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A Genetic Algorithm enhanced with Fuzzy-Logic for multi-objective Unmanned Aircraft Vehicle path planning missions*

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***Abstract*—The fast growth of computational-intelligence and computer vision-based approaches in the field of robotics have initiated the development of novel unmanned aircraft vehicles (UAVs) with additional capabilities for mission-critical applications, such as fire detection or delivery services. Path planning is a crucial part of the automated operation of a UAV to find the optimal path from a starting point to a target-goal point, satisfying in parallel specific criteria and constraints. To this end, traditional path planning algorithms, such as graph-based, heuristics or metaheuristics, have been adopted to address this problem. However, the complex operational environment combined with the demand for energy efficiency have emerged the need for dynamic and multi-objective path planning meeting the special characteristics of a UAV flight. To address the above challenges, in this study a novel Genetic Algorithm (GA) enhanced with Fuzzy Logic (GAF) is developed for solving the UAV multi-objective path planning problem. The proposed algorithm aims to find an optimal path with respect to contradicted objective terms, such as distance, energy efficiency and path's curvature. In the proposed developments, the novelty of GAF rises via a two-step procedure: (i) the evaluation stage of the energy efficiency of the paths; and (ii) the evaluation stage of the GA for the development of an energy efficient, smooth path of shortest possible traveled distance. The efficacy of the approach is illustrated via a comparative experimental evaluation.**

Keywords: Genetic algorithm, fuzzy logic, path planning, energy efficiency, unmanned aerial vehicles.

I. Introduction

The fast growth of computer vision and robotic automation have led to the increased use of Unmanned Aircraft Vehicles (UAVs) in numerous applications. For instance, UAVs are, nowadays, commonly used for security and surveillance, weather forecasting and traffic control [1]. Lately, the use of UAVs in transportation and delivery applications has attracted the interest of the scientific community and big companies, as well, such as Amazon [2]. Such real time applications are characterized by dynamic and complex environments imposing the need for multi-objective path planning to find an optimal path taking into account various criteria, such as distance, travel time, energy demand and safety among others.

Traditional path planning approaches for UAVs consist of single-objective methodologies where the optimal path is derived from the minimization of traveled distance or energy consumption [3], [4]. These problems are addressed with well-known routing algorithms, such as C-Space Representation Techniques, *i.e.* Decomposition-based approaches [5] and Voronoi, graph-based algorithms, *i.e.* Dijkstra, A* and D* [6], bio-inspired and nature-inspired algorithms, *i.e.* Particle Swarm Optimization algorithm [7], Ant Colony Optimization [8] and Genetic Algorithm (GA) [9], and learning-based approaches, *i.e.* neural networks [10]. Even if a lot of studies exist on the UAVs path planning problems there are still issues of target location and obstacle avoidance satisfying in parallel energy demands [11], [12].

To cope with multiple objectives a combination of the aforementioned techniques with mathematical processes for multi-objective optimization, such as scalarization, Pareto optimality and fuzzy logic (FL) should be adopted. Pareto approach finds a dominated and non-dominated solutions while the scalarization approach turns the multi-objective fitness function into a single objective by using weights in order to find a solution, *i.e.* the weighted sum method (WSM). The solution from the Pareto method is obtained by solving separately the multi-objective optimization problem and produces a compromise solution that can be displayed in the form of Pareto optimal front. Meanwhile, the solution with the scalarization method is in the form of performance indicators that define the scalar function that is incorporated in the fitness function. Limitations of the classical approaches

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include the need for right parameters and weight selection, failure in finding the concave (linear) optimal solution and the multiple possible solutions in case of Pareto. On the other hand, the fuzzy approach for solving multi-objective optimization problems is based on the expression of the fitness function with fuzzy sets. Such concepts lie on searching for some optimal options which best satisfy the most of the important objectives (as they are defined by the fuzzy sets and rules) differing significantly from the traditional notion of finding an optimal solution which best satisfies all the objectives [13], [14]. Additionally, based on expert knowledge it can accommodate uncertainty induced due to the dynamic nature of the problem.

In the literature the multi-objective path planning has been widely adopted for autonomous robotic vehicles and smart assistive systems [14]–[20]. In case of UAVs, multi-objective path planning is applied for: (i) terrain coverage path planning [21], [22]; (ii) monitoring and surveillance of critical infrastructures [23], [24]; (iii) rescue and emergency missions [25], [26]; (iv) single UAV missions [27]–[29]; (v) swarm of UAVs mission [30], [31]; and (vi) obstacle avoidance [32]–[34]. Even if these approaches include the use of GA or FL to address this problem, to the best of our knowledge, an attempt to hybridize GA with FL to solve the multi-objective path planning problem for UAVs mission has not been considered.

To this end, in this study the Genetic Algorithm in [35] is enhanced with the Fuzzy Logic framework for the determination of the optimal energy efficient and safe-flyable path for UAV missions. The multi-objective problem is formulated as the minimization of the traveled distance, the smoothness of the path, and the maximization of energy efficiency. In particular, the GA algorithm is hybridized with Mamdani FIS, is evaluated and compared with the standard GA.

