Mapping Lessons from Ants to Free Flight
An Ant-based Weather Avoidance Algorithm in Free Flight Airspace

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ABSTRACT

The continuing growth of air traffic worldwide motivates the need for new approaches to air traffic management that are more flexible both in terms of traffic volume and weather. Free Flight is one such approach seriously considered by the aviation community. However the benefits of Free Flight are severely curtailed in the convective weather season when weather is highly active, leading aircrafts to deviate from their optimal trajectories. This paper investigates the use of ant colony optimization in generating optimal weather avoidance trajectories in Free Flight airspace. The problem is motivated by the need to take full advantage of the airspace capacity in a Free Flight environment, while maintaining safe separation between aircrafts and hazardous weather. The experiments described herein were run on a high fidelity Free Flight air traffic simulation system which allows for a variety of constraints on the computed routes and accurate measurement of environments dynamics. This permits us to estimate the desired behavior of an aircraft, including avoidance of changing hazardous weather patterns, turn and curvature constraints, and the horizontal separation standard and required time of arrival at a pre determined point, and to analyze the performance of our algorithm in various weather scenarios. The proposed Ant Colony Optimization based weather avoidance algorithm was able to find optimum weather free routes every time if they exist. In case of highly complex scenarios the algorithm comes out with the route which requires the aircraft to fly through the weather cells with least disturbances. All the solutions generated were within flight parameters and upon integration with the flight management system of the aircraft in a Free Flight air traffic simulator, successfully negotiated the bad weather.

Keywords: Swarm Intelligence, Ant Colony optimization, Free Flight, Air Traffic Management, Weather Avoidance

1. INTRODUCTION

In recent years, a considerable increase in the number of weather-related flight delays has occurred, both due to increase in traffic as well as environmental factors. Weather is a major limiting factor in the Airspace capacity enhancement efforts under the umbrella of Free Flight **[12].** The aviation capacity enhancement plan lists weather as the leading cause of delays greater than 15 minutes, with terminal volume as the second cause **[3].** Weather related delays accounts for roughly 70% of all traffic delays **[4].** These delays are more significant particularly during the convective weather season (mid-May through mid-August) [Figure 1]. Moreover weather phenomenon and atmospheric activities are beyond human control and because safety must be maintained in the existence of weather-related hazards, therefore our ability to predict the weather and have robust solutions for safe negotiation will be critical towards designing the future air traffic management system **[5].** In this paper the problem of generating optimal weather avoidance routes under hazardous weather conditions is investigated under certain safety and performance constraints. This is done under the framework of swarm intelligence, a set of techniques called Ant Colony Optimization **[8]** were employed to solve the problem. It is demonstrated that an on board flight data management computer of an Free Flight air traffic simulator can be integrated with an Ant Colony Optimization (ACO) based weather avoidance system, generating optimal routes and negotiating bad weather within flight parameters.

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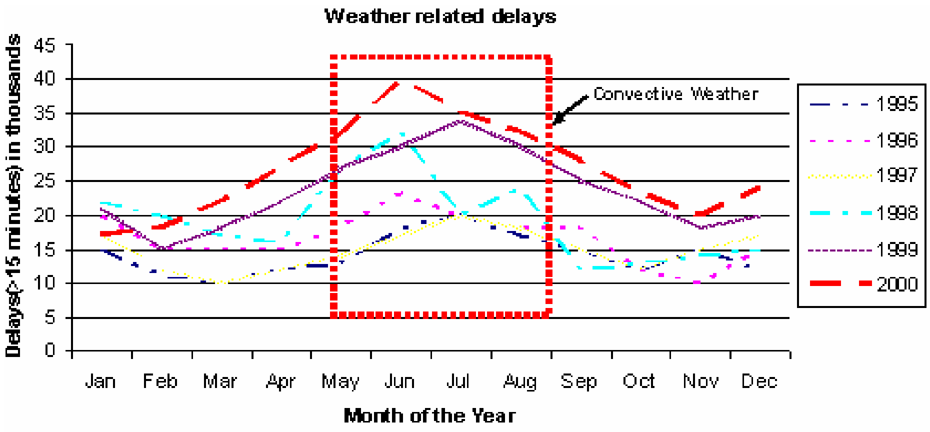

