Proceedings of the 2007 IEEE Symposium on Computational Intelligence in Multicriteria Decision Making (MCDM 2007)

Fuzzy Multi-Objective Mission Flight Planning in Unmanned Aerial Systems

Paul Wu, Reece Clothier, Duncan Campbell, *Member, IEEE*, Rodney Walker, *Member, IEEE*

***Abstract*—This paper discusses the development of a multi-objective mission flight planning algorithm for Unmanned Aerial System (UAS) operations within the National Airspace System (NAS). Existing methods for multi-objective planning are largely confined to two dimensional searches and/or acyclic graphs in deterministic environments; many are computationally infeasible for large state spaces. In this paper, a multi-objective fuzzy logic decision maker is used to augment the D* Lite graph search algorithm in finding a near optimal path. This not only enables evaluation and trade-off between multiple objectives when choosing a path in three dimensional space, but also allows for the modelling of data uncertainty. A case study scenario is developed to illustrate the performance of a number of different algorithms. It is shown that a fuzzy multi-objective mission flight planner provides a viable method for embedding human expert knowledge in a computationally feasible algorithm.**

I. Introduction

UNMANNED Aerial Systems (UAS), or robotic aircraft, will comprise a substantial component of future aviation. Already UAS, with their unique operational capabilities, have demonstrated successful applications in surveillance, communications, environmental monitoring, agriculture and defence. Ongoing advancements in enabling technologies, coupled with decreasing system and operational costs, will continue to strengthen the business case for UAS in a widening range of applications. As such, the expected growth in the Australian UAS market is estimated to increase by more than 198% between 2001 and 2010 [1]. However, there are a number of challenges which need to be addressed in order to realise the potential for this industry, one of which is gaining access to the National Airspace System (NAS) [2].

Manuscript received October 31, 2006. This work was supported by the Australian Research Centre for Aerospace Automation (ARCAA), Queensland University of Technology (QUT) and the Commonwealth Scientific and Industrial Research Organization (CSIRO), funded in part by the Queensland State Government, Smart State Research Fund.

Mr Paul Wu, is a graduate student with ARCAA, QUT, GPO Box 2434, Brisbane, 4000, Australia. *(phone: +61 7 31381400; e-mail: p.wu@qut.edu.au)*.

Mr Reece A. Clothier, is a graduate student with ARCAA, QUT, Brisbane, 4000, Australia. *(e-mail: r.clothier@qut.edu.au)*.

Associate Professor Duncan Campbell, is with the School of Engineering Systems and ARCAA, QUT, Brisbane, 4000 Australia. *(e-mail: da.campbell@qut.edu.au)*. He is currently a Visiting Professor with the Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, MA 02139 USA.

Associate Professor Rodney Walker is with the School of Engineering Systems and ARCAA, QUT, Brisbane, 4000, Australia. *(e-mail: ra.walker@qut.edu.au)*.

One of these challenges is the problem of mission flight (strategic) planning and in-flight (tactical) re-planning. To ensure the successful integration of UAS within the NAS, an Equivalent Level Of Safety (ELOS) to conventional aircraft operations must be demonstrated [3]. In addition, UAS must also operate under the existing rules and regulations governing the safe pilotage of conventional aircraft and must appear as 'transparent' users of the NAS [3]. In the absence of a technology able to provide an equivalent see-and-avoid capability for UAS (a requirement for the unsegregated operation of UAS alongside other aircraft, Civil Aviation Regulation 163A [4]); strategic flight planning plays an important role in the risk management, and subsequent approval, of UAS operations within the NAS. Mission flight planning must also ensure that the operation is conducted in accordance with the 'rules of the air' and that mission goals are achieved. A complex trade-off exists between mission goals, mission efficiency objectives and the rules of the air.

To add to the complexity of the problem, the airspace environment is highly dynamic and uncertain. As a result, changes may need to be made to the flight plan during an operation as a result of (i) new information (e.g. detection of other aircraft or hazardous weather conditions), (ii) changes in aircraft performance (e.g. as a result of system failures) or (iii) changes in the mission goals. Tactical changes to the flight plan (performed whilst the UAS is airborne) place significant time pressures on the planning process.

It is envisaged that the proposed mission flight planning process would help increase the level of autonomy within the UAS. It could conceivably allow UAS to operate at the sixth level in Parasuraman's model of autonomy [5]. With this level of autonomy, the plan is executed automatically unless there is intervention by a human operator.

This paper discusses the development and evaluation of an example mission flight planning system that addresses some of the requirements in operating UAS in the NAS. The first section provides a summary of existing approaches to the mission flight planning problem. The second section details the decision space, the costs and the rules governing the flight planning problem, and introduces a case study mission scenario. Following this, a number of potential multi-objective planning algorithms are presented and are implemented for the mission scenario. The final section discusses the results obtained with the different algorithms.

