JOURNAL OF AERONAUTICS AND SPACE TECHNOLOGIES
JANUARY 2014 VOLUME 7 NUMBER 1 (25-35)

AIR COMBAT WITH PARTICLE SWARM OPTIMIZATION AND GENETIC ALGORITHM

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***Received:**,24th September 2013 **Accepted:** 07th January 2014*

ABSTRACT
The future of aircrafts is in unmanned aerial vehicles (UAVs), and any improvement in UAVs will play an important role, especially when it comes to intelligence and capabilities for air combat manoeuvring. The ultimate goal in such work is to bring computers to the level of a pilot's intelligence capability in air combat. In order to achieve this goal, operations research is required. The present study is based on the fight or flight situation in air combat manoeuvring and aims to improve unmanned aircrafts and better understand the difficulties of modelling intelligence. Since the project's focus is on the problem of path planning for moving targets and enemy situations, particle swarm optimization and genetic algorithms are modelled and tested against each other in a dog fight scenario. Also, multiple targets and enemies' scenarios are developed to compare them against each other. Moreover, imperfect information affect and dynamic environment are evaluated in this research and required actions and options are analysed. Overall, this research aims to show the importance of artificial intelligence, articulate the role of the operations research and assess the implementation of intelligence through certain heuristics.

***Keywords**: Air Combat Manoeuvring, Path Planning, Artificial Intelligence, Particle Swarm Optimization, Genetic Algorithm.*

PARÇACIK SÜRÜ OPTİMİZASYON VE GENETİK ALGORİTMA İLE HAVA MUHAREBESİ

ÖZET
Uçak sektörünün geleceği İnsansız Hava Araçlarında (İHA) görülmekte ve İHA'larda gerçekleştirilecek herhangi bir gelişme de özellikle hava muharebe manevrası için gereken beceri ve zeka hususunda büyük bir rol oynayacaktır. Böyle bir çalışmada temel amaç, hava munarebesi hususunda bilgisayarları, pilotların zeka becerisi seviyesine getirmektir. Bu amacın gerçekleştirilmesinde de yöneylem araştırması olmazsa olmazdır. Mevcut çalışma, hava muharebe manevra konusunda savaş ve uçuş durumuna dayanmaktadır ve bu çalışma ile insansız uçakları geliştirmeyi ve zekanın modellenmesine dair problemleri ve zorlukları daha iyi anlamak hedeflenmiştir. Projenin hedef noktası, hareket halindeki hedefleri ve düşman saldırı durumları için rota planlama problemi olduğundan ötürü, parçacık sürü optimizasyonu ve genetik algoritmalar modellenmiştir ve bu algoritmalar, bir it-dalaşı senaryosunda birbirlerine karşı test edilmişlerdir. Ayrıca, çoklu hedefler ve düşmanlar üzerinden senaryolar, bu algoritmaların birbirlerine göre kıyaslanmaları için geliştirilmiştir. Bunların yanı sıra, eksik bilgi etkisi ve dinamik çevre, bu araştırma dahilinde değerlendirilmiş ve gerekli hareket ve opsiyonlar analiz edilmiştir. Genel olarak, bu çalışma, yapay zekanın önemini göstermeyi, yöneylem araştırmasının rolünün açıklanmasını ve belli sezgisel yöntemlerle zekanın uygulaması hedeflemiştir.

***Anahtar Kelimeler:** Hava Muharebesi, Yol Planlaması, Yapay Zekâ, Parçacık Sürü Optimizasyonu, Genetik Algoritma.*

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) are one of the most important developments in air combat because they represent the change from human-controlled systems to intelligent and autonomous systems for aerial vehicles. UAVs have proven their usefulness in long endurance mission as well as their capabilities in dangerous scenarios [1]. Furthermore, UAVs are used for surveillance, search and rescue, remote search, scientific research, domestic policing, fire-fighting and military operations. Today, the U.S. Air Force spends more than \$2.6 million to train a fighter pilot. However, the report, released in December by the service's Audit Agency suggests that 20 weeks of undergraduate pilot training can be decreased to 8 weeks of undergraduate pilot training and 12 weeks of graduate pilot training, coming to \$135,000 per pilot. UAVs can save \$1.5 billion according to this report. Today, according to the U.S. Air Force, Predator and Reaper flight hours have increased in recent years [2].

Fight-or-flight situations, dog fights or stealth missions are a few of the possible scenarios that UAVs might encounter in military application. Sometimes, these situations can be too dangerous for a human, in which case UAVs becomes a great advantage. However, UAVs are mostly semi-autonomous or autonomous systems. An important advantage of these intelligent systems is that computers can gain awareness and the capacity for decision making. This is important because effective operations can be achieved through less communication, seeing as the current system still depends on human users. Relying on humans can be disadvantageous for UAVs due to communication difficulties, threats such as cyber-attack vulnerabilities, bandwidth problems, weak awareness and response time.

