A SIMULATION MODEL FOR ANALYSING UNMANNED AERIAL VEHICLE FLIGHT PATHS

Halil Cicibas[a], Kadir Alpaslan Demir[a], Murat M.Gunal[b], Nafiz Arica[a]

[a] Department of Computer Engineering, Turkish Naval Academy Tuzla, Istanbul, Turkiye
[b] Department of Industrial Engineering, Turkish Naval Academy Tuzla, Istanbul, Turkiye

[a] halilcicibas@gmail.com; kadiralpaslandemir@gmail.com; narica@dho.edu.tr, [b] mgunal@dho.edu.tr

ABSTRACT
Unmanned Aerial Vehicles (UAVs) are used in a variety of operations in civilian and military domains including search and rescue, surveillance, monitoring, cadastral surveys, and package transportation. Although technological achievements in UAVs made them more intelligent than they were in the past, there is still human factor affecting their operations. Particularly in path planning, operators can improve effectiveness and efficiency of the mission by controlling static and dynamic criteria before the flight and during the flight. However, existence of multiple criteria has made the path planning a difficult task that operators can hardly achieve an optimal path for an UAV. In this paper, we propose a simulation model which can help UAV operators and planners achieve optimal paths. Our model considers environmental factors, performance limitations, basic aviation rules and UAV user requirements.

Keywords: Unmanned Aerial Vehicles (UAV), path planning, A Star Algorithm

1. INTRODUCTION
Intelligent machines have made human life easier than they made in the past. For example, Unmanned Aerial Vehicles (UAVs) are being used for high risk and high cost air-based tasks such as military surveillance, search and rescue, and geographical surveys. However currently, most UAVs are remote-controlled and require a human operator. Therefore, a considerable amount of studies conducted in the UAV domain focus on increasing the level of UAV intelligence and providing more capabilities. Enabling UAVs with autonomous path planning is a key research area in developing intelligent UAVs. Autonomous path planning is defined as the onboard capability of finding navigable sequence of waypoints from an initial location to a target location which minimizes the pre-defined path costs while satisfying several requirements. In addition to increasing the autonomy level of UAVs, autonomous path planning provides continuous satisfaction of flight requirements and objectives in a dynamic operational environment. It also increases the reliability of UAVs in case of system and communication failure in remote control (Wu et al 2009).

There is extensive literature on UAV autonomous path planning that address several constraints such as flight dynamics, obstacles and environmental factors. However, most of the studies do not address UAV domain-specific operational issues such as employment considerations and aviation rules. Furthermore, most studies are unable to propose solutions to generate suitable and realistic paths that satisfy UAV mission requirements.

We aim to develop a multi-criteria path planning simulation model for Medium Altitude Long Endurance (MALE) UAVs. The model generates paths for online and offline UAV employment. Our model extends the existing models (Wu 2006, Pettersson 2006, Qi 2010, Nikolos 2003) by placing a special emphasis on aviation rules and employment considerations. The distinction of our study compared to the others is that our research includes criteria that are either new or only covered in a few studies. Our simulation model aids in offline and online planning of optimal paths in terms of time, distance and fuel consumption, while taking the described flight criteria, environmental factors, performance limitations, basic aviation rules and UAV user requirements into account. In our study, we also investigated the behavior of various A* based path search algorithms by comparing them in different operational environments.

2. BACKGROUND INFORMATION
UAV path planning problem is a vehicle motion-planning problem under some constraints. It has significant differences from traditional mobile vehicles and manipulator robots (Goerzen 2009). UAV path planning problem is defined as a multi-objective, decision making problem that must take into account flight rules, mission efficiency, operational constraints, environmental conditions and flight limitations.

Modeling for path planning requires a way of representation of the world and its contents. “World space” is defined as the physical space, which contains the vehicle, start location, target location, and obstacles. It is divided into two regions as free-space and obstacle-space (Latombe 1991, LaValle 2006). Free-space defines the area through which the vehicle can move without collision. Obstacle-space is a set of points that lead to a collision between the vehicle and the obstacle (Hwang and Ahuja 1992). A “configuration” is a vector of parameters defining the shape of the vehicle in the world space. A configuration that is coupled with its rate of change is called a “state”.

