Discovering Delay Patterns in Arrival Traffic with Dynamic Continuous Descent Approaches using Co-Evolutionary Red Teaming

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***Abstract*—The gradual introduction of advanced ATM procedures such as Continuous Descent Approaches (CDA) creates a challenge when balancing the capacity-demand of arrival traffic in the presence of constrained ground (runway, taxiway, gate) resources. Part of the challenge is to understand the interdependency between spatial-temporal distribution of arrival traffic (traffic distribution) and the dynamics of ground resources to better manage, sustain and improve the airport throughput capacity and to minimize delays. In this paper, we use the Computational Red Teaming (CRT) Framework to identify patterns in arrival traffic and ground events that lead to delays in dynamic CDA scenarios. The scenarios represent the interaction of ground events with traffic distributions.**

The search engine in CRT relies on co-evolutionary search, with the reciprocal interaction of traffic distributions and ground events evolving to identify bottlenecks in the system. With each interaction a variety of metrics are recorded which are then data mined to identify patterns that lead to delays. Results identified scenarios whereby delays become seriously significant. For example, for a model of the Sydney domestic terminal area in a dynamic CDA scenario, flights arriving from the South-East direction with an average inter-arrival time of 53 sec can cause significant delays if runway 16L is impacted by a ground event. Another example identified taxiway C as a critical ground resource for arrival throughput capacity.

I. Introduction

It is now well recognized in the literature that air traffic management (ATM) challenges cannot be addressed in isolation. The US NextGen (Next Generation Air Transportation System) [1] highlights the need for modern airport ground movement processes that are strategically planned and better aligned with terminal area (TMA) and en-route constraints in order to achieve gate-to-gate trajectory-based operations.

In SESAR (Single European Sky ATM Research) [2] concept of operations, airports are fully integrated into the ATM network as nodes in the system. It is also envisioned in SESAR that the combination of Trajectory Management, Airborne Spacing tools and precision navigation techniques will reduce air and ground holding and sustain advanced ATM procedures such as Continuous Descent Approaches [3] (CDA), thus leading to reduced environmental impact of aviation as specified in the SESAR goals.

Existing demands on ATM systems routinely exceed the capacity of airports, leading to air-traffic-imposed ground and airborne delays of aircrafts. With the gradual introduction of advanced ATM procedures such as CDA, this problem takes on a whole new dimension: how to balance the capacity-demand of arrival traffic with constrained surface (runway, taxiway, gate) operations in order to derive maximum benefits from advanced ATM procedures. Understanding the interdependencies between the spatio-temporal distribution of arrival traffic and the dynamics of constrained ground resources (runways, taxiways and gates) is vital to better manage, sustain and improve the airport throughput capacity and to minimize delays.

The terminal area, generally a region of radius of 30-40 nm around an airport, forms the critical interface between the arrival airspace and the airport. EUROCONTROL CFMU's Network Operations Report for 2010 [4] shows that the proportion of terminal area and airport related delays increased significantly, accounting for 40% of the total delays. Possible solutions for reducing congestion in the terminal area can be divided into four major categories (in no particular order):

1) Reorganizing the existing flight schedule [5].
2) Rationing the use of existing capacity (limiting the number of landing slots) [6].
3) Physically increasing the landing capacity (ground infrastructure expansion) [7].
4) Using existing airport capacity more efficiently (improving the air traffic flow by better management of air and ground resources) [8]. This is the approach tackled in this paper.

Ground Events involves all the movements on runways, taxiway, and gate activities. Constrained Ground Events means a disruption to the available surface movement resources. For example, snow, ice, slush or water on a runway can reduce aircraft braking and directional control. The consequences for ground operations may include increased runway occupancy time; some shorter runways may not be usable; temporary runway closure due to the need to remove accumulated snow [9]. This, in turn, affects the options for runway exits, which affects taxi routing flexibility, potentially leading to arrival taxi delays and possible surface congestion. An increase in runway occupancy time leads to a reduction in airport arrival rate (throughput), due to the need for increased inter-arrival spacing. This reduction is aggravated by the closure of runways and when certain runways are unusable.

Innovative approaches are required to address this problem, especially in the terminal airspace area given constrained surface movements [10]. A system-level approach, where an ATM problem is addressed as part of the environment it operates, is vital to answer some of its key issues [11], [12]. As a complex system, it is the complex interaction between ground events (runway closure, gate not available, visibility levels etc.) and air events (traffic distribution, wake separations, bad weather, arrival sequence etc.) which affect the overall airport throughput capacity and delays.

In this paper, we use the Computational Red Teaming (CRT) [13] approach to identify vulnerabilities in dynamic CDA, ground movements and ground events interaction. CRT is a computational environment whereby problems compete with solvers; thus problems are evolved to stress-test a system to identify its points of failures. The idea here is to play the *devil's advocate* where we evolve increasingly complex traffic patterns and constrained ground events which may lead to identifying tipping points in an advanced air traffic procedure operations [14] and to discover implicit relations in the scenarios patterns that lead to them using data mining techniques.

Various approaches to CDA in the literature considers flight in the transition airspace only and do not consider their interaction with ground resources/events. The air and land side represent each a sub-network of the overall traffic network. Studying each sub-network in isolation may underestimate the impact of an event. For example, the *Dynamic CDA concept*, co-developed by authors [15], is used in this paper as the advanced ATM procedure for arrival traffic in the transition airspace. However, CDA or dynamic CDA needs to be integrated with ground movements to evaluate its real impact. This paper takes this extra step by incorporating the ground events in the evaluation of dynamic CDA. The high-fidelity Air Traffic Operations & Management Simulator (ATOMS) [16], is extended with an arrival manager to evaluate the scenarios. As a case study, the Sydney domestic TMA is used for the analysis in this paper. Co-evolution [17] is used as the search technique.

