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An Integrated ACO-AHP Approach for Resource Management Optimization

Kia Fallahi, Henry Leung, and Sandeep Chandana
Department of Electrical and Computer Engineering,
University of Calgary, Calgary, AB, Canada.
Email: kfallahi@ucalgary.ca, leungh@ucalgary.ca, schandan@ucalgary.ca

***Abstract*—The most often used operator to aggregate criteria in decision making problems is the classical weighted sum model or weighted sum model. However, in many problems, the criteria considered interact and a substitute to the weighted sum model has to be adopted. Multi-criteria decision making (MCDM) problems involve the ranking of a finite set of alternatives in terms of a finite number of decision criteria. Usually such criteria may be in conflict with each other. A typical problem in MCDA is concerned with the task of ranking a finite number of decision alternatives, each of which is explicitly described in terms of different characteristics often called decision criteria or objectives. This research applies an integrated multi-criteria decision making approach to design an optimal UAV resource management. In this approach, the ant colony optimization (ACO) is used firstly to obtain optimal solutions satisfying some path planning criteria, then, fuzzy analytic hierarchy process (AHP) is formulated to select the best set of UAVs. Due to vagueness and uncertainty, fuzzy set theory based AHP is employed in the decision making judgments, because it can handle uncertainty easily. The proposed method can be extended to any sensor network resource management problem.**

Keywords— Multi Criteria Decision Making, Analytic hierarchy process (AHP), Fuzzy, Resource Management, Path Planning, UAV, Ant colony optimization (ACO), B-Spline.

I. Introduction

Multi-Criteria Decision Making (MCDM) is one of the most widely used decision making methodologies in the sciences, business, and engineering fields. A typical problem in MCDA is concerned with the task of ranking a finite number of alternatives, each of which is explicitly described in terms of different criteria, also, called objectives which have to be optimized simultaneously. In resource management, sometimes multiple-objectives need to be met. In practice, it is impossible to treat all these objectives with equal importance. A method to identify the optimal configuration introduces a multi-objective optimization problem with both complexity and uncertainty. For instance, some of the objectives can be explicitly measured, and others can not. Optimal resource management is therefore expected to be a harmonization of required objectives with emphasis on the so-called main objectives.

One of the most prevalent MCDM techniques is the analytic hierarchy process (AHP) [1]. AHP is a structured technique for helping people deal with complex decisions. Rather than prescribing a “correct” decision, the AHP helps the decision makers determine one that suits their needs and understanding of the problem. Based on mathematics and psychology, it was developed by Thomas L. Saaty [2] in the 1970s and has been extensively studied and refined since then. The AHP provides a comprehensive and rational framework for structuring a problem, for representing and quantifying its elements, for relating those elements to overall goals, and for evaluating alternative solutions [3]. However, due to vagueness and uncertainty in the decision making judgments, fuzzy set theory based AHP approach is employed in this work, because it can handle uncertainty easily. The basic steps involved in fuzzy AHP are similar to the conventional (discrete) AHP. However, fuzzy numbers are used instead of discrete numbers in the process of pairwise comparisons [4].

Unmanned aerial vehicles (UAVs) are aircrafts which can be controlled remotely or autonomously. UAVs are initially designed for military applications. Introducing UAVs to the battlefield has greatly reduced the number of causalities in dangerous missions such as detecting enemy troops in hostile environments. One of the major studies in the autonomous control of UAVs is on path planning [5]. Path planning is usually defined as finding a path in a bounded terrain between an arbitrary starting point and an arbitrary ending point, provided that the path is optimized according to some constraints or requirements. Exact algorithms, such as dynamic programming [6], have shown to provide good results in some small scale path planning problems. The major drawback of exact algorithms is computational complexity of these algorithms increases drastically with the resolution of the search space, making them impractical to be applied in real scenarios. Meta-heuristic algorithms, such as genetic algorithms (GA) [7] and ant colony optimization (ACO) algorithms [8], are widely applied in large scale search problems.

In this paper, a multi-criteria decision making approach for UAV resource management using fuzzy AHP is proposed. The rest of the paper is organized as follow. Techniques for multi-criteria decision making is described in Section II. Section III presents the proposed MCDM method for UAV resource management optimization. Section IV presents the simulation results. Conclusions are given in Section V.