Cyber-attacks are one of the most dangerous weaknesses, as they allow hackers to disrupt a mission, damage or destroy the vehicle or hijack and gain control over it. There were few cyber-attacks on UAV systems until 2007, the main reasons for which being non-popularity, different network topology and lack of information [3]. Generally, UAV networks are similar to wireless sensor networks or mobile ad-hoc networks. Although UAVs use wireless communication protocols, there is wide variety in power requirements, amount of information carried, coverage area and number of nodes. These differences are one defence against cyber-attacks. However, the first reported cyber-attack took place in 2009 and targeted the UAV's video feed recording. The attack was discovered when members of a terrorist group were captured, and they had capitalized on the vulnerability of the system's unencrypted video feed. Interception between ground control and UAVs can be dangerous, as failure in ground control might result in the loss or damage of the UAVs. This situation makes ground control, which poses no advantage.

Information flow is another important aspect of UAV teamwork. During a mission, new objectives can arise and plans can be revised instantly [4]. These processes are constrained by the flow of information. Communication between UAVs and ground control is bound to bandwidth limitations, delays, range, and network topology limitations [4]. These constraints shape both the information that can be carried and the loss of information. Information loss may result in a lack of control, a delay in action, a loss of awareness and an inability to adapt to environmental changes. All of these are potential threats for UAVs in an active mission because a lack of control or a delay in action means that there is imperfect information and that orders may not be carried out as planned. In such conditions, unexpected threats to UAVs cannot be answered quickly enough to take control, which may result in the loss of the vehicle.

These risks are a result of imperfect information and the lack of adaptation on the part of the vehicle, since the vehicle itself needs to answer rather than waiting for an answer. These delays are a serious problem for UAVs, and possible solutions include minimizing unnecessary information, changing network topology or increasing the level of intelligence in UAVs. One must also consider the delay and burden of security for information flow. The encryption and decryption process causes a time delay, and, since every second counts, it is important to evaluate the trade-off between security and information flow.

Today, these difficulties can be solved with the autopilot feature. The literature discusses a multitude of autopilot components, such as shortest path planning, group coordination and control planning, tracking, delivery, pick up planning and many more. In one study, for example, particle swarm optimization (PSO) was used for path planning in a three-dimensional terrain model [5]. The PSO was improved for the genetic drift effect, as population-based heuristic methods tend to converge on the local optima and in order to solve it, a mutation operator was added. This adjustment was then tested with selected PSO algorithms in the UAV's path planning. Results showed that diversity was enhanced and optimization performance increased. This study demonstrates that the UAV decision making process can be modelled with modern heuristic techniques for a more effective and intelligent system.

Another study was conducted on the search mechanism in UAVs, in particular helping UAVs to track lost targets using a Bayesian method [6]. The model was able to search and develop possible locations for lost targets. This work suggests opportunity for improvement, indicating that more effective usage can be obtained. The model was especially beneficial with the remote sensing feature of UAVs, showing promise for more effective search and rescue operations. Furthermore, the study suggests that a small amount of intelligence such as Bayesian logic can dramatically improve the performance of UAVs. Tracking ability also improves the responsiveness of UAVs, which in some cases can play an important role in lethality and survivability.

Another study, based on risk minimized path planning [7], aimed to improve planning and coordination decisions for UAVs. The decision making process is very important, and sometimes the shortest path does not guarantee the safest road. The nature of the work demands stealth and takes place in dangerous conditions, making the problem more active and data-integrated, since it requires large data analysis and surveillance. These are potentially dangerous situations, and yet there is also the opportunity to take advantage of the computer's capacity for large data analysis in order to find the optimal path in a given circumstance. For this reason, operations research plays a vital role in UAVs planning.

Another solution may be adjusting for risk minimized path planning. One study hypothesized that the continuous environment (coordinates) can be modelled through discrete solutions [8]. This method can help to produce applicable solutions and find risk-free or minimal-risk paths. This field of research also includes the group planning and coordination of UAVs to create more effective planning, which in turn results in more effective solutions. More successful team coordination will lead to more effective group planning.

Another problem with the cooperative UAV model is delivery pick up, which is related to vehicle routing problems based on target selection and delivery to destination [9]. A more realistic model, it is constrained with anti-jam margins, operating range, data rate and cost, and the problem is optimized for minimization of total service time. This study offers a heuristic approach which compares optimal solutions. Results suggest that SMART is powerful and adaptable to a dynamic environment, as it finds an optimal solution with better computational performance [9].

Cooperative UAVs are very important for planning, as problems with efficient leading and timing can affect the desired action when it comes to pick up delivery or surveillance. With cooperative UAVs, there is a given task to complete. The action is constrained by environmental factors such as terrain features, operating range, anti-jam margins and counter-party surveillance [10]. There is also the problem of task assignment, since UAVs, missions and paths are planned for total service time. Therefore, group action can be realistic and beneficial as well. One study modelled this problem as a mixed integer linear program, solving with commercial programs and heuristic methods to compare them. Results show multiple advantages of this heuristic approach [10].

