MULTI-OBJECTIVE OPTIMAL ROUTING SCHEMES FOR HIGH MOBILITY VEHICULAR NETWORKS: A PATH TO EFFICIENCY

by

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This dissertation is dedicated to the memory of my beloved father, whose guidance and support remain with me every day. To my mother, whose constant love and sacrifices have been my greatest strength. To my sisters, who have been my source of encouragement and understanding. To my friends, whose companionship and support have made this journey possible.

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PREFACE

The rapid advancement of vehicular communication technologies has transformed vehicles into integral components of intelligent transportation systems (ITS). However, vehicular networks in ITS require efficient communication and routing schemes to accommodate Electric and Flying Vehicles (EnFVs), enabling a faster, better, and improved communication platform. This dissertation, "Multi-Objective Optimal Routing Schemes for High Mobility Vehicular Networks: A Path to Efficiency," explores an in-depth examination of EnFVs within ITS, emphasizing the need for a unified approach to address their unique challenges. It also thoroughly analyzes the role of Artificial Intelligence (AI), particularly Genetic Algorithms (GA), in optimizing communication decision-making for high-mobility vehicles. This comprehensive work extensively reviews existing solutions and the background of GA, underscoring the importance of multi-objective optimization algorithms.

This work would not have been possible without the support and guidance of my advisor, committee members, and colleagues at Oakland University. I am also deeply grateful to my family and friends for their unwavering support.

I hope this dissertation provides valuable insights for researchers, practitioners, and policymakers working to enhance the efficiency and reliability of vehicular network and advance the field of EnFVs.

ABSTRACT

MULTI-OBJECTIVE OPTIMAL ROUTING SCHEMES FOR HIGH MOBILITY VEHICULAR NETWORKS: A PATH TO EFFICIENCY

by

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Adviser: Mohamed A Zohdy, Ph.D.

Technological advancements in wireless communication networks have enabled futuristic applications that support massive device access and pervasive communications. Moreover, vehicular networks in Intelligent Transportation Systems (ITS) require efficient communication and routing schemes to accommodate Electric and Flying Vehicles (EnFVs). A centralized approach is often flawed due to the high mobility and dynamic nature of device movement. Therefore, efficient and novel solutions are required to provide connectivity to EnFVs without any centrally connected unit. Our main focus in this study is to enable a faster, better, and improved communication platform for EnFVs, support a wide range of applications.

This dissertation provides an in-depth examination of EnFVs within ITS, emphasizing the necessity for a unified approach to tackle the unique challenges they pose. Moreover, this study thoroughly analyzes the role of Artificial Intelligence (AI), specifically Genetic Algorithms (GAs), in optimizing communication decision-making for high-mobility vehicles. This comprehensive work extensively reviews existing

solutions and the background of GAs, highlighting the relevance of multi-objective optimization algorithms.

Communication and routing issues in EnFVs are examined from various angles. A novel multi-objective routing scheme addresses the diverse constraints and goals of EnFV networks, aiming to improve packet routing performance and efficiency. Our novel scheme prioritizes energy and transmission rate for routing decisions while focusing on vehicle connectivity time. The Genetic Algorithms employed identify the optimal solution for multi-objective routing problems. Significant findings include an optimized routing scheme that outperforms current solutions, achieving over 90% packet delivery ratio, extended connectivity time, reduced average hop distance, and efficient energy use. The research also explores the potential of Genetic Algorithms in solving complex optimization problems in EnFVs, demonstrating their effectiveness in dynamic routing scenarios.

Further enhancements to the solution improve route discovery methods, making the process lighter and more suitable for high-mobility UAV networks. The dissertation concludes with recommendations for future research to further improve the efficiency and effectiveness of routing algorithms in EnFV networks, aim for seamless integration into modern transportation systems and advance the field of EnFVs.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

BSM	Basic Safety Message
CMEM	Comprehensive Modal Emission Model
DSRC	Dedicated Short-Range Communications
EnFVs	Electric and Flying Vehicles
EV	Electric Vehicle
FANET	Flying Adhoc Network
GA	Genetic Algorithm
ILS	Iterated Local Search
IRP	Inventory Routing Problems
ITS	Intelligent Transportation System
MINLP	Mixed-Integer Non-Linear Programming
PSO	Particle Swarm Optimization
RREP	Route Reply
RREQ	Route Request
SA	Simulated Annealing
TSP	Traveling Salesman Problem
UAV	Unmanned Aerial Vehicle
VANET	Vehicular Adhoc Network

CHAPTER ONE

INTRODUCTION

In recent years, the transportation industry has undergone rapid transformation, drive of by technological advancements. Electric Vehicles (EVs) and Unmanned Aerial Vehicles (UAVs) have emerged as disruptive technologies, promising increased sustainability, reduced traffic congestion, and improved mobility in modern society. These developments are especially significant given the growing demand for environmentally friendly transportation and fast, dependable communication systems. However, the successful integration of EnFVs into our daily lives is dependent on intelligent transportation systems that enable seamless and predictive communication between these battery-powered devices [1].

The current state of research in EnFVs reveals significant progress, but it also highlights several gaps and limitations. While technological advancements have brought these vehicles into the mainstream, the protocols and systems that govern the interaction are still evolving. The need for intelligent and efficient message routing in the context of EnFVs is urgent, and current research focuses primarily on electric vehicles or UAVs in isolation[2], [3]. Only a few studies have addressed the specific challenges of unified EnFVs message routing. After conducting a comprehensive review of state-of-the-art schemes for message delivery in high mobility networks, we identified the following shortcomings that steer our motivation:

1. Limited Unified Approach: Existing research often takes a fragmented approach, treating EVs and UAVs separately. This local optimal approach lacks a comprehensive vision, resulting in missed opportunities for cooperation and collaboration in EnFV communication systems.
2. Single-Objective Routing: Current research focuses on single-objective routing schemes, which may not adequately address the multi-dimensional constraints and objectives of EnFV networks.
3. Limited Real-World Validation: Studies often rely on simulations or theoretical models instead of extensive real-world testing. This limits the findings' applicability in practical EnFV environments.

To address these limitations, this PhD dissertation aims to provide a comprehensive and unified framework for efficient message routing in EnFVs. Our research objectives include:

- Developing a Multi-Objective Routing Scheme: We intend to propose a novel multi-objective routing scheme that considers factors such as reliability, data rate, residual energy, and other essential parameters for EnFVs message routing.
- Real-World Validation: We will conduct an exhaustive evaluation using real geographical traces from New York City to ensure the practicality and efficiency of our proposed scheme.
- Handling Complex Optimization: Our study will focus on demonstrating the capability of Gas in handling complex optimization problems with multiple objectives in the context of EnFVs.

- Flexible and Adaptive Approach: We will showcase the flexibility and adaptability of GAs in addressing dynamic transportation systems, enabling real-time routing updates and adaptability to changing environmental conditions.
- Future Research Directions: Our exhaustive study of the proposed unified and efficient paradigm of EnFV opens great avenues. The use of GA and its application in the existing literature are noteworthy but our discussion takes it further to the EnFVs utility. There are several directions that our dissertation opens up including real-time data with experimental results, consideration of other objectives along with the proposed, comparative analysis of other optimization techniques, and improving upon the sustainability and reliability of decision-making in the EnFVs environment.

1.1 Our Motivation and Challenges in Message Routing in EnFVs:

The transportation industry is currently in the midst of a profound and transformative revolution. This revolution is being ushered in by the advent of EnFVs, which promise to not only reshape the way we move but also pose new and unique challenges in the realm of message routing. Traditional routing schemes that have been effective for conventional vehicles are ill-suited to address the complexities that EnFVs bring to the table. Thus, there is a significant need to propose innovative protocols that enable agile and predictive communication within this novel class of battery-powered devices. The primary motivation driving this Ph.D. dissertation is to confront head-on the manifold challenges that envelop message routing within the unified paradigm of electric and flying vehicles. We endeavor to present a fresh perspective on routing, one that transcends existing limitations and paves the way for a more sophisticated and efficient routing scheme.

The landscape of EnFVs is fraught with unique hurdles that demand a paradigm shift in message routing. These challenges include:

1. Battery Constraints: EnFVs, being entirely dependent on batteries, face the fundamental constraint of limited battery life. Any effective routing scheme must meticulously consider and accommodate these constraints, ensuring efficient use of available power.
2. High Mobility: EnFVs are inherently mobile and exhibit unpredictable movement patterns. Establishing and maintaining reliable communication links in an environment characterized by constant flux becomes a formidable task.
3. Multi-Objective Routing: EnFVs are part of a dynamic and heterogeneous environment that necessitates multi-objective routing over a single objective. Distinct constraints, goals and performance metrics, necessitate the development of a routing scheme capable of optimizing for various objectives. Key objectives include ensuring reliability, enhancing data transfer rates, and judiciously managing residual energy.

1.2 Genetics Algorithm for Message Routing in EnFVs

Utilizing a genetics algorithm for message routing within the realm of EnFVs offers a range of promising advantages, including:

1. Multi-Objective Optimization: Genetics algorithms are renowned for their prowess in optimizing multiple objectives simultaneously. In the context of EnFVs, this means that routing can be not just efficient but also reliably

responsive to multifaceted objectives like reliability, data transfer rate, and energy utilization[4].

2. Adaptability: EnFVs operate in dynamic environments, where conditions can change rapidly. A genetics algorithm provides the adaptability necessary to tackle these environmental shifts. Be it fluctuations in battery life or alterations in network topology, the algorithm ensures robust and flexible routing.

3. Scalability: With the potential for vast networks populated by numerous EnFVs, the scalability of the genetics algorithm ensures that the routing scheme is not confined to theoretical models but can be seamlessly applied to real-world, large-scale scenarios.

4. Pareto-Front: The genetics algorithm's ability to identify all conceivable solutions and outline the Pareto-Front is invaluable. It equips the routing scheme to offer a spectrum of optimal solutions, catering to the diverse needs and scenarios presented by EnFVs.

5. Performance: In exhaustive evaluations that employed real traces from Simulations of Urban Mobility (SUMO) and OpenStreetMap (OSM), the proposed scheme employing a genetics algorithm yielded exceptional results. These results include a packet delivery ratio exceeding 90%

The motivation behind this Ph.D. dissertation is rooted in the imperative need to address the intricacies of message routing in the realm of EnFVs. By proposing a novel routing scheme utilizing genetic algorithms, this research aims to overcome the challenges presented by battery constraints, high mobility, and multifaceted objectives. The ultimate goal is to provide a scalable, adaptable, and highly effective solution that contributes significantly to the development and integration of EnFVs into modern transportation systems. Nevertheless, our dissertation provides a comprehensive experiment study that focuses on three major aspects, as depicted in Figure 1.

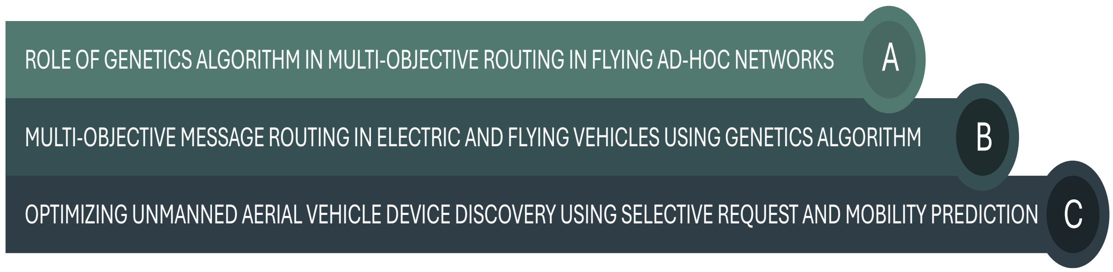


Figure 1 Major objectives of the dissertation.

Major Contributions of the Dissertation:

1. Genetic Algorithms: Exhaustive literature review and insights on genetic algorithms for vehicular communication and message routing.
    a. Insights into the potential of Genetic Algorithms in addressing complex optimization problems within the context of EnFVs, demonstrating their effectiveness in dynamic and adaptive routing scenarios.
2. Unified Paradigm: Our dissertation provides a unified perspective on EnFVs, bridging the gap between electric and flying vehicles and emphasizing the importance of a holistic approach to intelligent transportation systems.
3. Multi-Objective Routing: We contribute a novel multi-objective routing scheme that accounts for the diverse constraints and objectives of EnFVs networks.
    a. A multi-objective routing scheme that outperforms existing solutions, achieving a packet delivery ratio of over 90.
4. Real-World Applicability: By conducting real-world evaluations, we ensure that our research findings are directly applicable to practical EnFV environments.

a. A roadmap for future research, outlining directions to enhance the efficiency and effectiveness of routing algorithms for EnFVs, making them seamlessly integrated into modern transportation systems.

5. Efficient Routing in EnFVs: Reducing the control overhead in reliable message delivery in high mobility networks.

This dissertation addresses the pressing need for intelligent communication systems for EnFVs, bridging gaps in existing research and providing a unified, multi-objective routing framework. Through real-world validation and the use of GAs, this research will contribute to more efficient and sustainable transportation systems, thereby enriching the field of EnFVs and its integration into modern society.

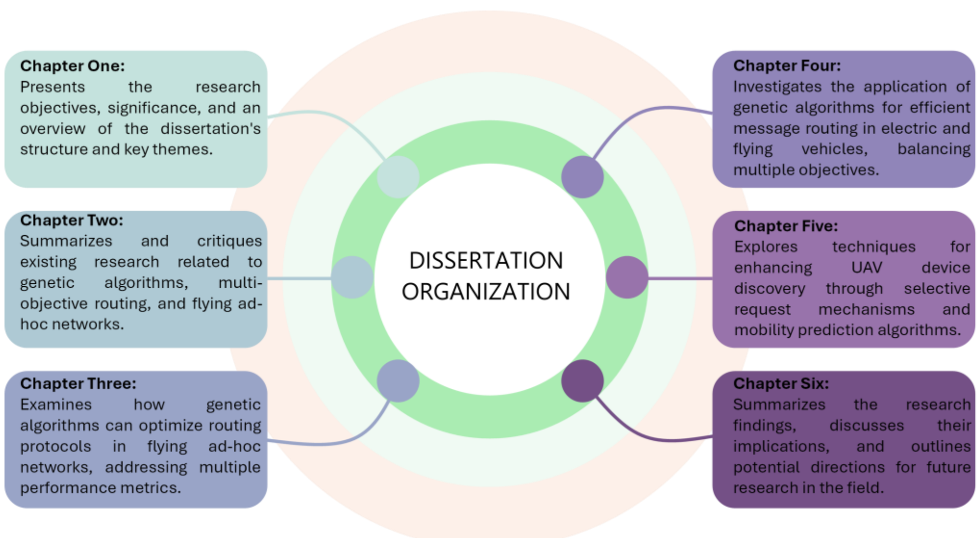


Figure 2 Chapter-wise organization of the dissertation.

This dissertation is organized to thoroughly explore the use of genetic algorithms for optimizing communication and routing in EnFVs. The organization of the dissertation is depicted in Figure 2. In Chapter One, we outline the research objectives, highlights the importance of the study, and provides an overview of the dissertation's structure and key themes. Chapter Two reviews and critiques existing research on genetic algorithms, multi-objective routing, and flying ad hoc networks, establishing a foundation for the study. Building on to the existing literature study, Chapter Three examines how evolutionary algorithms can enhance routing protocols in flying ad hoc networks by addressing multi-objectives. In Chapter Four, we propose to improve network performance in electric and flying vehicles using genetic algorithms for efficient and multi-objective message routing. Chapter Five explores methods to enhance UAV device discovery through selective request mechanisms and mobility prediction algorithms, thereby improving communication efficiency. Finally, Chapter Six summarizes the research findings, discusses their implications, and suggests future research directions in intelligent transportation systems.

CHAPTER TWO

LITERATURE REVIEW

Broadly speaking, the literature can be divided into two major categories where message routing is optimized for 1) Electric or Ground vehicles, 2) Flying or aerial vehicles. Our exhaustive literature review is given below.

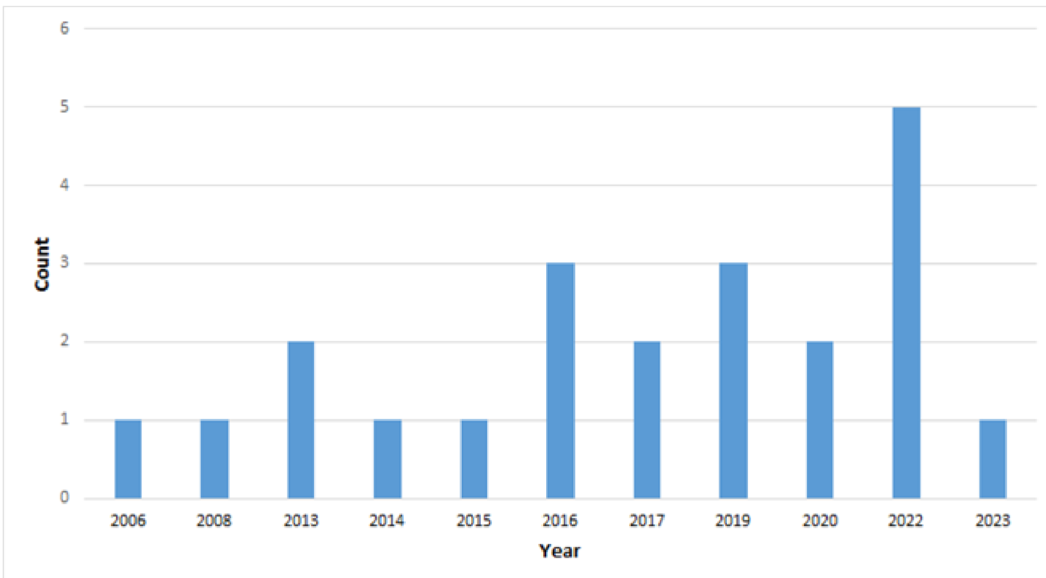


Figure 3 Existing papers published over years, focusing on routing optimization in electric vehicles.

2.1 Literature Review of State-of-the-art in Routing Optimization for Electric Vehicles

Numerous case studies have explored the effectiveness of Genetic Algorithms (GAs) in optimizing EV routing, as shown in Figure 3.

