Renewable Energy-Integrated UAV Path Planning for Sustainable and Efficient Medical Supply Delivery in Smart Cities Environments

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***Abstract*: This study proposes a renewable-energy-integrated UAV path-planning framework for medical delivery in smart cities. A hybrid Genetic Algorithm–Q-Learning (GA–QL) method is used to minimize travel distance, improve energy efficiency, and ensure safe navigation in environments with obstacles, weather effects, and recharging platforms. Simulation using TSPLIB instances shows that the proposed approach decreases logistics cost and completion time while increasing renewable-energy contribution. Results confirm the feasibility of hybrid optimization for sustainable and reliable UAV-based medical delivery.**

I. Introduction

Smart cities represent a transformative approach to urban development, where advanced digital infrastructure, real-time data analytics, and intelligent connectivity are leveraged to enhance the efficiency and sustainability of essential services [1]. Among these services, medical logistics plays a crucial role in ensuring the timely and reliable delivery of critical medical supplies such as medicines, vaccines, and blood products to hospitals and healthcare centers [2]. However, emergency medical delivery in densely populated urban environments faces persistent challenges such as traffic congestion, route unpredictability, and infrastructure limitations, which often lead to significant delays and compromise patient outcomes [3]. To overcome these constraints, Unmanned Aerial Vehicles (UAVs) have emerged as a promising alternative for healthcare logistics, capable of bypassing ground traffic, reaching remote or inaccessible areas, and enabling rapid delivery of medical essentials [4]. Recent studies have demonstrated the potential of UAV-based logistics in improving emergency responsiveness and reducing mortality rates, especially during critical situations such as pandemics and disaster relief operations [5]. Nevertheless, UAV deployment remains constrained by factors such as limited battery capacity, short flight endurance, and energy inefficiency [6]. To address these limitations, the integration of renewable energy sources, such as solar and hybrid energy systems, has been proposed to enhance UAV endurance, reduce operational costs, and promote environmental sustainability [7]. Renewable-powered UAV networks and solar charging infrastructures can significantly reduce carbon emissions, extend mission range, and ensure continuity of operations even in energy-scarce environments [8]. Building upon these insights, the present study aims to develop an optimized UAV path planning framework for emergency medical supply delivery in smart city environments, integrating renewable energy solutions to achieve both operational efficiency and sustainability. Specifically, the objectives are to design an energy-efficient route optimization model, incorporate renewable energy-based charging strategies, and evaluate performance based on delivery time, reliability, and environmental impact [9].

The remainder of this paper is organized as follows. Section II presents the problem formulation together with the proposed hybrid GA–Q-Learning methodology for renewable-energy-integrated UAV path planning. Section III describes the simulation scenario, dataset characteristics, performance metrics, and reports the computational results along with their discussion. Section IV concludes the paper and highlights directions for future research.

II. Methodology and Proposed Solution

A. Problem Formulation and Modeling

This study presents a fleet-based UAV delivery model designed for the distribution of medical supplies in crowded urban areas. The operational environment is represented as a directed network graph, where emergency sites, depots, and recharging platforms are modeled as nodes, and feasible UAV flight paths as edges. Each UAV in the fleet operates under predefined payload, energy, and endurance capacities while dynamically adapting to urban constraints such as obstacles, weather zones, and recharging availability platforms (Fig. 1). To ensure reliable and secure operations, the model assumes stable communication links, validated weather thresholds, and adherence to aviation and safety regulations, including geofencing and emergency-response protocols. Additional features, such as real-time GPS tracking, adaptive altitude control, and automated alerts support navigation accuracy and safeguard sensitive medical payloads. Although validated through simulation, real-world implementation remains crucial for handling stochastic variations and improving robustness.

The network graph is defined as $Gr = (S, D)$, where $S=\{s_0, s_1, \ldots, s_n\}$ represents the depot (s_0), delivery sites, and recharging

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stations, and $D = \{(s_x, s_y): s_x, s_y \in S, x < y\}$ denotes the set of directed paths connecting them. Each UAV $d_m \in M$ begins and ends its route at the depot, visiting a subset of $S \setminus \{s_0\}$ nodes. Each edge d_{ij} connects nodes i and j symmetrically and is associated with distance, time, and energy cost parameters. The model further integrates sets for obstacles (O), weather zones (W), time steps (T), and battery parameters including maximum energy E_{max} and consumption per distance $E_{cons}(d_{ij})$.

