Abstract—A majority of aircraft are now using Global Navigation Satellite System (GNSS) for navigation. This has led to an effect of reducing the magnitude of lateral deviations from the route center line and, consequently, increasing the probability of a collision, should a loss of vertical separation between aircraft on the same route occur. ICAO has introduced Strategic Lateral Offset Procedures (SLOP), which allows suitably equipped aircrafts to fly with 1nm or 2nm lateral offset to the right of airway centerline in oceanic airspace. However, very few aircrafts are using the SLOP procedure due to lack of understanding of its safety benefits and implementation issues in identifying correct lateral offset that can reduce the collision risk. This paper proposes an Evolutionary Computation framework using Differential Evolution process to identify optimal lateral offsets for each airway in a given airspace such that it reduces the overall collision risk. Airway specific lateral offsets are then correlated with airway-traffic features using Multiple Regression models to identify which features can explain the optimal lateral offset. The proposed approach establishes a generic mapping that can suggest optimal lateral offsets for a given airspace based on airway-traffic features to mitigate collision risk. The proposed methodology is applied for Collision Risk assessment of one day traffic data (710 flights) in Bahrain Upper Airspace (FL290-FL410) to estimate optimal lateral offset which resulted in significant reduction of collision risk. Further, number of flights and crossings on an airway were identified as key features affecting optimal lateral offset.

Keywords: Collision Risk, Lateral Airway Offset, Differential Evolution., Airspace Safety

I. INTRODUCTION

Most of the modern airliners are now equipped with sophisticated navigation equipment which allows them to fly very accurately on airway centerline of the planned route. Global Navigation Satellite Systems (GNSS) such as US’s GPS, EU’s Galileo, Russia’s GLONASS and China’s Compass provides position accuracy of 10 meters or even better [1]. Space based augmentation systems such as Wide Area Augmentation System (WAAS) improves GNSS accuracy to 3 meters [2]. This improvement in performance has had the unintended consequence of increasing the probability of loss of vertical separation incidents which, in turn, increases the risk of collisions [3].

With large number of aircraft flying in the Reduced Vertical Separation Minimum (RVSM) airspace (29,000 ft to 41,000 ft inclusive) the probability of loss of separation with other aircrafts flying on same routes nominally separated by 1000 ft vertical on adjacent flight levels can be very high [4]. Two aircraft can have loss of vertical separation due to normal height deviations (Altimeter System Errors) or from large height deviations (level burst, wake turbulence, TCAS resolution, coordination failure etc.) [5]. The Mid-Air Collision between Embraer Legacy and a 737-800 over Brazil in 2006 [6] due to Embraer Legacy aircraft’s assigned altitude deviation is such an example. Both aircrafts were flying, accurately on airway centerline, in opposite direction at the same altitude leading to collision.

Given SESAR’s target of improving safety by a factor of 10 by year 2020 [7], there is a need of innovative approaches in the manner that we manage our airspace and traffic flow to mitigate collision risk [8].

ICAO in PANS ATM Doc 4444 [3] has proposed Strategic Lateral Offset Procedures (SLOP) in oceanic and remote airspace which allow aircrafts to fly with 1 nm or 2 nm lateral offset to the right of airway centerline on a suitably equipped aircraft (automatic offset tracking by FMS). SLOP provides an additional safety margin and mitigates the risk of traffic conflict when non-nominal events (normal or large height deviations) occur [9]. However SLOP procedure has not resulted in desired reduction in airspace collision risk due to two main reasons:

- Limited implementation: SLOP is implemented in Oceanic airspace only and very few aircrafts uses this procedure.
- North Atlantic Planning Group has recently expressed concern that not enough aircraft appear to be flying the offset procedure in the north Atlantic thus negating, in part, the safety benefits [10].

Data Collected by UK National Air Traffic Services (NATS) which provides...
ATC services in the eastern part of North Atlantic shows that less than 10% of aircrafts are using the SLOP procedure due to lack of understanding of its safety benefits[11].