1-4244-0702-8/07/$20.00 ©2007 IEEE

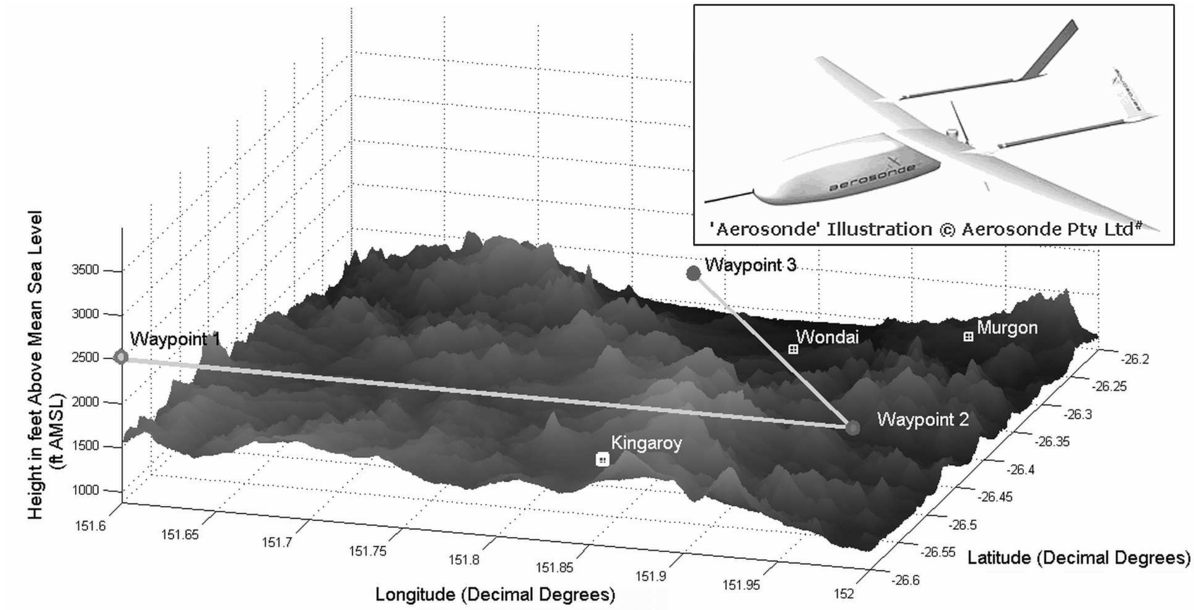

Fig. 1 Aerosonde Mark III (inset) and Operating Area

II. The Decision Space

This section introduces the complex decision space for a case study flight planning scenario of a UAS operation within the NAS. This case study will help illustrate the mission flight planner design process and demonstrate how different input variable types (used to evaluate mission objectives) are handled in a multi-objective mission flight planner. The scenario decision space comprises the:

A. Mission
B. Physical Environment
C. Decision Objectives

A. Mission

The mission flight planning task is specific to the UAS being operated, the decision objectives (such as flight rules and fuel rates) and the goals of the mission. A goal may be as simple as reaching a specific destination or can be more complex such as conducting a grid search.

An example scenario is presented here to highlight the different aspects of the proposed planning algorithms. The prospective UAS in the case study scenario is an Aerosonde™ Mark III, inset in Fig. 1[#]. The mission is to be conducted over the Kingaroy region in Queensland, Australia. As can be seen from Fig. 1, the Aerosonde™ must fly a mission which comprises a starting waypoint and two goal waypoints which are to be completed sequentially. The straight line path between each waypoint is also indicated.

For the sake of simplicity, three mission planning layers were defined at altitudes of 1500ft, 2500ft and 3500ft Above Mean Sea Level (AMSL). These layers correspond to the cruise altitudes defined by CAR173 [4]. Each layer comprises a 10 element by 10 element array of possible flight path nodes (not shown in Fig. 1). Thus the total three dimensional decision space comprises 300 possible flight path nodes.

B. The Physical Environment

The physical airspace environment comprises both static and dynamic aspects. Static elements include terrain, population areas, tall structures, location of aerodromes and designations of controlled or restricted airspace. Published aeronautical maps provide the *a priori* information necessary to generate mission flight plans ensuring the safe navigation of static aspects of the operating environment.

Flight planning for dynamic aspects of the physical environment, such as weather, other aircraft or birds, is often done just prior to, or during, the flight. In-flight re-planning can partially address the problem of dynamic changes in the environment.

For the case study scenario, the undulating terrain in the Kingaroy region is modelled using data obtained from the National Aeronautics and Space Administration (NASA) Shuttle Radar Topography Mission (SRTM) [6]. The resolution of the terrain data samples is three arc-seconds (approximately 90m) and is modelled as a surface using bilinear interpolation.

C. Decision Objectives

A UAS mission must be conducted in accordance with the rules and regulations governing the safe flight of conventional aviation. For the purposes of this scenario, the aircraft is assumed to operate under Visual Flight Rules (VFR) conditions. Only two rules are considered: namely Civil Aviation Regulation (CAR) 157 and 173.

CAR157 stipulates that aircraft must maintain a minimum altitude of 500ft above terrain except when performing

[#] Illustration © Aerosonde Pty. Ltd. www.aerosonde.com.au specific tasks with the approval of the regulator. The clearance above terrain, measured as the altitude Above Ground Level (AGL) is a decision objective that addresses this regulatory requirement. This AGL variable is classified as an independent variable because the AGL value remains the same regardless of the path chosen.

CAR173 relates to cruising levels [4]. Cruising altitudes are assigned based on the heading of the aircraft so as to reduce the likelihood of an aircraft encountering a head-on collision scenario. CAR173 states, that for headings from 0° to 179°, aircraft operating under VFR should cruise at altitudes of odd multiples of 1000ft plus 500ft AMSL (e.g. 1500ft, 3500ft, 5500ft AMSL). For headings between 180° and 359°, aircraft should cruise at even multiples of 1000ft AMSL plus 500ft (e.g. 2500, 4500, 6500ft AMSL) [4]. For operations below 5000ft AMSL, CAR173 is not a mandatory requirement but should be obeyed when terrain, weather and traffic conditions permit. This flight rule is encoded as another decision objective based on the aircraft's altitude and heading angle. Note that the heading angle is a dependent variable as it changes depending on the chosen path.