The rest of the paper is organized as follows: we give an overview of Dynamic CDA concept and Co-evolutionary approach, then we introduce the CRT framework and process followed by design of traffic and ground event scenarios. The experimental design are then presented followed by results and conclusions.

II. Background

A. Dynamic Continuous Descent Approaches

A variety of advanced air traffic procedures have been proposed and developed to manage the traffic growth in terminal airspace, such as Point Merge, Tailored Arrivals, Collaborative Decision Making (CDM) and CDA. In CDA, the descent is with no level altitude segments, which are common in traditional step-descent approaches. The goal of developing a CDA is to keep the aircraft thrust as low as possible and the aircraft at higher altitudes for as long as possible. An ideal CDA allows the engines to be at idle thrust during most of the descent.

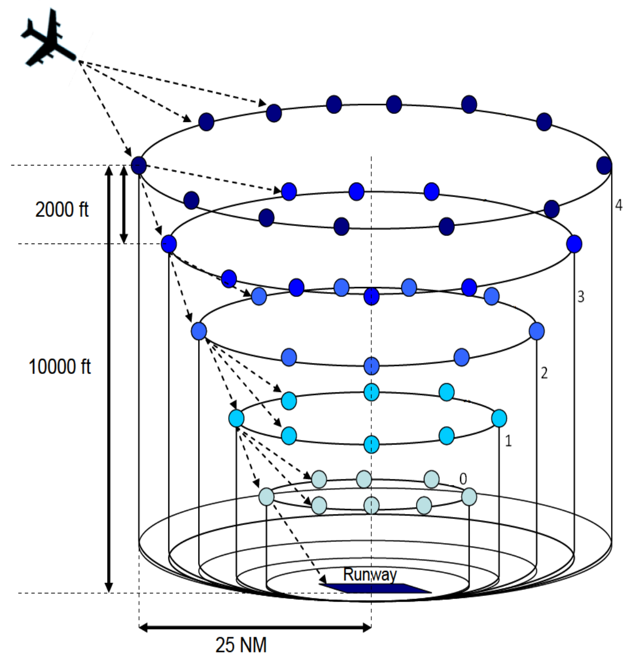

Fig. 1. Conceptual representation of transition airspace divided into concentric circles and wedges acting as trajectory change points for dynamic CDA trajectory generation.

In Dynamic CDA [15], aircraft-specific CDA routes are generated in real-time, that are both laterally and vertically optimized on given objectives (for e.g. noise, emission and fuel), from an Initial Approach Fix (IAF$= 10,000$ ft) to Final Approach Fix (FAF$= 2000$ ft). This approach has demonstrated that significant reduction of emission and noise can be achieved, compared to fixed CDA routes. The use of real-time aircraft position and performance envelope leads to inherently safe CDA routes, which can be converted into a set of artificial waypoints for continuous descent in transition airspace. With increased onboard computing power, advances in digital data transmission and proposed real time data link between controllers and pilots (CDPLC), up-linking and down-linking of trajectories is possible. This makes the realization of real time CDA route generation a near possibility.

As illustrated in Figure 1, these CDA trajectories are generated by discretizing the terminal airspace into concentric cylinders with artificial waypoints, and uses enumeration and elimination (using aircraft turn angle, deceleration rate & Speed) from one waypoint to another to identify all the possible routes. For each transition a variety of metrics are computed, including noise, emission and fuel burn. As illus-

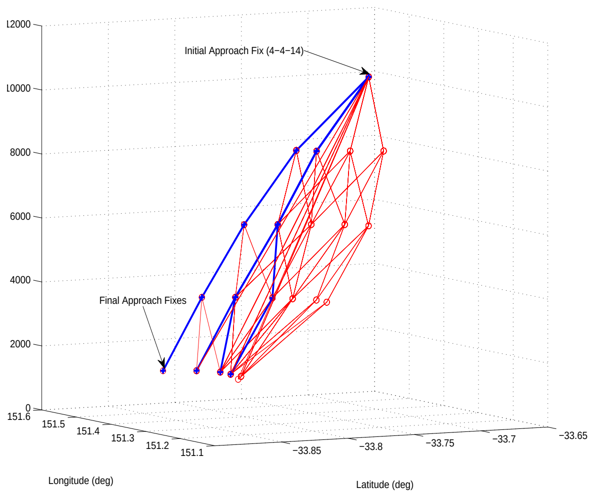

Fig. 2. 3D view of dynamic CDA trajectories generated from one of the entry point in the transition airspace. The figure also highlights the four non-dominated trajectories on noise, emission and fuel burn.

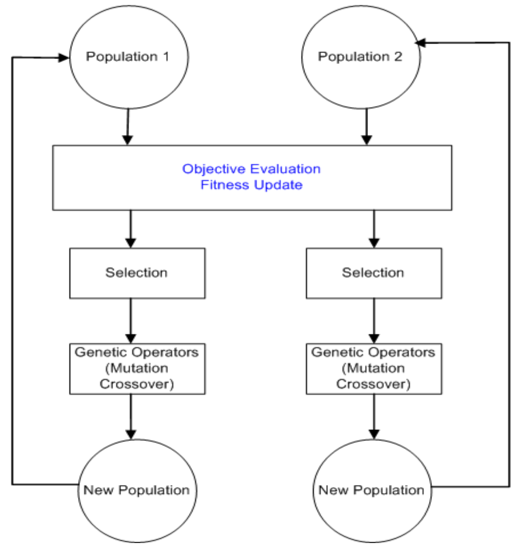

Fig. 3. A conceptual co-evolution model. The diagram demonstrates the idea of co-evolution as two or more independent populations evolve, with the fitness of an individual in one population relies on its reciprocal interaction with individuals from the other populations.

trated in Figure 2, from the resulting set of possible CDA routes, those routes are identified that represent the best trade-off on the given objectives. Then based on operational priority of each objective and using a simple search algorithm one of these routes is then uploaded in the flight FMS which then executes the CDA procedure. Dynamic CDA is used as an example arrival procedure in this paper, and distance and fuel burn are used as two objectives for CDA route planning.

