I. J. Computer Network and Information Security, **2026, 1, 99-115**
Published Online on February 8, 2026 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijcnis.2026.01.07

Bacterial Foraging Inspired Mamdani Fuzzy Inference based AODV (BF-MFI-AODV) for VANET Route Management Optimization

R. Jasmine Immaculate Shelly*
Department of Computer Science and Research Centre, S.T. Hindu College, Nagercoil, Affiliated to Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India
E-mail: shellyrvk@gmail.com
ORCID iD: https://orcid.org/0000-0002-2510-5795
*Corresponding author

M. Milton Joe
Department of Computer Science, St. Jerome's College, Nagercoil, Affiliated to Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India
E-mail: m.miltonjoe@gmail.com
ORCID iD: https://orcid.org/0000-0002-2626-3023

B. Ramakrishnan
Department of Computer Science and Research Centre, S. T. Hindu College, Nagercoil, Affiliated to Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India.
E-mail: ramsthc@gmail.com
ORCID iD: https://orcid.org/0000-0003-0328-5112

Received: 01 November 2024; Revised: 29 July 2025; Accepted: 25 August 2025; Published: 08 February 2026

Abstract: In this research, we propose an integrated routing protocol termed Bacterial Foraging inspired Mamdani Fuzzy Inference based AODV (BF-MFI-AODV) for Vehicular Ad-hoc Networks (VANETs), which combines Mamdani Fuzzy Inference System (MFIS) and Bacterial Foraging Optimization (BFO) techniques. The protocol aims to address the challenges of dynamic and unpredictable network conditions in VANETs by leveraging fuzzy logic and bio-inspired optimization principles. BF-MFI-AODV enhances route discovery, maintenance, and optimization mechanisms, resulting in improved adaptability, reliability, and efficiency of communication. Through extensive simulations and real-world experiments, the performance of BF-MFI-AODV is evaluated in terms of packet delivery ratio, end-to-end delay, routing overhead, and network lifetime. Our results demonstrate the effectiveness of BF-MFI-AODV in enhancing the overall performance of VANETs compared to existing routing protocols. The proposed protocol shows promise in providing robust and efficient communication solutions for dynamic vehicular environments, thus contributing to the advancement of intelligent transportation systems.

Index Terms: VANETs, Mamdani Fuzzy Inference System, Bacterial Foraging Optimization, Dynamic Routing, Route Maintenance.

1. Introduction

Vehicular Ad hoc Networks (VANETs) are dynamic wireless networks formed by vehicles equipped with communication technologies such as sensors and onboard computers, enabling real-time interaction with other vehicles and roadside infrastructure[1]. These self-organizing networks operate without fixed infrastructure, supporting data exchange on traffic conditions, hazards, and emergencies[2]. VANETs enable diverse applications including collision avoidance, traffic control, and infotainment services[3]. Key challenges include maintaining stable connectivity, handling rapid topology changes, and ensuring secure communication in highly mobile environments[4]. Current research continues to address these issues, aiming to enhance VANET reliability, safety, and efficiency in modern transportation systems.

Fuzzy inference systems (FIS) are computational frameworks that handle uncertainty by modelling vague or imprecise information using fuzzy logic[5]. They consist of fuzzification, rule evaluation, and defuzzification stages, enabling decision-making in complex and uncertain environments. The Mamdani fuzzy inference system (MFIS) is a type of FIS that uses linguistic variables and fuzzy rules to map input variables to output variables[6]. It employs fuzzy if-then rules, expressed in natural language, to capture expert knowledge and reasoning. MFIS is widely used in various applications, including control systems, pattern recognition, and decision support systems, due to its ability to handle vague inputs and provide human-like reasoning[7].

In VANETs, the MFIS plays a crucial role in enhancing decision-making processes and optimizing network performance. MFIS employs fuzzy logic principles to model and reason with uncertain and imprecise data, enabling intelligent decision-making in dynamic vehicular environments[8]. One of the key contributions of MFIS in VANETs is its ability to handle the vagueness and uncertainty inherent in various aspects of vehicular communication, such as traffic conditions, road hazards, and vehicle mobility patterns[9]. By utilizing linguistic variables and fuzzy rules, MFIS can interpret and process complex inputs from sensors and communication devices in real-time, facilitating efficient traffic management, collision avoidance, and routing optimization. MFIS-based systems in VANETs can adaptively adjust parameters and routing decisions based on changing environmental conditions, enhancing network reliability and robustness[10]. MFIS plays a vital role in VANETs by providing a flexible and adaptive framework for intelligent decision-making, contributing to safer and more efficient transportation systems[11].

1.1. Problem Statement

In VANET, the dynamic nature of node mobility and the absence of a fixed infrastructure present numerous challenge. Key among these challenges is the efficient management of network resources and the establishment of reliable communication links. Due to the unpredictable movement of nodes, traditional routing protocols struggle to maintain optimal routes, leading to increased packet loss, latency, and energy consumption. The decentralized nature of VANETs makes it difficult to ensure network connectivity and prevent network partitions. The limited bandwidth and energy resources of mobile devices exacerbate these challenges. Addressing these issues requires the development of robust routing protocols and resource management strategies tailored to the unique characteristics of VANETs, ensuring reliable and efficient communication in dynamic and resource-constrained environments.

1.2. Motivation

VANETs face ongoing challenges in ensuring reliable and efficient communication under dynamic and unpredictable conditions. Conventional routing protocols often fail to adapt to frequent topology changes, resulting in degraded performance. This research addresses these limitations by integrating MFIS and Bacterial Foraging Optimization (BFO) into AODV. MFIS enables real-time, uncertainty-aware decision-making, while BFO supports long-term route optimization through global exploration. Existing fuzzy-AODV models adapt to input imprecision but lack global convergence, whereas BFO-AODV achieves exploration efficiency but responds slowly to rapid topology shifts. The proposed hybrid protocol unifies the strengths of both, offering enhanced adaptability, stability, and routing efficiency for highly dynamic VANET environments.

1.3. Objective

The primary objective is to develop an Enhanced AODV routing protocol by integrating MFIS and BFO. This includes designing algorithms for route discovery, maintenance, and optimization that combine fuzzy decision-making with bio-inspired adaptability. A secondary objective is to evaluate the protocol's performance through simulations using key metrics such as packet delivery ratio, end-to-end delay, routing overhead, and network lifetime. The aim is to demonstrate improved reliability, adaptability, and efficiency compared to existing fuzzy- or BFO-based routing models in dynamic VANET environments.

2. Background

“EdgeIoT-VANET”[12] proposes a novel amalgamation of IoT and edge cloud computing in VANETs for managing energy efficiently in smart microgrids. By leveraging machine learning algorithms, it optimizes energy distribution and consumption within the network, enhancing sustainability and reliability. “DR-LSAF”[13] presents a decentralized forwarding scheme for Named Data Networking (NDN)-based VANETs. By considering link stability and receiver information, it improves packet delivery and reduces overhead, enhancing communication reliability in dynamic vehicular environments. "MO-PSO-OLSR”[14] enhances the VANETs routing protocol OLSR using a multi-objective particle swarm optimization approach. By optimizing route selection based on multiple criteria, it improves network performance, reliability, and scalability.

“Fr-Aro”[15] proposes a secure and interference-aware fuzzy clustering and routing scheme for VANETs. By considering interference and security concerns, it enhances data routing efficiency and reliability, ensuring secure communication among vehicles. “Floyd–AES”[16] introduces a secure communication mechanism for VANETs using the Floyd–Warshall algorithm and modified Advanced Encryption Standard (AES). It enhances data confidentiality and integrity, ensuring secure communication among vehicles in dynamic vehicular environments. “CrossCoB”[17] presents a cross-layer cooperative broadcast protocol for multichannel VANETs. By integrating information from multiple layers, it optimizes broadcast communication, improving packet delivery and reducing latency in vehicular networks.