Figure 1: Yearly trend (1995-2000) for weather related delays (Source: OPSNET database)

The organization of this paper is as follows: Section 2 explains Swarm Intelligence with particular reference to ACO and its application in solving optimization problems, Section 3 describes the weather related problems faced by the aviation industry worldwide and the enabling technologies for weather avoidance in a future air traffic managements system. Section 4 describes how ACO can be applied to solve the weather avoidance problem in a Free Flight simulation environment. Section 5 explains the simulation setup & experiments for hazardous & complex weather situations in a Free Flight environment. Section 6 discusses the results and conclusions of this work. Section 7 presents some future directions.

2. SWARM INTELLIGENCE & ANT COLONY OPTIMIZATION

Swarm Intelligence can be described as any attempt to design algorithms or distributed problem devices inspired by the collective behavior of social insect colonies and other animal societies **[2].** The ant based optimization algorithm was introduced by M. Dorigo **[9]** and experimental results have shown it to be a promising approach for solving discrete optimization problems. Ant based algorithms are based on the notion that a set of simulated artificial ants, the behavior of which is designed after that of real ants, can be used to solve combinatorial optimization problems. Ant based algorithms have been applied to other combinatorial optimization problems such as the quadratic assignment problem, graph coloring, job shop scheduling, and vehicle routing **[1][13]**. Results obtained by ant based algorithms are often as good as with other general purpose heuristic algorithms. **[2]**

There are several advantages in investigating the application of ACO techniques in a Weather constrained Free Flight environment:

a) Versatility: The convective weather situations are highly dynamic, rapidly changing and unpredictable for any aircraft; the versatile nature of ACO algorithms suits them very well for unforeseen weather situations.

b) Robustness: Fee Flight allows for in-flight dynamic route changes, robust algorithms that are simple and guaranteed to find a solution, if one exists, are highly desirable for highly complex scenarios emerging from the dynamic interaction of various sub system of a Free Flight environment.

c) Population based approach: Since ACO allows the exploitation of positive feedback as a search mechanism and makes the system amenable to parallel implementations (though this is not considered in this paper), it is highly desirable given the stringent real time nature of an air traffic management system.

Previous work done in this domain demonstrated that Swarm intelligence based techniques can be successfully implemented on aircraft landing scheduling problems, air transport logistics route optimization, and runway allocation **[1] [11]**.

3. WEATHER CONSTRAINTS ON AIRSPACE CAPACITY ENHANCEMENTS

Hazardous weather events such as convective weather (e.g., lightning, tornados, turbulence, icing, hail, etc.), extreme weather (hurricanes, blizzards), low visibility (fog, haze, clouds), air turbulence, snow, and winds shifts pose challenges to air traffic on a nearly daily basis**[4]**. Air traffic management being a highly complex system, where arrival & departure schedules are tightly linked to each other, such weather related delays are not entirely limited to an individual aircraft. Rather, such delays at one point in airspace causes a delay ripple propagating its effects to a larger portion of the neighboring airspaces as well. The expected increase in capacity of the future Air traffic management system is eventually limited to its capacity to ensure safe and efficient travel under all weather conditions **[5]**.

The key to greater airspace capacity envisioned in Free Flight lies in our ability to accurately predict and adjust the future state of air traffic according to predictions related to weather and its effects on aircraft and flight routes.

A weather avoidance system coupled with Flight management system is identified as one of the key enabling technologies for Free Flight **[12]**. Dynamic in flight route changes to negotiate bad weather, keeping an aircraft within its performance parameters is expected to enhance safety and efficiency in Free Flight airspace of the future **[6]**.

4. ACS IMPLEMENTATION FOR FREE FLIGHT WEATHER AVOIDANCE

The main characteristics of the Free Flight weather avoidance problem can be summarized as follows:

- Intrinsically distributed with stringent real time constraints: Weather cells are usually distributed over a large area, and aircrafts have to follow stringent time constraints in order to meet required time of arrival at arrival fixes.
- Stochastic and time varying: Convective weather cells are time varying and have severity which changes dynamically.
- Multi Objective: Several conflicting objectives are taken into account. Most important is the safety of the aircraft and its passengers.
- Multi Constraints: A variety of constraints are imposed on the system, including aircraft performance envelop, search window, passenger's comfort etc.