These are two types of constraints in the world space: environmental and motion. While environmental constraints consist of obstacles or meteorological factors such as wind or icing; motion constraints defines the maneuver limitations of the vehicle such as climb rate or turning capability. In our study, we use the terms “flight criteria” and “flight objective” instead of “constraints”. While flight objectives are the elements of cost function, flight criteria are the variables that must be implemented for flight safety and mission efficiency during flight.

Path planning in robotics has two major approaches. Although the first approach, combinatorial planning, gives optimal solutions, it is impractical since its computational complexity is high. The second approach, sampling based planning, is preferred since it is a sampling based planning and known to be superior for its efficiency, practicality, and simplicity in high dimensional environments.

Collision Detection (CD) and roadmap generation are the two other terminologies in sampling based path planning. CD algorithms are used to detect obstacles on the path. Roadmap generation is the constructing of a search tree or graph with connecting samples in free space.

Finally, it is noteworthy to mention the UAV path planning flight criteria that are considered in the literature. These are geographical structures, buildings, danger zones, above ground level rules, cruise level rules, mobile objects, cloud, mobile targets, mobile threats, wind, approach angle, and flight dynamics. Additionally, the flight objectives are generally based on distance, time, fuel consumption, risk, path smoothness, and hidability.

3. CONCEPTUAL MODEL

3.1. World Space and Roadmap Generation

Operational environment is represented with a regular grid sampling method. Every sample is represented by a cube in the world space that contains data related to the operational environment. Grid size of the sample cubes defines the level of detail in grids. The number of cubes increases process time and search time significantly.

The size of the sample cubes is determined based on UAV flight performance capabilities and maneuver limitations. Turn radius and ascend/descend angle are the main parameters to identify horizontal and vertical length of sample cubes respectively. . In our model, the size of the grid is set depending on the tactical range of the UAV, maximum fly altitude and computational limitations.

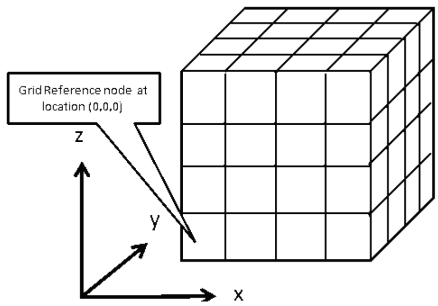


Figure 1: Grid based world space

Each node in the grid has the following fields;

- Latitude/Longitude
- Above Ground Altitude
- Above Mean Sea Level Altitude
- Time Moment
- Wind speed and direction
- Start or Target Indicator Flag
- Obstacle Space Indication Flag
- Cloud Indicator Flag

These fields are initialized with default parameters and then updated based on the information collected from the environment. Furthermore, nodes have additional fields to store the parent node and child nodes. These fields are filled in during adjacency creation process.

When the world space is represented as a 2D or a 3D grid then an algorithm can be applied to find a path in the grid. After moving forward one step on the path, if any change occurs in the operational environment, the path is re-calculated based on the updated grid until the vehicle reaches the goal state. Although this iterative approach runs faster, it produces inconsistent and costly paths in dynamic environments, because this approach is unable to predict the future status of the search space. However, advances in the sensor technology made the UAV’s predict ahead in time and therefore it is possible to plan the least cost paths in time varying environments. This can be represented with a “4 dimensional grid (4D)” where the forth dimension is the time.

4D grid consists of future status of mobile objects and dynamic criteria parameters in the world space. It can be expressed as a combination of 3D grids that represent an instant status of the world space in a time moment. Each time interval (Δt) between moments is equal to a specific duration. This duration is identified from UAV performance specifications and it is measured as the time elapsed during the travel from one hop to another hop, in other words from a parent node to a child node.

