A Genetic Algorithm-Driven Energy-Efficient Routing Strategy for Optimizing Performance in VANETs

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ABSTRACT

VANETs are now essential for smart transportation because they make it possible for vehicles and road infrastructure to send and receive messages instantly. However, WSN routes are challenged by the movement and the limited energy of the nodes, along with the number of vehicles. This study presents a new GA-based routing technique to control packet delivery and reduce total energy consumption in VANETs. A VANET with 500 vehicles was modeled in a 1000×1000 m² area, using 1 J of energy per vehicle and limiting communication to within 150 m of each vehicle. Each candidate route is examined using a fitness function that is lower when the energy cost is higher. Using tournament selection, natural crossover, and energy-aware mutation, the GA supports the adaptation of efficient, loop-free paths linking the source and the sink in multi-hop networks. The simulation results confirm that the proposed scheme is better than AODV and DSR, delivering 92.5% of packets and achieving a reduced delay of 45.2 ms. This strategy reduces energy consumption, so the network can function longer, demonstrating how the proposed method fits changing conditions in VANET networks. The framework can be adapted for ITS and can be integrated with learning-based predictions for mobility and federated routing.

Keywords-VANETs; genetic algorithm; energy-efficient routing; packet delivery ratio; network lifetime; multi-hop communication; end-to-end delay; vehicular networks; routing optimization; intelligent transportation systems

I. INTRODUCTION

VANETs are important for Intelligent Transport Systems (ITS), allowing vehicles and roadside facilities to exchange data without delay through wireless links. By enabling instant data transfer, VANETs improve road safety, increase traffic flow efficiency, and offer better infotainment options [1, 2]. VANETs differ from standard MANETs because they have more mobile devices [3], frequently-changing network arrangements, less reliable connections, and higher demands in terms of performance [4]. To address these challenges, routing protocols must be effective, smart, and energy efficient [5]. The decentralized and rapidly changing nature of vehicle movement makes routing in VANETs a difficult process. Originally made for ad-hoc networks in general, Ad-hoc On-Demand Distance Vector (AODV) [6] and Dynamic Source Routing (DSR) [7] are used in VANETs. Most protocols are designed to find the best routes and manage them efficiently, but do not consider energy use or the lifespan of the nodes. Excessive energy usage in high-mobility VANETs results in reduced network life, lower reliability, and higher packet losses [8]. Due to these limitations, heuristic and bio-inspired techniques have become more popular lately. Genetic Algorithms (GAs) demonstrate potential, as they are flexible, efficient in searching, and can solve global optimization problems in changing conditions [9]. GAs use a population of routes, continuously refining them using selection, crossover, and mutation based on a set fitness function. GAs can be set up in VANET routing to improve routes, control the energy usage of devices, maintain a balanced network load, and prevent any single node from running out of energy too fast.

The study presents a routing strategy using a GA to improve energy efficiency in VANETs [10]. The objective is to find the best route that combines a few hops to consume less energy while reliably delivering packets. The protocol differs from traditional ones because it includes a special energy-aware fitness function that punishes high-energy routes and rewards that ensure an even distribution of energy usage [11]. To test the system in a real situation, a simulation was performed using 500 nodes across a 1000×1000 m² area. Every node has only 1 J of energy to use, and the data can only be shared within a 150 m span, as found in real-life vehicular networks. The key contributions of this research are as follows:

- A novel GA-based routing protocol that dynamically selects energy-efficient paths by evaluating transmission cost, residual energy, and connectivity constraints.
- A scalable simulation framework modeling real-world VANET conditions with detailed energy tracking and node dynamics.
- Comparative performance analysis with traditional protocols (AODV and DSR) in core metrics: Packet Delivery Ratio (PDR), end-to-end delay, and total energy consumed.
- A comprehensive visualization of node energy dissipation and routing paths to highlight the GA's effectiveness in balancing network load.