The Ant Colony Optimization algorithm introduced by M. Dorigo, V.Maniezzo and A.Colorni **[7]** suits the problem dimensions and is implemented with some modifications to incorporate multi objective optimization **[10]** as dictated by the problem definition.

The problem of weather avoidance in a Free Flight context can be defined as, given a start node and end node in a two dimension mesh, find the most optimal route which avoids - if possible - bad weather cells, minimizes heading changes, minimizes distance traveled and reaches the end node within a constrained time. Figure 2 shows the high level system flow chart for the problem described.

The following assumptions were made for modeling the simulation environment

- There is a single aircraft in Free Flight airspace.
- The aircraft has a weather sensor which scans 50 nautical miles ahead of an aircraft on its flight trajectory.
- Weather cells are of a square size covering a region 10nm X 10nm and have a linear severity factor 1 to 10 denoting how bad the weather disturbance is in that cell.
- The aircraft is equipped with a flight management system, which is capable of making in flight dynamic route changes and flies the aircraft within its performance parameters.

The following constraints were considered in the algorithm

- Reach the target waypoint;
- Maintain flight performance envelop.
- Route search within the 1000 nm region surrounding the central bad weather cell.

The following optimization criteria were considered in the algorithm

- Bad weather cells avoidance;
- Minimize heading change;
- Minimize weather-resolution trajectory distance; and

The following modifications were made to the ACO to incorporate the previous three criteria:

4. 1 Tabu list: ACO maintains a tabu List for all the nodes it has visited so far. The search is repeated until the destination node is found or the ant has reached a node where there is no further states to move. This tabu list maintains the successful routes obtained by an Ant in one cycle. Based on the routes in the tabu list, the global best route is obtained and updated every cycle.

4.2 Transition rule: The transition probability of selecting a node j while at node i by an ant k at time t is given by

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}.[\tau'_{ij}(t)]^{\psi}.[\eta_{ij}]^{\beta}}{\sum\limits_{k\in AllowedRoutes}[\tau_{ik}(t)]^{\alpha}.[\tau'_{ik}(t)]^{\psi}.[\eta_{ik}]^{\beta}}\\ 0\end{cases}$$ if j is element of allowed paths k other wise [Equation 1]

where $[\tau_{ij}(t)]$ denotes the intensity of the trail on edge(i,k) at time t. $[\eta_{ij}]$ denotes the visibility and is the quantity $\frac{1}{\partial_{ij}}$, where ∂_{ij} denotes the heading change factor. α and β are parameters that control the relative importance of trail versus the visibility.

Pheromone intensity $[\tau^{t}_{ij}(t)]^{\psi}$ is introduced in the transition probability to incorporate the severity of weather. $[\tau^{t}_{ij}(t)]^{\psi}$ = {1/ Weather severity of Cell j at time t} and ψ denotes the relative importance of avoiding weather cells.

4.3 Global pheromone update

To encourage exploration, in every cycle all the ants that generated a successful tour are allowed to update the concentration of pheromones on every edge of the successful path and is given by

$$\Delta\tau_{ij}^{k}=\begin{cases}Q/L_k \ \ if\,(i,j)\in tour\ described\ by\ tabu\ list\\ 0 \quad otherwise\end{cases}$$ [Equation 2]

$$\Delta\tau_{ij}=\Delta\tau_{ij}+\Delta\tau_{ij}^{k}$$

Where Q is a constant and L_k = Tour Length + Heading Change Factor + Tour Weather Factor

Tour length is the number of cells traveled by the ant to reach the destination

Heading change factor gives summation of heading change performed during the tour. A straight heading have a factor of 0.5 and a heading change in either of the directions have a factor of 1.0.

Tour weather factor is the sum total of severity factor of weather cells encountered during the resolution maneuver. Weather cells are randomly created by the Free Flight air traffic simulator as 2D cells, generating a variety of weather scenarios ranging from simple to highly complex. Every cell represents a region of 10 nm X 10nm.