- Used of fixed Offset in SLOP: The underlying idea behind SLOP was that a random application of the procedure will dramatically reduce the risk of loss of separation events. The key to this dramatic reduction in risk is the randomness of offset application. In order to create this randomness it was recommended that aircraft operator procedures must not specify any one of the three offset options (centerline, 1 NM, and 2 NM). Most of the aircraft that fly SLOP elect to use fixed offset of 1 NM thereby defeating the underlying idea.

Further, no review has been undertaken of the implications of such offsets and there exists minimal advice to pilots and guidelines to safety planners/ATC supervisors on such offset procedures and safety benefits thereof [12]. Since the use of offsets could influence system safety there is a need to develop criteria enabling the identification of where and how offsets can be safety employed, and any limitations that need to be applied? It will also be necessary to define operational procedures and requirements for their application to ensure that such offsets can be employed in a safe manner.

Thus, the key research questions this paper looks into are: Instead of having a fixed lateral offset, can we achieve an airway specific lateral offset that can reduce the overall airspace collision risk. In other words, how local level optimization can be achieved while managing the system level performance. Secondly, which airway and traffic features affects the optimal lateral offset value. This understanding may provide valuable insight into lateral airway offset decisions by safety planners and airline operation office to mitigate collision risk in continental airspaces.

However, the large search space (possible solutions i.e. lateral offset values for each airway in a continuous range) and interaction of collision risk model with airway and traffic features makes traditional search methods unsuitable for this kind of problem [13]. Nature-Inspired techniques such as Evolutionary Computation [14] have emerged as an important tool to effectively address complex problems in the Air Transportation domain, in which traditional methodologies and approaches are infeasible.

In this paper we propose an Evolutionary Framework where we use Differential Evolution [15], a population based search approach, as lateral offset optimizer. Air Traffic Simulator ATOMS [16] as simulator for a given traffic scenario, ICAO Collision Risk Model [4] as an evaluator of collision risk, and Multiple Regression model as an identifier of correlation between airway-traffic features and optimal lateral offset.

This paper is structured as follows: we first present the proposed approach in an abstract manner. We then highlight the impact of lateral navigation precision on collision risk followed by some background on collision risk model, SLOP and Differential Evolution.

We then outline the methodology, where we further detail the evolutionary framework to evolve optimal lateral offset for each airway. Experimental design is then presented along with different parameter settings using in collision risk model as well as differential evolution process. Results are then presented and summarized followed by discussions and some future directions for this work.

Figure 1 illustrates, in an abstract manner, the proposed approach. As shown, let’s assume that for a given traffic data, airspace and time period, its collision risk is assessed to be above a certain threshold (No Offset scenario). Applying fixed lateral offset of 1 NM or 2 NM to the right of airway centreline may reduce collision risk (Fixed Offset scenario). Our approach is to design a framework that not only estimates the optimal lateral offset for each airway in the given airspace such that the overall collision is reduced, but also identifies the airway and traffic features which affect the offset value in order to predict the optimal lateral offset values without the need of an optimization process.

This is important because any optimization process for such a large number of possibilities is inherently an expensive process (computation time and resources) and would be impractical to run frequently.

Figure 1: Proposed approach for airspace collision risk management

II. PROPOSED APPROACH
III. NAVIGATION PRECISION AND COLLISION RISK

RVSM safety assessment shows that the precision of lateral navigation is an important factor with regard to vertical collision risk [17]. A general assumption is that 50% of the flying time is being made with GNSS navigation and the remaining 50% with VOR/DME navigation, while an extended use of GNSS navigation should have a risk increasing effect. For example: an increase of the GNSS flight time proportion to 75% would cause the estimate of the technical vertical risk to increase by a factor of approximately 1.5 nm [17]. Therefore, the risk mitigating effects of lateral offset are significant.

Further, there is no practical difference between two aircraft colliding on a “fixed” airway and two aircraft colliding who are coincidently flying the same random route; and there is no difference between two aircraft colliding on a fixed airway or two aircraft colliding over the same random waypoint contained in each of their random routes. In each instance, the collision might be avoided if one, or both, aircraft is flying an offset.

