A Hybrid GA-MOORA Approach for Objective Criteria Weighting in Multi-Criteria Decision Making

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Abstract: Multi-Criteria Decision-Making (MCDM) plays a critical role in identifying optimal solutions in complex environments where multiple, often conflicting, criteria must be considered. This paper presents a hybrid Artificial Intelligence (AI) framework that integrates a Genetic Algorithm (GA) with the Multi-Objective Optimization by Ratio Analysis (MOORA) method. The GA provides global search and optimization capabilities for determining criterion weights, while MOORA offers a computationally simple, robust, and rank-stable approach for evaluating alternatives. The proposed methodology consists of three stages: 1) identifying the decision alternatives and relevant evaluation criteria, 2) determining the criteria weights using a GA, and 3) ranking the alternatives using the MOORA method. The effectiveness of the hybrid GA–MOORA approach is validated through a comparative case study based on the dataset from [11] to determine the optimal weighting factors. Results demonstrate a strong agreement between MOORA and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Both methods identify Alternative 1 ($q = 0.9$) as the least favorable option (ranked 5th), while the mid-range alternatives (Alternatives 4 and 5) exhibit similar rankings. The proposed GA-MOORA model identifies Alternative 3 ($q = 0.5$) as having the highest net utility, with Alternative 2 ($q = 0.3$) performing comparably. This close performance provides decision-makers with flexible, reliable options for final selection.

1 INTRODUCTION

Real world decision-making problems such as selecting suppliers, projects, investments, or techn-ologies typically require evaluating multiple altern-atives against diverse and often conflicting criteria. Multi-Criteria Decision-Making (MCDM) provides a structured set of mathematical tools designed to support decision-makers in systematically ranking alternatives and selecting the most suitable option. Numerous MCDM techniques have been proposed, each offering unique advantages depending on the nature of the criteria and problem context. A fundamental requirement in most MCDM appro-aches is the assignment of weights to the evaluation criteria. The Weighted Sum Method (WSM) is one of the simplest MCDM techniques, calculating a total score for each alternative by summing the products of its normalized criterion values and the corresponding weights. WSM has been applied in various fields, such as evaluating workforce competence in the apparel industry [1] and selecting materials for femoral components in total knee replacement (TKR) applications [2]. Similarly, Athanasios et al. [3] employed WSM along with other MCDM methods in renewable energy system evaluations, while Agus and Abulwafa [4] compared WSM with the Multi-Attribute Decision Making Weighted Product (MADMWP) method to select the best elementary school in Indonesia.

The Weighted Product Method (WPM), another classical MCDM approach, ranks alternatives by multiplying normalized criterion values raised to their corresponding weights thus using a multi-plicative rather than an additive model. WPM has been combined with the Analytic Hierarchy Process (AHP) to assess flood susceptibility zones in the Wadi Hanifah drainage basin [5]. AHP is widely used for deriving weights through pairwise comparisons between criteria and alternatives. It has been applied in various engineering contexts, such as road selection [6] and evaluating fuel-efficiency improvements via natural-fiber polymer composites (NFPC) [7].

The Analytic Network Process (ANP) extends AHP by allowing interdependencies among criteria and alternatives, modeling decision problems as networks rather than hierarchies. ANP has been applied to identify optimal public private partnership structures for abandoned projects in Iraq [8] and to support policymakers in prioritizing resource allocation indicators [9].

More advanced ranking techniques include the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which evaluates altern-atives based on their distances to the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS). Applications of TOPSIS include multi-document text summarization [10] and determining optimal MCDM weight vectors via genetic algorithms [11].

Another widely used method, Multi-Objective Optimization by Ratio Analysis (MOORA), ranks alternatives by computing normalized assessment values, adding contributions from beneficial criteria, and subtracting contributions from non-beneficial (cost) criteria. MOORA has been applied to optimize machining parameters in wire electrical discharge machining [12], develop credit lending decision models in banking [13], and convert multi-response engineering problems into single-response problems through Taguchi-based integration [14], [15].

Additionally, Data Envelopment Analysis (DEA) provides a linear programming-based framework for comparing the efficiency of alternatives and is often integrated with MCDM techniques including TOPSIS, MOORA, and WPM to improve ranking robustness. Comprehensive formulations and applications of DEA can be found in [16]-[20].

