A decision-making methodology for material selection using genetic algorithm

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Abstract: Material selection is a challenging task for designers due to the immense number of different materials available today. Choosing the right materials plays an important role in numerous engineering applications because an inappropriate selection of materials can significantly affect the performance of the final product. As a result, a number of techniques have been proposed to select materials in the engineering design process. However, most of the proposed systems are knowledge intensive and cannot deal with the situation where the information of weight criteria is incomplete or unknown. So, in this paper a logical approach is presented for choosing an optimal material by employing the genetic algorithm. The proposed material selection procedure reduces the personal bias for assigning the weight of different attributes. Seven examples are included to demonstrate the applicability of the suggested approach. The findings of this work provide the insights for further researches on more complicated design problems such as simultaneous material selection and geometry optimisation.

Keywords: materials selection; genetic algorithm; multiple criteria analysis; multi criteria decision making; weighting factors; ranking.

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1 Introduction

Nowadays, choosing an appropriate material with desired attributes for a given application is a bewildering task for designers due to the availability of different materials, each of which has its own characteristics and merits. Also, the selection of optimal material cannot be achieved solely with the lowest price approach and decision makers should first define the decision matrix that encompasses different alternatives with their relevant properties. Usually, these properties in the decision context are considered as either positive attributes, if higher values are desirable (e.g., strength, hardness), or negative criteria if smaller values are always preferable (e.g., cost, density) (Farag, 1997). As a result, optimal material selection is considered as the multi criterion decision-making problem and various methods have been proposed to deal with this issue (Vincke, 1986; Anojkumar et al., 2015; Kaliszewski and Podkopaev, 2016). Perhaps transforming different criteria into a compatible measurement is the main step in MCDM methods and a lot of normalisation techniques have been developed to carry out this task (Jahan and Edwards, 2015).

Since an improper selection of materials can negatively affect the productivity of the ultimate component, many researchers have proposed different methods to assist the designers for selecting an optimal material among a host of alternatives (Jahan and Edwards, 2015; Ishak et al., 2016). Ashby (2016) has introduced material selection charts for a wide range of materials. He has also proposed a multi-objective optimisation technique in material design by employing utility function to determine the optimum point (Ashby, 2000). Although the method is simple, it becomes complicated when the number of material properties (criteria) increases. To overcome this challenge, multiple attribute decision-making (MADM) technique as the other branch of MCDM has been developed (Sen and Yang, 1998). The methods of MADM include weighted product method (WPM), technique for ordering preference by similarity to ideal solution (TOPSIS) (Pohekar and Ramachandran, 2004), ELECTRE, etc. The ranking order of materials in weighted properties method is derived according to their performance indices (Farag, 1997). Of the MADM method, TOPSIS is the more widely used method for decision making. Shanian and Savadogo (2006a) employed TOPSIS method as multiple-criterion decision support analysis for the material selection of metallic bipolar plates for the polymer electrolyte fuel cell. In another work, they had presented a material selection model known as ELECTRE (Shanian and Savadogo, 2006b). Chen et al. (1994) proposed a methodology that includes environmental costs in the material selection process. Chen and Hwang (1992) presented a numerical approximation method for converting qualitative attributes to their corresponding fuzzy numbers through using eight-point conversion scales. Later on an 11-point conversion scale was proposed by Rao (2006) along with graph theory and matrix approach for the material selection. Tzeng et al. (2005) presented a logical approach for a given engineering application known as VIKOR that can be applied to a wide range of material selection problems. Jahan et al. (2011) presented a new version of VIKOR method with a novel normalisation technique, which can cover all types of criteria. Yazdani and Payam (2015) investigated the results of Ashby (2000), VIKOR and TOPSIS methods as MADM technique to select the optimal materials for MEMS electrostatic actuators. Dehghan-Manshadi et al. (2007) enhanced the scaling procedure in the digital logic (DL) method (Farag, 1997) by developing a numerical method for the material selection combining nonlinear normalisation with the modified DL method. Fayazbakhsh et al. (2009) proposed the z-transformation method to solve the dimensionless of the decision matrix in weighted properties method. Edwards (2005) developed a checklist/questionnaire method, which reduced the risk of possible failure to achieve an optimal design solution by developing a structured set of questions. Prasad and Chakraborty (2013) integrated the voice of customers with the quality function deployment (QFD)-based approach to assure that the final product satisfies customers' needs. Khabbaz et al. (2009) used fuzzy logic approach for the selection of the best performance materials. Although their method reduced the volume of mathematics involved in other material selection approaches, it required many fuzzy IF-Then rules. The other examples of material selection processes based on artificial intelligence tools are multi-objective optimisation of the material selection via the integration of genetic algorithm (GA) with artificial neural networks proposed by Zhou et al. (2009), an expert system to perform the reasoning for the selection of plastic materials presented by Beiter et al. (1993) and the knowledge-based system developed by Sapuan and Abdalla (1998). Chen et al. (1993) proposed a decision-making support system for the composite material selection by integrating an expert system with a database system. The artificial intelligence methods have the potentiality to deal with the complex relationships in the material selection compared to the traditional MADM methods, but they are knowledge intensive and require advanced information, which most designers lack.

To select the optimal materials for tailoring the composite components, Sadagopan and Pitchumani (1998) explored the application of GA as the combinatorial optimisation technique. Xiujuan (2008) used the improved GA for selecting optimal material constituents of compositions and microstructures.

