The Effect of Swarming on a Voltage Potential-Based Conflict Resolution Algorithm

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***Abstract*— Several conflict resolution algorithms for airborne self-separation rely on principles derived from the repulsive forces that exist between similarly charged particles. This research investigates whether the performance of the Modified Voltage Potential algorithm, which is based on this algorithm, can be improved using bio-inspired swarming behavior. To this end, the collision avoidance function of the algorithm is augmented with the velocity alignment and flock centering swarming traits displayed by animals such as birds and fish. The basic and swarm augmented versions of the algorithm were compared using large-scale fast time simulations, for multiple traffic demand scenarios. For ideal conditions, the results show that the process of aligning with neighboring traffic triggered a large number of conflicts. However, when noise was added to scenarios, swarming led to a lower increase in the number of intrusions, which could indicate that it can be used to improve the robustness of the Modified Voltage Potential algorithm. Furthermore, the stability results suggest that both versions of the algorithm could reduce the number of conflict chain reactions with respect to simulations without resolution. Future research will further explore the effect of conflict resolution on airspace stability, as well as whether varying the relative weights of swarming elements can improve the safety of swarm augmentations.**

Keywords- Separation Management; Swarming; Modified Voltage Potential (MVP); Conflict Resolution; Self Separation; Free Flight; Airspace Stability; Domino Effect Parameter; BlueSky

I. INTRODUCTION

Birds are often seen flocking, or swarming, together as this offers several advantages in terms of searching for food, improving efficiencies for long distance migratory flights (using V-formations) and for protection from predators. Several other animals, such as fish and cattle, also display similar behavior. In fact, the complex en-route swarming patterns displayed by these animals can be modelled as a combination of three simple behavioral traits exhibited by each individual member of the group, namely collision avoidance (to avoid crashes with neighbors), velocity alignment (to move in the same general direction as neighbors), and flock centering (to remain close to neighbors) [1]. These bio-inspired characteristics have been used in the past to design collision-free path planning algorithms for systems with many interacting agents, such as formation flight of Unmanned Aerial Vehicles (UAVs) [2]. This study will investigate whether it is possible to use swarming traits to improve the performance of autonomous Conflict Resolution (CR) strategies for conventional aircraft.

The goal of this work is to investigate the effect of swarming-inspired flight maneuvers on self-separation under Free Flight conditions, when a voltage potential based separation method is applied. Here, the Modified Voltage Potential (MVP) algorithm, initially developed during the NLR-NASA Free Flight study, will be used as an example of such voltage potential based CR methods [3]–[5]. It is hypothesized that augmenting the collision avoidance capability of MVP with velocity alignment and flock centering functions will help prevent some conflicts from occurring, by aligning and reducing relative velocities between neighboring traffic. This should, in turn, make it easier for the MVP algorithm to resolve any remaining conflicts.

To investigate whether swarming can improve the performance of the MVP algorithm, a large-scale simulation experiment is performed, comparing the basic and swarm augmented versions of MVP. These simulations are performed using BlueSky [6], an open air traffic simulator developed at the Delft University of Technology. The two versions of MVP are subjected to multiple traffic demands, with heterogeneous Free Flight-like demand patterns. Performance of the CR algorithms is evaluated using safety, efficiency and stability metrics. To gain an understanding of the impact of uncertainties, the effect of measurement errors, turbulence, and the consequences of discrete state transmitting, is also studied in this work.

This paper is organized as follows: The basic and swarm augmented version of MVP, including implementation details, are described in Section II. This is followed in Section III with the setup of the simulation experiment used to compare the two CR algorithms. The results of the experiment are presented and discussed in section IV. The main conclusions and recommendations are summarized in section V.

II. Conflict Resolution Methods

To observe the effect of swarming, two CR methods are selected for comparison: a Modified Voltage Potential (MVP) [7] method and a formation flying method using swarm intelligence (SW) [2]. The underlying algorithms are discussed in the following paragraphs.

A. Modified Voltage Potential

The principle of MVP is to model conflicting aircraft as identically charged particles, that repel each other away from their Closest Points of Approach (CPA), such that a Loss of Separation (LOS), or intrusion, is no longer predicted. The resulting displacement vectors are used to compute necessary changes in aircraft velocities. The three steps of the principle are illustrated in Figure 1. The second step of the MVP algorithm is illustrated with more detail in Figure 2.