Risk is another independent variable that should be considered in the construction of a mission flight plan. The two primary hazards of unrestricted UAS operations within the NAS are that of a midair collision or the termination of flight in a populated area [7]-[9]. For the case study scenario, a single risk objective, the risk presented to people on the ground expressed as the number of ground casualties per flight hour of operation is considered. This was calculated using methods described in [10].

Fuel is another important consideration in the selection of a flight path. Optimum fuel performance is obtained by maintaining cruise or descending in altitude. Ascending comes at the expense of increased fuel consumption. For the case study scenario, an arbitrary fuel cost for each path segment is calculated based on the distance travelled and the pitch angle of the aircraft:

$$q_i = d\left(2\sin\theta_i + \cos\theta_i\right) \tag{1}$$

where q_i is the fuel consumed, d is the distance travelled and θ_i is the pitch angle for that path segment. This simple model is used purely for representative purposes as the case study does not consider aircraft velocity. However, fuel is a good example of a dependent, finite variable that is cumulative (accumulates value along the path).

III. Multi-objective Mission Flight Planner

Finding the 'best' path whilst considering multiple objectives is a path planning problem that involves the aggregation of multiple objectives, sometimes referred to as a multi-objective search problem. The problem is further compounded by uncertainty in input data. An examination of existing work in this field is presented here.

A. *Existing Work*

The focus of research in recent times in the field of path planning has been on techniques in computational geometry and graph theoretic planning [11]. It is common to employ a global planner (such as the mission flight planner described here) to generate an approximate plan which is then refined to obtain an exact trajectory using a more precise local planner [12]. Despite the existence of many path planning techniques (LaValle [13] provides a comprehensive study), there are relatively few methods that cater for multiple objectives.

One field that has seen much use of multi-objective path planning is hazardous materials (HAZMAT) transportation. This stems from the need to make compromises between risk and transportation costs [14]. Many HAZMAT planners have employed a general optimal graph search algorithm such as Dijkstra's or A* [13] and combined that with some form of weighted sum decision aggregation that computes an aggregated path cost [14]-[16]. However, the majority of these algorithms are confined to 2-dimensional searches in deterministic environments. [14]-[16]

There are also multi-objective iterative graph search algorithms such as Fujimura's algorithm [17] and Multi-Objective A* [18]. Unfortunately, MOA* is limited to acyclic graphs and Fujimura's implementation is computationally impractical for large state spaces.

Fuzzy logic and fuzzy Membership Functions (MFs) have also been employed in multi-objective path planning. Soltani and Fernando [19] present a planner for deterministic environments that uses fuzzy MFs and Dijkstra's search algorithm but does not employ fuzzy inferencing. Suzuki, Araki et al [20] describe a planner that uses fuzzy MFs to approximate the basic probabilities of input variables which are then aggregated using Dempster-Shafer theory. This aggregated probability is subsequently used as a cost value in a graph search algorithm. Again, fuzzy inferencing is not employed.

Perhaps the most relevant work in the field has been done by McManus [21] and Tompkins [11]. However, McManus' method does not make trade-offs between objectives. On the other hand, the Incremental Search Engine (ISE) developed by Tompkins, Stentz et al [11] does provide true multi-objective aggregation. It is a 2-dimensional, complete and optimal planner that, like the methods described above, combines a method for multi-objective aggregation with a graph search algorithm. It considers two types of variables, independent variables (such as spatial location) and dependent variables (such as energy and time). Tompkins, Stentz et al also consider four objectives, namely spatial location x, y, time and energy. To address the problem of dimensionality, they employ an aggregation function to collapse the energy dimension and perform a 3-dimensional search. However, their work differs from the work presented here in that they only plan for 2-dimensional Euclidean space and use a different method of aggregation that does not consider uncertainty.

It can be seen that the vast majority of multi-objective planners employ roadmap based planning by modifying the cost variable in a traditional graph search algorithm [11], [14]-[19]. This alleviates the computational complexity in searching a continuous state space with an infinite number of states. Therefore, this approach has been adopted.

B. Multi-objective Decision Making

It was found that relatively few multi-objective path planning algorithms were capable of planning under uncertainty. Traditional Bayesian probability based approaches are hindered by high computational costs and the need for accurate *a priori* knowledge of probability distributions. Non-deterministic methods, on the other hand, do not require any *a priori* knowledge. However, these methods can return highly sub-optimal solutions as decisions are made based on worst-case scenarios. [13]

A candidate method for planning with multiple objectives under uncertainty without *a priori* knowledge is fuzzy logic. Type 1 MFs can be used to represent uncertainty in input as a possibility distribution. Additionally, fuzzy inferencing can be used to embed expert knowledge when evaluating multiple competing objectives [22]. This is often also referred to as fuzzy Multi-Criteria Decision Making (MCDM) [23].

The ability to express expert knowledge is particularly advantageous as automated mission planning strives to replicate a human pilot's cognitive abilities. Rasmussen [24] describes a process for human decision tasks that reflects cognitive levels of the decision making process. The rule driven aspects of this model can be represented using a rule based system which is suited for implementation using a fuzzy rule base [24]. Furthermore, the application of fuzzy MFs can help address Zadeh's [25] principle of incompatibility, which observes that increased complexity corresponds to decreased precision in human cognition (hence a greater degree of approximate reasoning). Furthermore, fuzzy logic is completely deterministic, and when coupled with a deterministic path planner, produces deterministic solutions [22]. This is crucial to certification in the UAS environment.