Even though a lot of researches were reported in the past to select materials for a given engineering application, there was still a need for a simple method that assisted the designers to choose the most suitable materials with minimum effort. Moreover, according to Jee and Kang (2000), the procedure of material selection should be objective in order to minimise personal bias and time of a new product design. To address this issue in the present investigation, we used GA to assign attribute weights in order to take the proper material selection decision.

The reminder of this paper is organised as follows: in Section 2, we present the suggested material selection model using the GA. In Section 3, the practicality of the proposed method is illustrated using seven numerical examples. Finally, conclusion is presented in Section 4.

2 Method description

Generally, in a material selection problem with m alternatives (A_i, i = 1, 2, …, m) and n criteria (C_j, j =1, 2, …, n) the task of the decision maker is to choose better materials with respect to the relative importance of each criteria (weights). Designers carry out MADM problems by using a decision matrix as shown in Table 1. This decision table constitutes alternatives, attributes, weights of attributes and the measures of performance of alternatives x_{ij} (for i = 1, 2, …, m; j = 1, 2, …, n) . In order to have a valid comparison, all the elements in the decision table must be dimensionless and normalised to the same units. It may be added here that, for dealing with qualitative attributes (linguistic terms), an 11-point fuzzy conversion scale proposed by Rao (2006) is used, which can convert qualitative attributes to quantitative values (Table 2). The basic concepts of the method presented in this paper for the material selection are discussed in the following steps.

Step 1 Determining the most desirable values for all attributes in the decision matrix:

$$T = \{T_1, T_2, T_3, \ldots, T_j, \ldots, T_n\}$$
$$= \{Most\ \ favorable\ element\left(x_{ij}\right)\ or\ target\ value\ \ for\ criteria\}$$

Step 2 Normalising the decision table:

In multi attribute decision-making methods, the values associated with the criteria (x_{ij}) in the decision table may be in different units [e.g., material costs are expressed in dollars, yield strength (YS) is expressed in MPa, etc.]. Hence, they must be transformed into a compatible unit. Each attribute can have benefits, cost or target value concept, so, for covering all types of criteria, we use the normalisation method suggested by Jahan et al. (2011):

$$r_{ij} = 1 - \frac{\left|x_{ij} - T_j\right|}{Max\{x_j^{\max}, T_j\} - Min\{x_j^{\max}, T_j\}} \tag{1}$$

where r_{ij} is the normalised value of x_{ij} (property of the alternatives) and T_j is the most favourable element in criteria j. $x_j^{\max}$ and $x_j^{\max}$ are maximum and minimum values in criterion j respectively.

Step 3 Weighing the evaluation criteria

Assessing the weight or relative importance of attributes is a grand challenge since the weight of material properties plays an important role in the ranking results of alternatives (Diakoulaki et al., 1995). To date, several approaches have been utilised to calculate the weight of attributes. These methods can be categorised into three groups namely; subjective methods, in which the DM or designer assigns the relative importance of the criteria (Dehghan-Manshadi et al., 2007), objective methods, in which DM has no role in determining the importance of the criteria (Deng et al., 2000) and the combined weighing scheme of the two previous groups (Rao and Patel, 2010; Alemi-Ardakani et al., 2016). Although a considerable amount of research has been carried out on the weighing of material selection criteria, a systematic procedure for conducting designers to get optimum weight has not been reported yet. To overcome this shortcoming, we report a novel approach for the weighing of criteria by employing the GA.

Table 1 A typical decision matrix in MADM problem

Weights	W_1	W_2	…	W_n
Criteria	C_1	C_1	…	C_n
Material no.				
A_1	x_{21}	x_{12}	…	x_{1n}
A_2	x_{21}	x_{22}	…	x_{2n}
A_3	x_{31}	x_{32}	…	x_{3n}
⋮	⋮	⋮		⋮
A_m	x_{m1}	x_{m2}	…	x_{mn}

Table 2 Value of material selection attribute in 11-point scale format

Qualitative measure of material selection factor	*Assigned value*
Exceptionally low	0.045
Extremely low	0.135
Very low	0.255
Low	0.335
Below average	0.410
Average	0.500
Above average	0.590
High	0.665
Very high	0.745
Extremely high	0.865
Exceptionally high	0.955

2.1 Genetic algorithm

The ubiquity and applicability of GAs in the materials arena and multi attribute decision-making problems has been demonstrated in Chakraborti (2013). GA also would be beneficial for designers who aim to solve the complexities associated with material and geometric size of the product (Sakundarini et al., 2013). The material selection problem constitutes from both continuous and discrete variables (Tang et al., 2011). Several reasons make GA suitable approach for solving material selection problems. First, most of the engineering design solutions uses a traditional nonlinear discrete design variable. While traditional optimisation methods fail to deal with this setback, GA is capable of handling this efficiently. Second, GA provides quick and numerous solutions. Finally, in MADM problems, the goal is to find the optimum solutions within the design space which exactly in line with the aim of the GA and its capability. GA is capable of searching the design space for the global optimum value. In our study, we utilised GA in the attribute weighting process in order to reduce the complexities in decision making for designers.