In Figure 2, a conflict situation is exaggerated for clarity purposes. The relative velocity of aircraft B with respect to aircraft A is pointing through the Intruder Protected Zone (IPZ) of A. The strategy is to find the closest point of approach, point C, and from this point find the closest distance out of the IPZ, to O. Since a straight line from B to O would still cross the IPZ, the line CO must be multiplied by a factor, computed by [7] as:

$$\frac{|CO|}{|CO'|} = \left|\cos\left(arcsin\left(\frac{R}{AB}\right) - arcsin\left(\frac{AC}{AB}\right)\right)\right| \qquad (1)$$

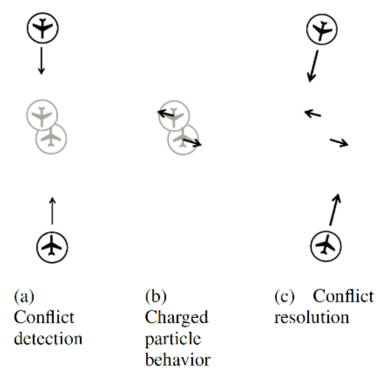

Figure 1: The three steps of MVP conflict resolution

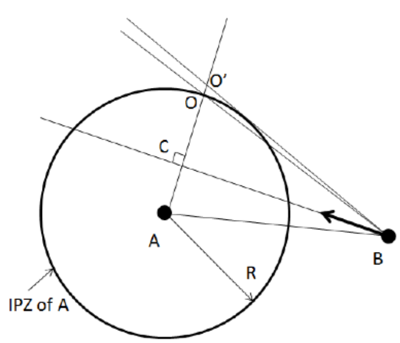

Figure 2: Finding the displacement vector in MVP

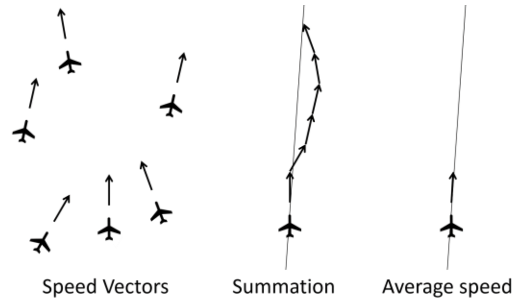

Figure 3: The three steps of VA

Once the distance vector CO' is determined, the resolution velocity vector is computed through Equation 2, where t_C is the time at which point *C* is predicted.

$$\vec{v}_{MVP} = \frac{\overrightarrow{CO'}}{t_C} + \vec{v}_{current} \qquad (2)$$

Conflict detection is executed with a linear extrapolation of the aircraft velocity vectors, for a look-ahead time of 5min. The separation requirements are 5nm horizontally and 1000ft vertically. Conflicts that are detected are solved with a safety margin of 5%.

Conflict resolution by MVP is implicitly coordinated cooperatively; both aircraft in a conflict will take (opposite) measures in order to evade the other. Additionally, if an aircraft would encounter multiple conflicts at the same time, each conflict is resolved separately and the resolution vectors are summed together, resulting in a general steering action.

B. Swarm Augmented Modified Voltage Potential

This algorithm is based on a model for coordination of UAVs that fly in large groups [2]. The motion of UAVs in groups has been modelled as combinations of three behaviors: Collision Avoidance (CA), Velocity Alignment (VA) and Flock Centering (FC).

1) Collision Avoidance

CA is performed using the MVP resolution strategy. CA is always active: if no conflicts are detected, the resolution vector of CA points in the target heading of the aircraft. CA therefore always returns a resolution velocity vector.

2) Velocity Alignment

For VA, each aircraft will align its velocity vector to match the average velocity of the surrounding aircraft. In order to do so, the velocity vectors of all aircraft are summed together. The resulting velocity vector is scaled to match the average speed vector length of the swarm. This process is illustrated in Figure 3.

3) Flock Centering

In FC, the aircraft flies to the center of the swarm. The goal of this is to reduce the size of swarms. This process also consists of three steps. In the first step, the swarm center is found by

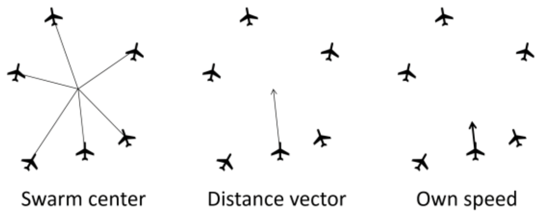

Figure 4: The three steps of FC

taking the average location of neighboring aircraft, expressed in Cartesian coordinates. The next step is to find the distance vector from the 'ownship' location to the swarm center. This distance vector is then scaled to match the current speed vector of the aircraft. These steps are illustrated in Figure 4.