An additional important problem for UAVs concerns air combat manoeuvring, which is much more complicated since it requires combining strategic formulation and decision making. This type of modelling may be considered relevant to a fight or flight situation, or as a subset of the path planning for moving targets or enemies. This problem is important because, if the connection between ground control and the UAV is intercepted or lost, the UAV must be able to escape from enemies or continue tracking the intruders. One research team modelled this problem using knowledge base architecture and an artificial immune system [1]. Knowledge base structure is a database for air combat manoeuvring, and an artificial immune system is used as a heuristic method to select the best movement for fitness function. Also, this problem forecasts the enemy's next movement in order to improve planning. This research shows that air combat manoeuvring can be performed, which is important for developing a model that can combat like a pilot. However, this solution is different than the other examples in that it uses a mathematical model which is limited to movements in the database.

Therefore, the present study aims to develop a simple model to track intruders or escape from enemies for UAV path planning. The model is constrained to a specific region. PSO and genetic algorithm heuristic methods are modified for this problem and are tested against each other in different cases. This research suggests a number of improvements and opportunities for UAVs.

2. PROPOSED MODEL

The proposed model can be described as dynamic path planning. The dynamic nature of the model limits the solution to one step; only the opposite decision can directly affect the action. Therefore, decision making is based on one step, unlike shortest path planning, where all steps are determined. The proposed model operates more like a chess game, where one action affects the opponent's decision.

There are two possible actions for better decision making in the proposed model: forecasting and operations research. These actions ensure the success and strength of the method while granting strategic and tactical opportunity. Forecasting gives the power of better judgment and helps to seize opportunities. It also helps to be prepared for potential threats. As better decisions can help to increase the chance of success, the decision making process is the heart of this research, and information processing and operations research are the key elements.

Decision making requires a mathematical model, as operations research is the science of decision making.

Figure 1 shows members of the problem environment as constants, available information, decision variables and constraints. Therefore, the mathematical model for three-dimensional air combat manoeuvring is as follows:

Index
i= Vehicle number (1,…,n).
j=Opponent number (1,…,m).

Constant
XC_i= Current x-coordinates of vehicle-i.
YC_i= Current y-coordinates of vehicle-i.
ZC_i= Current z-coordinates of vehicle-i.
XF_j= Forecasted x-coordinates of vehicle-j.
YF_j= Forecasted y-coordinates of vehicle-j.
ZF_j= Forecasted z-coordinates of vehicle-j.
Signal= Binary representation of the goal.

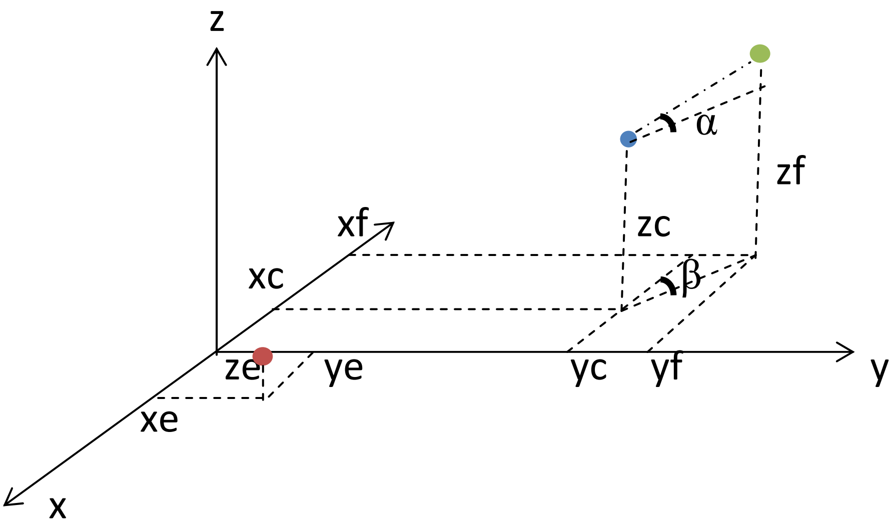

Figure 1. Example problem environment.

Decision variables
X_i=Next x-coordinate of the vehicle-i.
Y_i=Next y-coordinate of the vehicle-i.
Z_i=Next z-coordinate of the vehicle-i.
objf=Objective function value.

Equations
min *objf* =
i=1nj=1mXi−XFj2+Yi−YFj2+Zi−ZFj2−1Signal (0)

s. t.

$$1 \leq \sqrt{(X_i - XC_i)^2 + (Y_i - YC_i)^2 + (Z_i - ZC_i)^2} \leq 2 \quad \forall i \qquad (1)$$

$$\left|\frac{(Y_i - YC_i)}{(X_i - XC_i)}\right| \leq \sin 20 \quad \forall i \qquad (2)$$

$$\left|\frac{(Z_i - ZC_i)}{\left(\sqrt{(X_i - XC_i)^2 + (Y_i - YC_i)^2}\right)}\right| \leq \sin 20 \quad \forall i \qquad (3)$$

$$5 \leq X_i \leq 25 \ \forall i \qquad (4)$$

$$5 \leq Y_i \leq 25 \ \forall i \qquad (5)$$

$$5 \leq Z_i \leq 25 \ \forall i \qquad (6)$$

$$X_i, Y_i, Z_i \geq 0 \qquad (7)$$

Equation (0) is the objective function based on Euclidean distance for the current goal. If the signal is 1, the goal is tracking and the objective function becomes maximization. If the signal is 0, the goal is escaping and the objective function becomes minimization. Equation (1) is the maximum distance constraint, and it is scaled between 1 unit and 2 units. In order to follow a logical turning angle, equations (2) and (3) are angle constraints, using human vision as the limit (approximately 20~15 degree angle). However, these scalars can be changed depending on the nature of the problem.