In a notable study, the authors of [5] focused on the Personal Electric Vehicle Routing Problem (pEVRP), aiming to optimize travel time and charging costs for a single EV. The proposed objective function is formulated, which minimized both trip time and the charging process. The first three terms represented travel time from the source to the destination, while the next three terms accounted for the charging procedure.

$$min \sum_{i \in V} \frac{w_i^S d_{Si}}{v} + \sum_{i \in V} \sum_{j \in V} \frac{x_{ij} d_{ij}}{v} + \sum_{i \in V} \frac{w_i^D d_{iD}}{v} + \sum_{i \in V} \frac{z_i \delta_i}{v} + \sum_{i \in V} z_i w_i + \sum_{i \in V} \frac{z_i y_i C}{L_i} \quad (1)$$

The problem formulation included Real-life factors like traffic delays, detour distances, and variable pricing. The study set up a Mixed-Integer Non-Linear Programming (MINLP) model and used the ε-constraint approach to generate a set of optimal solutions. Meta-heuristic methods like PSO and GA were then applied to find the best solutions. Results showed these strategies effectively minimized travel time and recharging costs, offering valuable insights for EV routing decisions. Similarly, Alinaghian and Zamani in [6] addressed fuel usage and emissions in the transportation industry. The authors proposed to calculate fuel consumption and greenhouse gas emissions based on vehicle speed, load weight, and road gradient using the Comprehensive Modal Emission Model (CMEM). Let us consider k^h is vehicle type h engine friction and ξ mass rates of fuel to the air. Moreover, P^h is momentary engine power output vehicle type h (in kW), thus we can calculate fuel usage as given below:

$$FR^h = \xi \frac{k^h N^h V^h + \frac{P^h}{\eta}}{k} \quad (2)$$

where N^h is engine speed, and V^h is engine displacement vehicle type h. η and k are constant values and the diesel engines efficiency parameter and thermal value of diesel fuel, respectively.

To improve practicality, a bi-objective model considered the diverse fleet composition and used a multi-objective quantum algorithm to solve it. The algorithm outperformed existing and NSGA-II approaches. The proposed solution can easily improve inventory routing optimization. Moreover, the study suggested future research directions to enhance, fuel consumption, and environmental sustainability by adding new concepts, policies, and problem-solving methods. Liu et al. [7] focused on enhancing EV navigation by addressing real-time pricing challenges in fast charging. The authors proposed the Improved Chrono-SPT (ICS) algorithm for optimal charging and routing decisions and the Simplify-Charge-Control (SCC) algorithm to reduce computational complexity. Simulation results showed that ICS and SCC were effective, with SCC significantly reducing complexity while maintaining cost efficiency.

By treating the VRP with Time Windows (VRPTW) as a multi-objective optimization problem (MOP), [8] introduced a method using a GA with Pareto ranking. This approach considered total distance and vehicle count as separate dimensions, avoiding bias and allowing deeper solution exploration. The MOP framework recognized trade-offs between minimizing distance and vehicle count, enabling decision-makers to choose based on their priorities. Experimental results showed the method's competitiveness and computational efficiency. Liu et al. [9] tackled the Electric Vehicle Routing Problem with Time Windows (EVRPTW) by considering road terrain grades and battery State-of-Charge (SoC) dynamics. Their goal was to efficiently serve customers within specific time windows while minimizing electricity consumption. The problem formulated as a mixed-integer programming model and developed a hybrid GA that combined GA with the 2-opt algorithm. Simulation results showed that this method found better solutions faster than both GA and Simulated Annealing (SA), optimizing EV routing and energy consumption in logistics.

Another study [10] improved the EV Routing Problem with Time Windows (E-VRPTW) using GA and Tabu Search (TS) methods combined with fuzzy logic. Four indicators including travel cost, fuel cost, time cost, and vehicle cost are used to calculate the fitness value of the current population, offering an enhanced approach to route optimization.

$$\text{Fitness} = \frac{1}{\sum \text{Travel\_cost} + \sum Fuel\_cost + \sum \text{Time\_cost} + \sum \text{Vehicle\_cost}} \quad (3)$$

Authors applied fuzzy logic to add tolerance to time windows, allowing for flexible arrival times. Their E-VRPFTW model, using GA-TS and fuzzy logic, outperformed the E-VRPTW model, improving fitness values by 14.39% and 8.49% in trials. This approach also reduced mileage and the number of vehicles needed, demonstrating its effectiveness. In another study[11], the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) for a mineral water company was optimized using GA, Tabu Search, and a hybrid GA-Tabu method. The hybrid method reduced the overall route distance by 15.99%, achieving the best outcome with a travel distance of

789.673 km compared to 932.478 km for GA and 982.965 km for TS. Future research should consider customer time windows and visualize outcomes to enhance optimization.

Mohammed et al. [12] optimized UNITEN's shuttle bus services using the CVRP model and GA. The GA reduced costs and improved transportation efficiency by minimizing distances and enhancing route planning. However, the study noted limitations due to the simplicity of the problem with a single variable and finite bus stops. Future research should expand the algorithm's domain to handle more complex scenarios. Another study in [13] addressed distributing perishable goods with quality restrictions using a GA-based heuristic. This model considered deterioration rates and time windows, efficiently handling goods with short shelf lives. The results indicated an increasing need for more vehicles as constraints tightened but maintained computational efficiency. Future research should explore demand variability, traffic congestion, and multiple item distributions, as well as pickup operations.

A General Vehicle Routing Problem (GVRP) model was proposed in [14] to adapt to real-world complexities. This model included constraints like time windows, a heterogeneous fleet, order-to-vehicle compatibility, multiple services, distinct starting and ending points, route constraints, and driver working hours. An iterative improvement strategy adjusted the neighborhood structure during the search process. Computational experiments confirmed the model's effectiveness in managing multiple vehicles and transportation requests. Several authors explored traditional techniques for vehicle routing problems.

A heuristic in [15] was based on Tabu search addressed the Hybrid Vehicle Routing Problem (HVRP) with time windows and penalized delays, optimizing vehicle cost, distance traveled, and delay penalties. Mendez et al. [16] modeled the HVRP as a Mixed-Integer Linear Programming (MILP) problem with time windows and multiple visits, using Branch and Cut algorithms for optimization. Another approach by [17] used Iterated Local Search (ILS) with a variable neighborhood descent for different HVRP variants. A study in [18] introduced an HVRP model considering allowable overloads with penalties, assessed using Solomon's benchmark datasets. Another work in [19] used Solomon's benchmark datasets to assess the sequential insertion-based heuristic. Mungwattana et al. [20] focused on HVRP with multi-product deliveries and time windows, applying Branch and Bound and GA techniques in a real-world case study in Thailand. A green integrated routing problem (greenIRP) model in [21] included load-dependent fuel consumption and emission costs, using numerical tests to validate their model's effectiveness.

Cai et al. [22] focused on the multi-objective VRP with simultaneous pick-up and delivery and time windows (Mo-EVRPSDPTW). A multi-objective genetic algorithm (NSGA-II) is proposed to reduce logistics costs and enhance customer satisfaction, tackling issues like traffic congestion and dynamic power consumption. The improved algorithm showed stability and effectiveness in experiments, with suggestions for future research on queuing time and nonlinear charging. For EV routing, [23] examined the EVRPTW, modeling energy consumption with the EVRPTW-ECR MILP model to estimate EV range dynamically. The CPLEX solver handled instances with up to 25 customers optimally, while a heuristic approach tackled larger instances. This study emphasized the importance of considering EV characteristics and energy consumption for greener transportation. Another study [24] addressed EVRPTW with weight-related energy consumption and uncertain customer demand using an adaptive large neighborhood search heuristic and a robust optimization model. Experiments confirmed the method's efficacy in managing uncertainty and energy consumption for efficient EV distribution.

Goeke and Schneider [25] proposed the E-VRPTWMF for mixed fleets of internal combustion and electric vehicles, incorporating factors like speed, gradient, and cargo load into their energy consumption model. An Adaptive Large Neighborhood Search algorithm combined with local search is utilized, analyzing load distribution impacts on solution quality. The algorithm demonstrated strong performance, providing strategies for optimizing routes in mixed-vehicle fleets. In [26], the study focused on extending the range of autonomous urban electric buses using genetic algorithms (GA) for energy optimization. This research was part of the Sohjoa Baltic project, which aimed to improve public transportation around the Baltic Sea with autonomous electric minibusses. The authors enhanced the Speed Profile Optimization (SPO) framework to include these buses, taking advantage of regenerative braking and frequent stops to optimize speed profiles.

The Two-stage Electric Vehicle Routing Problem (2sEVRP) was introduced in [27] to better estimate energy consumption and schedule charging stops for electric commercial vehicle fleets. This method considered topography and speed profiles to accurately estimate energy costs. A two-step procedure was used to find optimal routes, addressing time-window and battery limitations. Comparative analysis showed that this approach improved time and energy estimations. Tests on Gothenburg's road network confirmed the method's effectiveness, indicating that energy demands were manageable with necessary charging stops included.

We have summarized the comparative discussion in Table 1 by considering the problem addressed, objectives, optimization approach, and contributions of each study.

Table 1 Comparative Analysis of Electric Vehicle Routing Optimization Papers.

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[5]	Personal Electric VRP (pEVRP)	Minimize travel time and recharging costs	ε-constraint method, GA, PSO	real-world elements like fluctuating prices and traffic jams being incorporated into the optimization model.
[6]	IRP	Optimize fuel consumption and pollutant emissions	Multi-objective quantum algorithm	taking into account the make-up of the fleet and contrasting performance with alternative approaches.
[7]	Navigation system optimization for EVs	Optimize routing and charging policies	Improved ChronoSPT (ICS) algorithm, Simplify-Charge-Control (SCC) algorithm	Real-time pricing policy integration and a decrease in computing complexity
[8]	VRP with Time Windows (VRPTW)	Multi-objective optimization using GA	GA with Pareto ranking	Considering the overall distance and the number of cars as distinct dimensions in the search space, and approaching VRPTW as a multi-objective issue.

TABLE 1 – Continued

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[9]	Electric VRP with Time Windows (EVRPTW)	Minimize total electricity consumption	Mixed-integer linear programming model, Hybrid GA	Battery charge state dynamics and terrain gradients considered in the model.
[10]	Electric VRP with Time Windows (E-VRPTW)	Optimize routes with fuzzy logic and time windows	GA, Tabu Search (TS), Fuzzy Logic	Fitness values enhanced with the introduction of tolerance in time windows with the use of fuzzy logic.
[11]	Capacitated VRP with Time Windows (CVRPTW)	Minimize total distance traveled	GA, Tabu Search Algorithm (TS), Hybrid approach	A comparison of the algorithms and a decrease in the overall distance traveled with the hybrid method.
[12]	Optimization of shuttle bus services	Minimize distances and improve route planning	GA	Application of GA to the Capacitated VRP (CVRP) in the context of shuttle bus services.
[13]	Distribution of perishable goods with quality constraints	Optimize distribution process considering time windows and deterioration rates	Mathematical programming model, Genetic Algorithm-based heuristic	Distribution of perishable items optimized with quality restrictions in mind.
[14]	General VRP (GVRP)	Optimize vehicle routes considering various complexities	Iterative improvement approach	Managing several vehicles, varying trip durations, order-to-vehicle interoperability.

TABLE 1 – Continued

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[15]	Hybrid VRP (HVRP) and time window constraints, penalized delays	Minimize vehicle cost, total distance traveled, and penalty cost of delays	Tabu search-based heuristic algorithm	Introduction of the HVRP's heuristic algorithm based on Tabu search.
[16]	HVRP with time window constraints and multiple vehicle visits	Optimal vehicle routes using MILP model	Branch and Cut algorithm-based commercial software package	Creation of the HVRP model as a MILP and optimization using commercial tools.
[17]	Iterated Local Search (ILS) for various HVRP variants	Optimal solutions for different HVRP variants	Iterated Local Search (ILS) metaheuristic	The ILS metaheuristic is introduced for HVRP optimization.
[18]	Variant of HVRP with permissible overloads	Sequential insertion based heuristic	Introduction of a sequential insertion-based heuristic for the variant of HVRP.	
[20]	HVRP with time windows, multi-product deliveries, and limited availability	GA, Branch and Bound approaches	Practical case study of a third-party logistics firm in Thailand	Utilizing Branch and Bound and GA methods in a real-world case study.

TABLE 1 – Continued

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[21]	Green IRP with heterogeneous fleet	Minimize total cost considering load-dependent fuel consumption and emission costs	Mixed-integer linear programming model	Green factors being taken into account in the IRP and performance evaluation.
[22]	Multi-objective VRP with simultaneous pick-up and delivery and time window constraints (MoEVRPSDPTW)	Minimize total logistics cost and maximize average customer satisfaction	Multi-objective GA (NSGA-II)	Inclusion of several goals and enhanced tactics in NSGA-II for the Mo-EVRPSDPTW.
[23]	EVRPTW considering energy consumption and time windows	Minimize total electricity consumption	Mixed-integer linear programming model	Two linearization techniques to tackle nonlinear relationships, dynamic calculation of EV maximum range based on speed and load.
[24]	EVRPTW considering uncertain demand and energy consumption	Robust optimization model, Adaptive Large Neighborhood Search heuristic	Robust optimization model based on un-certain set, efficient solution approach	Taking into account the erratic nature of demand and energy usage in EVRPTW.
[25]	Electric VRP with Time Windows and Mixed Fleet (E-VRPTWMF)	Optimize routing for mixed fleet of electric and conventional vehicles	Adaptive Large Neighborhood Search algorithm	Effective solution strategy and incorporation of a realistic energy consumption model.

TABLE 1 – Continued

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[27]	Two-stage Electric VRP (2sEVRP)	Precise prediction of energy consumption and planning of charging stops	Two-stage approach, improved energy consumption estimation	Incorporation of certain elements for precise energy consumption estimation, such as terrain and speed profiles.

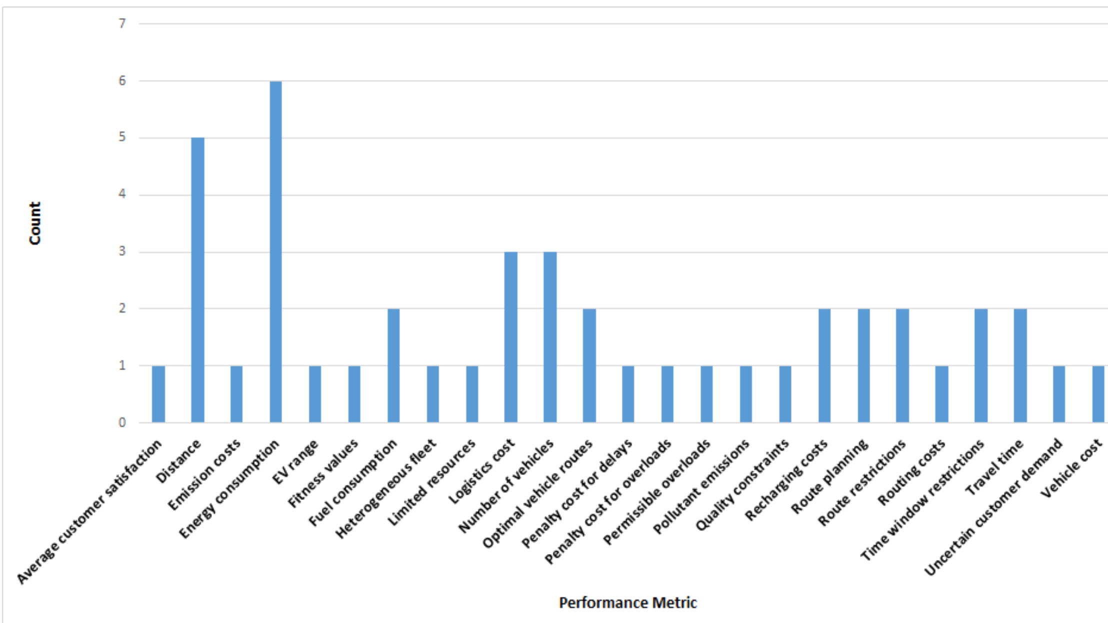


Figure 4 A graphical representation of metrics used in various GA schemes.

Various performance evaluation metrics have been used to assess the effectiveness of GA-based approaches for multi-objective message routing in EVs. These metrics offer insights into the efficacy and efficiency of the routing solutions achieved. As shown in Figure 4, most researchers focus on two main variables: distance traveled and energy consumption. Emphasizing these metrics highlights the importance of optimizing energy efficiency and minimizing total distance in EV routing. Prioritizing these goals helps in developing more sustainable EV transportation options. It's important to note that different studies may include additional performance metrics to address specific needs and practical constraints in their EV routing scenarios. These case studies illustrate the effectiveness of GAs in optimizing EV routing. GA-based techniques yield promising results in enhancing route efficiency and sustainability by considering multiple objectives, such as energy consumption, travel time, and customer satisfaction. The integration of dynamic constraints and real-time data further improves the performance of the EV routing optimization process.

The results of GA research for electric car routing-based applications are compiled in Table 2. A comprehensive assessment of several publications addressing GA-based optimization methods for electric VRPs is shown in Table 2. Numerous application domains are covered by the studies, including distribution of perishable goods [13], inventory routing [6], personal EV routing [5], and EV navigation. To solve these problems, a variety of optimization techniques are used, such as GAs, mathematical programming models, and metaheuristic algorithms. Overall, the studies show how well the suggested optimization strategies work to improve a range of performance metrics, including total electricity consumption, fuel consumption, emissions of pollutants, trip time, costs associated with recharging, logistics costs, and customer satisfaction [14], [16]. The findings show that the optimization techniques aid in decision-making in VRPs and offer insightful information. Several studies emphasize how crucial it is to include real-world variables in the optimization models, such as terrain grades, detour distances, traffic delays, and variable pricing [5], [11]. These elements have a big effect on how well EVs operate and how much energy the fleet uses. The studies show better optimization results and better alignment with real-world conditions by taking these factors into account. In contrast, the studies make use of various optimization strategies and tactics, each customized to the particular issue at hand. GAs and metaheuristic algorithms such as adaptive large neighborhood search, tabu search, and particle swarm optimization are commonly used to effectively search the solution space and identify optimal or nearly optimal solutions. In terms of computational efficiency and solution quality, these strategies frequently beat more established approaches such as exact algorithms [21] [28], [29] .

Additionally, some studies deal with multi-objective VRPs, where it's necessary to balance competing goals like reducing the number of vehicles and the total distance traveled [24], [27], [30]. Adopting multi-objective optimization frameworks, like non-dominated sorting and Pareto ranking, enables the production of a set of solutions that represent various trade-offs between objectives. This flexibility makes the optimization process more realistic and efficient by allowing decision-makers to choose solutions based on particular priorities and constraints. It is noteworthy that a number of studies [22], [25], [30], [31] suggest future research directions to improve optimization models and techniques even more. Additional ideas and policies should be included, along with nonlinear charging and queuing times, integration of clustering algorithms, handling of pickup operations, and investigation of dynamic elements like demand variability and traffic congestion. These upcoming paths seek to increase the optimization techniques' robustness and suitability for a wider range of real-world situations. The studies provide insightful information, suggest novel strategies, and open new research directions for streamlining vehicle routing procedures, cutting expenses, boosting productivity, and advancing environmentally friendly transportation.