4.4 Pheromone Evaporation Rule

Let $\tau_{ij}(t)$ be the intensity of the trail on edge (i,j) at time t. Each ant at time t chooses the next node, where it will be at time t+1. Therefore, if we call an iteration of the ACO algorithm the m moves carried out by the m ants in the interval (t, t+1), then every n iterations of the algorithm each ant has completed a tour. At this point the trail intensity is updated according to the following formula

$$\tau_{ij}(t+n)=\rho.\tau_{ij}(t)+\Delta\tau_{ij}$$ [Equation 3]

Where ρ is a coefficient such that $1-\rho$ represents the evaporation of trail between time t and t+n,

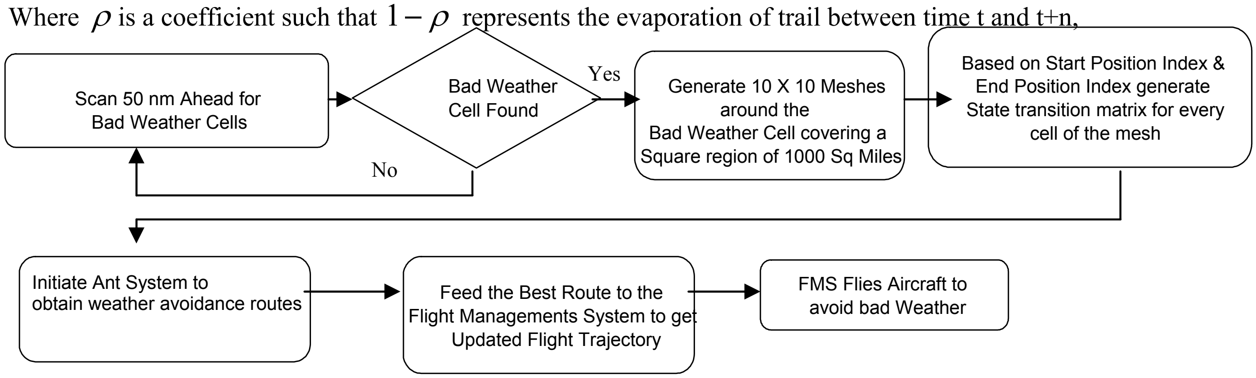

Figure 2: A High level system flow chart

5. SIMULATION SETUP & EXPERIMENTS

The Simulations & experiments were performed on a high fidelity Free Flight air traffic management simulation facility at the Artificial Life & Adaptive Robotics Lab, UNSW@ADFA.

As shown in Figure 4, the 10 nm X 10nm mesh generated centering on the bad weather cell covers a region of 1000 nm and forms the optimal route search envelop for the aircraft. Each mesh block is represented as a cell and has a state transition value, i.e. which cell it can go to, the weather severity in that cell. Each cell can have max 3 states assuming forward only motion by aircraft and maximum heading change of 45 degrees keeping in mind the aircraft performance parameters, as shown in Figure 3

- b->Straight ahead (0 Degrees relative to current heading)
- a->Left (315 Degrees relative to current heading)
- c->Right (45 Degrees relative to current heading)

Each cell is represented by I J K, and characterized by its latitude, longitude and altitude.

Flight possesses continues coordinates in terms of Lat-Lon-Alt-Time and the cells are discrete references points in the airspace. Weather cells are referred in 2D, i.e. latitude & longitude and the color code denotes the relative severity of the weather in those cells.

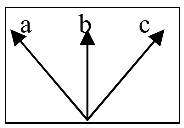

Figure 3: State transition in a Cell relative to current heading (b) of an aircraft in the cell

We implemented the Ant Colony Optimization algorithm with modifications to suit the problem and investigated the strengths and weaknesses in different scenarios by experimentation. The parameters which we measured here are those that influence the computation of the transition probability pheromone trail intensity, and weather severity.