II. Techniques for Multi-Criteria Decision Making

The process of optimizing a collection of objective functions, systematically and simultaneously, is called multi-objective optimization. The general multi-objective optimization problem can be formulated as following:

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$$\min_{x} \mathbf{F}(\mathbf{x}) = \left[F_1(\mathbf{x}), F_2(\mathbf{x}), ..., F_k(\mathbf{x})\right]^T \quad (1)$$

$$\text{subject to: } g_j(\mathbf{x}) \leq 0,\ j = 1, 2, ..., m, \quad (2)$$

$$h_l(\mathbf{x}) = 0,\ l = 1, 2, ..., e, \quad (3)$$

where k is the number of objective functions, m is the number of inequality constraints, and e is the number of equality constraints. $\mathbf{x} \in E^n$ is a vector of design variables (also called decision variables), where n is the number of independent variables x_i. $\mathbf{F}(\mathbf{x}) \in E^k$ is a vector of objective functions $F_i(\mathbf{x}) : E^n \to E^1$. $F_i(\mathbf{x})$ are also called objectives, criteria, payoff functions, cost functions, or value functions [9].

In the multi-objective optimization, it often happens that several functions may compete with each other, since they might be either equally important or preferred by the designer. In other words, this raises a realistic optimization problem that may require simultaneous optimization of more than one objective [10]. The problem of selecting an action among a set of alternatives becomes harder when the decision making process involves several criteria rather than a single criterion. Such problems are referred to as multi-criteria decision making problems. MCDM is the study of discrete decision making involving two or more criteria (sometimes conflicting) or objectives. In MCDM problems, the goal is to select an alternative from a set of relevant alternatives by evaluating a set of criteria. Let us now generalize the problem of MCDM by taking a finite number of actions and criteria. Let $\Omega = \{s_1, s_2, ..., s_m\}$ and $\mathbf{X} = \{x_1, x_2, ..., x_n\}$ be a set of alternatives and a set of criteria, respectively. The decision making process proceeds by formulating a **decision matrix**, $\mathbf{A}$, given by: Each entry a_{ij} denotes the degree to which the

	Criteria			
	c_1	c_2	...	c_n
Alts.	$(w_1$	w_2	...	$w_n)$
A_1	a_{11}	a_{12}	...	a_{1n}
A_2	a_{21}	a_{22}	...	a_{2n}
.	.		.	
.	.		.	
.	.		.	
A_m	a_{m1}	a_{m2}	...	a_{mn}

criterion x_j is satisfied by the alternative s_i. The idea is how to reduce the multi-criteria problem into a single global criterion problem by aggregating all the elements of matrix $\mathbf{A}$, given by $a = \mathbf{H}(a_{1j}, a_{2j}, .., a_{mj})$, where $\mathbf{H}$ is the aggregation operator. Historically a common method used to solve multi-criteria or multi-objective problems is by a weighted arithmetic mean (aggregation operator) of the objectives, in this way creating a singe-objective function to optimize.

A. Weighted Sum Model (WSM)

The weighted sum model (WSM) is the simplest and the most commonly used aggregation operator in MCDM [1]. However, despite its simplicity it has a drawback in that it assumes that the criteria are independent. The basic principle behind this technique is the additive utility assumption. That is, if the performance of each alternative in terms of each criterion in the decision problem (i.e., a_{ij} values) is measurable and is of the same unit where higher is better, then the alternative

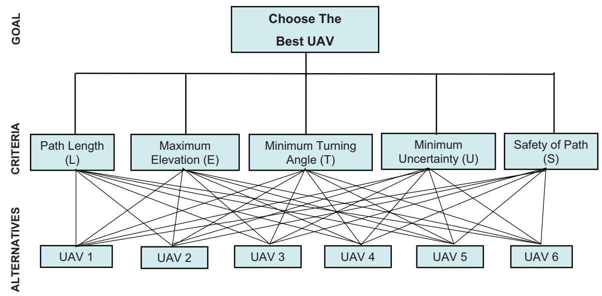

Fig. 1. AHP structure in UAV resource management

with the largest cumulative value is the best. For example, if all the criteria represent benefit, then the most preferred alternative is the one for which the preference value (denoted as P_i) satisfies the following expression (for the maximization case):

$$P^*_{WSM} = \max_i P_i = \max_i \sum_{j=1}^{n} a_{ij} w_j \text{ for } i = 1, 2, .., m \quad (4)$$

where P^*_{WSM} is the WSM preference value of the best alternative. Next, the alternatives can be ranked according to their P_i values.