Table 2: Comparative Analysis of GA Studies for Optimizing Electric Vehicle Routing-based Applications.

Study	Application Domain	Optimization Technique	Performance Metrics	Results
[5]	Personal Electric VRP (pEVRP)	Mixed-Integer Non-Linear Programming (MINLP), ε -constraint method, GA, PSO	Travel time, Recharging costs	The suggested techniques efficiently reduce trip time and the cost of recharging, offering insightful information for personal electric car routing decision-making.
[6]	IRP	Multi-objective quantum algorithm	Fuel consumption, Pollutant emissions	The suggested algorithm works better than alternative techniques, exhibiting enhanced efficacy in maximizing fuel usage and emissions of pollutants.
[7]	EV navigation system	Improved ChronoSPT (ICS) algorithm, Simplify-Charge-Control(SCC) algorithm	Routing and charging policies	The SCC algorithm considerably reduces computation complexity while keeping an acceptable degree of departure from the optimal cost. The ICS and SCC algorithms are both effective.
[8]	VRP with Time Windows (VRPTW)	GA with Pareto ranking	Number of vehicles, Total distance traveled	The suggested method offers a computationally advantageous solution that is competitive with current techniques while avoiding search bias.
[9]	Electric VRP with Time Windows (EVRPTW)	Hybrid GA	Total electricity consumption	The suggested method optimizes EV routing and energy usage by outperforming the simulated annealing (SA) algorithm and GA in discovering better solutions in less computing time.

TABLE 2 – Continued

Study	Application Domain	Optimization Technique	Performance Metrics	Results
[10]	Electric VRP with Time Windows (EVRPTW)	GA, Tabu Search (TS), Fuzzy Logic	Fitness values, Number of vehicles, Distance	Fuzzy logic in conjunction with the GA-TS approach optimizes the E-VRPTW problem by achieving shorter mileage, fewer cars, and greater fitness values.
[11]	Capacitated VRP with Time Windows (CVRPTW)	GA, Tabu Search Algorithm (TS), Hybrid approach	Total distance traveled, Number of vehicles	In comparison to other algorithms, the hybrid GA-TS technique produces the best result, lowering the total distance by 15.99%.
[12]	Capacitated VRP (CVRP)	GA	Distances, Route planning	GA lowers expenses while increasing the effectiveness of shuttle bus services.
[13]	Distribution of perishable goods	GA-based heuristic	Logistics cost, Quality constraints	When taking into account time frames and deterioration rates, heuristics offer computationally efficient solutions with the least amount of solution quality loss.
[14]	General (GVRP) VRP	Iterative improvement approach	Time window restrictions, Heterogeneous fleet, Route restrictions	The suggested method effectively manages several cars and transportation requests in the GVRP.
[15]	Hybrid (HVRP) VRP	Tabu search-based heuristic	Vehicle cost, Total distance traveled, Penalty cost for delays	Heuristic algorithms with time window limits and penalty delays successfully handle HVRP.
[16]	Hybrid (HVRP) VRP	MILP	Optimal vehicle routes	In HVRP, the Branch and Cut algorithm-based method yields the best vehicle routes.

TABLE 2 – Continued

Study	Application Domain	Optimization Technique	Performance Metrics	Results
[17]	Hybrid (HVRP) VRP	Iterated Local Search (ILS) metaheuristic	Optimal solutions for HVRP variants	For HVRP variations with varying customer counts and fleet sizes, the ILS metaheuristic offers the best possible options.
[18]	Hybrid (HVRP) VRP	Sequential insertion based heuristic	Permissible overloads, Penalty cost for overloads	Heuristic algorithms that take into account allowable overloads and the associated penalty costs efficiently handle HVRP.
[20]	Hybrid (HVRP) VRP	GA, Branch and Bound	Time windows, Multiproduct deliveries, Limited resources	When faced with time constraints, multiple product delivery, and resource constraints, HVRP can be optimally solved using GA and Branch and Bound techniques.
[21]	Green IRP	Mixed-integer linear programming model	Total cost, Fuel consumption, Emission costs	By accounting for load-dependent fuel consumption and pollution costs, the mixed-integer linear programming model lowers overall costs.
[22]	Multi-objective VRP with pick-up and delivery and time window constraints (MoEVRPSDPTW)	Multi-objective GA (NSGA-II)	Total logistics cost, Average customer satisfaction	An enhanced NSGA-II algorithm optimizes the distribution process by lowering logistics expenses while preserving high customer satisfaction levels.
[23]	Electric VRP with Time Windows (EVRPTW)	MILP	Energy consumption rate, EV range	The MILP model highlights the EV features in route planning by efficiently solving EVRPTW examples with up to 25 consumers. A heuristic technique is employed for bigger instances.

TABLE 2 – Continued

Study	Application Domain	Optimization Technique	Performance Metrics	Results
[24]	Electric VRP with Time Windows (EVRPTW)	Robust optimization model, Adaptive large neighborhood search Heuristic	Uncertain customer demand, Energy consumption	Robust optimization approach supports practical and effective distribution activities by effectively addressing EVRPTW with variable customer demand and weight-related energy usage.
[25]	Electric VRP with Time Windows and Mixed Fleet (E-RPTWMF)	Adaptive Large Neighborhood Search algorithm	Energy consumption, Routing costs	Taking into account a realistic energy consumption model, the algorithm optimizes routing in fleets consisting of both conventional internal combustion vehicles (ICCVs) and electric commercial vehicles (ECVs).
[27]	Two-stage Electric VRP (2sEVRP)	Two-stage process, Detailed energy cost estimation	Time, Energy estimations	For the purpose of optimizing electric vehicle routes, a two-stage approach offers precise time and energy estimates.

2.2 Literature Review of State-of-the-art in Routing Optimization for Flying Vehicle

Several studies have proposed novel solutions into the realm of flying vehicle routing optimization using GAs. These investigations address unique challenges associated with UAV or drone routing, considering factors like airspace regulations, battery limitations, and diverse mission objectives. Figure 5 illustrates the distribution of these studies over the years considered in this analysis. A notable study by [32] presents a GA-based Routing (GAR) protocol tailored for Flying Ad-Hoc Networks (FANETs), tackling issues related to high node mobility. By incorporating variables such as node energy, link stability, and bandwidth, the protocol enhances routing efficiency. The GA's selection, crossover, and variation operators are optimized to maximize route planning effectiveness. Experimental findings indicate that GAR significantly improves network throughput, reduces latency, and enhances network stability in FANETs. However, the

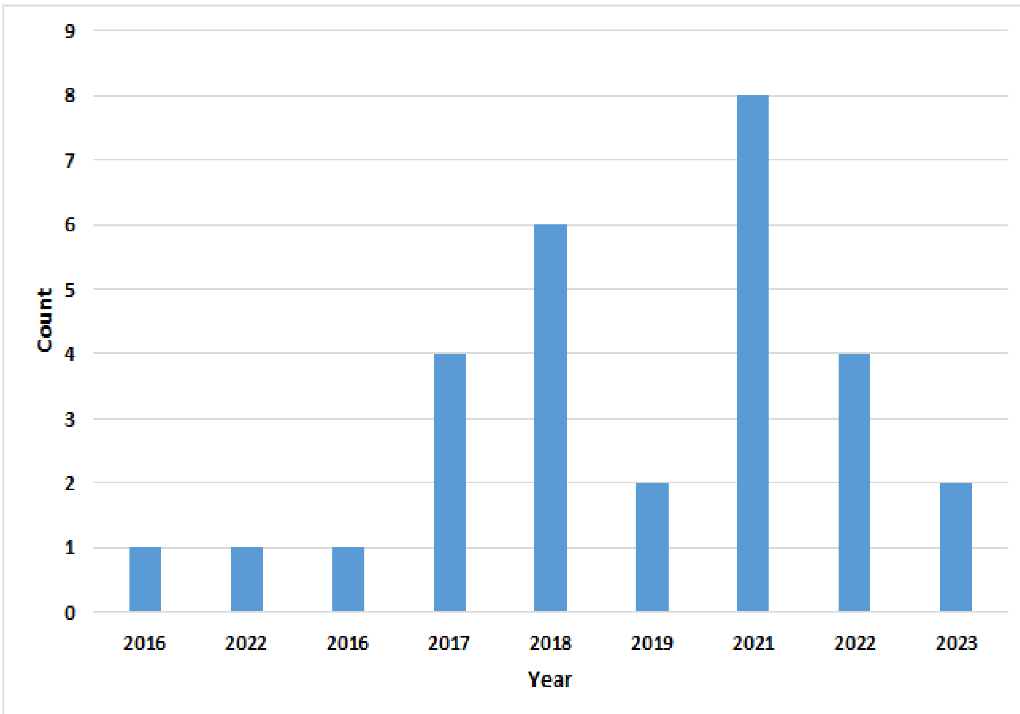


Figure 5 A bar chart showing year-wise distribution of GA-based FV Routing Optimization Studies.

study acknowledges the need for further research to fully grasp energy consumption dynamics in practical settings.

In contrast, [33] introduced two strategies for UAV path planning in real 3D environments. One method utilized a GA to generate multiple trajectories based on a Pareto front, while the other relied on the A-Star algorithm, providing real-time path planning capabilities. Both approaches computed 2D trajectories while considering the

UAV's dynamic characteristics, with a recursive algorithm computing the missing dimension. With an average computation time of 836 ms, the A-Star method demonstrated its real-time capability, while the GA method offered performance and flexibility by identifying tactical situational failures and providing various solutions. Experimental results showed that the GA improved the A-Star solution's fitness by an average of 44.5%. The paper concluded by highlighting the potential for integrating these approaches into a fully functional system and suggesting future research directions to enhance estimator quality and explore parallelization strategies.

Dai et al. [34] introduced a coverage and path planning scheme tailored for UAV networks navigating complex terrains. Their solution focused on energy-efficient path planning for multiple UAVs and a waypoint generation algorithm to ensure comprehensive coverage with adequate spatial resolution. Simulation results indicated enhanced coverage and reduced energy consumption compared to conventional methods. Interesting future direction include exploring online coping mechanisms for unforeseen events and efficient communication channels for delivering sensed images to users. Additionally, the solution is expected to incorporate relay UAV nodes and consider deadline constraints and image quality.

An exploration conducted in [35] on how wind conditions could be factored into task allocation and path planning for fixed-wing UAVs. Their aim was to optimize flight paths and minimize task completion time in the presence of constant wind. A Variable-Speed Dubins Path VRP (VS-DP-VRP) model that considers UAVs' minimum turning radius and adjusts ground speed based on airspeed and wind speed is proposed.

Employing a GA with tailored crossover and mutation operators are embedded in the model. Authors demonstrated the method's practicality and effectiveness, while also assessing its sensitivity to different parameters. The study concluded that the proposed model and algorithm provide a viable solution for managing UAV task distribution and path planning under steady wind conditions. In a different but interesting approach, [36] proposed a modular method for using flight paths for small UAVs, considering priority assignment, obstacle avoidance, and computational constraints. Their algorithms included a quadratic program for generating minimum-snap polynomial trajectories to avoid static obstacles, a projective algorithm for finding the shortest paths around obstacles, and a GA for optimizing the travelling salesman problem concerning priorities and obstacle avoidance. These methods have been successfully applied in real-time situations, enabling efficient motion planning in both 2D and 3D environments. In their study [37], the focus is on UAV path planning, where two parallel optimization algorithms are introduced: the particle-swarm optimization-based ant colony optimization algorithm (PSO-ACO) and the improved GA (IGA). Their aim is to find optimal path planning solutions for UAVs by solving the Traveling Salesman Problem (TSP), with mission targets represented as cities and UAVs as traveling salesmen. Both algorithms, PSO-ACO and IGA, efficiently solve the TSP model, resulting in practical and effective UAV path planning schemes. Comparative experiments demonstrate that these algorithms outperform alternative methods, providing more sensible and valuable solutions for UAV path planning. This research contributes to advancing UAV path planning techniques and underscores its critical role in ensuring successful UAV missions.

A novel work in [38] introduced a coverage path-planning algorithm tailored for quadrotors navigating a 2D workspace while avoiding obstacles. The algorithm comprises two key components: first, the RRT*FN algorithm identifies optimal paths between points and their neighbors, and then GAs connects these paths to form the shortest overall route. This approach scales well and addresses energy consumption concerns through a savings technique. Points of Interests (POIs) are defined based on a discretized map, facilitating obstacle avoidance and energy efficiency. Numerical simulations indicate the algorithm's potential effectiveness in diverse coverage scenarios. Ferrandez et al. in [39] explored the potential of unmanned aerial delivery vehicles in delivery networks.

Authors compare the efficiency of truck-drone networks versus standalone truck or drone systems in terms of delivery time and energy consumption. Moreover, authors focused on developing mathematical formulas to estimate the optimal number and locations of launch sites. An optimization algorithm using GA and K-means clustering is proposed for best launch locations determination, minimizing costs with a parabolic convex function. Results indicated that utilizing multiple drones per truck saves both time and energy, outperforming standalone systems. In another study, [6], the focus was on addressing fuel consumption and environmental impact in the transportation sector. A bi-objective model for Inventory Routing Problems (IRP) is introduced, separating goals related to fuel consumption and pollutant emissions. To enhance real-world applicability, a diverse fleet composition is considered. The model emphasizes optimizing fuel consumption to improve economic efficiency and mitigate environmental concerns. Compared to existing approaches, their model offers a promising solution for IRP, contributing to advancements in logistics and transportation by tackling fuel consumption and environmental impact issues. In [40], the tri-objective is tackled, with two-echelon capacitated vehicle routing problem (2E-CVRP) for perishable product distribution. The aim is to reduce overall travel costs, client wait times, and carbon dioxide emissions. The formulation of the model is a mixed integer linear programming problem after using linearization techniques. Using a Non-Dominated Sorting GA (NSGA-II), to solve the problem efficiently. The study compares the NSGA-II algorithm with the Lp-metric method for small-sized problems and the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm for medium- and large-sized problems. Results demonstrate the NSGA-II algorithm's speed and accuracy in finding near-optimal solutions within a reasonable computational time. This research provides valuable insights into optimizing vehicle routing for perishable goods, highlighting the importance of considering environmental sustainability to enhance customer satisfaction. Comparing different algorithms sheds light on their effectiveness in solving the 2E-CVRP.

Multiple Depot Vehicle Distribution Routing Problem (MDVRP) is a major focus in [41], concerning perishable goods distribution. Their approach involves using a Fuzzy Logic Controller (FLC) to optimize parameters and a GA to determine the optimal route, aiming to minimize product spoilage risk while finding the shortest route. Combining GA and FLC enhances distribution system efficiency and optimization outcomes, effectively reducing product deterioration risks. Meanwhile, [42] addresses challenges posed by rugged terrain and limited UAV capabilities by proposing a joint UAV-vehicle delivery model for logistics distribution in mountainous cities. Their model aims to shorten delivery routes and boost efficiency. By employing a three-step route distribution method and GA-based end optimization, significant improvements in addressing logistics challenges in such areas. The study also highlights potential advancements in UAV technology and suggests future research directions, including extending the model to multiple vehicles and UAVs, considering factors like signal interference and weather, and exploring its applicability in diverse urban settings. The focus of [43] was on optimizing emergency logistics distribution using a cooperative model involving both vehicles and UAVs. By considering waiting, penalty, and start-up costs, the authors developed a model aimed at reducing overall logistics distribution costs. Comparing this model to vehicle-only and UAV-only approaches in a Xi'an city county-level district revealed substantial cost savings and enhanced customer satisfaction. However, the study didn't explore the impact of traffic congestion restrictions or the sizes of vehicles and UAVs on collaborative delivery in emergency scenarios. Meanwhile, [44] focuses on the economics and logistics of a drone delivery system, with a particular emphasis on how launch and recharge stations should be set up and how drone specifications can be optimized to reduce system costs. The authors assessed the financial viability of such a system using metaheuristic algorithms such as a hybrid GA and a GA. They also proposed future research directions involving capacitated models, fuzzy programming techniques, congestion models, and evaluations of environmental sustainability.

In order to address the scheduling and routing issues in UAV-assisted delivery systems, Sajid et al. in [45] suggested a joint optimization approach. They offer mixed-integer linear programming models that take into consideration variable payload impacts on transit time as well as accidental operations. To maximize journey time while avoiding local optima, a hybrid genetic and simulated annealing (HGSA) approach is proposed for

UAV routing. Furthermore, UAV-route scheduling algorithms like UAV-Oriented MinMin (UO-MinMin) seek to minimize makespan without compromising quality. To evaluate the hybridization probability of GA and SA in the HGSA method, Monte Carlo simulations were run. The results showed that the HGSA algorithm performed better than GA, PSO-SA, DE-SA, and HHO. Additionally, the UO-MinMin algorithm performed better than baseline algorithms like MCT and OLB, demonstrating its efficacy with varying numbers of UAVs. In [46], the focus was on crafting safe routes for autonomous UAVs in target coverage scenarios. Multiple algorithms, labeled GA 1 through GA 5, were introduced to address challenges like terrain collisions. These algorithms were tested across diverse 3D landscapes, urban and rural alike. Among them, GA 5 stood out, significantly reducing the number of cost function evaluations needed. GA 5 relies on cluster centers derived from collision points, offering more precise waypoints compared to others. While GA 3 and GA 4 also performed well, accuracy in cluster centers proved crucial for their success. However, GA 5's exclusive consideration of collision points leads to more confident outcomes. Overall, GA 5 emerged as a highly effective solution for UAV path planning, particularly in averting terrain collisions.