The use of fuzzy logic enables the multi-objective mission flight planner to handle uncertainty through approximation. Uncertainty stems from noisy input variables, uncertainty in the meaning of linguistic variables, in the rule consequents and in the tuning of the rules [26].

Non-singleton (NS) fuzzification, sometimes referred to as vector fuzzification, can be used to capture input uncertainty by modelling the input value as a fuzzy MF. This way, inferencing can be performed on actual possibility distributions (and thus capture input variable uncertainty) instead of crisp sample values (as is done with singleton fuzzification). For p input variables X_k on universes of discourse (UoD) x_k, one constructs fuzzy MFs $\mu_{X_k}(x_k)$. By Zadeh's compositional rule of inference, the implicated consequent MF Y^l of each rule l is found by taking the t-norm ($\wedge$) of the consequent MF $\mu_l(y)$ and the supremums of the t-norms of each input MF and its antecedent MF $\mu_{F_k^l}(x_k)$ [27].

$$Y^l = \bigvee_{k=1..p} \left\{ \mu_l(y) \wedge T_{k=1}^{p} \left(\sup \left[\mu_{X_k}(x_k) \wedge \mu_{F_k^l}(x_k) \right] \right) \right\} \tag{2}$$

Note that $T_{k=1}^{p}$ denotes a sequence of t-norm operations.

C. Path Planning

The D* Lite graph search algorithm was chosen as it is an efficient, complete, optimal and deterministic planner which is suited to in-flight re-planning [28]. The algorithm performs an incremental, heuristic backwards search and has been shown to be more efficient than D* [29], which in turn has a worst case computational complexity of $O(V^{3/2})$ (where V is the number of nodes in the graph) [30].

A condensed pseudo-code representation of the D* Lite algorithm is shown in Fig. 2. For more detail, refer to [28].

$Key(x)$

$k_1 = \min\left(g(x), rhs(x) + h(x_I, x)\right) \quad k_2 = \min\left(g(x), rhs(x)\right)$

$UpdateState(x)$

$if\left(\overline{visited}(x)\right)\{g(x) = \infty\}$

$if\left(x \neq x_G\right)\left\{rhs(x) = \min_{x' \in Parents(x)}\left[c(x,x') + g(x')\right]\right\}$

$if\left(x \in Queue\right)$ {remove x from queue}

$if\left(g(x) \neq rhs(x)\right)$ {insert x into queue with $key(x)$}

$ComputeShortestPath()$

$while\left(\min_{s \in Queue}\left(key(x) < key(x_I)\right) \vee \left(rhs(x_I) \neq g(x_I)\right)\right)$

  $Queue.pop(x)$

  $if\left(g(x) > rhs(x)\right)$

    $\left\{\begin{array}{l} g(x) = rhs(x) \\ \forall x' \in Neighbors(x), UpdateState(x) \end{array}\right\}$

  $else$

    $\left\{\begin{array}{l} g(x) = \infty \\ \forall x' \in Neighbors(x) \cup x, UpdateState(x) \end{array}\right\}$

Fig. 2 Pseudo-code of the D* Lite Algorithm. Note that x, x_I and x_G are the current, initial and goal states respectively; $g(x_I)$, $rhs(x_I)$ and $g(x_G)$ are each initialised to ∞, $rhs(s_G)$ is initialized to 0. Each iteration of D* Lite corresponds to an execution of *ComputeShortestPath* [29].

A prioritised queue is employed so that the most promising states (defined here as a location in three dimensional space) are explored first. A state's priority in the queue is determined by a key $Key(x)$ which is calculated based on a heuristic estimate $h(x_I,x)$ of the cost to reach the start state. The estimate could be as simple as the Euclidean distance but must be admissible (guaranteed to underestimate the actual cost) to guarantee optimality. At each iteration, $g(x)$ (the cost to reach state x from the goal x_G) and the one step look-ahead cost $rhs(x)$ is calculated and the queue updated. Additionally, the parent state of x is set; this is used to build up a path by tracing through the parent's of each state all the way to the goal. A parent of x is selected based on its g value and the cost $c(x,x')$ to reach x from that state. D* Lite finds the path that minimizes the total summed cost to produce a globally optimal path. When there are multiple objectives, it is possible to find a globally optimal path by changing the way in which the actual cost $c(x,x')$ is calculated as this influences the way in which parent states are chosen. The introduction of dependent variables does not affect the optimality of D* Lite as, like D*, it is a form of dynamic programming and therefore there is no assumption of prior knowledge of edge costs [13].

D. *Integration of Path Planning and Decision Making*

In order to plan with multiple objectives using D* Lite, it is necessary to change:

- the way that parents are chosen – which entails a change in the way costs are calculated and stored
- the heuristic $h(x_t,x)$

It is important to note that an optimal path constitutes a series of segments which are themselves optimal [13]. Therefore, it is possible to retain optimality by replacing the calculation of *rhs(x)* in *UpdateState* (Fig. 2) with a multi-objective method that finds the optimal parent of x. This corresponds to changing the function $c(x,x')$ and the method for choosing the best parent state of x (refer Fig. 3). Even though the heuristic needs modification to reflect the multi-objective cost $g(x)$ (which can be determined through analysis of the fuzzy inferencing engine), the most important aspect of integrating multi-objective decision making with D* Lite lies in modifying *UpdateState* with a suitable multi-objective decision making algorithm.