4) Swarming Weights

The resulting action of the algorithm is a weighted combination of the three swarming elements. Each element results in a separate resolution vector. The total resolution vector is found by computing a weighted sum of the resolution vectors from each element. The weights of the three elements are determined by trial and error. This procedure aimed to find values for VA and FC as high as possible, to increase swarming. However, swarming should not be so strong that it is impossible for aircraft to leave a group. The resulting weights can be seen in Table I.

TABLE I: SWARM WEIGHTS

Swarming element	**Weight value**
Collision avoidance (CA)	10
Velocity alignment (VA)	3
Flock centering (FC)	1

5) Swarming Criteria

For VA and FC, all aircraft that are within predefined swarming criteria are considered. These criteria are defined from an aircraft perspective: each aircraft defines a swarm around itself. The criteria are defined as:

- Horizontal distance < 7.5nm
- Vertical distance < 1500ft
- Difference in heading < 90 degrees

C. Qualitative Analysis

It is noted that the SW algorithm approaches the problem of CR from a fundamentally different concept than the MVP algorithm. Although the CA algorithm is identical, the SW algorithm can provide steering resolutions even if no conflicts are detected. If this is effective, conflicts will be prevented from even occurring, as aircraft are flocking together with other aircraft flying in the same direction.

III. Experiment Design

This part contains a description of the experiment. This is found in four sections: the simulation platform, the construction of traffic scenarios and the dependent and independent experiment variables.

A. Simulation Environment

The experiment of comparing the CR methods was performed using BlueSky. BlueSky is an open-source air traffic management simulator, written in Python, capable of simulating thousands of simultaneous aircraft. The program contains a graphical user interface that allows for real-time controlling of the air traffic, as well as logging facilities for post-analysis of the results.

1) Traffic Modelling

In the current version of BlueSky, several default constraints to the aircraft performance are present. These are the following:

- When making corners, the bank angle is 25 degrees
- If no vertical speed is specified, aircraft climb and descend with 1500 feet per minute
- Horizontal acceleration is equal to one knot per second
- Vertical acceleration is instantaneous to the desired vertical Speed

2) Noise

In order to observe the performance of the CR methods under imperfect circumstances, simulations with and without noise will be performed. The implementation of noise consists of three different elements, discussed in the following paragraphs. A summary of the noise is given in Table II.

1. *Measurement Noise*: The measurements of relative positions of aircraft, expressed in polar coordinates to each other are distorted.

2. *Turbulence*: Turbulence is added for flights as an additional velocity vector in the aircraft reference frame. Since turbulence is a continuous phenomenon, the magnitude of the turbulence is multiplied with the square root of the simulation time step.

3. *Sampling Effect*: Each aircraft is not aware of the current position of the other aircraft. Aircraft transmit their exact locations once every time period. When performing conflict detection, aircraft compare their own real positions to the last transmitted positions of the surrounding aircraft. The transmission period is modelled to be constant.

Figure 5: Size of the test and initialization region compared to the Netherlands

TABLE II: NOISE MAGNITUDES

Type of Noise	Standard Deviation
Measurement error (bearing)	1°
Measurement error (distance)	100 m
Measurement error (altitude)	100 ft
Lateral turbulence	0.1 m/s^2
Vertical turbulence	0.1 m/s^2
Sampling period	1 s

B. *Traffic Scenarios*

A program has been developed which is capable of generating and saving simulation scenarios, for testing the performance of the CD&R algorithms. Several elements of the software design are discussed. These scenarios are developed offline by the program, in advance of performing the simulations. By doing so, each tested CD&R method will be subjected to the same traffic scenario and therefore tested under the same conditions.