An improved GA was introduced in [29] for coverage path planning in fixed-wing UAVs, aiming to tackle the energy inefficiency of standard scan-type methods. By integrating random interval inverse mutation operators and heuristic crossover, derived from the good point set algorithm, the algorithm mitigates the risk of local optimization. Simulation results demonstrate superior solution quality compared to traditional GAs, particularly with increasing path numbers. The authors suggest future exploration of region segmentation algorithms for larger areas and expanding coverage path planning into three-dimensional space. Authors in [47] discussed using UAVs for emergency medical aid delivery, aiming to provide a safe and efficient navigation algorithm from hospitals to emergency sites. An algorithm focusing on path planning optimization is proposed to reduce computation time and transportation costs. CVRP outperformed various vehicle routing algorithms like PSO, ACO, GA, especially with increased vehicle capacity, suggesting improved real-time medical assistance delivery. Addressing energy consumption in VRPs, Euchi and Abdel Jawed in [48] proposed utilizing UAVs as battery-powered delivery systems. With the rise of commercial drone delivery services like Amazon and Google, a new VRP variant, VRPD, integrates drones and cars for package delivery. Authors formulated VRPD as a MILP model and proposed a hybrid GA for the solution. Experimental results demonstrated the effectiveness of their algorithm in solving this VRP variant. The observations offered insights into the usage of UAVs for eco-friendly and efficient deliveries, benefiting logistics optimization for businesses. The authors focused on optimizing package delivery using a fleet of drones with varying capabilities, extending the classic VRP to schedule operations in a package depot center [49]. The problem is formulated as minimizing delivery time for a group of packages using a Mixed-Integer Programming (MIP) model. Two GAs, FBGA and RBGA, were developed to tackle computational complexity. RBGA integrates an optimization model based on rescheduling to modify drone operations and reduce completion time. Tests showed these algorithms outperform the MIP technique, especially for larger instances, highlighting their efficiency for real-world drone-assisted package delivery systems. An study in [50] aimed to streamline UAV delivery routes for efficient delivery in urban logistics and e-commerce. Their multi-objective path planning problem sought to maximize customer satisfaction while minimizing overall cost. A new GA based on NSGA-II with constraints is proposed, using specialized variation operators and represented decision vectors as 1-dimensional chromosomes. With less computational complexity, the algorithm efficiently found numerous non-crowding Pareto optimal solutions. A case study on a subset of the Solomon dataset demonstrated the algorithm's ability to quickly find sparse and well-distributed non-dominant solutions with a small population size.

During the COVID-19 epidemic, Shi et al. [30] addressed the critical requirement for effective medical supplies delivery. The advantages of drone delivery are emphasized, particularly with regard to reducing contact with COVID-19 patients and avoiding traffic. However, the unique needs of delivering medical supplies during public health emergencies are not well met by the drone delivery models now in use. The authors developed a unique bi-objective mixed integer programming model for the multi-trip drone location routing problem in order to address this. Concurrent pick-up and delivery are made possible by this concept, guaranteeing prompt and efficient delivery of medical supplies to the required locations. To solve this model, a modified version of the NSGA-II algorithm is created, and double-layer coding improves its efficiency. The authors showed through rigorous data studies that simultaneous pick-up and delivery performs much better than separate modes, leading to improved safety, faster delivery times, and optimal resource usage. Sensitivity analysis also offered insightful information for managing drone-based medical supply delivery. All things considered, their approach appears to be working well to address the special requirements of providing medical supplies during public health emergencies. In [51], the potential of drone delivery for reducing carbon emissions and optimizing delivery routes was explored through the VRP with Drones (VRPD) model. This model integrates drones with trucks to enhance delivery efficiency, with each truck equipped with a drone. Using NSGA-II to solve the VRPD, the study demonstrated high-quality solutions, as indicated by favorable metrics. Significant tests confirmed the advantages of drone use in reducing delivery time and carbon emissions. Meanwhile, [52] focused on scheduling drone-assisted package delivery, proposing a GA as a solution. The GA outperformed other methods in terms of speed and solution quality, thanks to optimized operations. However, the study's scope was limited to scenarios involving single-package transport, leaving out the complexities of multi-package deliveries.

Authors in [53] highlighted the economic and environmental impacts of using drones for last-mile delivery. Analysis is presented on how drones affect costs and CO2 emissions. Proposing a mixed-integer green routing model, aim was to optimize sustainability by considering factors like carbon emissions and energy usage. Using a GA, complex model tackled and validated through experiments. The results indicated that employing drones for package delivery and routing could lead to reduced energy consumption and carbon emissions, showcasing the economic and environmental advantages. Another study in [54], drones were used to address the pickup and delivery optimization challenge, incorporating time windows and intermittent connectivity. By employing the NSGA-II algorithm and addressing UAV-specific constraints like refueling, success is achieved. Solution generation, crossover, and mutation processes were enhanced by introducing a novel representation of individuals alongside related heuristics and algorithms. Experiment outcomes demonstrated the efficacy of the NSGA-

II method in solving the PDPTW-UAV problem, with or without considering refueling constraints. The highlighted future work included refining refueling management and improving the formula to calculate refueling time based on UAV energy requirements to further enhance the efficiency.

A model was introduced in [55] to assess drone delivery's energy consumption. A cost function was introduced, considering drone reuse, aiming for practical solutions. MILP and Simulated Annealing (SA) optimized overall cost and delivery time. Results showed over 10% improvements by optimizing battery weight and encouraging drone reuse, compared to scenarios with uniform battery weights. In [28], a nonlinear MIP formulation was proposed to optimize homogeneous drone operations, considering disposal effects and battery wear. A custom branch-and-price algorithm was presented, successfully resolving cases with up to 100 clients within the designated time frame. This approach offers practical applicability for optimizing drone-based logistics. Interestingly, a three-stage stochastic IP model in [56] was proposed to minimize delivery costs while considering distance constraints and uncertainties in takeoff and breakdown conditions. Authors employed an L-shape decomposition method to efficiently compute solutions, addressing the high complexity of this optimization challenge. Table 3 summarizes the key variables and contributions of each publication, enabling a comparative comparison of the problem addressed, objectives, optimization approach, and major contributions of each study.

Table 3: Comparative Analysis of Flying Vehicle Routing Optimization Papers.

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[32]	GA-based Routing (GAR) protocol for FANETs	Improve routing in FANETs considering link stability, link bandwidth, and node energy	GA	Notable enhancements in FANETs' network throughput, latency reduction, and stability
[33]	Path planning of UAVs in a 3D environment	Real-time path planning, generating multiple trajectories based on a Pareto front	GA, A-Star algorithm	Better path planning options, increased A-Star solution fitness, adaptability, and real-time capabilities
[34]	Quality-aware coverage and path planning for UAV networks in complex environments	Achieve full coverage with satisfactory resolution, energy-efficient path planning	Waypoint generation algorithm	Increased coverage, reduced energy use, and recommended next study paths
[35]	Optimization of task allocation and path planning for fixed-wing UAVs in the presence of steady wind	Minimize time required for UAVs to complete tasks in steady wind	GA	VS-DP-VRP, an efficient model for variable-speed Dubins path vehicle routing problem, is used to allocate tasks to UAVs and plan their paths in a steady breeze.
[36]	Motion planning for a miniature UAV considering computational constraints, obstacle avoidance, and priority assignment		GA	Modular approach for generating state trajectories, efficient motion planning in 2D and 3D environments.

TABLE 3 – Continued

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[37]	UAV path planning using improved GA and particle-swarm optimization-based ant colony optimization algorithm	Solve the TSP for UAVs, find optimal path-planning solutions	Improved Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization	More sensible and sensible options than the contrast technique are practical and reasonable UAV route planning schemes.
[38]	Coverage path-planning algorithm for quadrotors in a 2D workspace with obstacle avoidance	Find optimal paths between points and their neighbors, connect points to form shortest path	RRT*FN algorithm, GAs	An efficient way to handle scenarios including the avoidance of obstacles and energy conservation
[39]	Performance comparison of truck drone network, standalone truck, and drone delivery systems	Minimize delivery time and energy consumption	GA, K-means clustering	Standalone systems and closed-form mathematical solutions for the ideal number of launch sites.
[6]	Bi-objective model for the IRP	Optimize fuel consumption and pollutant emissions	GA	A novel method for addressing IRP that takes fuel use and environmental effects into account
[40]	Capacitated VRP (CVRP) for distributing perishable products	Minimize total travel cost, waiting times, and carbon dioxide emissions	NSGA-II	Effective and efficient 2E-CVRP solutions that take customer happiness and environmental sustainability into account.

TABLE 3 – Continued

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[41]	Multiple Depot Vehicle Distribution Routing Problem (MDVRP) for perishable product distribution	Minimize risk of product spoilage by determining shortest route	GA, FLC	Best possible route planning and a lower chance of product degradation
[42]	UAV-vehicle joint delivery model for logistics distribution in mountainous cities	Improve delivery efficiency, reduce total delivery route length	GA	An efficient method for distributing supplies in mountain cities, with recommendations
[43]	Optimization of emergency logistics distribution using collaborative delivery model with vehicles and UAVs	Minimize overall logistics distribution cost, improve distribution efficiency	GA	Compared to vehicle- and UAV-alone models, the total cost was lower, and efficiency and customer satisfaction increased.
[44]	Optimization of drone delivery system considering drone specifications and configuration of launch and recharge stations	Minimize total costs of the system	GA	An understanding of the resources, investment viability, and logistics needed to set up an aerial delivery system.
[45]	Joint optimization framework for UAV-routing and UAV-route scheduling problems in UAV-assisted delivery systems	Minimize travel time and makespan	Hybrid genetic and simulated annealing algorithm	UAV route scheduling and optimization outperformed previous techniques.

TABLE 3 – Continued

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[46]	Safe and efficient path planning for autonomous UAVs in target coverage scenarios	Minimize costs, consider battery wear and disposal effects	Branch-and-price algorithm	Optimized battery weight, practical applicability, and homogenous drone operations.
[52]	Optimization of scheduling for parcel delivery using drones	Minimize delivery route makespan	GA	More effectiveness, speed, and caliber of solution in comparison to alternative algorithms.
[53]	Environmental and cost-saving implications of using UAVs for last-mile parcel deliveries	Minimize energy consumption and carbon emissions	GA	Lower energy use and carbon emissions, as well as economical and ecologically responsible last-mile logistics.
[54]	Optimization of pickup and delivery with UAVs in intermittent connective-ity network	Solve pickup and delivery problems with a time window, intermittent connectivity network, and UAV- constraints	NSGA-II	Superior resolutions for the PDPThe TW-UAV issue: effectively managing restrictions unique to UAVs.
[55]	Model for energy consumption in drone delivery considering suboptimal solutions	Minimize overall cost and delivery time	SA heuristic	Enhanced efficiency in comparison to the solver for integer programming, and the detection of less-than-ideal answers.

TABLE 3 – Continued

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[28]	Optimization of homogeneous drone operations considering battery wear and disposal effects.	Minimize costs	Tailored branch and price algorithm	Reliability in practice and computation of a successful solution.
[56]	Stochastic IP model for last-mile delivery considering uncertainty and traveling distance limitations.	Minimize total delivery costs	L-shape decompositio n method	Effective computing of solutions, taking uncertainty and constraints into account.
[29]	Coverage path planning for fixed-wing UAVs using improved GA	Optimize coverage path planning for fixed-wing UAVs using an improved GA	Improved GA for coverage path planning	Increased number of paths and improved solution quality for coverage path planning.
[47]	Algorithm for efficient UAV navigation in medical emergency delivery	Develop an algorithm for efficient and safe UAV navigation from hospital to medical emergency location.	Path planning using Capacitated VRP (CVRP) algorithm	increased effectiveness and security in the delivery of medical emergencies.
[48]	Optimization of VRP using UAVs	Optimize VRP (VRP) using UAVs for energy-efficient and environmentally friendly deliveries.	MILP model and hybrid GA	Effective VRP solution utilizing UAVs that promote environmental sustainability and increased energy efficiency.

TABLE 3 – Continued

Study	Problem Addressed	Objective(s)	Optimization Approach	Key Contributions
[49]	Optimization of package delivery using fleet of drones	Minimize delivery time for packages using a fleet of drones with different capabilities	MIP model, FBGA, and RBGA genetic algorithms	Package delivery optimization that is more effective and uses better solutions than the MIP approach
[50]	Optimization of UAV delivery paths for e-commerce and urban logistics	Minimize total cost and maximize customer satisfaction in UAV delivery paths for e-commerce and urban logistics	NSGA-II	Effective identification of Pareto optimum solutions that don't overcrowd and use less computing power
[30]	Optimization of medical supply delivery using drones during COVID-19	Optimize delivery of medical supplies using drones during public health emergencies	Bi-objective mixed integer programming model and modified NSGA-II algorithm	Delivery of medical supplies in a timely and effective manner during public health emergencies
[51]	Optimization of delivery routes using trucks and drones	Minimize delivery route makespan and carbon emissions by combining trucks and drones in a delivery system	VRP with Drones (VRPD) model and GA	drone integration results in delivery systems with shorter makespan and lower carbon emissions.

Table 4: Comparative Analysis of GA Studies for Optimizing Flying Vehicle Routing-based Applications.

Study	Application Domain	Optimization Technique	Performance Metrics	Results
[32]	FANETs	GA	Throughput, Delay, Network Stability	increased network stability, decreased latency, and increased throughput

TABLE 4 – Continued

Study	Application Domain	Optimization Technique	Performance Metrics	Results
[33]	Path Planning	GA, A-Star	Fitness Improvement	GA increases the 44.5% fitness of the A-Star solution.
[34]	UAV Networks	GA	Coverage, Energy Consumption	Improved coverage, reduced energy consumption
[35]	UAV Task Allocation	GA	Task Allocation, Path Planning	Effective task allocation and path planning in steady wind conditions
[36]	UAV Motion Planning	GA, Projective algorithms, Quadratic programs	Efficient Motion Planning	Efficient motion planning in 2D and 3D environments
[37]	UAV Path Planning	GA, PSO	TSP Optimization, Path Planning	More rational and effective solutions for UAV path planning.
[38]	Quadrotor Path Planning	GA, RRT*FN	Coverage, Obstacle Avoidance, Energy Efficiency	Effective path planning with obstacle avoidance for quadrotors.
[39]	Delivery Networks	Clustering, GA	Delivery Time, Energy Consumption	When it comes to delivery time and energy consumption, tandem truck-drone delivery performs better than independent solutions.
[6]	Inventory Routing	GA	Fuel Consumption, Pollutant Emissions	Bi-objective model to reduce environmental problems and maximize fuel consumption.

TABLE 4 – Continued

Study	Application Domain	Optimization Technique	Performance Metrics	Results
[40]	Capacitated VRP	NSGA-II	Travel Cost, Waiting Time, CO2 Emissions	NSGA-II algorithm provides near-optimal solutions for the 2E-CVRP.
[41]	MDVRP	GA, FLC	Routing Efficiency	When GA and FLC are used together, the distribution system's efficiency increases.
[42]	Logistics Distribution	GA	Delivery Efficiency, Route Length	The joint delivery strategy shortens routes and increases delivery efficiency.
[43]	Emergency Logistics	GA	Distribution Cost, Customer Satisfaction	GA minimizes overall logistics distribution cost
[44]	Drone Delivery System	GA	Total Costs	The hierarchical facility location model minimizes the total costs of the system.
[45]	UAV Routing	MILP, GA, SA	Travel Time Optimization, UAV-Route Scheduling	Hybrid genetic and simulated annealing algorithms provide effective solutions for UAV-assisted delivery systems.
[46]	UAV Path Planning	GA	Safe Path Construction	Algorithms offer autonomous UAVs with safe and effective path planning, overcoming obstacles including collisions with terrain surfaces.
[29]	Fixed-wing UAVs	GA	Energy Efficiency, Solution Quality	Enhanced energy economy in comparison to traditional scan-type path planning techniques.

TABLE 4 – Continued

Study	Application Domain	Optimization Technique	Performance Metrics	Results
[47]	Emergency Aid Delivery	Capacitated (CVRP)	VRP UAV Navigation Efficiency	Effective and secure UAV guidance from a hospital to the site of an urgent medical situation.
[48]	VRPD	GA	Energy Efficiency, Environmentally Friendly Deliveries	Tailored GA for optimizing UAV deliveries with battery-powered drones.
[49]	Drone-assisted Delivery	GA	Makespan, Carbon Emissions	GAs outperform MILP approach, reducing both makespan and carbon emissions.
[50]	E-commerce, Logistics	NSGA-II	Multi-objective Path Planning	In a short amount of time, a genetic algorithm produces well-distributed, sparse non-dominant solutions.
[30]	Medical Supply Delivery	Modified NSGA-II, Mixed-integer programming	Delivery Time, Safety, Resource Savings	The simultaneous pick-up and delivery option reduces delivery times, boosts security, and uses fewer resources.
[51]	Delivery Optimization	GA	Carbon Emissions, Makespan	GA uses drones to expedite deliveries while cutting down on carbon emissions.
[52]	Parcel Delivery	GA	Speed, Solution Quality	GA outperforms other algorithms in terms of speed and solution quality

TABLE 4 – Continued

Study	Application Domain	Optimization Technique	Performance Metrics	Results
[53]	Last-Mile Delivery	GA	Energy Consumption, Carbon Emissions	Mixed-integer green routing model maximizes sustainability benefits, reducing energy consumption and carbon emissions
[54]	Pickup and Delivery	GA	Optimization Quality	Tailored GA generates high-quality solutions for pickup and delivery optimization with UAVs
[55]	Drone Energy Consumption	SA	Energy Consumption Optimization	Cost function considers drone reuse, identifies sub-optimal solutions in real-life scenarios
[28]	Drone Operations	Branch-and-price algorithm	Battery Wear, Disposal Effects	When optimizing homogeneous drone operations, the branch-and-price algorithm takes battery wear and disposal impacts into account.
[56]	Delivery Optimization	L-shape decomposition method	Uncertainty Handling, Delivery Conditions	The delivery conditions' constraints and uncertainties are taken into account by the three-stage stochastic IP model.

CHAPTER THREE

ROLE OF GENETICS ALGORITHM IN MULTI-OBJECTIVE ROUTING IN FLYING AD-HOC NETWORKS

The emergence of EnFVs has brought about a dramatic shift in the transportation business, offering more mobility, reduced congestion, and enhanced sustainability [46], [51], [52]. These cutting-edge forms of transportation, such as UAVs and EVs, have the power to completely transform urban logistics and mobility. Nevertheless, these dynamic systems present distinct difficulties for efficient message routing and transmission that need specialized fixes [53]. Genetic algorithms offer an effective avenue for handling multi-objective optimization problems where the goal is to find the best and optimal solution. GA is a heuristic-based algorithm that considers all possible solutions and evaluates them on fitness function. The selection, mutation and convergence ensure that in every iteration, the solutions are reduced to the optimal set. At the end, an optimal solution (or list of optimal) is generated over the Pareto front. Inspired by genetics and natural selection, GAs [53] provides a potent optimization method for handling multi-objective, complicated issues, such as message routing optimization in EnFVs. Finding optimal or nearly optimal results through iteratively enhancing a population of viable solutions is the fundamental idea behind GAs.