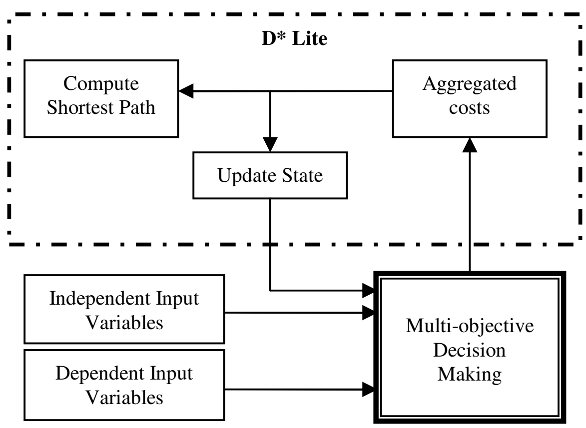

Fig. 3 Integration of Multi-objective Decision Making with D* Lite – compare with Fig. 2.

It is important to note that the suitability of each of the candidate (or alternative) parent states is dependent on all 4 objectives and is not necessarily a monotonic function of input variables. Consequently, it is advantageous to employ a full fuzzy inferencing module (using (2)) as opposed to fuzzy number manipulation operations.

The output of the fuzzy inferencing process is itself a fuzzy MF. In order to choose the optimal parent state, it is necessary to calculate the total aggregated cost to reach the current state via each candidate parent state. These costs can then be ranked to determine the optimal parent state.

The centre of gravity (CoG) method was selected for calculating aggregated costs as it not only takes into account the support of the MFs, but also the degree of membership at each point [31]. Therefore, the cost value for each alternative parent j at state x_i is:

$$rhs_j(x_i) = g_j(x_{i+1}) + \frac{\int y\mu_{B'}(y)dy}{\int \mu_{B'}(y)dy} \tag{3}$$

where y is the output UoD and $\mu_{B'}(y)$ is the aggregation of the implicated output MFs.

E. *Case Study Application*

A specific mission scenario is presented to illustrate the various components in the mission flight planning framework.

The problem comprises the evaluation of four objectives, namely: altitude Above Ground Level (AGL), risk, heading angle and fuel. Uncertainty in these input variables is also taken into consideration. The state space is defined as 3 dimensional Euclidean space (latitude, longitude and altitude). A graph data structure was derived from a cubic cell representation of this state space where each node is located in the corner with smallest x, y, z coordinate values.

1) *Input Variables*

For the purposes of this case study, uncertainty in the AGL variable was modeled (based on sensor and SRTM data error) as Gaussian with a 90% confidence interval of 100ft. The uncertainty in the calculated risk values was arbitrarily modeled as Gaussian with a spread of 0.05×10^{-6} casualties per hour of flight.

The cruising levels heading rule was implemented by calculating the minimum angle θ_a (as measured from the longitude axis) of deviation from the boundaries of the acceptable heading angles at that cruising level.

$$\theta_a = \begin{cases} -\min\left[|\theta|, 180-|\theta|\right] & \theta_{rl} \le \theta < \theta_{ru} \\ \min\left[|\theta|, 180-|\theta|\right] & otherwise \end{cases} \tag{4}$$

where θ is the heading angle and θ_{rl} and θ_{ru} are the lower and upper acceptable heading angles respectively. This value is then modelled as a Gaussian fuzzy number with a standard deviation of 10 degrees.

Fuel was also modelled as a Gaussian fuzzy number dependent on the amount of fuel "consumed" and the estimated fuel needed to reach the start state Q_e. The fuel required to reach state x_i (given by Q_i) from x_{i+1} (since this is a backwards search) is calculated recursively given the incremental fuel cost q_i (refer (1)) associated with transitioning from x_{i+1} to x_i:

$$Q_i = Q_{i+1} + \overline{q}_i \,. \tag{5}$$

At the same time, a heuristic estimate of the fuel required to reach the start state is computed based on (1). Then, given the known crisp value of total fuel available Q_t, the remaining fuel as a ratio of total fuel can be computed:

$$R_i = \frac{1}{Q_t}\left(Q_t - Q_i - Q_e\right). \tag{6}$$

There are advantages in using R_i instead of Q_i. Consider a state x_i which has two candidate parent states x'_{i+1} and x''_{i+1} each with equal fuel costs Q_{i+1}; additionally, the incremental fuel cost to reach x_i is equal. Therefore, it is impossible to distinguish between these two states in terms of fuel costs when considering just Q_i. However, by incorporating Q_e, it is now possible to distinguish between these two distinct states as the Euclidean distance to the start state is almost certainly different. A direct consequence of this is that more promising states will be investigated first which can potentially decrease the number of states explored.

2) Inferencing

As multiple fuzzy inferencing operations are performed at each iteration of D* Lite, it is desirable to minimise the number of rules and also the number of antecedent and consequent MFs. The implemented fuzzy logic system is a four input single output system with 13 rules.

When designing the fuzzy rule antecedent MFs, it should be noted that there are regions on the UoD for AGL, risk and heading that do not influence the suitability of the outcome. For example, values of risk less than the lower decision threshold are all equally desirable and do not change the suitability of the path choice. Therefore, these antecedent MFs were modelled as trapezoidal MFs. Fuel on the other hand requires a different response for every change on the input UoD; hence, triangular MFs were used.