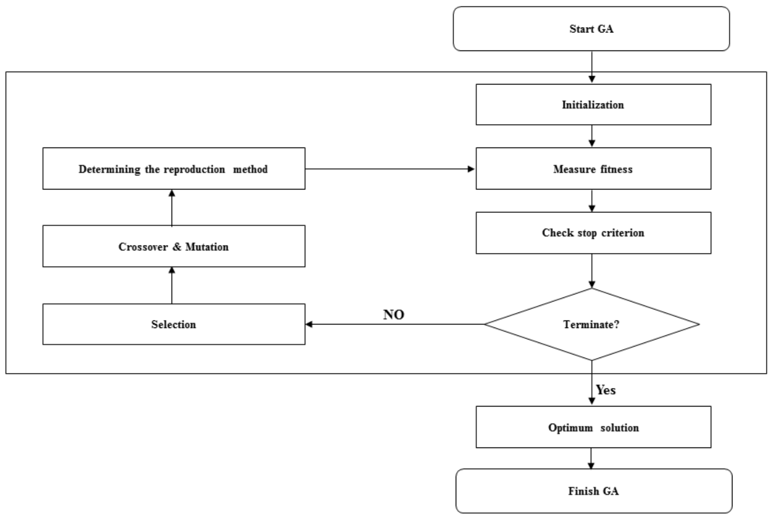
The GA is a powerful stochastic search and optimisation technique based on the principles from evolution theory suggested by Holland (1975).There are three main biological processes in GAs, namely: selection, crossover and mutation. Basically the simple GAs try to select better candidates among the elements in the initial population (IP) by emulating three aforementioned operations.

In the selection phase, better candidates are chosen to form a mating pool for the next generation, where the cost function of each solution is used as the metric for comparison between different candidates. A better fitness of a solution signifies higher probability for a chromosome to be selected for the mating pool. New chromosomes are, then, generated by integrating the existing chromosomes in the mating pool. The integration process can be fulfilled with either the crossover or mutation operation. While crossover operation generates a new offspring without changing the genes of the candidates in the population, mutation makes a small, probabilistic change in the genetic makeup of the individuals, which enables the GA to search for a broader space.

Table 3 GA properties

Option	*Value*
Crossover function	Heuristic
Crossover fraction	0.8
Elite number	5
Initial penalty	10
Mutation function	Adaptive feasible
Penalty factor	100
Population initial range	[–1, 1]
Population size	100
Population type	Bit string
Selection function	Stochastic uniform

Figure 1 Schematic diagram of the GA process



2.2 The proposed weighing scheme

The developing procedure for updating the weight of criteria using GA is shown in Figure 1; also, the assigned variables to implement the method in MATLAB are available in Table 3. The related explanation is described in Table 3.

2.2.1 Creating IP

The IP is defined by a $L * N$ matrix as:

$$IP = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1N} \\ w_{21} & w_{22} & \cdots & w_{2N} \\ \vdots & \vdots & & \vdots \\ w_{L1} & w_{2} & \cdots & w_{LN} \end{bmatrix}$$

where the element w_{ij} ($1 \leq i \leq L$, $1 \leq j \leq N$) is a random number, which represents the weight of the criteria; and N is the number of attributes for a given material selection problem. Herein, the IP size is 100 (i.e., $L = 100$).

2.2.2 Handling constraints

Optimisation problems often involve the inequality and equality constraints. To solve the constrained optimisation problems using GAs, penalty function methods have been the most popular approach, because of their simplicity and ease of implementation (Deb, 2000). In this paper, for assigning the weight of the criteria in any material selection problem, the following constrained optimisation problem is considered:

Objective function:

$$Min\ F(\vec{x})$$

Subject to:

$$\begin{cases} g_k(\vec{x}) \geq 0, k = 1, \ldots, K. \\ h(\vec{x}) = 1, \\ x^L \leq x_j \leq x^U, j = 1, \ldots, n. \end{cases}$$

where $g_k(\vec{x})$ represents inequality constraints between weight of attributes and $h(\vec{x})$ is the equality constraint that satisfies $\sum_{j=1}^{n} w_j = 1.$ The proposed GA should try to minimise the objective function without violating any specified constraints and manipulating the weighed vector ($[W = w_1, w_2, \ldots, w_j]$) within the range of $[x^L, x^U]$ specified by the designer (superscript L and U denote the lower and upper bounds).

2.2.3 Determining the fitness function

The fitness function can be considered as a factor of the merits of the chromosome. The closer a chromosome is to the optimum, the greater its fitness is. For the maximisation problem, the function value itself is a good indicator of fitness, but for a minimisation problem, a transformed function, such as $-f(x)$ or $1 / [1 + f(x)]$ is generally used (Chakraborti, 2013). Herein, the following procedure is proposed for calculating the fitness value of each chromosome:

1 Constructing the weighed normalised matrix by multiplying the relative importance of each attribute with the normalised elements of the decision matrix:

$$\upsilon_{ij} = w_{ii} \times r_{ij},\ j = 1, 2, \ldots, n,\ i = 1, 2, \ldots, m \tag{2}$$

2 Obtaining the ideal value for each criteria from υ_{ij}:

$$\begin{aligned} V^I &= \left\{V_1^I, V_2^I, \ldots, V_n^I\right\} \\ &= \left\{\mathrm{Max}_i \upsilon_{ij}\right\}; j = 1, \ldots, n, i = 1, 2, \ldots, n. \end{aligned}$$

3 Computing the difference matrix $\tilde{D}$ by subtracting elements of the weighed normalised matrix from the relative ideal criteria:

$$\begin{aligned} \tilde{D} &= \left[\tilde{D}_{ij}\right]_{m \times n} \\ &= \begin{bmatrix} \left|\upsilon_{11} - V_1^I\right| & \left|\upsilon_{12} - V_2^I\right| & \cdots & \left|\upsilon_{1n} - V_n^I\right| \\ \left|\upsilon_{21} - V_1^I\right| & \left|\upsilon_{22} - V_2^I\right| & \cdots & \left|\upsilon_{2n} - V_n^I\right| \\ \cdots & \cdots & \left|\upsilon_{ij} - V_j^I\right| & \cdots \\ \left|\upsilon_{m1} - V_1^I\right| & \left|\upsilon_{m2} - V_2^I\right| & \cdots & \left|\upsilon_{mn} - V_n^I\right| \end{bmatrix}; i = 1, 2, \ldots, m; j = 1, 2, \ldots, n. \end{aligned}$$