B. Fuzzy Analytic Hierarchy Process (Fuzzy AHP)

Details about AHP method can be found in [2]. In a decision making problem, there are normally three kinds of fundamental elements, i.e., Goal (G), Criteria (C), and Alternatives (A). Goal is the objective to be reached of the decision to be made. Alternatives are a finite set of options to be chosen and ordered. They represent possible candidates to the solution. The alternatives comparison is made taking into account specific set of evaluation criteria and evaluation criteria can take multiple layers. As shown in Fig. 1, the relationship among these elements are organized as a hierarchical structure. The hierarchic representation of a system can be used to describe the way how priority changes in lower level affect higher levels priorities.

We need to quantify the relative importance of each criterion against the Goal. AHP achieves this by comparing the elements on each level in pairs. For two elements X_i and X_j in criteria layer, the value is set to a_{ij}, the relative importance of X_i against X_j. Defining w_i as the true weight of X_i, we have $a_{ij} = w_i/w_j$ ideally. Let $\mathbf{A}$ and $\mathbf{w}$ denote a matrix of pairwise comparisons, a_{ij}, and a vector of w_i, respectively. By multiplying $\mathbf{A}$ by $\mathbf{w}$, we get $\mathbf{A}\mathbf{w} = n\mathbf{w}$, where n is the number of elements in the layer. Therefore, $\mathbf{w}$ is the principal eigenvector and n is the maximum eigenvalue. Alternative comparisons are also made in the evaluation phase, according to each of the criteria. Comparisons are made pair-by-pair indicating which alternative is preferable in relation to another. Comparisons are registered in pairwise matrix, where again element a_{ij} represents a comparison between alternative i versus alternative j. When comparing two factors, one must assign a number to define how much a factor is

TABLE I
SCALE OF MEASUREMENT FOR CONVENTIONAL AHP AND FUZZY AHP

Conventional AHP (r_{ij})	Fuzzy AHP ($\tilde{r}_{ij}$)	Definition	Membership Function
1	$\tilde{1}$	Equally important	(1,1,2)
3	$\tilde{3}$	Moderately important	(2,3,4)
5	$\tilde{5}$	Strongly important	(4,5,6)
7	$\tilde{7}$	Very strongly important	(6,7,8)
9	$\tilde{9}$	Extremely important	(8,9,9)
2, 4, 6, 8	$\tilde{2}, \tilde{4}, \tilde{6}, \tilde{8}$,	Intermediate values	
Reciprocals	Reciprocals	Used to reflect dominance of the second alternative over the first	

better or more important than the other. The value of a_{ij} ranges from $\{1, 2, 3, ..., 9\}$ in the case of convetional AHP [11]. However, in fuzzy AHP, fuzzy number $\tilde{a}_{ij}$ is used to assign to the user preferences [12]. In this paper, triangular fuzzy number, $\tilde{1} - \tilde{9}$, are used to represent subjective pairwise comparisons of selection process to consider the vagueness. The memberships function for a triangular fuzzy number $\tilde{a} = (x_{min}, x_{ave}, x_{max})$ can be defiend as

$$\mu_{\tilde{a}}(x) = \begin{cases} 0 & for\ x \leq x_{min} \\ (x - x_{min})/(x_{ave} - x_{min}) & for\ x_{min} < x \leq x_{avg} \\ (x_{max} - x)/(x_{max} - x_{ave}) & for\ x_{avg} < x \leq x_{max} \\ 0 & for\ x > x_{max}. \end{cases} \tag{5}$$

Triangular fuzzy numbers, $\tilde{1} - \tilde{9}$, are utilized to improve the conventional nine-point scaling scheme. The triangular fuzzy numbers with the corresponding membership function are defined and shown in Table I and Fig. 2, respectively.