B. The Search Technique

The CRT framework requires a search engine. In this paper, we use co-evolution, an extension of traditional evolutionary algorithms (EAs). Two types of co-evolution exist: cooperative and competitive. the former is characterized as evolution of a host species and its parasites in which both parties benefit. Whereas evolution of a predator and prey is an example of a competitive co-evolutionary relationship.

Initial co-evolutionary models were extended by De Jong [18], Paredis [19], and others, resulting in a new type of algorithms called *Co-Evolutionary Algorithms*. In the evolutionary computation community, co-evolution is defined as a phenomenon occurring when [18]

- Two or more populations of solutions simultaneously evolve, and presumably improve;
- There is no single and static fitness function;
- Each solution's fitness is a function of its interactions with solutions from other co-evolving populations. In this case, a dynamic evaluation of fitness for both populations takes place.

One of the methods for defining cooperative co-evolutionary models, which is used in this study, involves two species. Each species is evolved in its own population, and adapts to the environment through the repeated application of EAs. To evaluate individuals from one species, collaborations are formed with representatives (best individuals from each species) from each of the other species. A simple model of co-evolution is illustrated in figure 3.

The challenge here lies in how to identify and represent each species, provide an environment in which they can interact and co-adapt, and assign credit to them for their contributions to the problem-solving activity such that their evolution proceeds without human involvement.

III. The Computational Red Teaming Framework

CRT is a framework for identifying vulnerabilities in systems. It designs a blue population, representing the concepts we are interested to test, and a red population representing the events or agents attempting to create the vulnerability in the system. The blue and red populations then play against each others through evolutionary, co-evolutionary or other type of search methods. Data are recorded then analyzed using data mining, visualization and other data analysis approaches. Patterns of vulnerabilities are grouped and summarized to the decision maker.

Figure 4 illustrates the cooperative co-evolutionary technique as the search technique for the CRT framework. As shown in figure 4, there are two populations of partial solutions which evolve together:

- a population of Arrival Traffic Scenarios
- a population of Surface Events Scenarios

A candidate solution is formed by combining a member from a population of traffic scenarios with a member from a population of event scenarios. This implies that the fitness of any member from the population of traffic scenarios or of the population of surface events scenarios cannot be determined independent of the other population.

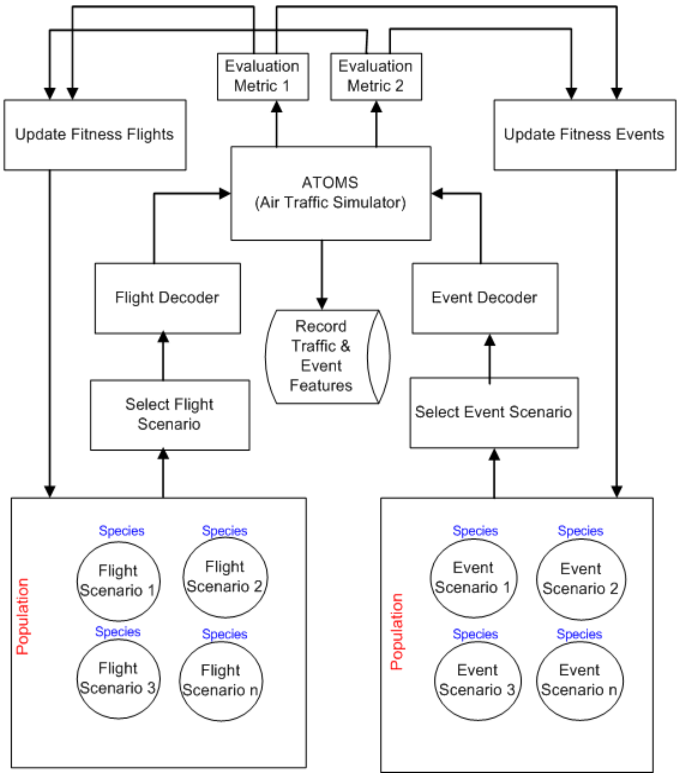

Fig. 4. CRT Framework using co-evolutionary search with Flight population and Ground Event population.

This candidate solution is then feed into air traffic simulator which simulates and evaluates the scenario for the given objective values. This objective value is then used to updated the fitness of the candidate solution (higher the delay in a scenario higher the fitness). With each evaluation a variety of metrics are recorded which are (after a certain number of evaluation) then analyzed to identify implicit patterns that lead to delays in the air and ground traffic scenarios.

The populations of air traffic scenarios and event scenarios co-evolve as follows. First, each population (traffic and event) is initialized. Attention turns first to the population of traffic scenarios, as shown in the lower left part of Figure 4. This population is evaluated by selecting each individual and combining it with a randomly selected member of the population of event scenarios. These two combined individuals form a complete candidate solution for an air traffic scenario. This candidate solution is evaluated in ATOMS: its fitness value is calculated and assigned to the individual from the population of traffic scenarios only. This process is repeated for all individuals in the traffic population. Once the entire population of traffic scenarios has been evaluated, the best individual(s) is selected to be used in evaluating the individuals in the population of event scenarios. Evolutionary operators (mutation and crossover) are then applied to produce a new generation of traffic scenarios.

At this point, the algorithm's focus switches to the population of event scenarios (the lower right part of Figure 4). Each individual from the population of event scenarios is combined with the previously determined representative(s) from the population of traffic scenarios, and its fitness value is evaluated. Representative event scenarios are selected to be used in the next round of evaluating individuals from the population of traffic scenarios, and evolutionary operators are applied to produce a new generation of event scenarios. The focus then switches back to the population of traffic scenarios. The entire process is repeated for the pre-determined number of generations, which is one of the parameters of the co-evolutionary algorithm.

