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# Hybridization of genetic algorithm and fuzzy based TOPSIS method to solve the robot path planning problem for multi objectives

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***Abstract*---**A variety of approaches are employed to solve the Mobile Robot Path Planning Problem (MRPP), which is the essential domain of research from industrial automation to domestic appliances. Since MRPP is categorized as an NP-hard problem, non-deterministic approaches are preferred to obtain optimal results. The Genetic Algorithm (GA) is the popular methodology for determining the optimal path for robot navigation. The complexity increases in finding the optimal path for the MRPP problem, if more than one objective is to be considered. To reduce the complexity, one of the multi-criteria decision analysis (MCDA) methodologies with fuzzy logic is hybridized to solve MRPP without losing the advantage of the GA approach. In this article, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is employed for determining the best path out of given paths. As a preprocessing of the population, a Genetic Algorithm (GA) is employed, which is having the advantage of exploring the population with crossover, mutation, and selection operators. The output of the GA is given to the Fuzzy TOPSIS method where the degree of preference is given as the linguistic variable. The linguistic variables for specifying preferences are easier for determining the level of significance for the individual objectives which are easier for the decision-makers instead for specifying absolute values. This model is tested and justified by applying different preference levels assigned to the objectives.

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**Introduction**

The relevance of mobile robots geared up the industrial automation which served in multiple ways. In addition to that, it is used in the field of health organization, space exploration, defense, etc. So the path planning of the robot to traverse towards the target is a significant research area. It is not only determining the path to reach the goal point but also considering the different objectives to be satisfied while deriving the path.

The MRPP is solved by so many approaches[1] and combined[2]–[5] with the existing approach to enhance the efficiency at the same time reduce the time complexity of the algorithm. Traditionally the different models were conceived only by considering the length as a primary objective[6]. To accommodate more than one objective, different methodologies[7]–[10] were adopted which are having both advantages and disadvantages.

The MRPP is an NP-hard problem, therefore the non-deterministic approach is so relevant to solving the MRPP problem. In robot path planning problems, GA[11][12] is used in mobile robot path optimization problems, since it is an heuristic approach. if the number of objectives[13]–[16] to be satisfied is increased, then the computational complexity increases, the convergence time will increase in many fold. The GA is exploited to generate the population by exploring the solution space. Due to the computational complexity for convergence to the optimal path of GA, the output of GA is fed as an input to the fuzzy TOPSIS method. This methodology is proposed using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)[17], [18] with a fuzzy approach[17] to derive the best path. It is one of the popular multi-criteria decision-analysis (MCDA), which is exploited to solve multi-objective robot path planning. In this article, two methodologies are hybridized to exploit the advantages of both.

The multi-criteria decision analysis (MCDA) methodologies are applied in a variety of disciplines[17], [19], [20] of study. A variety of multi-criteria decision analysis (MCDA) approaches has been created to tackle a variety of issues in a variety of domains to solve real-time challenges. Specifically, the MCDA methodologies tried in management decision making, manufacturing industry, and logistics in organizations supply chain management and many other fields of engineering as well as management.

A lot of variations are done to complete the requirements of applications and to enhance the solution. Distinctively, the TOPSIS is refined with a fuzzy approach, where the solutions are ranked based on the criteria and preference level. The great advantage of this method is not to be stated with an appropriate constraint function or accurate numerical value

The following section explores the related works and Section 3 describes the Fuzzy TOPSIS for MRPP(FT-MRPP) approach to solve the MRPP problem. Section 4 and subsections are dedicated to explaining the implementation of the proposed methodology. The results obtained and the validation of the results is discussed in section 4. Section 5 concludes the proposed methodology.

