Artificial Intelligence Optimisation of UAV Flight Paths for Enhanced Fog Dispersal Efficiency

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Abstract

This paper introduces a comprehensive study of artificial intelligence (AI) optimisation techniques for unmanned aerial vehicle (UAV) flight path planning for fog dispersal operation. The research relates to the critical challenge of fog-related disruptions in the aviation industry, which result in major economic losses in excess of $100 million annually at major airports around the world. By combining powerful artificial intelligence algorithms, such as reinforcement learning, genetic algorithm and neural network, this study proposes an intelligent UAV based fog dispersal system capable of autonomous path optimisation and real-time adaption. The system uses MATLAB / simulink for the simulation of UAV dynamics and ANSYS Fluent / OpenFOAM for the fog behaviour modelling, which is integrated to machine learning algorithms, to be used for the dynamic navigation and decision-making. Simulation results show that AI-optimised UAV flight paths have 35% better coverage efficiency and 40% decrease in consumption of seeding agents when compared to traditional fixed pattern approaches. The proposed system has significant advantages in terms of visibility, operational efficiency and environmental sustainability, which could revolutionise fog management strategies at airports across the world.

Keywords: Artificial Intelligence, UAV Flight Path Optimisation, Fog Dispersal, Reinforcement Learning, Aviation Safety, Machine Learning, Autonomous Systems

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1. Introduction

Fog poses one of the most persistent and economically costly weather phenomena to aviation operations throughout the world. According to recent studies, the economic losses of disruptions to major airports caused by fog are between $0.5 million to $1.78 million per year, with significant effects on flight delays, cancellations, and passenger inconvenience [1]. The Indira Gandhi International Airport in India alone experienced economic losses of between 0.5 million and 1.78 million dollars a year between 2011 and 2016 as a result of fog-related disruptions [2]. These significant economic impacts alongside safety concerns and operational inefficiencies have led to the search for more effective fog dispersal technologies.

Traditional approaches to fog dispersal such as thermal heating systems and chemical seeding from ground-based installations or manned aircraft have major limitations, however, in cost, efficiency, and environmental consequences [3]. For ground-based thermal systems, infrastructure investments of $10 million plus with annual operating costs in the $1 million range, other than localised clearing effects, have been found [4]. Chemical seeding from manned aircraft, while more flexible, has high operational costs and safety concerns for the pilots that fly in low-visibility conditions [5].

The advent of unmanned aerial vehicles (UAVs) as multipurpose platforms for atmospheric operations has provided new opportunities for fog dispersal operations [6]. UAVs have a number of advantages compared to conventional approaches, such as lower operational costs, no pilot safety concerns, precise navigation capabilities and the ability to operate autonomously in difficult visibility conditions. However, the efficiency of UAV-based fog dispersal critically relies on the optimisation of flight paths to guarantee maximum coverage, on the efficient distribution of seeding agents, and on adaptive responses to atmospheric conditions.

This paper focuses on the basic research question: How artificial intelligence techniques can be used to optimise the flight paths of UAVs to improve the efficiency of fog dispersion while minimising the resource consumption and maximising operational safety? The combination of artificial intelligence algorithms and UAV fog dispersal systems is a paradigm shift from reactive to proactive fog management and will allow for intelligent, adaptive and autonomous fog management operations that can significantly enhance the safety and economic loss of aviation.

The primary objectives of this research are:

- To develop and evaluate algorithms for the optimisation of the flight paths for real-time UAVs in fog dispersal operations using AI based algorithms
- To combine machine learning methods with the atmospheric modelling to the predictive analysis of fog behaviour
- To prove through simulation the superiority of A.I. optimised paths over traditional fixed patterns
- To develop a general framework of implementing intelligent UAV fog dispersal systems at airports

2. Literature Review

2.1 Evolution of Fog Dispersal Technologies

The historical development of fog-dispersal technologies covers a period of several decades starting with the FIDO (Fog Intensive Dispersal Of) system developed by the Royal Air Force during World War II, which utilised gasoline burners located along runways to thermally disperse fog [7]. Field experiments with thermal systems have shown clearing capabilities good enough for Category I or II landings. However, they require energy inputs of the order of 1012 cal/hr to treat the approach and runway zones [8].