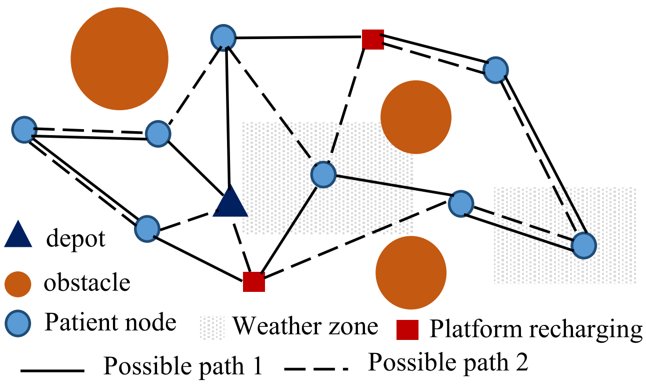

Fig 1: UAV path planning

A fleet of drones, each with a maximum capacity D_m, is deployed to satisfy delivery demands without exceeding payload or energy constraints. The Decision variables include x_{ij}, indicating whether a drone travels directly from node i to node j: y_w, representing weather zone traversals; E_i, the remaining energy at node i; and t_i, the drone's arrival time at node i. The objective is to optimize delivery routes across the fleet while balancing total travel distance, energy efficiency, recharging requirements, and environmental safety.

The objective is to minimize fleet-wide travel distance and environmental penalties while balancing energy usage, recharging opportunities, and safety.

$$\min \sum_{i \in N} \sum_{j \in n} d_{ij} x_{ij} + \sum_{w \in W} p_w y_w \qquad (1)$$

Constraints

1. Flow Conservation:

$$\sum_{j \in n} x_{ij} = 1 \;\; \forall\, i \in N \; (Each\ node\ is\ visited\ once) \qquad (2)$$

$$\sum_{i \in n} x_{ij} = 1 \;\; \forall\, j \in N \; (Each\ node\ is\ left\ once) \qquad (3)$$

2. Battery Energy Constraints:

$$E_j \le E_i - E_{cons}(d_{ij}) + M(1 - x_{ij}) \quad \forall\, i, j \in N \qquad (4)$$

$$E_i \le E_{max} \quad \forall\, i \in N \qquad (5)$$

3. Recharging and Renewable Energy Integration:

If solar available:

$$E_i = E_i + R_{solar} * t_{sun}, \qquad E_{renew} = E_{renew} + R_{solar} * t_{sun} \quad (6)$$

$$E_i = E_{max}, \forall\, i \in Recharging\ Platforms \qquad (7)$$

4. Obstacle Avoidance:

$$X_{ij} = 0 \quad \forall i, j \in O \qquad (8)$$

5. Weather Zone Crossing:

$$y_w \ge x_{ij} \;\; \forall\, i, j \in W \qquad (9)$$

6. Time Constraints:

$$t_j \ge t_i + \frac{d_{ij}}{S} - M(1 - x_{ij}) \quad \forall\, i, j \in N \qquad (10)$$

7. Start and End Depot Conditions:

$$t_{start} = 0, \;\; E_{start} = E_{max} \qquad (11)$$

The proposed fleet-based UAV delivery model minimizes travel distance and weather-related penalties (Eq. 1), while ensuring that each delivery node is served exactly once (Eqs. 2–3). It enforces energy and renewable recharging limits (Eqs. 4–7), ensures obstacle and weather safety (Eqs. 8–9), and maintains temporal feasibility (Eq. 10). At each recharging platform, drones can replenish their energy either through direct charging or from available solar energy sources. The renewable charging constraint is defined as $E_i = E_i + R_{solar} \times t_{sun}$, where R_{solar} denotes the solar recharge rate (kWh per unit time), and t_{sun} represents the solar exposure duration. The depot initialization condition (Eq. 11) synchronizes fleet operations with full charge and zero initial time. Collectively, these formulations ensure sustainable, energy-efficient, and coordinated fleet operations for medical UAV delivery in complex urban environments.