Equations (4), (5) and (6) are limits for a specific range, which are arbitrary except for the z-coordinates, which represent the lowest and highest point of the vehicle, the lowest point referring to landing and the highest point referring to the vehicle’s capability. Also, the x- and y-coordinate limits can be used as the maximum distance to the ground control based on fuel capacity. For this problem, these points are selected arbitrarily, and for testing and simulation, the environment is assumed to be a cube.

The proposed model is designed as the template structure for UAV air combat manoeuvring in Figure 1. Figure 2 summarizes the proposed system and offers a structural representation of the system, which starts based on a call from another process or situation, collects information and analyses it for forecasting, applies the heuristic method and finally makes a decision. This process repeats until termination conditions occur.

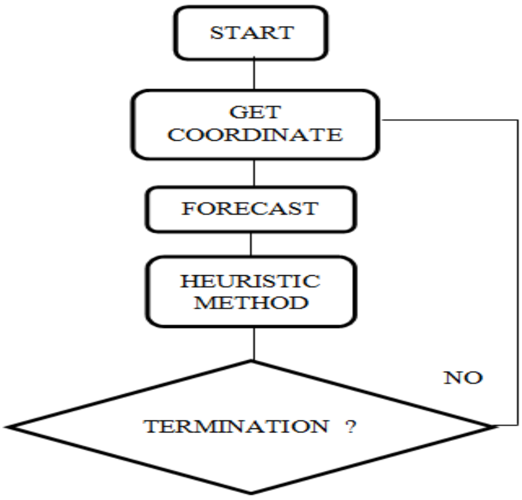

Figure 2. Proposed model.

2.1. Forecasting

Forecasting in this problem can show the opponent's logic and potential behaviour or attitude toward outcomes. The goal of forecasting is to determine whether to get closer or farther away from the opponent, a measure which also serves as the primary indicator.

The goal is important to recognize, but sometimes previous actions and assumptions about the limits and environment can be used to predict future movements.

In particular, the vehicle's capacity and certain environmental features can help to determine its path, but forecasting the entire path is not advisable, since actions are also part of the forecasting and can thus limit both sides and force the vehicle to adapt or change its current course. Therefore, long predictions are not effective for path planning, whereas frequency and range represent an important decision because it takes time for the algorithm to conduct forecasting and decision making. The dynamic nature of the model and its information might not be useful if there is a long process time; on the other hand, too high a frequency is not effective, either, since current position may change without decision making.

Thus, forecasting in this model is based on the worst case scenario or the best movement for the minimum use of speed. The forecasting method for a tracker is shown in Figure 3.

$$\frac{\mathbf{2}}{\sqrt{(\boldsymbol{xc}-\boldsymbol{xe})^2+(\boldsymbol{yc}-\boldsymbol{ye})^2+(\boldsymbol{zc}-\boldsymbol{ze})^2}}=\frac{(\boldsymbol{zf}-\boldsymbol{zc})}{(\boldsymbol{ze}-\boldsymbol{zc})}=\frac{(\boldsymbol{xf}-\boldsymbol{xc})}{(\boldsymbol{xe}-\boldsymbol{xc})}=\frac{(\boldsymbol{yf}-\boldsymbol{yc})}{(\boldsymbol{ye}-\boldsymbol{yc})} \tag{8}$$

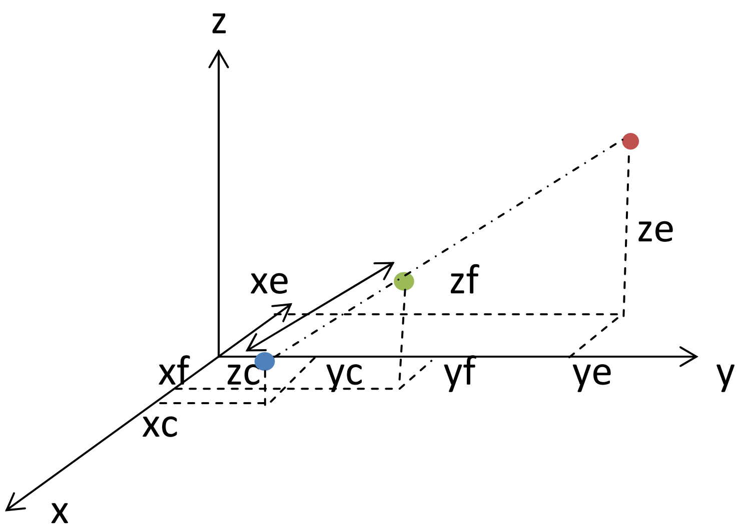

Figure 3. Forecasting the tracker's next position.