In 4D grid generation, as shown briefly in Figure 2, the first step is to detect movements of moving targets and to sense environmental factors. Based on this data, future locations are estimated and projected to 3D grid. These are then combined with 4D grid and least-cost pats are calculated. The UAV proceeds to the next grid. This whole process is repeated until the UAV reaches to the destination.

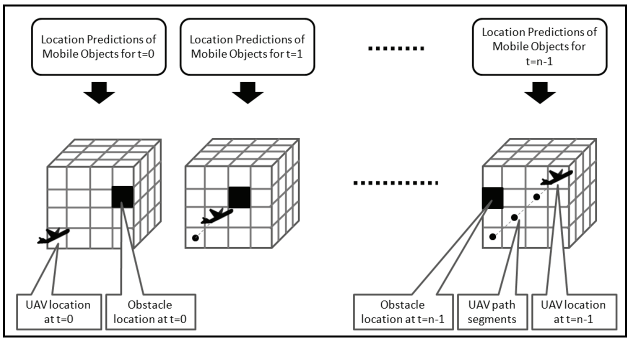
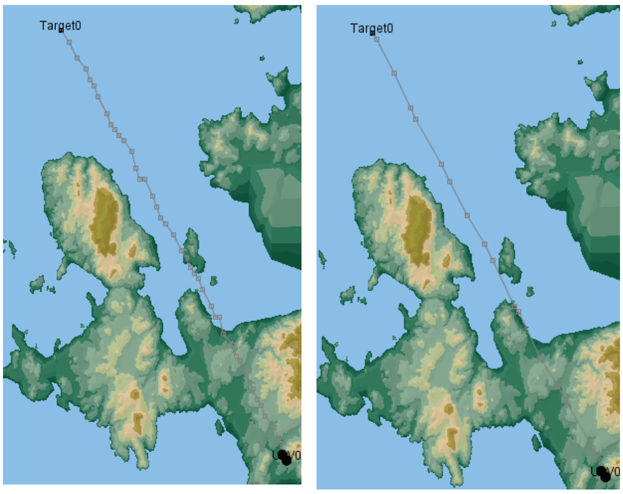


Figure 2: 4D Grid generation

In the roadmap generation phase of the model, multi-resolution grids are used. This is done based on a successor operator. After the partitioning process, the model checks the flag parameters of every node in the regions. If any node in a region is an obstacle node, the model identifies this region as a high-resolution region. Otherwise, the region is classified as a low-resolution region. In other words, the regions without obstacles are marked as low resolution regions.

The distance between node pairs in the high-resolution regions is defined with a successor vector. Nodes in the range of successor distance are adjacency candidate nodes. Successor-based adjacencies provide multiple angular turns for UAVs. Thus, path optimality and path smoothness are achieved in the model. Although multiple angular turns ensure optimality and smoothness, in some cases it may increase computational complexity and graph size. Therefore, there is a trade-off between successor length and computational time. Note that adjacency generation time increases by the successor length, however long successors provide finding least cost paths and more smooth paths compared to a shorter ones. Figure 3 shows how a path changes when max. successor length changes.



Max Successor Length=3 Max Successor Length=12
Figure 3: Paths with different successor lengths

Adjacency creation procedure works as follows; the grid is divided into regions as low and high resolution. Depending on the node the UAV is located currently, successor length is determined for each node. The nodes are then connected and a graph is formed. Obstacle space indicator of every node pairs are then check to remove the links between obstacle nodes. Travel time is calculated and finally adjacency relations are added to the world space.

3.2. Flight Criteria and Flight Objectives

In our model we have two types of flight criteria that we considered; static and dynamic. Static criteria do not change in time and therefore there is no need to update the locations and other properties during flight time. These include geographical structures, buildings, danger areas, above ground level (AGL) rule, and cruise level rule.