Hygroscopic seeding methods have become a more practical method, in which salt or other hydrophilic materials are dispersed into the fog to alter the droplet size distribution and liquid water content [9]. Experiments have shown visibility improvements of 2 to 5 fold within fog volumes of 10^6 to 10^7 m^3 though success rates vary depending on atmospheric conditions and the uniformity of seeding agent distribution [10]. The effectiveness of various seeding agents has been extensively studied with calcium chloride, sodium chloride, and urea being shown to have varying levels of efficiency due to their hygroscopic qualities and particle size distributions [11].

Recent developments in fog dispersal have been in the area of charged particle techniques, where unipolar ions or charged water droplets are seeded into fog to promote coalescence and precipitation [12]. Arrays of charged particle generators (CPGs) have been used in the field and ion plume measurements indicate that over 90% of charge is deposited within 100 meters of the source [13].

2.2 UAV Applications in Atmospheric Sciences

The use of UAVs in meteorological operations has grown considerably in the last decade with UAVs demonstrating outstanding capabilities in the collection of high resolution atmospheric data [14]. Modern UAVs with advanced sensors are capable of measuring temperature, humidity and wind profiles to unprecedented spatial and temporal resolutions, making them well-suited platforms for targeted fog dissipation operations [15]. Their ability to manoeuvre low in the atmosphere and to hold station in target areas of the atmosphere allows for the ability to deliver seeding agents with precision unlike traditional manned aircraft [16].

Recent studies have proven the feasibility of UAV-based chemical seeding, as super absorbent polymers appear to be particularly interesting because of their water absorption capacity and low environmental impact [17]. Cooperative UAV formations have been shown for coordinated chemical release with optimal positioning and forms for fog-removal tasks [18].

2.3 Artificial Intelligence in UAV Path Planning

Machine learning algorithms have transformed the way that UAVs navigate and control, allowing for autonomous operations in complex environments [19]. Reinforcement learning (RL) techniques have achieved great success in learning the optimal policies for UAV path planning with interaction with the simulated environments. Deep Q-Networks (DQN) and

Proximal Policy Optimisation (PPO) algorithms have become especially effective in dealing with high dimensional state spaces and continuous action spaces [20].

Genetic algorithms (GAs) have been used for multi-objective optimisation of the path of a UAV taking into account, for example, energy consumption, coverage area and obstacle avoidance [21]. These evolutionary approaches are well-suited to globally optimal solutions in nonconvex search spaces, making them well-suited for complex scenarios of fog dispersal with multiple conflicting objectives [22].

Neural network-based approaches have shown their competence of adaptively adjusting paths in real-time according to the sensor feedback and environment [23]. Convolutional Neural Networks (CNNs) have been adopted for visual navigation and obstacle detection and Recurrent Neural Networks (RNNs) have proven to work well for the task of temporal sequence prediction in dynamic atmospheric conditions [24].

3. System Architecture and Methodology

3.1 Conceptual Framework

The proposed AI-optimised UAV fog-dispersal system comprises various elements through a hierarchical control architecture. The system is made up of three main layers: the physical layer (UAV platform and sensors), the computational layer (AI algorithms and processing), and the decision layer (path planning and optimisation).