If there are $n(i, j = 1, 2, 3, .., n)$ decision elements, the decision maker needs to perform $n(n-1)/2$ comparisons. The possitive fuzzy reciprocal pairwise comparison matrix, $\tilde{\mathbf{A}}$, can be expressed as

$$\tilde{\mathbf{A}} = \begin{pmatrix} \tilde{a}_{11} & \tilde{a}_{12} & ... & \tilde{a}_{1n} \\ 1/\tilde{a}_{12} & \tilde{a}_{22} & ... & \tilde{a}_{2n} \\ ... & ... & ... & ... \\ 1/\tilde{a}_{1n} & 1/\tilde{a}_{2n} & ... & \tilde{a}_{nn} \end{pmatrix} \tag{6}$$

where $\tilde{a}_{ij} = (x_{min}, x_{ave}, x_{max})$, $1/\tilde{a}_{ij} = (1/x_{max}, 1/x_{ave}, 1/x_{min})$, and $\tilde{a}_{nn} = (1, 1, 1)$.

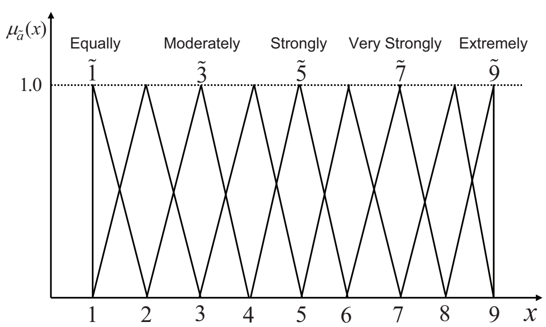

Fig. 2. Fuzzy membership function.

*1) **Consistency Ratio**:* In practice, it is difficult to consistently set $\tilde{a}_{ij}$ for all pairs elements, so we need to judge the degree of inconsistency. Letting λ_{max} denote the maximum eigenvalue of $\tilde{\mathbf{A}}$, we have $\lambda_{max} \geq n$ [2]. So, we can judge the degree of inconsistency using the consistency index C.I. defined by

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{7}$$

λ_{max} decreases as the consistency index increases, and $\lambda_{max} = n$ when $\tilde{\mathbf{A}}$ is a consistent matrix. Hence, the degree of consistency increases as C.I. decreases. Then the C.I. is compared with a consistency index from a random generated matrix. Random evaluations represent the maximum degree of inconsistency, because they have no interdependency relation. The typical random consistency index, statistically obtained from n order matrices from 3 to 9 are given in Table II. The consistency index obtained by Eq. 8 must be compared with random consistency ratios (RI) in Table II.

$$CR = \frac{CI}{RI} \tag{8}$$

Pairwise comparison is normally accepted when the value of consistency ratio is smaller or equal to 0.1. If the Consistency Ratio (CR) is greater than 0.1, we need to revise the subjective judgment.

III. THE PROPOSED MCDM METHOD FOR UAV RESOURCE MANAGEMENT USING FUZZY AHP

The optimization problem in this paper includes two main steps. First step is concerned with finding a path in a bounded terrain between an arbitrary starting point p_s and an arbitrary ending point p_e, provided that the path is optimized according to a desirability function for each resource, and the second step is resource management by multi-criteria decision making using fuzzy AHP in selecting the best resource to perform the assigned task. In the proposed method, quantitative criteria can be handled by ant colony optimization and both qualitative and quantitative criteria can be handled by fuzzy AHP. The block diagram of the proposed integrated multi-criteria decision making resource optimization technique is shown in Fig. 3. As it can be seen in Fig. 3, the weights for path criteria, $w_1, w_2, ..., w_{N-M}$ are given to ACO block in which WSM method is used as the aggregation operator in this step. Then, the optimized path criteria values for alternatives, $O_1, O_2, ..., O_{N-M}$ will be passed to the fuzzy AHP block. In the fuzzy AHP block, new weights will be given to the whole set of criteria, $c_1, c_2, ..., c_N$.

