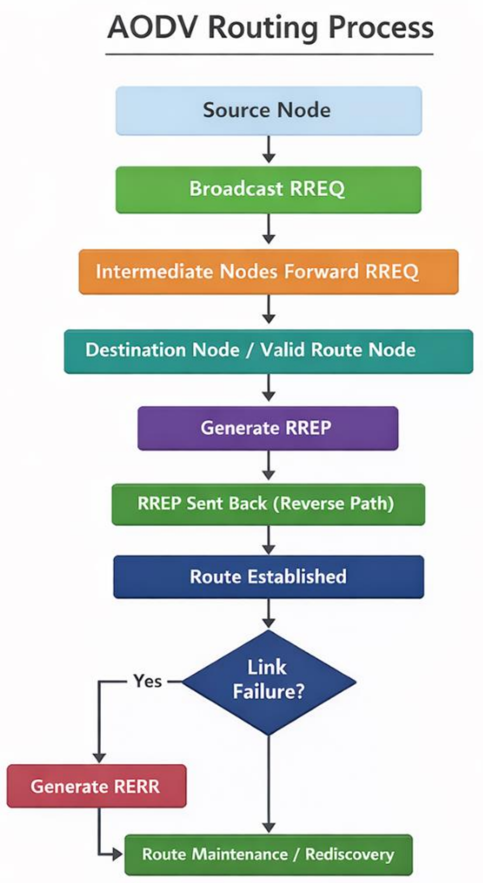

Figure 1: Flow Chart of AODV Routing Protocol

The AODV architecture consists of source nodes, intermediate forwarding nodes, and destination nodes. The routing process involves route discovery using Route Request (RREQ), route establishment using Route Reply (RREP), and route maintenance using Route Error (RERR) messages.

IV. Energy Consumption Model in WSN

Energy efficiency plays a crucial role in AODV-based routing protocols for Wireless Sensor Networks (WSNs), as sensor nodes operate with limited battery power. The energy consumption model is typically used to evaluate the cost of transmitting and receiving data packets over varying distances. In this model, energy is consumed during both transmission and reception, and it increases significantly with distance, which justifies the use of multi-hop routing in WSNs to reduce overall energy expenditure.

- **Transmission Energy**

$$E_{tx}(k,d) = E_{elec} \cdot k + E_{amp} \cdot k \cdot d^{n}$$

- **Receiving Energy**

$$E_{rx}(k) = E_{elec} \cdot k$$

- **Free Space & Multipath Model**

$$E_{tx}(k,d) = \begin{cases} E_{elec}k + \epsilon_{fs} k d^{2}, & d < d_0 \\ E_{elec}k + \epsilon_{mp} k d^{4}, & d \geq d_0 \end{cases}$$

These equations indicate that energy consumption increases rapidly with transmission distance, especially in multipath environments. Therefore, minimizing long-distance communication through multi-hop routing significantly reduces energy consumption and enhances the overall network lifetime in AODV-based WSNs.

V. Recent Advances in AODV

- Reinforcement Learning-Based AODV (RL-AODV):

  Recent studies such as the work by Rani and Charaya (2023) and subsequent improvements in 2024 propose the integration of reinforcement learning into the AODV routing protocol to enable adaptive and intelligent routing decisions in Wireless Sensor Networks. In these approaches, each node in the network acts as an autonomous learning agent that interacts with the network environment and progressively improves its routing strategy through experience.

  The workflow begins with the node observing the current network state, which includes parameters such as residual energy, link quality, node mobility, and traffic load. Based on this state, the node selects an action, typically determining the next-hop node for packet forwarding. After data transmission, the network provides feedback in the form of a reward or penalty depending on the success or failure of the transmission. The routing policy is then updated using reinforcement learning techniques such as Q-learning, SARSA, or Deep Q Networks (DQN). This iterative learning process enables the system to gradually improve routing decisions and adapt to changing network conditions.