To play devil-advocate, the co-evolutionary process attempts to maximize the delay of the system by evolving combinations of arrival traffic distribution and ground events which ranked higher (generated higher delays) in the co-evolutionary process.

At the conclusion of the search, data mining techniques are used to mine the data generated by co-evolution to extract patterns. In this paper, we rely on visualization and summarization as the data mining tools but we can also use more complex methods when needed as we demonstrated in some of our previous work [14].

A. Population of Traffic Scenarios

Each scenario is represented by a chromosome, this chromosome has a set of values (genes) characterizing the temporal and spatial distribution of flights in the airspace, aircraft type (light, medium, heavy) and the designated runway at the destination airport. As shown in figure 5, there are 12 genes in each chromosome. The gene values that are encoded are as follows:

- Time (T): Parameter for inter-arrival time distribution. This varies in the interval [45 90] seconds.
- σ_{GA} controls the distribution around the flight activation point. This value is selected randomly from the interval [0 1];
- μ represents the selection probability of a flight activation point on the Outer Marker [0 103];
- (A_n) There are three genes that determines the aircraft type (light, medium and heavy). It is randomly selected from the interval [0 3] and floored;
- R_n There are six genes that determines the runway selection probability. It is randomly selected from the interval [0 1].

T controls the activation time (Temporal dimension) of a flight. The aircraft type and runway A_n and R_n are selected probabilistically according to the probability values in the chromosome. μ and σ_{GA} parameters control the flight activation point (Spatial dimension). If N represents the maximum number of activation points on the outer most circle (see Figure 7), then the activation point σ of a flight is generated by the following equations:

$$\sigma_{db} = \frac{\sigma_{GA} \times min\{N - \mu, \mu\}}{3} \quad (1)$$

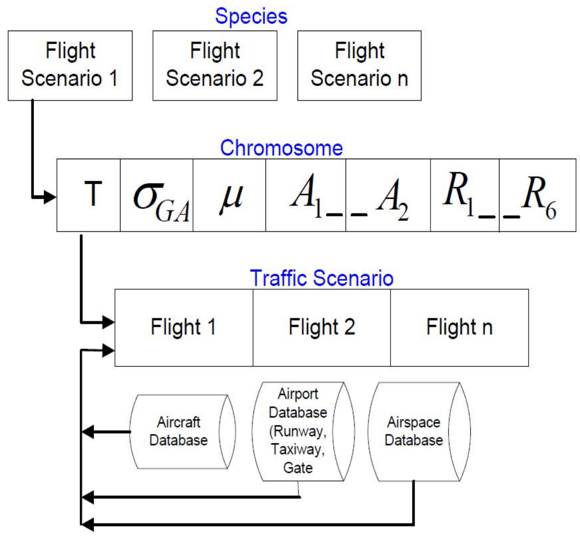

Fig. 5. Traffic chromosome design, showing the genomes which encode spatial and temporal distribution for a flights in a scenario.

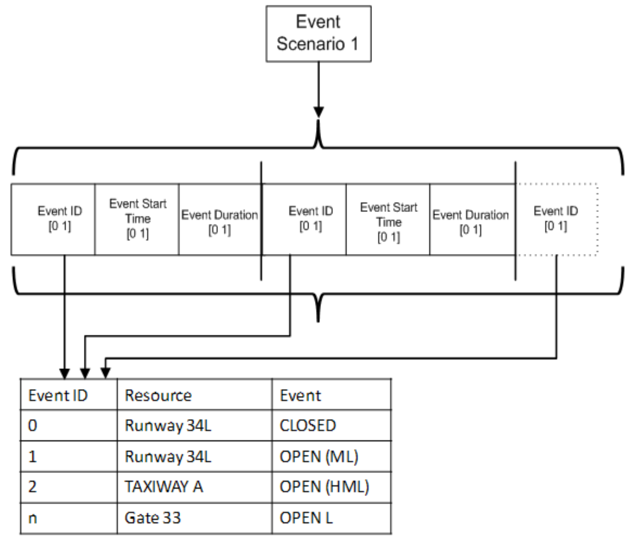

Fig. 6. Event chromosome design, showing the genomes which encode the event id, event activation time and its duration. The Event table which encodes all the possible events associated with a surface movement resource is also shown.

$$Z = Gaussian[0 \quad 1] \tag{2}$$

$$\sigma = \sigma_{db} \times Z + \mu \tag{3}$$

Each chromosome is decoded into a set of flights by re-sampling it a desired number of times. The decoding process uses aircraft aerodynamic data, airport data (to assign taxiway and gate based on assigned runway and aircraft type) and airspace configuration data to generate flight plans for desired number of flights (100 in our case) in a traffic scenario.

B. Population of Event Scenarios

An event population represents a set of constrained ground events. To encode this into a chromosome we first developed an "event-table" data structure, which contains all the ground resources (runway, taxiway and gate) along with all the possible events that can be associated with these resource. As illustrated in figure 6, each combination of a surface resource with an event is given a unique event id. For each resource there are seven possible events.

- E1: Resource available for heavy and medium aircrafts only;
- E2: Resource available for heavy and light aircrafts only;
- E3: Resource available for heavy aircrafts only;
- E4: Resource available for light aircrafts only;
- E5: Resource available for medium aircrafts only;
- E6: Resource available for heavy, medium and light aircrafts ;
- E7: Resource unavailable;

Each event scenario in a population has 10 chromosomes (for 10 events), and each chromosome has 3 genes. The first gene in the chromosome is Event-Id, uniformly initialized in the interval [0 1], this value is then used to select Event-ID value from the event table in the decoding process.

Every event in a scenario is assigned an activation time and a duration for which it will be active. As illustrated in figure 6 the second gene in event chromosome is the Event-Start-Time which is uniformly initialized in the interval [0–180] minutes and the third gene is Event-duration-time which is uniformly initialized in the interval of [0-120] minutes. This chromosome are then translated into a set of ten events for a given traffic scenario.