In designing the fuzzy rule base, it should be noted that numerous trade-offs are required. For example, an altitude of 500ft should be maintained unless when approaching mission waypoints. The heading angle should adhere to the cruising levels rule but this is not mandatory below 5000ft, hence it can be traded off against other objectives (such as if running low on fuel) when 'necessary'. Additionally, it is necessary to enforce hard limits of a minimum of 50ft AGL to avoid impact with terrain, a maximum permissible risk of 10^{-6} casualties per flight hour and a maximum fuel load. These "hard limits" are difficult to enforce in a fuzzy system especially if centre of gravity (CoG) defuzzification is employed. This is because multiple rules may be fired which results in non-zero truncation values for other consequent MFs – this changes the CoG result. Instead, the one tailed confidence interval for the input fuzzy number (which are Gaussian) is calculated and compared with the hard limit. A confidence interval of 90% was arbitrarily chosen.

IV. Experiments and Discussion

In this investigation, three different methods for multi-objective decision making were evaluated with regards to planner performance when integrated with D* Lite (as described in section IIID). The first method employed weighted sum aggregation (a similar approach to [14]-[16]) under the Analytic Hierarchy Process (AHP) [32]. This was compared with the NS fuzzy planner described in section III and a variant of that which used singleton fuzzification (hence it does not model input uncertainty). Both fuzzy planners also use the same rule base and therefore are expected to produce similar results.

For the mission scenario described in Fig. 1, the planner is executed twice to find a path from waypoint 1 to waypoint 2, and then again from waypoint 2 to waypoint 3. The solution given by the NS fuzzy planner is shown in Fig. 4 along with the costs for each of the four objectives when traversing from waypoint 2 to waypoint 3. The three layers in each subplot correspond to the three AMSL cruising layers. A number of different scenarios were also simulated to evaluate the performance of these planners.

One method for measuring planner performance is the computational complexity. This provides an indication of the practical feasibility of the planner. Computational complexity can be measured in terms of time latency and also in terms of the number of iterations of D* Lite (which, along with the number of states explored, heavily influences the computation time). As well, the total costs and incremental costs for each objective can be examined to evaluate the decision trade-offs that were made at each step.

Unsurprisingly, AHP required the least computation time, followed by singleton fuzzy and non-singleton fuzzy planners. Fuzzy calculations incur greater processing delays per iteration. Furthermore, computation time increases with the overall path distance due to the need to explore more states (refer Fig. 5). It was also observed that when performing re-planning (or in-flight re-planning), D* Lite tends to only expands states that change the optimality of the current path. This was found to significantly reduce computation time as reported by [28],[30].

Given that there are 300 nodes, all three planners required fewer than $O(V^{3/2})$ iterations to find an optimal path (refer Fig. 5); this empirically verifies the computational feasibility of augmenting D* Lite with multi-objective decision making. As well, it was observed that the fuzzy based planners tended to explore fewer states than the AHP planner and thus use fewer search iterations as shown in Fig. 5. This can be attributed to the fact that fuzzy rules provide the ability to create highly non-linear relationships which results in a cost that more accurately reflects the suitability of a certain path choice. With AHP, the cost is calculated as a linear weighted sum of the constituent objectives. However, the need to make complex trade-offs often results in non-linearities. For example, a lower risk trajectory should be followed except when the fuel levels are low, in which case higher levels of risk are acceptable (within the upper bounds of course). The inflexibility of AHP was demonstrated in several scenarios where even with sufficient fuel, the planner still adopts a higher risk path instead of reverting to the longer, but safer route.

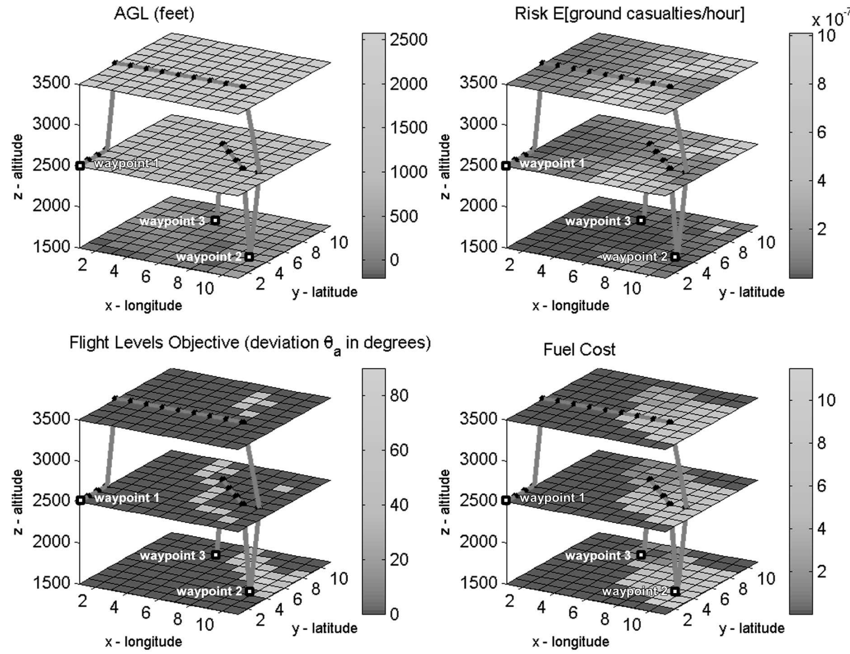

Fig. 4 Mission flight plan (path shown by gray line) given by the NS fuzzy planner for the case study with variable values shown for each objective. Note that the planned path avoids regions that exceed hard limits and is of minimal length. Furthermore, the planner chooses to climb in altitude when flying east to comply with the flight levels rule and to avoid low terrain as stipulated by AGL requirements.