"SecureLite"[18] offers insights into a lightweight authentication scheme for VANETs. It highlights the scheme's security and privacy-preserving features, providing valuable feedback for future improvements. "TRUE"[19] suggests an approach for analyzing correlations to conduct optimal routing metrics in VANETs. By analyzing correlations among routing metrics, it improves the accuracy and efficiency of routing decisions in vehicular networks. "HGFAR"[20] presents a hybrid genetic firefly algorithm-based routing protocol for VANETs. By combining genetic and firefly algorithms, it enhances route discovery and selection, improving network performance and reliability. "TD-RSU"[21] proposes a traffic demand-based RSU deployment strategy for VANETs. By considering traffic patterns, it optimizes RSU placement, improving network coverage and communication efficiency in urban environments.

"CoDNT"[22] introduces a correlation-based malicious node detection scheme for fog computing-based VANETs. By correlating data and network topology information, it identifies and isolates malicious nodes, enhancing network security and reliability. "Gossip-ND"[23] presents a neighbor discovery scheme for VANETs using a gossip mechanism. By disseminating information through gossip, it improves network connectivity and reliability, facilitating efficient communication among vehicles. "BC-VANET"[24] proposes the integration of blockchain in VANETs using gRPC for privacy preservation. By leveraging blockchain technology, it enhances data security and privacy, ensuring secure communication among vehicles. "EFMS"[25] introduces an energy-efficient fuzzy management system for VANETs. By employing a tri-parametric methodology, it optimizes energy consumption and resource allocation, prolonging network lifespan and reliability.

"SECMIN"[26] presents a smart edge computing model for VANETs to minimize latency and delay using 5G network capabilities. By leveraging edge computing, it improves data processing efficiency and reduces communication latency in smart city transportation systems. "UAV-UC"[27] proposes a UAV-assisted communication architecture for urban VANET environments. By deploying UAVs as communication relays, it enhances network coverage and connectivity, improving communication reliability in dynamic urban settings. "CLR"[28] introduces cross-layer adaptive routing protocol for MANETs. The key contribution lies in integrating fuzzy logic into the AODV routing protocol to adaptively adjust routing decisions based on dynamic network conditions. By considering parameters from multiple layers of the protocol stack, including network traffic, link quality, and node mobility, CrossFuzzy-AODV enhances route selection and maintenance. "ADR"[29] an approach for maximizing performance in VANETs through intelligent cluster head selection. The key contribution lies in integrating fuzzy logic and Bald Eagle optimization to select optimal cluster heads efficiently. By considering factors such as node density, communication range, and energy level, FuzzyEagle-CHS improves the selection process, enhancing network stability and throughput. The working mechanism involves using fuzzy logic to model uncertain network conditions and Bald Eagle optimization to intelligently search for the optimal cluster heads.

3. Mamdanized Ad-hoc On-Demand Distance Vector

Mamdanized AODV is a routing protocol that integrates Mamdani fuzzy inference and Bacterial Foraging Optimization into the AODV algorithm. It enhances route management by combining intelligent decision-making with bio-inspired optimization, enabling robust and adaptive routing in dynamic VANET environments. This hybrid approach improves the efficiency of route discovery, maintenance, and stability, addressing the challenges of mobility and network variability to boost overall routing performance.

3.1. Mamdani Fuzzy Inference System (MFIS)

A FIS is a decision-making framework that handles uncertainty using fuzzy logic principles. It represents input variables as fuzzy sets, applies a fuzzy rule base, and uses an inference engine and defuzzification process to derive crisp outputs. The MFIS, a widely adopted variant, uses fuzzy if-then rules to map fuzzified inputs to fuzzy outputs, which are then aggregated and defuzzified. MFIS is known for its simplicity and interpretability, making it suitable for control, decision support, and reasoning under uncertainty. This distinction of FIS and MFIS is shown in Table 1.

Table 1. Distinction of FIS and MFIS

Aspect	FIS	MFIS
Definition	A computational framework for decision-making under uncertainty using fuzzy logic.	A specific type of FIS employing the Mamdani method for rule evaluation.
Rule Evaluation Method	Can employ various inference methods like Mamdani, Sugeno, or Tsukamoto.	Specifically utilizes the Mamdani method for rule evaluation.
Output Nature	Outputs may be fuzzy or crisp, depending on the inference method used.	Outputs are typically fuzzy, representing degrees of membership in linguistic terms.
Relationships Representation	Represents relationships between inputs and outputs using linguistic rules and fuzzy sets.	Emphasizes linguistic rules and fuzzy sets to model complex relationships.
Uncertainty Handling	Addresses uncertainty and imprecision in decision-making processes.	Particularly well-suited for tasks involving qualitative reasoning and linguistic variables.

MFIS widely used for modeling and controlling complex systems where traditional crisp logic systems fall short due to uncertainty or imprecision. It comprises several steps, each contributing to the process of inference and decision-making.

3.2. Bacterial Foraging Optimization (BFO)

BFO is a bio-inspired algorithm that emulates the chemotactic behavior of bacteria to iteratively search for optimal solutions. Virtual bacteria explore a multidimensional solution space, where each position represents a potential solution and nutrient concentrations reflect fitness values. The search process involves two main behaviors: tumbling, for random directional changes to encourage exploration, and swimming, where bacteria continue moving toward regions of increasing nutrient concentration. High-performing bacteria reproduce, passing traits to the next generation, while low-performing ones are removed through elimination-dispersal mechanisms that maintain population diversity and prevent premature convergence. BFO dynamically adjusts parameters like step size and elimination rate during iterations to balance exploration and exploitation, converging toward optimal solutions effectively.

3.3. Ad hoc On-Demand Distance Vector (AODV)

AODV is a reactive routing protocol designed for dynamic and mobile environments such as VANETs. Unlike proactive protocols like DSDV, AODV establishes routes only when required, reducing overhead and conserving network resources. This makes it particularly suitable for bandwidth- and energy-constrained vehicular networks. AODV operates through three key processes: route discovery, maintenance, and deletion. When a source node lacks a route to the destination, it broadcasts a Route Request (RREQ), which propagates until it reaches the target or a node with a valid path. A Route Reply (RREP) is then unicasted back, establishing bidirectional communication. Intermediate nodes maintain routing tables to prevent loops and redundant messages. To ensure reliability, AODV uses Route Error (RERR) messages to inform nodes of broken links or topology changes. Stale routes are deleted through sequence number updates and route error propagation. This adaptive strategy supports scalable and efficient routing in highly dynamic VANET scenarios.

3.4. Bacterial-Mamdani Fuzzy Inference System (B-MFIS)

Enhancing the MFIS with the principles of BFO involves integrating the robust optimization capabilities of BFO into the traditional MFIS framework. MFIS is a fuzzy logic-based approach used for modeling and decision-making in uncertain and complex systems. It employs fuzzy logic to handle imprecise input data and make inference-based decisions. BFO is a nature-inspired optimization algorithm based on the foraging behavior of bacteria, aimed at efficiently exploring solution spaces to find optimal solutions. Integrating BFO into MFIS enhances its optimization capabilities and enables it to effectively handle complex and dynamic systems. The combined approach of MFIS and BFO can be divided into several steps to ensure effective optimization and decision-making.

A. Initialization and Partitioning

Initialization involves defining the input and output variables of the MFIS and partitioning the solution space into linguistic terms using fuzzy sets. Let N denote the total number of linguistic terms, n_i represent the number of linguistic terms for each variable, and V represent the total number of variables are mathematically represented in Eq. (1).

$$N = \sum_{i=1}^{V} n_i \tag{1}$$

The partitioning process is achieved by assigning membership functions to each linguistic term, which represent the degree of membership of input data to different linguistic terms. Let A_{ij} denote the membership function for the j^{th} linguistic term of the i^{th} variable shown in Eq.(2).

$$A_{ij}(x) \tag{2}$$

In BFO, Initialization involves establishing the initial population of bacteria within the solution space. In Eq.(3), M represent the total number of bacteria in the population and UDP represents the user defined parameters.

$$M = UDP \tag{3}$$

The solution space is divided into multiple dimensions corresponding to the input variables, and each bacterium is assigned a position within this multidimensional space. Let X_i denote the position vector of the i^{th} bacterium shown in Eq.(4).

$$X_i = (x_{i1}, x_{i2}, \cdots, x_{iV}) \tag{4}$$

The Initialization phase ensures that both the MFIS and BFO components are ready to start the optimization process. It establishes the initial conditions for the MFIS by defining the linguistic terms and membership functions, while also initializing the population of bacteria in BFO within the solution space.