B. Genetic Algorithm

Genetic Algorithms (GAs) have been widely applied in UAV path optimization due to their ability to operate effectively in complex and dynamic environments. In this method, a population of candidate paths encoded as chromosomes is iteratively evolved through selection, crossover, and mutation operations [10]. Each chromosome represents a sequence of waypoints $W_i(x, y)$ that define the UAV's flight trajectory. During each iteration, the fitness of every chromosome is evaluated according to predefined objectives related to flight performance. The GA continues to evolve the population by retaining the best individuals through elitism until a stopping condition, such as convergence or a maximum number of iterations, is met [11,12]. The fittest chromosome from the final generation represents the optimal UAV path, ensuring stable and efficient mission execution [12].

C. Q-Learning (QL) Algorithm

Q-learning (QL), a model-free reinforcement learning (RL) technique, is widely employed to optimize UAV path planning through adaptive interaction with the environment. By modeling the problem as a Markov Decision Process (MDP), Q-learning iteratively derives an optimal policy that minimizes energy consumption while maximizing task-related rewards [13]. The UAV's state S represents its current environmental condition (e.g., position, velocity, remaining energy, and proximity to obstacles), while the action set A defines available maneuvers such as waypoint selection, speed adjustment, or altitude change [14].

During training, a Q-table $Q(S,A)$ is initialized to estimate the long-term value of each state–action pair. An ε-greedy policy balances exploration and exploitation, allowing the UAV to discover energy-efficient behaviors. After each interaction, Q-values are updated using the standard rule:

$$Q(s,a)= Q(s,a)+\alpha[r+\gamma \max Q(s',a') - Q(s,a)] \quad (12)$$

Where α is the learning rate, γ the discount factor, r the reward, and s' the next state. Rewards are assigned based on energy efficiency and mission performance, while penalties discourage collisions and excessive power use. Training continues until convergence, producing an optimal policy that enables the UAV to navigate safely and efficiently under dynamic environmental conditions [15].

D. Hybrid GA–QL Based Optimization Framework

To enhance UAV path planning efficiency, a hybrid optimization framework combining Genetic Algorithms (*GA*) and *Q*-learning (*QL*) is proposed. In this approach, GA provides robust global search capabilities to explore diverse candidate paths, while *Q*-learning refines these paths through adaptive interaction with the environment. The synergy between GA's exploration and *Q*-learning's exploitation ensures improved convergence, energy efficiency, and operational adaptability [16].

The core of the hybrid *GA–QL* method lies in fitness evaluation. Each GA chromosome, representing a potential UAV path, is assessed using a fitness function designed to minimize energy consumption, travel time, and obstacle risk. During successive generations, new chromosomes are generated and evaluated to identify optimal solutions. *Q*-learning further refines these candidates by assigning cumulative rewards as dynamic fitness measures, enabling the algorithm to iteratively learn and adapt from environmental feedback. This integration ensures that each solution evolves not only through genetic variation but also through reinforcement-driven experience, leading to more intelligent and energy-efficient UAV navigation. [17]

Algorithm 1 represents the central coordination mechanism of the proposed hybrid GA/Q-learning-based multi-drone delivery system. The process begins with the initialization of system constants, drone parameters, and environmental factors such as obstacles, weather zones, and charging stations. A population of candidate fleet routes is then generated, where each chromosome encodes multiple drone paths separated by the depot node. In each generation, the algorithm evaluates every fleet chromosome by decomposing it into drone-specific routes, computing their fitness values based on environmental dynamics and energy consumption, and updating drone states following route execution. The resulting fitness measures guide the evolutionary process through the application of hybrid genetic operators combined with reinforcement-driven learning updates, thereby improving route efficiency and adaptability. The iterative optimization continues until convergence or the completion of all delivery tasks. Finally, a comprehensive delivery planning phase consolidates total distance, time, and cost metrics to produce an optimized summary of fleet performance.