α : The relative importance of the pheromones,

ψ : The relative importance of the weather severity

β : The relative importance of the visibility

ρ : Pheromone persistence, $0 <= \rho < 1$ ($1-\rho$) can be interpreted as trail evaporation);

Q: A constant related to the quantity of pheromones laid by ants

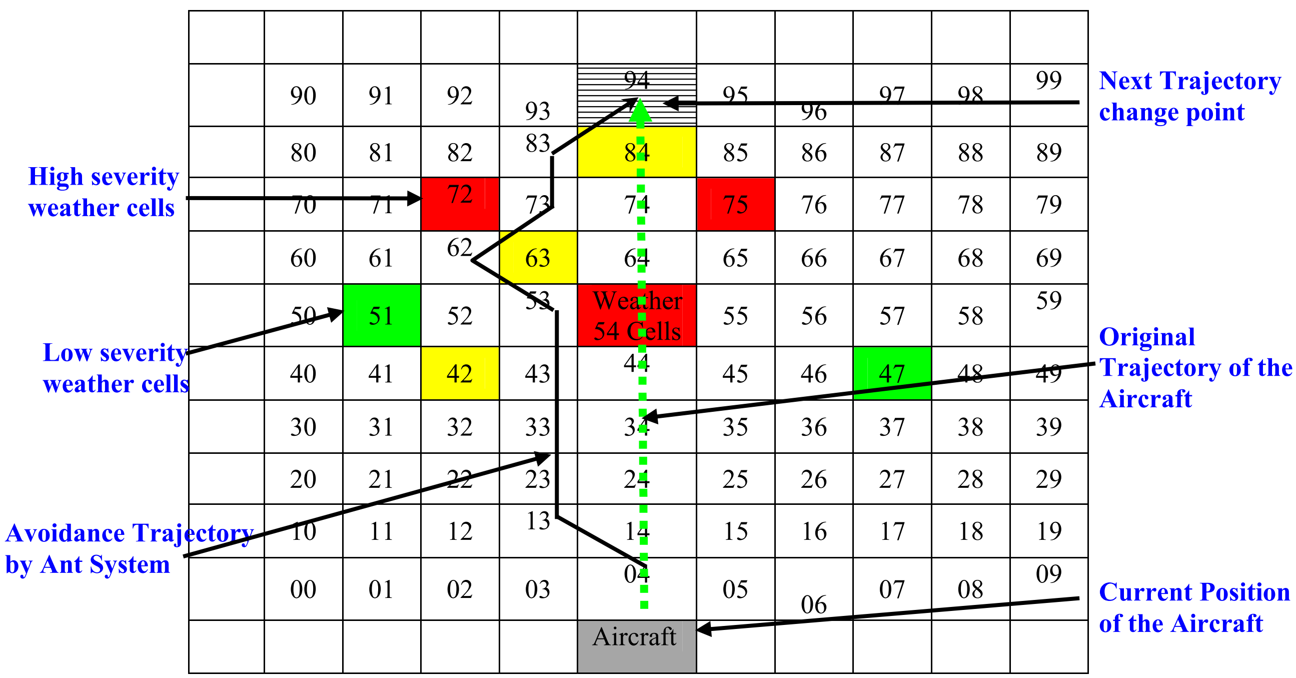

Figure 4: Illustration of bad weather cells in a 2D environment

There can be multiple routes between the current position of the aircraft and destination cell. The ACO algorithm tries to find the most optimal route given the optimization criteria. However if the geometry of the weather cells in the search envelop is such that there exist no route which may avoid the bad weather cells then routes which passes through least weather severity cells are considered by the ACO algorithm.