For the geographical structures, the terrain is represented as an obstacle that the UAV cannot pass through. We obtain terrain elevations from Digital Terrain Elevation Data Level 1 (DTED L1) maps. Buildings are represented with polygons which the size and location information are gathered from geographic terrain elevation databases. A danger area is a land region that poses any kind of threat to UAV flight. For example, an anti-air defense system is a kind of threat that a military UAV should stay out of its range. We make a distinction between the aerial threats and the threats on the ground. Danger areas are related to threats found on the ground. In our model, we draw a half-sphere on the location of the threat. The center of this virtual sphere corresponds to the location of the threat.

Dynamic flight criteria include mobile obstacles, mobile threats, mobile targets, cloud, and wind. Properties of these criteria may change in time and therefore the locations and properties of the dynamic criteria should be updated in time until UAV reaches its goal location. The model calculates the future locations of the dynamic criteria based on historical information obtained with UAV sensors.

Other aircrafts in the operational environment are referred as mobile obstacles. Our model prevents the UAV from colliding with other aircrafts by marking mobile obstacles as “obstacle space” in the world space. For the representation of mobile obstacles, flying objects are mapped into cylindrical shapes which the dimensions of the cylinders around mobile targets are computed in such a way that UAV is able to maneuver at an adequate distance to a safe course to avoid a collision with the mobile target.

Clouds may prevent UAVs to accomplish some of its missions such as reconnaissance via photographing or video capturing. In such circumstances, to increase detection quality, UAVs should descend to lower altitudes below the floor level of clouds. Our model enhances mission efficiency by enabling UAVs to go under clouds when the weather is cloudy above the target location. At other times during flight, the UAV can fly through clouds. We represent the clouds with polygonal and cylindrical shapes. Likewise, wind is a significant factor for UAVs’ path planning. In our model, we assume that in the operational environment there are wind fields with a constant speed and direction.

The objective of the model is to find minimum cost paths in terms of time, distance, and fuel consumption. These terms are included in the objective function with different weights that are determined based on the mission requirements. Details are as follows;

- Flight distance: Distance is a widely used flight objective in similar studies as it can be calculated with simple algorithms. In our model, it is calculated as Euclidian distance such as;

$$f_{dist(s_i,s_j)} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}$$

- Flight time: Although distance and time objectives seem alike, flight time is not just a function of distance since wind vector effects the flight time. In order to calculate the time cost, we use the following equation. The equation finds the cost of each trajectory between node pairs based on distance and resultant vector of UAV engine and wind speed. $\overrightarrow{v_c}$ is UAV engine speed, and $\overrightarrow{v_w}$ is wind speed.

$$f_{time(s_i,s_j)} = \frac{f_{dist(s_i,s_j)}}{\left|\overrightarrow{v_c} + \overrightarrow{v_w}\right|}$$

- Fuel consumption: We construct a fuel consumption model for the UAV based on EngineSim (NASA, 2012). The UAV uses maximum throttle for climbs, minimum throttle for descents and optimum throttle for the cruise. Similar to aircraft engines, our UAV consumes less fuel in higher altitudes and in lower speeds. Fuel consumption is calculated as follows;

$$F_{fuel}(x_{alt}, x_{spd}, x_{temp}, x_{payload}, x_{rate}) = g\left(\begin{matrix} f_{alt}(x_{alt}), f_{spd}(x_{spd}), f_{temp}(x_{temp}), \\ f_{payload}(x_{payload}), f_{rate}(x_{rate}) \end{matrix}\right)$$

where $f_{alt}(x_{alt})$ is the fuel consumption at altitude x, $f_{spd}(x_{spd})$ is the fuel consumption at speed x, $f_{temp}(x_{temp})$ is the fuel consumption at temp x, $f_{payload}(x_{payload})$ is the fuel consumption at payload x and $f_{rate}(x_{rate})$ is the fuel consumption at rate x.

4. SIMULATION MODEL

Based on the conceptual model described in the previous section, a simulation model is built in Java using Simkit (Buss 2001) and OpenMap (OpenMap 2012) APIs. Simkit is a Discrete Event Simulation (DES) API in Java and works with Event Scheduling DES approach. OpenMap is also in Java and an open source Geographical Information System which can process geographical data such as elevations. Gunal (2010) is a latest example of how these two packages can work together.