Algorithm 1: Framework of the Proposed Algorithm

```
Initialize system constants,
Generate initial fleet population,
While (termination condition not met) do
    For each chromosome in the population do
        Split chromosome into drone-specific routes.
        For each drone route do
            Evaluate route.
            Execute delivery route
        end for
        Aggregate fleet fitness and results.
        Apply hybrid GA/Q-Learning operations.
    end for
    Check convergence
end while
Perform final delivery planning optimization.
Return mission results.
```

E. Algorithmic Design for Hybrid Renewable-Energy UAV Delivery

The proposed Hybrid Renewable-Energy UAV Delivery Algorithm (**Algorithm 2**) aims to optimize autonomous drone-based logistics under dynamic environmental and energy constraints. The algorithm integrates obstacle avoidance, weather adaptation, and renewable energy utilization to enhance delivery reliability and sustainability. Each UAV is assigned a set of delivery nodes and operates under time-window, payload, and energy limitations. During operation, the algorithm continuously computes travel distance and time, performs local replanning when obstacles or adverse weather conditions are detected, and manages energy through hybrid renewable sources such as solar and auxiliary hybrid systems. When renewable energy is insufficient, drones are directed to the nearest charging station to ensure mission continuity. Throughout the process, cumulative performance indicators including total distance, total time, operational cost, and energy efficiency are updated, providing a holistic evaluation of the delivery system's performance.

Algorithm 2: Renewable Energy-Integrated UAV Routing and Delivery Optimization

Input: Nodes X[0..n], Drones D[1..m], Obstacles, Weather zones, Charging stations
Output: Total_Distance, Total_Time, Total_Cost, Energy_Efficiency, Delivery_Schedule
Step 1. Initialize:
Total_Distance = 0, Total_Time = 0, Total_Cost = 0
j = 1, Battery_Level = E_max, Remaining_Capacity = Max_Capacity
R_solar, η_hybrid, E_renew = 0
Step 2. For each node i in X:
a. Compute Distance_To_Next and Travel_Time
b. If path intersects obstacle/weather → local replanning
c. Update Total_Time, Arrival_Time
Step 3. Check time windows:
If Arrival_Time < ET_i → wait
If Arrival_Time > LT_i → j = j + 1
Step 4. Energy Management:
Energy_Needed = Distance_To_Next * (Base_Consumption + Payload*Coefficient)
If Battery_Level < Energy_Needed:
If solar available → Battery_Level += R_solar * t_sun; E_renew += harvested

Else if hybrid available → Battery_Level += η_hybrid * Hybrid_Energy

Else → go to nearest charging station; update Battery_Level, Total_Cost, Total_Time

Step 5. Delivery:

Deliver package at node i

Total_Distance += Distance_To_Next

Battery_Level -= Energy_Needed

Update Remaining_Capacity

Step 6. Log renewable energy:

Efficiency = (E_renew / E_total_consumed) * 100%

Step 7. Output Total_Distance, Total_Time, Total_Cost, Efficiency, Delivery_Schedule

III. Computational Experiment and Simulation Results and Discussion

A. Experimental Setup and Benchmark Evaluation

The proposed Hybrid GA–QL algorithm was implemented in Java and executed on an Intel Core i5-8250 CPU operating at 1.8 GHz with 8 GB RAM. To evaluate the optimization capability and convergence behavior of the proposed framework, benchmark instances from TSPLIB [23] and CVRPLIB were employed. Initially, three classical TSP benchmark instances, namely Berlin-52, Eil-101, and Ch-150, were solved to assess route optimization performance and algorithmic stability. The comparative results against conventional optimization methods including Genetic Algorithm (GA), Simulated Annealing (SA), Tabu Search (TB), and Particle Swarm Optimization (PSO) are summarized in Table 1 (Available at the end of the paper.). The Average Error (AE%) metric was used to quantify deviation from the optimal or best-known solution. The obtained results demonstrate that the proposed GA–QL algorithm consistently achieves optimal or near-optimal solutions with superior convergence stability and significantly lower optimality gaps compared with traditional metaheuristics.