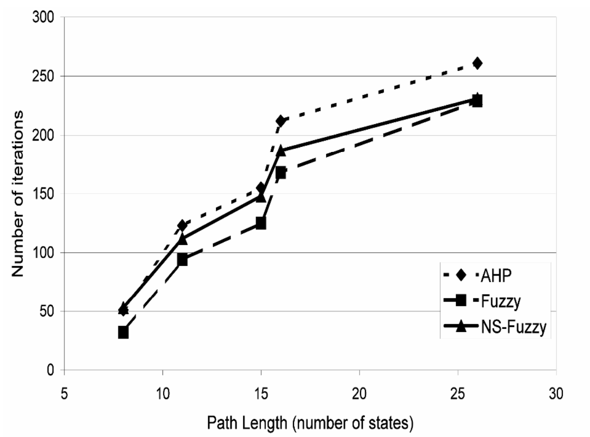

Fig. 5 Number of search iterations needed versus path length

Both fuzzy planners chose similar paths with similar costs for each objective. This was as expected given that the rule bases were identical. However, changing the rule base drastically changes the planned path; this shows that the rules significantly influence the performance of the planner; therefore, the challenge remains in effectively eliciting and encoding, as rules, the knowledge from human experts.

The primary difference between the results of the two fuzzy planners arose from the handling of hard limits. All the paths in each experiment adhered to hard limits, but the non-singleton fuzzy planner avoided some cells not avoided by the fuzzy planner, even though these cells were within the bounds of the hard limits. The application of fuzzy numbers and confidence intervals creates an extra buffer due to uncertainty. This is a desirable trait given uncertainty in fuel usage, aircraft position and map accuracy in real UAS operations. The effects of these hard limits become more pronounced over longer paths and can be attributed to the hard limits and the activation of more rules in the non-singleton planner [27]. An example of average path risk is shown in Table 1.

TABLE 1: AVERAGE PATH RISK ($\times 10^{-7}$)

Path length	AHP	Fuzzy	NS Fuzzy
8	0.946	0.703	0.582
11	2.29	1.11	1.19
15	2.00	1.76	1.68
16	2.40	1.00	0.953
26	9.61	8.07	8.07

As D* Lite has been shown to find the least cost path [28], therefore, all three planners return a globally optimal path which is of the least aggregated cost. This is supported by the fact that in every simulation, the path that each method returns is always of the same length in terms of the number of state transitions.

Both AHP and fuzzy based planners are completely deterministic and produce identical responses to identical scenarios with deterministic time delays every time. This provides an advantage over evolutionary and randomised search based methods (e.g. ant colony optimisation) from a certification standpoint which is an important aspect in all aviation software systems. It is conceivable that a panel of experts could create and verify the fuzzy rule base by examining the output costs for all possible combinations of input singletons.

Even though a specific mission scenario was presented here, the methodology is extensible to a wide variety of multi-objective path planning problems.

V. Conclusion

The evaluation of three methods of augmenting D* Lite in mission flight planning has shown that fuzzy rule based methods provide distinct advantages over conventional AHP MCDM methods. These include fewer search iterations and more flexibility in trading-off between competing objectives. It was also found that the computational efficiency of the D* Lite algorithm is preserved even when evaluating multiple objectives. By incorporating uncertainty in the input variables, a more conservative path is constructed. The results demonstrate that NS fuzzy planning provides a computationally feasible method for finding an optimal path, under input uncertainty, for multiple objectives in three dimensional space. This is currently not possible with existing multi-objective path planning algorithms especially when the graph can be cyclic. By incorporating hardware fuzzy processing, it is envisaged that real time re-planning is possible [33]. Furthermore, the algorithm is completely deterministic and as such could be certified under existing aviation software certification standards.

It was demonstrated through the case study that a NS fuzzy multi-objective mission flight planning algorithm process is well-suited in efficiently calculating an optimal mission flight plan. Therefore, this framework can be applied to a wide variety of UAS missions with different objectives (such as time and dynamic obstacles).

Acknowledgment

The authors wish to thank Gilles Coppin, Visiting Professor, Humans and Automation Laboratory, MIT for his helpful suggestions in the preparation of this paper.