1) *Testing Region*

A circular airspace is constructed for simulating the air traffic. Around the airspace, a circular initialization region is formed. Aircraft are generated at the outer edge of the initialization region, and conflicts that occur outside the test area are neither detected nor solved. The radii of the concentric regions are 45 nm and 68 km. An indication of the size of these regions is given in Figure 5. Vertical limits on the airspace are not implemented, so as to give aircraft freedom for vertical resolution maneuvers. Aircraft are deleted when they are outside the testing area and flying away from the circle center. It is possible that aircraft do not enter the test area at all, as they might deviate before entering the circle. This is saved in the logs and aircraft that do not enter the test region are filtered out of the results. The aircraft which are generated outside of the logging hour are not considered in the results.

TABLE III: NORMAL AIRCRAFT PARAMETERS

Parameter	Mean value	Standard Deviation
TAS	140 m/s	10 m/s
CAS	109 m/s	8 m/s
Altitude	5000 m	305 m (1000 ft)
Climb rate	0 m/s	0.5 m/s

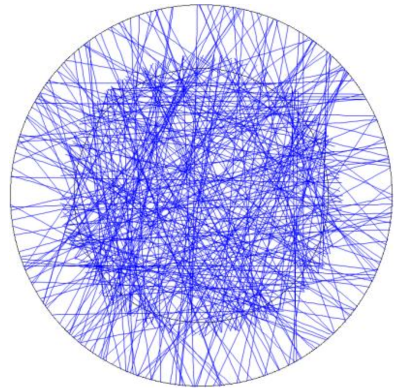

Figure 6: Horizontal aircraft trajectories without resolution after a traffic scenario of *125 ac/hr* traffic demand

2) *Aircraft Parameters*

The aircraft in the simulation fly with different horizontal and vertical velocities. Aircraft were created randomly on the outer range of the initialization region. All headings are possible as long as the aircraft trajectory is planned to cross the test region, with a 5% margin in order to prevent flight plans that are almost tangent to the test region edge. The remaining aircraft parameters follow a normal distribution and are summarized in Table III.

3) *Traffic Scenarios Creation*

A genetic algorithm is used to create random traffic scenarios with as much conflicts as possible. Each scenario is constructed with random numbers that specify the planned flight paths through the airspace.

Scenarios are evaluated for comparison. The number of conflicts is predicted by the scenario generator, and counted as positive score. Negative points are rewarded for the root-mean-squared error between the predicted and theoretical distributions of specific parameters, expressed in 10-binned histograms. The specific parameters are the locations of aircraft at start and end of the flight, and the locations of the predicted conflicts.

Each scenario is evaluated and an evolutionary principle is applied. This principle consists of 1000 iterations of survival, parenting, inheritance, mutation and again evaluation. Afterwards, the best evaluated scenario is saved to be used as test scenario in the experiment. An example of a saved scenario is given in Figure 6, where the resulting flight paths through the airspace are indicated.

C. *Independent Variables*

One independent variable has already been introduced: the CR method that is used. CR method is a factor with three levels: no conflict resolution, and resolution by MVP or swarming. Traffic demand, defined as the rate at which new aircraft are generated at the edge of the test region, is a factor with 5 levels. The traffic demand can be 50, 125, 200, 275 and 350 aircraft per hour. This results in 15 (3x5) conditions. For each condition, 5 repetitions are made with different scenarios. This is done by running the scenario generator with different random seeds.

D. Dependent Variables

The dependent variables of this research are sorted in three categories: safety, efficiency and airspace stability. These are logged during the 1-hour experiment, which starts after 35 minutes of initialization time, and is followed by 35 minutes of cooling-down time.

Safety is expressed in numbers of intrusions and conflicts per flight. Definitions of flights, intrusions and conflicts are determined as:

- A flight is a simulation of an aircraft which does enter the test region at any moment in its lifetime.
- An intrusion is a violation of separation requirements between two simulated aircraft at any time when at least one of the two is in the test region.
- A conflict is a prediction of an intrusion within the set look-ahead time as a consequence of linear trajectory propagation of actual states of simulated aircraft.