Compared to state of the art methods, the benefit of the proposed approach is the inclusion of expert knowledge for the blending of the objective terms, rather than setting some a priori defined fixed weights (ie. in the weighted sum method). Additionally, due to the characteristics of the fuzzy framework, it can cope with uncertainty induced due to the dynamic nature of the path planning problem. Finally, it can be applied to a reasonably large class of systems and is not UAV platform specific for the description of the energy requirements (ie. contrary to . [36], [37]). The proposed developments are part of the European funded AIROUS project (Artificial Intelligence Robust Offshore Unmanned System - https://airous.eu/), where new distributed biologically inspired decision making approaches are applied for the problem of offshore smart delivery.

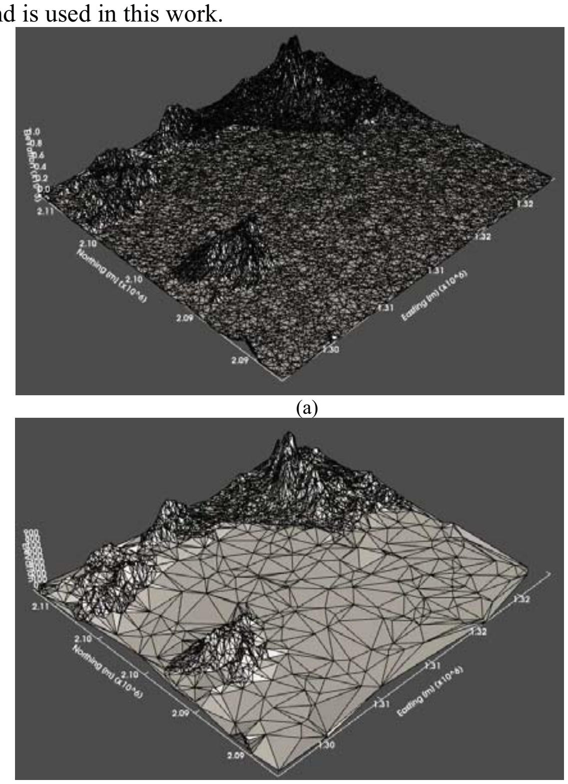
In the remainder of this article the terrain representation, the mechanism for the generation of collision free paths, and the GA setup are included in Section II. Then the details of the hybridisation of the GA with the fuzzy logic framework, and the novel GAF algorithm are included in Section III. In Section IV, a computation evaluation is included where both algorithms (ie. GA and GAF) are compared for a UAV deployed to safe-flyably navigate in a map, in the most energy efficient means. Finally, concluding remarks are addressed in Section VII.

II. Preliminaries

A. Map representation

In this work real geospatial data, provided by surveying organisations, are considered. Those are mapped to the Cartesian coordinate format. In particular, the Digital Terrain Elevation Data (DTED) is converted to a Cartesian frame with an arbitrarily chosen origin for the stage of path planning and then convert back to the desired format. It is shown in [35] that via the use of the Delaunay trangulation [38] the algorithm is simplified since curvilinear coordinates are not considered.

Since the overall performance depends on the map size, the available terrain data has been sampled and a sampling frequency has been judiciously selected to balance performance/computational time and accuracy. After the application of the triangulation, the result is used to linearly interpolate any point that is encompassed in the convex hull for all the available sampling points by using barycentric coordinates according to the method described in [35]. The triangle vertices are the sampled data points, and the resulting surfaces are created with linear interpolation. An example of the sparcification procedure is illustrated in Fig.1 and is used in this work.



(a)

(b)

Figure 1. Example of: (a) the original area of operations and (b) the sparsified representation of the area of operations.

B. Genetic Algorithm

GA belongs to the family of evolutionary algorithms. It is inspired by the process of evolution and natural selection. GA uses a population of candidate solutions to be evolved towards a better solution. This evolution consists of an iterative process where various genetic operators, such as

Figure 2. Flowchart of GA enhanced with the fuzzy logic framework.

crossover, mutation and selection, are involved [30], [39]–[41].

Algorithm 1. Pseudo-code of genetic algorithm

Algorithm 1: Choice of optimal path via the Genetic algorithm setup

Results: The best candidate path/solution
Data: Problem setup, path generation algorithm configuration, genetic algorithm configuration
/* Initialize a random population of N_c chromosomes and N_g genes, where each gene is a random point in the map */
population ← random_population(N_c, N_g)
best_overall_score ← ∞
iterations ← 0
while *not converged* **do**
  iterations ← iterations + 1
  /* Create new generation, with crossover and mutations */
  for *each random pair of chromosomes in population* **do**
    offspring ← crossover(chromosome1, chromosome2)
    offspring ← propabilistic_mutation(offspring)
    population ← population + offspring
  end