IV. BACKGROUND

A. Vertical Collision Risk

A mid-air collision between two aircraft nominally separated by 1,000 ft could occur only if either one or both aircraft were to deviate vertically from their assigned flight level such that the vertical separation between the aircraft is lost. There are two main reasons why an aircraft may not be at its assigned flight level – normal height deviations and large height deviations.

Normal height deviations arise because of typical assigned altitude deviation (AAD) and altimetry system errors (ASE), whereas large height deviations occur because of operational issues such as a level burst or TCAS alert. The focus of this paper is on normal height they happen for purely technical reasons.

Technical vertical risk is computed, using a mathematical model, using historic flight data and takes into account, among several factors, the accuracy of navigation, the airway structure, the aircraft population, and the total flying time within the region.

B. Strategic Lateral Offset Procedure (SLOP)

Strategic Lateral Offset Procedure (SLOP) are ICAO approved procedures [3] that allow aircraft to fly on a parallel track to the right of the center line relative to the direction of flight to mitigate the vertical overlap probability due to increased navigation accuracy and wake turbulence encounters in Oceanic and remote airspace.

As illustrated in Figure 2, the SLOP allows the discretion to fly either on the airway centerline or conversely offset to the right by maximum of 1 NM or 2 NM depending upon the spacing between route center lines (30 NM or more) in oceanic or remote airspace.

The decision to apply a strategic lateral offset shall be the responsibility of the flight crew. The flight crew shall only apply strategic lateral offsets in airspace where such offsets have been authorized by the appropriate ATS authority and when the aircraft flight management system (FMS) is equipped with automatic offset tracking capability.

C. Differential Evolution

Differential Evolution [15] is a stochastic, population-based optimization algorithm belonging to the class of Evolutionary Computation algorithms. Differential Evolution algorithms are highly effective in optimizing real valued parameter (lateral offset values in our case) and real valued function (minimize collision risk in our case). They are also highly effective in finding approximate solutions to global optimization problems (airspace collision risk in our case) [18].

V. PROBLEM FORMULATION

The problem formulation consist of two stages, first is the Optimization stage, where the optimal lateral offset for each airway is determined such that overall airspace collision risk is minimized and the second is the Correlation stage where for a given optimal lateral offset of an airway, correlation, if any, with that airway and traffic features is identified such that the optimal lateral offset can be estimated. This is formulated as follows:

A. Optimization Stage

Given an Airspace Z with J airways and Traffic data Di where i=1 to m where m is the number of aircrafts flying through airspace Z, determine the lateral offset in the direction of traffic (right to the airway centerline) to maximum of K NM in decimal latitude interval for each airway N’ such that it
minimize the overall collision risk of the airspace $Z$. The Optimization function is expressed as follows:

$$
\min f(CR)_Z \text{ s.t. } g(N_z \rightarrow N_z') \text{ where } N_z' \in [0, K] \tag{1}
$$

B. Correlation Stage

This stage determines the best set of parameters (airway and traffic features), such that the model predicts experimental value $y^*$ (lateral offset) of the dependent variable $y$ as accurately as possible. We also determine whether our model itself is adequate to fit the observed experimental data and check whether all terms in our model are significant. The function is expressed as follows:

$$
y^* = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n \tag{2}
$$

subject to

$$
\min f(r_j) = y_j^* - y_j \tag{3}
$$

Where $y$ is dependent variable (predicted by a regression model), $y^*$ is dependent variable (experimental value), $b_0$ is intercept (constant), $x_i (i = 1, 2, \ldots, n)$ is the $i$th independent variable from total set of $p$ variables, $b_i (i = 1, 2, \ldots, n)$ is the $i$th coefficient corresponding to estimated value and $j=1, 2, \ldots, n$ are data points.

VI. METHODOLOGY

A. Evolutionary Framework

The proposed methodology to evolve Optimal Lateral Offsetting for each airway in a given airspace such that it minimizes the overall collision risk is illustrated in Figure 3. There are two set of processes in the methodology illustrated with two different color schemes. The process components depicted in white color are of Air Traffic Simulation which evaluates a given traffic data for collision risk in airspace with lateral offset applied. The process components depicted in blue color are of Evolutionary Computation which involves Differential Evolution to evolve optimal lateral offset values using evolution operators.

