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RESEARCH ARTICLE

Optimizing Ad-Hoc Routing Protocols in WSN to Enhance QoS Parameters Using Evolutionary Computation Algorithms

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Abstract – Wireless Sensor Networks (WSNs) have garnered considerable attention within the research community focused on fraternity due to their extensive utilization in healthcare, environmental surveillance, disaster avoidance, farming methods, wildfire detection, and other practical applications. Enormous applications have been developed in the Internet of Things (IoT) era resulting in an ever-increasing number of connected WSN devices. As a result, WSNs consistently face challenges in delivering the required quality of service (QoS) affecting the average end-to-end delay, energy utilization, and packet loss throughout the transmission process. An efficient routing protocol must be designed to address these constraints and improve the operational efficiency of WSNs regarding Quality of Service (QoS) metrics. Motivated by these challenges, this paper presents an advanced routing algorithm by integrating optimization in the AODV routing protocol for ad hoc networks employing Particle Swarm Optimization (PSO). The proposed multipath protocol is termed the EPSO-AODV algorithm. The proposed algorithm is assessed through numerous simulations carried out with varied system setups and parameters. Additionally, the efficiency of the proposed protocol is assessed in comparison to conventional routing protocols including AODV, Dynamic Source Routing (DSR), Destination-Sequenced Distance Vector (DSDV), and Optimized Link State Routing (OLSR) protocols. It is observed from the experimental findings that the proposed approach outperforms existing algorithms and offers several benefits including better energy efficiency, ensuring high packet delivery ratio, throughput, and minimal end-to-end delay delay, reduced normalization load. The proposed protocol efficiently distributes energy usage to enhance throughput and enhance the performance of wireless sensor networks. As per the simulation results, the packet delivery ratio has improved from 81.58% to 91.60% whereas the throughput is observed to be 36.32 kbps for conventional AODV and 74.21 kbps for the proposed algorithm. The routing overhead is lowered by approximately 40% and the AE2E delay was found to be 0.04 lower in comparison to AODV. The residual energy in the context of the EPSO-AODV proposal is less (4981 Joules) than AODV (6344 Joules) which proves the superior efficiency of the proposed algorithm.

Index Terms – Ad Hoc On-Demand Distance Vector Routing, Particle Swarm Optimization, Machine Learning, Network Lifespan, Energy Balancing, Localization, Clustering, Routing Overhead, Throughput, End-to-End Delay.

1. INTRODUCTION

The next generation of wireless technologies is anticipated to support enormous connections offering ultra-fast transmission rates with a concurrent reduction in energy usage and communication latency. The IoT era has witnessed the transition of communication technologies from traditional human-centric cellular communication to machine-centric communication resulting in the development of a WSN environment. These cutting-edge networks revolutionize the way we observe and comprehend our surroundings by working seamlessly to collect data and collaborating wisely to transmit their findings to a central prime node. WSNs comprise numerous individual sensor nodes dispersed around an area and work together to track various environmental and physical parameters like motion, temperature, pressure, vibration, sound, and pollution. A network with a large number of sensors can accomplish a variety of difficult tasks, including monitoring traffic, and buildings for structural integrity, monitoring fires, conducting security surveillance, tracking and sensing in military operations, Measurement of seismic activity through distributed systems, and real-time monitoring of pollution levels, studying animal behavior in their natural habitat and monitoring their movements. wildfires are essential applications [1]. WSNs have risen to the top of the list of essential technologies due to the capability to self-organize many energy-constrained tiny sensors and work autonomously to communicate the required

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information at the sink base station (BS) [2, 3] in an IoT network.

However, the WSNs employed in these IoT devices have limited processing power and energy to support mobility and cost-effectiveness, which results in several design challenges. To cater to these challenges, transferring sensor data to the central station (CS) is carried out by the sensor module by utilizing carefully designed effective routing algorithms. The utilization of the routing algorithm results in enhanced data throughput, Enhanced scalability, and optimized energy usage contributing to making the network more economically viable and operationally feasible. Hence, the development of an effective communication and resourceful routing protocol significantly contributes to the overall effectiveness of WSNs in overcoming the inconsistencies within wireless networks with limited power capabilities and limited resources that are usually inadequate for quality of service (QoS) requirements [4]. Practical WSNs are dynamic and self-organizing, making wireless channel connections between devices and traditional routing methods impractical given the highly ever-changing nature of the topology. Furthermore, the development of routing protocols is also required to extend network lifetime, elevating core Quality of Service (QoS) prerequisites and enabling extra features like heightened packet delivery ratio, minimal latency, ensuring information security and optimizing energy usage, and adaptable network topology [5]. An intelligent optimization-based routing protocol integrating multipath awareness is an open area of research and a necessary prerequisite for many IoT applications.

The structure of a typical in Figure 1 illustrates the implementation of wireless sensor networks designed for applications in the internet of things. The multi-hop path and gateway used to relay sensor information from the point of origin to the intended destination can be visualized in Fig. 1. The network routing algorithm empowers a sender node to select the most optimal route for transmitting data from a set of potential paths identified through the computation of a fitness metric, which aids in determining the best routing path [6]. The overall performance of a WSN relies primarily on the choice of routing algorithm. Enhancing the effectiveness of routing algorithms, recently, a variety of bio-inspired evolutionary methods, particularly swarm intelligence techniques, have found extensive application. Some of the key examples include particle swarm optimization (PSO) and ant colony optimization (ACO) algorithms, which are used to find the best routes in Internet of Things applications utilizing WSN [5-8]. These algorithms operate on the fundamental principle of iteratively computing an evaluation across a population while concurrently evaluating the cost or fitness [9].