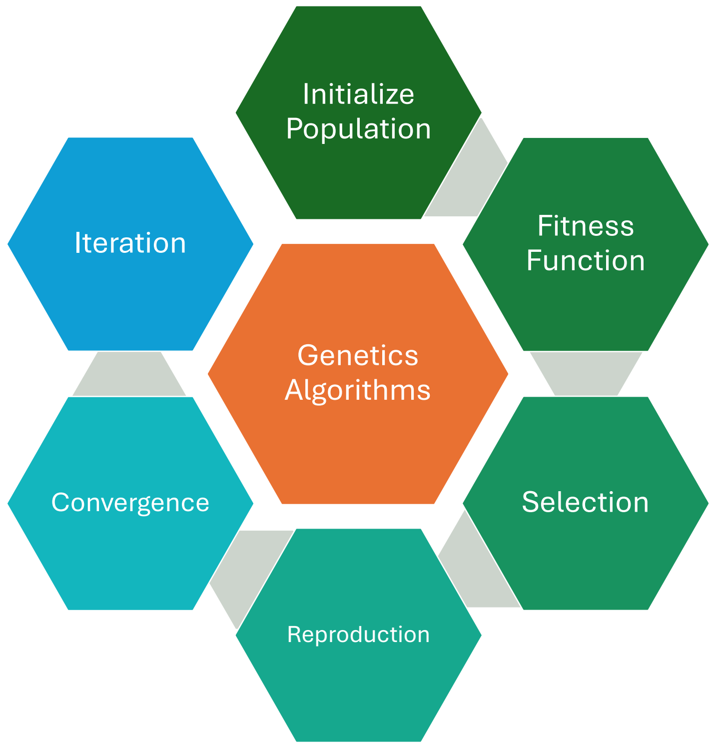


Figure 6 Generic genetic algorithms iterative process.

A GA's essential elements include crossover, mutation operators, fitness assessment, selection, and solution representation and encoding. Figure 6 outlines the generic process of the GA. Considering our unique yet realistic unified framework of EnFVs, it is imperative to consider multiple objectives. Advances in intelligent transportation systems have significant potential, but they also introduce multiple constraints due to heterogeneity. Innovations in transportation, fueled by EVs and UAVs, provide sustainability, reduced congestion, and improved mobility. Due to the heterogeneous nature of the involved devices, it is crucial to consider multiple objectives and required constraints. For instance, EVs are dependent on electric charge and battery life, while UAVs face constraints such as high stochastic mobility.

Given the heterogeneous requirements and potential opportunities, it is necessary to accommodate the distinct environments as a single entity. Without a unified consideration of EnFVs, realizing an optimal solution is not possible. In this chapter, we highlight the need for genetic algorithms in light of existing literature. We have conducted an exhaustive literature review on the application of genetic algorithms. Our study identified pivotal questions regarding genetic algorithms and their potential as the best solution for optimal decision-making in our unified framework. Our investigation includes queries such as: Why is multi-objective message routing in the EnFV environment under-researched specifically with GA? What has been the major focus of the research community related to multi-objective optimizations in EnFVs? How has the dynamic nature of electric vehicular networks or flying networks been addressed? What are the major advantages and drawbacks of using GA for the unified model that requires multi-objective optimization? How can it be ensured that sustainability, reliability, and efficiency are attended to in our scenario or part of the unified environment?

Through this chapter, we aim to provide effective and convincing answers to these queries. We discuss the role of genetic algorithms and their viability while introducing the background study of various aspects. Along with the workings of genetic algorithms, we highlight the challenges, opportunities, and effectiveness of genetic algorithms, along with future directions and possible work.

A key problem in EnFV operations is multi-objective message routing. It requires the concurrent optimization of multiple goals, such as saving travel time, cutting energy use, increasing dependability, and fostering environmental sustainability [54], [57]. Let us consider multi-objective message routing in EnFVs [31], where it is crucial to integrate different paradigms. Making the best and optimal decision is complex due to the conflicting nature of objectives [5]. Utilizing electric and sustainable solutions in mobility is vital in combating global warming. Moreover, UAVs have a broad spectrum of applications in ITS. In this chapter, we examine the use of GAs in the unified paradigms of EnFVs and provide a detailed background based on recent state-of-the-art research. The chapter focuses on the following objectives:

- Identify the multi-objective challenges within the unified ITS framework.
- Study distinct solutions utilizing GAs to solve multi-objective routing in electric or flying ITS.
- Discuss the process, advantages, and formulation of GA-based schemes.
- Explore the potential of GAs in various applications, especially in ITS.
- Present our encoding and representation of multi-objective optimal message routing in unified EnFV networks.

Our objective is to present comprehensive, yet informative, information about GAs and their uses in EnFV paradigms. This paper contributes to the understanding of multi-objective message routing in EnFVs by providing a thorough review and analysis. For researchers and practitioners hoping to employ GAs for dependable and effective communication in these cutting-edge transportation systems, it offers insightful information. The study tackles important problems with message routing for EnFVs and suggests a number of interesting lines of inquiry for further investigation. Overcoming the drawbacks of conventional routing algorithms requires creating routing algorithms that optimize message routing in dynamic transportation systems [37]. Let us discuss the basic but essential reasons of why Multi-objective optimization is particularly important for EnFVs [50], [58], [28]:

In the context of the EnFV paradigm, a few noteworthy goals are energy efficiency, trip duration, emission reduction, battery use, comfort, and regulatory compliance. Finding the best answers requires just multi-objective optimization, which balances trade-offs between different goals. EnFVs work in extremely mobile and complicated surroundings, navigating through urban areas, fluctuating traffic situations, varying weather patterns, and the availability of infrastructure for recharging or charging. These cars are able to adjust to these settings and make well-informed decisions by using multi-objective optimization approaches. Multi-objective optimization, which develops solutions that incorporate many objectives at once, is beneficial for EnFVs because they have limited resources, like as fuel availability or battery capacity. This strategy encourages creativity and the creation of cutting-edge EnFV technologies. It encourages the integration of cutting-edge technology like sophisticated energy management systems, intelligent routing algorithms, and vehicle-to-vehicle communication by examining different trade-offs and identifying the best solutions.

For Electric and Flying Vehicles, multi-objective optimization is crucial because it helps resolve conflicts between goals, adjust to changing conditions, maximize resource utilization, take stakeholder and user preferences into account, and promote innovation for further advancement. In order to maximize efficiency and progress the sustainability of EnFVs in the transportation industry, it is essential.

3.1 Problem formulation in GA

Considering all possible solution in the solution space, GAs search and efficiently explore the possible optimality while ensuring the various multiple objectives. Moreover it supports the constraint-oriented approach where a realistic problem can be formulated in detail [28]. Please note that Multi-objective optimization (MOO) is a process of problem formulation where realistic problems are identified and converged towards the required convex or concave solutions (minimization or maximization). The formulated problem accompanied with various multiple constraints can not only allow realistic mathematical representation but also provides a universally understood notion. Considering a minimization problem where function of x decision variables with M solutions is:

Minimize:

$$f_1(x), f_2(x), \dots, f_m(x) \tag{4}$$

Subject to constraints: [40]

$$\begin{aligned} g_i(x) \leq 0, i = 1,2, \dots, p \\ h_i(x) = 0, j = 1,2, \dots, q \end{aligned} \tag{5}$$

In this case, the quantities to be minimized are represented by the objective functions fi(x), and the inequalities and equalities are represented by the constraints gi(x) and hi(x), respectively. The feasible region for the decision variables x is defined by these constraints.

To maximize, one would substitute "maximize" for "minimize" in the issue statement. The main problem in MOO is to gather a set of solutions that illustrate trade-offs between the competing aims. From the solution space, the GA may select the solution that is most dominant. The representation and encoding of routes, fitness assessment and goal functions, crossover and mutation operators, selection, and the ideas of Pareto dominance and non-dominated sorting—which are covered in the ensuing subsections—are the fundamental elements of a genetic algorithm [50].

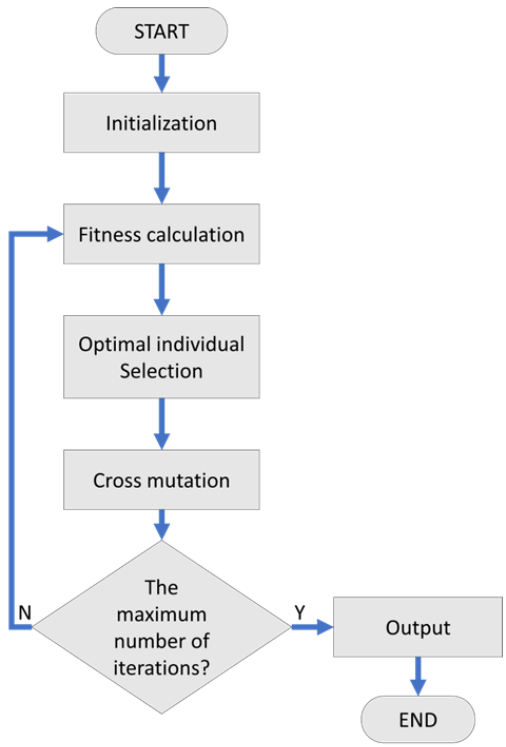


Figure 7 Iterative process of GA

3.2 Multi-objectives route encoding, representation and process in GA

For multi-objective message routing in EnFVs, GAs must include both route representation and encoding. Figure 7 outlines the iterative process of GA where selection, mutation and iterations identify optimal solutions. The algorithm's ability to investigate different solutions inside the search space is strongly impacted by the representation that is selected. To record the order of waypoints, charging stations, and flight trajectories, efficient encoding is essential [59], [60]. A popular method is chromosome-based representation, in which every chromosome represents a possible path. A series of genes make up chromosomes, and each gene corresponds to a distinct route or charging station. The sequence of visits is determined by the gene order on the chromosome. Energy usage and charging requirements may also be included in route encoding for EVs. Genes for remaining battery capacity at waypoints or energy levels at each charging station can be added to chromosomes. Encoding for UAVs may contain airspace regulations, altitude constraints, and flight restrictions. A chromosome's genes may contain information about altitude ranges, flight routes, and particular requirements for every waypoint. Computational complexity and representational capacity must be balanced in the encoding system. It should make it possible to explore a variety of paths while guaranteeing workable and effective answers. Based on particular routing requirements, different encoding techniques can be investigated. For example, discrete decisions can benefit from binary encoding, finite options from integer encoding, order-based problems from permutation encoding, continuous representation from real-valued encoding, complex relationships from tree-based encoding, and composite encoding from combining multiple schemes. The problem, the decision variables, and the multi-objective GA's objectives all influence the encoding decision. Choosing a suitable encoding method is essential. It facilitates precise issue representation, solution space exploration, and accurate fitness evaluation during optimization. Fitness evaluation in multi-objective message routing for EnFVs assesses the quality of each solution. Using objective functions to measure goal satisfaction and enable comparison and selection of superior solutions, this technique assesses how well alternatives satisfy the routing problem's many objectives and constraints. When routing an EnFV, objective functions take into account variables including energy consumption, trip time, distance, traffic, availability of charging stations, flight limits, and environmental impact. By managing trade-offs between competing aims, these objectives seek to balance the needs of the transportation system and the cars. To balance competing aims and achieve intended performance, the design of these functions should take into account the unique characteristics of the system as well as its special purposes.

Important components of the GA-based optimization framework are the selection, crossover, and mutation operators. In order to direct the algorithm toward the optimal solutions, they assist in exploring and utilizing the solution space. Using techniques like tournament selection and rank-based selection, the selection operator selects the most physically fit members of the present population to produce the next generation. By utilizing strategies like one-point crossover, the crossover operator creates kids by combining the genetic material of two parents. In order to preserve diversity and investigate new parts of the solution space, the mutation operator adds random modifications. Techniques such as bit-flip mutation are used to fine-tune solutions and prevent convergence to local optima. In multi-objective message routing for EnFVs, these operators support the GA's exploration, maintenance of variety, and convergence toward optimal solutions. A key idea in multi-objective optimization for EnFVs is Pareto dominance, which is utilized to assess and contrast solutions [50]. If a solution improves on at least one goal without degrading any other goal, it is deemed superior. Figure 8 shows a graphical representation of the Pareto front in a two-objective solution space. This idea aids in determining trade-offs between competing goals and in locating the best answers. Non-dominated sorting divides the population into various fronts, each containing solutions that are not dominated by any other, and classifies solutions according to Pareto dominance. Pareto-optimal solutions are those that can't be improved upon without sacrificing another goal. This approach aids in identifying them.

The effectiveness of Genetic Algorithms (GAs) and their capacity to converge to optimal or nearly optimal solutions are significantly influenced by a number of critical parameters. Finding a balance between investigating novel ideas and utilizing existing solutions requires fine-tuning these factors. The population size, crossover rate, mutation rate, and termination criterion are the key variables that require adjusting. A key factor is population size, which establishes the number of individuals (routes) in each GA generation. Although it raises computing needs, a bigger population size improves exploration. A smaller population, on the other hand, can result in less ideal solutions and early convergence. The intricacy of the issue and the available computing power determine the appropriate population size. The probability of carrying out a crossover operation between two parent routes in order to generate offspring is known as the crossover rate. An excessively high crossover rate can result in the loss of good solutions, but it also improves exploration and solution diversity. Convergence may be slowed by a lower rate. Maintaining high-quality solutions and the necessity for investigation should be balanced by the crossover rate. The mutation rate indicates the likelihood of haphazardly altering a route's genes (locations). Maintaining variety and pursuing uncharted territory in the solution space depend on mutation. While it can hinder convergence, a higher mutation rate promotes exploration. A lower rate puts poor solutions at danger of early convergence. Given the intricacy of the situation, the mutation rate needs to balance these requirements. The GA should terminate when the specified criteria are met. Achieving a target fitness level, hitting a predetermined computational time limit, or attaining a maximum number of generations are examples of common criteria. These requirements ought to line up with the features of the issue, the computational power at hand, and the optimization objectives. Optimizing the

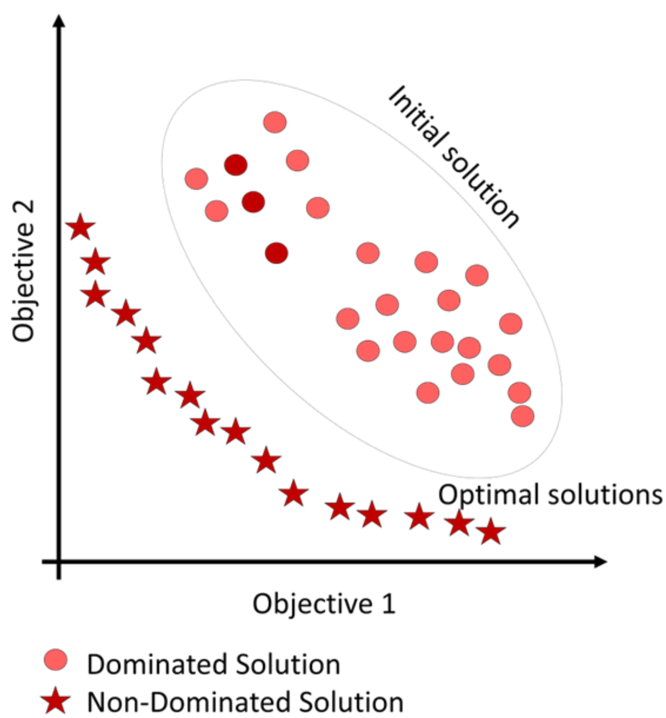


Figure 8 Pareto front in the solution space

performance of GAs in multi-objective message routing for EnFVs requires effective parameter tweaking. To establish the ideal balance between exploration and exploitation, taking into account the intricacy of the problem, the computational resources at hand, and the particular optimization goals, this calls for extensive testing and analysis.

CHAPTER FOUR

NOVEL MULTI-OBJECTIVE GENETICS ALGORITHMS TECHNIQUE FOR OPTIMAL MESSAGE ROUTING IN FLYING AND ELECTRIC VEHICLES

The ITS helps facilitate communication in Flying Ad Hoc Networks (FANETs) and Electric Vehicular Ad Hoc Networks (E-VANETs). However, the unique characteristics and limitations of FANETs and E-VANETs pose challenges for creating an efficient message routing protocol. There has been significantly increased interest in recent years and both networks are now widely used in both civil and military applications [1], [61]. There exist several challenges in both the scenarios and environments. UAVs can move in any direction since they are not limited by geographical obstacles. In contrast, EVs are more independent but have to rely on Dedicated Short-Range Communications (DSRC) or cellular networks for connectivity. UAVs, though energy-constrained, support higher data transmission rates compared to EVs. The ideal protocol should ensure fast message transmission for UAVs without draining their energy and also maintain reliability and connectivity for the entire network. There are several proposed solutions for using FANETs to support E-VANET communication, but none consider both networks as a unified system. The main challenge is to develop an efficient message routing protocol for this combined system [62], [63].

In [63], the authors propose a predictive message routing scheme for FANETs that predicts the connectivity time by identifying the current geographical coordinates of a target vehicle and assuming an unchanged direction. The scheme uses a quadratic equation-based time estimation but does not address the common possibilities of having any real solution or multiple real solutions. In contrast, the multi-objective routing scheme called EORB (Energy-saver) discussed in [64] considers both node energy and buffer capacity to select the best route. This scheme predicts trajectory and velocity for communication and uses a utility function for relay selection. Another study in [65] introduces a Q-learning-based routing protocol. This protocol actively interacts with the environment and readjusts its actions accordingly. Additionally, [62] highlights the importance of metrics such as charging stations, VANET-supporting networks, and trajectory-based systems, with further detailed proposals found in studies [66], [67], [68], [69], [70], [71], [72], [73]. A thorough review of existing schemes reveals that an effective routing scheme should not focus on a single objective while ignoring the impact of its byproducts. This comprehensive approach is essential for developing a more efficient and reliable message routing protocol that integrates the unique features of both FANETs and E-VANETs.

It is also important to note that none of the current routing methods consider the vehicular domain as a single entity. By addressing multiple objectives and considering the interconnected nature of these networks, researchers can create solutions that improve communication and connectivity in intelligent transportation systems. Let us consider a multi-objective scheme that often relies on evolutionary algorithms and techniques like genetic algorithms (NSGA-I, II, etc.). These algorithms take multiple solutions and reduce them to the Pareto front, which represents the best possible solutions. However, most optimization methods consider a large population set, leading to increased iterations and resulting in high space and time complexity.

In this chapter, we propose reducing the solution space before applying an optimization technique. This approach identifies the Pareto front and then selects the best solution. The genetic algorithm used in our method finds the Pareto front and then narrows it down to the optimal solution. For mobile battery-powered cars, we offer a multi-objective routing strategy that uses two objective functions: residual energy and data rate. In addition to guaranteeing faster data transfer, taking data rate into account also validates that UAVs are included in most communication paths. Better propagation, less blocking, and quicker communications are the results of this. However, concentrating on residual energy not only helps the UAV maintain its power but also smartly steers clear of overusing the same communication equipment over several routes. Moreover, our scheme guarantees the reliability by confirming that the selected path stays connected during the whole transaction.