To further validate the framework under capacitated routing conditions relevant to UAV medical delivery systems, additional experiments were conducted using standard CVRPLIB benchmark instances, including A-n32-k5, A-n60-k9, and A-n80-k10. The proposed Hybrid GA–QL approach was compared with classical GA, PSO, and Q-learning-assisted evolutionary algorithms (QL-EA). All experiments were repeated over 20 independent runs to ensure statistical consistency and robustness. The comparative results presented in Table 2 show that the proposed framework achieves the lowest average optimality gaps across all benchmark instances, with an average deviation of only 0.44% from benchmark optimal solutions.

The convergence performance illustrated in Table 3 demonstrates that the proposed GA–QL framework converges significantly faster than the classical GA and standalone QL-EA methods. This improvement is primarily attributed to adaptive operator selection and reinforcement-learning-guided exploration strategies, which improve solution quality while reducing unnecessary search iterations.

In addition to optimization quality and convergence speed, the proposed framework incorporates renewable-energy-aware UAV routing mechanisms. Therefore, the sustainability evaluation focuses on reducing total energy consumption and increasing renewable energy utilization during UAV operations. Table 4 summarizes the energy performance improvements achieved by the proposed framework. The Hybrid GA–QL model reduces total energy consumption by up to 6.95% compared with the conventional GA while simultaneously increasing renewable energy utilization by up to 8.70%.

To evaluate the operational feasibility of the proposed framework under realistic UAV medical delivery conditions, extensive simulation experiments were conducted across multiple delivery scenarios with varying payload capacities and city scales, as summarized in Table 5. The evaluation considered several operational and energy-related performance metrics, including the number of cities, UAV payload capacity, number of delivery trips, operational distance (OD), operational time (OT), total energy consumption (E_total), harvested renewable energy (E_renew), energy efficiency, and mission status. The simulation environment modeled renewable-energy-assisted UAV operations within dynamic urban settings characterized by weather disturbances, restricted flight zones, charging stations, and multiple operational constraints. UAV routing and scheduling decisions were dynamically adapted according to battery status, renewable energy availability, payload limitations, and mission feasibility conditions. The experimental results demonstrate that increasing payload capacity significantly raises total energy consumption and may result in mission abortion due to battery limitations, especially in large-scale delivery scenarios. In contrast, lower payload configurations improve mission success rates, operational stability, and overall routing efficiency. Furthermore, the integration of renewable energy harvesting mechanisms substantially enhances energy efficiency and extends UAV operational endurance. Overall, the results confirm that the proposed Hybrid GA–QL framework achieves highly competitive optimization performance while improving convergence behavior, renewable energy utilization, mission sustainability, and operational reliability in complex dynamic urban environments.

B. Scenario and Optimization Objective

This study proposes a renewable energy-integrated UAV path planning framework for efficient navigation within obstacle-filled urban environments. The problem is formulated as an optimization task aiming to minimize energy consumption while ensuring complete area coverage and obstacle avoidance [21,22]. The operational domain is modeled as a 2D region (X*Y) containing six static obstacles with predefined geometries and locations. Within this setting, the UAV must determine an optimal trajectory represented as a sequence of (x, y) waypoints that guarantees safe traversal and full coverage under relevant operational and collision-avoidance constraints [23]. Beyond geometric feasibility, energy consumption is incorporated as a critical optimization factor, as suboptimal routing can increase flight time and compromise mission sustainability. The integration of renewable energy resources further enhances operational efficiency by supporting intelligent charging and energy-aware decision-making throughout the mission.

This study examines an efficient drone-based medical delivery system using total logistics distance (OD), total completion time (OT), total consumed energy, renewable-energy, efficiency and status of battery as key metrics, with each simulation capped at three hours. A clustered 2D region contains a central depot serving variation demand points (0.1–0.9 kg) in function of instance dimension. The UAV payload carries up from 7 to 20 kg, travels 50 km per charge, consumes 0.1 kWh/km, and recharges at five platforms within 30–60 min. Wind-influenced zones, restricted areas (180–200 m radius), and obstacle towers (40–75 m radius) introduce operational risks and penalties. Equipped with LiDAR/ultrasonic sensors and IP54 weather tolerance, the UAV navigates safely through constrained environments to support optimal renewable-energy-aware routing.