  /* Grade the generated paths according to the fitness function */
  for *chromosome in population* **do**
    chromosome_path ← generate_path_from_chromosome
    chromosome_score ← fitness_function_evaluation(chromosome_path)
  end

  sort_population_by_fitness

  /* Check for convergence */
  if *current_best_score* < *best_overall_score* **then**
    best_overall_score ← current_best_score
    /* Keep population number in check */
    while *population_count* > N_c **do**
      discard_lowest_performing_chromosome()
    end
  else
    if *iterations* > *max_iterations* **then**
      converged ← true
    end
  end
end

In Algorithm 1, the pseudocode of the GA variant used in this study is illustrated. The implementation of the GA algorithm is based on [35] where the weighted sum approach was adopted to address the multi-objective path planning of UAV. The GA setup is of a standard form. It incorporates random mutations and a crossover operator which produces new generations. Then the chromosomes are ranked according to the fitness function, and the fittest is chosen. In particular, initially a population of M chromosomes is generated representing collision-free candidate trajectories for the UAV, whilst satisfying initial and terminal constraints. The collision-free paths are generated using principles of physics. The interested reader is referred in article [35] (ie. Section III) for a detailed treatment. Then the candidate paths are ranked according to the fitness function and the best candidate is selected. Thereafter the crossover and mutation operators are used for each of the genotypic representations. These are included to overcome possible local optima, as suggested in article [42]. By the former, gene-swapping is performed. By the latter, each gene is mutated. This is performed via the use of a vector with low probability amplitude. The intuition of the latter is to produce 'child' path solutions that their characteristics are 'close' to its parent's flight envelope. Since the path generation algorithm is only tasked with generating a safe and flyable path, any other form of control over the path characteristics comes from the GA.

Adopting the notation in [35], the fitness function used involves the weighted sum of three agnostic terms, namely to penalize each candidate path with respect to overall Euclidean distance travelled, smoothness and energy requirement. The fitness function can be expressed as:

$$z = w_1 L + w_2 D + w_3 E \ (Eq. 1)$$

where w_i are the weights, that are free to modify on a per-mission basis. L corresponds to the overall Euclidean distance of the path (in meters). D term is calculated from the arccosine value (in degrees) of the angle formed by the unit vectors of 3 consecutive points of the path in 3D space. The interested reader is referred to article [27] (Appendix C) for the procedure of this calculation. E corresponds to energy efficient paths with respect to environmental conditions (*i.e.* wind magnitude and direction in the vicinity of operations) and is generated via the fuzzy logic procedure outlined in the next Section. For our cause, rather than describing the energy demand for the UAV considered (*i.e.* [36], [37]) which is case sensitive, a more relaxed approach is adopted. In particular, it is favourable for a UAV to avoid crosswind conditions which incur increased control effort. In general, headwind conditions are favourable since they minimise the cross-sectional area of the craft to the wind, and they provide extra airspeed (*i.e.* lift) at little to no energy expense. For our cause the velocity profile and relative bearing (among the vehicle's heading and the wind profile heading) are considered to describe the energy demand. Thus for two paths of the same wind magnitude, if the heading of the vehicle is collinear with the heading angle of the wind profile, this path is preferred.

III. Methodology

A. Genetic Algorithm enhanced with Fuzzy Logic (GAF)

To enhance the ability of GA to solve multi-objective optimization problems by avoiding, in parallel, the limitations of the traditional approaches, FL is incorporated in a two-step approach as a mean to evaluate the energy efficiency of the generated paths and the candidate solutions of each iteration (Figure 3). Figure 2 illustrates the flowchart of GAF. This approach enables the automated decision making of an optimal path based on fuzzy rules. Mamdani FIS was selected due to its advantages. The main advantage of Mamdani FIS is that the output can be presented both linguistically and by using a crisp value due to the implementation of the defuzzification process with a fuzzy set. This constitutes the Mamdani FIS as an effective approach to decision making systems [43]. However, algorithms combined with fuzzy logic present the weakness of high computational expense [44].

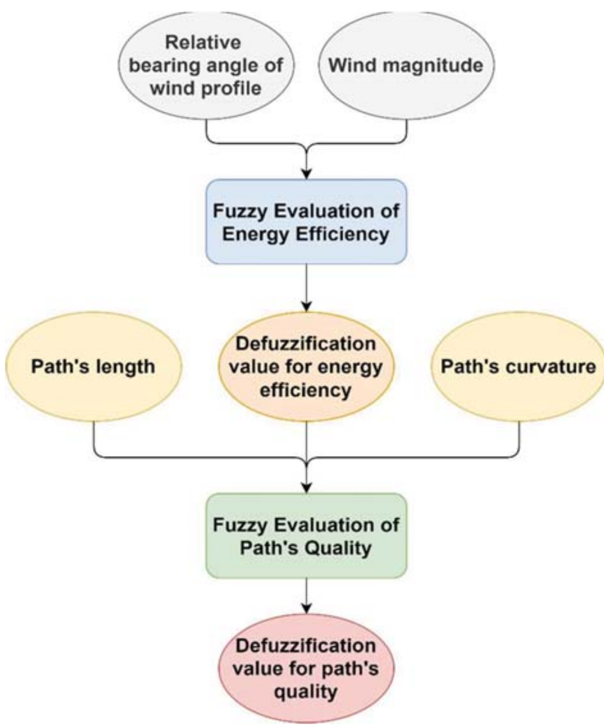


Figure 3. Flowchart of the two-step Fuzzy Evaluation approach of GAF.