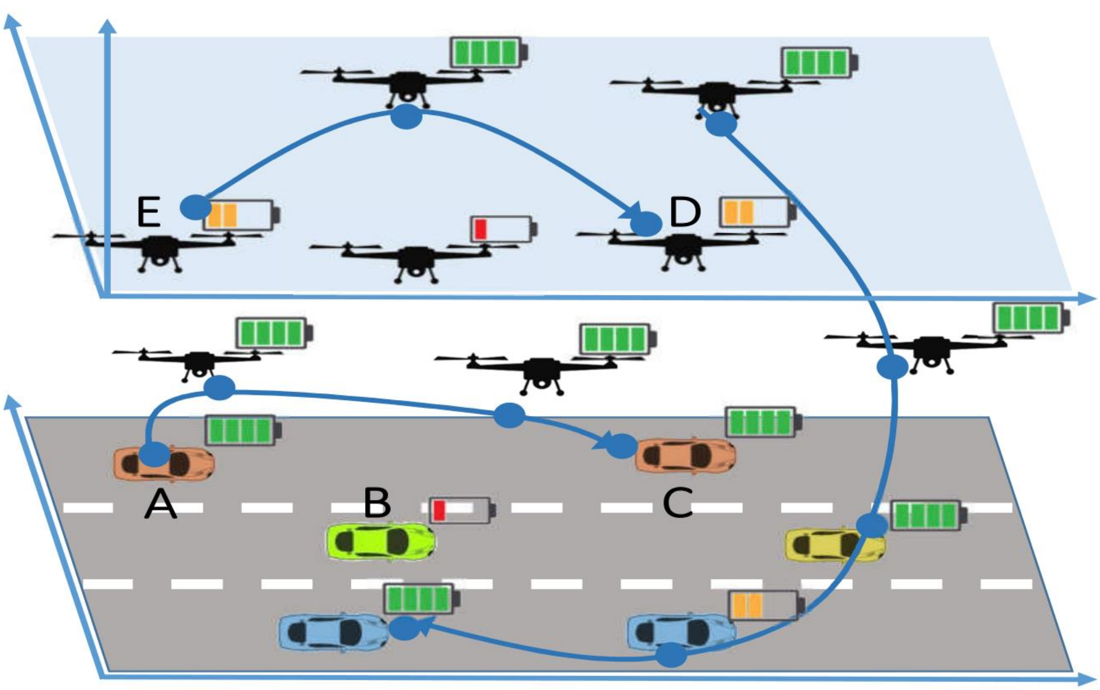


Figure 9 Proposed FA-VANET paradigm

The innovative optimal multi-objective solution proposed in this study shows strong potential and applications for various similar problems. To the best of our knowledge, no existing scheme offers an analytical optimal solution for multi-objective routing in the high mobility networks of EnFVs. Figure 9 provides a snapshot of the proposed solution where a unified environment of EnFV is considering multi-hop routing in high mobility environment. Our method holds great potential for advancing the creation of dependable and effective message routing systems for these ever-changing contexts. We provide an innovative and effective message routing strategy that considers mobile cars with limited battery capacity. The objective is to create a dependable and effective routing method that facilitates fast data transfer in high-mobility ad hoc contexts. To use a genetic algorithm for message routing, a multi-objective problem must be mathematically modeled. A key component of our methodology is a thorough performance assessment for urban mobility utilizing actual simulation traces. To accomplish this, we make use of programs like OpenStreetMap (OSM) and SUMO (Simulation of Urban Mobility). Comparing the results to previous solutions, there is a noticeable improvement of over 90% in successful packet delivery.

4.1 Mobility model and system formulation

For any device or vehicle in a flying or electric vehicular network, the main feature is its 3D location denoted by ($l_i(x_i, y_i, z_i)$) and velocity (γ_i). For any possible communication between moving vehicles, it is essential to consider their locality and mobility information. However, with high mobility devices, the problem intensifies, and it becomes harder to keep track of the channel state information in time varying channel.

Moreover, it should also be noted that mobility has a major impact of doppler effect on the communications. Nevertheless, a transmission range $(R_i)$is always a good way to represent the communication range of devices. The straight-line distance (ΔD_{ij}) between vehicle i and vehicle jis determined using the formula:

$$\Delta D_{\{i,j\}} = \sqrt{\left(x_j - x_i\right)^2 + \left(y_j - y_i\right)^2 + \left(z_j - z_i\right)^2} \quad (6)$$

An important aspect of the proposed unified model is that all EVs are ground vehicles and positioned at (z = 0). On the other hand, we have considered that the UAVs can have a positive z value and exhibit heights.

It is highly likely that from time t=0, we can predict the future movements and location of vehicles. With the assumption of uniform velocity and unchanged direction for all vehicles at time (t=0), the future position of a vehicle can be predicted. This prediction, $(\Delta D_{\{i,j\}}(t_0 + \tau))$, at time $(t_0 + \tau)$ uses the current position and the movement vector. The formula for this prediction is based on the current position at time (t_0) and the known velocity and direction. Our system model includes vehicles (UAV or EV) having important properties such as 3D location represented by $l_i(x_i, y_i, z_i)$ along with velocity of γi. These mobile vehicles can communicate with each other within a transmission range Ri. The straight-line distance $\Delta D\_\{i, j\}$ between a vehicle i and j can be identified using $\Delta D\_\{i, j\} = \sqrt{}((x\_j - x\_i)\text{^}2 + (y\_j - y\_i)\text{^}2 + (z\_j - z\_i)\text{^}2)$. It is assumed that all EVs are at z = 0 position in the 3rd dimension, whereas UAVs can have a positive z value. With the assumption of uniform velocity and direction unchanged for all vehicles at time t=0, the future position of a vehicle can be predicted, as

($\Delta D_{i,j}(t_0 + \tau)$) at time $t_0 + \tau$ using current position at current time and movement vector, as given below:

$$\Delta D_{i,j}(t_0+\tau) = \sqrt{\left[\left(x_j + v_{x,j}\times\tau\right) - \left(x_i + v_{x,i}\times\tau\right)\right]^2} + \sqrt{\left[\left(y_j + v_{y,j}\times\tau\right) - \left(y_i + v_{y,i}\times\tau\right)\right]^2} + \sqrt{\left[\left(z_j + v_{z,j}\times\tau\right) - \left(z_j + v_{z,j}\times\tau\right)\right]^2} \quad (7)$$

A movement vector indicates the acceleration of a vehicle in one, two, or all three dimensions within a unit of time, such as seconds. UAVs can include movement vectors $\left(v_{\{x,i\}}, v_{\{y,i\}}, v_{\{z,i\}}\right)$ in their beacon or hello messages. For EVs, the available information is typically the velocity (γ_i) and acceleration direction (θ_i). EVs periodically broadcast Basic Safety Messages (BSM) under the DSRC communication protocol, which include location, velocity, and direction data.

To determine the movement vector for an EV, we consider the top view where north is always at (90°). The (360°) circle is divided into equal quadrants \((Qs)\), with \(Qs = (45°)) creating eight quadrants and an offset of (Qs/2 = (22.5°)). If a vehicle's direction angle falls between (0° ~ 22.5°) or (337° ~ 360°), a positive value with a velocity (γ_i) on the x-axis is considered for ($v_{x,i}$).

We use a simple movement direction metric ($\theta'_i = (\theta_i + offset)/Qs$, which identifies whether the EV is moving positively or negatively along the x-axis, y-axis, or both. With this metric, we can estimate the movement of an EV on the x-axis and y-axis within a single time unit, assuming the direction remains unchanged.

Given the current position $l_i(x_i, y_i, z_i)$ and velocity(γ_i), the straight-line distance ($\Delta D_{i,j}$) between two vehicles i and j is calculated. In our model, EVs are assumed to be at (z=0) while UAVs can have positive z values. This allows us to predict the future position of a vehicle, ($\Delta D_{\{i,j\}}(t_0 + \tau)$), at time $(t_0 + \tau)$ using its current position and movement vector. This prediction is crucial for maintaining effective communication in high-mobility environments where vehicle positions and trajectories are constantly changing.

$$v_{x,i} = \begin{Bmatrix} (+1) \times \gamma_i & \text{, if } 0 \le \theta_i' < 2 \text{ or } \theta_i' > 7 \\ (-1) \times \gamma_i & \text{, if } 3 \le \theta_i' < 6 \\ (0) \times \gamma_i & \text{, if } 2 \le \theta_i' < 3 \text{ or } 6 \le \theta_i' < 7 \end{Bmatrix} \quad (8)$$

$$v_{y,i} = \begin{Bmatrix} (+1) \times \gamma_i & \text{, if } 1 \le \theta_i' < 4 \\ (-1) \times \gamma_i & \text{, if } \theta_i' \ge 5 \\ (0) \times \gamma_i & \text{, if } 0 \le \theta_i' < 1 \text{ or } 4 \le \theta_i' < 5 \end{Bmatrix} \quad (9)$$

With ($v_{\{z,i\}} = 0$), velocity (γ_i), and vehicle direction (θ_i), we can formulate a movement vector$v_{\{x,i\}}, v_{\{y,i\}}, v_{\{z,i\}}$ for an EV i. While it is unlikely for a vehicle to maintain the same direction for an extended period, even a short prediction window can ensure reliable communication. We identify reliable data transfer using a metric ($\omega_{i,j}$) that takes into account the data rate and the data size ($D_{t_{ij}}$) between two vehicles. This metric is defined as: $\omega_{i,j} = \frac{\tau_{i,j} \times Tx_{i,j}}{Dt_{i,j}}$

where τ represents the connectivity time between vehicles i and j. A value of ($\omega_{i,j} < 1$) indicates unreliable and incomplete data transmission.

Algorithm 1 The algorithm implemented in each communicating vehicle

Initiate and distribute a vehicle discovery message
For all responses regarding the target vehicle
if no direct link exists between source and the destination **then**
  for all Loop-free responses with target vehicle **do**
    Route $\omega_{s,d} = min(\omega_{s,1}, \omega_{1,2}, \ldots, \omega_{l,d})$,
    while calculate all $\omega_{i,j}$ for hops between s and d **do**
      while $\Delta D_{i,j}(t_0 + \tau) < R_{i,j}$ and $\omega_{i,j} < 1$ **do**
        $\tau_{i,j} = \tau_{i,j} + \alpha$
        Find $\Delta D_{i,j}(t_0 + \tau)$ for hop i and j.
        Identify $\omega_{i,j} = \frac{\tau_{i,j} \times Tx_{i,j}}{Dt_{i,j}}$
      end while
    end while
    if $\omega_{s,d} < 1$ **then** Remove the response as unreliable
    end if
  end for
  Call Multi-objective Genetics algorithm() with remaining responses messages
else
  Direct link between source and the destination supersedes all possible paths.
end if
Return the optimal route as transmission path.

Algorithm 4.1

We discuss our novel method in Algorithm 4.1, to estimate the reliability (ω_{ij}) of a link between vehicles i and j where the connectivity time (τ_{ij}) can be estimated easily with incremental values. The process halts when reliable connectivity $\omega_{i,j} < 1$ is achieved or when both vehicles move out of communication range (R_{ij}). Although a quadratic solution can predict ($\Delta\, D_{\{i,j\}}(t_0 + \tau)$), extensive trial and error has shown that multiple or no solutions often lead to unreliable predictions. In our solution, we use mobility metrics to estimate connectivity time. Please note that the proposed scheme does not require probe messages to gather network metrics like throughput or bandwidth. This reliability check does not require further network information for prediction; it solely makes use of the data that is currently available, such as BSM messages.

Nevertheless, the route reliability procedure in our novel Algorithm 4.1 increases connectivity time by(α) (0.5, 1, etc.) time units (seconds) in each iteration, continuously verifying that both vehicles remain within communication range ($\Delta D_{\{i,j\}}(t_0 + \tau)) < R_{ij}$. The stopping or convergence criteria of the Algorithm 1 is when the reliability metric (ω_{ij}) reaches 1, indicating successful data transmission $D_{\{i,j\}}$. It is evident that our novel and scalable process allows for the identification of reliable communication links, while there is no extra burden of probe messages. For the first objective O1, the average data rate of the source and all intermediate nodes in a route (p) between a source (s) and destination (d) can be calculated as:

$$O_{s,d}^{1} = \left(\text{sum}\left(Tx_{s,i}, Tx_{i,j}, \dots, Tx_{l,d}\right)\right) / \text{ hops} \tag{10}$$

We define the residual energy in a selected path (p) as the minimal energy among all the hops used to transmit packet from a source (s) and destination (d), and with ξi,j is the residual energy of vehicle i, it can be calculated as:

$$O_{s,d}^{2} = min\left(\xi_{s,i}, \xi_{i,j}, \dots, \xi_{l,d}\right) \tag{11}$$

where a reliable route (ωi,j ≥ 1) having the highest O1 and O2 values prioritizes UAVs in the path whilst keeping their residual energy afloat.

4.2 Our proposed novel multi-objective genetic algorithm solution

Let G(V, E) be a directed graph representing the communication paradigm of UAVs and EVs. Here, V denotes the set of vehicles, and E denotes the communication edges between them. In a multi-hop environment, a communication route exists if it satisfies the specified constraints, C. When multiple routes exist between a source and a destination, the selected route must satisfy the following objective functions (O1, O2):

1. Objective Function O1: Maximizing Data Rate

The chosen route should maximize the data rate to ensure swift and efficient data transmission. This involves selecting paths that support higher transmission speeds and stable connections.

2. Objective Function O2: Minimizing Energy Consumption

The route should minimize the energy consumption of the UAVs and EVs. This is crucial for maintaining the battery life of these vehicles, especially UAVs which have limited energy resources.

These objective functions help in determining the most efficient and reliable communication path. By focusing on these criteria, the proposed routing scheme aims to optimize both the speed of data transmission and the energy efficiency of the network.

The graph (G(V, E)) is constructed in such a way that each edge ($e \in E$) is associated with metrics that impact the objective functions. For instance, data rate and energy consumption metrics are considered for each edge to evaluate the overall performance of the route. This allows the algorithm to dynamically select the most optimal path based on the current network conditions and the movement of the vehicles.

In this model, each vehicle periodically broadcasts its status, including its position, velocity, and energy level. This information is used to update the graph (G(V, E)) in real-time, ensuring that the routing decisions are based on the latest available data. The algorithm then evaluates potential routes against the objective functions ((O1, O2)) to select the best possible path for data transmission. Through this approach, the proposed routing scheme aims to enhance the reliability and efficiency of communication in a highly dynamic and energy-constrained environment. By continuously monitoring and adapting to changes in the network, the scheme ensures that data is transmitted quickly and efficiently, while also conserving the energy resources of the UAVs and EVs.

$$\begin{aligned}
&\operatorname{argmax}_{p\in M(s,d)}\ O^1\\
&\operatorname{argmax}_{p\in M(s,d)}\ O^2\\
&\text{s.t. } C1{:}\ \forall \operatorname{argmin}_p \left(\omega_{s,1},\omega_{1,2},\dots,\omega_{m,d}\right) > 1\\
&C2{:}\ 0 < \forall \xi_i \le 100\\
&C3{:}\ \forall T x_i > 0,
\end{aligned} \tag{12}$$

where M(s, d) represents the solution space of all possible paths between s and d, considering all initial inquiries. The objective functions O1 and O2 are defined in the equations earlier.

The procedure by which a sender vehicle finds and assesses several routes to a destination is explained in Algorithm 4.1. Route Request (RREQ) messages are sent to all linked vehicles by the sender vehicle. Additional details for the suggested scheme are included in every Route Reply (RREP) message received from the destination or any intermediary vehicle with a path to the destination, specifically:

1. $\min \omega_{i,d} = \min\left(\omega_{ij}, \min \omega_{j,d}\right)$ (13)

2. $\min \xi_{i,d} = \min(\xi_{i,j}, \min \xi_{j,d})$ (14)

3. $\sum T_{x_{i,d}} = \sum T_{x_{ij}}, \sum T_{x_{jd}}$ (15)

4. Hop count

Each route reply message includes this additional information to aid in route evaluation. Upon receiving all route replies to messages, if there is a direct route between the source and destination, the source vehicle selects that route and terminates further route evaluation. Otherwise, the algorithm calculates ($\omega_{s,d}$) for each route and discards all unreliable paths where ($\omega_{s,d} < 1$).

This approach ensures that only reliable routes are considered for data transmission, optimizing both the data rate and energy efficiency. The inclusion of metrics such as $\min \omega_{i,d}$, $\min \xi_{i,d}$, $\min T_{x_{i,d}}$, and hop count in the route reply messages provides a comprehensive evaluation of each potential path. This detailed information allows the algorithm to make informed decisions, selecting routes that maximize reliability and efficiency.

By integrating these metrics into the routing protocol, the proposed scheme enhances the overall performance of the network. It ensures that data is transmitted over paths that not only meet the required data rate but also minimize energy consumption and maintain connectivity. The methodical evaluation of each route, considering various factors, leads to more robust and efficient communication in dynamic and energy-constrained environments. A multi-objective optimal route algorithm is then applied to the remaining routes, and it computes the two objective functions (O1, O2) that correspond to each route. Ultimately, the source device selects the optimal path from the list of options by considering these objective functions.

This procedure is explained by Algorithm 4.2 with the population (M(s, d)). It is possible to create a multi-objective issue with given constraints, where all values of the objective function are normalized between [0, 1]. This formulation is compatible with a wide range of goals and limitations. The suggested plan takes into account three limitations in addition to the two objective functions, highest minimal residual energy (O2) and maximum average data rate (O1).

Reliability ($\omega_{s,d} < 1$) is a critical constraint. (O1) ensures that a route with UAVs

Algorithm 2 Multi-objective genetics algorithm

```
1: M(s,d) is the solution space population having all possible but filtered routes
2: O^1 and O^2 are maximized along with constraints C
3: Problem modeling according to Equation 6
4: if constraint satisfied with optimal solution then
5:     Output the solution
6: else
7:     Perform Selection, mutation and crossover
8:     Update population
9:     Repeat Step 2
10: end if
```

Algorithm 4.2

is prioritized, while (O2) avoids UAVs with low residual energy. Since these objectives can be contradictory, a multi-objective solution allows a fair trade-off where both objectives have higher values. Typically, a multi-objective optimization algorithm calculates the Pareto front for all solutions. This front is a set of non-dominant solutions where no other solution outperforms any on the front. However, not all solutions on the Pareto front are favorable to all objectives.