TABLE II
CONSISTENCY RATIO FOR RANDOM MATRICES

n	3	4	5	6	7	8	9
RI	0.58	0.90	1.12	1.24	1.32	1.41	1.45

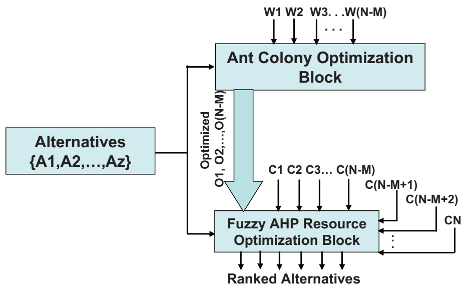

Fig. 3. Block diagram of the integrated resource optimization method

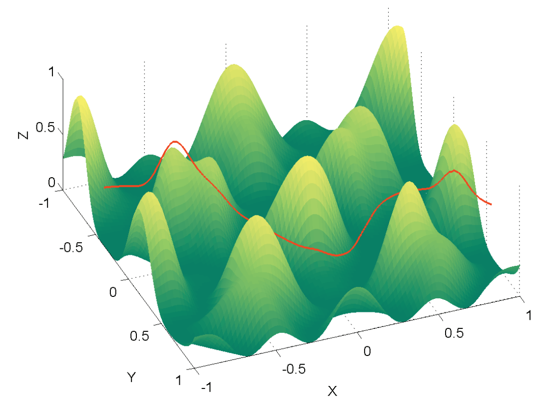

Fig. 4. Illustration of the terrain model considered in this paper. The red line is the path of a UAV.

A. UAV Path Planning Optimization

The first part of the proposed algorithm is the path planning block which is optimizing a number of criteria to obtain an optimized path for each resource which is a UAV in this work.

1) Scenario Under Study: The scenario under study is a meshed 3-D model mimicking a hilly landscape which is shown in Fig. 4. The model can be expressed by the following mathematical function:

$$z(x,y) = \sigma[a\sin(b\sqrt{y^2+x^2})+c\cos(x)+\sin(y+d)+e\sin(y)]^2 \quad (9)$$

where a, b, c, d, e are arbitrary constants. Parameter σ is the normalizing factor such that $z(x,y)$ will lie within the range [0,1].

2) Desirability of a Path: The desirability of a path is measured by a desirability function δ. The desirability function is the weighted sum of three constraint functions s_i, where $i = 1,2,3$. The desirability function using the Eq. 4 is expressed as:

$$\delta = \frac{\sum_{i=1}^{3} w_i s_i}{\sum_{i=1}^{3} w_i} \quad (10)$$

where w_i are the weightings of the constraints. The constraint functions are in terms of the path length, the minimum turning angle of the path, and the maximum pitch rate. Optimization is done to maximize desirability of the path.

A shorter path is more desirable than a longer path. Function s_1 is inversely proportional to the length of the path. Paths consisting of sharp turnings are undesirable for the navigation of UAVs. Function s_2 is a function proportional to the minimum turning angle θ of the path. To collect data from the ground, an UAV has to maintain its altitude at a constant level relative to the ground. Paths with frequent climbing and descending motions are undesirable in the sense of fuel consumption. Pitch rate is defined as the change of the altitude of an aircraft over time. Therefore, it is preferred to minimize the maximum pitch rate of the path. Function s_3 is inversely proportional to the maximum pitch rate of the path.

3) ACO Path Optimization using B-spline Curves: In the proposed path planner, the path of a UAV is represented by a B-spline model with a number of control points. The trajectory of the spline model is controlled by the locations of the control points. In order to maximize the UAVs path fitnesses, locations of these control points are optimized using an ant colony optimization (ACO) algorithm. A B-spline curve is a piecewise polynomial curve comprising a number of polynomial segments. The continuity nature of B-spline curves makes them most suitable for the representation of aircraft trajectories. In this work, all paths of the UAVs are represented by B-splines curves which are constructed by the de Boor's algorithm.

ACO is a meta-heuristic algorithm for the approximate solution of combinatorial optimization problems that has been inspired by the foraging behavior of real ant colonies. An ant will leave a trace of chemical called pheromone on the path it has traveled. The instinct of an ant will make itself biased to a path with higher concentration of pheromone. In ACO, the computational resources are allocated to a set of relatively simple agents that exploit a form of indirect communication mediated by the environment to construct solutions to the finding the shortest trajectory from ant nest to a considered problem. More details about the type of ACO for global optimal trajectory planning of UAV which is used in this work can be found in our previous work [13].

B. UAV Resource Management Optimization using fuzzy AHP

The second block of the proposed method is the fuzzy AHP resource optimization block. The optimized path criteria values of alternatives will be passed from the ACO block to the fuzzy AHP block. The new weights (importance) will are given to the pass criteria. Because of using AHP, more criteria can be added to the problem and we can have more qualitative and quantitative criteria in the decision making problem. In this paper, we have three criteria for the ACO block which are: path length (PL), maximum elevation (ME), minimum turning angle (MT). In the AHP block, Two more criteria, minimum uncertainty (MU), and security of path (SP) are added to the problem, which means totally 5 criteria in the decision making step.