Specifically, compared to [35] rather than only using the chirp signal for the energy demand of the candidate path this is enhance via the fuzzy-logic framework. Thus, this term is estimated from a fuzzy evaluation process based on the environmental data acting along the generated path. The Mamdani Inference System (FIS) is adopted to calculate the energy efficiency level (*i.e.* wrt magnitude and heading of the wind profile) at a pre-defined number of points along the path. The bearing is calculated from the following formula:

$$psi(w) = \sum_{i=1}^{N-1} \frac{\sin(\theta(i))}{N-1} \; (Eq.2)$$

where for N-1 consecutive segments in the trajectory and $\theta(i)$ is the angle calculated from difference of the aircraft heading and the actual wind bearing. The wind magnitude is calculated from the norm of its components in the 3D space. The heading profile of the aircraft is available via elementary trigonometric calculations given two consecutive waypoints forming a segment.

The energy efficiency value of the path is defined as the mean value of the defuzzification values in these points. The membership functions for the input variables (bearing and magnitude of the wind profile), as well as, the membership function for the output variable (energy efficiency) are illustrated in Figure 4, Figure 5 and Figure 6, respectively, while Table I shows the fuzzy rules used in this approach.

For the evaluation of the path quality, a second fuzzy evaluation stage is introduced based on the Mamdani FIS, as well. The input variables are the objective terms: path's length, path's curvature and path's energy efficiency. Their membership functions are depicted in Figure 7, Figure 8 and Figure 9, respectively. The output variable is the path quality with its membership function was set as shown in Figure 10. Table II presents the fuzzy rules that were defined for this fuzzy evaluation stage. The final output of the Mamdani FIS is calculated as the weighted average over all rule outputs:

$$Path\ Quality = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i} \; (Eq.3),$$

where N is the number of rules, z_i the rule output level of i[th] rule and w_i the rule firing strength derived from the rule antecedent.

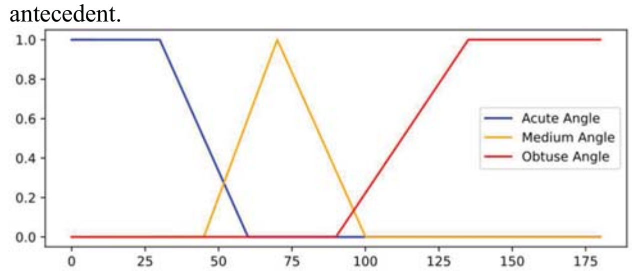


Figure 4. Membership function of relative bearing angle of wind profile.

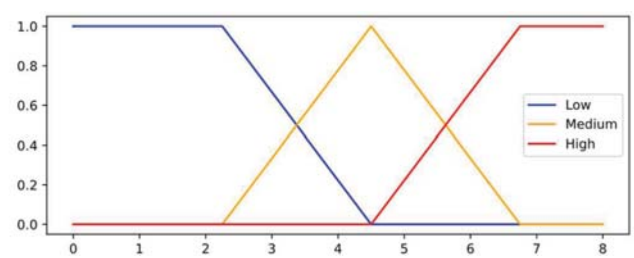


Figure 5. Membership function of wind magnitude.

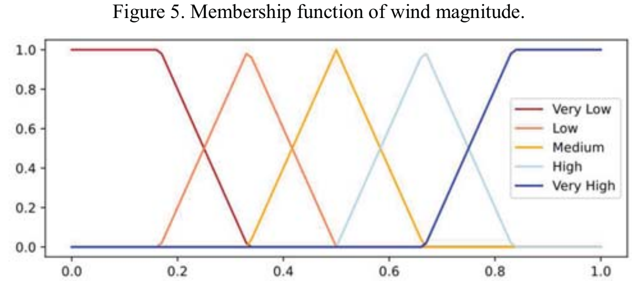


Figure 6. Membership function of energy efficiency.