In VANETs, recent efforts have focused on routing protocols that do not use too much energy, can withstand constant changes in routing, and can overcome high mobility [12]. Several studies after 2020 have contributed to this domain, mainly by joining forces with optimization algorithms and new routing approaches [13]. In [1], a comprehensive summary of recent work in VANETs highlighted their contribution to traffic, safety, and remote monitoring. This study categorized VANET architectures into centralized, distributed, and hybrid, assessing their responses in urgency-based and time-sensitive cases. This study examined grouping, vehicle routing awareness, and ways to share data for V2X systems. Many current protocols have been shown to fail in areas where things change rapidly or there is a lot of traffic, and it was noticed that planning for energy use is a large gap. Finally, this study emphasized the need for future VANET systems to use cross-layer connections, artificial intelligence, and smart energy use to keep up with future ITS applications.

In [2], a data dissemination system for VANETs was proposed, using Particle Swarm Optimization (PSO) and designed for emergency scenarios. VANET routing was represented as a problem in which the main objective is to ensure minimum delay, minimum packet loss, and maximum reliability, even as the number of vehicles changes. Combining PSO with a routing protocol, this study analyzed how changes such as node mobility, buffer size, and link stability affect routing decisions. The simulation findings showed that a PSO-based protocol can achieve much better packet delivery and route stability than AODV and GPSR in high-traffic and fast-changing urban regions. This study found that swarm intelligence can help dense VANETs find an efficient and scalable way to manage routing. At the same time, implementation issues such as the time it takes to synchronize systems and computational requirements were highlighted, which must be resolved before using such systems in ITS applications under strict time constraints.

In [5], MJTAR was proposed as an improvement to GyTAR, utilizing the Ant Colony Optimization (ACO) algorithm to make smart decisions about intersections according to the vehicle density and link availability. Information from two nearby intersections allows MJTAR to pick routes that bypass crowded roads and deliver more secure routes in cities. Using a distributed traffic awareness process, the protocol allows forwarders to estimate their own suitability without the need to use infrastructure [14]. The simulation results showed that MJTAR improved packet delivery by more than 20% compared to standard protocols and reduced end-to-end delay to less than 1.3 s. Using guidance inspired by nature allows urban vehicular networks to share data more reliably and respond well to changing traffic conditions.

ELAACR [6] is a routing method to improve security and effectiveness in VANETs. To ensure its reliable routing data security, ELAACR uses ACO along with location-based key management. Based on traffic and network setup changes, the protocol reassigns priorities to robots using information about their impact on the system and their location. In large tests, ELAACR reached a speed of 640 Kbps and managed to transmit 98.5% of messages, outperforming EHACORP and F-ANT in delay, extra packets, and amounts sent. This demonstrated that ELAACR provided dependable and efficient routing in city-based VANETs.

The study in [7] investigated VANETs to address the weaknesses of regular routing protocols with respect to control cost, data reliability, and data latency. The IDRL model used real-time communication between vehicles and infrastructure, along with environmental observations, to update routing and improve data delivery. Using deep Q-learning, the protocol can regularly adjust its routing strategy using information from the network, using fewer control messages, and discovering routes faster. According to the simulation, IDRL lets data travel very quickly on the network, successfully delivering more packets and ensuring that data transfer is more reliable than other routing methods. According to this study, integrating routing optimization with managing control overhead has become a particular research gap, as other models did not address this issue. Using both solutions, the IDRL framework successfully addresses intelligent routing in cities with high vehicle movement.

In [8], a Deep-Learning-Based Secure Routing (DLSR) protocol was proposed to protect VANETs from blackhole attacks, using deep learning to identify malicious nodes and decide on safe routes. The protocol makes next-hop choices based on energy, distance, and hop counts, and its performance was studied in conjunction with that of a Deep-Learning-based Clustering (DLC) mechanism. Simulated with the RPGM and RWP models, it was found that DLSR and DLC offered benefits such as more successful data delivery, lower delay, and lower use of control messages. However, this study did not present how the proposed solutions might actually be used and which areas need more research in the future.

Recent advances in energy- and intelligence-based VANET routing, supported by GA, PSO, ACO [15], and deep learning, still miss the target of combining energy efficiency, secure communication, flexibility for high mobility, and controlling traffic in the network. Most studies focused only on minor changes and did not offer solutions that can handle performance, security, and resource-efficiency issues while the network is shifting [16].