C. Ground Resource Allocation

Ground resources include runway, taxiway and gates. Each one of them can only be used exclusively by an aircraft to which it is assigned to for a certain duration. An aircraft is assigned its designated runway, taxiway and allocated gate at the arrival airport in the decoding process. However, this may change, at the time of CDA route generation, based on ground events such as runway closure, taxiway unavailability, gate closure, etc.

The interconnection between these resources, and how one leads to another, is modeled as a network. This network data structure stores all the possible connections from runways to different taxiways, and from taxiways to different gates. If for example an arriving aircraft is assigned a particular gate, the network stores the link for various networks available to route the aircraft to that gate.

If an aircraft is to assign a new runway/taxiway/gate due to unavailability of a certain resource, then the aim is to meet the scheduled surface route while minimizing changes in the existing route. If there is no possible alternative to lead an aircraft from its assigned runway to its assigned gate then an alternative gate is selected. If the runway is completely closed, the search is performed using the next available runway and the aircraft ground route is updated accordingly.

D. Objective Function

The objective evaluation (Flight Delay) is based on the total delay for all the flights. This include delay in air due to holding/speed control and their surface movement delay due to rerouting to an alternate route. The co-evolutionary process attempts to maximize the delay of the system by evolving combinations of arrival traffic distribution and ground events which ranked higher (generated higher delays) in the co-evolutionary process.

Flight Delay (from Outer Marker to Gate) is defined as: Average flight delay time from Outer Marker to Gate, and is a measure of induced delay due to unavailability of air and ground resources. It is estimated by taking the difference between the ETA (Estimated time of arrival) of a flight from its Outer Marker (OM) to the requested Gate and the ATA (Actual Time of Arrival) of the flight to the assigned Gate from its respective outer marker, averaged over 100 flights in a given scenario.

$$Delay = [\frac{1}{N}\Sigma_{i=1}^{100}(ATA_i - ETA_i)]_G^{OM} \tag{4}$$

IV. Experimental Design

As shown in Figure 1, we define the problem search space (transition airspace) as a set of five concentric cylinders (to equally divide transition airspace with 5 nm safety separation) with runway (touchdown point) at the center. The height of the transition airspace is set to 10,000 ft, and the radius to 25 nm. The outer most cylinder (denoted Ring 4) is of radius 25 nm (transition airspace radius (TAR)), and inner cylinders (Rings 4, 3, 2, 1 and 0) have radii of 25, 20, 15, 10 and 5 nm as calculated in Equation 5. The outermost cylinder's height is 10,000 ft, corresponding to the start altitude of CDA, and the inner cylinders have heights of 8000, 6000, 4000 and 2000 feet. Thus the transition airspace is divided into 5 levels, with each level divided into 2000 ft to give a typical jet aircraft enough vertical height to manoeuver given low thrust setting.

$$RingRadius = \frac{TAR \times \ (Ring\,Number + 1)}{5} \tag{5}$$

Each cylinder has wedges which represent transition points from one level to another. These wedge points are spaced 1.5 nm apart, for safe separation between approaching aircraft [20]. The number of wedges for a given cylinder is calculated as follows:

$$Number\,of\,Wedges = \frac{2\pi \times Ring\,Radius}{Separation\,Distance} \tag{6}$$

The angle between the wedges is calculated as follows:

$$Wedge\,Angle = \frac{2\pi}{Number\,of\,Wedges} \tag{7}$$

A transition airspace radius of 25 nm and a separation distance of 1.5 nm gives the number of wedge points as 104, 83, 62, 41, and 20 for rings 4, 3, 2, 1 and 0 respectively.

At 2000 ft before touchdown the aircraft follows the final approach path on the Instrument Landing System (ILS) glide scope (3°) and lands on the designated runway using final approach speed and descent thrust. The landing-gear was fixed at 3000 feet and Eurocontrol's Aircraft Database (BADA) [21] aircraft-specific flap configuration for approach and landing and corresponding stall speeds were used. The transition from one wedge point to other wedge point is based on individual aircraft performance parameters, derived from BADA.

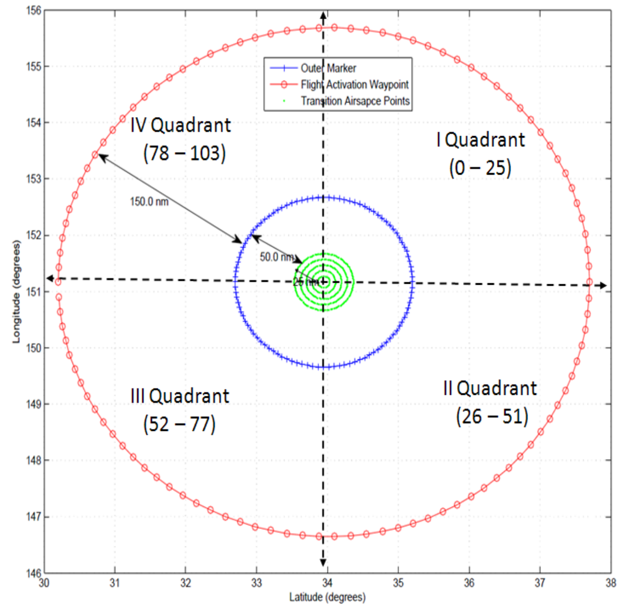

Fig. 7. Optimization Airspace showing activation points in each quadrants. Activation points are 150 nm from the outer marker and the outer marker points is 50 nm from the Initial Approach Fix.

For any given entry point (Initial Approach Fix) in the outermost ring and exit point (Final Approach Fix) in the innermost ring, full enumeration of the search space is performed to find all the possible dynamic CDA routes, then a search is performed on the ground resources, using the ground resource network, to check if the ground resources are available, else rerouting is done. Figure 8 shows the process flow chart for a flight from the point it enters the transition airspace and until its final route (dynamic CDA and Ground) is computed.