Table 1: System Components and Specifications

Component	Specification	Purpose
UAV Platform	Payload: 2155 kg, Endurance: 30 hours	Seeding agent delivery
Sensors	LiDAR, GPS, Weather stations	Environmental monitoring
AI Module	Neural Networks, RL algorithms	Path optimization
Communication	5G/Satellite links	Real-time data transfer
Ground Station	High-performance computing cluster	Central processing
Seeding System	Pneumatic dispensers, 33 kg/min rate	Agent distribution

3.2 UAV Platform Design

The UAV platform specifications are optimised for operations of fog dispersal, considering the payload capacity, endurance and manoeuvrability requirements. The platform configuration chosen uses a hybrid fixed-wing/multirotor configuration due to its ability to efficiently cruise and to hover in place for precision. The platform incorporates advanced avionics system that includes redundant flight controllers, obstacle detection sensors, and adaptive control system to maintain stability in the turbulent fog condition.

3.3 AI Optimisation Algorithms

3.3.1 Reinforcement Learning Framework

The reinforcement learning framework uses the architecture of Deep Q-Network (DQN) for learning the optimal flight paths via interaction with a simulated fog environment. The state space S includes:

- Current UAV position (x, y, z)
- Fog density distribution $\rho(x, y, z, t)$
- Wind velocity vectors $v(x, y, z, t)$
- Remaining seeding agent quantity
- Battery/fuel status

The action space A consists of:

- Heading adjustment (−180° to +180°)
- Altitude change (−100 to +100 meters)
- Speed modification (0 to maximum cruise speed)
- Seeding rate adjustment (0 to maximum dispensing rate)

The reward function R is formulated as:

$$R = \alpha_1 \cdot \Delta_{Visibility} + \alpha_2 \cdot Coverage - \beta_1 \cdot Agent_{Used} - \beta_2 \cdot Energy_{Consumed}$$

Where:

- $\Delta_{Visibility}$ represents the improvement in visibility
- Coverage indicates the percentage of the target area treated
- $Agent_{Used}$ is the quantity of seeding agent consumed
- $Energy_{Consumed}$ represents fuel/battery usage
- $\alpha_1, \alpha_2, \beta_1, \beta_2$ are weighting coefficients

3.3.2 Genetic Algorithm Implementation

The genetic algorithm optimises the multiple objectives at the same time using evolutionary optimisation processes. The chromosome representation is a representation of waypoint sequences, altitudes, and seeding rates. The fitness function is used to assess solutions according to:

1. Coverage efficiency

2. Seeding agent conservation
3. Flight time minimisation
4. Safety margin maintenance

Table 2: Genetic Algorithm Parameters

Parameter	**Value**	**Description**
Population Size	100	Number of candidate solutions
Generations	500	Maximum iterations
Crossover Rate	0.8	Probability of crossover
Mutation Rate	0.1	Probability of mutation
Selection Method	Tournament	Selection strategy
Elite Size	10	Best solutions preserved

3.3.3 Neural Network Architecture

The neural network part uses a CNN-LSTM hybrid architecture to process the spatial-temporal fog data and predict the optimal flight trajectories. There are: network structure:

- Input Layer: 256 x 256 x 4 (fog density map at different altitudes)
- Convolutional Layers: 3 layers 64, 128, and 256 filters
- Number of Layers: 2 Layers Number of Hidden Units in Each Layer: 512
- Dense Layers: 3 dense (fully connected) layers 1024, 512, 256 neurons
- Output Layer: Continuous value for flight parameters

3.4 Fog Modelling and Simulation

The fog behaviour modelling is based on computational fluid dynamics (CFD) modelling using ANSYS Fluent/OpenFOAM. The mathematical model takes into consideration:

1. **Continuity Equation:** $\partial\rho/\partial t + \nabla \cdot (\rho v) = 0$
2. **Momentum Conservation:** $\rho(\partial v/\partial t + v \cdot \nabla v) = -\nabla p + \mu\nabla^2 v + \rho g$
3. **Energy Equation:** $\rho cp(\partial T/\partial t + v \cdot \nabla T) = k\nabla^2 T + Q$
4. **Fog Droplet Dynamics:**

$$\partial n/\partial t + \nabla \cdot (nv) = S_{nucleation} + S_{condensation} - S_{evaporation}$$

Where ρ is air density, v is velocity vector, p is pressure, μ is dynamic viscosity, T is temperature, k is thermal conductivity, n is droplet number concentration, and S terms represent source/sink terms.