In many practical situations, a number of different action sequences exist which can be used to accomplish a certain

TABLE III

RATIONALE AND INTENSITIES FOR PL, ME, MT, MU, AND SP

PL	ME	MT	MU	SP	Definition	Intensity
$98.0\% <$	$90.0\% <$	$< 128.0\%$	$< 104.0\%$	$< 104.0\%$	Equally preferred	$\tilde{1}$
98.0%	90.0%	128.0%	108.0%	108.0%		$\tilde{2}$
95.5%	80.0%	156.0%	112.0%	112.0%	Moderately preferred	$\tilde{3}$
93.0%	70.0%	184.0%	116.0%	116.0%		$\tilde{4}$
90.5%	60.0%	212.0%	120.0%	120.0%	Strongly preferred	$\tilde{5}$
88.0%	50.0%	240.0%	124.0%	124.0%		$\tilde{6}$
85.5%	40.0%	268.0%	128.0%	128.0%	Very strongly preferred	$\tilde{7}$
83.0%	30.0%	296.0%	132.0%	132.0%		$\tilde{8}$
$< 83.0\%$	$< 30.0\%$	$296\% <$	$132.0\% <$	$132.0\% <$	Extreme importance	$\tilde{9}$

task or to reduce uncertainty in the sensed information. The controller itself contains a set of utility functions and the action sequences are chosen such that the expected utility is maximized. System missions are transformed into optimization criteria which are then encoded in terms of the utility functions. Given a probabilistic prior on the action parameters and an expected cost function eliciting the desirable path to reduce uncertainty, AHP determines the most cost effective UAV location. Situation assessment will evaluate each path for the possible uncertainty and assigns a number to each path of the UAVs. The fuzzy AHP block then considers the minimum uncertainty (MU) of each path which is the fourth criteria (c_4). The optimal path which is obtained from the ACO path planning block will be analyzed to evaluate its susceptibility to danger and a value will be assigned to each path of the UAVs. Therefore, the fuzzy AHP block considers the security of the path as the fifth criteria (c_5) in the evaluation phase.

IV. SIMULATIONS

The ACO method will be first applied to a path planning problem and the objective is to obtain 5 optimized paths for 5 UAVs. Then, in the second step, resources (UAVs), according to their fitnesses will be ranked using fuzzy AHP.

The base of the 3D terrain is defined as a 2-by-2 square units with the center located at the origin (0,0). The starting point p_s and the ending point p_e of the UAVs are located at (-1,-0.4) and (1,0.4), respectively. The terrain is divided into 25×25 grids. The number of iterations (t) for ACO is 10, and number of ants per iteration (k) is 5. The number of intermediate control points (r) is 5 and phermone evaporating rate (ν) is 0.75. Order of B-spline curve is 4. More details about the the path optimization using ACO is given in our previous work [13]. The weights for path objectives are $w_{PL} = 6$, $w_{ME} = 3$, and $w_{MT} = 4$. The ACO optimization block will generate 5 paths which are optimized for path length, maximum elevation, and minimum turning angle. The optimized criteria for these paths and also the results from situation assessment and security blocks have been shown in Table. IV

Priorities are numbers associated with the nodes of the hierarchy. By definition, the priority of the Goal is 1.000. The priorities of the children of any criterion can vary, but always add up to 1.000. To incorporate judgements about the elements in the hierarchy, decision makers compare the elements two by two. The criteria will be compared as to how important they are to the decision makers with respect to the Goal. Table V shows the criteria pairwise judgments and the calculated weights (priorities) by fuzzy AHP. Table III shows the rationale and intensities for 5 different criteria. The complete pairwise judgments between alternatives (UAVs) are given for path length, maximum elevation, minimum turning angle, minimum uncertainty, and security of path in Tables VI–X, in which the maximum eigenvalue and consistency index are also given. As it can be seen, C.I. for all cases are less than 0.1. The local and global priorities for five UAVs for each criteria are also given in the mentioned tables. The local priorities for each criteria show how much each alternative contributes to that criterion. The global priorities

TABLE IV

ACO OPTIMIZED CRITERIA AND SITUATION ASSESMENT AND SECURITY BLOCKS OUTPUTS FOR 5 ALTERNATIVES (UAVS).