TABLE I Fuzzy rules for the fuzzy energy efficiency evaluation stage

Fuzzy Rules	Angle	Velocity	Energy Efficiency
Rule 1	Low	High	Very High
Rule 2	Low	Medium	High
Rule 3	Low	Low	High
Rule 4	Medium	High	Medium
Rule 5	Medium	Medium	Medium
Rule 6	Medium	Low	Medium
Rule 7	High	Medium	Low
Rule 8	High	Low	Low
Rule 9	High	High	Very Low

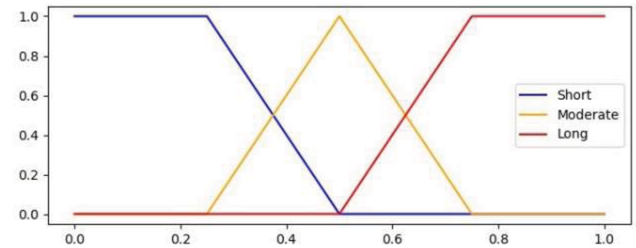


Figure 7. Membership function of path's length.

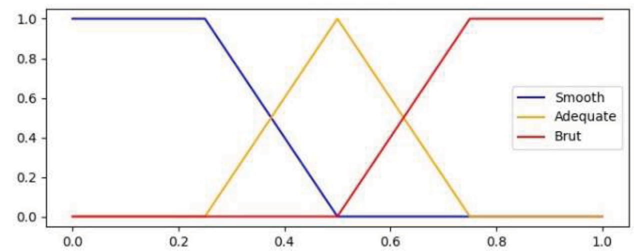


Figure 8. Membership function of path’s curvature.

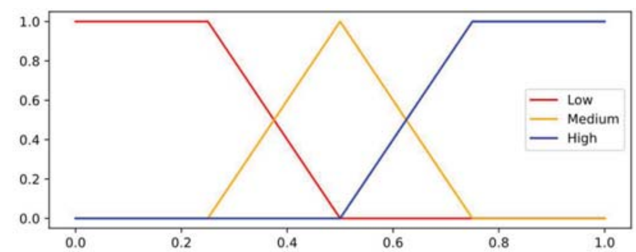


Figure 9. Membership function of path’s energy efficiency.

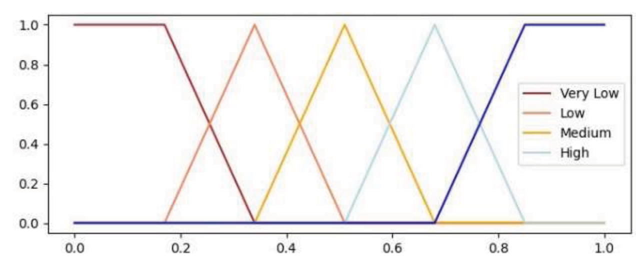


Figure 10. Membership function of path’s quality.

TABLE II FUZZY RULES FOR THE FUZZY EVALUATION STAGE OF THE PATH’S QUALITY

Fuzzy Rules	Path’s length	Path’s curvature	Path’s energy efficiency	Path Quality
Rule 1	Short	Smooth	High	Very High
Rule 2	Short	Smooth	Medium	Very High
Rule 3	Short	Adequate	High	Very High
Rule 4	Moderate	Smooth	High	Very High
Rule 5	Short	Smooth	Low	High
Rule 6	Short	Adequate	Medium	High
Rule 7	Short	Brut	High	High
Rule 8	Moderate	Smooth	Medium	High
Rule 9	Moderate	Adequate	High	High
Rule 10	Long	Smooth	High	High
Rule 11	Short	Adequate	Low	Medium
Rule 12	Short	Brut	Medium	Medium
Rule 13	Short	Brut	Low	Medium
Rule 14	Moderate	Smooth	Low	Medium
Rule 15	Moderate	Adequate	Medium	Medium
Rule 16	Moderate	Brut	High	Medium
Rule 17	Long	Smooth	Medium	Medium
Rule 18	Long	Smooth	Low	Medium
Rule 19	Long	Adequate	High	Medium
Rule 20	Long	Brut	High	Medium
Rule 21	Moderate	Adequate	Low	Low
Rule 22	Moderate	Brut	Medium	Low
Rule 23	Moderate	Brut	Low	Low
Rule 24	Long	Adequate	Medium	Low
Rule 25	Long	Adequate	Low	Low
Rule 26	Long	Brut	Medium	Low
Rule 27	Long	Brut	Low	Very Low

IV. COMPUTATIONAL EVALUATION

A. *Evaluation methodology*

To evaluate the proposed metaheuristic algorithm GAF, a case study on UAV path planning problem is considered. In particular, a UAV is deployed in a known area of operations and it is required to safe-flyably reach a terminal location from an initial location in an energy efficient manner. The GAF is compared with the GA with WSM presented in sub-section II.B. A 3D map with the following margins was used: longitude: [23.25, 23.75]; latitude: [37.50, 38.00]; and flight level: [0, 200]. This area corresponds to the Saronic Gulf in Greece, where Greek islands, such as Aegina are located. Therefore, in this comparative evaluation the ability of the GAF and the GA to generate paths with high quality with respect to the objective terms will be tested.