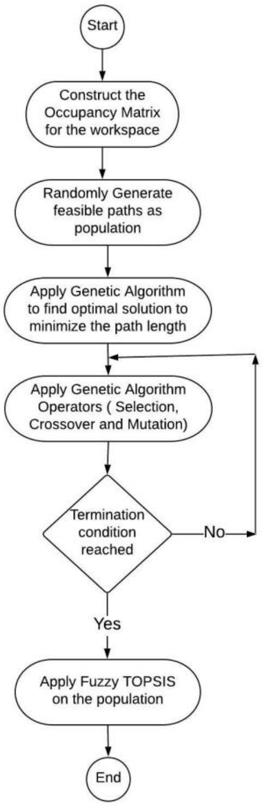


Figure 1 Flow chart for the proposed hybridization model

**Related works**

Classically the MRPP is solved using deterministic methods[21] to obtain the best path at the cost of computational complexity. The non-deterministic approaches[22], [23] overcome the drawbacks of the traditional methodologies. Using the non-deterministic approaches, the near-optimal solution is achieved with a single objective. If the number of objectives increases the convergence time proportionate increases. Therefore GA is employed with single objective to obtain a better solution space after pre determined number of genereatins or until reaches the number of paths derived. The fuzzy TOPSIS is a multi-attribute utility theory in which decision-makers' preferences[17], [24] for objectives are naturally attributed using linguistic variables rather than absolute value, making it easier for them to make decisions.

**Workflow of the proposed methodology for MRPP**

The steps for the proposed hybridization model is as in Figure 1. Randomly generated paths from the occupancy matrix form the initial population and apply the GA principle for n number of generations. To produce the population for the next generation, the only the length of the path has been accounted as an objective to reduce the computational cost. The candidate paths are derived after applying GA for a certain number of iterations in order to apply the TOPSIS method.

The solution space of the MRPP is derived by constructing a matrix for the environment by denoting the obstacles and free cells where the number of cells and size of the cell are determined by the required resolution for the path and size of the robot.

From the matrix, the feasible paths are enumerated followed by estimating objective values for three objectives with respective units. As in Figure 2, the steps are to be implemented for achieving the best path from the derived paths concerning the preferences of the objectives. In this methodology, three objectives namely length, turns, and safety are calculated in terms of the number of cells crossed, the number of turnings, and the penalty value for the angle of turns respectively. The objective values are appraised and the corresponding linguistic variables are generated. The linguistic variables are converted into calculated triplet values according to the triangular fuzzy system.

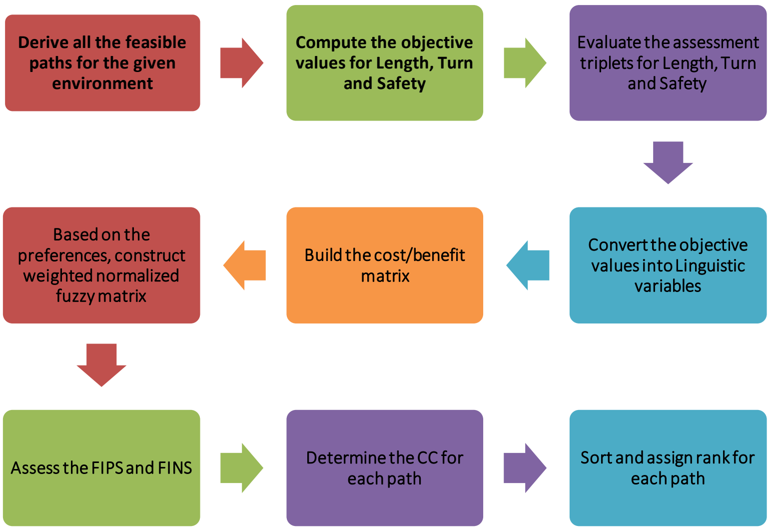


Figure 2 Steps to implement second phase of the Hybrid methodology

The table formed with these Triplet values is the Decision matrix for the given objective values. Therefore, for each path, nine values are generated corresponding to the three different objectives. From the decision matrix, the cost/benefit matrix is built by considering whether the objective has to be maximized or minimized. The outcome is the normalized fuzzy decision matrix which has to be used to construct the weighted normalized fuzzy decision matrix by multiplying the preference triplets. The preference matrix is fuzzified triplets evaluated from the minimum and maximum of the objective values of the individual objectives. The source of the preference matrix is the preferences in the form of linguistic variables for each objective.