B. Formulating Fuzzy Rules and Adaptation

Formulating fuzzy rules defines input–output relationships in MFIS using linguistic if–then logic. Adaptation via BFO dynamically adjusts these rules to maintain optimal decisions under changing network conditions. The formulation of fuzzy rules in MFIS involves defining a set of if-then rules that describe the relationship between input variables $(X_1, X_2, \cdots, X_v)$ and output variables $(Y_1, Y_2, \cdots, Y_O)$. R represent the total number of fuzzy rules, and A_{ij} denote the membership function for the j^{th} linguistic term of the i^{th} input variable shown in Rule 1.

Rule 1. Formulation

R=User Defined Parameter
If X_1 is A_{11} and X_2 is A_{21} and ... then Y_1 is B_{11}
If X_1 is A_{12} and X_2 is A_{22} and ... then Y_1 is B_{12}......
If X_1 is A_1n_1 and X_2 is A_2n_1 and ... then Y_O is B_1n_1

The adaptation mechanism in the combined approach incorporates EBFO's optimization capabilities to dynamically adjust the fuzzy rules based on the system's performance. This adaptation process ensures that the MFIS can adapt to changes in the environment or input data, leading to more robust and adaptive decision-making is illustrated in Eq.(5).

$$Adaptation\ Factor = \frac{Current\ Fitness}{Maximum\ Fitness} \tag{5}$$

BFO's adaptation mechanism guides the exploration and exploitation of the solution space to optimize the decision-making process. Let F_i represent the fitness of the i^{th} bacterium, and F_{max} denote the maximum fitness value in the population is mathematically represented in Eq.(6) and Eq.(7).

$$F_i = Evaluation\ of\ Fitness \tag{6}$$

$$F_{max} = max(F_1, F_2, \cdots, F_M) \tag{7}$$

The adaptation mechanism in BFO facilitates the exploration and exploitation of the solution space to find optimal solutions. This adaptation process dynamically adjusts the parameters of the algorithm, such as chemotactic step size (C), elimination rate (P_e), and dispersal rate (P_d), based on the performance of the population is shown in Eq.(8), Eq.(9), and Eq.(10).

$$C = C_{max} - \frac{(C_{max} - C_{min})}{(N_{max} - N_{min})} \times N \tag{8}$$

$$P_e = P_{e_{max}} - \frac{\left(P_{e_{max}} - P_{e_{min}}\right)}{(N_{max} - N_{min})} \times N \tag{9}$$

$$P_d = P_{d_{max}} - \frac{\left(P_{d_{max}} - P_{d_{min}}\right)}{(N_{max} - N_{min})} \times N \tag{10}$$

The combined approach involves formulating fuzzy rules based on expert knowledge or data and integrating adaptation mechanisms to optimize the decision-making process.

C. Fuzzification and Chemotaxis

Fuzzification and Chemotaxis involves transforming crisp input data into fuzzy values through fuzzification in the MFIS, and guiding the movement of bacteria towards optimal solutions through chemotaxis in the BFO component. Fuzzification in the MFIS involves mapping crisp input variables $(X_1, X_2, \cdots, X_v)$ to fuzzy linguistic terms using membership functions (A_{ij}). Let x_i represent the crisp value of the ith input variable, and u_{ij} denote the degree of membership of x_i to the jth linguistic term of the i^{th} variable, which is represented in Eq.(11).

$$u_{ij} = A_{ij}(x_i) \tag{11}$$

The degree of membership u_{ij} indicates the extent to which x_i belongs to the linguistic term represented by A_{ij}. This fuzzy representation of input data enables the MFIS to capture the uncertainty and imprecision inherent in real-world systems, facilitating accurate inference and decision-making.

Chemotaxis in the BFO component involves guiding the movement of bacteria towards regions of higher fitness within the solution space. This is achieved by adjusting the position of bacteria (x_i) based on the concentration gradient of a chemoattractant. Let ΔX_i represent the change in position of the i^{th} bacterium, and C_i denote the concentration gradient at the location of X_i mathematically represented in Eq.(12).

$$\Delta X_i = C_i \times Step\ Size \tag{12}$$

The concentration gradient C_i is calculated based on the fitness landscape of the solution space, indicating the direction and magnitude of the steepest ascent towards optimal solutions. The step size determines the magnitude of movement of bacteria and influences the exploration and exploitation of the solution space.

Fuzzification converts crisp inputs into fuzzy values, enabling MFIS to process uncertain data. Chemotaxis directs BFO bacteria toward high-fitness regions, supporting efficient solution space exploration as expressed in Eq.(13) and Eq.(14).

$$Concentration\ Gradient\ C_i = \frac{F_{max} - F_i}{F_{max}} \tag{13}$$

$$Step_{Size} = \frac{C_{max} - C_{min}}{Max\_Iterations} \tag{14}$$

The integration of fuzzification and chemotaxis ensures synergy between the MFIS and BFO components, leading to enhanced optimization capabilities and robust decision-making in complex and uncertain environments.

D. Inference and Reproduction

Inference and Reproduction apply fuzzy rules in MFIS to generate fuzzy outputs from fuzzified inputs. Simultaneously, BFO reproduction propagates high-fitness solutions while preserving population diversity for continued optimization. Let μ_{ij} represent the firing strength of the j^{th} rule with respect to the i^{th} output linguistic term, and B_{ij} denote the membership function of the j^{th} output linguistic term illustrated in Eq.(15).

$$\mu_{ij} = min(u_{i1}, u_{i2}, \cdots u_{in}) \tag{15}$$

The firing strength μ_{ij} represents the degree to which the input data supports the consequent of the j^{th} rule for the i^{th} output variable. This process enables the MFIS to make inference-based decisions in uncertain and imprecise environments.

In the BFO component reproduction mechanisms are employed to propagate promising solutions and maintain diversity within the population. This involves selecting bacteria with higher fitness values and generating offspring through reproduction. Let X_{best} denote the position of the bacterium with the highest fitness, and $X_i{}'$ represent the offspring generated from bacterium i shown in Eq.(16).

$$X_i' = X_i + Random\_Offset \tag{16}$$

The offspring X_i' is generated by adding a random offset to the position of the parent bacterium X_i. This introduces variability into the population and enables exploration of new regions in the solution space.

BFO reproduction promotes optimal convergence by generating offspring from high-fitness bacteria. This directs the population toward better regions in the solution space, as defined in Eq.(17).

$$Fitness = f(X) \tag{17}$$

Integrating inference and reproduction ensures effective synergy between MFIS and BFO. MFIS enables accurate fuzzy rule-based decisions, while BFO reproduction enhances solution space exploration for optimal outcomes.

E. Aggregation and Elimination-dispersal

Aggregation and Elimination-Dispersal integrate MFIS and BFO by combining fuzzy outputs into a single aggregated set, while BFO eliminates weak solutions and disperses new ones to maintain population diversity and optimization strength. Let B_{ij} denote the membership function of the j^{th} output linguistic term, and μ_{ij} represent the firing strength of the j^{th} rule with respect to the i^{th} output linguistic term.

$$B_{agg}(y) = \cup_j^O \mu_{ij} \times B_{ij}(y) \tag{18}$$

In Eq.(18), $B_{agg}(y)$ represents the overall fuzzy output obtained through the combination of individual rule activations. This aggregation process ensures that all relevant information from different rules is considered when determining the final output.