  These approaches demonstrate improvements in packet delivery ratio, throughput, and end-to-end delay, while also enhancing adaptability in dynamic network scenarios. At the same time, it may be noted that RL-AODV primarily focuses on learning-based optimization, and there remains scope for further enhancement in areas such as energy prediction, lightweight computational design, and multi-metric decision integration to support more efficient and sustainable operation in resource-constrained Wireless Sensor Networks.[1], [6]

- Fuzzy Logic-Based AODV (FL-AODV):

  Recent studies, such as the work by Alameri et al. (2023), propose the integration of fuzzy logic into the AODV routing protocol to enhance routing decisions under uncertain conditions in Wireless Sensor Networks. In this approach, multiple network parameters, including residual energy, node distance, link stability, and delay, are considered as input variables to a fuzzy inference system for improved decision-making.

  The workflow begins with fuzzification, where crisp input values are transformed into linguistic variables such as Low, Medium, and High. These fuzzy values are then processed through a predefined rule base consisting of IF–THEN rules. The inference engine evaluates these rules to determine the suitability of nodes for routing. Finally, the defuzzification process converts the fuzzy output into a numerical routing score, which is used to guide node selection during the route discovery process.

  This multi-criterion decision-making approach contributes to improved route stability, enhanced energy efficiency, and increased network lifetime by preferentially selecting more reliable nodes. At the same time, it may be observed that FL-AODV generally depends on static rule sets and predefined membership functions, which may limit its adaptability in highly dynamic network environments. In addition, the absence of learning-based adaptation and predictive capability suggests that there is scope for further enhancement in rapidly changing Wireless Sensor Network scenarios.[3]

- Machine Learning-Based AODV (ML-AODV):

  Recent studies, such as the work by Hassan et al. (2024) and Kumar et al. (2025), propose the integration of machine learning techniques into the AODV routing protocol to enable predictive and intelligent routing decisions in Wireless Sensor Networks. In these approaches, machine learning models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and hybrid learning frameworks are utilized to analyse network behaviour and improve routing efficiency.

  The workflow begins with the collection of historical and real-time network data, including node energy levels, traffic patterns, link quality, and transmission delay. This dataset is used to train machine learning models that identify hidden patterns and relationships within the network. Once trained, the model is deployed to predict optimal routing paths, detect potential link failures, and estimate node reliability. During runtime, current network parameters are provided as input to the trained model, which outputs the most suitable next-hop node for packet forwarding. This predictive mechanism enables more proactive routing decisions, thereby improving packet delivery ratio, reducing packet loss, and enhancing overall network performance.

  The primary advantage of ML-AODV lies in its ability to learn complex network patterns and support data-driven routing decisions, leading to improved Quality of Service (QoS), higher stability, and better adaptability in dynamic environments. At the same time, it may be observed that these approaches introduce higher computational requirements and depend on large training datasets, which may limit their suitability for resource-constrained Wireless Sensor Networks. In addition, there is scope for further enhancement in handling uncertainty and improving real-time adaptive learning capabilities in dynamic network conditions.[2], [6]

- Energy-Aware AODV:

Recent studies, such as the work by Kumar et al. (2025), propose energy-aware enhancements to the AODV routing protocol to improve energy efficiency and extend network lifetime in Wireless Sensor Networks. In these approaches, routing decisions are optimized by incorporating energy-related metrics such as residual energy, energy drain rate, and transmission cost, instead of relying solely on hop count as in traditional AODV.

The workflow begins with continuous monitoring of node energy levels across the network. During route discovery, each node evaluates the energy required for packet transmission and reception, and a combined routing cost metric is computed. This cost function is then used to select routes that aim to minimize overall energy consumption while maintaining network connectivity. Additionally, some approaches incorporate energy-aware control of Route Request (RREQ) flooding, where nodes with higher residual energy are more likely to forward control packets, thereby helping to reduce unnecessary overhead and balance energy consumption across the network.