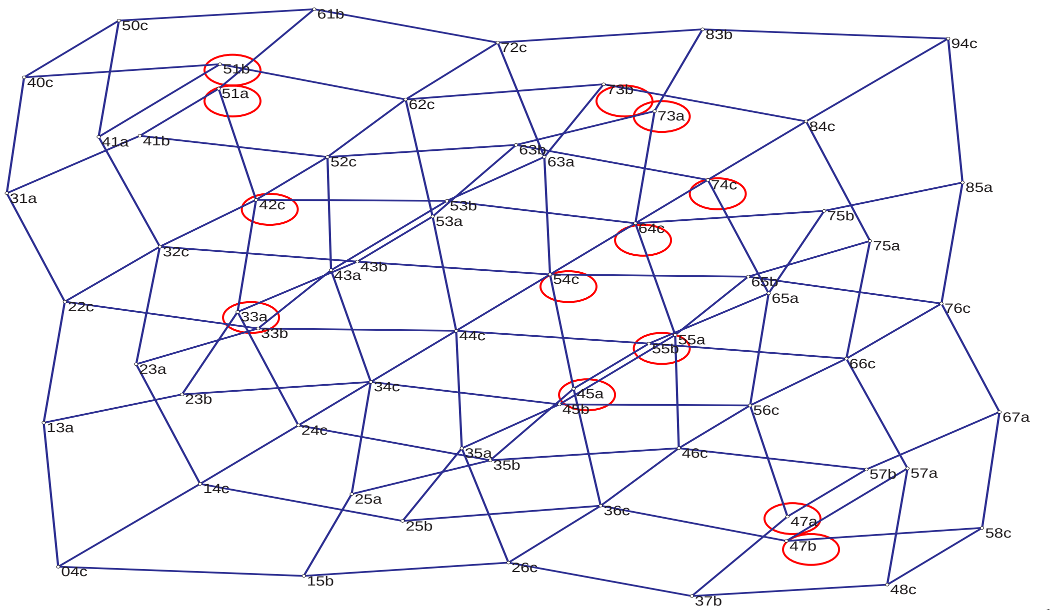

Figure 5: An illustration of all possible paths between the start-cell (04c) to end-cell (94c), circles denotes presence of hazardous weather in that cell. Network of 64 edges and 116 vertices.

An ant colony of 100 ants were run over 100 cycles to obtain optimal routes

Different weather scenarios were generated ranging from simple to highly complex and the behavior of the modified version of ACO algorithm was analyzed.

The default value of the parameters was α =1, β =1, ψ =1, ρ =0.1, Q=10. In each experiment only one of the values was changed, except for α and β, which have been tested over different sets of values. The values tested were: α ={0,0.5,1,2,5}, β ={0,1,2,3}, ψ ={1,3,5,7,9}, ρ = {0.1, 0.3, 0.5, 0.9, 0.999} and Q={1, 10, 100}. Preliminary results, obtained on high fidelity Free Flight simulator capable of generating complex weather scenarios, averaged over 30 runs for each scenario have been presented here.

Simulation		Best Route obtained 100 Cycles for a colony of 100 Ants (30 Runs for each scenario)		
Best Parameters Set	**Weather Scenario**	**Tour Weather Factor**	**Tour Length**	**Heading Change Factor**
α =1, β =1, ψ =5, ρ =0.1 Q = 10	**Simple**	**0.09**	**10**	**4.5**
	Complex	**0.09**	**12**	**6.5**
	Very Complex	**12.01**	**16**	**10**

Table 1: Simulation and results obtained for the best parameter Set

For simulation purpose weather scenarios were defined as

- Simple weather situation: Single bad weather cell on trajectory.

- Complex weather situation: More than one bad weather cell in the region distributed evenly in a large area and an optimum route exist which can avoid bad weather. The avoidance vector is not very complicated.
- Very complex weather situation: More than one bad weather cell in the region distributed tightly around the central weather cell in a manner that avoidance requires either very complicated maneuver involving more then three heading changes or going through bad weather cells with least severity.