Figure 7 illustrates the overall airspace, where the activation points (104 in number) are 150 nm from the outer marker. The outer marker points are 50 nm away from the initial approach fix points. The flights get activated at their designated activation point based on the traffic distribution parameters μ and σ_{GA} . Once the flight reaches the outer marker the optimization process (dynamic CDA route computation on distance & fuel burn) starts.

Flight activation time for two successive flights is based on inter-arrival time distribution where the aircraft are generated using a Poisson process with value of T uniformly initialized during the first generation in the interval of [45 90].

Two traffic-handling business rules are used when there is no route available, in air or ground) for a flight (See Figure 8).

- Speed Control: The speed is reduced every time by 10kts

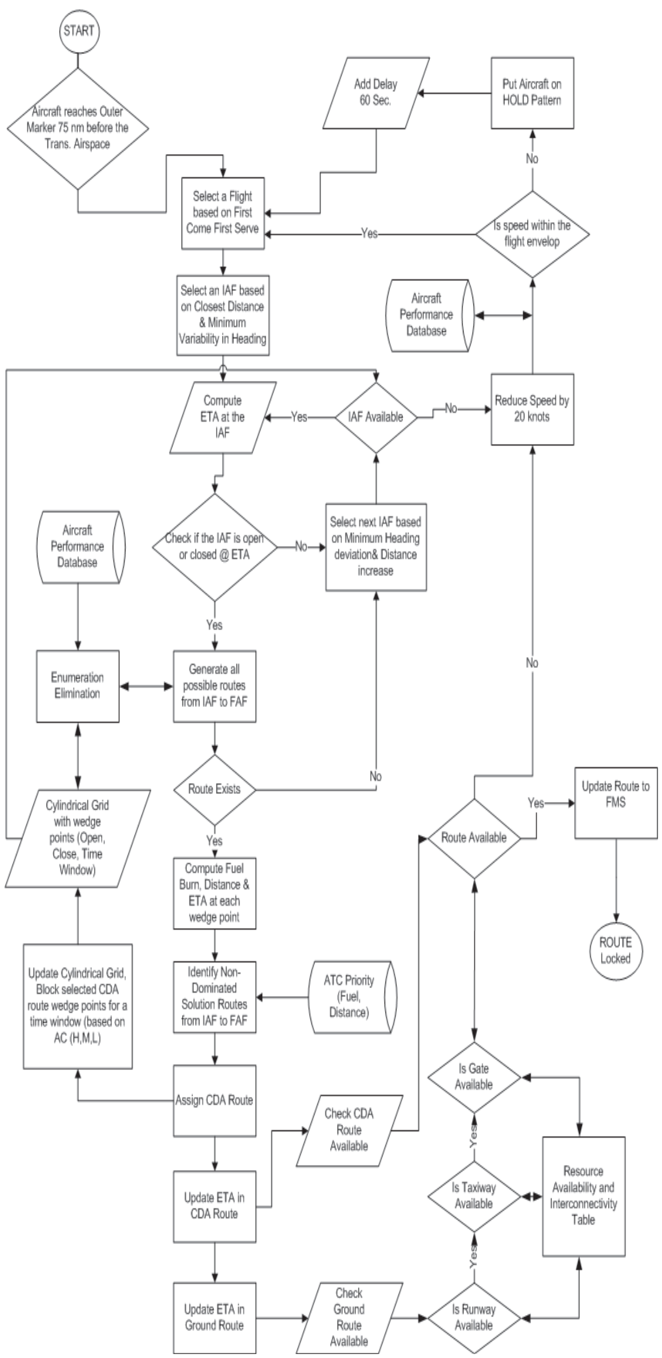

Fig. 8. Flowchart illustrating the dynamic CDA route selection and ground route assignment process for a flight.

until it is within its minimum speed V_{min} envelope.

$$V_{min} = C_{V\,min} \times V_{stall} \tag{8}$$

where V_{stall} is the stall speed of the aircraft. If the aircraft is in approach configuration we use $V_{stall}AP$, if in landing configuration we use $V_{stall}LD$ from BADA.

- Hold: The flight is put in hold pattern for 60 seconds with the fuel burn being calculated.

The domestic area of Sydney Airport's terminal area is

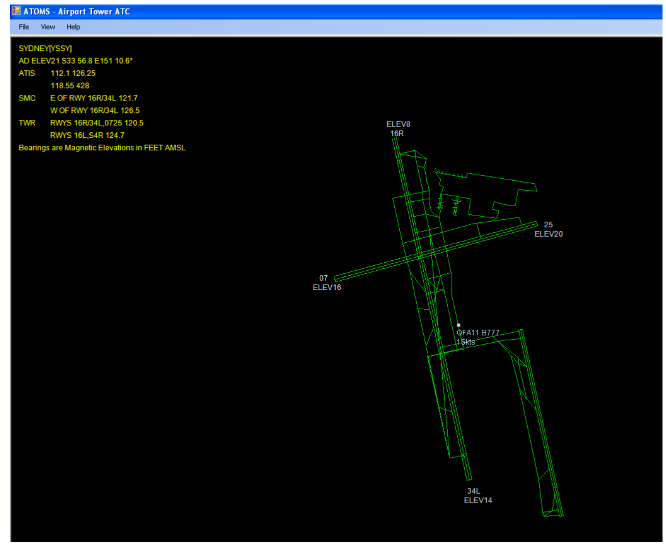

Fig. 9. Snap shot of ATOMS simulator runway client showing the flight movement on Sydney Airport

used as an example. It has three runways: medium spaced parallel runways in the north-south (16/34) direction (3,962m and 2,438m) and an intersecting/cross runway in the east-west (07/25) direction (2,530m). In total there are 6 runways, 10 taxiways and 23 gates.