In Evolutionary Computation process part, we first establish Upper and Lower bound for airway offset (in NM). We then randomly initialize (within these bounds) a population of solutions representing a set of vector where the size of each vector is equal to number of airways i.e. each vector comprises of offset values for each airway in a given airspace. These vectors undergo mutation and recombination to generate two vectors which we call Target Vector and Trial Vector. These two vectors compete with each other with their set of offset values in the Air Traffic simulator. The vector which minimizes the collision risk for a given Traffic data is admitted to the next generation and the process continues until maximum generation is reached. At this stage the best performing solutions (vectors) are selected from the final population.

B. Biological Representation of Airway Offsets

The solution vectors are encoded into a genetic data structure (chromosome) to facilitate exchange and crossover of information in the evolutionary process of optimization. Each population of solution consists of several chromosomes, depending upon the population size, as illustrated in Figure 4.

![Figure 3: Optimal Offset evolution methodology using Air Traffic simulator, Differential Evolution and Collision Risk Model](image)

![Figure 4: Chromosome design with Offset values for each airway in the given traffic scenario](image)
C. The Airway Structure and Lateral Offset

We have chosen maximum lateral offset as 4 NM right to the airway centre line. We propose this value for continental airspace based on airway structure, illustrated in figure 5, in radar control environment. This offset may be widened if midpoint between two NAVAIDS is more 51 NM.

![Airway structure with 4 NM spacing from airway centerline if distance between two VOR is less than 51 NM](image)

**Figure 5: Airway structure with 4 NM spacing from airway centerline if distance between two VOR is less than 51 NM**

D. The Differential Evolution Process

Given function $F$ to optimize with $D$ real parameters. First select the size of the population $N$ (it must be at least 4). The parameter vectors have the form:

$$x_{i,G} = [x_{i,1,G}, x_{i,2,G}, \ldots, x_{i,D,G}] | i = 1, 2, \ldots, N.$$  

(4)

where $G$ is the generation number.

In Initialization phase we define upper and lower bounds for each parameter such that:

$$x_{j,l}^L \leq x_{j,l,1} \leq x_{j,u}^U$$  

(5)

The lower bound is set to 0.0 nm i.e. the centerline and the upper bound is 4.0 nm i.e. maximum proposed offset value in continental airspace. We then randomly select the initial parameter values uniformly on the intervals: $[x_{j,l}^L, x_{j,u}^U]$. After initialization each of the $N$ parameter vectors undergoes mutation, recombination and selection.

In the mutation phase, which expands the search space. For a given parameter vector $x_{i,G}$ we randomly select three vectors $x_{r1,G}$, $x_{r2,G}$ and $x_{r3,G}$ such that the indices $i$, $r1$, $r2$ and $r3$ are distinct. We then add the weighted difference of two of the vectors to the third

$$v_{i,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G})$$  

(6)

The mutation factor $F$ is a constant from $[0, 2]$ $v_{i,G+1}$ is called the Donor Vector.

Recombination incorporates successful solutions from the previous generation. The trial vector $u_{i,G+1}$ is developed from the elements of the target vector, $x_{i,G}$ and the elements of the donor vector, $v_{i,G+1}$. Elements of the donor vector enter the trial vector with probability $CR$.

$$u_{i,j,G+1} = \begin{cases} v_{i,j,G+1} & \text{if } rand_{j} \leq CR \text{ or } j = I_{rand} \\ x_{i,j,G} & \text{if } rand_{j} > CR \text{ and } j \neq I_{rand} \end{cases}$$  

(7)

$rand_{j} \sim U[0, 1]$. $I_{rand}$ is a random integer from $[1, 2, \ldots, D]$ and $I_{rand}$ ensures that $u_{i,G+1} \neq x_{i,G}$.