Energy-aware AODV variants generally contribute to improved network lifetime, reduced energy consumption, and better load balancing among sensor nodes. At the same time, it may be observed that these approaches primarily utilize current energy information and do not consider future energy consumption trends. In addition, there is scope for further enhancement through the integration of predictive and adaptive decision-making mechanisms, particularly in highly dynamic Wireless Sensor Network environments.[4]

- Hybrid Intelligent AODV Approach:

Recent studies, such as the works by Hassan et al. (2024) and Sharma et al. (2024), propose hybrid intelligent enhancements to the AODV routing protocol by integrating multiple computational intelligence techniques, including fuzzy logic, machine learning, reinforcement learning, and bio-inspired optimization algorithms. These approaches aim to enhance routing efficiency, energy utilization, and Quality of Service (QoS) in Wireless Sensor Networks (WSNs) by leveraging the complementary strengths of different intelligent paradigms.

The workflow of hybrid AODV approaches generally follows a multi-layer decision-making framework. Initially, fuzzy logic is applied to evaluate node suitability by considering parameters such as residual energy, delay, link stability, and distance. This stage assists in identifying and filtering relatively weak or unstable nodes under uncertain network conditions. Subsequently, machine learning or reinforcement learning techniques are employed to analyse historical and real-time network data for predicting more optimal routing paths and improving adaptability. Finally, optimization algorithms such as Particle Swarm Optimization (PSO) or Artificial Bee Colony (ABC) are utilized to refine route selection by identifying efficient paths based on a fitness function incorporating energy consumption, delay, and reliability metrics.

These hybrid approaches generally lead to improved energy efficiency, enhanced routing stability, and better overall network performance compared to traditional AODV. At the same time, it may be observed that the integration of multiple techniques introduces higher computational complexity due to layered processing. In addition, many existing hybrid models may not follow a unified lightweight framework suitable for real-time deployment in resource-constrained Wireless Sensor Networks. There is also scope for further enhancement in incorporating predictive energy modelling and dynamic multi-metric routing score mechanisms to better support highly dynamic network environments.[2], [7]

Recent research in AODV routing primarily focuses on improving energy efficiency, routing reliability, adaptive decision-making, and Quality of Service (QoS) in Wireless Sensor Networks. These enhancements integrate intelligent techniques such as fuzzy logic, machine learning, reinforcement learning, and hybrid optimization strategies to address the challenges of dynamic and resource-constrained network environments.

Limited studies provide unified lightweight intelligent routing frameworks suitable for practical real-time deployment in resource-constrained Wireless Sensor Networks.

Intelligent AODV Routing Techniques

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├── Energy-Aware AODV

├── Fuzzy Logic-based AODV

├── Machine Learning-based AODV

├── Reinforcement Learning-based AODV

└── Hybrid Intelligent AODV

VI. Comparison of AODV Variants

Technique	**Energy Efficiency**	**QoS (Delay, PDR, Throughput)**	**Complexity**	**Adaptability**	**Limitation**
AODV	Moderate	Good delay, moderate PDR	Low	Medium	High routing overhead in highly dynamic networks

Technique	Energy Efficiency	QoS (Delay, PDR, Throughput)	Complexity	Adaptability	Limitation
DSDV	Low	Low delay, stable routes	Low	Low	Periodic updates consume energy
DSR	Moderate	Good PDR, higher delay	Medium	Medium	Packet header overhead increases with path length
LEACH	High	Good throughput, balanced load	Medium	Low–Medium	Not suitable for mobile and dynamic topology
FL-AODV (Fuzzy Logic AODV)	High	Improved QoS via adaptive fuzzy decision-making	High	High	Increased computational overhead due to fuzzy rules
ML-AODV (Machine Learning AODV)	Very High	High PDR, reduced delay through predictive routing	Very High	Very High	Requires training data and model maintenance
Hybrid AODV (FL + ML / Energy-Aware Hybrid)	Very High	Optimized QoS with balanced routing decisions	Very High	Very High	Integration complexity and resource consumption
RL-AODV (Reinforcement Learning AODV)	Very High	High PDR, low delay, adaptive optimal routing	Very High	Very High	High training time and computational cost