- Runways: 34L, 16R, 25, 07, 16L, 34R
- Taxiways: U1, B, C, T, T2, B2, G, L, U, B4
- Gates: 40, 2, 32, 56, 6, 3, 1, 9, 58, 35, 31, 52, 4, 33, 8, 36, 7, 39, 38, 34, 10, 54, 5

In ATOMS, for the sake of simplicity only domestic terminal operations are modeled. Each runway is treated separately i.e. runway 16 and runway 34 are independent. Taxiway speeds are derived from BADA database (ground movement data), and landing ground roll distances are calculated aerodynamically by taking into account aircraft type, weight, wing span and runway type. Figure 9 shows a snapshot of the ATOMS simulator runway client with an aircraft taxing out at a speed of 15 knots on taxiway C, towards runway 34R.

V. Experimental Results

Figure 10 shows a typical scenario run in ATOMS with inter-arrival time (T) = 52 sec and μ = 40 with most of the flights are coming from Quadrant II.

While the inter-arrival time, activation points, distribution parameter were all initialized uniformly, at the end of the co-evolutionary run, the best solutions in all populations of flights achieved an inter-arrival time of 52±6 seconds, and activation points of 50±6. These parameter values produce higher delays for the given traffic scenario and the associated events as compared to earlier generations. It can be seen from the data that the flights which have an average inter-arrival time of 53 seconds and which are spatially distributed in the II quadrant (South-East) (see figure 7) of the research airspace can cause significant delays in a Dynamic CDA scenario.

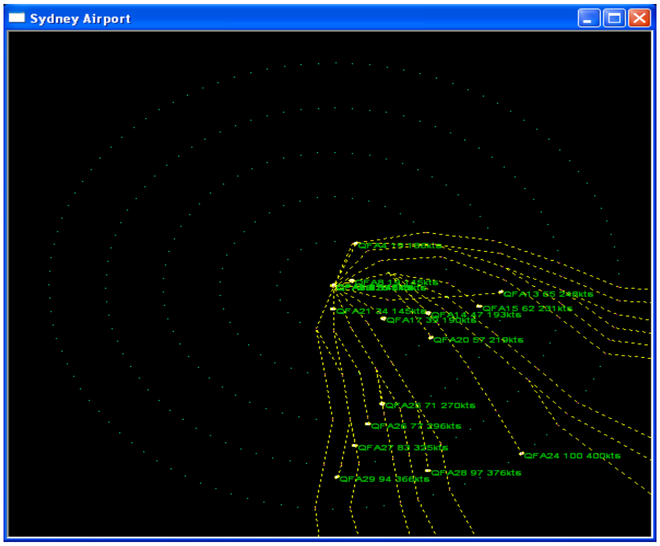

Fig. 10. A Snapshot of ATOMS simulating a given traffic scenario with inter-arrival time (T) = 53 sec and μ = 40.

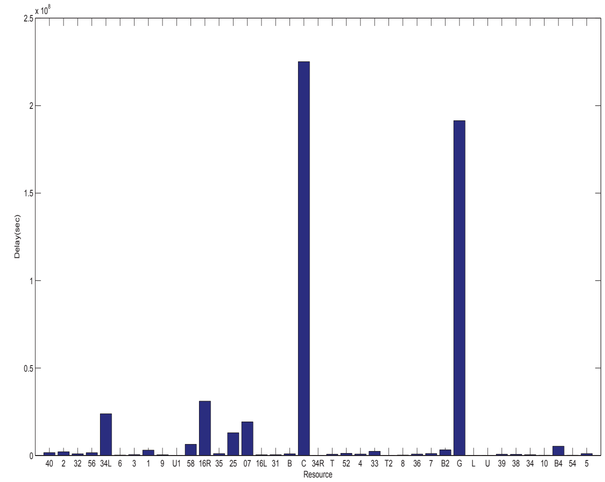

Fig. 12. Number of aircraft affected by individual resources (summed over 100 generations for all seeds).

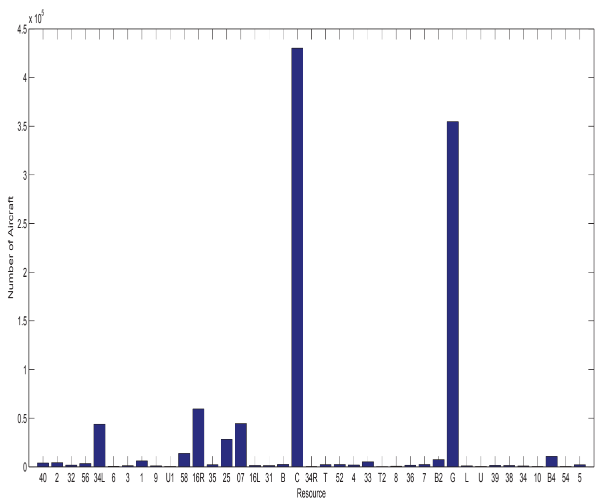

Fig. 11. Number of aircraft affected by individual resources (summed over 100 generations for all seeds).

We then looked into how many aircraft were affected by unavailability of ground resources. Figure 11 shows the number of aircraft affected by each ground resource. The data is summed over all the 100 generations for all seeds. It can be seen that taxiway G, taxiway C and runway $16R$ affected the majority of the flights while taxiway C appears to be a bottleneck and affected the highest number of aircraft.

We then analyzed overall flight delay caused by each of the ground resources. Figure 12 shows the overall delay summed over all the 100 generations for all seeds. It displays a similar trend to Figure 11. Here also taxiway G, taxiway C and runway $16R$ contributed to the highest number of delays, with taxiway C contributing the highest.