Criteria / Alt.	PL	ME	MT	MU	SP
A_1	1.31	0.41	63.52	0.84	0.79
A_2	1.44	0.15	35.21	0.73	0.87
A_3	1.21	0.23	114.52	0.70	0.84
A_4	1.19	0.68	56.98	0.80	0.91
A_5	1.46	0.40	59.38	0.67	0.75

TABLE V

CRITERIA PAIRWISE JUDGMENTS AND WEIGHTS (PRIORITIES).

Alternatives	PL	ME	MT	MU	SP	Weights
PL	1	$\tilde{5}$	$\tilde{3}$	$\tilde{2}^{-1}$	$\tilde{3}^{-1}$	0.2020
ME	$\tilde{5}^{-1}$	1	$\tilde{2}^{-1}$	$\tilde{3}^{-1}$	$\tilde{4}^{-1}$	0.0656
MT	$\tilde{3}^{-1}$	$\tilde{2}$	1	$\tilde{3}^{-1}$	$\tilde{4}^{-1}$	0.0917
MU	$\tilde{2}$	$\tilde{3}$	$\tilde{3}$	1	$\tilde{2}$	0.2443
SP	$\tilde{3}$	$\tilde{4}$	$\tilde{4}$	$\tilde{2}^{-1}$	1	0.3964
					Total	1.0000
$\lambda_{max} = 5.2342$, $C.I. = 0.0530$						

TABLE VI

PATH LENGTH (PL) JUDGMENTS AND PRIORITIES FOR 5 UAVS.

Alt.	A_1	A_2	A_3	A_4	A_5	Local Priority	Global Priority
A_1	1	$\tilde{5}$	$\tilde{4}^{-1}$	$\tilde{5}^{-1}$	$\tilde{5}$	0.1326	0.0268
A_2	$\tilde{5}^{-1}$	1	$\tilde{8}^{-1}$	$\tilde{8}^{-1}$	$\tilde{2}$	0.0450	0.0091
A_3	$\tilde{4}$	$\tilde{8}$	1	$\tilde{2}^{-1}$	$\tilde{8}$	0.3258	0.0658
A_4	$\tilde{5}$	$\tilde{8}$	$\tilde{2}$	1	$\tilde{9}$	0.4634	0.0936
A_5	$\tilde{5}^{-1}$	$\tilde{2}^{-1}$	$\tilde{8}^{-1}$	$\tilde{9}^{-1}$	1	0.0332	0.0067
					Total	1.0000	0.2020
$\lambda_{max} = 5.2582$, $C.I. = 0.0646$							

TABLE VII
MAXIMUM ELEVATION (ME) JUDGMENTS AND PRIORITIES FOR 5 UAVS

Alt.	A_1	A_2	A_3	A_4	A_5	Local Priority	Global Priority
A_1	1	$\tilde{7}^{-1}$	$\tilde{5}^{-1}$	$\tilde{5}$	$\tilde{1}^{-1}$	0.0799	0.0052
A_2	$\tilde{7}$	1	$\tilde{4}$	$\tilde{9}$	$\tilde{7}$	0.5487	0.0360
A_3	$\tilde{5}$	$\tilde{4}^{-1}$	1	$\tilde{8}$	$\tilde{5}$	0.2631	0.0173
A_4	$\tilde{5}^{-1}$	$\tilde{9}^{-1}$	$\tilde{8}^{-1}$	1	$\tilde{5}^{-1}$	0.0284	0.0019
A_5	$\tilde{1}$	$\tilde{7}^{-1}$	$\tilde{5}^{-1}$	$\tilde{5}$	1	0.0799	0.0052
					Total	1.0000	0.0656
$\lambda_{max} = 5.4219$, $C.I. = 0.0934$							

TABLE VIII
MINIMUM TURNING ANGLE (MT) JUDGMENTS AND PRIORITIES FOR 5 UAVS.