Additionally, the proportion of intrusions that were successfully avoided, the Intrusion Prevention Rate, is computed:

$$IPR = \frac{Conflicts - Intrusions}{Conflicts} \tag{3}$$

For each intrusion, the intrusion severity is measured. Intrusion severity is defined using Equation 4. In this equation, d and R are the distance between two aircraft and the separation requirement, respectively. Subscripts h and v denote horizontal and vertical variables.

$$int_{severity} = min\left(1 - \frac{d_h}{R_h}, 1 - \frac{d_v}{R_v}\right) \tag{4}$$

Efficiency is monitored through the route efficiency metric, i.e., the ratio between the shortest and the actual route flown, in the horizontal plane:

$$\eta_{route} = \frac{d_{shortest}}{d_{flown}} \tag{5}$$

Airspace stability is observed using the Domino Effect Parameter (DEP) [8]. The DEP is computed by comparing the number of conflicts in simulations with and without Conflict Resolution (CR), as indicated in Equation 6:

$$DEP = \frac{Conflicts_{withCR}}{Conflicts_{withoutCR}} - 1 \tag{6}$$

IV. Results and Discussion

In this section, data obtained from the simulation experiments are used to compare the MVP and SW CR algorithms in terms of safety, efficiency and stability metrics. Additionally, the impact of noise on the safety of the two CR algorithms, as well as the effect of varying the relative importance of the three components of the SW method, are also discussed.

A. Traffic Volume

Before analyzing the dependent variables mentioned above, it is first necessary to consider the traffic volumes that were actually realized during the experiment, see Figure 7. Here it can be seen that the MVP and SW methods resulted in slightly more aircraft in the simulations compared to no conflict resolution, even though all CR methods were subjected to the same traffic scenarios. This is because resolution maneuvers increase flight distances, and therefore cause aircraft to exist for longer durations within the experiment area (see Efficiency section below). To account for these differences in density, and thus to allow for a fair comparison between the two CR methods, whenever appropriate, dependent variables are computed relative to the number of flights simulated during the logging hour.

B. Safety

The number of conflicts and intrusions per flight are displayed in Figures 8 and 9 respectively. Here it can be seen that the MVP algorithm resulted in the lowest number of conflicts and intrusions. Although SW caused significantly higher number of conflicts, in terms of intrusions, the difference between these two CR methods is small. This is because the CA component of SW also used the MVP algorithm for avoiding intrusions. For the same reason, no noticeable differences between MVP and SW were found in terms of intrusion severity, see Figure 10.

It is interesting to note that the MVP algorithm resulted in even fewer conflicts than the no resolution setting, see Figure 8. This was an unexpected trend; as resolution maneuvers increase flight distances and the consequent probability of encountering other aircraft, both MVP and Swarming were expected to cause an increase in the number of conflicts compared to simulations without resolutions, as already described in [8]. This unusual result is further analyzed using stability metrics.

Given the similarity and the low number of intrusions for MVP and SW, it is not surprising that both CR methods achieved high IPR scores for all demand scenarios, see Figure 11. While IPR for the no resolution case was low, it was not equal to zero. This means that not all conflicts resulted in intrusions, even though aircraft did *not maneuver* during simulations without resolutions. A detailed analysis revealed that this effect was caused by atmospheric variations of air density with altitude, and the ensuing differences between True Air Speed (TAS) and Calibrated Air Speed (CAS). This caused

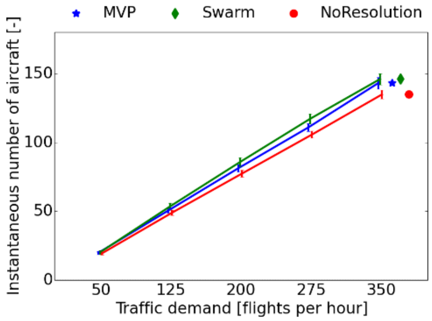

Figure 7: Traffic volume
(mean + standard deviation)

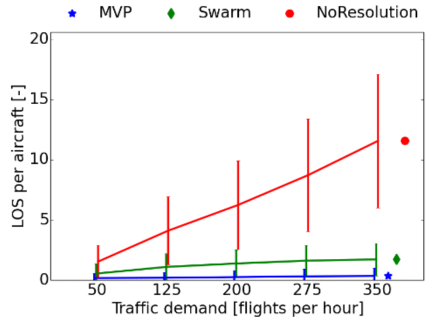

Figure 9: Number of intrusions per flight
(mean + standard deviation)

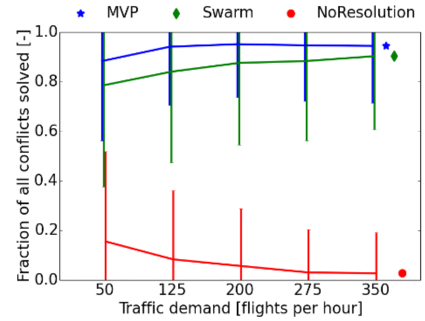

Figure 11: Intrusion Prevention Rate (IPR)
(mean + standard deviation)