Despite the wide range of MCDM techniques available, many still rely on subjective assignment of criterion weights by decision-makers or require sophisticated weighting procedures such as AHP or entropy-based approaches. Subjectivity in weight determination often leads to bias, affecting the reliability of the final ranking. Moreover, several MCDM methods involve complex computational steps, which may increase susceptibility to rank reversal.

To address these limitations, this paper proposes a hybrid approach that integrates a Genetic Algorithm (GA) with the MOORA method. In the proposed framework, GA is employed to determine optimal criterion weights objectively, while MOORA is used to rank alternatives based on these optimized weights. This integration aims to improve ranking stability, reduce subjectivity, and enhance the overall decision-making process.

2 MATHODS

2.1 Genetic Algorithm

GA is a more efficient optimization approach that used to solve both discrete and continuous functions [21]-[23]. This algorithm is based on natural evolution and genetics to find out near optimal solutions for large combinatorial optimization problems. The computational proce-dure of GA algorithms begins with initialization which creates a population of chromosome. After that, fitness function is used to obtain fitness score for each individual. Following that, population is updated using crossover and mutation operators of GA. Finally, termination criteria specify when the algorithm should be terminated. Genetic algorithm is described in Figure 1.

2.2 MOORA Method

Multi objective optimization by ratio analysis (MOORA) is an efficient approach that used to rank the alternatives based on the weights of criteria. As in [12-15]. MOORA algorithm starts with decision matrix in which the criteria represent the columns of the matrix and the alternatives represent the rows of the decision matrix. Following that, normalized decision matrix is calculated using the following:

$$X_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^{2}}} \quad i = 1,2,\ldots,m \; and \; j = 1,2,\ldots,n \qquad (1)$$

Next, we calculate the criteria weights and then calculate the weighted normalized decision matrix. After that, based on the normalized values of the weighted decision matrix of beneficial criteria and non-beneficial criteria, performance score is calculated using the following:

$$y_i^{*} = \sum_{j=1}^{g} W_j X_{ij}^{*} - \sum_{j=g+1}^{n} W_j X_{ij}^{*} \qquad (2)$$

MOORA approach can also described in Figure 2.

2.3 Integrated GA-MOORA Method

The computational procedure for GA-MOORA model is described as follows:

Step1: determine clearly the alternatives and important criteria.

Step2: For the given criteria find the weights using GA as follows: or numbered list style:

1) Initialization: Create initial population;
2) Fitness Assessment: Calculate fitness scores for each individual using fitness function;
3) Update population: Create new population using crossover and mutation operators of GA.

Step 3: Termination:

a) Iteratively process weight learning until termination condition is reached.

b) if termination condition met, then the process terminates and returns a set of optimal criteria weights, otherwise go to 2.

Step 4: rank the given alternatives using MOORA as follows:

1) Construct the decision matrix;
2) Construct the normalized decision matrix using (1);
3) Calculated the weights of criteria and then construct the weighted normalized decision matrix and finally calculate the final score using (2).

This computational procedure can be described in Figure 3.

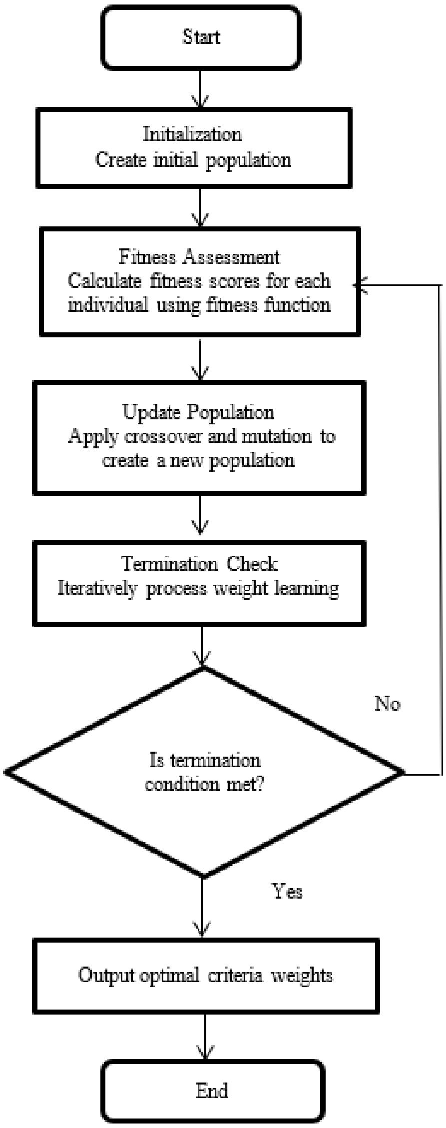

Figure 1: Genetic algorithm.