Equation (8) is based on triangle scaling, where path distance is 1 unit to determine the next position, as it is between their current distances. The forecasting method for an escaper is shown in Figure 4.

$$\frac{\sqrt{(\boldsymbol{xc}-\boldsymbol{xe})^2+(\boldsymbol{yc}-\boldsymbol{ye})^2+(\boldsymbol{zc}-\boldsymbol{ze})^2}}{\sqrt{(\boldsymbol{xc}-\boldsymbol{xe})^2+(\boldsymbol{yc}-\boldsymbol{ye})^2+(\boldsymbol{zc}-\boldsymbol{ze})^2}+\mathbf{2}}=\frac{(\boldsymbol{zf}-\boldsymbol{ze})}{(\boldsymbol{zf}-\boldsymbol{ze})}=\frac{(\boldsymbol{xf}-\boldsymbol{xe})}{(\boldsymbol{xc}-\boldsymbol{xe})}=\frac{(\boldsymbol{yf}-\boldsymbol{ye})}{(\boldsymbol{yc}-\boldsymbol{ye})} \tag{9}$$

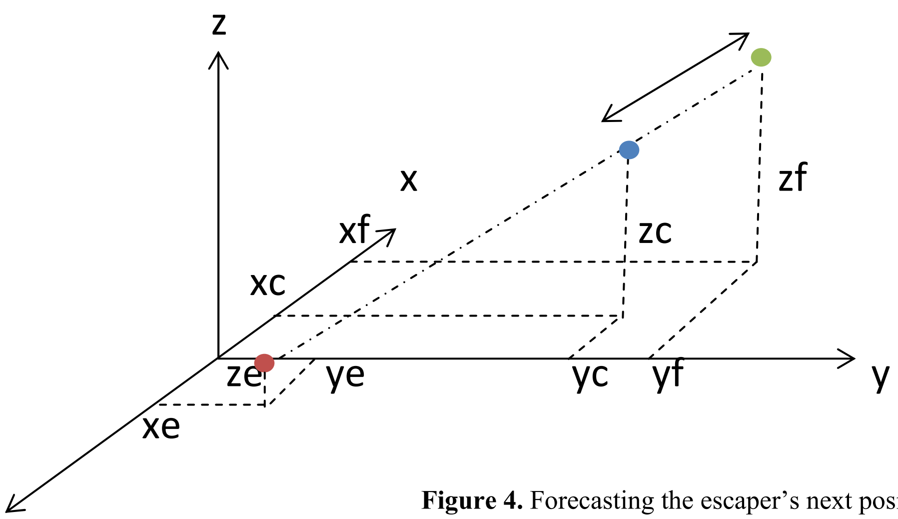

Figure 4. Forecasting the escaper's next position.

Similarly, equation (9) is based on triangle scaling, where the distance is 1 unit to find the point closest to the next position for their current positions. These geometric calculations (equations 8 and 9) show the worst case scenarios, and the forecasting methods help the heuristic method to prepare for the worst possible case. There is another consideration in forecasting with angle limits. Angle limits are based on 20 or -20 degree controls, and forecasting is revised for angle limitations. These adjustments give more logical estimation, as every vehicle would follow them. This adjustment is based on fixing maximum length, and the method re-calculates other features in order to determine the best distance.

2.2. Decision Making

2.2.1. Particle Swarm Optimization

Particle swarm optimization (PSO) is a population-based random search method, where search is based on velocity. Each individual in the population has a distance to the best solutions, and this distance is used to conduct the random search. Thus, velocity becomes the method for the next iteration solutions or change in individuals. PSO is based on group learning and searching, as randomness is limited with global and local optimum found in a population. Additionally, diversity is based on the initial population. Figure 5 shows the basic PSO algorithm steps.

Classic PSO velocity is calculated for individual-*i*, $X_i(t)=(x_{i1}(t),\ldots, x_{in}(t))$, in t^{th} iteration for $P_g(t)$ (the best solution until t^{th} iteration) and $P_i(t)$ (the best solution in t^{th} iteration) [5]:

$$v_{ij}(t) = v_{ij}(t-1) + c_1 r_1\big(p_{ij}(t-1) - x_{ij}(t-1)\big) + c_2 r_2\big(p_{gj}(t-1) - xij(t-1)\,\forall i,j \qquad (10)$$

$$x_{ij}(t) = x_{ij}(t-1) + v_{ij}(t) \forall i,j \qquad (11)$$

Equations (10) and (11) are used for the procedure of update in solutions of the next iteration, and velocity can be seen as the next position based on $c1$, $c2$, $r1$ and $r2$. $c1$ and $c2$ are coefficients for the closeness to $P_g(t)$ or $P_i(t)$, and $r1$ and $r2$ are random searches [5].

Although velocity calculation is continuous, it can be easily adjusted for integer and binary solutions. Also, PSO quickly converges to local optima – a result of velocity limitations, since velocity causes limited search within the area of the local optimum and global optimum. Only the random numbers of r1 and r2 can provide randomness and the range of search, but it limits the distance to $P_g(t)$ and $P_i(t)$. There are a number of techniques for improving the diversity and the quality of solutions.

Therefore, the problem is modelled for PSO based on 10 individuals where any solution is within the length of path, turning angle and rising angle. An example solution after 100 iterations can be seen in Figure 6.