4 Integrating a $m \times n$ matrix of zero, which shows the optimum difference value for each criterion with difference matrix $\tilde{D}$:

$$\tilde{D}^{modified} = \begin{bmatrix} |\upsilon_{11} - V_1^I| & |\upsilon_{12} - V_2^I| & \cdots & |\upsilon_{1n} - V_n^I| & \\ |\upsilon_{21} - V_1^I| & |\upsilon_{22} - V_2^I| & \cdots & |\upsilon_{2n} - V_n^I| & 0_{m\times n} \\ \cdots & \cdots & |\upsilon_{ij} - V_j^I| & \cdots & \\ |\upsilon_{m1} - V_1^I| & |\upsilon_{m2} - V_2^I| & \cdots & |\upsilon_{mn} - V_n^I| & \end{bmatrix}$$

$;i = 1, 2, \ldots, m; j = 1, 2, \ldots, n.$

5 Valuating the relative closeness of a particular alternative to the ideal solution:

$$C_i = \left(\frac{1}{N-1} \sum_{J=1}^{N} \left(\tilde{D}_{ij}^{modified} - \mu_i \right)^2 \right) + \left(\sqrt{\frac{1}{N-1} \sum_{j=1}^{N} \left(\tilde{D}_{ij}^{modified} - \mu_i \right)^2} \right); \quad (3)$$

$N = 1, 2, \ldots, 2n; i = 1, 2, \ldots, m.$

$$\mu_i = 1/N \sum_{J=1}^{N} \tilde{D}_{iJ}^{modified}; N = 1, 2, \ldots, 2n$$

The value of C_i is considered as 0.01 when it becomes zero.

6 Measuring the fitness function for each chromosome:

$$F_i(\vec{x}) = -f_i(\vec{x}) + P_i \quad (4)$$

$$f_i(\vec{x}) = \max\left(\sum_{i=1}^{n} Y_i * W_i \right) \Big/ \min(C_i) \quad (5)$$

here Y_i represents the normalised value of each property of material A_i ,and W_i is the weight of the criteria. The parameter P_i is the penalty parameter of the i^{th} chromosome which depends on the constraint violation $g_k(\vec{x})$.

2.2.4 Determining the selection method

In this paper, roulette wheel selection is adopted for choosing the best chromosomes as it is the simplest selection approach and provides a zero bias (Chakraborti, 2013).

2.2.5 Determining the method of genetic operations

The single-point crossover which is the most common crossover operator along with adaptive feasible mutation operation for mating two individuals are used in the present work. In the single point crossover (Chakraborti, 2013), two chromosomes are selected randomly from the mating pool. A random integer value as a cross-site between one and the length of an individual string is also selected. The exchange of the genes before and after the crossover point in the parent chromosomes resulted in generating two new offspring.

2.2.6 Determining the reproduction method and stop criteria

After the genetic operations, offspring with 80% population have been generated by crossover operations. Then the elitist selection scheme is used to ensure that the best chromosomes in the population are always passed onto the next generation. The number of generations is considered as the stop criterion for evaluation process.

Step 4 Ranking orders of alternatives:

The weights obtained from GA are employed for computing the preference selection index (I_i) of each alternative:

$$I_i = \left(\sum_{i=1}^{n} Y_i * W_i\right) / (C_i) \tag{6}$$

The alternatives are then ranked in the descending order of the performance index values and the material with the highest value is selected as the best choice for the considered problem.

3 The verification of the method

To illustrate the applicability of the proposed material selection method in engineering design process, it is applied to eight examples.

3.1 Example 1: material selection for cryogenic storage tank

Dehghan-Manshadi et al. (2007) proposed a material selection method by combining nonlinear normalisation with a modified DL method. As cryogenic tank was designed for transportation of liquid nitrogen, the suitable material should have good weld ability, lower density and specific heat (SH), a smaller thermal expansion (TE) coefficient and thermal conductivity (TC), adequate toughness at the operating temperature and also should be sufficiently strong and stiff. For the material selection problem, seven alternative materials and seven attributes were considered. In the present work, the alternatives and the attributes are the same as those of Dehghan-Manshadi et al. (2007). The attributes are: toughness index (TI), YS, Young's modules (YM), density (D), TE, TC and SH. Table 4 shows the candidate materials, criteria and objectives of designer. The detailed steps of the methodology proposed in Section 2 are described below:

Step 1 Determining the most favourable values for all criteria:

$T_j = (770, 1{,}365, 217, 2.68, 9.4, 0.016, 0.06)$

Step 2 Obtaining the normalised decision matrix of data in Table 4 by using equation (1). Table 5 presents normalised data (Y_i).