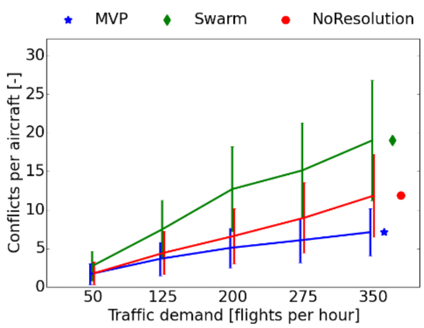

Figure 8: Number of conflicts per flight (mean + standard deviation)

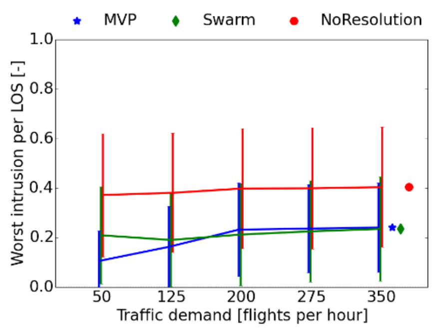

Figure 10: Intrusion severity
(mean + standard deviation)

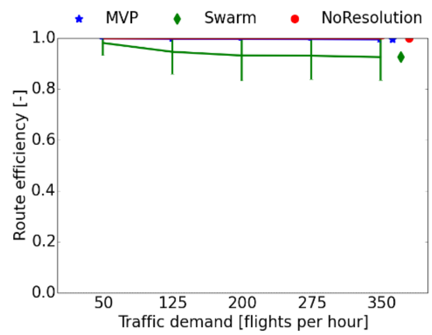

Figure 12: Route efficiency
(mean + standard deviation)

prediction errors for aircraft positions, which adversely affected the Conflict Detection (CD) process; as aircraft flew using constant CAS, altitude changes would result in acceleration/decelerations, while CD was performed assuming constant TAS. Consequently 'false conflicts' would be predicted, particularly for climbing/descending traffic, due to differences between the actual and predicted flight paths. When simulations were performed with a modified atmosphere model, where the density at all altitudes was equal to sea-level density, the number of intrusions without resolutions exactly equaled the number of conflicts (not shown). This example illustrates the need to take notice of 'small' details in simulations of conflict detection and resolution.

Based on the safety results, it can be concluded that the MVP algorithm results in a higher safety under ideal conditions. This is because the MVP method solves conflicts with minimal steering resolutions and only when intrusions are predicted. On the other hand, the VA and FC components of the SW algorithm caused aircraft to group together in the air. For the traffic densities simulated, this resulted in significantly higher number of conflicts and degrading safety.

C. Efficiency

The route efficiency results are displayed in Figure 12. As expected, simulations without resolutions resulted in optimal efficiency. As MVP used minimal steering maneuvers and suffered a lower number of conflicts, it resulted in shorter routes, and therefore, better efficiency than SW. It is also noted that the efficiencies of both CR methods are not significantly affected by demand changes. This suggests that the airspace did not reach saturation levels with the current demand scenarios.

D. Stability

The results for the Domino Effect Parameter (DEP), which is used to assess airspace stability, are shown in Figure 13. It is seen that for each simulated traffic density, the resulting DEP for MVP is lower than zero. Here, a negative DEP implies a net stabilizing effect of tactical CR whereby conflict chain reactions are outweighed by those that are solved without pushing aircraft into secondary conflicts. On the other hand, positive DEP values indicate the opposite: airspace instability.

As expected, the DEP for simulations with no resolutions is always zero as these simulations are compared with themselves. For the MVP method, the DEP was consistently negative, and also decreased with demand. This indicates that MVP is actually improving the stability of the airspace at higher densities, corresponding with the lowest number of conflicts for all CR methods noted earlier in the safety analysis. Although the DEP for SW is positive for all demand conditions, at higher demands, a negative trend is also observed for this CR method.