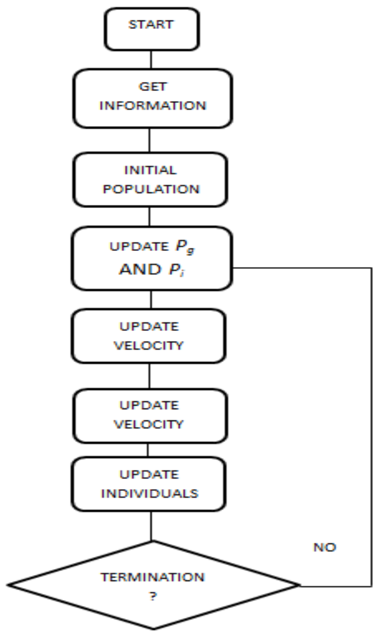

Figure 5. Basic PSO algorithm.

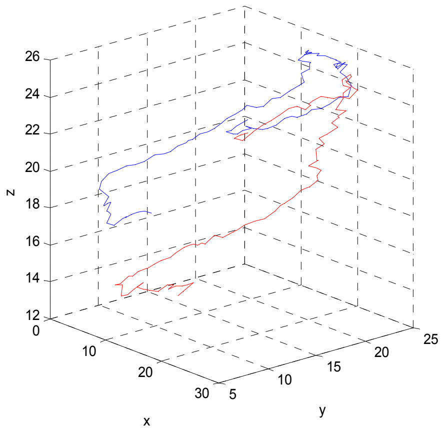

Figure 6. PSO tracker and PSO escaper example path in three dimensions after 100 iterations.

2.2.2. Genetic Algorithm

Genetic algorithm (GA) is a population-based random search method which is based on Darwin's theory of evolution. Generally, crossover, mutation, parent selection, elitism and new population selection strategy are the operators. Unlike PSO, GA uses the logic that the best one always survives, meaning the global optimum is the best solution and solutions will converge to it at the end. GA focuses on the exchange between parts of the solution, which is then used to improve the quality of solutions [11].

GA is more suitable for binary or integer programming, but it can be modelled to work with any optimization problem. Basic GA steps can be seen in Figure 7. GA is modelled with 10 members and runs for 100 iterations.

GA's operators and strategies are:

1. Crossover: this is the basic operator for GA, as it is analogous to biological reproduction. Crossover in this problem is based on two parents and one child. The child is produced based on the exchange between angles and path length.
2. Mutation: this is a necessary operator for every GA, as it ensures that the GA continues to search even in cases of genetic drift after a certain number of iterations. Mutation in this model is the adjustment for coordinates.

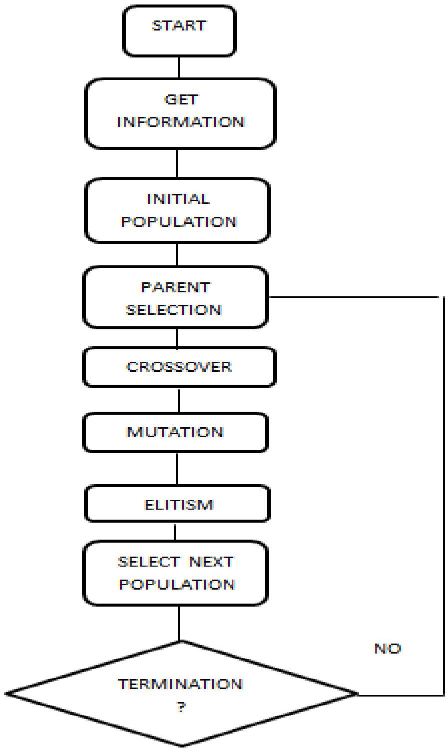

Figure 7. Basic GA algorithm.

3. Parent Selection: this is a strategy for improving crossover performance, as parent selection locates the search around the best solutions. This model does not use any parent selection techniques, as they would result in inefficient computation time and workload.
4. Elitism: the best members of the population take place in new populations. Elitism is very similar to parent selection, and it can cause genetic drift for increasing the similarity to the best solution after iterations.
5. New population strategy determines the quality of improvement and new solutions in the next steps. This stage of the algorithm decides the next stages' improvement policies. This model is based on a steady state method where few members of the population (less than half) are from new solutions.

Example solution of GAs is seen in Figure 8.

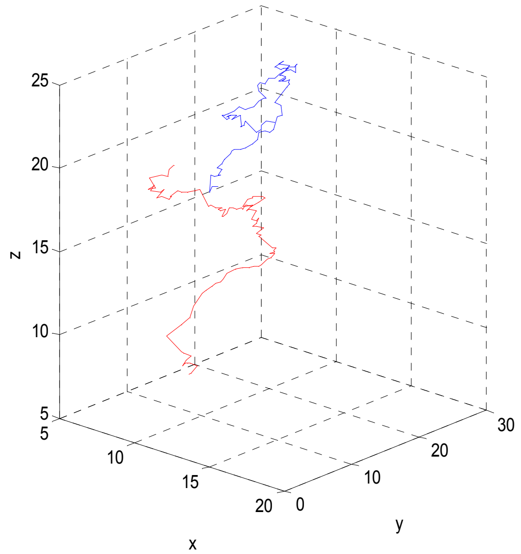

Figure 8. GA tracker and GA escaper example path in three dimensions after 100 iterations.