The Pareto front for a solution set can be found and reduced with the aid of genetic algorithms and conventional evolutionary algorithms. The suggested technique reduces the solution space before implementing the evolutionary algorithm, incorporating dependability and complete message delivery utilizing the (ω) factor. Notably, Algorithm 4.1's dependability check has already filtered the population (M(s,d)) in Algorithm 4.2, necessitating very little processing. It is therefore a simple multi-objective optimum process.

The full procedure for the suggested genetic algorithm-based multi-objective optimization is described in Algorithm 4.2. Initially, objective functions with the constraints given by, are assigned to the reduced population (M(s, d)). To become an updated population, the solution space is subjected to crossover and selection mutations. When a solution (also known as the Pareto front) is found, this iterative process converges.

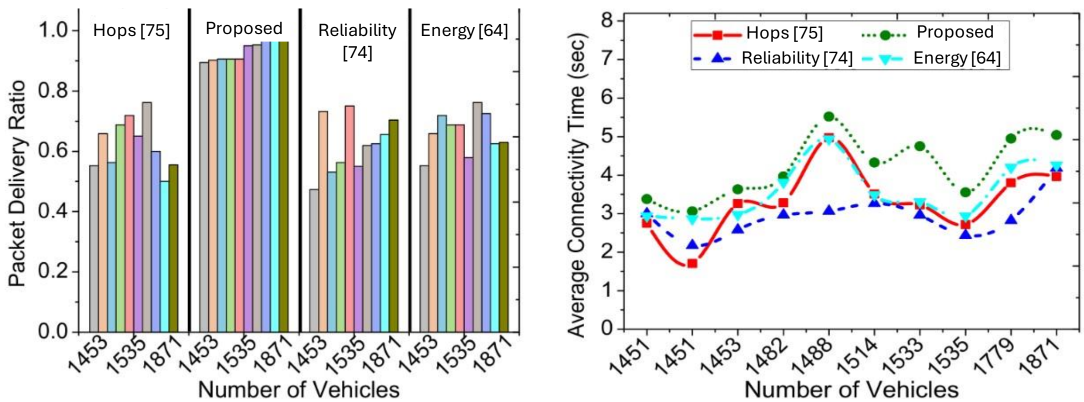
By employing these methods, the algorithm ensures that selected routes maximize data rate and minimize energy consumption while maintaining reliability. This approach efficiently balances multiple objectives, leading to optimal routing decisions in complex communication environments. The use of genetic algorithms further enhances the robustness and adaptability of the solution, making it suitable for dynamic and energy-constrained networks.

4.3 Experimental Results and Evaluations

Three current cutting-edge routing techniques are carefully compared to the suggested GA-based multi-objective solution. Communication technology must take into account the important energy consumption of battery-powered mobile vehicles. Accurate representation of the environment requires realistic numerical evaluation. Using real traffic traces from New York City, our comprehensive comparison study covers an area of 4x3 KM2 and involves 400–900 EVs and 1000 UAVs. In addition to their complete capability kits, every EV and UAV comes with a battery and two communication modules.

Every car has two 40 Mb connectivity connectors for data transmission. Compared to UAVs, which have a communication range of 500 meters and a data rate of 30 Mbps, EVs have a communication range of 250 meters at a rate of 20 Mbps. While the UAVs drive according to a random waypoint model with velocities varying from 10 to 50 m/s [73], the EV mobility pattern obeys commands from the SUMO simulator [74]. We created a thorough, specially made, event-driven Python simulation. In this simulation, UAVs and SUMO traces with EVs are integrated, producing hundreds of packets for arbitrary source and destination pairs. On a Dell PowerEdge T430, the simulation was executed on an Intel Xeon E5-2600 v3 12-core processor operating at 3.5 GHz. By compiling all feasible paths from the source to the destination, the simulator enables the suggested plan and the three current solutions to choose one route according to their respective routing criteria and conditions. Each scenario's performance metrics are computed after the procedure is repeated more than 100 times for a different total number of vehicles at each timestamp. This thorough analysis shows how well our suggested method works in actual situations.

Figure 10 (a) displays the packet delivery ratio for the proposed scheme compared with three existing solutions: Hop-based [75], Reliable Routing [74], and Energy-saver [64].



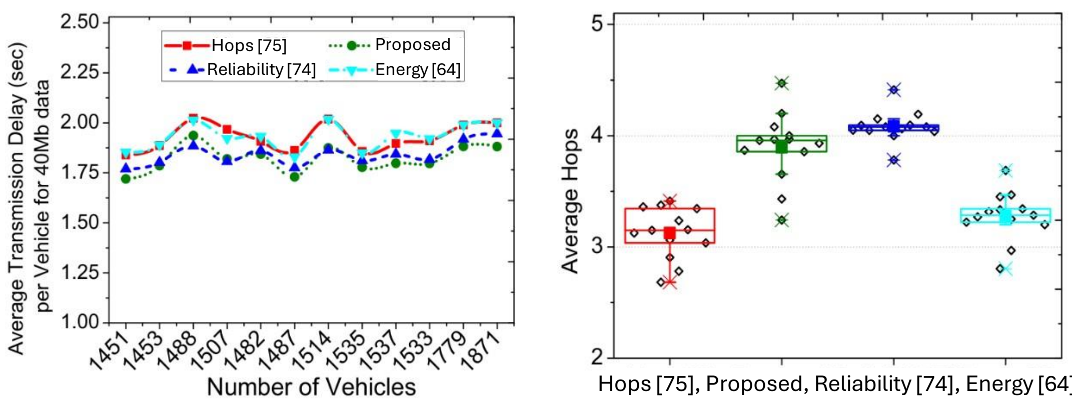
(a) Successful packet delivery **(b)** Route connectivity time

Figure 10 Performance evaluation using packet delivery success and connectivity time

The analysis primarily focuses on reliable routing [74] and energy-saver [64], using Hop based as a legacy benchmark. Each bar section represents evaluations over timestamps with 1453 to 1871 vehicles. Our proposed scheme consistently achieves over 90% success. Notably, as vehicle numbers increase, Hop-based performance drops to 50% success, while Reliable Routing fares better at 70% packet delivery. Energy-saver delivers packets successfully 50% to 70% of the time.

Figure 10 (b) demonstrates that the selected route in our suggested scheme stays connected for 3 to 6 seconds, while Hop-based, Energy-saver, and Reliable Routing vary from 1 to 5 seconds, 1 to 4 seconds, and 3 to 5 seconds, respectively. Extended periods of connectivity result in increased packet delivery ratios and decreased likelihood of incomplete transmissions. Real traffic traces from New York City, complete with turns, intersections, and other road infrastructure, are used in these extensive tests. Our suggested strategy works better than current ones despite these difficulties, attaining high packet delivery with longer connecting periods.

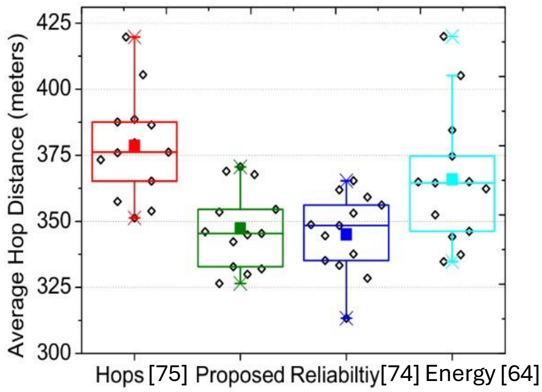
In Figure 11 (a), the average transmission delay per vehicle is shown. Most schemes exhibit a delay between 1.7 to 2 seconds, depending on the transmission capabilities of the vehicles. This delay metric excludes propagation and queuing delays. Nonetheless, our scheme achieves the lowest transmission delay per vehicle among the compared solutions. This lower delay results from an extra hop in the chosen route of the proposed scheme, as illustrated in Figure 11(b). Both the proposed scheme and reliable routing have a maximum of 4 hops, whereas hop-based and energy-saver have around 3 hops.



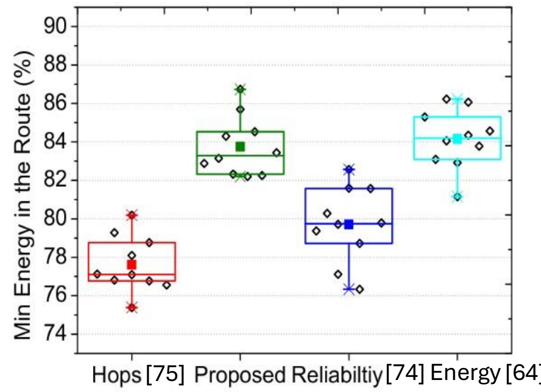
(a) Transmission delay for vehicle **(b)** Number of hops

Figure 11 Performance evaluation using transmission delay for vehicle and Number of hops

Figure 12 (a) shows that our suggested scheme and Reliable Routing have the lowest average distance between each hop. Better communication, less propagation delay, and less transmission losses result from this shorter distance. Up to 87% residual energy is found in the selected route as a result of our suggested strategy and Energy-saver prioritizing residual energy as a crucial route selection parameter. In Figure 12 (b) the metric indicates the residual energy of a vehicle on the route with the lowest battery



(a) Average hop distance



(b) Residual energy of chosen route

Figure 12 Performance evaluation using average hop distance for vehicle and residual energy

level. In contrast, Hop-based and Reliable Routing do not consider energy, resulting in minimum energy levels as low as 75% for intermediate vehicles.

The proposed scheme surpasses three leading routing methods in several areas, showing improved packet delivery, longer connectivity, shorter transmission delays, the shortest hop distances, and better energy conservation. Electric Vehicles (EVs) periodically share necessary information using Basic Safety Messages (BSM). UAVs must include movement vectors with route reply messages. This modification means route reply messages need to deliver extra information for at least four float values.

Additionally, the proposed scheme requires analytical processing of routing metrics (O1, O2, maxHV, and κ). However, this lightweight calculation is straightforward and requires minimal effort, comparable to most existing schemes. By reducing the solution space for evolutionary algorithms and Pareto front calculation, the proposed multi-objective optimal routing achieves outstanding results. Evaluations indicate that the trade-off of extra processing is justified by the significant gains in reliable communication and performance.

4.4 Chapter Summary

A new and unified multi-objective optimum routing system for FANETs and EnFVs was presented in this chapter. The main routing criteria taken into account by this approach are residual energy, data rate, and dependability. Our method provides a faster optimization by formulating an analytical optimal solution by narrowing the solution space for optimization algorithms. The suggested remedy calls for EVs to use Basic Safety Message (BSM) are exchanges regularly. To provide additional information for at least four float values, UAVs must incorporate movement vectors with route reply messages. Although some analytical processing of the routing metrics (O1, O2, maxHV, and κ) is necessary for this, the lightweight calculation is simple and similar to the majority of existing methods.

Exhaustive simulations using New York City's traffic traces demonstrated that our scheme achieved a 90% packet delivery ratio. The proposed scheme maintained longer route connectivity, between 3 to 5 seconds, and resulted in shorter hop distances. These outcomes surpassed the performance of three existing state-of-the-art routing solutions. Moreover, the evaluations revealed that our scheme's trade-off of additional processing was justified by the significant gains in reliable communication and overall performance. In addition to reducing the solution space for Pareto front calculations and evolutionary algorithms, the suggested multi-objective optimal routing produces remarkable outcomes in terms of packet delivery, route connectivity, and energy conservation. Our innovative routing scheme addresses the crucial problems of energy consumption, data rate, and reliability in communication technologies, providing a strong solution for high-mobility ad-hoc environments.

CHAPTER FIVE

OPTIMIZING UAV DEVICE DISCOVERY USING SELECTIVE REQUEST AND MOBILITY PREDICTION

In our proposed routing protocol, we introduce selective RREQ flooding to optimize route discovery. The flooding is triggered based on conditions where connection time exceeds the average Round-Trip Time (RTT). This approach enhances efficiency by selectively initiating route requests. Additionally, our protocol employs multi-objective optimization for route selection, integrating metrics such as hyper-volume and using GA. This ensures that the chosen routes not only meet connectivity requirements but also consider multiple objectives for optimal decision-making in dynamic environments.

The use of UAVs in various applications such as surveillance, search and rescue, and delivery has significantly increased in recent years[38], [45], [65], [76]. With the growing number of UAVs, developing effective methods to manage communication between these vehicles is essential. Communication overhead and information sharing are critical challenges in UAV communication and significantly impact the system's efficiency and scalability.

Multi-objective optimization has been widely used in various fields to address complex optimization problems. Recently, multi-objective optimization has been applied to UAV communication to reduce communication overhead and increase information sharing[22], [77]. One approach to achieving this is by implementing UAV clustering, which involves dividing a large number of UAVs into smaller groups, each with its communication infrastructure.

UAVs have become an integral part of modern society, with numerous applications in fields such as aerial photography, search and rescue, and environmental monitoring[76]. Communication between UAVs is critical for their effective operation, especially in missions that require coordination among multiple UAVs. In traditional UAV communication approaches, each UAV communicates directly with a central command center, leading to increased communication overhead and information sharing. However, UAV clustering can provide an efficient solution to this problem by grouping UAVs into clusters, reducing the amount of information that needs to be shared and thus reducing communication overhead. In a UAV cluster, a single cluster head communicates with the central command center, and inter-cluster communication is facilitated by the cluster heads. This approach can improve the overall efficiency of UAV communication and lead to more effective coordination in UAV missions.

In this chapter, we proposed a multi-objective UAV clustering approach that minimizes communication overhead and maximizes information sharing between UAVs. Unlike existing ad hoc message routing algorithms, we propose that the devices discovery message must be considered as a integral part. Earlier schemes [67], [74], [75] have considered RREQ as a process to collect the messages and details about potential message delivery paths. With high mobility networks, RREQ cannot be considered just as a scout message activity. It must be used to filter out all the routes and paths that do will not fulfil the route selection mechanism's requirements. We are the first to identify the impact of mobility on the devices discovery and ad hoc message delivery.

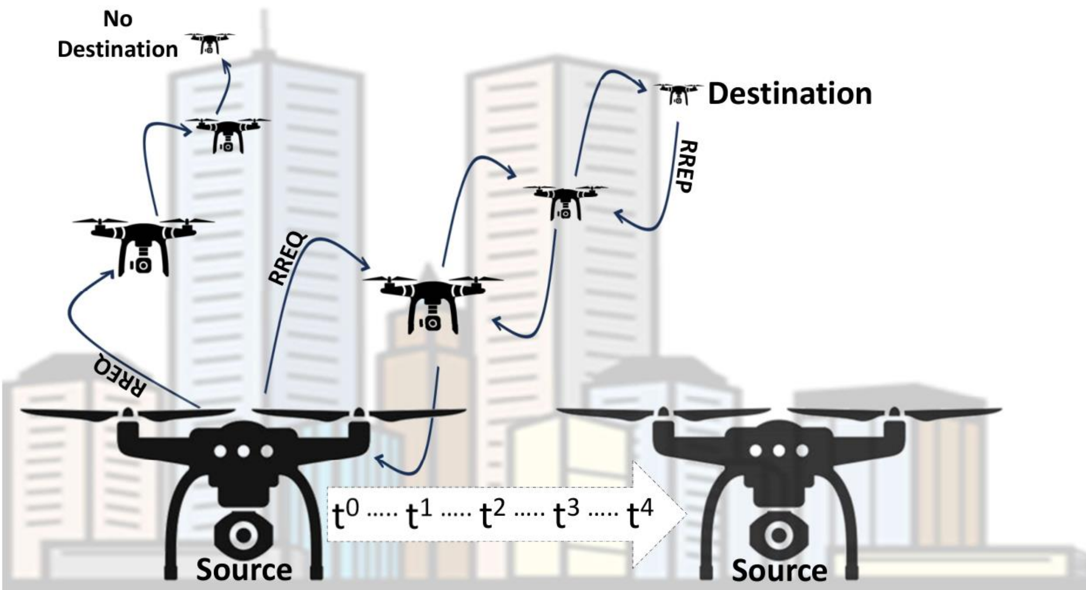


Figure 13 The proposed selective RREQ in action

Our proposal is two-part, 1) We consider that RREQ message should filter the routes while disseminating the route and destination requirements, 2) Using GA as the optimization tool to select the best and optimal route among all the available paths. Figure 13 illustrates the concept of the proposed scheme in the high mobility flying ad hoc networks where the source changes location while RREQ message is still collecting information. Our solution not only improve the ad hoc routing mechanism but also reduces the overhead of ad hoc messaging in terms of cellular resources. Our approach considers multiple objectives such as communication distance, node density, and communication load balance to create a more efficient and effective UAV cluster. To the best of our knowledge, there have been few studies that have combined multi-objective optimization and UAV clustering to reduce communication overhead and increase information sharing. The works of [1], [2], and [3] have demonstrated the potential of using multi-objective optimization in UAV communication; however, they only considered a limited number of objectives. Our proposed approach is unique in that it considers multiple objectives in UAV clustering to create a more effective and efficient communication infrastructure.

5.1 System model

We consider a network consisting of UAVs, denoted as $U = \{U_1, U_2, \dots, U_N\}$, where N is the total number of UAVs in the network. Each UAV U_i is equipped with communication capabilities and can act as both a source and a relay node. The communication between UAVs is characterized by the link quality $L(U_i, U_j)$, representing the quality of the communication link between UAV U_i and UAV U_j. This link quality metric could be based on signal-to-noise ratio (SNR), received signal strength indicator (RSSI), or other relevant parameters. Additionally, each UAV has a residual energy level denoted as $E(U_i)$, representing the amount of energy available at UAV Ui for communication and other tasks. Our objective is to find the optimal multi-hop route between a given source UAV U_{source} and destination UAV $U_{destination}$, such that we maximize both the link quality and the residual energy of the UAVs along the path, while satisfying the following constraints:

Communication Range Constraint: Each UAV Ui can only communicate with other UAVs U_j that are within its communication range $Rcomm(U_i)$. *Energy Consumption Constraint:* The energy consumed by each UAV Ui during communication should not exceed its available energy budget $Emax(U_i)$. *Traffic Load Constraint:* Limit the amount of data traffic that can be transmitted through each UAV to prevent network congestion.

This can be represented by a maximum traffic load threshold. *Dynamic Movement Constraint:* Ensure that the speed and direction of each UAV remain constant during the transmission process to maintain communication stability.