VII. Performance Metrics

The performance of AODV-based routing protocols in Wireless Sensor Networks (WSNs) is evaluated using several key metrics. **Packet Delivery Ratio (PDR)** measures the ratio of successfully received data packets at the destination to the total packets sent by the source, indicating the reliability and effectiveness of the routing protocol. **End-to-End Delay** represents the average time taken for a data packet to travel from source to destination, including route discovery, transmission, and propagation delays, where lower values indicate faster communication. **Energy Consumption** refers to the total energy used by sensor nodes during transmission, reception, and route maintenance, and it is a critical factor in extending network lifetime. **Network Lifetime** defines the operational duration of the network until the first node or a significant portion of nodes deplete their energy, reflecting overall energy efficiency and load balancing. **Routing Overhead** measures the additional control packets (such as RREQ, RREP, and

RERR) generated during route discovery and maintenance, where lower overhead indicates better bandwidth and energy efficiency. Together, these metrics provide a comprehensive evaluation of routing efficiency, energy utilization, and overall network performance in WSN environments.

Packet Delivery Ratio (PDR)

$$PDR = \frac{\text{Packets Received}}{\text{Packets Sent}} \times 100$$

End-to-End Delay

$$Delay = \frac{\sum(Receive\ Time - Send\ Time)}{Total\ Packets}$$

Routing Overhead

$$Routing\ Overhead = \frac{Control\ Packets}{Data\ Packets}$$

Protocol	Energy	PDR	Delay	Network Lifetime
AODV	Medium	Good	Medium	Medium
FL-AODV	High	Very Good	Low	High
ML-AODV	Very High	Excellent	Low	Very High
Hybrid AODV	Very High	Excellent	Very Low	Very High

VIII. Research Gap

Despite significant advancements in AODV-based routing protocols for Wireless Sensor Networks (WSNs), existing studies still present several opportunities for further enhancement. Most current approaches focus on individual aspects such as fuzzy logic for uncertainty handling, machine learning for predictive routing, reinforcement learning for adaptive decision-making, or energy-aware mechanisms for improving network lifetime. However, these techniques are often applied independently, and limited work addresses their integration into a unified routing framework that can simultaneously handle uncertainty, prediction, and energy efficiency. In addition, many learning-based routing models rely on offline training or static decision policies, which may restrict their adaptability in highly dynamic network conditions where node energy, link quality, and topology change frequently. Energy-aware routing approaches primarily consider current residual energy, while future energy consumption trends remain less explored, which can affect long-term network stability. Furthermore, the integration of multiple intelligent techniques in hybrid models often leads to increased computational complexity, making them less suitable for resource-constrained sensor nodes. Another important aspect is that most existing approaches optimize a limited set of metrics such as energy or delay, whereas multi-metric optimization involving energy efficiency, routing stability, delay, and reliability is still not fully addressed in a unified manner. These observations indicate the need for more lightweight, adaptive, and integrated routing frameworks for next-generation Wireless Sensor Networks.

IX. Conclusion

AODV is one of the widely adopted routing protocols in Wireless Sensor Networks due to its simplicity and on-demand route discovery mechanism. In dynamic and resource-constrained network environments, several enhancements have been explored to improve its performance in terms of energy efficiency, routing stability, and Quality of Service (QoS). Recent research incorporating fuzzy logic, machine learning, reinforcement learning, and energy-aware strategies has demonstrated improvements in adaptive routing decisions, reliability, and overall network efficiency. Future research is expected to focus on lightweight AI-driven routing frameworks incorporating federated learning, TinyML, and deep reinforcement learning for scalable and real-time WSN applications.

These developments indicate a gradual progression toward more intelligent and context-aware routing frameworks capable of addressing diverse network requirements. At the same time, it is observed that each approach contributes in different ways, and there remains scope for further integration of these techniques to better support multi-metric decision-making and adaptability in highly dynamic scenarios. Future routing protocols are expected to evolve toward more unified, adaptive, and energy-efficient frameworks, enabling reliable communication in next-generation Wireless Sensor Networks and Internet of Things (IoT) applications.

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