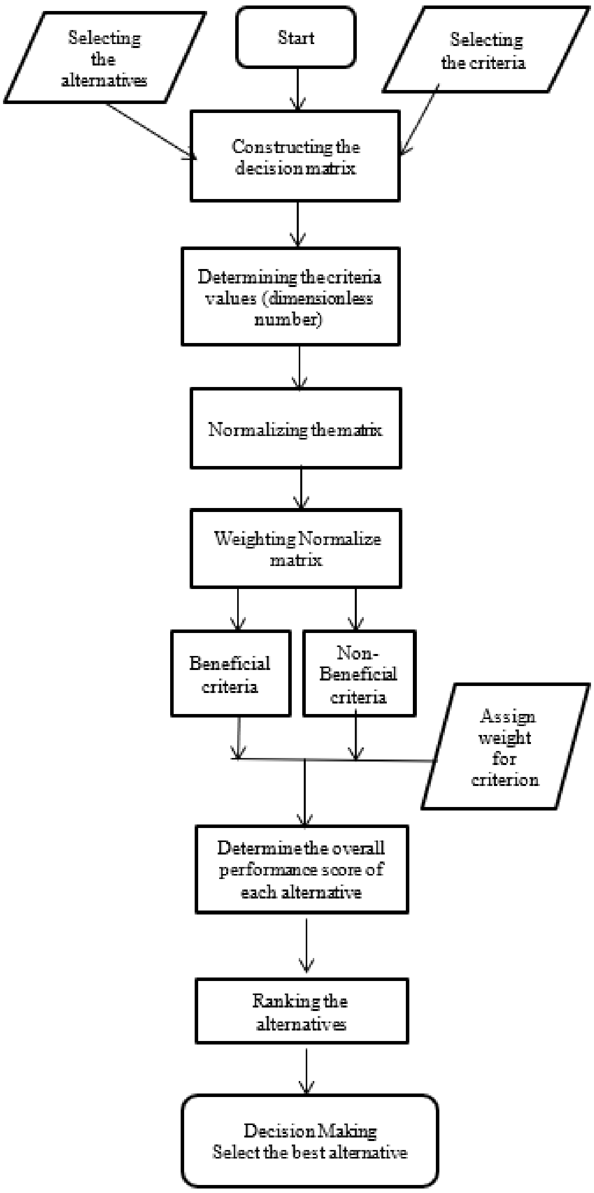

Figure 2: MOORA algorithm.