Alt.	A_1	A_2	A_3	A_4	A_5	Local Priority	Global Priority
A_1	1	$\tilde{4}$	$\tilde{4}^{-1}$	$\tilde{1}$	$\tilde{1}$	0.1451	0.0133
A_2	$\tilde{4}^{-1}$	1	$\tilde{9}^{-1}$	$\tilde{3}^{-1}$	$\tilde{3}^{-1}$	0.0460	0.0042
A_3	$\tilde{4}$	$\tilde{9}$	1	$\tilde{5}$	$\tilde{4}$	0.5423	0.0497
A_4	$\tilde{1}^{-1}$	$\tilde{3}$	$\tilde{5}^{-1}$	1	$\tilde{1}^{-1}$	0.1306	0.0120
A_5	$\tilde{1}^{-1}$	$\tilde{3}$	$\tilde{4}^{-1}$	$\tilde{1}$	1	0.1360	0.0125
					Total	1.0000	0.0917
$\lambda_{max} = 5.0379$, $C.I. = 0.0095$							

show how much the criteria of each alternative contributes to the overall goal of choosing the best UAV. A summary of global priorities of each alternative is given in Table XI. UAV_4, is the alternative that contributes the most to the goal of choosing the best UAV with a priority of 0.3494. The second choice is UAV_3 with priority of 0.2187.

V. CONCLUSIONS

In this paper, an integrated MCDM approach is designed to assist in optimal UAV resource management using fuzzy AHP. The proposed method has two steps. The first step is concerned with path planning for the UAVs. The path of each UAV is represented using a B-spline curve with a number of control points. The position of these control points are optimized using an ACO algorithm. Path length, minimum turning angle, and maximum pitch rate, have been simultaneously optimized using the ACO algorithm. The second step is the UAV resource management using fuzzy AHP. The AHP method provides a comprehensive and rational framework for structuring the problem, for representing and quantifying its elements, for relating the elements to the overall goal, and for evaluating alternative solutions. Finally, the best UAV is chosen by fuzzy AHP to perform the assigned task.

TABLE IX
MINIMUM UNCERTAINTY (MU) JUDGMENTS AND PRIORITIES FOR 5 UAVS

Alt.	A_1	A_2	A_3	A_4	A_5	Local Priority	Global Priority
A_1	1	$\tilde{5}$	$\tilde{6}$	$\tilde{2}$	$\tilde{7}$	0.4700	0.1148
A_2	$\tilde{5}^{-1}$	1	$\tilde{2}$	$\tilde{3}^{-1}$	$\tilde{3}$	0.1158	0.0283
A_3	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	1	$\tilde{5}^{-1}$	$\tilde{2}$	0.0706	0.0172
A_4	$\tilde{6}^{-1}$	$\tilde{3}$	$\tilde{5}$	1	$\tilde{6}$	0.2970	0.0726
A_5	$\tilde{7}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{6}^{-1}$	1	0.0466	0.0114
					Total	1.0000	0.2443
$\lambda_{max} = 5.0910$, $C.I. = 0.0228$							

TABLE X
SAFETY OF THE PATH (SP) JUDGMENTS AND PRIORITIES FOR 5 UAVS.

Alt.	A_1	A_2	A_3	A_4	A_5	Local Priority	Global Priority
UAV_1	1	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{5}^{-1}$	$\tilde{2}$	0.0763	0.0302
UAV_2	$\tilde{4}$	1	$\tilde{2}$	$\tilde{2}^{-1}$	$\tilde{5}$	0.2728	0.1081
UAV_3	$\tilde{3}$	$\tilde{2}^{-1}$	1	$\tilde{3}^{-1}$	$\tilde{4}$	0.1732	0.0687
UAV_4	$\tilde{5}$	$\tilde{2}$	$\tilde{3}$	1	$\tilde{6}$	0.4271	0.1693
UAV_5	$\tilde{2}^{-1}$	$\tilde{5}^{-1}$	$\tilde{4}^{-1}$	$\tilde{6}^{-1}$	1	0.0506	0.0201
					Total	1.0000	0.3964
$\lambda_{max} = 5.0976$, $C.I. = 0.0244$							

TABLE XI
CHOOSE THE BEST RESOURCE (UAV) USING FUZZY AHP.

Alternative	PL	ME	MT	MU	SP	TOTAL
A_1	0.0268	0.0052	0.0133	0.1148	0.0302	0.1903
A_2	0.0091	0.0360	0.0042	0.0283	0.1081	0.1857
A_3	0.0658	0.0173	0.0497	0.0172	0.0687	0.2187
A_4	0.0936	0.0019	0.0120	0.0726	0.1693	0.3494
A_5	0.0067	0.0052	0.0125	0.0114	0.0201	0.0559
TOTAL	0.2020	0.0656	0.0917	0.2443	0.3964	1.0000
	1.0000					

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