Fig 6(a) A Simple weather scenario

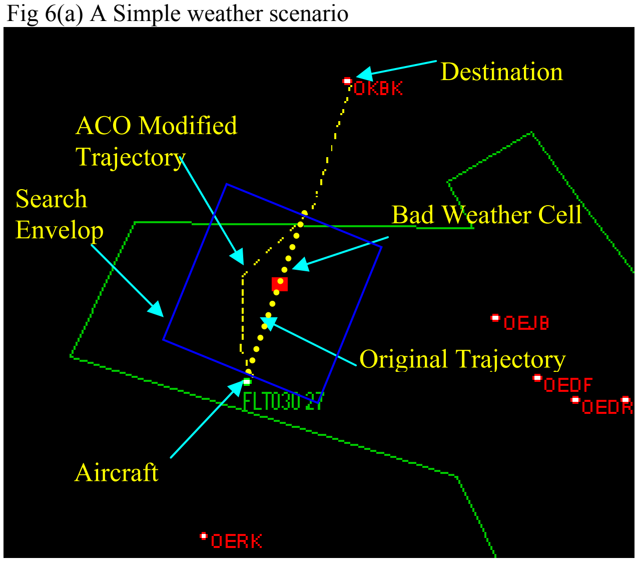

Fig 6(b) A Complex weather scenario

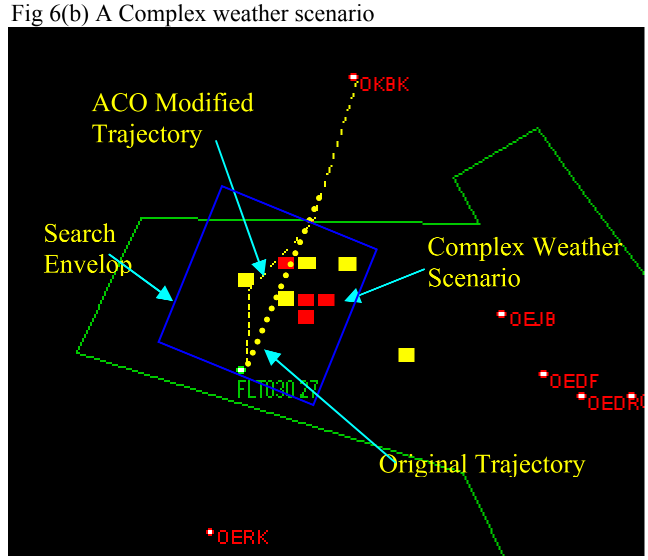

Fig 6(c) A very complex weather scenario

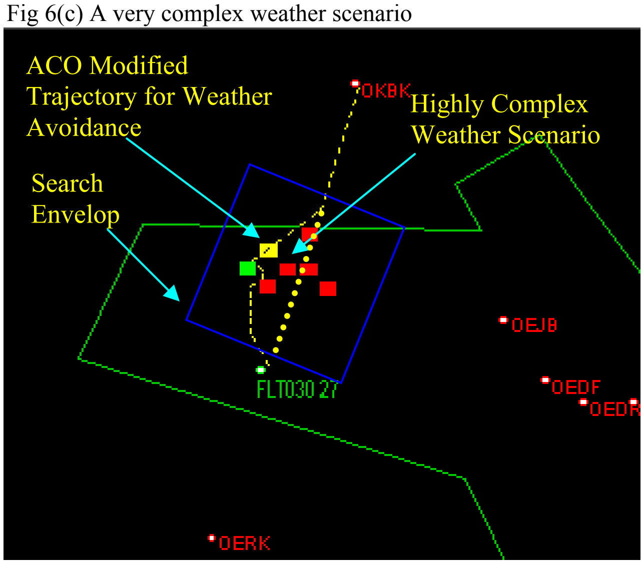

Fig 6(d) A very complex weather scenario

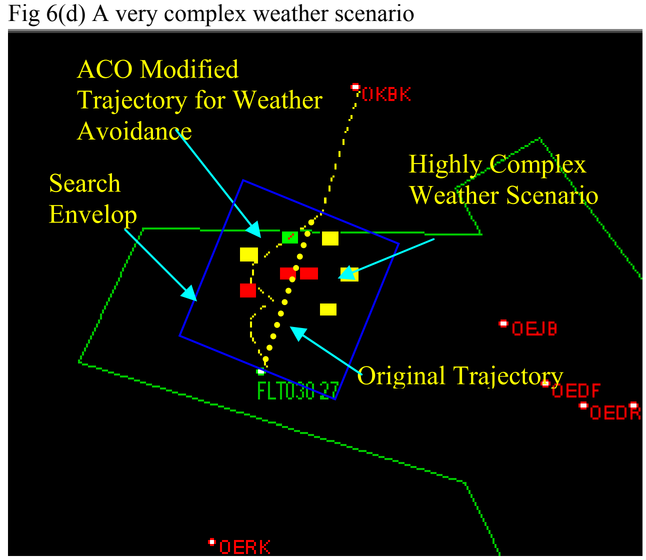

Figure 6: Ant Colony generated avoidance routes in various weather scenarios

6. RESULTS AND ANALYSIS

The ACO algorithm was able to find weather free routes every time if they existed. In the case of highly complex scenarios the ACO algorithm finds the route which requires the aircraft to fly through the weather cells with least disturbances. All the solution generated were within flight parameters and upon integrating the proposed solution with the flight management system of the aircraft in a Free Flight air traffic simulator, it successfully negotiated the bad weather. For best results obtained over 30 runs each for different scenarios it is seen that the transition probability between visibility (β) and trail intensity (α) is given equal weight and the weather avoidance is given higher weight

(ψ) as bad weather avoidance given all other factors equal, have the highest weight for the algorithm. The optimal value of ρ (ρ=0.1) can be explained by the fact that the algorithm, after using greedy heuristics to guide search in the early stages of computation, starts exploiting the global information contained in the value $[\tau_{ij}]$ of trail, in order to better utilize the new global information.