4.1. Flow of Simulation

Movements of external system entities are handled by methods provided with Simkit. Movement behaviors include start, stop, pause, and accelerate. OpenMap is used to visualize generated paths. A screenshot is shown in Figure 4. It also enables to easily visualize the terrain structure and simulated entities.

Since the simulation provides the movements of entities, static and dynamic criteria parameters are calculated to predict mobile object locations beforehand. This causes the 3D grid to be searchable for a path. In our simulation we used A* algorithm to find the shortest path.

4.2. Inputs

In our model we have three groups of inputs; UAV, Environment, External Systems' parameters.

UAV parameters are;

- weight,
- payload,
- endurance,
- max.speed,
- max.flight
- altitude,
- tactical range,
- fuel consumption,
- turn radius,
- ascend/descend rate.

Environmental parameters are;

- Field size,
- Wind direction and speed,
- Cloud origin,
- Temperature,
- Number of regions,
- High and low resolution,
- Goal and start location altitudes,
- Rules and safe limits.

External systems' parameters are;

- Number of threats,
- Number of aircrafts,
- Mobile target speed,
- Mobile aircraft speed.

4.3. Outputs

Since we wanted to examine the model's performance, our main output variables are grid generation time and search time. Additionally we looked at the path cost for the three objectives; distance, time, and fuel.