References

[1] "Partnering in the global context: An Australian aerospace industry for the 21st century, report of the aerospace industry action agenda," Department of Industry, Tourism and Resources (DITR) 2003.
[2] M. T. DeGarmo, "Issues concerning integration of Unmanned Aerial Vehicles in civil airspace," MITRE, Center for Advanced Aviation System Development, McLean, Virginia 2004.
[3] "UAV task-force final report, a concept for European regulations for civil unmanned aerial vehicles (UAVs)," The Joint JAA/EUROCONTROL Initiative on UAVs, 2004.
[4] "Civil aviation regulations 1988 (CAR 1988)," Civil Aviation Safety Authority (CASA), Australia 2003.
[5] R. Parasuraman, T. B. Sheridan, and C. D. Wickens, "A model for types and levels of human interaction with automation," *IEEE Trans. Systems, Man and Cybernetics, Part A*, vol. 30, pp. 286-297, 2000.
[6] NASA Jet Propulsion Laboratory, (2006). Shuttle radar topography mission [Online]. Available: http://www2.jpl.nasa.gov/srtm/
[7] R. Clothier and R. Walker, "Determination and evaluation of UAV safety objectives," in *21st International Unmanned Air Vehicle Systems (UAVS) Conf.*, Bristol, United Kingdom, 2006.
[8] R. Weibel and R. Hansman, "An integrated approach to evaluating risk mitigation measures for UAV operational concepts in the NAS," in *AIAA 4th Infotech@Aerospace Conf.*, Arlington, Virginia, U.S., 2005.
[9] G. Marsters and M. Sinclair, "Integrating UAVs with conventional air operations: Some regulatory issues," in *18th Bristol Int. UAV Systems' Conf.*, Bristol, United Kingdom, 2003.
[10] R. Clothier, R. Walker, N. Fulton, and D. Campbell, "A casualty risk analysis for unmanned aerial system (UAS) operations over inhabited areas," in *Twelfth Australian Int. Aerospace Congress (AIAC12)*, Melbourne, Australia, 2007.
[11] P. Tompkins, A. T. Stentz, and W. R. L. Whittaker, "Mission-level path planning for rover exploration," in *8th Conf. on Intelligent Autonomous Systems (IAS-8)*, March 2004.
[12] D. Ferguson and A. Stentz, "Using interpolation to improve path planning: The field D* algorithm," *Journal of Field Robotics*, vol. 23, pp. 79-101, 2006.
[13] S. M. LaValle, *Planning algorithms*. New York: Cambridge University Press, 2006.
[14] G. F. List, P. B. Mirchandani, M. A. Turnquist, and K. G. Zografos, "Modeling and analysis for hazardous materials transportation - risk analysis, routing scheduling and facility location," *Transportation Science*, vol. 25, pp. 100-114, 1991.
[15] P. Leonelli, S. Bonvicini, and G. Spadoni, "Hazardous materials transportation: A risk-analysis-based routing methodology," *Journal of Hazardous Materials*, vol. 71, pp. 283-300, 2000.
[16] M. Zhang, Y. Ma, and K. Weng, "Location-routing model of hazardous materials distribution system based on risk bottleneck," in *Int. Conf. on Services Systems and Services Management (ICSSSM)*, 2005, pp.362-368 Vol. 1.
[17] K. Fujimura, "Path planning with multiple objectives," *IEEE Robotics & Automation Magazine*, vol. 3, pp. 33-38, 1996.
[18] B. S. Stewart and I. Chelsea C. White, "Multiobjective A*," *J. ACM*, vol. 38, pp. 775-814, 1991.
[19] A. R. Soltani and T. Fernando, "A fuzzy based multi-objective path planning of construction sites," *Automation in Construction*, vol. 13, pp. 717-734, 2004.
[20] N. Suzuki, D. Araki, A. Higashide, and T. Suzuki, "Geographical route planning based on uncertain knowledge," in *Proc. 7th Int. Conf. on Tools with Artificial Intelligence*, 1995, pp.434-441.
[21] I. McManus, "A multidisciplinary approach to highly autonomous UAV mission planning and piloting for civilian airspace," Ph.D. Thesis, School of Engineering Systems, QUT, 2004.
[22] E. H. Ruspini, P. P. Bonissone, and W. Pedrycz, *Handbook of fuzzy computation*. New York: Wiley, 1996.
[23] C. Carlsson and R. Fuller, "Fuzzy multiple criteria decision making: Recent developments," *Fuzzy Sets and Systems*, vol. 78, pp. 139-153, 1996.
[24] J. Rasmussen, "Diagnostic reasoning in action," *IEEE Trans. Systems, Man and Cybernetics*, vol. 23, pp. 981-992, 1993.
[25] L. A. Zadeh, "Outline of a new approach to the analysis of complex systems and decision processes," *IEEE Trans. Systems, Man and Cybernetics*, vol. 3, pp. 28-44, 1973.
[26] J. M. Mendel and R. I. B. John, "Type-2 fuzzy sets made simple," *IEEE Trans. Fuzzy Systems*, vol. 10, pp. 117-127, 2002.
[27] G. C. Mouzouris and J. M. Mendel, "Nonsingleton fuzzy logic systems: Theory and application," *IEEE Trans. Fuzzy Systems*, vol. 5, pp. 56-71, 1997.
[28] D. Ferguson, M. Likhachev, and A. T. Stentz, "A guide to heuristic-based path planning," in *Int. Conf. on Automated Planning and Scheduling (ICAPS)*, Monterey, CA, 2005.
[29] S. Koenig and M. Likhachev, "Improved fast replanning for robot navigation in unknown terrain," in *Proc. IEEE Int. Conf. on Robotics and Automation*, Washington, D.C., 2002, pp.968-975 vol.1.
[30] C. Tovey, S. Greenberg, and S. Koenig, "Improved analysis of D*," in *Proc. IEEE ICRA*, 2003, pp.3371-3378 vol.3.
[31] D. Bailey, A. Goonetilleke, and D. Campbell, "A new fuzzy multicriteria evaluation method for group site selection in GIS," *Journal of Multi-Criteria Decision Analysis*, vol. 12, pp. 337-347, 2003.
[32] T. L. Saaty, "How to make a decision The analytic hierarchy process," *European Journal of Operational Research*, vol. 48, pp. 9-26, 1990.
[33] P. Wu, P. Narayan, D. Campbell, M. Lees, and R. Walker, "A high performance fuzzy logic architecture for UAV decision making," in *IASTED Int. Conf. on Computational Intelligence*, San Francisco, 2006.