C. Simulation Results and Discussion

The simulation results demonstrate the strong impact of payload configuration on system performance, operational distance, and energy consumption. As the payload decreases from 15 kg to 7 kg for the eil51 and Eil-101 instances, the number of required trips increases to satisfy delivery demand, leading to higher operational distances and total energy usage. However, this increase is well managed by the proposed routing and energy management framework, as reflected by consistently high efficiency values reaching 98–99%. The use of renewable energy remains substantial across all scenarios, contributing significantly to the sustainability of the system. For large-scale instances such as a280, the model maintains excellent performance even with increased problem complexity and longer operating times. Mission abortion is observed primarily under heavy payload configurations, indicating physical and operational constraints of the drone fleet, while lighter payloads ensure full mission success. Overall, the results confirm that the proposed approach effectively balances delivery workload, energy consumption, and operational feasibility. The system exhibits strong adaptability to varying logistics demands, making it suitable for real-world urban drone delivery applications.

IV. Conclusion

The proposed GA–QL framework effectively improves UAV medical delivery by reducing cost, travel time, and battery dependence through renewable-energy harvesting and intelligent recharging. Increasing recharging platforms enhances feasibility and lowers cost, though renewable benefit depends mainly on mission duration relative to distance. Overall, integrating hybrid optimization and renewable energy provides sustainable and efficient UAV routing. Future work will explore multi-UAV coordination, real-time forecasting, and practical implementation in smart-city emergency systems.

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TABLE. 1. Evaluation Results on TSPLIB Benchmark Instances.

Instances	No. Cities	Opt.	Algorithm	Avg.	Best	S. dev.	A.E %
Berlin-52	52	7542	Ga	8259.24	7647.2	79.48	1.39
			SA	9276.67	8645.3	188.87	14.63
			TB	9238.71	8167.7	389.48	8.30
			PSO	24659.1	12568.8	4157.87	66.65
			GA – QL	7583.75	7542	74.19	0
Eil-101	101	629	Ga	1502.71	1349.8	81.54	114.59
			SA	888.44	799.22	48.58	27.06
			TB	821.606	753.88	41.08	19.85
			PSO	1873.5	1576.2	108.7	150.59
			GA – QL	637.6	629	7.5	0
Ch-150	150	6528	Ga	24356.17	19775	3774.56	202.93
			SA	11882.33	10500	725.86	60.85
			TB	11085.08	9875.6	611.69	51.28
			PSO	--	--	--	--
			GA – QL	6573.2	6528	30.25	0

TABLE. 2. Comparative Solution Quality on CVRPLIB Instances.

Instance	Opt.	GA	PSO	QL-EA	GA–QL	A.E %
A-n32-k5	784	801	796	790	**786**	**0.26%**
A-n60-k9	1354	1398	1382	1369	**1360**	**0.44%**
A-n80-k10	1763	1835	1810	1789	**1774**	**0.62%**

TABLE. 3. Convergence Performance (Iterations to Stability).

Instance	GA	QL-EA	GA–QL
A-n32-k5	420	350	**290**
A-n60-k9	780	640	**510**
A-n80-k10	1150	960	**720**

TABLE. 4. Renewable Energy Performance Comparison.

Instance	Energy Reduction vs GA	Renewable Energy Increase vs GA
A-n32-k5	3.75%	6.30%
A-n60-k9	5.85%	7.80%
A-n80-k10	6.95%	8.70%

TABLE. 5. Results of applying the proposed algorithm to various instances.

Instance	No. Cities	Payload (kg)	Number of trips	OD (km)	OT (s)	E_total (kWh)	E_renew (kWh)	Eff. (%)	Status
eil51	51	15	2	648	267	1283	385	99	ABORTED
		10	3	851	266	1354	406	99	SUCCESS
		7	4	931	266	1152	346	99	SUCCESS
Eil-101	101	15	4	1362	523	2498	750	99	ABORTED
		10	6	1764	527	2550	765	99	ABORTED
		7	8	2075	530	2537	761	99	SUCCESS
a280	280	20	9	1014	1415	2650	804	98	SUCCESS
		15	10	1067	1414	2288	686	98	SUCCESS
		10	15	1217	1415	1946	584	98	SUCCESS
		7	21	1420	1417	1794	538	98	SUCCESS