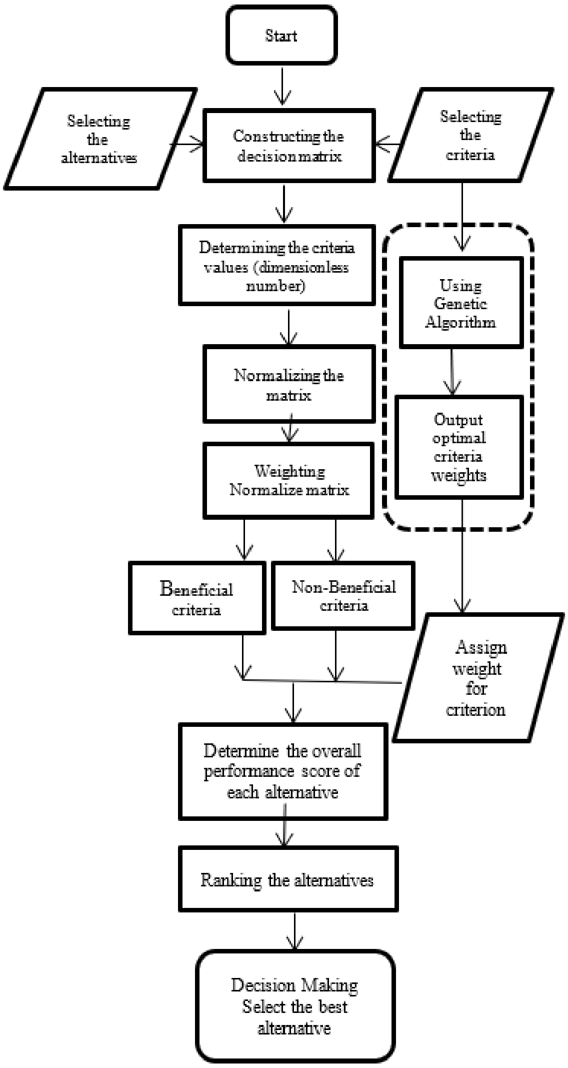

Figure 3: Integrated GA-MOORA approach.

3 RESULTS AND DISCUSSION

3.1 A Case Study

To show the effectiveness of the presented GA-MOORA approach, we use the data in [11].

Which consist of five alternatives (q=0.1, q=0.3, q=0.5,q=0.7, q=0.9) represent various weight factor values and six criteria (Group Efficiency (GE), System Utilization (SU), System Flexibility (SF), Number of Voids (NV), Exceptional Elements (EE), and Total Cost (TC)). The goal as in [11] is to identify the most favorable solution for both flexible cell information and machine layout within each cell.

3.2 Implementation of Integrated GA-MOORA Approach

Step1: The alternatives and criteria were specified by [11] as: Alternatives (q=0.1, q=0.3, q=0.5,q=0.7, q=0.9) represent various weight factor values and six criteria (Group Efficiency (GE), System Utilization (SU), System Flexibility (SF), Number of Voids (NV), Exceptional Elements (EE), and Total Cost (TC)).

Step2: Identifying the weight of criteria using GA as in [11] in Table 1 as follows:

Table 1: GA weights of the criteria

Criteria	Type	GA -Weights
GE	Beneficial	0.20
SU	Beneficial	0.20
SF	Beneficial	0.20
NV	Non- Beneficial	0.10
EE	Non- Beneficial	0.10
TC	Non- Beneficial	0.20

Step3: Identify the most favorable solution for both flexible cell information and machine layout using MOORA as follows in Table 2.

Table 2: MOORA scores for the values of q.

q	MOORA Scores	MOORA rank
q=0.1	-0.088	5
q=0.3	0.178	2
q=0.5	0.183	1
q=0.7	0.149	3
q=0.9	0.147	4

3.3 The Discussion

Based on the obtained results using GA-MOORA and the results of TOPSIS as in [11] and we compare these results in Table 3 and Figure 4 and Figure 5 as follows:

Form Table 2, Figure 2 and Figure 3 we conclude that the alternative (q=0.1) is the worst alternative based on both Methods. Also, the alternatives (q=0.3 and q=0.5) are best alternatives.

Table 3: Comparison between MOORA and TOPSIS ranks.

Alterna-tive q	TOPSIS		MOORA		Consensus
	score	rank	score	rank	
q=0.3	0.83546	1	0.17835	2	Top 2 choice
q=0.5	0.75114	2	0.18356	1	Top 2 choice
q=0.9	0.73957	3	0.14781	4	Good Middle Option
q=0.7	0.71548	4	0.14921	3	Good Middle Option
q=0.1	0.25914	5	-0.08845	5	Worst Choice