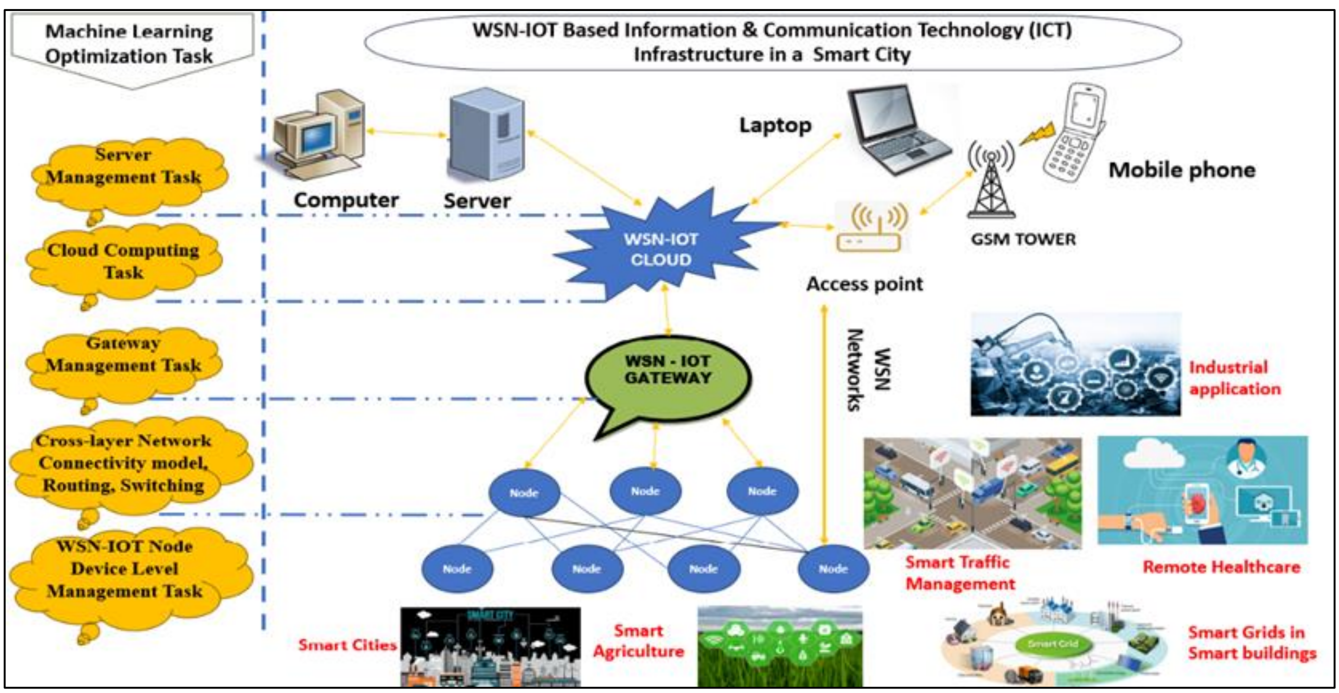

Figure 1 Implementing Wireless Sensor Networks for Applications in the Internet of Things

The protocol proposed in this study improves upon the conventional DSDV routing protocol by taking into account multiple paths as compared to only one path in DSDV. Additionally, the proposed algorithm offers an optimization

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mechanism for selecting the optimal route between source and destination nodes to maximize load balancing and QoS while preserving power. The effectiveness of the proposed algorithm is evaluated using extensive simulations and contrasted against the traditional AODV, DSDV, DSR, and OLSR protocols. The remaining sections of the paper are organized as follows: Section 2 offers a summary of the current advancements in literature, outlines the motivation for the undertaken work and the contribution and objective of this paper is highlighted. Section 3 discusses the suggested strategy, Section 4 evaluates the effectiveness of the suggested procedure, and Section 5 discusses the research's conclusion.

2. BACKGROUND AND MOTIVATION

Positioning, synchronization, data fusion, safeguarding, optimizing power consumption and lifetime of WSNs, and advanced algorithms tailored for sensor-specific application problems are some of the primary obstacles encountered in wireless sensor networks. This section discusses the literature related to multipath routing strategies and the shortcomings of methods as justification for the proposed investigation. The authors in [10] developed a routing method for rechargeable WSNs in which anchor points move under the specified trajectory and wireless power transmissions are used to refresh the installed sensors. Different security issues and algorithms are also presented in [10] to devise a routing protocol focused on energy efficiency and enhanced Quality of Service attributes. Two different routing algorithms for WSNs: AODV and DSR are presented in [11]. In WSN, a variety of routing techniques are usable for data transmission. They primarily focused on the widely used techniques of AODV and DSR [11]. In conducting a performance-based comparison of end-to-end delay, throughput, and packet delivery ratio calculations. The effectiveness of the system is computed using a simulation using the Network Simulator Version-2 software regarding packet delivery ratio. It is observed in [11] that AODV is significantly superior to DSR for packet delivery ratio, whereas, in terms of throughput, DSR is significantly superior to AODV. After that, another comparison of the AODV and DSDV protocols is presented in [12] concerning routing overhead, packet delivery ratio, throughput, and end-to-end delay. According to [12], AODV has increased PDR, throughput, routing overhead than DSDV. In comparison to AODV, DSDV operates as a proactive routing system, featuring a desirable end-to-end delay. Further, authors in [13] present that the premature failure of extensive dense WSN deployments can be prevented by the adoption of energy-efficient cluster-based routing with a focus on sustainability architecture [13]. Authors in [14] presented the optimal approach considering Metrics associated with incorporating Quality of Service (QoS), including throughput, Packet Delivery Ratio (PDR), and latency. They concentrated on classifying the clustering strategy using a fuzzy rule-based methodology. The recommended routing strategy in [14] evenly distributes the network traffic volume across the sensor networks. The document outlines the AODV, OLSR, Dynamic Mobile Ad Hoc Network On-Demand Routing (DYMO) protocols and Bellman-Ford [15]. The effectiveness of these protocols is shown to be affected by variables such as the typical end-to-end delay, throughput, and power consumption. Authors in [16] present a comparative analysis of OLSR, AODV, and DSR algorithms.

The authors of [17] suggest A network using a Multipath DSDV-Based Routing Protocol (MDW) that integrates WIA-PA Wireless Networks for Manufacturing Automation-Process Automation (WIA-PA) It uses a disjoint node method and a link stability-based routing selection criterion. Their approach outperformed DSDV multipath (DSDVM) in terms of the evaluation of the protocol faces constraints due to a fixed network topology, and it does not consider mobility or other challenging environmental factors when assessing QoS metrics like the mean end-to-end delay, PDR, and remaining average energy in the path. NCMDSDV (The Neighbor Coverage Multipath DSDV is the solution put forth by the authors in [18]. Nonlinked paths among the source node and destination nodes are produced by the routing table's implementation of the "Second-hop" and "Link-id" values. The multipath DSDV protocol achieves increased throughput and enhanced packet delivery performance, according to the results. It is quicker in comparison because of its lower packet loss and shorter end-to-end latency. The WSN quality is used as the basis for the routing algorithm optimization in [19]. The authors conducted a comparison of networks employing various algorithms, including AODV, Genetic Algorithm (GA), Dijkstra's, GA-based Dijkstra's, based AODV [19]. Authors in [20] present a heterogeneous wireless sensor network (HWSN) based energy-efficient clustering protocol (EECP). The proposed protocol is designed to facilitate communication among three distinct node types: general, advanced, and superb and this protocol increased the network's longevity, stability, throughput, and energy efficiency. In [21], a routing system with low energy consumption for IoT applications based on a WSN is proposed with network inequality caused by high traffic loads. The suggested protocol takes into account the following three elements to choose the best path: lifespan, ensuring dependability, and evaluating the congestion levels within the succeeding hop node. The suggested protocol saves more energy than previous protocols, has an increased packet delivery ratio, reduced end-to-end delay, and extended network lifespan. The authors in [22] provide a distance-based energy-aware model. Additionally, the suggested approach can extend the IoT lifetime and create the optimal node energy balance.

In [23], the authors present a routing scheme for energy harvesting-based WSNs. In [24], the authors introduced a clustering-based multipath routing protocol (OQoS-CMRP) for WSNs, aiming to enhance QoS and decrease energy usage in the vicinity of the sink. The approach involves establishing clusters and appointing cluster leaders within the region near the sink using a clustering algorithm modified with Particle Swarm Optimization to tackle the energy depletion challenge. In [25], the authors introduce a multipath routing framework designed to tackle wireless interference and emphasize energy conservation within the network. The route exploration approach in [25] chooses the succeeding node, potentially decreasing the link cost. The authors of [26] proposed a PSO-based energy-efficient routing system. Energy and latency are utilized as two constraints to simplify the PSO problem. Results from [26] indicate that the proposed PSO-based system surpasses Genetic Algorithms (GA) in terms of routing performance. Table 1 summarizes the view of methodology, findings, algorithms used, and limitations in literature research.