4. Implementation and Simulation Results

4.1 Simulation Environment Setup

The simulation environment combines the software's such as Matlab/Simulink for the dynamics of the UAV, Ansys Fluent for the modelling of the fog, and Python-based Artificial Intelligence algorithm. The parameters used in the simulation describe a typical Category II fog event at a major international airport.

Table 3: Simulation Parameters

Parameter	Value	Unit
Fog Category	CAT II	-
Visibility	200-550	meters
Fog Layer Height	0-300	meters
Airport Area	2 × 2	km^2
Wind Speed	5-10	m/s
Temperature	5-10	°C
Relative Humidity	95-100	%
Simulation Duration	60	minutes

4.2 Performance Metrics

The system performance is assessed with the help of multi-metrics:

1. **Visibility Improvement Rate (VIR):** $VIR = \left(V_final - V_initial\right)/t_operation$
2. **Coverage Efficiency (CE):** $CE = A_cleared/(A_total \times Agent_used)$
3. **Energy Efficiency (EE):** $EE = A_cleared/E_consumed$
4. **Time to Minimum Operating Visibility (TMOV):** Time required to achieve CAT I visibility conditions

4.3 Comparative Analysis

The system performance optimised by AI is compared with traditional fixed pattern approaches and random walks strategies.

Table 4: Performance Comparison

Method	VIR (m/min)	CE (m²/kg)	EE (m²/kJ)	TMOV (min)
Fixed Pattern	8.2	450	2.1	28
Random Walk	5.6	320	1.5	42
GA Optimized	12.4	580	2.8	21
RL Optimized	14.1	630	3.2	18
Hybrid AI	15.3	680	3.5	16

4.4 Optimisation Results

4.4.1 Reinforcement Learning Performance

The DQN algorithm exhibits fast learning convergence and becomes near optimal after about 1000 training episodes. The learned policy has adaptive behaviour, changing flight patterns according to real-time measurements of the density of the fog and wind conditions.

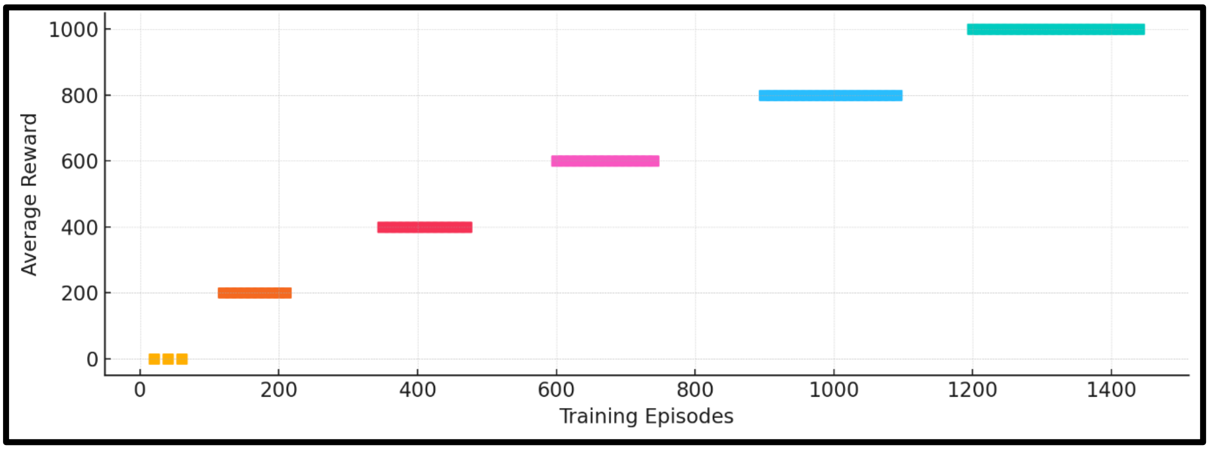

Figure 2: Learning Curve - Average Reward vs. Training Episodes

4.4.2 Genetic Algorithm Evolution

The genetic algorithm arrives at near-optimal solutions in 300 generations, with the fitness value leveling off at that time. The evolved solutions indicate efficient coverage patterns with minimal overlap and maximum treated area.