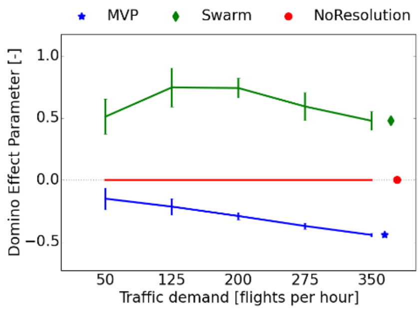

Figure 13: DEP, original simulations (mean + standard deviation)

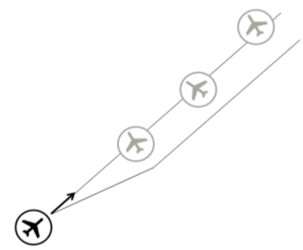

Figure 15: Negative DEP example: a line of conflicts solved by one resolution

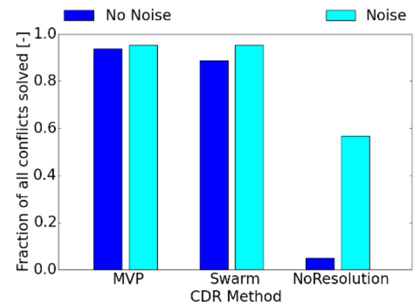

Figure 17: Effect of noise on the Intrusion Prevention Rate (IPR)

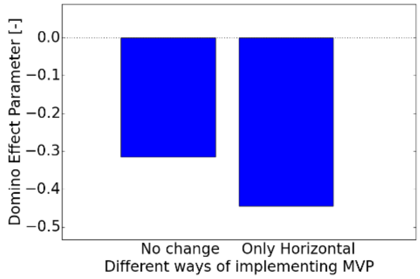

Figure 14: Effect of three-dimensional simulations on the Domino Effect Parameter (DEP)

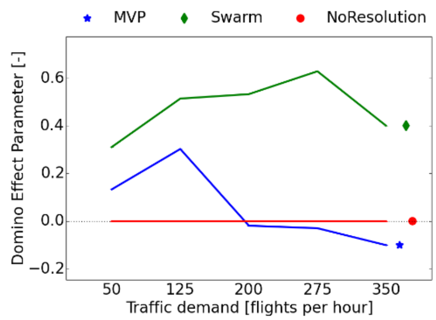

Figure 16: Effect of scenario generation on the Domino Effect Parameter (DEP)

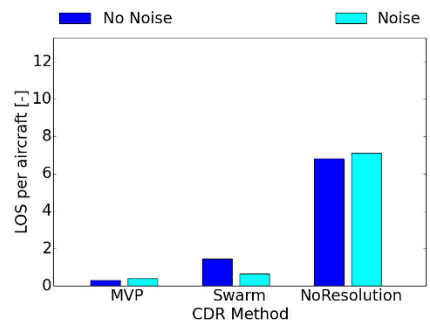

Figure 18: Effect of noise on the number of intrusions per flight

To analyze these unexpected trends in the DEP, particularly the reduction of DEP with increasing demand, several potential explanations have been put forth. These are discussed in the following subsections.

1) Three-Dimensional Simulations

Due to the three-dimensional nature of the simulations, aircraft could have used vertical CR maneuvers to 'escape' other traffic, reducing the total number of conflicts relative to the no resolution setting. To verify this hypothesis, additional simulations were performed for the MVP algorithm during which all flights were created at the same altitude, with aircraft constrained to use only horizontal resolution maneuvers. This test was performed for a traffic demand of 200 ac/hr, using a single scenario repetition. If this hypothesis is true, the DEP for flights constrained to a single altitude should be higher than the DEP for three-dimensional flights. It was also assumed that this effect is independent of CR method, hence separate simulations were not performed for SW.

The results of this test, see Figure 14, show that the two-dimensional flights resulted in an even lower DEP. However, this is not because MVP was better at resolving conflicts when constrained to using horizontal resolutions, but because the number of conflicts without resolution increased by a much greater amount compared to the number of conflicts with the MVP algorithm, for the two-dimensional simulation. Thus, the three-dimensional nature of the simulations is not the cause of negative DEP values.

2) Influence of Logging Period

Because conflicts increased flight distances, it is possible that some conflicts, which took place during the experiment hour for the no resolution case, occurred after the experiment time for the MVP and SW methods. This would lead to a reduction in the number of conflicts logged for both CR methods, leading to a negative DEP. To verify this hypothesis, the DEP was recomputed using conflicts from the entire duration of each simulation. This DEP showed very little differences with the original logging procedure (not shown), thus the logging method did not affect the DEP.