Table 1 Comparative Analysis of Routing Protocols Research Studies

References	Focus	Methodology	Findings	Algorithms Used	Limitations
[10]	Multipath routing for WSN-based IoT	Proposed MPSORP using PSO algorithm	Improved energy efficiency, low end-to-end delay, high packet delivery ratio, high throughput	Particle Swarm Optimization (PSO)	Experimental validation is limited to the simulation environment, and findings may not fully reflect real-world scenarios
[11]	AODV vs. DSR comparison	Conducted simulation-based performance analysis	AODV showed superior Packet Delivery Ratio (PDR), DSR had better throughput	AODV, DSR	The simulation environment may not fully reflect real-world scenarios
[12]	AODV vs. DSDV comparison	Evaluated metrics to compare routing protocols	AODV demonstrated higher PDR, throughput, and lower routing overhead	AODV, DSDV	Findings may be specific to evaluated metrics and scenarios
[13]	Performance analysis of AODV and DSDV	Analyzed AODV and DSDV protocols in MANET	AODV showed better performance in terms of throughput, packet delivery ratio, and routing overhead; DSDV exhibited lower end-to-end delay	AODV, DSDV	Limited to performance comparison of specific routing protocols in MANET environment, may not fully represent other network scenarios
[14]	Green cluster-based routing scheme	Proposed routing scheme for large-scale WSNs	Even traffic distribution improved QoS	Fuzzy logic, distributed clustering algorithm	Specific to the clustering approach, it may require further validation in diverse scenarios
[15]	Routing protocol overview	Analyzed protocol effectiveness across metrics	Protocol performance varied based on evaluation metrics	AODV, OLSR, DYMO, Bellman-Ford	Limited evaluation metrics may not cover all aspects
[16]	OLSR, AODV, DSR comparison	Compared algorithm performance using various metrics	Algorithms exhibited diverse performance across metrics	OLSR, AODV, DSR	Findings may not generalize beyond specific algorithms

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[17]	Multipath DSDV for WIA-PA	Developed multipath routing protocol for specific network	Outperformed traditional DSDV, but constrained by fixed topology	DSDV	Limited to fixed topology, lacks consideration for mobility
[18]	Neighbor Coverage Multipath DSDV	Implemented routing table strategy for increased performance	Achieved improved throughput and packet delivery	DSDV	Specific to routing strategy, scalability concerns
[19]	Routing algorithm optimization	Compared performance of different routing algorithms	Limited generalization beyond specific algorithms and scenarios	AODV, Genetic Algorithm (GA), Dijkstra's	Limited to specific algorithms, scalability concerns
[20]	Wireless sensor network routing comparison	Simulated performance comparison among various routing algorithms	GA shows better performance in various network configurations	Genetic Algorithm (GA), Dijkstra algorithm, AODV, GA-based AODV Routing (GA-AODV), Grade Diffusion (GD) algorithm, Directed Diffusion algorithm, GA combined with GD algorithm	Assumed the presence of faulty nodes and dynamic nodes with different mobility speeds, simulation environment limitations
[21]	Energy-efficient clustering protocol for HWSN	Design and evaluation of the EECPEP-HWSN protocol	Outperforms LEACH, DEEC, and SEP protocols in terms of energy efficiency and performance	EECPEP-HWSN	Specific to the clustering approach, it may require further validation in diverse scenarios
[22]	Energy-efficient routing protocol for WSN-based IoT	Proposed EOMR protocol for improved QoS	Outperformed REER and Rumour protocols in terms of end-to-end delay, residual energy, packet delivery ratio, and throughput	Heuristic or optimization-based routing algorithm	The simulation-based study may have limitations in real-world applicability
[23]	Energy-aware and distance-aware backpressure data collecting scheme	Proposed EDA scheme based on LIFO queue model	Reduced end-to-end delay and energy consumption, balanced energy in large-scale sensor networks	EDA scheme based on the LIFO queue model	Specific to the proposed scheme, a congestion control strategy is needed for better performance and real-time demand for emergency packets is not guaranteed

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[24]	Backpressure-based clustering multipath routing protocol	Proposed OQoS-CMRP for WSNs	Enhanced QoS and reduced energy consumption near the sink	OQoS-CMRP	Specific to the proposed protocol, it may require further validation in real-world scenarios
[25]	Energy balanced delay aware multi-path routing using PSO	Employed PSO for energy-balanced delay-aware multi-path routing	Improved network lifetime and energy balance	Particle Swarm Optimization (PSO)	Specific to PSO-based routing, it may require further validation in diverse scenarios
[26]	PSO-based energy-efficient routing system	Proposed PSO-based routing system considering energy and latency constraints	Outperformed Genetic Algorithms (GA) in terms of routing performance	PSO-based routing system	Limited to simulation-based study, real-world applicability may vary

The research presented in the literature does not take into account enhancing the efficiency of multipath routing protocols on the network. Motivated by the gaps in the literature, this paper proposes a novel routing algorithm termed as EPSO-AODV algorithm. The primary contributions of this paper include:

- Designing a reliable system of routing to locate the best route in a complex practical WSN.
- Enhancing the network's key performance indicators (KPIs), such as optimizing bandwidth, improving packet delivery rates, and reducing end-to-end delays, is a primary focus of the suggested methodology.
- Evaluating the efficiency of the suggested methodology and conducting a comparative analysis against traditional AODV, DSDV, DSR, and OLSR protocols is a crucial aspect of this study.

The main objective of this research is to suggest a powerful routing recovery method that enables the mobile sink to move seamlessly while carefully reviewing and updating the best-transmitting path. Models for routing with fault tolerance are generated to maintain network robustness, boost operational efficiency, reduce energy consumption, extend network lifespans, and continuously improve network robustness and dependability. We depart from earlier work in the following ways: in contrast to most of the prior work, we provide an upgraded multipath routing algorithm for mobile wireless sensor networks utilizing particle swarm optimization that increases network reliability and efficiency; our experiment uses sink mobility as opposed to optimum routing with a static sink to conserve energy, lower packet loss, enhanced throughput, and prolong the network lifetime and finally, alongside the energy limitations constrained by the network's operational life, we apply reliability and imposing restrictions on sink mobility to mitigate routing challenges related to delays.

3. METHODS AND MATERIAL

This section delineates the proposed routing approach for WSNs with mobile sinks. The routing algorithm can be represented as a multi-objective optimization issue where there is a need to enhance throughput while there is a requirement to minimize latency. The suggested method aims to facilitate the data transfer between sources and sink nodes through a wireless channel efficiently with increased throughput, reduced latency, and the overhead in routing, along with energy consumption. Firstly, the AODV routing protocol and PSO are presented and thereafter, an explanation of the proposed AODV routing protocol utilizing PSO is provided.