Step 3 Using GA to determine the relative importance of different attributes:
In this case, the same subjective weights of the method proposed by Dehghan-Manshadi et al. (2007) are considered, to determine the following constrained optimisation problem:

Minimise:

$F(\vec{w})$

Subject to:

$$g_1(\vec{w}) \equiv w_7 - w_6 \le 0,\ g_2(\vec{w}) \equiv w_6 - w_3 \le -0.01,$$
$$g_3(\vec{w}) \equiv w_3 - w_2 \le -0.01,\ g_4(\vec{w}) \equiv w_2 - w_5 \le 0,$$
$$g_5(\vec{w}) \equiv w_5 - w_4 \le -0.01,\ g_6(\vec{w}) \equiv w_4 - w_1 \le -0.01,$$
$$h(\vec{w}) = \sum_{j=1}^{7} w_j = 1,\ 0.083 \le w_j \le 0.214,\ j = 1, 2, \ldots, 7.$$

The constrained optimum solution is w^* = (0.2140, 0.1360, 0.1280, 0.1450, 0.1370, 0.1200, 0.1190) with a function value equal to F* = –18.9501. Figure 2 illustrates the feasible solutions for this example.

Step 5 The preference index values for each of the alternative materials are computed using equation (6). For example, using weights obtained from GA, the preference of alternative materials 1 (i.e., Al 2024-T6) and 2 (i.e., Al 5052-O) are computed as follows:

$$I_i = \left.\begin{pmatrix} 0*0.214 + 0.26*0.136 + 0.03 \\ *0.128 + 0.98*0.145 + 0.05 \\ *0.137 + 0*0.0120 + 0*0.119 \end{pmatrix}\right/ 0.0756 = 2.49$$

$$I_2 = \left.\begin{pmatrix} 0.03*0.214 + 0*0.136 + 0 \\ *0.128 + 1.00*0.145 + 0*0.137 \\ +0.11*0.120 + 0*0.119 \end{pmatrix}\right/ 0.0772 = 2.13$$

Table 4 Candidate materials for cryogenic storage tank

Objectives	*Max*	*Max*	*Max*
Materials	*Toughness index*	*Yield strength (MPa)*	*Young's modulus (GPa)*
Al 2024-T6	75.5	420	74.2
Al 5052-O	95	91	70
SS 301-FH	770	1365	189
SS 310-3AH	187	1120	210
Ti-6Al-4V	179	875	112
Inconel 718	239	1190	217
70Cu-30Zn	273	200	112

Objectives	*Min*	*Min*	*Min*	*Min*
Materials	*Density (gm/cm^3)*	*Thermal expansion*	*Thermal conductivity*	*Specific heat*
Al 2024-T6	2.80	21.4	0.370	0.16
Al 5052-O	2.68	22.1	0.330	0.16
SS 301-FH	7.90	16.9	0.040	0.08
SS 310-3AH	7.90	14.4	0.030	0.08
Ti-6Al-4V	4.43	9.4	0.016	0.09
Inconel 718	8.51	11.5	0.310	0.07
70Cu-30Zn	8.53	19.9	0.290	0.06

Table 5 Normalising property values for cryogenic storage tank

Materials	Y_1 Toughness index	Y_2 Yield strength (MPa)	Y_3 Young's modulus (GPa)	Y_4 Density (gm/cm^3)
Al 2024-T6	0	0.26	0.03	0.98
Al 5052-O	0.03	0	0	1.00
SS 301-FH	1.00	1.00	0.81	0.11
SS 310-3AH	0.16	0.81	0.95	0.11
Ti-6Al-4V	0.15	0.61	0.29	0.70
Inconel 718	0.23	0.86	1.00	0.003
70Cu-30Zn	0.28	0.09	0.29	0

Materials	Y_5 Thermal expansion	Y_6 Thermal conductivity	Y_7 Specific heat
Al 2024-T6	0.05	0	0
Al 5052-O	0	0.11	0
SS 301-FH	0.41	0.93	0.8
SS 310-3AH	0.61	0.96	0.8
Ti-6Al-4V	1.00	1.00	0.7
Inconel 718	0.83	0.17	0.9
70Cu-30Zn	0.17	0.23	1.00

Table 6 Comparing rankings of candidate materials for example 1

Materials	WPM (Farag, 1997)		The method of Dehghan-Manshadi et al. (2007)		Proposed decision-making method	
	Performance index	Rank	Performance index	Rank	Performance index	Rank
Al-2024-T6	42.2	5	–1.17	5	2.4913	6
Al-5052-O	40.1	6	–8.75	7	2.1308	7
SS 301-FH	70.9	1	47.40	1	18.9501	1
SS 310-3AH	50.0	4	31.88	4	10.1619	3
Ti-6AL-4V	59.8	2	43.52	2	11.1986	2
Inconel 718	53.3	3	33.44	3	9.1520	4
70 Cu-30 Zn	35.9	7	-3.07	6	4.2822	5
Correlation coefficient	0.8571			0.9286		