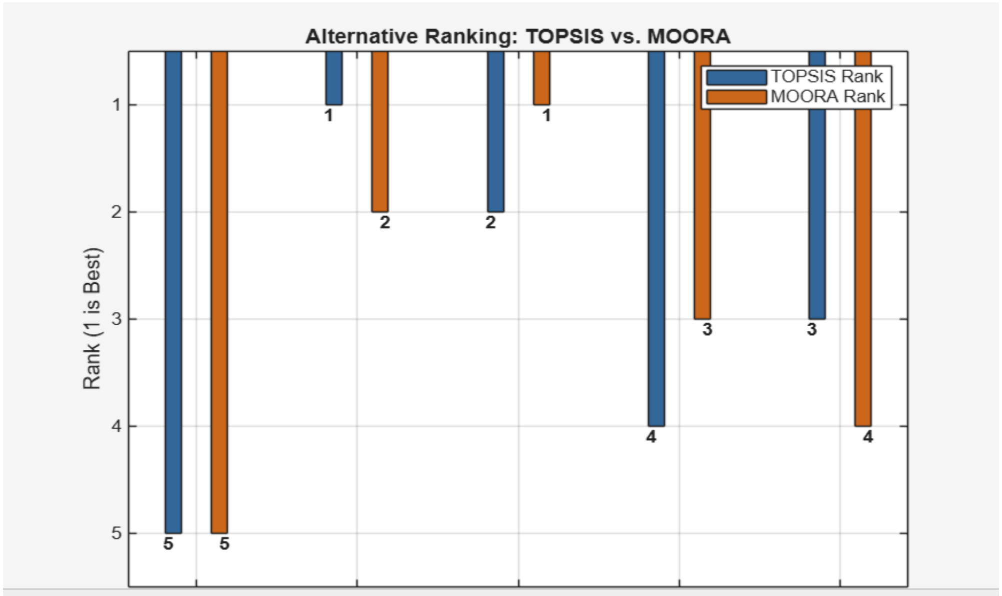

Figure 4: Comparison of MOORA and TOPSIS results.

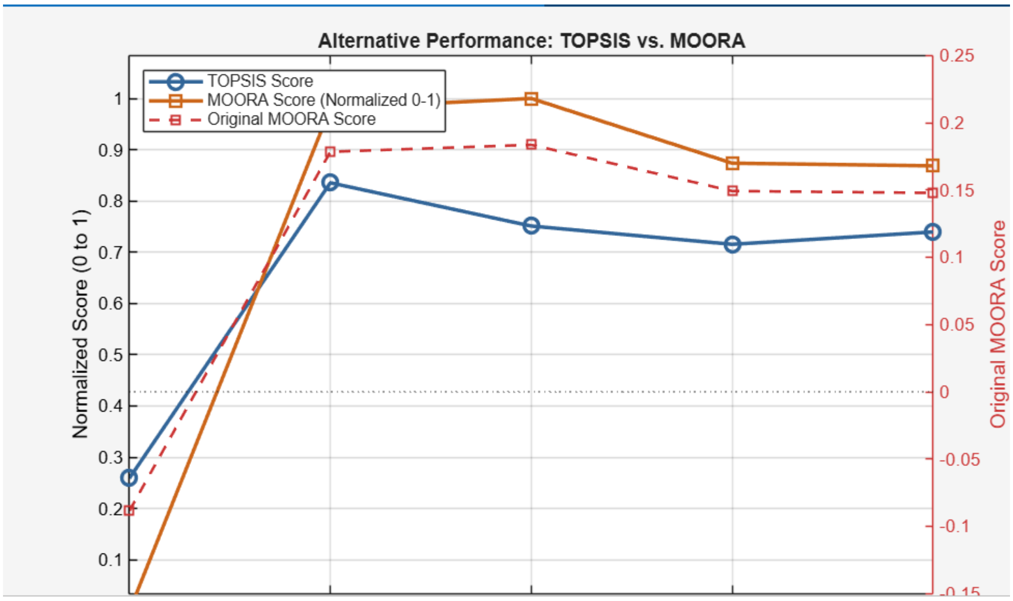

Figure 5: Comparison of the actual scores from both methods.

4 CONCLUSIONS

An integrating multi criteria decision making approach which is called as GA-MOORA has been successfully presented. This approach has strong mathematical foundation based on a hybrid Artificial Intelligence (AI) model that synergizes the global optimization power of a Genetic Algorithm (GA) with the intuitive logic of the MOORA technique. The validity of the presented approach has tested using data from [11] and compared with the results of this reference. Our study shows that the integrated GA-MOORA approach has computational simplicity and minimalism, which leads to inherent robustness and reduced susceptibility to rank reversal. The study also shows the ranks of three alternatives are match the results using TOPSIS as in [11]. Moreover, alternative 3 is ranked as the first and alternative 2 is ranked the second where the weights of these alternatives that obtained using GA-MOORA are very close. Which will help the decision maker to determine the most suitable value for the weighting.

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