As show in Table 1, for a simple weather scenario where there is only one weather cell to negotiate. The ACO algorithm finds the optimal solution by one avoidance vector and comes back to the original trajectory in 10 optimal steps while minimizing the changes in heading and bad weather avoidance. Whereas in a highly complex scenario the aircraft has to choose to go through the least disturbed weather cells as there exists no other route within the search envelop of the aircraft. In this case the aircraft negotiate through those cells which have the least severity factor. However it increases the tour length as well as requires more changes in heading.

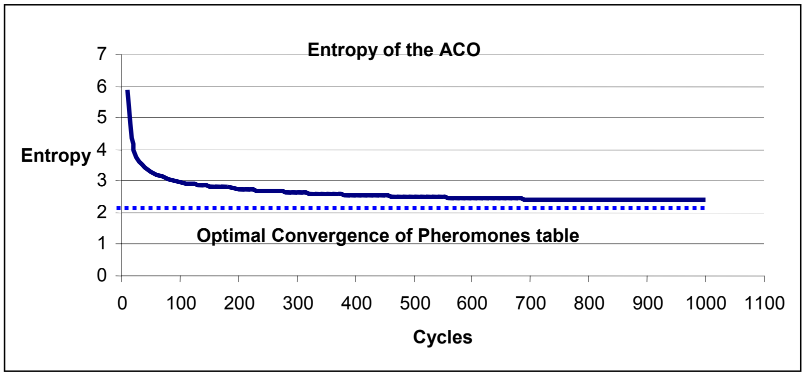

Figure 6: Graph showing the entropy of the ACO algorithm over 1000 cycles

The entropy of the ACO algorithm for a complex scenario is shown in figure 7, which shows the measurement of the pheromone chaos in the system. As the number of cycle reaches 700, the system stabilizes; with an entropy value of 2.4. This entropy shows that the ants system converges towards a stable solution and do not fixes on a sub optimal solution too early. The dotted blue line in Figure 6 shows the optimal convergence value 2.21 of the pheromone table as such the close the base line the better the entropy of the ACO algorithm. However the ACO algorithm may not reach this line because of the following reasons

- It tries to maintain balance between exploration and exploitation to avoid stagnant behavior.
- There might be more than one optimal solution and expected entropy is higher than the graph.

7. FUTURE WORK

This work is a serious attempt towards creating a swarm based weather avoidance system in a Free Flight environment. Convective weather cells change rapidly and the ability to have swarm intelligence based distributed time varying solution for weather avoidance will be one of the key areas this work will be extended to. The Free Flight environment is 4D with the capability of simulation the weather cells in 3D, however for the experiments the weather cells were simulated as 2D, extending them to 3D will enable us to model and investigate the weather avoidance problem more accurately.

Dynamically moving bad weather cells and dynamically created bad weather cells will give the problem a highly complex dimension. The problem representation in 4D will enable us to generate the resolution maneuver in 4D (Heading change, speed controls, climb, and descent), leading to more efficient flight maneuvers and route optimization. It is envisioned that in a Free Flight Environment there will be imposition of required time of arrival (RTA) on Aircrafts to streamline the operation in the vicinity of an airport; it is believed by the authors that ACO with multi objective optimization will be able to encapsulate the intricacies of the complex behavior of such a highly constrained system. The initial setup and simulations were performed on a single aircraft in Free Flight airspace simulation, and are now being extended to a multi aircraft environment. It will be interesting to see how the various systems, viz. conflict detection & resolution, ACO algorithm for weather avoidance and dynamic route planning, will interact with each other and give rise to new complex situations never been imagined by planners of future air traffic management system.

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