2.2.3. Assignment of Opponents in Group

Group missions are one of the most important scenarios, as their capabilities and capacities are increased and models become more realistic. Individuals acting for the benefit of the group can also be modelled for air combat manoeuvring.

This group planning is based on the combination of forecasting and decision making, with distance used to select a tracker or escaper. For escapers, assignment considers the closest threat based on forecasting. Trackers, however, require group planning and the best assignments. To cover all opponents requires using the Hungarian algorithm or Kuhn–Munkres algorithm [12]. Figure 9 outlines the steps for the Hungarian algorithm.

The distance between trackers and escapers is used for assignments in the Hungarian algorithm; after assignments, it becomes a dog fight with the closest opponent. Assignments refer to choosing the most beneficial act, and they focus on the current threat or the threat that can be handled by a tracker or escaper. Although the algorithm forces the number of trackers and escapers to be equal, it can be solved with dummy variables.

Hungarian Algorithm / Kuhn–Munkres algorithm:

1. Prepare *Cost Matrix* (*nxn*)
2. Subtract the smallest entry in each row for values in its row of *Cost Matrix*.
3. Subtract the smallest entry in each column for values in its column of *Cost Matrix*.
4. Draw the minimum number of lines to cover all zero elements in *Cost Matrix*
5. Count number of draw lines.
4. If number of draw line is less than *n*:

Then

Determine smallest entry of not covered with lines

Subtract the smallest entry from not covered with lines.

Add it to the each covered column.

5. Else assigns tasks to machines according to 0 values in *Cost Matrix*.

Figure 9. Hungarian or Kuhn–Munkres algorithm.

3. SIMULATION

After the models and forecasting method were built in MATLAB, they were compared and tested against each other to find the best possible method.

The methods were tested 10 times with different starting points. The comparison was based on Euclidean distance between trackers and escapers, a distance which was calculated for the 1st through 100th iteration to measure the change after 100 iterations:
$i=1,..,n$ ($n \geq 1$).
$j=1,..,m$ ($m \geq 1$).

TX_i= tracker-i's x-coordinate.
EX_j= escaper-j's x-coordinate.
TY_i= tracker-i's y-coordinate.
EY_j= escaper-j's y-coordinate.
TZ_i= tracker-i's z-coordinate.
EZ_j= escaper-j's z-coordinate.

Equation (12) shows the change in distance rate. If equation (12) is less than one, it shows the degree of the escaper's superiority; a value greater than one represents the tracker's degree of superiority. Equation (12) is used to improve the methods.

First of all, each method was tested against each other as a tracker or escaper. Results showed the superiority of GA as tracker or escaper because GA trackers got closer than the PSO trackers were able to. Also, results suggested that the escaper was not as successful as the tracker was. Table 1 shows the results of the comparison method, and Figures 10 and 11 show example matches between the GA and PSO models.

$$\text{mean}\left(\max\left(\frac{\sqrt{\left(TX_i(1)-EX_j(1)\right)^2+\left(TY_i(1)-EY_j(1)\right)^2+\left(TZ_i(1)-EZ_j(1)\right)^2}}{\sqrt{\left(TX_i(101)-EX_j(101)\right)^2+\left(TY_i(101)-EY_j(101)\right)^2+\left(TZ_i(101)-EZ_j(101)\right)^2}}\right),\forall j\right) \quad (12)$$

Table 1. PSO and GA methods compared against each other for possible tracker-escaper scenarios (Change in Distance Rate).

		Escaper	
		PSO	GA
Tracker	PSO	5.9426	1.8787
	GA	2.5874	3.4452

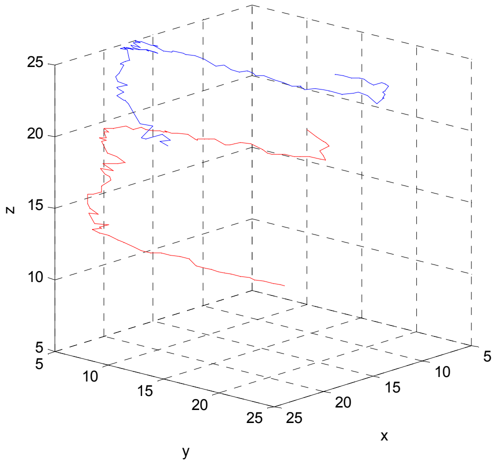

Figure 10. PSO tracker and GA escaper example path in three dimensions after 100 iterations.

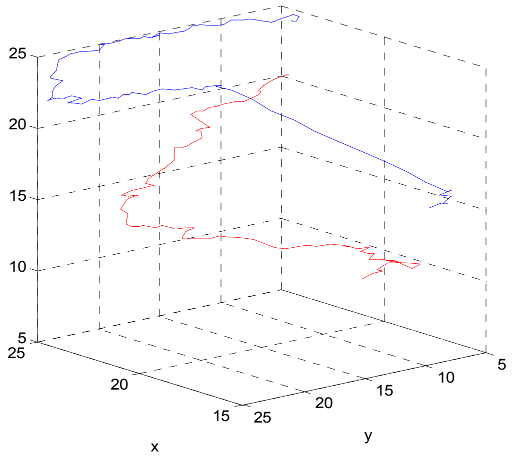

Figure 11. GA tracker and PSO escaper's example path in three dimensions after 100 iterations.