In Selection, the target vector $x_{i,G}$ is compared with the trial vector $u_{i,G+1}$ and the one with the lowest function value (Collision Risk) is admitted to the next generation.

$$x_{i,G+1} = \begin{cases} u_{i,G+1} & \text{if } f(u_{i,G+1}) \leq f(x_{i,G}) \\ x_{i,G} & \text{otherwise} \end{cases}$$  

(8)

Mutation, recombination and selection continue until some stopping criterion is reached (number of generations). Best individual is selected from the final population. This represents the optimal lateral offset values for the airways that minimize the overall airspace collision risk.

E. Airway Traffic Features

In this paper, we have focused on upper airspace region also known as Reduced Vertical Separation Minima (RVSM) airspace for its significance in airspace collision risk assessment. Each flight level which is vertically separated by 1000 ft treated as a unique airway. Even bidirectional routes are treated as unique (one for each side).

Based on our previous research in Collision Risk assessment [13, 19, 20] we have identified following airway and traffic features as of interest in exploring correlation with the Optimal Lateral Offset:

- **Airway distance (NM):** This is the great circle distance (NM) from entry waypoint to exit waypoint including intermediate waypoints for a given airway.
- **Number of Aircrafts:** This is the number of flights that fly on a given airway (each way independent).
- **Intermediate Waypoints:** This is the number of waypoints on a given airway between its entry and exit waypoint.
- **Average Flying Time (minutes):** This is the average flying time of all the aircrafts on a given airway.
- **Airway Crossings:** This is the number of other airways that crosses a given airway. Bidirectional routes are counted as two crossings.

F. Regression Analysis

The objective of regression analysis is to predict some criterion variable better. The multiple regression model determine the best set of parameters $b_0, b_1, b_2, \ldots, b_p$ in the model $y = b_0 + b_1x_1 + b_2x_2 + \ldots + b_px_p$ by minimizing the error sum of squares. These coefficients allow us to calculate predicted value of the dependent variable $y$ (optimal lateral offset).

To make specific predictions using the model, we would need to substitute all the five airways and traffic features scores into the equation and then come up with the predicted
lateral offset value. The difference in the predicted Offset and the actual Offset is called as residual error $r_j$ which is the difference between the observed value $y^*$ of the dependent variable for the $j$th experimental data point and corresponding value $y^*$ given by the above regression model.

If there is an obvious correlation between the residuals and the independent variable $x$ (say, residuals systematically increase with increasing $x$), it means that the chosen model may not be adequate to fit the experiment. A plot of residuals is very helpful in detecting such a correlation.

VII. EXPERIMENTAL DESIGN

We first estimate the baseline collision risk for the given air traffic data. We then estimated Collision Risk with 1 NM offset and 2 NM to the right of airways for the given traffic data. Evolutionary framework was then employed with differential evolution to find optimal offset values for each airway along with associated airway-traffic features. Multiple Regression model is applied to come up with equation that can predict the optimal offset value given airway-traffic features.

A. Airsapce

For the experiments we used one day traffic data (710 flights) from Bahrain airspace. The traffic data used was of Bahrain Upper Airspace. i.e. RVSM with flight level 290 to FL4190 inclusive. Thus there were 13 flight levels and as we treated each airway uniquely even bi-directional ones, in total there were 94 airways in the Bahrain airspace. Figure 6 illustrates the Bahrain airspace which is characterized by three well identified crossing meshes as seen in the figure.

B. Lateral Overlap Probability

For Bahrain region it is assumed that 75% of flights are using GNSS and 25% of flights are using VOR/DME for navigation. Following the RVSM global system performance specification, the standard deviation for VOR/DME navigation is taken as 0.3 NM and a standard deviation of 0.06123 NM will be used for the GNSS. i.e. $\sigma_{\text{VOR/DME}} = 0.3$ NM and $\sigma_{\text{GNSS}} = 0.06123$ NM.