For a generation of the collision free path the approach presented in [35] was followed. The sparcification of the raw terrain data was performed via the trangulation procedure suggested in [35]. In this example a UAV is deployed in an a-priori known map to safely and energy efficiently navigated from an initial ([23.5567500, 37.9500000, 20.0000])) to a terminal location ([23.4275600, 37.7439570, 20.00000]). In particular, in both setups (*i.e.* GA and GAF), the solution path is required to satisfy the need for the shortest possible travelled distance, with smooth curvature, and maximum possible energy efficiency. For the standard GA setup the fitness function used has the form of the weighted sum Eq.(1). For the GAF the decision procedure detailed in Section III. In particular, three input chirp signals are used (i.e. travelled distance, curvature of path and energy efficiency based on the relative bearing and magnitude of wind profile). These are mapped to the membership functions illustrated in Figure 7, Figure 8 and Figure 9. Additionally, via the former step of GAF the chirp signals that correspond to characteristics of the wind profile a fuzzified and ranked thus the energy efficiency is determined for the resulting path (according to rule-base Table I). All these act as inputs for the latter step of GAF where the fuzzy blending is performed. The fuzzified output is performed according to Eq.(3) thus the candidate path is ranked. This procedure is iterated in the GA and the best possible solution is determined. The same settings were used for both algorithms: the maximum number of iterations was set to 10, while the population size was set to 4. For the initialization, 2 chromosomes were randomly generated. Although a larger population size and iterations can be used, those are chosen judiciously with a sacrifice of computational time and accuracy. The algorithms and the tests were implemented in Python, on Microsoft Windows 10 Environment as operational system, with AMD Ryzen 7 3800X 8-Core Processor at 3.89 GHz and 32GB RAM.

B. Results and discussion

Figure 17 depicts the results of both competitive algorithms. The path generated by the GAF and GA algorithms are presented with red x and black o, respectively. For the GAF algorithm the current best path for the 1st, 5th and 10th iteration is illustrated in Figure 11, Figure 12 and Figure 13, respectively. Similarly, the same results are presented in Figure 14, Figure 15 and Figure 16. For a comparative presentation of both algorithms, Figure 17 shows the best paths found by GAF (red x) and GA (black o), while Figure 18 depicts the results derived from the fuzzy energy efficiency evaluation. The results show that GA enhanced with Fuzzy Logic succeeded in finding a shorter and smoother path of higher energy efficiency compared to GA equipped with the weighted sum method.

Regarding the convergence velocity of the algorithms under examination, Figure 19 and Figure 20 show the convergence of the GA and GAF algorithms, respectively, with respect to the number of iterations and the fitness score. It is illustrated from the same figures that GAF outperforms GA since GAF converges faster compared to the GA.

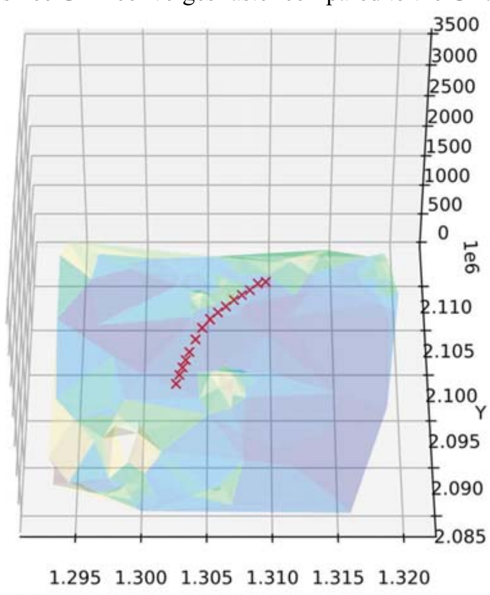


Figure 11. The current best path from GAF in 1st iteration.

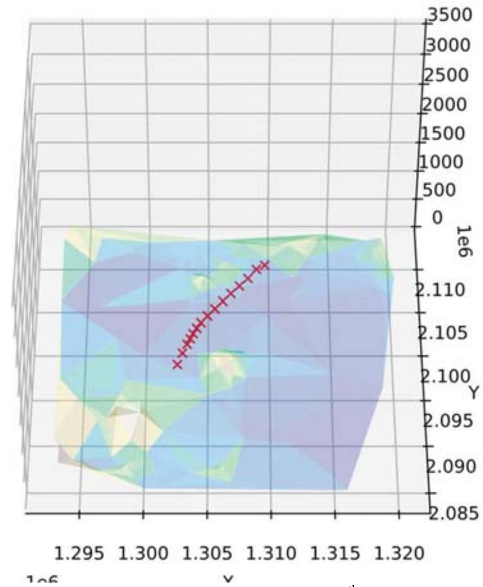


Figure 12. The current best path from GAF in 5th iteration.