Figure 2 The objective function value of example 1

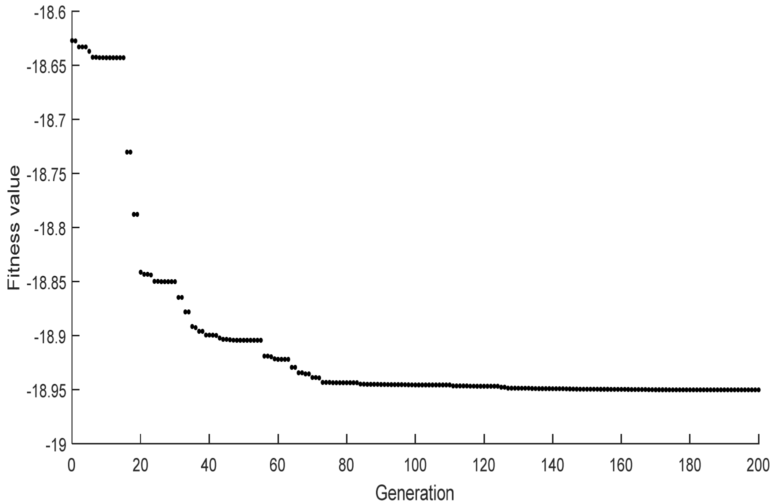


Table 6 presents the obtained results and compares the corresponding ranking of the alternative materials with the results reported in Farag (1997) and Dehghan-Manshadi et al. (2007) on the same problem. From the obtained results, it can be understood that material SS 301-FH is proposed as the first choice. The high Spearman's rank correlation coefficient (Table 6) supports the validity of the ranking result. The same ranking is obtained by the Manshadi and WPMs' method for the first five choices. However, by Manshadi's method the calculated performance indices for the last three choices are appeared to be negative. This explains that the approach refuses to accept the two aluminium alloys and brass materials as a possible alternative for this application. In contrast the WPM method considered the last three materials as possible choices. Interestingly, the GA approach provides similar ranking for the first four choices and the major differences show up between the performance indices of the last three materials (i.e., the two aluminium alloys and brass) and other alternative materials. Considering the obtained results so far, there would be two important notes to make. First, for this test case, the GA approach introduced verifies its capability in ranking of the candidate materials in comparison with the existing methods. Second, the superiority of the presented method over WPM approach and its performance comparability with the method of Dehghan-Manshadi et al. (2007) is evident. The main point here is the three rejected candidates by the method of Dehghan-Manshadi et al. (2007). The performance indices calculated by the WPM for these materials are high compared to the value of the material ranked first by this method (i.e., higher than 50%). This means that the WPM method gives a high selection chance to these materials in comparison to the material ranked first. By contrast, in the proposed approach this ratio is found below 12% which reveals that these materials find a much smaller chance to be selected as top ranked materials. In compared to the method suggested by Dehghan-Manshadi et al. (2007), the proposed GA approach seems more genuine and has ranked the alternative materials more logically. A close look at the values of the attributes for the materials 1 and 7 along with their corresponding ranking in the two approaches can support the aforementioned advantages of the presented GA approach.

3.2 Example 2: material selection for a high-speed naval craft

Rao and Patel (2010) used an integrated MADM for material selection of a naval craft. Torrez (2007) solved this problem by using the modified DL method. The following properties are required for this case:

1 YS

2 Young's modules

3 fire resistance

4 reparability

5 resistance to corrosion

6 fabrication cost

7 risk

8 density

9 overall potential for weight savings.

Six alternative materials, nine material selection criteria and objectives of criteria are shown in Table 7. Fuzzy conversion scale proposed in Table 2 by Rao (2006) has been used to convert the qualitative values to quantitative values. The same subjective weight of the method proposed by Rao and Patel (2013) is used, in order to determine the following constrained optimisation problem:

Minimise:

$$F(\vec{w})$$

Subject to:

$$\begin{aligned}
&g_1(\vec{w}) \equiv w_5 - w_7 \le -0.01,\ g_2(\vec{w}) \equiv w_7 - w_4 \le 0,\\
&g_3(\vec{w}) \equiv w_4 - w_3 \le -0.01,\ g_4(\vec{w}) \equiv w_3 - w_2 \le -0.01,\\
&g_5(\vec{w}) \equiv w_2 - w_6 \le -0.01,\ g_6(\vec{w}) \equiv w_6 - w_1 \le -0.01,\\
&g_7(\vec{w}) \equiv w_1 - w_8 \le -0.01,\ g_8(\vec{w}) \equiv w_8 - w_9 \le -0.01,
\end{aligned}$$

The constrained optimum solution after 200 generation is with a function value Table 8 displays the preference index values and ranking orders of the candidate materials. Based on Table 8, ranking orders of alternatives are exactly the same as the method suggested by Rao and Patel (2010), which supports the exactness of the proposed model in this paper. Similar to the Rao and Patel (2010) method the GA approach gives more logical and genuine ranking for this material selection problem compared to the ranking of materials for this application suggested by Fayazbakhsh et al. (2009).

Table 7 Properties of candidate materials for high-speed naval craft

Objectives	*Max*	*Max*	*Max*	*Max*	*Max*	*Min*	*Min*	*Min*	*Max*
Material	*YS*	*YM*	*FR*	*RY*	*RC*	*FC*	*R*	*D*	*WS*
1	234.4	204.1	H	VH	L	A	L	7,800	None
2	137.9	67	L	H	H	L	A	2,700	H
3	268.9	67	A	A	H	A	A	1,800	VH
4	379.2	204.1	H	A	H	VH	H	5,200	H
5	1,496.2	227.5	L	A	VH	VH	A	1,800	VH
6	220.6	53.9	VH	VH	VH	L	VH	2,500	H

Notes: Materials: 1: Grade A steel; 2: single skin aluminium (A5086-H34); 3: aluminium sandwich (honeycomb core); 4: LASCOR steel, 5: composite (CFRP); 6: carbon w/ vinyl ester resin; and 6: DUCTAL (UHP2C). Attributes: yield strength: YS (MPa); Young's modulus: YM (GPa); fire resistance: FR; reparability: RY; resistance to corrosion: RC; fabrication cost: FC; risk: R; density: D (kg/m^3); and Overall potential for weight saving: WS; low: L (0.335); average: A (0.5); high: H (0.665); very high: VH (0.745).