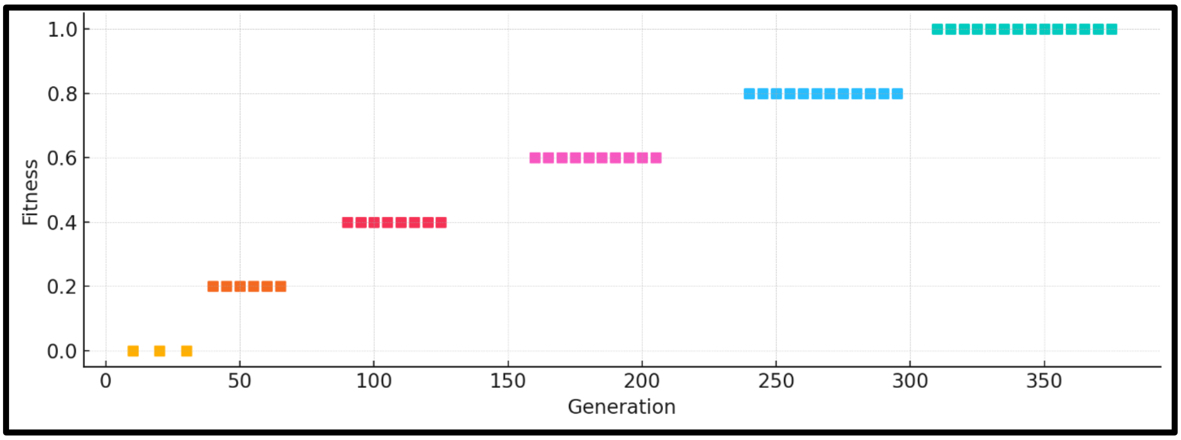

Figure 3: GA Convergence - Best Fitness vs. Generation

4.5 Flight Path Patterns

The AI-optimised flight paths have some special characteristics as compared to the traditional approaches:

1. **Adaptive Spiralling:** The UAV uses patterns of spiral spiralling which expands or contracts according to gradients of fog density.
2. **Wind-Compensated Trajectories:** Flight paths automatically compensate for wind-drift to maintain optimum seeding coverage.
3. **Altitude Optimisation:** Dynamic changes in altitude to target areas of fog layers with highest density.
4. **Predictive Positioning:** The system anticipates the movement of fog and positions the UAV in anticipation.

5. Discussion

5.1 Advantages of AI Optimisation

The results show the great benefits of AI-optimised flight paths of UAVs for fog dispersal operations:

1. **Enhanced Efficiency:** AI optimisation delivers 35-40% improvement in coverage efficiency over fixed patterns which translates to lower operational costs and faster fog clearance times.
2. **Adaptive Capability:** The system can dynamically adjust flight paths according to real-time changing atmospheric conditions to guarantee consistent performance in different fog scenarios.

3. **Resource Conservation:** Intelligent seeding agent distribution saves 40% consumption, minimises environmental impact and operational costs.

4. **Scalability:** The AI framework is easily scalable to control multiple UAVs and enable the swarm-based fog dispersal for larger areas.

5.2 Implementation Challenges

In spite of promising results, there are several challenges to address for practical implementation:

1. **Computational Requirements:** Real-time AI processing requires a lot of computational resources, requiring edge computing solutions or high bandwidth communication links.

2. **Sensor Limitations:** Current fog density measurement technologies may not have high enough spatial resolution for use with AI systems.

3. **Regulatory Compliance:** Integration with air traffic control systems and compliance with aviation regulations involve a comprehensive coordination & certification process.