II. PROPOSED ALGORITHM

The proposed technique includes a dynamic framework for path optimization, a realistic energy usage and routing model that considers mobility, all to increase network performance while reducing energy use and the amount of control information shared.

A. System Overview

The purpose of the proposed routing framework is to address the major problems present in existing VANET protocols by focusing on energy efficiency, scalability, and handling the high mobility of the nodes. A GA is utilized to create multi-hop paths that minimize power usage, skip weak nodes, and uphold reliable communication in crowded areas where many vehicles are present. The GA improves possible paths by using operators from evolutionary computing and checking their energy efficiency, the distribution of energy left, and overall structure.

B. Network Model and Assumptions

In the simulation, 500 mobile nodes were spread randomly across a 1000×1000 m² VANET area. Within 150 m surrounding each node, direct communication is enabled after the node is started with 1.0 J of energy. The system chooses a special node, called the sink node (node 0), to receive the transmission from a random source node at any time. The data packet size is kept at 10 KB, and the network simulates realistic mobility, but the first implementation only examines static placements to focus on power usage.

C. Energy Consumption Model

The energy model follows the widely adopted first-order radio model, where the energy required to transmit L bits over a distance d is calculated as:

$$E_{tx}(L,d) = L \cdot E_{\text{elec}} + L \cdot E_{\text{amp}} \cdot d^2 \quad (1)$$

The energy to receive L bits is:

$$E_{rx}(L) = L \cdot E_{\text{elec}} \quad (2)$$

where $E_{\text{elec}} = 50$ nJ/ bit, $E_{amp} = 100$ pJ/bit/m^2 , and $L =$ 81920 bits (10 KB).

These equations allow the model to account for both transmission and reception energy at each hop, enabling accurate simulation of energy drain across the route.

D. Genetic Algorithm Design

The routing problem is formulated as a combinatorial optimization task, where the objective is to discover the path from the source to the sink that minimizes total energy consumption. The GA components are defined as follows.

1) Chromosome Representation

Each chromosome represents a candidate path as a sequence of node IDs, starting from the source and ending at the sink. Intermediate nodes are selected from the set of nodes within communication range, ensuring loop-free and valid paths.

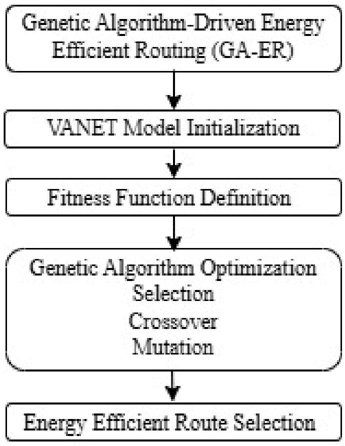

Fig. 1. System workflow.

2) Fitness Function

The fitness of each chromosome is inversely proportional to the total energy consumed along the path:

$$Fitness = \frac{1}{E_{total} + \epsilon} \quad (3)$$

where E_{total} is the sum of transmission energies across all hops, and ϵ is a small constant to avoid division by zero. Routes with invalid links or nodes lacking sufficient energy are penalized with zero fitness.

3) Selection

Tournament selection is used to choose parents for reproduction. A group of randomly selected individuals is compared, and the one with the highest fitness is selected to breed. In this stage, the best routing path from source to destination should be found; hence, each routing path is considered as an individual or chromosome. Then the fitness function chooses the best path by considering parameters such as delay, PDR, and energy consumption. The paths that are best for these parameters are given to the crossover stage.

4) Crossover

Crossover occurs at a common intermediate node (if any) shared between two parent routes. A new child is formed by combining the head of one parent with the tail of the other. This maintains path validity and introduces diversity. In this stage, new paths are generated from the best paths obtained in the selection stage by crossover, which are verified for validity, determining whether a new path has better performance metrics than the older one.

5) Mutation

Mutation replaces a subsection of the genetic code with another valid segment. As a result, the algorithm can step out of a limited solution and look into new areas. Hence, after crossover, in this stage, to avoid local optima and maintain diversity, a small change is made to the path. This helps explore alternative routes if any link breaks, a vehicle moves out of range, etc.