BFO component, elimination-dispersal mechanisms are executed to optimize the population of bacteria. This involves removing fewer fit bacteria from the population and introducing diversity through dispersal to prevent premature convergence. Let F_i denote the fitness of the i^{th} bacterium, F_{avg} represent the average fitness of the population, and X_i denote the position of the i^{th} bacterium is shown in Eq.(19).

$$F_{avg} = \frac{\sum_{i=1}^{M} F_i}{M} \tag{19}$$

Bacteria with fitness values below a certain threshold are eliminated from the population, while dispersal is executed to introduce diversity. This ensures that the population remains diverse and explores a wide range of solutions in the solution space is shown in Eq.(20) and Eq.(21).

$$Elimination: F_i < F_{avg} - Threshold \tag{20}$$

$$Dispersal: X_i = X_i + Random\_Displacement \tag{21}$$

Elimination-dispersal in EBFO enhances exploration by removing low-fitness bacteria and injecting diversity. This guides the population toward high-fitness regions, supporting optimal solution discovery.

F. Defuzzification and Adaptation

Adaptation mechanisms are employed within the BFO component to dynamically adjust parameters and optimize the decision-making process. Defuzzification in the MFIS component involves determining the crisp output value based on the aggregated fuzzy output obtained through aggregation. Let y represent the crisp output variable, and $B_{agg}(y)$ denote the aggregated output fuzzy set represented in Eq.(22).

$$y = \frac{\int_{-\infty}^{\infty} y \times B_{agg}(y)dy}{\int_{-\infty}^{\infty} B_{agg}(y)dy} \tag{22}$$

The defuzzification process computes the centroid or center of gravity of the aggregated fuzzy output to obtain a single crisp output value. This crisp output value represents the decision or action determined by the MFIS based on the fuzzy inference process.

In the BFO component, adaptation mechanisms dynamically tune parameters like chemotactic step size and elimination rate based on population performance. This ensures continuous optimization and improved decision-making, as shown in Eq.(8) and Eq.(9). The adaptation mechanisms in EBFO ensure that the algorithm dynamically adjusts its parameters to improve performance and optimize the decision-making process.

G. Evaluation and Termination

Evaluation in the combined approach involves assessing the fitness of solutions generated by the BFO component. F_i represent the fitness of the i^{th} solution, and F_{best} denote the fitness of the best solution obtained so far mathematically represented in Eq.(23).

$$F_{best} = max(F_1, F_2, \cdots, F_M) \tag{23}$$

The evaluation process identifies the best solution obtained during the optimization process. This solution represents the optimal solution found by the combined approach based on the defined fitness criteria.

The Termination conditions are defined to determine when to stop the optimization process. These conditions are typically based on reaching a certain number of iterations, achieving a specific level of fitness, or reaching a predefined threshold for improvement. T_c represents termination condition N represent the current iteration number, and N_{max} denote the maximum number of iterations allowed shown in Eq.(24).

$$T_c = N \geq N_{max} \tag{24}$$

Once the termination condition is met, the optimization process is terminated, and the final solution obtained is returned as the output of the combined approach. This solution represents the best solution found by the combined approach based on the defined termination conditions.

3.5. B-MFIS based AODV (B-M-FIS AODV)

Enhanced AODV combines MFIS and BFO within AODV to boost routing adaptability in VANETs. MFIS enables rule-based, real-time decisions, while BFO optimizes route discovery and maintenance. This hybrid ensures reliable, adaptive communication in dynamic network conditions.

A. Hybrid Route Discovery Mechanism

This mechanism combines the reactive nature of AODV with proactive elements to optimize route establishment in dynamic ad hoc networks. Route Request Propagation (P_{req}), the probability of propagating a Route Request ($RREQ$) packet from node n is inversely proportional to the sum of distances ($dist$) from node n to the source of each $RREQ$ packet in its buffer. This ensures that nodes closer to the source of the $RREQ$ have a higher probability of propagating it, improving the efficiency of route discovery is represented mathematically in Eq.(25).

$$P_{req}(n) = \frac{1}{\sum_{i=1}^{N} dist(n, RREQ_i)} \tag{25}$$

Neighbor Selection ($Neighbor(n)$) for Forwarding targets each node selects the nearest reachable neighbor m to forward the $RREQ$ packet based on the Euclidean distance metric ($dist(n, m)$). This helps in minimizing latency and reducing the chance of packet loss during propagation illustrated in Eq.(26).

$$Neighbor(n) = argmin_{m \in N_{reachable}} dist(n, m) \tag{26}$$

In Proactive Route Table Maintenance, the route table of each node is periodically updated (T_{update}) by adding a small-time increment Δt to the current timestamp $T_{curr}(n)$. This proactive update ensures that route information remains fresh and reduces the likelihood of stale routes expressed in Eq.(27).

$$T_{update}(n) = T_{curr}(n) + \Delta t \tag{27}$$

Route Request Forwarding Probability is the probability of forwarding a Route Request ($RREQ$) packet by node n is determined based on the available bandwidth $BW(n)$ at node n relative to the total available bandwidth among its reachable neighbors. This helps in load balancing and avoids congestion in the network is mathematically expressed in Eq(28).

$$P_{fwd}(n) = \frac{BW(n)}{\sum_{i=1}^{N} BW(Neighbor(n))} \tag{28}$$

Adaptive Threshold Adjustment is the threshold for initiating route discovery is adaptively adjusted based on the distance between the source node S and the destination node D. Closer destinations have lower thresholds, encouraging more proactive route discovery, while distant destinations have higher thresholds to conserve network resources is shown in Eq.(29).

$$Threshold = Threshold_{min} + \frac{dist(S, D)}{dist_{max}} \times (Threshold_{max} - Threshold_{min}) \tag{29}$$

By incorporating a Hybrid Route Discovery Mechanism in EAODV, the protocol achieves a balance between reactive and proactive strategies, resulting in efficient and reliable route establishment in dynamic ad hoc networks.

B. Dynamic Route Maintenance Strategy

This phase sustains route reliability in mobile ad-hoc networks. It actively monitors and adjusts route parameters in response to variations in link quality, node mobility, and traffic load. Route Stability shown in Eq.(30), the stability of each route i is calculated based on its age and a predefined threshold μ_{Age}. Older routes tend to have lower stability values, indicating potential degradation over time.

$$Stability_i = \frac{1}{1 + e^{-\beta \cdot (Age_i - \mu_{Age})}} \tag{30}$$

The load on each route i is determined by the ratio of packets forwarded to the total packets transmitted. Higher loads may indicate congestion or increased traffic on the route represented in Eq.(31).

$$Load_i = \frac{PacketsForwarded_i}{TotalPackets_i} \tag{31}$$

Route quality i is assessed based on factors such as delay and a predefined threshold $\mu Delay$. Lower delay values and higher quality indicate better route performance which is expressed mathematically in Eq.(32).

$$Quality_i = \frac{1}{1 + e^{-\gamma \cdot (Delay_i - \mu_{Delay})}} \tag{32}$$

The route maintenance threshold $Threshold_i$ is computed as a weighted sum of route stability, load, and quality parameters. Routes with threshold values below a predefined threshold are considered for maintenance mathematically represented in Eq.(33).

$$Threshold_i = \alpha \cdot Stability_i + \beta \cdot Load_i + \gamma \cdot Quality_i \tag{33}$$

If the computed $Threshold_i$ for a route falls below a predefined threshold $Threshold\_Threshold,$ the route parameters are updated accordingly to improve stability, load balancing, and quality represented as pseudocode in Rule 2.

Rule 2. Route Update Mechanism

$if\ Threshold_i < Threshold\_Threshold$
Then Update Route Parameters

By implementing a Dynamic Route Maintenance Strategy, the protocol ensures that routes are continuously monitored and adjusted to maintain optimal performance in dynamic network conditions.