C. Collision Risk Model

ICAO Collision Risk model [4] is used to compute Vertical Collision Risk. This is different than the basic Reich collision risk model because of the complexity and variability of the traffic patterns in most continental radar controlled airspace it accounts for. The model has three main parameters, the probability of vertical overlap, the frequency of horizontal overlap events per flight hour, and the weighted average of kinematic factors. The latter is the combined parameters dependent on the geometry of the proximate pairs.

D. Differential Evolution (DE) Parameters;

For DE process the number of generations is set to 100 and the population size (individual solutions) is set to 30. This imply that for the traffic scenario there are 30 independent set of airways offset (in nautical miles) with the bound of 0nm to 4nm with 0.1 NM for 710 flights and the evaluation is repeated 100 times.

E. Air Traffic Simulation

For air traffic scenario simulation we have used Air Traffic Operations & Management Simulator (ATOMS). ATOMS is a
high fidelity, 4D, point-mass model based, 5 degrees of freedom air traffic simulator developed by the lead author. The Collision Risk Model is integrated into ATOMS such that every flight pair is evaluated, in each discrete time interval, for collision risk. ATOMS is thus used as the evaluation objective function for traffic scenarios: every time it is called with a scenario, it computes the collision risk and other parameters.

**VIII. RESULTS AND ANALYSIS**

The Collision risk per flight hour for baseline traffic without any offset is 8.853 × 10⁻³, with 1 NM offset to the right is 9.033 × 10⁻³, and 2 NM offset to the right is 8.892 × 10⁻³. We then present the how the evolution progressed over 100 generations. As shown in Figure 8, the evolutionary process manages to drive the population of initial solutions towards optimal solution (minimize the overall collision risk). Initially the average collision risk, with randomly intitlzed Lateral Offset values in the interval of [0.0-4.0] NM for each airway, was 8.9 × 10⁻³ collisions per flight hour and the best solution in that population had the fitness value of 8.1 × 10⁻³ collisions per flight hour.

By 10⁰th generation, we can see the DE process has converged and the best solution has the average fitness of 3.8 × 10⁻³ collisions per flight hour and the best fitness of 3.85 × 10⁻³ collisions per flight hour, a significant reduction in Collision risk.

This illustrate the effectiveness of DE process in evolving solutions (Lateral Offsets) for individual airways such that overall collision risk of a given airspace and traffic data is minimized.

![Figure 8: Convergence of Differential Evolution process over 100 generations](image)

Table 1 tabulates the evolved Lateral Offset values, in the best individual of the final population, for 94 airways in Bahrain airspace. The table also shows the airway and traffic features (distance, intermediate waypoints, number of crossings, number of flights, average flying time). We then present the frequency chart for the offset values in the range of [0.0, 4.0] for the best individual of the evolved population after 100 generation. Figure 9 shows the number of occurrence of offset values for each value on the range discretized by 0.1 NM.
Figure 10 shows that the DE process has come up, for 94 airways, an even distribution of offset values in the given intervals. This implies that evenly distributed lateral offset values result in minimization of collision risk in an airspace.

Figure 9: Number of Offset occurrence in each discrete lateral offset interval in the [0,4] NM range

We then present results from Multiple Regression analysis. Table 2 presents the ANOVA analysis which provides the breakdown of the total variation of the dependent variable (Lateral Offset) into the explained and unexplained portions. SS Regression is the variation explained by the regression line which in our case is 9.8% of which number of flights (6.04%) and number of crossings (1.8%) is the main contributors. Out of 94 airways the model was able to predict in 5 cases only.