Mathematically, we aim to find a path x from U_{source} to $U_{destination}$, such that:

$$\text{Maximize } \begin{cases} g(x) = \min_{i=1}^{k-1} L(U_i, U_{i+1}) \\ f(x) = \min_{i=1}^{k} E(U_i) \end{cases} \tag{16}$$

$$\text{subject to } \begin{cases} L(U_i, U_j) \geq 0, \text{ for } i, j \text{ such that } U_j \in R_{\text{comm}}\,(U_i) \\ E(U_i) \geq 0, \text{ for } i = 1,2,\ldots,k \\ \sum_{\text{all paths}} \text{traffic load } \leq \tau_{\max} \\ \text{speed}(U_i) = \text{ constant, for } i = 1,2,\ldots,k \end{cases} \tag{17}$$

Link Quality

The link quality LinkQi,j between two communicating vehicles i and j can be estimated as given below:

$$LinkQ_{i,j} = \frac{p_j^{rcvd} - p_{min}^{rcvd}}{p_{min}^{rcvd}} \tag{18}$$

where P_j^{rcvd} is j's received power (dBm) of the message from the previous node i. $P_{\text{min}}^{\text{rcvd}}$ is the minimum decodable power (dBm) based on the coding rate, channel bandwidth, and other factors.

Whereas the minimum link quality between a multi-hop path having total k intermediate hops can be identified as given below:

$$g_{s,d}(x) = min(\text{Link}\, Q_{s,1}\,, \text{Link}\, Q_{1,2}\,, \ldots, \text{Link}\, Q_{k,d}) \tag{19}$$

Techniques such as tournament selection, crossover, mutation, and replacement to iteratively evolve a population of paths. These techniques help in exploring the search space effectively, promoting diversity, and converging towards Pareto optimal solutions that offer the best trade-offs between link quality and residual energy for multi-hop route selection in UAV networks.

The energy consumption by a UAV to send a message to another UAV can be affected by various factors, including the transmission power, distance between the sender and receiver, data rate, and the communication protocol used. Considering E is the energy consumption (in Joules), P is the power consumption rate (in Watts) and T is the duration of transmission (in seconds), the energy consumption can be calculated using the following formula: $E = P \times T$. The power consumption rate P can be calculated using:

$$P = P_{idle} + P_{tx} \tag{20}$$

where: P_{idle} is the idle power consumption rate (power consumption when not transmitting) and P_{tx} is the power consumption rate during transmission. The duration of transmission T depends on the data rate and the size of the message being transmitted. It can be calculated using:

$$T = \frac{L}{R} \tag{21}$$

where: L is the size of the message (in bits) and R is the data rate (in bits per second).

It’s important to consider that energy consumption can also be affected by other factors such as signal attenuation, interference, and environmental conditions. Additionally, UAVs may have different hardware configurations and power management strategies that can affect energy consumption. Therefore, these calculations provide a basic framework, but the actual energy consumption may vary based on specific circumstances and hardware configurations.

Algorithm 1 Source devices devices discovery procedure

1: Broadcast RREQ in neighbors
2: Piggyback additional information in the RREQ message
3: Receive all T_{RREP} RREP messages
4: **while** $t \in T_{RREP}$ **do**
5: Add entry in M solution set
6: **end while**
7: Forward M solution set to multi-objective optimization algorithm
8: Collect optimal solution M^0 as response
9: Initiate communication on M^0

Algorithm 5.1

5.2 The proposed scheme

Algorithm 5.1 outlines the proposed algorithm for source device discovery begins by broadcasting a RREQ message to all neighboring devices, which includes additional information such as current position and intended destination. This enhanced RREQ helps in route selection by providing comprehensive data to the neighboring devices. Upon receiving the RREQ, these devices respond with RREP messages. The source device collects all RREP messages, forming a set denoted as T_{RREP}. Each RREP contains details about a potential route to the destination. The algorithm then iterates through each message in T_{RREP}, adding the route information to a solution set M. This set encompasses all discovered potential routes. Subsequently, the solution set M is forwarded to a multi-objective optimization algorithm, which uses Genetic Algorithms to evaluate and select the optimal route based on criteria such as minimizing communication overhead and maximizing information sharing. The optimization process yields an optimal route, M^0, which is then used by the source device to initiate communication. This approach ensures that the selected route meets the necessary connectivity requirements and balances multiple objectives, resulting in efficient and reliable communication.

Algorithm 2 Intermediate device procedure after receiving $RREQ_{j,i}$

Calculate $\gamma_{th} = \frac{\text{Packet Size}}{\text{Transmission Rate}}$
Calculate initial euclidean distance $d(0)$
Set $t \leftarrow 1$
while $d(t) \leq R_i$ and $d(t) \leq R_j$ and $\gamma_{ij} \leq \gamma_{th}$ **do**
  Increment t
  Calculate new euclidean distance $d(t)$ at time t
  $\gamma_{ij} = t$
end while
if $d(t) >$ commRange or $\gamma_i > \gamma_{th}$ **then**
  Discard the message
else
  $\gamma_{ij} = t$
  Piggyback additional information in the $RREQ$ message
  Forward the message to next devices
end if

Algorithm 5.2

Algorithm 5.2 outlines the process of an intermediate devices, that receives a devices discovery request as an input. Upon receiving a Route Request ($RREQ_{j,i}$), the intermediate device first calculates the threshold transmission time, γ_{th}, by dividing the packet size by the transmission rate. Next, it determines the initial Euclidean distance (d(0)) between itself and the source. The time variable t is initialized to 1. The device then enters a loop where it continues as long as the distance d(t) at time t is within the communication ranges (R_i) and (R_j), and the calculated transmission time $\gamma_{i,j}$is less than or equal to γ_{th}. Within the loop, t is incremented and the Euclidean distance (d(t)) is recalculated. The transmission time γ_{ij} is updated accordingly. If at any point the distance (d(t)) exceeds the communication range or the Transmission Time (γ_i) surpasses the threshold γ_{th}, the message is discarded. Otherwise, the intermediate device updates the transmission time γ_{ij}, adds additional information to the RREQ message, and forwards it to the next devices. This process ensures that only viable routes that meet the communication and transmission criteria are considered, optimizing the routing process.

Algorithm 3 Destination UAV Procedure after Receiving $RREQ_{j,i}$

$\gamma_{th} \leftarrow \frac{\text{Packet Size}}{\text{Transmission Rate}}$
Calculate initial Euclidean distance $d(0)$
$t \leftarrow 1$
while $d(t) \leq R_i$ and $d(t) \leq R_j$ and $\gamma_{ij} \leq \gamma_{th}$ **do**
  $t \leftarrow t + 1$
  Calculate new Euclidean distance $d(t)$ at time t
  $\gamma_{ij} \leftarrow t$
end while
if $d(t) >$ commRange or $\gamma_i > \gamma_{th}$ **then**
  Discard the message
else
  Create Route REPLY (RREP) message
  Piggyback additional information in the RREP message
end if

Algorithm 5.3

On the other hand, Algorithm 5.3 delineates the process of a destination that receives RREQ. When the destination UAV receives a Route Request $RREQ_{j,i}$, it first calculates the threshold transmission time, γ_{th}, by dividing the packet size by the transmission rate. The UAV then determines the initial Euclidean distance (d(0)) from the source and sets the time variable t to 1. The UAV enters a loop where it checks if the distance (d(t)) at time (t) is within the communication ranges (R_i) and (R_j), and if the calculated transmission time (γ_{ij}) is less than or equal to (γ_{th}). If these conditions are met, (t) is incremented, the new Euclidean distance (d(t)) is recalculated, and (γ_{ij}) is updated. If at any point the distance (d(t)) exceeds the communication range or the transmission time (γ_i) is greater than the threshold (γ_{th}), the message is discarded. Otherwise, the UAV creates a RREP message, includes additional information, and sends it back. This ensures that only feasible routes are considered for reliable communication.

The modified version of the GA outlined in Algorithm 5.4, begins by initializing a population (P) with random paths. Each path's fitness is evaluated based on link quality and residual energy. The algorithm then sets the maximum number of generations (G), mutation rate (m), crossover rate (c), and population size (N), along with the termination criteria. Starting with (t) at 0, the algorithm enters a loop that continues until (t) reaches (G). In each generation, parents are selected from the population (P) using tournament selection. Crossover is performed between selected parents with a probability of (c), and mutation is applied to the offspring with a probability of (m). The fitness of the offspring is then evaluated. The worst individuals in (P) are replaced by the new offspring. The process repeats, incrementing (t) with each iteration. Once the loop completes, the algorithm selects non-dominated solutions from the final population (P). These non-dominated solutions are returned as the output, representing the optimal paths considering both link quality and residual energy.

Algorithm 4 Genetic Algorithm

Initialize population P with random paths
Evaluate the fitness of each path in P based on link quality and residual energy
Set maximum number of generations G
Set mutation rate m, crossover rate c, population size N
Set termination criteria
$t \leftarrow 0$
while $t < G$ **do**
    Select parents from population P using tournament selection
    Perform crossover between selected parents with probability c
    Perform mutation on offspring with probability m
    Evaluate the fitness of offspring
    Replace the worst individuals in P with offspring
    $t \leftarrow t + 1$
end while
Select non-dominated solutions from final population P
return Non-dominated solutions

Algorithm 5.4

5.3 Performance Evaluation and Chapter Summary

The proposed scheme aims to outperform existing solutions in two key areas. First, it reduces device discovery messages by incorporating filters at intermediate devices. This approach minimizes the ad hoc message routing process and the message overhead on cellular networks. However, it's important to assess the impact of these restrictions on the packet delivery ratio. Our solution proposes using multi-objective optimal message routing in EnFVs environments. Through an innovative use of Genetic Algorithms (GA) and multi-objective problem formulation, we present an efficient solution. To evaluate our solution against existing ad hoc message routing methods, we

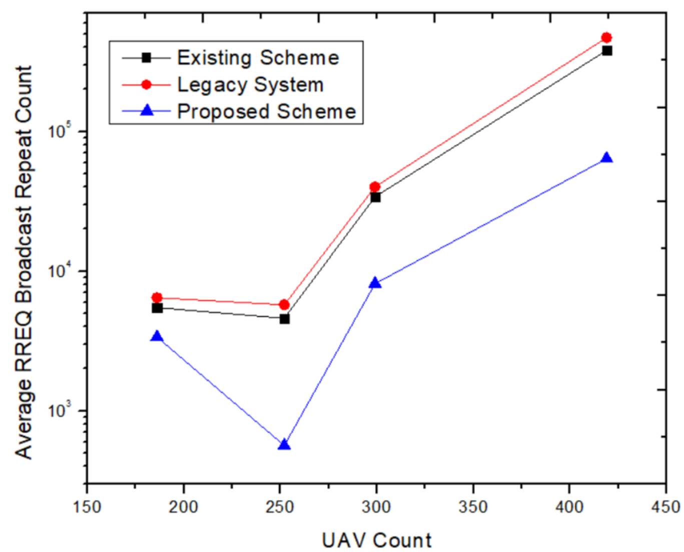


Figure 14 Average RREQ message count and comparative analysis

created a discrete event simulation in Python. This object-oriented simulation assigns each UAV features such as location (x, y, z), mobility (movement vector, speed, direction), and specifications (transmission rate, energy, number of transactions, communication range). UAVs are generated using a Poisson Point distribution controlled by λ. Their movement follows a smooth mobility model using EGMM3D. Additionally, UAVs can move or remain stationary, implemented in our model using a Binomial distribution. We compared our scheme with a legacy system and an existing scheme. The legacy system [75] forwards RREQ messages to all UAVs within communication range, selecting the shortest path based on minimum hops. The existing scheme [74] forwards RREQs to all possible devices, collecting information via RREP messages. The source device then selects the path with the highest connectivity time using predictive mobility paths. In contrast, our scheme filters messages at intermediate nodes and uses a heuristic GA with multi-objective routing for decision-making. Our results in Figure 14, show a significant reduction in RREQ messages with our proposed scheme. With an increase in the number of devices, RREQ messages typically increase, but our scheme reduces them by approximately 70% to 80%. This reduction is due to the filtering of messages at intermediate devices, which eliminates paths that won't be considered by the decision-making module. Consequently, unnecessary paths are removed, reducing message flooding overhead.

Another benefit demonstrated in Figure 15, of our filtering approach is reduced energy consumption, improving overall system energy efficiency. Each message incurs additional energy costs on the device's residual energy. Our results show that the

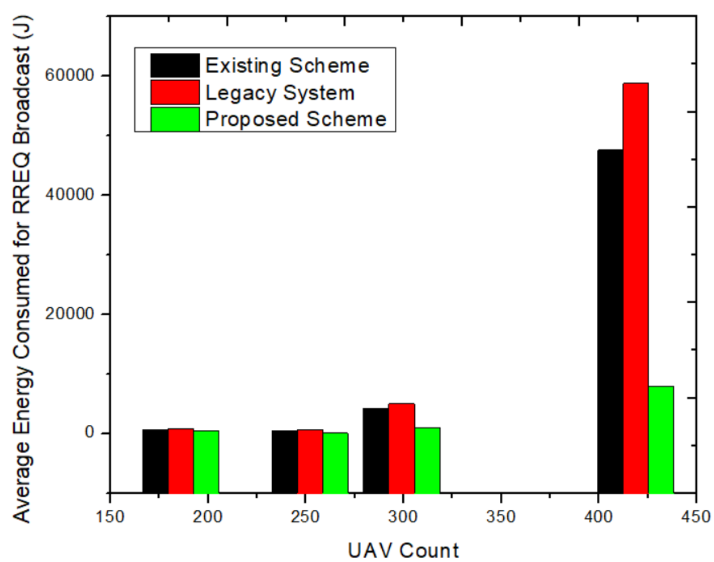


Figure 15 Comparative analysis of the proposed scheme with average energy consumption in device discovery

proposed scheme outperforms existing and legacy systems in terms of energy consumption during the device discovery process. While one might initially worry that our filtering could reduce the packet delivery ratio, a deeper inspection reveals that the scheme only removes unnecessary paths. This reduction in solution space emphasizes useful and candidate routes. Our multi-objective routing scheme, using GA optimization, identifies the best routes effectively. Our results shown in Figure 16 indicate that the proposed scheme offers a 60% to 70% improvement over existing and legacy systems.

As the number of devices increases, the performance of other solutions degrades. However, our scheme performs well with both high and low numbers of devices, demonstrating its robustness and efficiency.

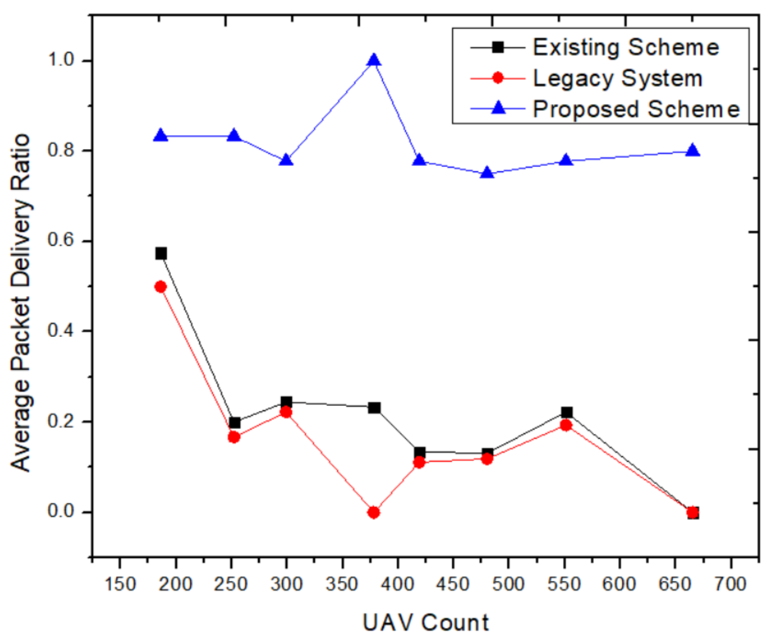


Figure 16 Average packet delivery ratio

In summary, the proposed scheme is a step in the right direction to consider high mobility networks. The existing literature is filled with the optimal solutions without the consideration of realistic nature of UAV networks and respective challenges. Through our research, we are the first to identify this gap and propose a novel and efficient solution. The proposed scheme not only reduces the message broadcast but also consider novel metrics to filter the message forwarding. Moreover, the proposed multi-objective decision making improve the packet delivery ratio in the high mobility networks.

CHAPTER SIX

CONCLUSION AND FUTURE WORK

In this dissertation, we explored communication and routing challenges in EnFVs within intelligent transportation systems. We recognized the need for decentralized solutions due to the high mobility and dynamic nature of these vehicles. Our focus was on creating a faster, more reliable communication platform for EnFVs to support various applications. We provided a comprehensive analysis of EnFVs and their integration into intelligent transportation systems. This involved examining the role of Artificial Intelligence, particularly Genetic Algorithms, in optimizing communication decisions for highly mobile vehicles. Our study highlighted the effectiveness of multi-objective optimization algorithms in addressing the unique challenges of EnFV networks. We developed a novel multi-objective routing scheme that considers diverse constraints and objectives. This scheme prioritizes energy efficiency and transmission rates while maintaining vehicle connectivity. Using Genetic Algorithms, we identified optimal solutions for these multi-objective routing problems. Our findings showed that the proposed scheme outperforms existing solutions. It achieved a packet delivery ratio of over 90%, extended connectivity times, reduced average hop distances, and improved energy efficiency.

Further, we demonstrated the potential of GAs in solving complex optimization problems in dynamic routing scenarios. This study contributes to the field by proposing a more efficient route discovery method suitable for high-mobility UAV networks. Future research should focus on several areas to enhance the efficiency and effectiveness of routing algorithms in EnFV networks. Firstly, integrating real-time data analytics could further optimize routing decisions. Secondly, developing more advanced AI-based algorithms could improve adaptability to changing network conditions. Lastly, extensive field testing with real-world EnFV scenarios would provide valuable insights and validate the practical applications of the proposed schemes. By addressing these future directions, we can continue to advance the field of EnFVs, aiming for seamless integration into modern transportation systems and further enhancing their operational efficiency and reliability.

Our detailed study of the proposed unified and efficient EnFV paradigm opens many new opportunities. The use of GA in existing research is significant, but our discussion extends it to EnFVs. Our dissertation opens several new directions, including real-time data with experimental results, considering other objectives, comparing different optimization techniques, and improving the sustainability and reliability of routing decisions in the EnFV environment.

Future work could involve testing the proposed scheme in real-world scenarios. This would provide practical data to support our findings. Additionally, we could explore other objectives that might be important for EnFVs. For example, safety, cost, and latency could be considered. Comparing our approach with other optimization methods could also be valuable. Techniques like PSO or ACN might offer different benefits.

Moreover, enhancing the sustainability of the routing decisions is crucial. This means ensuring that the routes chosen are not only efficient but also environmentally friendly. We can look at ways to minimize energy consumption further. Improving the reliability of these routing decisions is another area for future research. This involves making sure that the routes remain stable and efficient under various conditions. Our study lays a strong foundation for these future explorations, aiming to make EnFVs more effective and reliable.

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