The next step is assessing the Fuzzy Positive Ideal Solutions (FPIS) from the maximum value of each triplet of all the paths. Similarly, the matrix is derived for Fuzzy Negative Ideal Solutions (FNIS) from the minimum of triplets. The FPIS and FNIS are aggregated for each objective in turn determine the fuzzy distance of each path.

From these two aggregated distances for objectives of each path, the Closeness Coefficient (CC) factor is computed. The final step of this methodology is enumerating the CC for the paths and sorting them out in descending order to determine the rank of the candidate paths.

Table 1
The objective values for sample paths and their corresponding Linguistic variables generated from the assessment

| | Length | Turns | Penalty |
|---|---|---|---|
| Path 1 | 6 | 3 | 4 |
| Path 2 | 7 | 6 | 5 |
| Path 3 | 8 | 5 | 2 |
| Path 4 | 9 | 4 | 2 |
| Path 5 | 9 | 5 | 1 |
| Path 6 | 10 | 3 | 6 |
| Path 7 | 12 | 1 | 2 |
| Path 8 | 12 | 4 | 1 |
| Path 9 | 11 | 4 | 7 |
| Path 10 | 13 | 2 | 7 |
| Path 11 | 17 | 4 | 8 |
| Path 12 | 18 | 5 | 6 |
| Path 13 | 18 | 2 | 5 |
| Path 14 | 18 | 5 | 4 |
| Path 15 | 18 | 4 | 3 |
| Path 16 | 18 | 5 | 2 |
| Path 17 | 18 | 6 | 1 |
| Path 18 | 18 | 6 | 5 |
| Path 19 | 19 | 5 | 5 |
| Path 20 | 21 | 2 | 6 |

| Length | Turns | Penalty |
|---|---|---|
| L | L | L |
| L | H | M |
| L | M | L |
| L | M | L |
| L | M | L |
| L | L | M |
| L | L | L |
| L | M | L |
| L | M | M |
| M | L | M |
| M | M | H |
| M | M | M |
| M | L | M |
| M | M | L |
| M | M | L |
| M | M | L |
| M | H | L |
| M | H | M |
| H | M | M |
| H | L | M |

The rank states the order of the paths concerning the objective values of the path as well as the preference of objectives. With the series of paths, the best and worst paths were also identified.

**Implementation of the FT-MRPP**

This article is to explore the possibility of employing the Fuzzy based TOPSIS method to solve the MRPP problem. To test the proposed FT-MRPP methodology, arbitrarily the sample objective values are created with different combinations for 20 paths. The linguistic variables are enumerated for each objective value of the paths according to the assessment values assumed. The assessment values can be assigned intuitively or derived from the minimum and maximum values of the individual objectives.

The assessment triplets and the mapped linguistic variables are enumerated in the table. The sample linguistic variables and the corresponding triplets are listed from which the weighted normalized fuzzy triplets are calculated. The FPIS and FNIS are estimated to find the distance from ideal solutions. The CC is calculated for each path for the given candidate paths.

**Environment for experiments**

By implementing the FT-MRPP, the CC is estimated for each path, and the CC is sorted in descending order to rank the path based on CC values.

Table 2
Triangular fuzzy values for 3 objectives

| | Length | Turns | Penalty |
|---|---|---|---|
| | 6 | 1 | 1 |
| LOW | 9 | 2 | 3 |
| | 12 | 3 | 4 |
| | 12 | 3 | 4 |
| MID | 15 | 4 | 6 |
| | 18 | 5 | 7 |
| | 18 | 5 | 7 |
| HIGH | 21 | 6 | 9 |
| | 24 | 7 | 10 |