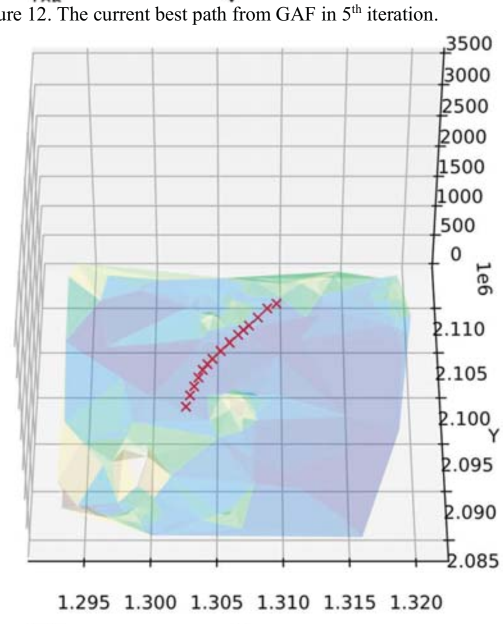


Figure 13. The current best path from GAF in 10th iteration.

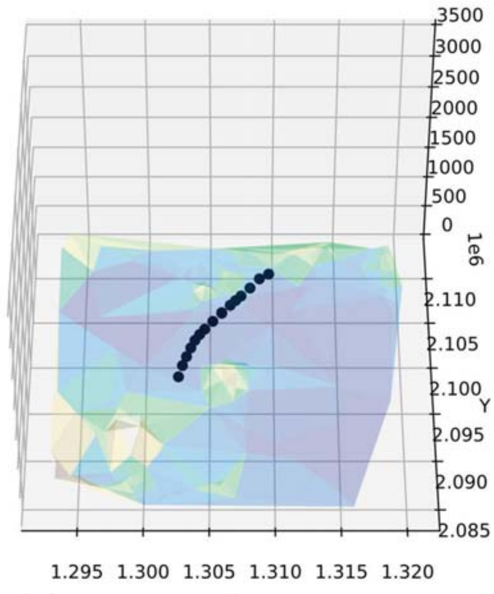


Figure 14. The current best path from GA in 1st iteration.

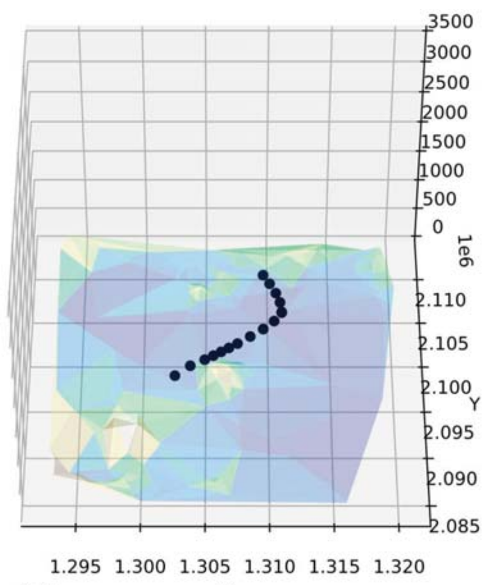


Figure 15. The current best path from GA in 5th iteration.

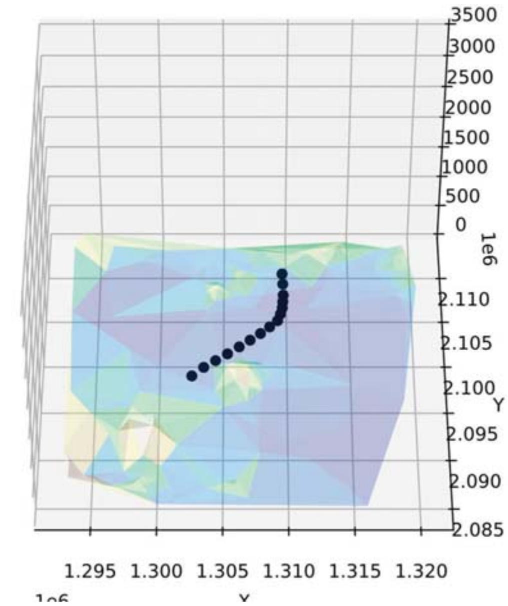


Figure 16. The current best path from GA in 10th iteration.

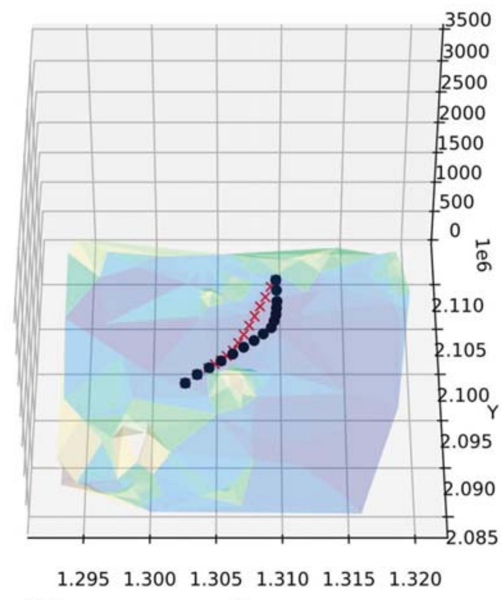


Figure 17. The best paths generated from GAF (red x) and GA (black o).