Another comparison was based on the meaningfulness of forecasting, since decisions are based on forecasting. Forecasting was compared with the results of no forecasting. There was a discernible difference, as seen especially in Table 2: the PSO tracker and escaper were superior to the GAs.

Table 2. PSO and GA methods compared against each other for possible tracker-escaper scenarios (Change in Distance Rate).

Tracker vs. Escaper	Forecasting	No Forecasting
PSO vs. PSO	5.9426	4.8348
PSO vs. GA	1.8787	1.7741
GA vs. PSO	2.5874	3.9507
GA vs. GA	3.4452	3.5230

Also, simulation was used to evaluate the success of forecasting, which was calculate for the root of the mean square error. Error was approximately 2, which was the maximum length of the path. This result shows the usefulness of the forecasting method, although it also suggests that the forecasting method could still be improved. The root of the mean square error results are shown in Table 3.

Table 3. PSO and GA methods compared against each other for possible tracker-escaper scenarios.

Tracker vs. Escaper	Root of Mean Square Error (unit)
PSO vs. PSO	2.1898
PSO vs. GA	2.2869
GA vs. PSO	2.1802
GA vs. GA	2.4473

The results of group-based air combat manoeuvring (see Table 4) show similar conclusions: GA in group performed better than the group PSO, and GA offers better leading as escaper or tracker. Figures 12 and 13 show example path planning in group.

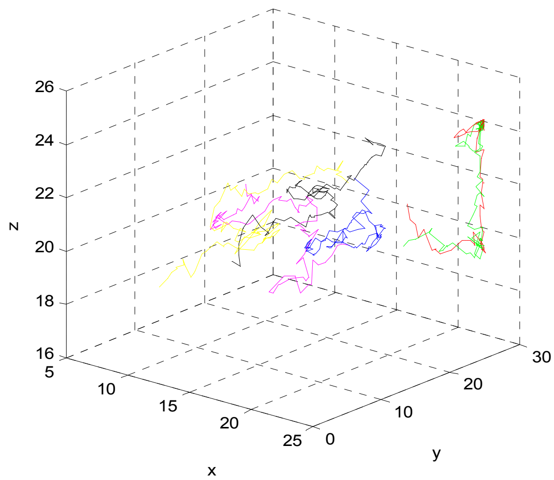

Figure 12. Example paths of a group of 3 PSO trackers and a group of 3 GA escapers in three dimensions after 100 iterations (Blue, green and black lines are PSO trackers; red, yellow and magenta lines are GA escapers).

Table 4. A group of 3 PSOs and a group of 3 GAs are compared against each other for possible tracker-escaper scenarios.

Trackers vs. Escapers	Change in Distance Rate
PSO vs. GA	1.0377
GA vs. PSO	1.3416

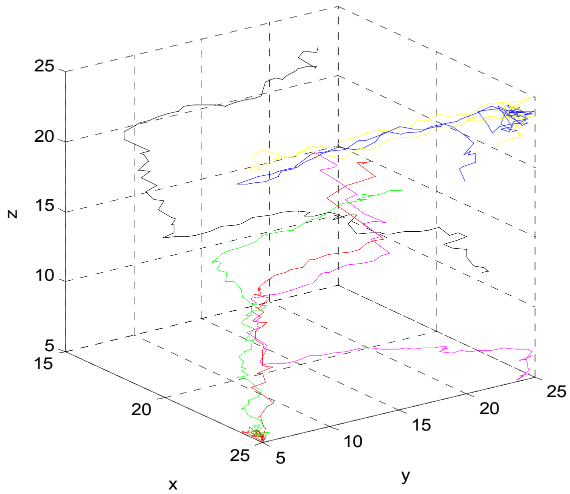

Figure 13. Example paths of a group of 3 GA trackers and a group of 3 PSO escapers in three dimensions after 100 iterations (Blue, green and black lines are GA trackers; red, yellow and magenta lines are PSO escapers).

4. CONCLUSION

Air combat manoeuvring is more akin to chess-playing than it is to shortest path planning, since decisions are set according to the opponent's next step. However, the modelling of UAV decision making is different than normal models, since UAVs entail different scenarios and opportunities, all of which can be improved with different models. This problem is vital for UAVs, considering that their missions often take place in hostile environments. The results of the present study show how to achieve and evaluate results. Moreover, when comparing PSO modelling with GA modelling, GA can be seen to be more effective for decision making

However, since this model does not consider the effects of terrain or weather constraints, the model stands to be improved in forecasting and decision making relative to environmental challenges. Moreover, goal determination was not considered, so the model may also be improved by accounting for a more realistic environment.

Despite the simplicity of the model, this research shows how to model air combat manoeuvring for UAVs using modern heuristics methods, and the results are promising for such a complicated problem.

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VITAE

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