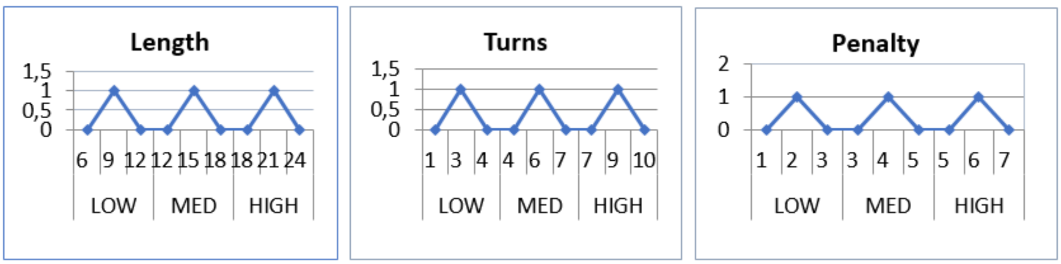


Figure 3 Fuzzy Triplets for objectives Length, Turns, and Safety

The preferences of the objectives are as in **Error! Reference source not found.**. The experiments are conducted with 6 arbitrarily selected combinations of the preferences of the objectives. The ranking of the paths for the selected combinations is listed and justified in the next session. The triangular fuzzy value assigned for the LOW, MED, and HIGH is taken as in Table 2. The fuzzy values for the objectives are depicted as a graph as in Figure 3. The preferences are symbolized with the linguistic variable as LOW, MED, and HIGH where LOW is to represent fuzzy triplets 1,2,3, the MED is for 4,5,6, and the HIGH for 7,8,9.

**Validation of results**

The results have listed in **Error! Reference source not found.** for the sample paths specifically the best and worst cases are listed with the objectives of the path for comparison with corresponding preferences of objectives. In the table, the notation LLL denotes the preferences of the objectives LENGTH, TURNS, and Penalty respectively as LOW. Similarly, H is for HIGH and M is for MED.

**Result and Discussion**

**Error! Reference source not found.**, it is obvious that there is no change in the best path which is always Path 1 because the linguistic variables derived for the objective values of the given path are LOW for all three objectives. The same exists in the case of path 7. So, both are considered the best cases. For any preference, the best path is path 1 only.

Table 3
The best and worst paths for different sample preferences of objectives

| | | Path Number | Objective Values | | | Linguistic Variables | | |
|---|---|---|---|---|---|---|---|---|
| | | | Length | Turns | Penalty | Length | Turns | Penalty |
| LLL | Best | 1 | 6 | 3 | 4 | L | L | L |
| | Worst | 19 | 19 | 5 | 5 | H | M | M |
| HHH | Best | 1 | 6 | 3 | 4 | L | L | L |
| | Worst | 19 | 19 | 5 | 5 | H | M | M |
| LHH | Best | 1 | 6 | 3 | 4 | L | L | L |
| | Worst | 18 | 18 | 6 | 5 | M | H | M |
| HHL | Best | 1 | 6 | 3 | 4 | L | L | L |
| | Worst | 19 | 19 | 5 | 5 | H | M | M |
| LHL | Best | 1 | 6 | 3 | 4 | L | L | L |
| | Worst | 18 | 18 | 6 | 5 | M | H | M |
| HLH | Best | 1 | 6 | 3 | 4 | L | L | L |
| | Worst | 19 | 19 | 5 | 5 | H | M | M |

| Path Number | Objective Values | | | Linguistic Variables | | |
|---|---|---|---|---|---|---|
| | L | T | S | L | T | S |
| 1 | 6 | 3 | 4 | L | L | L |
| 19 | 19 | 5 | 5 | H | M | M |
| 18 | 18 | 6 | 5 | M | H | M |

On the other side, the worst-case varies with respect to the preferences of the objectives for paths such as LHH and LHL. Comparing the two paths numbered 18 and 19, even though the length of path 18 is less than path 19, due to the preference, path 18 becomes the worst.

In the above two cases, the Penalty is the same and HIGH for the Turn. Therefore, comparing the Turn with high preferences, since the Turn is assessed as HIGH, path 19 becomes the worst path. According to the results acquired, it is observed that the ranking of the paths varies with the preferences of the objectives assigned.

## Conclusion

The FT- MRPP is implemented to obtain the best path for the given preferences and compare them with different combinations of preferences. In this article, the methodology adopts TOPSIS which is one of the multi-criteria decision-analysis to find the solution for the MRPP problem. TOPSIS is applied on the ouput of GA after getting predefined number of paths which reduces the complexity for the multi objective optimization for mobile robot path path planning problem . Different preferences for the three objectives are exercised to obtain the best solution for the given paths. The best and worst solution different preferences are derived and compared to justify the results.

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