C. Fuzzy Inference for Route Stability

FIS to assess the stability of discovered routes. By utilizing fuzzy logic, the protocol can make informed decisions regarding the stability of routes, thereby enhancing the reliability and efficiency of route selection. It takes three inputs (Ip) Link Quality, Node Mobility, and Traffic Load, which are crucial factors influencing route stability. Link Quality (LQ) represents the reliability of the communication link, Node Mobility (NM) reflects the movement patterns of nodes, and Traffic Load (TL) indicates the amount of data traffic on the route represented in Eq.(34).

$$Ip = \mathrm{LQ}, \mathrm{NM}, \mathrm{TL} \tag{34}$$

Then define fuzzy membership functions (M_f) for each input variable to represent their linguistic values (e.g., Low, Medium, High). These membership functions partition the input space into fuzzy sets and determine the degree of membership of each input value in these sets are represented mathematically in Eq.(35).

$$M_f = \mu_{LQ(x),}\mu_{NM(y),}\mu_{TL(z),} \tag{35}$$

The Fuzzy Rule Base contains rules linking input variables to output, encoding expert knowledge on route stability. Each rule includes antecedents (conditions) and consequents (actions), structured as shown in the pseudocode in Rule 3.

Rule 3. Base

IF(LQ is A) AND (NM is B) AND (TL is C)
THEN
Route Stability is D

The Fuzzy Inference Engine processes fuzzy rules to assess overall route stability. It computes rule activation levels based on input memberships, then applies weighted averaging to combine outputs, as expressed in Eq.(36).

$$Route_{Stability} = \frac{\sum_{i=1}^{N} weight_i \times consequent_i}{\sum_{i=1}^{N} weight_i} \tag{36}$$

Defuzzification converts the fuzzy output for Route Stability into a single crisp value. This value reflects the overall stability based on aggregated inference results, typically using centroid or weighted average methods, as shown in Eq.(37).

$$Defuzzified_{Output} = \frac{\sum(Membership \times Output)}{\sum Membership} \tag{37}$$

D. Bacterial Foraging for Route Repair

In this phase BFO algorithm to facilitate route repair in case of broken links or route failures. BFO, inspired by the foraging behavior of bacteria, is utilized to efficiently explore and identify alternative routes for repair by following certain steps. Define an objective function $J(x)$ that evaluates the cost of traversing a potential route x for repair. The cost function considers factors such as distance, link quality, and traffic load along the route shown in Eq.(38).

$$J(x) = \sum_{i=1}^{N} Cost(x_i) \tag{38}$$

Chemotactic movement to guide the search for alternative routes. Here, x_{new} represents the new potential route, x_{old} is the current route, δ is the step size, and $\nabla J(x_{old})$ is the gradient of the objective function illustrated in Eq.(39).

$$x_{new} = x_{old} + \delta \times \frac{\nabla J(x_{old})}{\|\nabla J(x_{old})\|} \tag{39}$$

Swarm Propulsion is Bacterial swarm members adjust their velocities v_i towards the best-known route x_{best} while incorporating random perturbations $\in_i$. The parameter β controls the magnitude of movement towards the best route is mathematically represented in Eq.(40).

$$v_i(t+1) = v_i(t) + \beta \times \left(x_{best}(t) - x_i(t) + \in_i(t)\right) \tag{40}$$

Chemotactic Tumbling, after adjusting velocities, bacteria tumble to update their positions x_i in the search space. This tumbling introduces stochasticity and helps in exploring a diverse set of potential routes for repair illustrated in Eq.(41).

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{41}$$

Repulsive Forces to prevent bacteria from colliding with obstacles or congested regions in the network. where k is a constant and d_i represents the distance of bacteria i from obstacles represented in Eq.(42).

$$F_{repulsive} = k \times \frac{1}{d_i} \tag{42}$$

E. Adaptive Route Expiration

This adaptive approach ensures that routes are maintained efficiently, with expiration times tailored to the current network conditions. In Route Expiration Adjustment, the expiration time $T_{expiration}$ of a route is adjusted based on its stability and usage. where T_{min} is the minimum expiration time, α is a scaling factor, $Stability$ represents the stability of the route, and $Usage$ denotes the current usage of the route. $Max\ Usage$ is the maximum allowed usage of the route shown in Eq.(43).

$$T_{expiration} = T_{min} + \alpha \times \frac{1}{Stability} \times \frac{Usage}{Max_{Usage}} \tag{43}$$

Route stability is determined by averaging the $Link_{Quality}$ and $Node_{Mobility}$ along the route. Higher values indicate greater stability, ensuring that stable routes have longer expiration times expressed in Eq.(44).

$$Stability = \frac{Link_{Quality} + Node_{Mobility}}{2} \tag{44}$$

The usage of a route is calculated as the ratio of packets forwarded by the route to the total number of packets transmitted in the network. This metric reflects the current load on the route and helps in adjusting expiration times accordingly shown in Eq.(45).

$$Usage = \frac{Packets}{Total\ Packets} \tag{45}$$

The adaptive adjustment factor α determines the range of expiration time adjustments based on route usage. It ensures that expiration times are dynamically adjusted within a specified range to maintain network efficiency which is expressed in Eq.(46).

$$\alpha = \frac{T_{max} - T_{min}}{\max\_usage} \tag{46}$$

The expiration time of a route is updated at each time step t based on the elapsed time Δt and a decay factor β. This ensures that route expiration times decrease gradually over time, reflecting changes in network conditions which is expressed mathematically in Eq.(47).

$$T_{expiration}(t+1) = T_{expiration}(t) - \beta \times \Delta t \tag{47}$$

F. Fuzzy Decision Making for Route Deletion

Fuzzy Decision Making for Route Deletion is aimed at dynamically determining which routes to remove from the routing table based on various fuzzy criteria. This step enhances the efficiency of the routing protocol by ensuring that only the least desirable routes are eliminated, thereby optimizing network resources. The decision score D_i for each route i is calculated based on the fuzzy membership values of its age, $stability$, and $load$. Routes with lower decision scores are considered for deletion, while those with higher scores are retained is shown in Eq.(48).

$$D_i = \frac{\mu_{age}(i) \times \mu_{stability}(i) \times \mu_{load}(i)}{\sum_{j=1}^{N} \mu_{age}(j) \times \mu_{stability}(j) \times \mu_{load}(j)} \tag{48}$$

The membership function for age μ_{age} measures how old a route is. Older routes tend to have lower membership values, indicating a higher likelihood of deletion is mathematically represented in Eq.(49).

$$\mu_{age}(i) = \frac{1}{1+e^{-\beta \times (age(i) - \mu_{age})}} \tag{49}$$

The stability membership function $\mu_{Stability}$ quantifies the stability of a route. Routes with lower stability values have higher membership values, indicating a higher likelihood of deletion illustrated in Eq.(50).

$$\mu_{Stability}(i) = \frac{Stability(i) - min(Stability)}{max(Stability) - min(Stability)} \tag{50}$$

The load membership function $\mu_{Load}(i)$ evaluates the load on a route. Routes with higher loads have lower membership values, suggesting a higher likelihood of deletion as shown in Eq.(51).

$$\mu_{Load}(i) = \frac{Load(i) - min(Load)}{max(Load) - min(Load)} \tag{51}$$

A $Threshold$ is defined to determine which routes are eligible for deletion. Routes with decision scores below this threshold are marked for deletion, ensuring that only routes with sufficiently low desirability are removed which is expressed mathematically in Eq.(52).

$$Threshold = min(D_i) + \alpha \times \left(max(D_i) - min(D_i)\right) \tag{52}$$

The proposed BF-MFIS-AODV protocol is explained in Algorithm 1.