AODV is a network protocol for mobile networks without infrastructure. Utilizing the on-demand routing technique, it establishes routes among diverse network nodes as indicated in [27]. The “request-response” method and the sequence number technique are the main technologies to prevent routing loops. A typical WSN employing AODV routing is shown in Figure 2(a). Disseminating RREQ messages through flooding to neighboring nodes in AODV results in significant control message overhead during the path-finding process. Furthermore, the initiation of a network storm may be initiated by the establishment of a reverse route and result in significant packet loss. Node stability and energy reserves are not taken into account while building the route, which might lead to a connection break, data loss, and a decrease in the dependability of the routing process. The optimal relay node is chosen in the next step by balancing several characteristics to create the best route and improve routing accuracy. As a reactive protocol, AODV often has less overhead (fewer route maintenance messages) than proactive protocols. Understanding the dynamics of AODV involves analyzing a network with five nodes labeled 'S,' 'A,' 'B,' 'C,' 'D,' 'E,' and 'F,' positioned at equal distances from one another. In this

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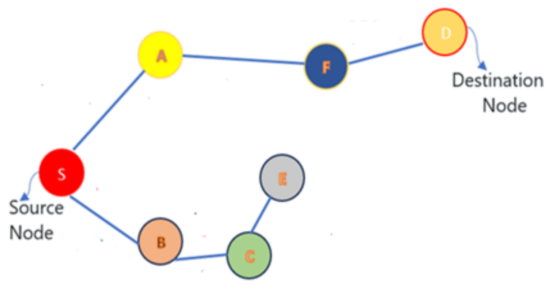
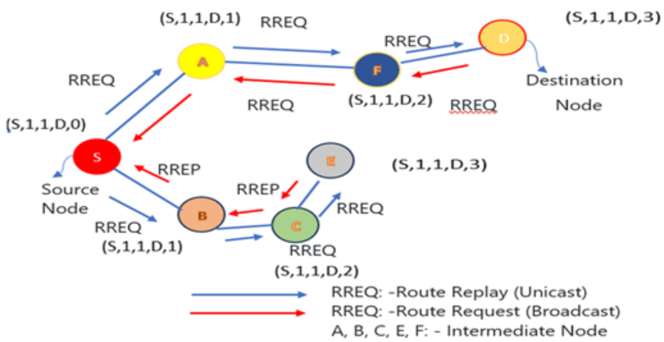
scenario, 'S' represents the source node, while 'D' serves as the destination, as illustrated in Figure 2(b).



(a)



(b)

Figure 2 (a) A typical WSN Employing AODV Routing and (b) STRUCTURE of WSN During AODV Routing [12]

AODV's routing is determined by the following parameters within the RREQ packet: Destination IP, Destination Sequence Number, Source IP, Source Sequence Number, and Hop Count. A key goal of AODV routing is to manage data packets through identification, discovering, and preserving determining the most efficient path from the source to the destination. AODV searches the routing table to ascertain the next-hop information when a node receives a message from an upper layer, such as an application or TCP.

3.1. Particle Swarm Optimization Algorithms

Particle Swarm Optimization is a distinctive method within the realm of Artificial Intelligence. Within Swarm Intelligence, there exist two categories of optimization techniques: Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). Within PSO, a swarm denotes a collection of candidate solutions for the optimization task. An individual particle represents each potential solution. Within the framework of PSO, a swarm is a group of candidate solutions for the optimization challenge, each depicted through a particle. PSO endeavors to determine the position of each particle that evaluates an objective function of a given fit the best [28-30]. Each particle provides a position within the search space, which is then traversed, with updates made to the position of the particle to the personal best position. Mathematically, the particle position is updated throughout the flow equation represented in Eq. (1):

$$v_i(t+1) = \omega\, v_i(t) + c_1 r_1 (y(t) - x_i(t)) + c_2 r_2 (z(t) - x_i(t)) \quad (1)$$

Where $v_i(t+1)$ is the updated velocity of a particle i at the next time step, $v_i(t)$ is the velocity of a particle i at time t, $y(t)$ is the personal best solution of a particle i at time t, $z(t)$ is the global best solution, $x_i(t)$ is the current position of a particle, ω is inertial weight, and c_1 is cognitive constant, this is a personal cognition factor, reflecting the significance of the particle's own past experiences. On the other hand, the parameter c_2 is the social learning parameter, and both serve as acceleration coefficients. The position is updated in Eq. (2):

$$x_i(t+1) = x_i + v_i(t+1) \quad (2)$$

At the subsequent time step, x_i (t + 1) denotes the updated position of particle i, where x_i represents its current position. v_i (t + 1) represents the revised velocity of particle i. The cognitive aspect is influenced by the particle's proximity to its optimal personal position as represented in Eq. (3):

$$c_1 r_1 (y(t) - x_i(t)) \quad (3)$$

The social element is determined by the particle's proximity to the global best position mathematically represented as in equation (4):

$$c_2 r_2 (z(t) - x_i(t)) \quad (4)$$

3.2. Proposed PSO-based AODV Model

The flooding mechanism in AODV is controlled by restricting RREQ packets sent from a node that receives the RREQ for the first time during the route discovery mechanism. The network's lifespan diminishes as a consequence of energy depletion caused by flooding and can cause early death of some nodes that have been frequently used in route discovery mechanism, data forwarding, and when they act as source or destination [31]. In many applications, nodes are distributed randomly throughout the network initially. Therefore, the density of the nodes at any certain area is uncontrolled. This causes highly populated regions and scarce regions in the network. There is considerable loss of energy when the RREQ enters in highly populated area due to the front and back movement of RREQ between the nodes as well the nodes in such regions will send RREQ to all its neighbouring nodes. The scarce regions, where there are few nodes are deficient in neighbours and become the cause of poor coverage and connectivity. In such cases, there is the possibility of network breakdown if the nodes lying in such areas are used frequently [32, 33]. We propose to modify the AODV routing in the route discovery phase restricting the flooding in densely populated regions of the network and improving the coverage and connectivity in the scarcely populated region during the reception of the first RREQ by any node. The mechanism ensures the conservation of energy as well it also improves the density of the scarce region. The energy conservation is obtained by allowing only those nodes that have a certain amount of energy for their neighbourhood and the network energy. The density in terms of neighbours is improved by the re-localization of nodes using Particle Swarm Optimization as it is applicable in an improved version of the paper [31]. The PSO iterates to find optimum spatial coordinates for the node in a radius of 20m from its initial location where its neighbour's density is increased to improve the connectivity as well as coverage. The radius of 20 m is selected to maintain or secure the old neighbours of the node and find new ones. On reception of RREQ packet by any node in the network, the following parameters are computed as shown in Eq. (5) -Eq. (13):

1) The Average density of the network (Avg_{nw})

The parameter is measured by determining the neighbours for every node within the network and then finding the average number of neighbours. The mechanism is explained in Figure 3. Mathematically, Avg_{nw} is calculated as Eq. (5):

$$Avg_{nw} = \frac{1}{N} \left[\sum_{x=1}^{M} \left\{ \sum_{y=1}^{Ngb} \left[N_{xy} \right] \right\} \right] \quad (5)$$

Where, $\sum_{y=1}^{Ngb} \left[N_{xy} \right]$ represents the neighbourhood nodes of N_x and N_{gb} denotes the number of nodes within the specified range transmitting node N_x.