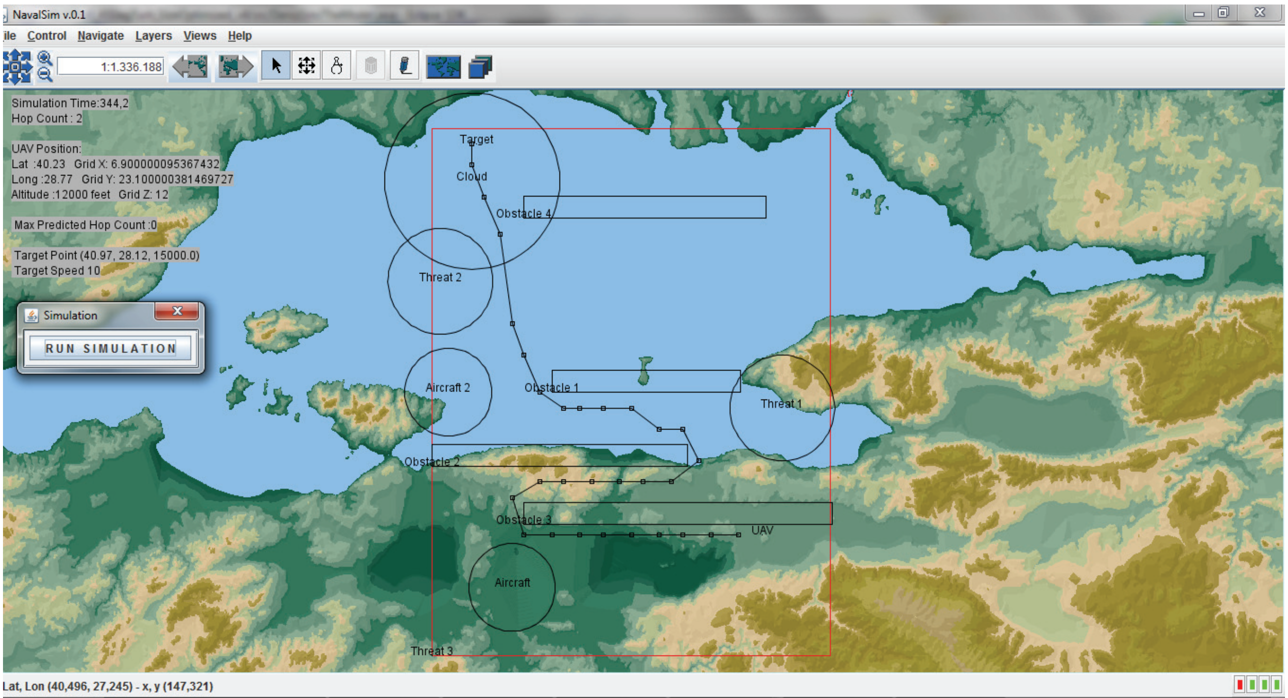


Figure 4: Simulation screen

5. EXPERIMENTAL RESULTS

The model is evaluated with various scenarios containing both static criteria and dynamic criteria. The simulations are conducted with a personal computer (PC) with 2.93 GHz Intel i5 processor and 3 GB RAM. The world space is represented in a 60nm*60nm*31000ft*10t grid which is sampled with nodes in a dimension of 2nm*2nm*1000ft. In Figure 4, dotted line represents UAV optimal path, which is from south to north. Other shapes in the figure represent obstacles such as buildings, threats and aircrafts. UAV geographical location, UAV altitude, target information and simulation parameters are shown in the left side of the OpenMap environment. We created 48 scenarios to achieve the following in our experiments;

- Validate and verify the model in various scenarios,
- Analyze the performance of the model under different constraints,
- Analyze the effects of criteria and grid dimension on path costs,
- Test the modifiability and extendibility properties of the model

Simulation results show that the model is able to generate sensible results. Model architecture provides enhanced modifiability as various scenarios were easily adapted with minor modifications. In addition, the model is able to find collision-free paths in different scenarios. Developed model can generate resolution optimal paths in static and dynamic environments under different constraints. Besides, it is found that the model reacts properly to the changes in criteria properties and obstacle locations.

We analyzed the simulation performances of 3D and 4D grids in terms of grid generation time and search time in various scenarios for different flight objectives (Table 1). Simulation performance results show that target type does not affect grid generation time and search time in 3D and 4D grids. However, the number of obstacles and obstacle sizes are the main factors on grid generation time. In addition, they increase the search time if obstacles are at locations that intersect with UAV flight path. The search time increases as the number of obstacles increase, since search algorithm needs more time while expanding nodes to find the least-cost path. On the other hand, the increase in the number of obstacles decreases grid generation time as search space becomes smaller. In addition, grid generation time and search time is higher in 4D grid. In fuel consumption objective, search time is longer than search times in other objectives as additional parameters are incorporated in the calculation of fuel consumption. In every scenario, UAV moves from south to north. PNF refers to “Path not found” in the tables. Wind speed is zero.

The model finds the same paths in the calculation of time objective and fuel objective in static environments (Scenario 1, 2, 5 and 6). Besides, path costs in static environments are equal in 3D and 4D grid since there is not any mobile objects in the operational environment. It is also found that, in fuel consumption objective, UAV climbs to an optimal altitude and proceed in this altitude for a while, then descend to target altitude to reduce the fuel consumption.

Scenario	**Number Of Static Obstacles**	**Number Of Dynamic Obstacles**	**Target Type**	**Grid Dimension**	***Distance***		***Time***		***Fuel Consumption***	
					Grid Generation Time (sec)	***Search Time (sec)***	***Grid Generation Time (sec)***	***Search Time (sec)***	***Grid Generation Time (sec)***	***Search Time (sec)***
1	**0**	**0**	**S**	3D	2	1	2	1	2	1
2				4D	23	1	23	1	23	1
3	**0**	**0**	**M**	3D	2	1	2	1	2	1
4				4D	18	1	23	1	25	1
5	**4**	**0**	**S**	3D	1	2	2	2	1	19
6				4D	8	2	9	3	11	66
7	**4**	**0**	**M**	3D	1	2	2	2	1	14
8				4D	8	2	9	3	10	64
9	**4**	**4**	**S**	3D	2	2	1	2	2	21
10				4D	5	2	6	3	5	58
11	**4**	**4**	**M**	3D	2	2	1	2	2	22
12				4D	5	2	6	3	6	63
13	**0**	**4**	**S**	3D	2	1	2	1	2	1
14				4D	20	1	17	1	15	1
15	**0**	**4**	**M**	3D	PNF	PNF	PNF	PNF	PNF	PNF
16				4D	19	1	15	1	15	1