3) Effect of Scenario Generation

As mentioned earlier, experiment scenarios were generated using a genetic algorithm script that aimed to maximize the number of conflicts per flight. It is hypothesized that this design choice could have created scenarios in which several conflicts line up one after another. For such 'conflict lines', resolving the first conflict could also solve the remaining conflicts, as illustrated in Figure 15. This would, in turn, reduce the number of conflicts relative to the no resolution setting, and cause a negative DEP. Furthermore, it is reasonable to expect that these 'conflict lines' grow in size at higher demand levels, explaining the decrease of DEP with demand. To verify this hypothesis, the goal of maximizing the number of conflicts was removed from the GA's objective function, and new scenarios, with one repetition per traffic demand volume, were created.

The DEP results for these new simulations are displayed in Figure 16. While numeric values have changed, the updated scenarios have not changed the major trends noted earlier for the original scenarios; MVP still displays negative DEP values with a negative trend, and the SW causes the DEP to decrease at higher traffic demand volumes (compare Figure 13 with Figure 16). Thus, while the scenario generation does affect the DEP results, it is not the predominant cause of the negative DEP values or negative DEP gradient.

4) *Inherent Behaviour of CR Methods*

Given that the three previous explanations do not fully explain the unexpected DEP trends observed, it is hypothesized that these characteristics are inherent to the CR methods considered. The methods could cause an implicit restructuring of the randomly distributed traffic in such a way that the DEP reduces for higher traffic demands considered here. For MVP, it is expected that the charged particle behavior used to resolve conflicts will also disperse aircraft over the available airspace, both vertically and horizontally. This greater utilization of the airspace would reduce the chance of aircraft encounters and lead to a reduction in the number of conflicts. For SW, grouping aircraft with similar directions does cause problems during the alignment process, but it is possible that the benefits of swarming pay off for higher densities. While these effects are likely to improve stability at relatively low densities, at extremely high traffic demand levels, the congestion of the airspace, would make it progressively more difficult to solve conflicts without triggering additional conflicts. Preliminary results of a study focusing on the relation between stability and CR can be found here [9].

E. *Effect of Noise and Swarming Component Weights on CR Performance*

To study the effect of uncertainties on safety, the CR methods were subjected to the three forms of noise mentioned in section IIIA2, at a traffic demand of 200 ac/hr. Figure 17 shows that the intrusion prevention rate is increased by the presence of noise for all CR methods, as the number of false alerts increases significantly with noise. This is particularly true for the no resolution setting, where the number of conflicts with noise was thirteen times greater than without noise. In terms of the number of intrusions per flight, Figure 18 shows that swarming (SW) actually benefits from the presence of noise. It is believed that flocks of aircraft maintain more separation inside the group when noise is present, and therefore less intrusions take place. On the other hand, as (Modified Voltage Potential) MVP only uses the minimum resolutions needed to resolve conflicts, noise increases the number of intrusions.

To gain an initial understanding on the effects of varying the weights of the three SW components, additional simulations were performed with greater emphasis on VA and FC, separately, at a traffic demand of 200 ac/hr. However, these simulations did not reveal any significant differences when the relative weights of VA and FC were changed. A more detailed analysis is needed to arrive at a conclusive verdict on this.

V. Conclusions

This study focused on the effect of swarming for free flight. The algorithm is tested in large-scale traffic simulations created with a focus on having as many conflicts as possible. The results of swarming are compared to results when no swarming is performed and to results when no steering is performed at all.

The best results of safety, efficiency and airspace stability are achieved for self-separation performed without swarming. The safety of the methods decreases when turbulence and position uncertainties are added to the simulation, but swarming appears to increase the robustness of the resolution strategy with respect to noise. Airspace stability is influenced by the way in which the traffic scenarios are generated. The performance of the swarming algorithm is also altered by tuning the method’s parameters.

It is found that airspace stability, measured by the Domino Effect Parameter, can become negative. This indicates a stabilizing effect caused by the conflict resolution strategies. Research should be performed to explain why the resolution methods stabilize the airspace.

This study has shown that decentralized conflict resolution strategies have potential in delivering safety and efficiency in complicated three-dimensional traffic situations. More resolution strategies should be tested and compared to each other. Also, research should be done to the phenomenon of negative airspace stability observed in the project.

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