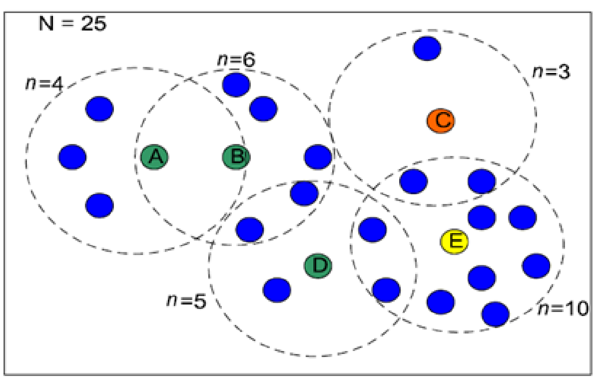


Figure 3 Mechanism to calculate Average Density

Node A, B, C, D, and E has 4, 6, 3, 5, and 10 neighbors respectively. The average density will be 6 $\left(\frac{4+6+3+5+10}{5}\right)$.

2) Average density in one-step neighbourhood (Avg_{nbr})

One-step neighbours are a node's neighbor's neighbours. It is found in a similar way as shown in Figure 3, if we consider A, B, C, D, and E are neighbors of nodes who have received the RREQ packet, the Avg_{nbr} is calculated by Eq. (6):

$$Avg_{nbr} = \frac{1}{m} \left[\sum_{i=1}^{m} \frac{1}{N_b} \left\{ \sum_{j=1}^{N_b} \left[N_{ij} \right] \right\} \right] \quad (6)$$

Here N_b are the count of neighboring nodes associated with the current node under examination and N represents any specific node within the neighborhood.

3) The Density of the Node (N_{curr})

It is the number of immediate neighbors of the node receiving the RREQ packet calculated using Eq. (7):

$$N_{curr} = \sum_{k=1}^{n_b} \left[N_k \right] \quad (7)$$

Here n_b denotes the count of neighboring nodes associated with the present node within the context consideration and signifies any particular node within the vicinity.

4) Average Energy of the Network (n_{NET})

It is calculated as the mean energy level across all 'N' nodes within the network represented in Eq. (8):

$$n_{net} = \frac{1}{N} \sum_{k=1}^{N} \left[E_k \right] \quad (8)$$

5) Average Energy of the Neighbourhood (n_{nei})

It is the energy average of neighbouring nodes calculated using Eq. (9):

$$n_{nei} = \frac{1}{Nb} \left\{ \sum_{j=1}^{Nb} \left[E_{ij} \right] \right\} \quad (9)$$

6) Energy of the Node (Eg)

It denoted the node's energy in Eq. (10):

$$E_g = E_k \quad (10)$$

Where E_k is the node energy.

3.3. Restricted Flooding Mechanism

In a restricted flooding mechanism, the intermediate nodes are restricted from forwarding the RREQ packets to their neighbours. The following ratios are mathematically calculated using Eq. (11)- Eq. (13):

$$V_1 = \frac{E_g}{n_{nei}} \quad (11)$$

$$V_2 = \frac{AE_g}{n_{NET}} \quad (12)$$

$$V_3 = \frac{Avg_{nbr}}{Avg_{nw}} \quad (13)$$

Also, we used a threshold $T = 0.12N$, for determining the scarce region. It is set assuming that a node should have at least 3 nodes in each of the 4 quadrants of a node placed at the origin or center. If the density of neighbours falls below the threshold T, the node is assumed to be in the scarce region while when the number of neighbours is above the threshold value, the node is considered to be in a populated region. The position of the node lying in the scarce region is optimized

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using PSO. That is the PSO finds a new location for the node in a radius of 20 m where it will have a higher number of neighbours than it has initially. The process of how RREQ packets are restricted is shown in Figure 4 and Table 2 outlines the differences between AODV and Proposed EPSOAODV in various aspects.

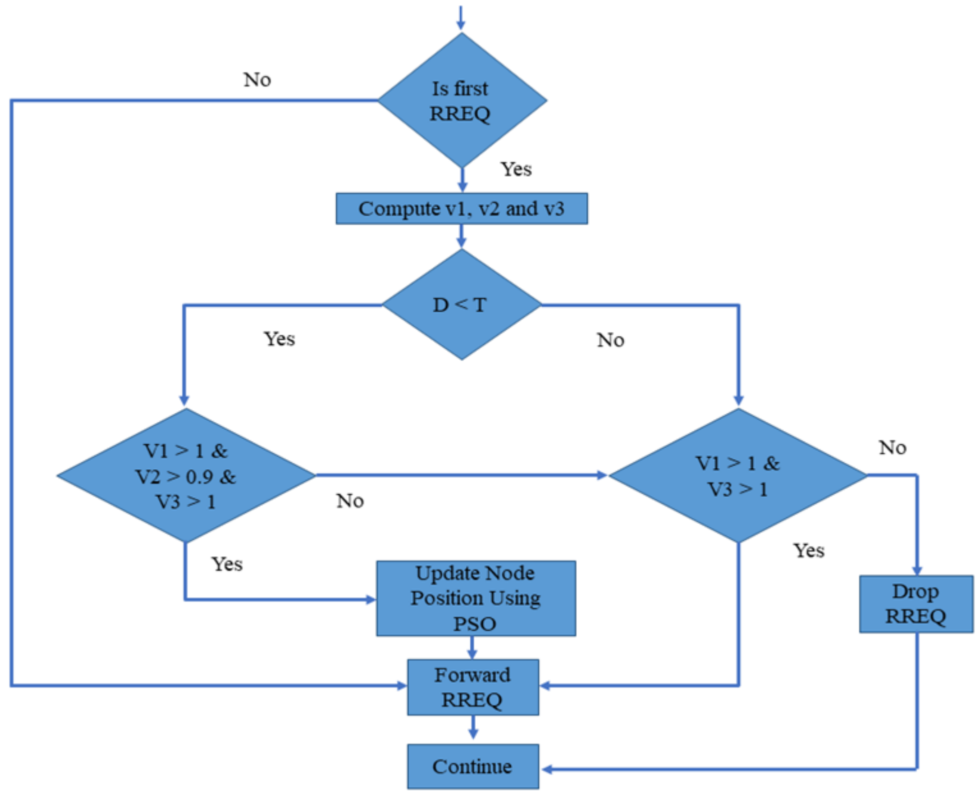

Figure 4 Flowchart of Proposed EPSO-AODV Routing Protocol

Table 2 The differences between AODV and Proposed EPSO-AODV

Aspect	AODV	Proposed EPSO-AODV
Energy Efficiency	Moderate	Optimized for energy efficiency
Position Awareness	No	Yes
Security	Basic mechanisms	Enhanced security features with encryption
Routing Method	On-demand, distance vector	On-demand, energy-efficient, position-based
Overhead	Moderate to high	Lower due to energy-aware optimizations
Scalability	Moderate	Improved scalability with energy awareness
Mobility Support	Good	Enhanced due to position-based optimizations
Implementation	Widely implemented	Requires additional position awareness
Communication Overhead	High due to route discoveries	Reduced due to energy-efficient design

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3.4. Calculating Optimized Location Using PSO

To calculate the optimized location in a network, the initialization of PSO's parameters is undertaken. These parameters encompass the particle count, iteration count, minimum and maximum positions of particles within their network space, minimum and maximum velocities for particle acceleration, and their initially assigned best position. The initial values chosen for these parameters are shown in Table 3.