Table 1: Experimental results (M:Mobile, S:Stationary)

6. CONCLUSION

As the use and application areas of UAVs increase, new challenges and issues arise in developing UAVs. Many studies in UAV domain focus on increasing intelligence capability of these systems. The studies aim to provide UAVs with the capability to perform without human interference opposing different adversities. An important challenge in developing more intelligent UAVs is autonomous path planning.

In this paper, we present a multi-criteria path-planning model for UAVs performing in dynamic environments. The main contribution of the study is the development of a path planning model that provides online and offline planning of resolution-complete, smooth and optimal paths while meeting distance, time and fuel consumption objectives in dynamic environments for Medium Altitude High Endurance UAVs (MALE UAVs). We implement flight criteria and objectives in our model based on employment considerations, environmental factors, performance limitations, basic aviation rules and user requirements. In addition, the presented model takes into consideration of operational efficiency presented in UAV Roadmaps. Operational environment is represented with a 4D grid that includes future status of mobile objects. Taking into consideration of possible changes in the operational field would increase path efficiency and provide least cost paths. In our study, we develop a modular architecture that enables integrating various UAV models, environmental parameters, search algorithms and various flight criteria/objectives with minimum efforts. In the development of the model and simulation, open source tools and environments are utilized. We simulate our model in multiple scenarios. The model is able to find optimal and collision-free paths in static and dynamic environments under several flight constraints.

ACKNOWLEDGMENTS

The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of any affiliated organization or government.

REFERENCES

Buss A. 2001. Discrete Event Programming with Simkit, Simulation News Europe, August 2001.

Goerzen, C., Kong, Z., Mettler.B. 2009. A Survey of Motion Planning Algorithms from the Perspective of Autonomous UAV Guidance. Journal of Intelligent and Robotic Systems, 2009.

Günal M.M. 2010. Notes on Naval Simulation, Technical Report, Turkish Naval Academy, Istanbul 2010.

Hwang, Y.K., Ahuja, N. 1992. Gross motion planning - a survey. ACM Computing Surveys (CSUR) Volume 24 Issue 3, Sept. 1992.

Latombe, J.C. 1991. Robot Motion Planning". Kluwer Academic Publishers, Norwell, MA, USA, 1991.

LaValle, S. M. 2006. Planning Algorithms. Cambridge University Press (also available at http://msl.cs.uiuc.edu/planning/).

Nikolos,I.K., Valavanis,K.P., Tsourveloudis,N.C., Kostaras, A.N. 2003.Volutionary algorithm based offline/online path planner for UAV navigation, IEEE Trans. Systems, Man Cybernetics, vol 33, pt. B, pp. 898-912, Dec. 2003.

NASA Glenn Research Center (2012) EngineSim Version 1.7a Official Web site: http://www.grc.nasa.gov/WWW/K-12/airplane/ngnsim.html [Access Date: 20 May 2012]

OpenMap. 2012. BBN Technologies, http://openmap.bbn.com. Access Date: 20 May 2012

Pettersson, P. O. 2006. Sampling-based Path Planning for an Autonomous Helicopter, Thesis, Linkoping University.

Qi, Z., Shao, Z., Ping, Y.S., Hiot,L.M., Leong, Y.K. 2010. An Improved Heuristic Algorithm for UAV Path Planning in 3D Environment, Second International Conference on Intelligent Human-Machine Systems and Cybernetics, 2010

Wu, P., Campbell, P.Y., Duncan, A., Merz, T. 2009. On-board multiobjective mission planning for unmanned aerial vehicles, In IEEE Aerospace Conference Montana, 2009.

Wu, P.2006. Multi-Objective Mission Planning in Civil Unmanned Aerial Systems, PhD Thesis, 2009.