Table 8 Rankings of alternative materials of example 2

No.	*Proposed decision-making method*	
	Performance index	*Rank*
1	6.4675	6
2	13.0860	4
3	13.5800	3
4	11.0175	5
5	19.3009	1
6	15.4230	2

3.3 Example 3: flywheel

This example deals with the selection of the most suitable material for the design of a flywheel (Behzadian et al., 2012) (Table 9). Chatterjee et al. (2009) used VIKOR and ELECTRE and Jahan et al. (2010) implemented a linear assignment technique to solve the same problem. To make comparison of the results obtained by the proposed method with those reported by other researchers (Chatterjee et al., 2009; Jahan et al., 2010), the same subjective weights are considered in this paper. The constrained optimisation problem is defined as follows:

Minimise:

$$F(\vec{w})$$

Subject to:

$$g_1(\vec{w}) \equiv w_4 - w_3 \leq -0.01,\ g_1(\vec{w}) \equiv w_3 - w_2 \leq -0.01,$$

$$g_1(\vec{w}) \equiv w_2 - w_1 \leq -0.01,\ F(\vec{w}) = \sum_{j=1}^{4} w_j = 1,\ 0.1 \leq w_j \leq 0.4,\ j = 1, 2, 3, 4.$$

Table 9 Decision matrix for design of flywheel

No.	*Objectives*	*Max*	*Max*	*Min*	*Max*
	Materials	*a*	*b*	*c*	*d*
1	300 M	100	8.6125	4200	Poor (0.335)
2	2024-T3	49.6454	13.4752	2100	Poor (0.335)
3	7050-T73651	78.0142	12.5532	2100	Poor (0.335)
4	Ti-6AL-4V	108.8795	26.0042	10,500	Poor (0.335)
5	E glass-epoxy FRP	70	10	2735	Excellent (0.955)
6	S glass-epoxy FRP	165	25	4095	Excellent (0.955)
7	Carbon-epoxy FRP	440.2516	22.0126	35,470	Fairly good (0.745)
8	Kevlar 29-epoxy FRP	242.8571	28.5714	11,000	Fairly good (0.745)
9	Kevlar 49-epoxy FRP	616.4384	34.2466	25,000	Fairly good (0.745)
10	Boron-epoxy FRP	500	23	315,000	Good (0.59)

Notes: Material selection attributes: a: fatigue limit of the material/density (σ_{limit} / ρ); b: fracture toughness of the material/density (K_{IC} / ρ); c: material price per unit mass (*P*); d: fragmentability (*F*).

The constrained optimum solution after 100 generation is w^* = (0.3999, 0.3909, 0.1101, 0.1) with a function value equal to $F^* = -85.1598$. Table 10 displays the preference index values and ranking orders of the materials by the reported model. The Spearman's rank correlation coefficients between the proposed method and the VIKOR, ELECTRE (Chatterjee et al., 2009) and linear assignment (Jahan et al., 2010) are 0.9879, 0.9515 and 0.9030 respectively. The high Spearman's rank correlation coefficient between the rankings confirms the applicability of the suggested material selection method. Table 10 depicts that all the methods suggest material numbered as 9 (i.e., Kevlar49-epoxy FRP) as the first choice. This confirms the validity of the presented method. The ELECTRE method used by Chatterjee et al. (2009) implements the concept of outranking relationship and this makes the procedure rather lengthy. VIKOR method also involves more computation. In addition, VIKOR and ELECTRE methods presented by Chatterjee et al. (2009) did not clarify the quantisation process for the qualitative attributes. This imperfection along with unclear explanation for obtaining the weights of the attributes also applies to the linear assignment method suggested by Jahan et al. (2010).

Table 10 Comparing ranking orders of materials for flywheel

No.	*VIKOR*	*ELECTR*	*Linear assignment*	*Proposed decision-making method*	
	Rank			*Performance index*	*Rank*
1	9	10	7	0.7825	10
2	10	9	10	1.0456	9
3	8	8	8	1.0972	8
4	6	6	6	3.1446	6
5	7	7	9	1.2895	7
6	5	3	5	4.4771	5
7	2	2	3	9.0491	2
8	4	4	4	6.5575	4
9	1	1	1	85.1598	1
10	3	5	2	8.9908	3

Table 11 Candidate materials and ranking for example 4

Objectives	*Min*	*Max*	*Results*
Alternatives	$\sqrt{E}$	σ_f / E	*Rank*
Diamond	34.64	0.83	16
Si_3N_4	17.97	3.10	13
Al	8.37	4.29	8
SiO_2	8.54	13.70	5
Polymmide	2.83	5.00	7
Ti	10.77	4.31	10
Ni	13.89	2.59	12
PVDF	1.52	21.74	2
Au	8.37	4.29	8
Ni-Fe	10.95	13.33	6
SiC	21.21	4.44	14
Al_2O_3	16.58	7.27	11
Quartz	10.34	15.89	4
W	20.27	1.70	15
PMMA	1.55	33.33	1
Si	12.65	25.00	3

3.4 *Example 4*

Another example related to the material selection for a MEMS electrostatic actuator capable of large displacement with low actuation voltage. Table 11 shows the candidate materials, criteria and objectives. Yazdani and Payam (2015) solved the same problem using TOPSIS. By using the same subjective weights for handling constraints in our method, we resolved the material selection problem. The constrained optimum solution after 50 generation is $w^* = (0.5, 0.5)$ with a function value equal to $F^* = -5095.8$ The ranking orders of materials by the reported model which is exactly the same as the results reported by Yazdani and Payam (2015), using TOPSIS technique is shown in Table 11. The stability of the applied algorithm is verified as the first choice material is similar. Furthermore, the obtained ranking order by TOPSIS and suggested GA are the same, so very high degree of coefficient is understood. The TOPSIS method used by Yazdani and Payam (2015) for material selection involves lengthy calculations to obtain the ideal and negative ideal measures of the attributes and the closeness coefficients of the alternatives. In comparison to the TOPSIS method by Yazdani and Payam (2015), the MADM method presented here is simple, convenient and helps the decision maker to arrive at a precise decision about the weights of importance of the attributes.