Table 3 PSO's Initial Parameters

Parameters	Initial values	Remark
No. of particles (M)	20	
No. of Iterations/Epoch (k)	10	
Initial best positions - Pbest	Same as the initial node location	For all M=20 particles
Initial Global best position -Gbest	0.0	
Minimum and maximum velocities	vmin = 0.0 and vmax = 5.0	
Minimum and maximum displacement for any particle	xmin = 0 and xmax = 20	The initial position x and the displacement when added should not exceed the network space
Constant c1 and c2	2.0	
Inertial weight defining factor (t)	0.9 to 0.4 in steps of 0.5/epoch	

The swarm involving particles of a finite predefined number say N_p. Each D-dimensional particle $P_{n,d}$ in $N_p(1 \leq n \leq N_p)$ is capable of solving convergence to the multidimensional problem. Each particle $P_{n,d}$ retains its position $X_{n,d}$ $(1 \leq d \leq D)$, and velocity $V_{n,d}$ in the d^{th} multidimensional space. The population of the particles can be represented as in equation (14).

$$P_n = [X_{n,1}(t), X_{n,2}(t), X_{n,3}(t), \dots X_{n,D}(t)] \quad (14)$$

Each of the individual particles is then subjected to a fitness function and the quality of the solution is judged concerning a zero or permissible error. The particle corresponding to the best solution called the Global best (G_{best}) is monitored in each step while the particle's personal or own best performance from all the previous steps is memorized and called the Particle best (P_{best}). To reach the goal, each particle updates its respective velocity $V_{n,d}$ and position $X_{n,d}$ using the current position (P_{curr}), global best position (G_{best}), and the particle's own best position (P_{best}). In each iteration or step, the velocity $V_{n,d}$ and position $X_{n,d}$ in dimension D are updated as defined in Eq. (15) – Eq.(17):

$$V_{n,d} = w * V_{n,d}(k-1) + c_1 r_1 \{P_{best} - X_{n,d}(k-1)\} + c_2 r_2 \{G_{best} - X_{n,d}(k-1)\} \quad (15)$$

$$X_{n,d}(k) = X_{n,d}(k-1) + V_{n,d} \quad (16)$$

$$w = w_{max} - \frac{w_{max} - w_{min}}{w_{maxIterations}} k \quad (17)$$

where, $maxIterations$ = The maximum iterations, k = the present iteration count ($1 \leq k \leq maxIterations$), w = a parameter that adapts itself and corresponds to the inertial weight with w_{max}=0.9 and w_{min}=0.4, c_1 *and* c_2 *represent* acceleration constants within the specified range($0 \leq c_1, c_2 \leq 2$) and r_1 and r_2 are randomly assigned values.

The updated values of velocity and positions are then subjected to lower and upper limits so that the particle remains in the search space and contributes in achieving the goal. The values of the limits depend on the minimization or the maximization optimization problem. The new values are then used to evaluate the fitness function for obtaining the new values of P_{best} and G_{best}. In the context of a minimization problem, the updated values for P_{best} and G_{best} can be computed by mathematical Eq. (18) and Eq. (19).

$$P_{best} = \begin{cases} P_{curr}, & if \{fitness(P_{curr}) < fitness(P_{best})\} \\ P_{best}, & Otherwise \end{cases} \quad (18)$$

$$G_{best} = \begin{cases} P_{curr}, & if \{fitness(P_{curr}) < fitness(G_{best})\} \\ G_{best}, & Otherwise \end{cases} \quad (19)$$

If the PSO can find a new location in the 20m radius space about the increased neighborhood for the node under which is in a scarce region, the node is positioned at the new locations found in Gbest. If the PSO fails to find such a new position, the node remains at its position until another node is displaced in its neighborhood. The contribution of this research is outlined as follows.

1. The existing AODV protocol wastes a large amount of memory in the route discovery mechanism. The RREQ packets are sent and received by nodes and thereby dropped on receiving duplicate or the same packets from the neighbouring nodes. Our proposed work restricts the RREQ packets (first RREQ) in the flooded region and allows flow for better connectivity and coverage in the scarce region.
2. Many applications deal with mobile nodes and the topology of the network goes on changing making the situation dynamic. In most medical applications, static nodes are required but suffer from the drawback of connectivity and coverage in the scarce region and require relocation to improve their neighbourhood. We adopted Particle Swarm Optimization to relocate such deserted nodes to improve the neighbourhood.
3. The nodes in the populated region are allowed to flood RREQ packets based on randomly generated factors or thresholds. When the density ratios satisfy the condition, they are allowed to forward the RREQ packets, otherwise restricted. This prevents unnecessary RREQ flooding.
4. We allow nodes to have sufficient energy to participate in the control and data packet transmission process. The node energy, its energy in the neighbourhood, and the average energy are taken into consideration and allow a node to participate when it has energy higher than the neighbourhood and energy in the neighbourhood is greater than the network average energy.
5. Even though there had been considerable trade-offs between various performance parameters, we have achieved superior results and improved parameters without affecting the other parameters.

4. RESULTS AND DISCUSSION

To validate the efficiency of the EPSO-AODV algorithm, a comparative analysis is conducted against the conventional AODV. Simulations are performed within a 1641m x 897m square area, where nodes are randomly dispersed and their residual energy diminishes over time with a uniform decline in energy consumption rates per node. This study meticulously evaluates and contrasts the routing proficiency among the three algorithms within identical scenarios, focusing on key performance metrics such as average reliability of paths, delay from end to end, number of hops, connectivity of links, and longevity of routes. Ad-hoc networking groups typically employ network simulators. It is software with an open-source nature that is used to analyze and test new network protocols before they are implemented. Many Internet protocols can be simulated using the NS2 emulator. We may dynamically generate a variety of wireless network conditions, such as mobility-induced connection losses, network traffic congestion, and security breaches, using NS2's event-driven simulation capabilities. Considering that nodes exchange data via a wireless medium by sharing the wireless medium, there are no visible physical links in the network name. Rearranging nodes within the NAM tool through a drag-and-drop action, it is also able to inspect the network. The Simulation Presentation using NAM NS2 Simulator of 10 nodes is shown in Figure 5. The bottom section of the network animation window showcases a continuous representation of the ongoing network process and can be annotated using the trace annotate option. Table 4 provides a comprehensive overview of the simulation parameter settings. The Performance parameters are as follows:

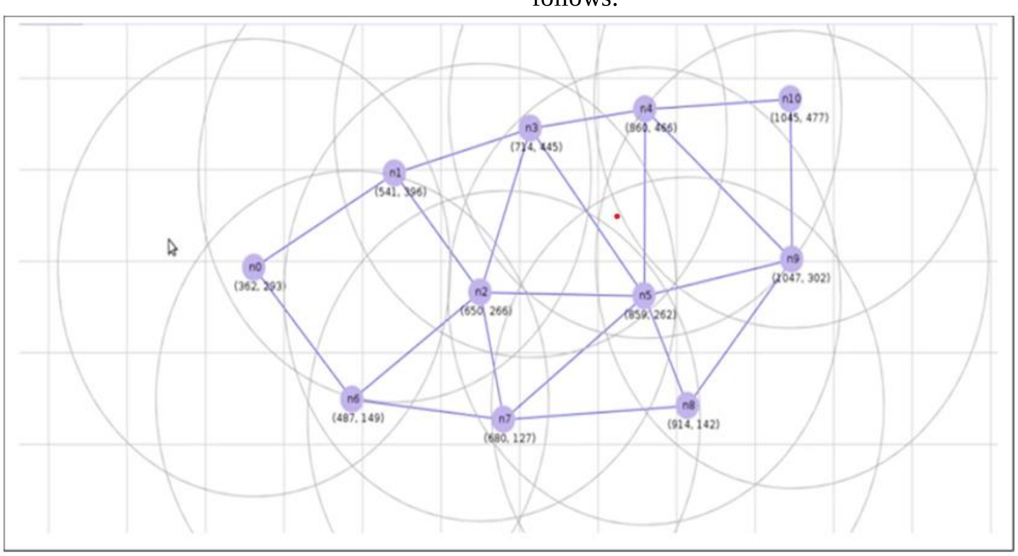

Figure 5 Simulation Presentation Using NAM NS2 Simulator of 10 Nodes

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Table 4 Parameter Setup for Simulation of the Proposed Algorithm

Parameters for Simulation	Value
Time of simulation	100s
Network Area Dimension	1641 m x 897 m
Node count	200
Forwarding Range	250 m
Data Rate	2.0 Mbps
Medium Access Control (MAC) Protocol	802.11
Data transmission category	TCP
Packet capacity	1500 Bits
Network routing	AODV, EPSO-AODV
Initial Node Energy	1000J
Velocity of nodes	[5 – 45 m/s]
Movement	Random movement within a specified range [-50 50]
Queue Length	50

4.1. Packet Delivery Ratio (PDR)

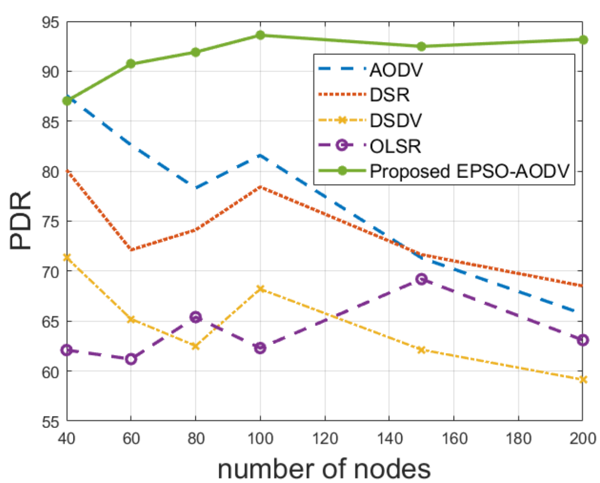

Figure 6 PDR v/s no. of Nodes for the Proposed EPSO-AODV Protocol and its Comparison with AODV, DSR, DSDV, and OLSR Protocol

Packet Delivery Ratio acts as an indicator of the delivery ratio's effectiveness [34]. A superior network performance is indicated by a higher PDR value. The PDR result of the suggested approach is presented in Figure 6 with different values of the number of nodes. From Figure 6, it is evident that the outcomes of the proposed EPSO-AODV algorithm are comparable to the conventional AODV algorithm for N=40 but the proposed algorithm outperforms AODV when the number of nodes is increased to 60,80, 100, 150, and 200 nodes. Further, the proposed algorithm outperforms DSR, DSDV, and OLSR algorithms and showcases superior PDR.

4.2. Delay (End-To-End Delay)

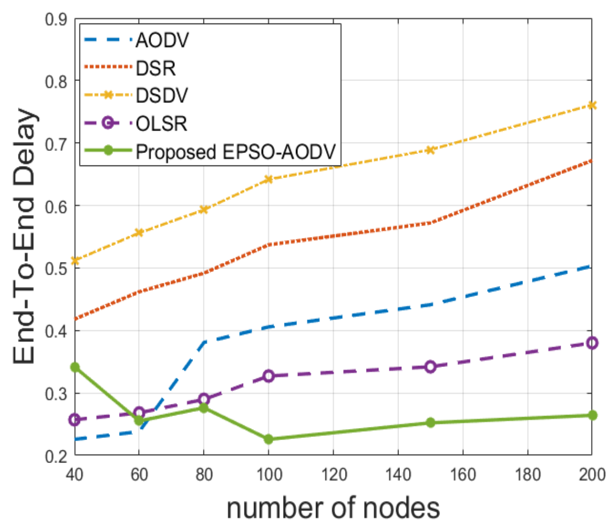

Figure 7 Analysis of Performance of Proposed EPSO-AODV Using End-to-End Delay v/s Number of Nodes PDR v/s Number of Nodes and its Comparison with AODV, DSR, DSDV, and OLSR Protocol

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End-to-end delay denotes the time required for a packet to traverse a network, moving from a sender node to a receiver node. Delay is one of the important parameters for evaluating the quality of service. A reduced delay value indicates enhanced network quality. The end-to-end delay results for the proposed EPSO-AODV algorithm are presented in Figure 7. It can be visualized from Figure 7 that the end-to-end delay of EPSO-AODV diminishes as the number of nodes increases in comparison to AODV, DSR, DSDV, and OSLR. This signifies the proposed algorithm exhibits superior latency compared to these conventional algorithms.

4.3. Throughput (t)

Throughput is characterized as the efficient rate of data transfer and is expressed in bytes per second (bps). This establishes how much traffic can be handled by an application in the network [35]. The throughput analysis with different numbers of nodes for the EPSO-AODV and AODV algorithms is presented in Figure 8. An observation reveals that the throughput of conventional AODV decreases from 60.54 to 10.51 with an increasing number of nodes from 40 to 200 whereas the throughput of the proposed system improves from 40.19 to 78.36 for the same variation in the number of nodes. At N=100, the throughput of proposed EPSO-AODV, AODV, DSR, DSDV, and OSLR is 74.21, 36.32, 31.76, 28.12, and 25.12 respectively. This implies that the proposed EPSO-AODV algorithm is more suitable for practical scenarios with a higher number of nodes.