Table 2: Analysis of variance

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Seq SS</th>
<th>Adj MS</th>
<th>F-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>5</td>
<td>9.864</td>
<td>1.9729</td>
<td>1.4</td>
</tr>
<tr>
<td>Distance (nm)</td>
<td>1</td>
<td>0.732</td>
<td>0.4141</td>
<td>0.29</td>
</tr>
<tr>
<td>Intermediate Waypoints</td>
<td>1</td>
<td>0.867</td>
<td>2.6341</td>
<td>1.86</td>
</tr>
<tr>
<td>Crossings</td>
<td>1</td>
<td>1.803</td>
<td>0.899</td>
<td>0.64</td>
</tr>
<tr>
<td>Number of Flights</td>
<td>1</td>
<td>6.042</td>
<td>4.9425</td>
<td>3.5</td>
</tr>
<tr>
<td>Average Flying Time</td>
<td>1</td>
<td>0.421</td>
<td>0.421</td>
<td>0.3</td>
</tr>
<tr>
<td>Error</td>
<td>89</td>
<td>125.804</td>
<td>1.4135</td>
<td></td>
</tr>
<tr>
<td>Lack-of-Fit</td>
<td>85</td>
<td>122.749</td>
<td>1.4441</td>
<td>1.89</td>
</tr>
<tr>
<td>Pure Error</td>
<td>4</td>
<td>3.055</td>
<td>0.7637</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>94</td>
<td>135.669</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The standard error of the regression is 1.188 NM, which is an estimate of the variation of the observed Optimal Lateral Offset, in NM, about the regression line.

Table 3: Summary of Regression Statistics

<table>
<thead>
<tr>
<th>Regression Statistics</th>
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</thead>
<tbody>
<tr>
<td>Multiple R</td>
</tr>
<tr>
<td>R Square</td>
</tr>
<tr>
<td>Standard Error</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>

The results of the estimated regression line include the estimated coefficients, the standard error of the coefficients, the calculated t-statistic, the corresponding p-value, and the bounds of 95% confidence intervals.

Table 4: Regression Coefficients

<table>
<thead>
<tr>
<th>Coefficients</th>
</tr>
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<tbody>
<tr>
<td>Term</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>Distance (nm)</td>
</tr>
<tr>
<td>Int. Waypoints</td>
</tr>
<tr>
<td>Crossings</td>
</tr>
<tr>
<td>Number of Flights</td>
</tr>
<tr>
<td>Average Flying Time</td>
</tr>
</tbody>
</table>

As shown in Table 4, the independent variables that statistically significant in explaining the optimal Lateral Offset values are the number of crossings and number of flights, as indicated by (1) calculated t-statistics that exceed the critical values, and (2) the calculated p-values that are less than the significance level of 5%. Thus the Regression Equation is given by:

\[
\text{Evolved Offset (nm)} = 1.809 + 0.00161 \times \text{Distance (nm)} - 0.1331 \times \text{Intermediate Waypoints} + 0.0222 \times \text{Crossings} - 0.01259 \times \text{Number of Flights} - 0.0059 \times \text{Average Flying Time} \quad (9)
\]
We then plotted the residual plots for number of Crossings and number of flights as shown in figure 11 and 12 respectively. As there is no obvious correlation between the residuals and the independent variable Lateral Offset (residuals do not systematically increase with increasing crossings and number of flights), it indicates that the chosen model may be adequate to fit the experiment.

![Crossings Residual Plot](image1)

Figure 11: Error residual plot for number of airway crossings.

![Number of Flights Residual Plot](image2)

Figure 12: Error residual plot for number of flights.

IX. CONCLUSIONS

The proposed evolutionary framework using Differential evolution successfully evolved optimal lateral airway offsets such that the overall collision risk was minimized. An interesting observation was that evolved Lateral Offsets were evenly distributed in the respective lateral latitude bands. There was weak correlation between airway and traffic features with only 7.2 % of the variation in the dependent variable (Optimal Lateral Offset) can be explained by the independent variables. Number of flights and airway crossings were two features that correlated with optimal lateral offset with their error residual plots indicating usefulness of the model.

Applying airway specific optimal lateral offset in airspace may achieve the desired reduction in collision risk. Further identifying airway and traffic features that affect the lateral offset may give airline safety and ATC managers an insight into how to manage traffic flow in their respective airspace.

However, in a high density radar controlled environment, lateral offsets may not significantly reduce the system safety as crossing traffic generates the dominant risk. In many parts of Middle East region the route spacing is at or close to the minimum that can be supported by the navigation performance requirement. In our future work, we would investigate how the application of lateral offsets in such situations may increase the risk associated with the passing traffic on the neighboring track and how to mitigate it.

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BIOGRAPHIES
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