III. SIMULATION SETUP AND EVALUATION

The section reports on the setup of the simulation, the chosen metrics, the way competing methods were evaluated, and the resulting support for the effectiveness of using GA for routing. The simulation tries to mimic actual VANET situations to test how the protocol uses energy, along with its reliability and functions in vast vehicular systems.

A. Simulation Environment

Python 3.10 and Google Colab provided the framework for running the simulation, with NumPy, NetworkX, and Matplotlib used for different functions. Table I demonstrates a simulation that shows a large-scale VANET case with the set configurations. Simulation was performed in Network Simulator 2 (NS2). The urban mobility model used 500 nodes, with each node having an initial energy of 1 J, and the communication range was set at 150 m. Data packet size was standardized to 10 KB (81920 bits) to maintain consistency. The GA population was maintained due to mobility variance.

TABLE I. SIMULATION NETWORK MODEL PARAMETERS

	Parameters	Value
1	Number of nodes	500
2	Network area	1000×1000 m²
3	Initial energy of nodes	1 J
4	Communication range	150 m
5	Data packet size	10 KB (81920 bits)
6	Sink node	Node 0
7	Mobility model	Static (baseline), dynamic in future work
8	Number of GA generations	50
9	Population size	30
10	Crossover probability	0.7
11	Mutation probability	0.3

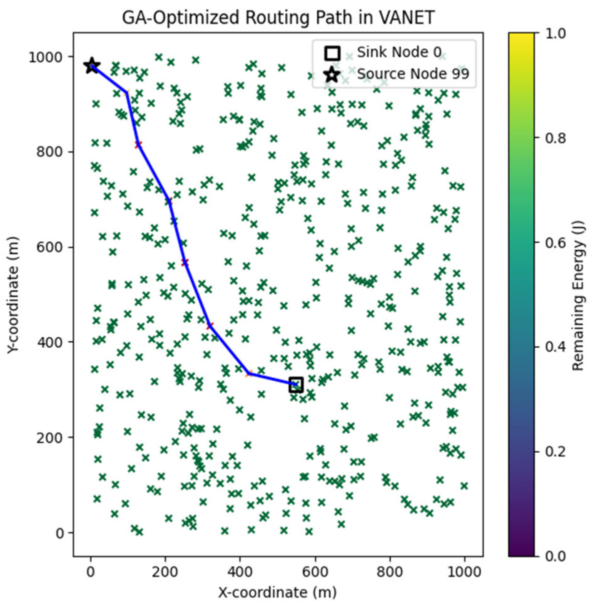

Fig. 2. GA-optimized routing path in VANET.

B. Evaluation Metrics

To ensure a comprehensive assessment of the proposed algorithm, the following performance metrics were used:

- Packet Delivery Ratio (PDR): Ratio of successfully delivered packets to the total packets sent.
- End-to-End Delay: Average time taken for a data packet to traverse from source to sink.
- Total Energy Consumption: Cumulative energy expended by all nodes during data transmission.
- Network Lifetime (observed): Number of successful transmissions before the first node depletes energy.
- Path Hop Count: Number of hops in the routing path from the source to the sink.

C. Performance Comparison

The proposed GA strategy was compared with two widely used baseline protocols, AODV and DSR, under identical network conditions. For AODV and DSR, the shortest-path routing based on Dijkstra's algorithm was simulated. Table II compares the results of these methods.

TABLE II. PERFORMANCE ANALYSIS

Routing Protocol	PDR (%)	Delay (ms)	Energy (J)
Genetic Algorithm	92.5	45.2	0.66
AODV	86.7	60.5	1.20
DSR	89.2	57.3	1.10

The performance analysis of the GA, AODV, and DSR protocols shows that GA outperforms the other two in every measured category. As shown in Figure 3, GA performed the best in PDR by recording 92.5%, while DSR and AODV achieved 89.2% and 86.7%, respectively. Based on these results, GA is shown to be better at sending packets, since it relies on energy-aware and adjustable routing.