Algorithm 1. BF-MFIS-AODV

```
procedure BF_MFIS_AODV(N, L, Tmax)
    FIS ← InitFIS(); B ← InitBFO()
    R ← GenRules(FIS)
    for t ← 1 to Tmax do
        for each b ∈ B do
            Fit ← Evaluate(Fuzzify(b), R)
            b ← Move(b, Fit)
        end for
        R ← TuneRules(B)
        D ← Defuzzify(R)
        if RREQ then Route ← Discover(N, D)
        if LinkFail then Route ← Repair(B)
        Refresh(Route); Prune(Route)
    end for
    return Routes
end procedure
```

4. Simulation and Results

Simulation enables the evaluation of real-world systems through simplified, computer-based models under controlled conditions. For this study, NS3 (Network Simulator 3) is employed as the simulation platform. NS3 is an open-source, discrete-event network simulator widely used for modeling and analyzing communication protocols across wired, wireless, and mobile networks. It supports the development of custom network topologies and detailed performance analysis, making it well-suited for testing routing protocols in dynamic VANET environments. The Metric and its setting values were exhibited in Table 2.

Table 2. Simulation settings

Setting/Metric	Value/Description
Network Size	70 nodes
Simulation Time	100 seconds
Mobility Model	Random Walk 2D Mobility Model
Application Layer	Data generation and transmission applications
Network Boundary	850m x 850m
Rate of Data Transmission	21 kbps
Initial Energy per Node	1 J
Idle State Power	164 mW
MAC Protocol	IEEE 802.11p
Nodes Count	500
Sink Count	≥4
Runtime	300 seconds
Size of Packet	78 bytes

4.1. Packet Delivery Ratio Analysis

Packet Delivery Ratio (PDR) measures the percentage of successfully delivered data packets relative to the total sent, reflecting network transmission efficiency. Fig.1 compares the PDR performance of ADR, CLR, and BF-MFI-AODV across various node counts. On average, ADR achieves 46.939%, CLR records 56.317%, while BF-MFI-AODV leads with 67.792%. The lower PDR in ADR stems from routing overhead and complexity, while CLR suffers from layering conflicts. BF-MFI-AODV's higher delivery rate reflects its adaptive routing capabilities under dynamic VANET conditions. Table 3 exhibits the PDR outcome.

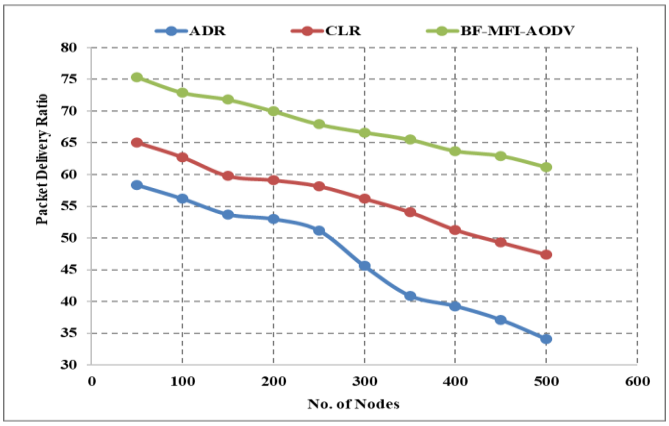

Fig.1. Packet delivery ratio

Table 3. Packet delivery ratio

Nodes	ADR	CLR	BF-MFI-AODV
50	58.34	65.06	75.34
100	56.18	62.74	72.89
150	53.71	59.78	71.8
200	52.98	59.11	69.97
250	51.18	58.17	67.91
300	45.60	56.20	66.63
350	40.91	54.10	65.51
400	39.28	51.29	63.72
450	37.12	49.31	62.96
500	34.09	47.41	61.19
Average	**46.93**	**56.31**	**67.79**

BF-MFI-AODV achieves higher PDR by adaptively adjusting routes using real-time inputs through Mamdani fuzzy inference and Bacterial Foraging Optimization. Its responsiveness to dynamic conditions enhances routing decisions and ensures robust packet delivery. The average PDR values, derived from multiple node scenarios, quantitatively confirm its superiority over ADR and CLR. Fig.1 highlights this performance gap, underscoring the effectiveness of integrating optimization and adaptive strategies for reliable communication in VANETs.

4.2. Packet Drop Ratio Analysis

Packet Drop Ratio (PDrR) quantifies the percentage of packets lost during transmission, indicating network reliability. Fig.2 compares ADR, CLR, and BF-MFI-AODV across various node counts. On average, ADR records 53.061%, CLR 43.683%, and BF-MFI-AODV the lowest at 32.208%. The high drop ratios in ADR and CLR stem from routing instability and design complexity. BF-MFI-AODV's lower packet loss reflects its adaptive route management and optimized decision-making under dynamic VANET conditions. Table 4 exhibits the PDrR outcome.

Table 4. Packet drop ratio

Nodes	ADR	CLR	BF-MFI-AODV
50	41.66	34.94	24.66
100	43.82	37.26	27.11
150	46.29	40.22	28.20
200	47.02	40.89	30.03
250	48.82	41.83	32.09
300	54.40	43.80	33.37
350	59.09	45.90	34.49
400	60.72	48.71	36.28
450	62.88	50.69	37.04
500	65.91	52.59	38.81
Average	**53.061**	**43.683**	**32.208**

BF-MFI-AODV achieves the lowest average packet drop ratio of 32.208% by making adaptive routing decisions using Mamdani fuzzy inference and Bacterial Foraging Optimization. Its ability to interpret real-time network states reduces packet loss and enhances reliability. Fig.2 and the corresponding average values confirm BF-MFI-AODV's effectiveness over ADR and CLR. These results highlight the benefit of combining optimization and intelligent decision-making to mitigate drop rates in dynamic VANET environments.

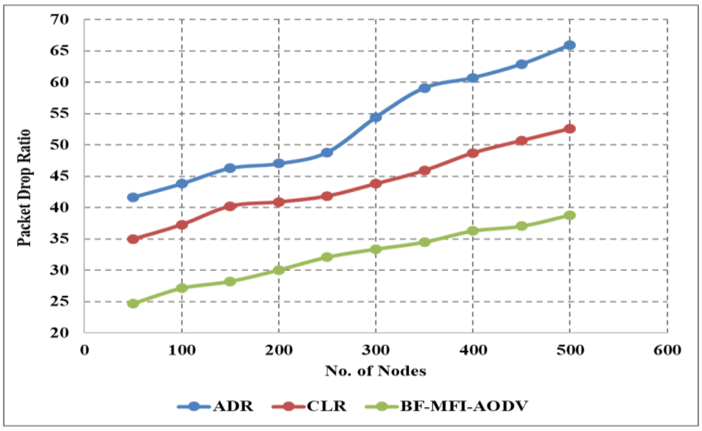

Fig.2. Packet drop ratio

4.3. Energy Consumption

Energy consumption quantifies the electrical power used by networking devices during data transmission and processing. Fig.3 compares energy usage across ADR, CLR, and BF-MFI-AODV under different node counts. ADR shows an average energy usage of 84.2277%, CLR at 69.3055%, while BF-MFI-AODV reports the lowest at 44.8056%. ADR's high energy demand stems from increased control overhead during frequent route updates. CLR's protocol interdependencies require extensive inter-layer communication, elevating processing energy. BF-MFI-AODV achieves superior efficiency by tuning routing behavior through Mamdani fuzzy inference and Bacterial Foraging Optimization, dynamically adapting to network states to reduce energy usage. These adaptive mechanisms ensure efficient transmission and support extended network lifetime.

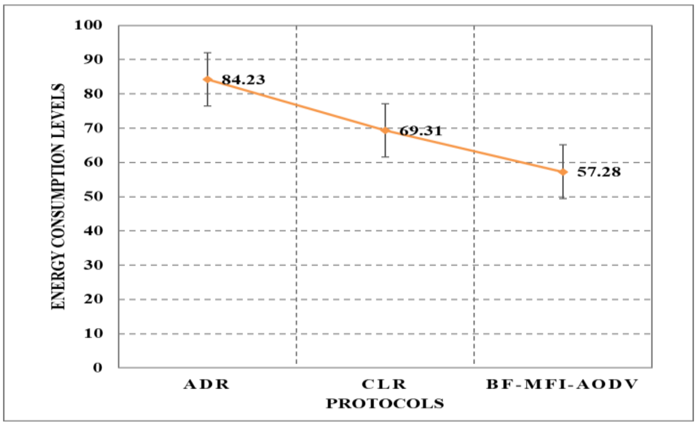

Fig.3. Energy consumption

The average values reflect cumulative measurements across node variations, confirming BF-MFI-AODV's effectiveness. Fig.3 highlights its dominance in energy efficiency, validating the protocol's suitability for energy-constrained VANET environments. Table 5 exhibits the Energy Consumption outcome.