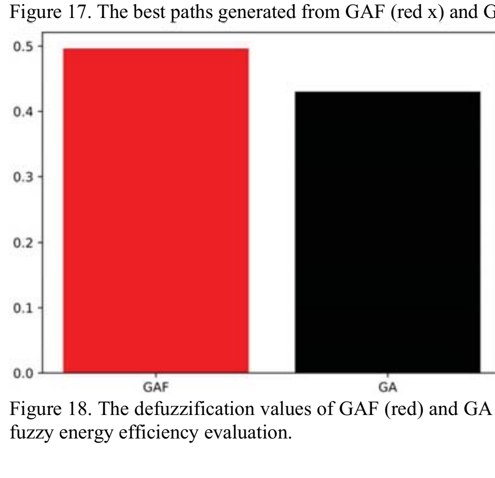


Figure 18. The defuzzification values of GAF (red) and GA (black) from the fuzzy energy efficiency evaluation.

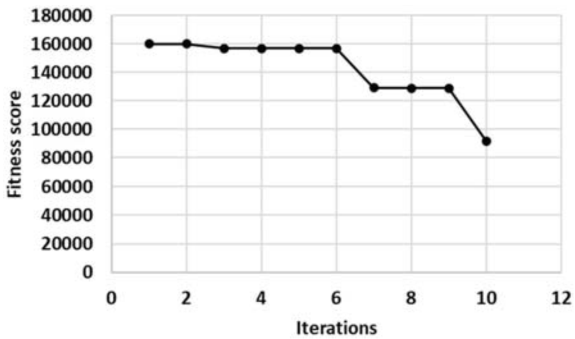


Figure 19. Convergence of GA with WSM at 10 iterations.

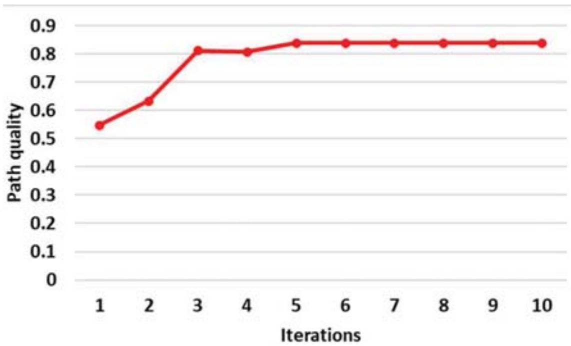


Figure 20. Convergence of GAF at 10 iterations.

V. Conclusion

In the literature, the majority of multi-objective path planning (MOPP) problems are addressed with computationally demanding approaches, such as global optimization techniques and software for linear/integer programming, *e.g.* CPLEX and path-search algorithms, *e.g.* Dijkstra or A*. To find an optimal solution under various conflicting objectives, a percentage of the aforementioned studies adopt the conventional strategy of WSM or Pareto optimality. In WSM approach, the objectives are combined into a single objective scalar function. This generates an efficient solution for the MO problem, but the results may vary significantly depending the selection of the weights. This can lead to local optima traps. The Pareto optimality approach overcomes the aforementioned limitations by providing multiple solutions to the user/decision maker. This advantage makes its application most popular.

Most of the presented heuristic algorithms for solving the MOPP are Pareto optimality-based approaches which aim to converge to Parent front. In these cases, the number of improved criteria (objectives), the extent of these improvements and, also, the preference information of each criterion (objective) are not considered during the calculation procedure. Furthermore, these limitations are crucial in real applications since only one 'compromise' Pareto solution is the preferable. Consequently, an additional multi-criteria decision-making method is necessary for avoiding subjective or undesirable choice of a solution.

Such approach consists of the use of Fuzzy Logic for a better decision making and trade off among the objective terms [15], [19], [20], [45], [46]. This approach enables the automated decision making of an optimal path based on fuzzy rules. These approaches employ mainly the conventional fuzzy control systems, such as the Mamdani fuzzy control and Takagi–Sugeno–Kang fuzzy (TSK) control [45], [47]–[50]. In this study the Mamdani FIS was selected due to its advantages to enhance the performance of the GA algorithm. This approach was evaluated and compared to the GA with WSM.

The results presented above, showed that the GAF algorithm is capable of generating paths with better trade-off among the objective terms since it achieved to find a path of better quality compared to GA. Indeed, from the Figure 17 the GAF path is shorter and smoother compared to the one generated from the GA algorithm. Also Figure 18 illustrates that GAF outperforms the GA with respect to energy efficiency. Therefore, the GA algorithm enhanced with Fuzzy Logic can be considered as an effective and suitable approach/solution for solving MOPP problems. This conclusion is aligned with the literature, where the limitations of the weighted sum approaches are reported for addressing multi-objective optimization problems [15], [19], [20], [45], [46].

As future work, a further analysis and comparative evaluation will be conducted regarding the evolutionary ability of the algorithm and the convergence velocity.

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