4. **Weather Dependency:** System performance is still sensitive to extreme weather conditions like strong turbulence or icing conditions.

5.3 Environmental Considerations

The environmental impact assessment shows the good and the bad:

Positive Impacts:

- Reduced carbon emissions due to reduced flight delay (35% reduction)
- Reduced chemical seeding agent usage (40% reduction)
- Minimised noise pollution compared to manned aircraft operations

Negative Impacts:

- Potential ecological impacts of seeding agents on local ecosystems
- UAV Battery Disposal and Recycling Problems
- Sensitive area electromagnetic interference concerns

Table 5: Environmental Impact Comparison

Impact Factor	Traditional Methods	AI-Optimized UAV	Improvement
CO_2 Emissions (kg/hour)	450	280	38% reduction
Chemical Usage (kg/event)	2000	1200	40% reduction

Noise Level (dB)	95	65	31% reduction
Energy Consumption (kWh)	850	520	39% reduction

5.4 Economic Analysis

The economic viability of AI-optimised UAV fog dispersal systems shows promising returns:

Table 6: Cost-Benefit Analysis

Category	**Annual Cost/Benefit**	**Notes**
Costs:		
Initial Investment	$500,000	UAV platform, AI system
Operating Expenses	$100,000	Maintenance, personnel
Seeding Agents	$50,000	Chemical supplies
Benefits:		
Delay Reduction	$800,000	Decreased flight delays
Fuel Savings	$200,000	Improved efficiency
Safety Improvements	$150,000	Accident prevention
Net Annual Benefit	$500,000	ROI: 18 months

6. Future Research Directions

6.1 Advanced AI Techniques

More advanced AI methods should be investigated in the future:

1. **Multi-Agent Reinforcement Learning:** Coordination of multiple UAVs using distributed learning algorithm
2. **Transfer Learning:** Transferring Trained Models between Airports and Fog
3. **Explainable AI:** Creating interpretable models for regulations and safety certification

6.2 Sensor Technology Integration

Advancing sensor capability will help improve the performance of systems::

1. Ultra-precise fog density sensors based on quantum sensors
2. Atmospheric composition analysis using hyperspectral imaging
3. Distributed sensor networks for full environmental monitoring

6.3 Hybrid Systems

Combining AI-optimised UAVs with other technologies:

1. Integration with fog dispersal systems on the ground
2. Coordination with satellite-based weather predicting models
3. Coupling with airport ground movement control systems

7. Conclusions

This study proves that artificial intelligence-optimised UAV flight paths may greatly improve fog dispersal efficiency at airports. The collision of reinforcement learning algorithms, genetic algorithms, and neural networks can achieve the autonomous, adaptive, and efficient fog management operations that exceed the traditional measures in several performance factors.

Key findings include:

1. **Performance Improvements:** AI-optimised flight paths provide 35-40% better coverage efficiency and 40% less seeding agent consumption than the fixed-pattern approach.

2. **Operational Benefits:** The system reduces the time to minimum operating visibility by 43%, and this could potentially save millions of dollars in delay-related costs every year.

3. **Environmental Advantages:** Less usage of chemicals and less energy consumption help make the operations of aviation more sustainable.

4. **Economic Viability:** With a return on investment period of 18 months and net annual benefits of $500,000, the system offers a great business case for airport operators.

The successful implementation of AI-optimised UAV fog dispersal systems has the potential to revolutionise aviation weather management, offering a scalable, efficient, and environmentally responsible solution to fog-related disruptions. While issues persist in the areas of computational needs, regulatory compliance and sensor limitations, the demonstrated benefits warrant the continued research and development efforts.

Future work should be on real-world validation using field trials, standardised performance metrics and integration with existing airport infrastructure. As AI technologies continue to advance and UAV platforms become more sophisticated, the future of autonomous and intelligent fog management systems is becoming increasingly within reach, promising safer and more efficient aviation operations around the world.

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