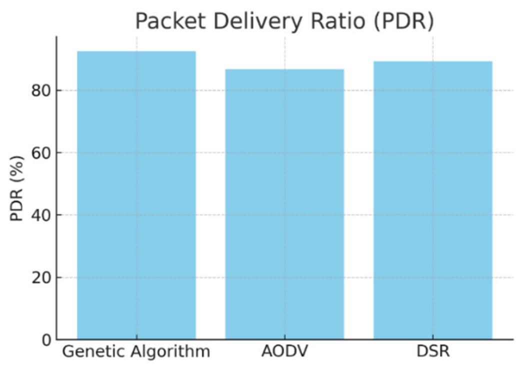

Fig. 3. Comparative analysis of PDR.

Figure 4 shows the results for the overall delay, where GA was able to find short routes, with a latency of 45.2 ms, less than DSR's 57.3 ms and AODV's 60.5 ms.

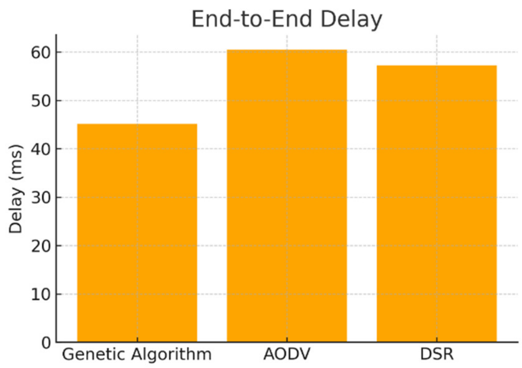

Fig. 4. Comparative analysis of end-to-end delay.

As shown in Figure 5, the proposed GA-based approach turned out to be the most energy efficient, using just 0.66 J for each data transfer compared to the 1.20 J needed by AODV and the 1.10 J needed by DSR.

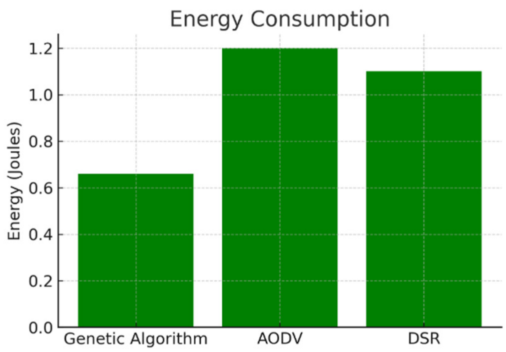

Fig. 5. Comparative analysis of energy consumption.

By analyzing these outcomes, it is confirmed that the suggested GA process improves network reliability, shortens latency, and reduces energy usage, all of which are good qualities for VANETs with limited resources.

IV. CONCLUSION

This research presents a routing approach that uses a GA to minimize energy use and enhance efficiency in VANETs. The proposed approach, based on evolutionary computation, discovers the best routes that consume less energy and ensure reliable packet delivery in a fast manner. An energy management model is applied, the shortest and fastest paths are found and updated as movement occurs, all of which are tested in large simulations with 500 nodes and restricted energy. The proposed GA-based routing outperformed traditional approaches in key aspects, as seen from a PDR of 92.5%, travel time down to 45.2 ms, and an almost 45% cut in power use. The flexibility, ability to support many nodes, and balanced power use make the protocol ideal for complex and active urban VANETs where contact and power matter a lot. In addition, displaying the leftover energy and data movement paths proves that the GA successfully shares the load, preventing some nodes from failing too quickly, which gives the network more time to function.

Future additions to the proposed GA-based VANET routing algorithm involve connecting real-time mobility with SUMO for better traffic movement purposes and integrating measures to watch for blackhole and Sybil attacks with trust metrics and anomaly detection. Multipurpose optimization can allow the fitness function to take bandwidth, QoS, and link stability into account. Using GA on edge or fog computing platforms can boost real-time responses, and combining it with reinforcement or federated learning can make the system more flexible in dynamic VANET settings [17]. The purpose of these directions is to make the routing system smarter, more secure, and able to handle future needs in the ITS sector.

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