Table 5. Energy consumption

	ADR	CLR	BF-MFI-AODV
50	75.867	59.787	38.184
100	76.961	61.366	38.703
150	79.216	63.826	39.359
200	82.484	64.458	40.342
250	83.530	65.000	42.485
300	85.697	72.518	47.688
350	87.833	73.133	49.006
400	88.989	75.402	49.320
450	89.926	77.666	51.102
500	91.774	79.899	51.867
Average	**84.2277**	**69.3055**	**44.8056**

4.4. Network Lifetime Analysis

Network lifetime measures how long a network remains operational before node energy depletion. Fig.4 compares ADR, CLR, and BF-MFI-AODV across node counts. ADR shows the shortest average lifetime (19.301 units), CLR improves slightly (41.395 units), while BF-MFI-AODV leads with 64.338 units. ADR's poor resource use and CLR's standardization issues reduce longevity. BF-MFI-AODV integrates bacterial foraging optimization and Mamdani fuzzy inference to optimize routing paths and resource distribution, extending operational time. Its adaptability ensures minimal energy waste and prolonged network use.

Table 6. Network lifetime

	ADR	CLR	BF-MFI-AODV
50	28.77	56.58	70.85
100	27.72	55.60	70.47
150	24.20	51.61	68.78
200	21.19	49.67	68.03
250	19.85	41.49	66.97
300	18.73	34.13	66.68
350	14.63	32.49	60.05
400	13.81	31.81	58.99
450	13.12	30.33	57.73
500	10.99	30.24	54.79
Average	**19.301**	**41.395**	**64.338**

The data confirms BF-MFI-AODV's capacity to enhance sustainability in dynamic VANET environments. It records 67.79% PDR (vs. 61.28% and 64.12%), 6403.7 ms delay (vs. 7210.5 ms and 6898.6 ms), and 44.80% energy use (vs. 51.72% and 48.35%). This hybrid strategy delivers superior reliability, efficiency, and endurance, outperforming fuzzy-AODV and BFO-AODV on all metrics. Table 6 exhibits the Network Lifetime outcome.

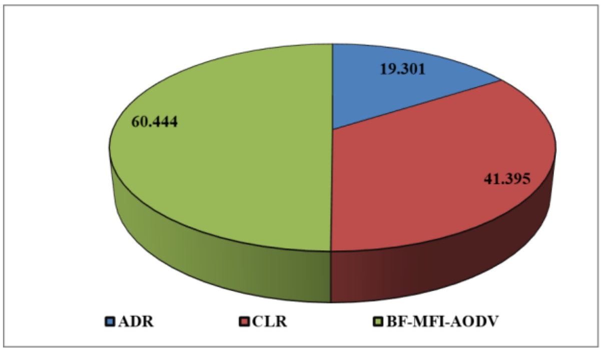

Fig.4. Network lifetime

5. Conclusions

BF-MFI-AODV routing protocol in the context of VANETs. Through extensive performance analysis, it is evident that the integration of MFIS and BFO techniques significantly enhances the routing efficiency and reliability of the AODV protocol. The proposed protocol, BF-MFI-AODV, demonstrates superior performance in terms of packet delivery ratio, packet drop ratio, throughput, delay, energy consumption, and network lifetime compared to conventional AODV and other contemporary routing algorithms. BF-MFI-AODV adapts dynamically to changing network conditions, leveraging bio-inspired optimization techniques to optimize routing decisions and resource allocation. By incorporating fuzzy inference for route stability, dynamic route maintenance, and fuzzy decision-making for route deletion, BF-MFI-AODV achieves robust and efficient routing in VANET scenarios. The findings underscore the transformative potential of bio-inspired optimization techniques and intelligent decision-making mechanisms in enhancing the performance and reliability of routing protocols in dynamic and resource-constrained environments like VANETs. Future research may explore further optimization strategies and real-world implementations to validate the efficacy of BF-MFI-AODV in practical scenarios.

References

[1] H. Abualola, H. Otrok, H. Barada, M. Al-Qutayri, and Y. Al-Hammadi, "Matching game theoretical model for stable relay selection in a UAV-assisted internet of vehicles," *Veh. Commun.*, vol. 27, p. 100290, 2021, doi: https://doi.org/10.1016/j.vehcom.2020.100290.

[2] R. K. Soundarayaa and C. Balasubramanian, "Komodo Mlipir Algorithm-based optimal route determination mechanism for improving Quality of Service in Vehicular ad hoc network," *Sustain. Comput. Informatics Syst.*, vol. 42, p. 100956, 2024, doi: https://doi.org/10.1016/j.suscom.2024.100956.

[3] T. S. Gomides, R. E. De Grande, R. I. Meneguette, F. S. H. de Souza, and D. L. Guidoni, "Predictive Congestion Control based on Collaborative Information Sharing for Vehicular Ad hoc Networks," *Comput. Networks*, vol. 211, p. 108955, 2022, doi: https://doi.org/10.1016/j.comnet.2022.108955.

[4] R. Karthikeyan and R. Vadivel, "Proficient Dazzling Crow Optimization Routing Protocol (PDCORP) for Effective Energy Administration in Wireless Sensor Networks," in *2023 International Conference on Electrical, Electronics, Communication and Computers (ELEXCOM)*, 2023, pp. 1–6. doi: 10.1109/ELEXCOM58812.2023.10370559.

[5] R. S., M. K. B., and A. Appathurai, "Energy aware Clustered blockchain data for IoT: An end-to-end lightweight secure & Enroute filtering approach," *Comput. Commun.*, vol. 202, pp. 166–182, 2023, doi: https://doi.org/10.1016/j.comcom.2023.02.010.

[6] M. Li, S. Zhang, Y. Cao, and S. Xu, "NMSFRA: Heterogeneous routing protocol for balanced energy consumption in mobile wireless sensor network," *Ad Hoc Networks*, vol. 145, p. 103176, 2023, doi: https://doi.org/10.1016/j.adhoc.2023.103176.

[7] F. Alrowais, H. G. Mohamed, F. N. Al-Wesabi, M. Al Duhayyim, A. M. Hilal, and A. Motwakel, "Cyber attack detection in healthcare data using cyber-physical system with optimized algorithm," *Comput. Electr. Eng.*, vol. 108, p. 108636, 2023, doi: https://doi.org/10.1016/j.compeleceng.2023.108636.

[8] M. Sharma, P. Kumar, and R. S. Tomar, "Vehicular connectivity algorithm for cooperative transportation systems," *Comput. Electr. Eng.*, vol. 102, p. 108199, 2022, doi: https://doi.org/10.1016/j.compeleceng.2022.108199.

[9] Q. Pan, J. Wu, J. Nebhen, A. K. Bashir, Y. Su, and J. Li, "Artificial Intelligence-Based Energy Efficient Communication System for Intelligent Reflecting Surface-Driven VANETs," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 10, pp. 19714–19726, 2022, doi: 10.1109/TITS.2022.3152677.

[10] S. Chen, Y. Liu, J. Ning, and X. Zhu, "BASRAC: An efficient batch authentication scheme with rule-based access control for VANETs," *Veh. Commun.*, vol. 40, p. 100575, 2023, doi: https://doi.org/10.1016/j.vehcom.2023.100575.

[11] P. Garrad and S. Unnikrishnan, "Reinforcement learning in VANET penetration testing," *Results Eng.*, vol. 17, p. 100970, 2023, doi: https://doi.org/10.1016/j.rineng.2023.100970.