We then investigated the progress of each resource, that significantly contributed to the overall delay, over generations. Figure 12 shows the delay induced by taxiway C (top-left), taxiway G (top-right) and runway 16R (bottom) summed over all seeds for 100 generations. The figure shows that cooperative co-evolution was able to evolve ground events for resources which were able to maximizes the delays.

When looking at the events that evolved over 100 generations, Table I shows the set of events in the first and last generation. It can be seen from the data that in the final generation, event E5 (Resource available for medium aircraft only), is a major contributor for ground resources.

VI. Conclusions & Future Work

This paper presented the application of computational red teaming as an approach to identify patterns of failures (major delays) for the interdependency of dynamic CDA, arrival traffic distribution and ground events. Co-evolution was used as the search engine to evolve the reciprocal interaction of arrival patterns and ground events.

The work demonstrated the power of computational red teaming in identifying and analyzing vulnerabilities of advanced ATM concepts and evaluating their performance using co-evolutionary algorithms. The approach concurrently searches the solution spaces of arrival traffic distribution and constrained ground resources. The study was conducted to demonstrate the usefulness of evolving complex scenarios by using incremental feedback by the system, rather than hand-designing the scenarios.

We conducted a series of computational experiments with different arrival traffic distributions (both spatial and temporal) and different ground resource constraints scenarios. The parameters impacting the delay performance were co-evolved with our synthetic models of a terminal airport area (runways, taxiway and gates). Results indicate that for the Sydney TMA using the future concept of dynamic CDA, flights which are

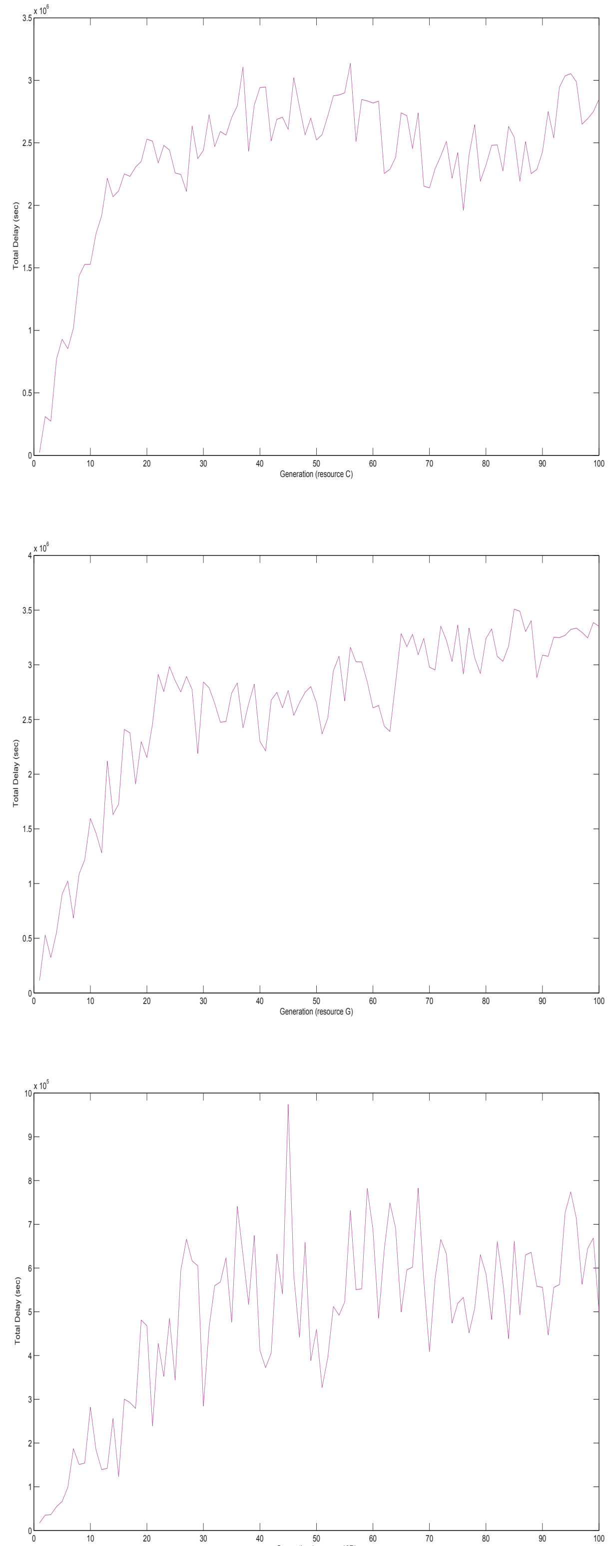

Fig. 13. Delay induced by taxiway C (top), taxiway G (middle) and runway 16R (bottom) summed over all seeds.

TABLE I
EVENTS AT THE BEGINNING AND END OF CO-EVOLUTIONARY RUNS.

Events at the start of co-evolutionary run:			
Resource	**Event**	**Start T**	**End T**
B6	E2	1639	838
1	E3	820	1174
A3	E5	4835	1123
07	E4	9304	103
56	E5	8358	319
5	E1	435	1419
A2	E7	4113	139
B8	E3	7252	1902
T2	E3	3604	2177
52	E6	3860	47
Events at the end of co-evolutionary run:			
T1	E3	6946	3118
B	E2	7897	153
16R	E5	2613	2206
B6	E3	6371	3184
07	E5	37	1602
32	E5	9425	1869
C	E5	5249	2148
G	E3	2977	2685
34 L	E1	6019	1314
B4	E7	791	2433

from the lower end of second quadrant with inter-arrival time of 53 seconds, where the Runway 16L, taxiway G and taxiway C are effected by an event which leads to their closure for medium aircraft, leads to higher delays.

Co-evolutionary algorithms were able to identify spatial and temporal distributions of arrival traffic that lead to higher delays in dynamic CDA for a large spectrum of ground event scenarios. The data analysis identified vulnerabilities of the Dynamic CDA algorithm with respect to certain traffic distributions and ground events.

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