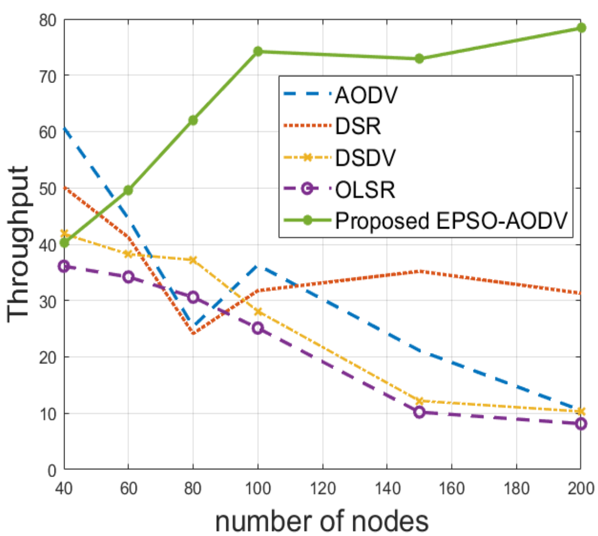

Figure 8 Throughput v/s Number of Nodes for Proposed EPSO-AODV Protocol and its Comparison with AODV, DSR, DSDV, and OLSR Protocol

4.4. Routing Overhead

Routing protocols send control information (packets) to find routes. These control packets essentially encompass route requests, route replies, and route error packets that have been sent. It is important to look at how many control packets are sent by the protocol to assess the effectiveness of determining routes to a destination. The greater the routing overhead of a protocol (measured in packets or bytes), the more bandwidth will be wasted. From Figure 9, it is apparent that the proposed algorithm offers lower routing overhead as compared to the conventional algorithm.

For example, at N=100, the routing overhead of AODV, DSR, DSDV, and OSLR is 3554, 3821, 3541, and 4725 respectively whereas for the proposed algorithm is only 1619 which is significantly lower. The overall performance of the proposed EPSO-AODV for network configuration with 40, 60, 80, 100, 150, and 200 nodes is shown in Table 5. From Table 5, it is evident that the failure rate of the proposed algorithm is very low and an average improvement of 32.84% is obtained in connectivity with the proposed EPSO-AODV algorithm.

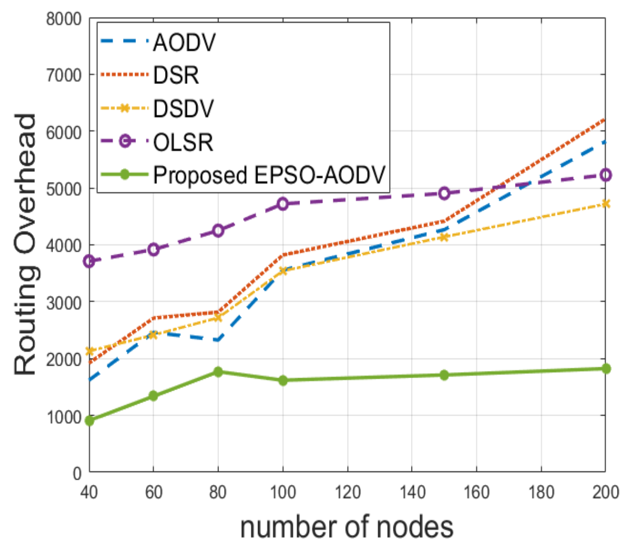

Figure 9 Performance Analysis of Proposed EPSO-AODV using Routing Overhead v/s Number of Nodes and its Comparison with AODV, DSR, DSDV, and OLSR Protocol

The static network considered for this novel research work provides mobility in terms of node re-localization using the proposed EPSO-AODV routing scheme during the route discovery phase. For one round of simulation, the proposed scheme improves connectivity by 31% which is improved in subsequent rounds and a better topology can be obtained to provide improved connectivity and coverage within the network space conserving energy.

Table 6 shows the average value of the QoS parameters over all the configurations which provides a clear picture to conclude that the proposed EPSO-AODV performed better than the existing AODV protocol.

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Table 5 Overall Performance of Proposed EPSO-AODV for Network Configuration

Sr. No.	No. of Nodes	Nodes in Populated Region	Nodes in Scarce Region	PSO Success	PSO Failure	Connected Nodes	Improved Connectivity	% Improvement
1	40	16	22	14	08	81	106	30.86
2	60	25	33	25	08	210	271	29.04
3	80	31	47	41	06	331	439	32.62
4	100	42	56	51	05	515	693	34.56
5	150	71	77	70	07	854	962	32.71
6	200	94	104	98	06	1331	1472	37.26
Average Improvement in connectivity								*32.84*

Table 6 Average Values of QoS Parameters Over all Configurations

QoS Parameters	AODV	Proposed EPSO-AODV
Total Packets Sent	128	148.25
Total Packets Received	106.75	135.75
Total Packets Forwarded	1037	1513.25
Total Hello Packets Sent	2867.75	2875.25
Total Hello Packets Drop	863.25	1303
Packet Delivery Ratio	0.825175	0.908075
Throughput of the network (Kbps)	41.6992	53.027375
Total hop count	5424.25	8933
Average Hop Count	52.25	61.5
Routing Overhead	2490	1409
Normalized Routing Load	26.5098	11.419975
Total Energy Residue	6344.202185	4980.506301
Average End-to-End Delay	0.312582962	0.27474004

5. CONCLUSION

The lifespan of a wireless network is contingent upon the energy consumption of its nodes. Optimization stands as one of the vital techniques for extending prolonging the network lifespan through energy consumption. In this paper, we introduced optimization models, evaluating their performance on an ad-hoc network across different network sizes. We implemented the models using the NS2 network simulator and visualized the results through the NAM tool. Here, the simulation focuses on the routing technique in Ad-Hoc Networks utilizing traditional methods AODV, DSDV, DSR and OLSR protocols and We improved routing using PSO methods, specifically enhanced AODV through EPSO. Following performance analysis, it was observed that the proposed EPSO-AODV exhibited superior performance compared to the conventional AODV routing. Nodes in scarce regions are allowed to forward first and subsequent RREQ packets freely in the network and relocated using PSO to improve their neighbourhood for better connectivity and coverage. Nodes in the populated region are governed by energy ratios and are granted permission to forward the initial RREQ packets only when they satisfy the energy conditions. Excessive flooding depletes energy and affects the network's

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lifetime. The EPSO-AODV helps to improve connectivity and coverage and lengthen the lifetime conserving the node energies. This scheme is efficient in maintaining the proper balance of QoS parameters works well for high-density networks and can restructure network topology obtaining better connectivity. The proposed EPSO-AODV outperforms the traditional AODV, DSDV, DSR, and OLSR protocols in all node configurations. The packet delivery ratio of proposed protocol is found to be 91.48 as compared to AODV, DSDV, DSR and OLSR with PDR = 77.85, 74.15, 64.76 and 63.88 respectively. Similarly, the throughput of proposed protocol is found to be higher than the existing protocols for all values of N. The routing overhead was low by approximately 40%. The AE2E delay was found to be consistent in proposed algorithm with increasing number of nodes whereas the delay increases abruptly in other conventional protocols. The energy residue in the case of proposed EPSO-AODV is less (4981 Joules) than the value of AODV (6344 Joules) which is the cost paid for a higher packet delivery ratio. The overall neighbourhood connectivity was improved by 32.84%. These improved values signify the practical applications of the proposed EPSO-AODV protocol.

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