[12] U. Arul, R. Gnanajeyaraman, A. Selvakumar, S. Ramesh, T. Manikandan, and G. Michael, "Integration of IoT and edge cloud computing for smart microgrid energy management in VANET using machine learning," *Comput. Electr. Eng.*, vol. 110, p. 108905, 2023, doi: https://doi.org/10.1016/j.compeleceng.2023.108905.

[13] W. U. I. Zafar, M. A. U. Rehman, F. Jabeen, R. Ullah, G. Abbas, and A. Khan, "Decentralized Receiver-based Link Stability-aware Forwarding Scheme for NDN-based VANETs," *Comput. Networks*, vol. 236, p. 109996, 2023, doi: https://doi.org/10.1016/j.comnet.2023.109996.

[14] H. Yang, C. Pu, J. Wu, Y. Wu, and Y. Xia, "Enhancing OLSR protocol in VANETs with multi-objective particle swarm optimization," *Phys. A Stat. Mech. its Appl.*, vol. 614, p. 128570, 2023, doi: https://doi.org/10.1016/j.physa.2023.128570.

[15] G. Kaur and D. Kakkar, "Fr-Aro: Secure interference aware fuzzy based clustering and hybrid optimization driven data routing in VANETs," *Ad Hoc Networks*, vol. 151, p. 103298, 2023, doi: https://doi.org/10.1016/j.adhoc.2023.103298.

[16] K. Nova, U. A, S. S. Jacob, G. Banu, M. S. P. Balaji, and S. S, "Floyd–Warshalls algorithm and modified advanced encryption standard for secured communication in VANET," *Meas. Sensors*, vol. 27, p. 100796, 2023, doi: https://doi.org/10.1016/j.measen.2023.100796.

[17] A. Srivastava, A. Prakash, and R. Tripathi, "A cross layer based cooperative broadcast protocol for multichannel VANET," *Ad Hoc Networks*, vol. 131, p. 102840, 2022, doi: https://doi.org/10.1016/j.adhoc.2022.102840.

[18] S. A. Chaudhry, "Comments on 'A Secure, Privacy-Preserving, and Lightweight Authentication Scheme for VANETs,'" *IEEE Sens. J.*, vol. 22, no. 13, pp. 13763–13766, 2022, doi: 10.1109/JSEN.2022.3168512.

[19] Z. Bi, G. Meng, A. Hawbani, S. K. Goudos, S. Wan, and L. Zhao, "TRUE: A Correlation Analysis Approach for Conducting Optimal Routing Metrics in VANETs," *IEEE Netw. Lett.*, vol. 5, no. 1, pp. 55–58, 2023, doi: 10.1109/LNET.2022.3225297.

[20] G. D. Singh, M. Prateek, S. Kumar, M. Verma, D. Singh, and H.-N. Lee, "Hybrid Genetic Firefly Algorithm-Based Routing Protocol for VANETs," *IEEE Access*, vol. 10, pp. 9142–9151, 2022, doi: 10.1109/ACCESS.2022.3142811.

[21] H. Yu, R. Liu, Z. Li, Y. Ren, and H. Jiang, "An RSU Deployment Strategy Based on Traffic Demand in Vehicular Ad Hoc Networks (VANETs)," *IEEE Internet Things J.*, vol. 9, no. 9, pp. 6496–6505, 2022, doi: 10.1109/JIOT.2021.3111048.

[22] K. Gu, X. Dong, and W. Jia, "Malicious Node Detection Scheme Based on Correlation of Data and Network Topology in Fog Computing-Based VANETs," *IEEE Trans. Cloud Comput.*, vol. 10, no. 2, pp. 1215–1232, 2022, doi: 10.1109/TCC.2020.2985050.

[23] Z. Wei, Q. Chen, H. Yang, H. Wu, Z. Feng, and F. Ning, "Neighbor Discovery for VANET With Gossip Mechanism and Multipacket Reception," *IEEE Internet Things J.*, vol. 9, no. 13, pp. 10502–10515, 2022, doi: 10.1109/JIOT.2021.3122023.

[24] A. K. Singh, J. Grover, and S. Mishra, "Integration of Blockchain in VANET Using gRPC for Privacy Preservation of Vehicles," *SN Comput. Sci.*, vol. 5, no. 1, p. 110, 2023, doi: 10.1007/s42979-023-02438-0.

[25] A. M. C. Blessy and S. Brindha, "Energy-efficient fuzzy management system using tri-parametric methodology in vanet," *Wirel. Networks*, vol. 30, no. 2, pp. 617–635, 2024, doi: 10.1007/s11276-023-03505-3.

[26] M. Wang *et al.*, "Smart City Transportation: A VANET Edge Computing Model to Minimize Latency and Delay Utilizing 5G Network," *J. Grid Comput.*, vol. 22, no. 1, p. 25, 2024, doi: 10.1007/s10723-024-09747-5.

[27] A. Raza, Z. Iqbal, and F. Aadil, "UAV-assisted ubiquitous communication architecture for urban VANET environment," *J. Supercomput.*, vol. 79, no. 13, pp. 14602–14632, 2023, doi: 10.1007/s11227-023-05223-1.

[28] F. Safari, H. Kunze, J. Ernst, and D. Gillis, "A Novel Cross-Layer Adaptive Fuzzy-Based Ad Hoc On-Demand Distance Vector Routing Protocol for MANETs," *IEEE Access*, vol. 11, pp. 50805–50822, 2023, doi: 10.1109/ACCESS.2023.3277817.

[29] M. C. Blessy A and B. S, "Maximizing VANET performance in cluster head selection using Intelligent Fuzzy Bald Eagle optimization," *Veh. Commun.*, vol. 45, p. 100660, 2024, doi: https://doi.org/10.1016/j.vehcom.2023.100660.

Authors' Profiles

Mrs. R. Jasmine Immaculate Shelly is a research scholar (Reg. No. 20123152282032) at Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India. She holds an M.Phil. (2010) and M.Sc. (2009) in Computer Science from the same university and Loyola College, Chennai, respectively, and a B.Sc. in Computer Science from Nesamony Memorial Christian College (2007). Her research interests include Vehicular Ad Hoc Networks, Network Security, Blockchain, and Wireless Communication.

Dr. M. Milton Joe holds a Ph.D. in Computer Applications from Manonmaniam Sundaranar University, India. He is currently an Assistant Professor at St. Jerome's College, Nagercoil, with 13 years of teaching and research experience. He has published 30 research papers, including 9 SCIE and 19 SCOPUS-indexed articles. He authored the book "Vehicular Ad Hoc Network and Web Vehicular Ad Hoc Network: An Overview" (ISBN: 978–3–330-02628-5). His research interests include VANET, Social Network Security, Wireless Communications, and Image Processing.

Dr. B. Ramakrishnan is an Associate Professor (Retried) in the Department of Computer Science and Research Centre at S.T. Hindu College, Nagercoil. He holds M.Sc. from Madurai Kamaraj University, M.Phil. from Alagappa University, and a Ph.D. in Computer Science from Manonmaniam Sundaranar University. With 31 years of teaching and 25 years of research experience, he has published over 75 papers, including 22 SCIE articles in Springer journals and 35 SCOPUS-indexed works. He authored the book "Vehicular Ad Hoc Network and Web Vehicular Ad Hoc Network: An Overview" (ISBN: 978-3-330-02628-5). His interests include Vehicular Networks, Cloud Computing, Green Computing, and Network Security.

How to cite this paper: R. Jasmine Immaculate Shelly, M. Milton Joe, B. Ramakrishnan, "Bacterial Foraging Inspired Mamdani Fuzzy Inference based AODV (BF-MFI-AODV) for VANET Route Management Optimization", International Journal of Computer Network and Information Security(IJCNIS), Vol.18, No.1, pp.99-115, 2026. DOI:10.5815/ijcnis.2026.01.07