3.5 *Example 5: metallic bipolar plates for polymer electrolyte fuel cell*

In this case study, the objective is to select an optimum material for metallic bipolar plates of polymer electrolyte fuel cell (Shanian and Savadogo, 2006a, 2006c). In

Table 12, the criteria, objectives and alternative materials are given. The same problem was considered earlier by Shanian and Savadogo (2006a) and Jahan et al. (2010) using comprehensive VIKOR technique. To define constraints in the optimisation model the same subjective weights are determined by those Jahan et al. (2010) applied:

Minimise:

$$F(\vec{w})$$

Subject to:

$$g_1(\vec{w}) \equiv w_{10} - w_2 \leq -0.01,\ g_2(\vec{w}) \equiv w_2 - w_5 \leq -0.01,$$
$$g_3(\vec{w}) \equiv w_5 - w_3 \leq -0.01,\ g_4(\vec{w}) \equiv w_3 - w_1 \leq -0.01,$$
$$g_5(\vec{w}) \equiv w_1 - w_7 \leq -0.01,\ g_6(\vec{w}) \equiv w_7 - w_4 \leq -0.01,$$
$$g_7(\vec{w}) \equiv w_4 - w_9 \leq -0.01,\ g_8(\vec{w}) \equiv w_8 - w_6 \leq -0.01,$$
$$g_9(\vec{w}) \equiv w_6 - w_9 \leq -0.01,\ g_2(\vec{w}) \equiv w_9 - w_{11} \leq -0.01,$$
$$h(\vec{x}) = \sum_{j=1}^{11} w_j = 1,\ 0.0024 \leq w_j \leq 0.3119,\ j = 1, 2, \ldots, 11.$$

Table 12 Alternatives for example 5

Objectives	*Max*	*Max*	*Max*	*Max*	*Max*	*Max*	*Min*	*Min*	*Min*	*Max*	*Min*
Materials	*a*	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*i*	*j*	*k*
1	0.729	2.812	0.147	19.02	270.9	253.5	71	5.089	0.081	0.7	5.1
2	0.84	2.781	0.094	29.31	251	44.15	80	10.83	0.081	0.7	5.4
3	0.867	3.214	0.133	24.1	244.4	174	74	7.142	0.23	0.7	5.3
4	0.768	2.714	0.111	24.43	269.6	322	69	5.184	0.081	0.7	2.2
5	2.474	5.814	0.036	158.8	629.4	4.224	3.9	50	2	0.9	160
6	0.822	3.24	0.246	13.12	295.4	76.6	65	4.954	0.105	0.75	0.69
7	0.891	3.141	0.2	15.7	305.8	28.95	55	5.69	0.105	0.75	0.69
8	0.821	3.1	0.198	15.63	292	51.49	57	5.53	0.105	0.75	0.69
9	0.95	3.351	0.159	20.97	267.3	42.52	62	5.76	0.105	0.75	0.69
10	1.018	3.735	0.092	40.26	232	12.42	77	5.99	0.081	0.7	5.4
11	1.824	5.792	0.142	40.67	203.9	4.385	60.3	34.56	0.061	0.65	0.32
12	0.952	3.342	0.2	16.64	237.3	50.56	40	10.37	0.005	0.3	4.2

Notes: Materials: (1) 316 austenitic stainless steel; (2) 310 austenitic stainless steel; (3) 317L austenitic stainless steel; (4) 316L austenitic stainless steel; (5) aluminium (gold plated); (6) AISI 446 ferritic stainless steel; (7) AISI 436 ferritic stainless steel; (8) AISI 444 ferritic stainless steel; (9) AISI 434 ferritic stainless steel; (10) 304 austenitic stainless steel; (11) titanium (coated with nitride); (12) A560 (50Cr–Ni). Material selection attributes:

$$a:\frac{E^{1/a}}{\rho};b:\frac{\sigma_F^{1/2}}{\rho};c:\frac{\sigma_t}{E\alpha};d:\frac{\alpha}{k}e:\frac{k}{\mu^{1/2}};f\,\frac{k_t^2}{E}$$

g: resistivity ($\mu ohmcm$); h: cost (CAN$/kg); i: corrosion rate (in/year); j: recycle fraction; k: hydrogen permeability. E = elastic modulus of bipolar plate; ρ = density; σ_F = tensile strength; α = expansion coefficient; k = thermal conductivity; μ = thermal diffusivity; k_t = fracture toughness.

The constrained optimum solution after 300 generation is w* = (0.0398, 0.0127, 0.0308, 0.0578, 0.0218, 0.1770, 0.0488, 0.1630, 0.1888, 0.0037, 0.2550) with a function value equal to $F^* = -50.9272$ To investigate the efficiency of our method we compare the results with the ranking obtained by Jahan et al. (2011), see Table 13. Spearman's rank correlation coefficient illustrates 0.9930 agreements between the two methods which is a high correlation for the ranking proposed by the two approaches. However, a close look at the values of the attributes for the materials 8 and 12 reveal that material 12 is comparatively better than material 8 in the case of seven attributes (namely; a, b, c, d, g, i and k) and comparatively worse in the case of four attributes (i.e., E, f, h and j). Thus suggesting material 12 as the fifth choice and material 8 as the sixth alternative which is given by the proposed GA method seems more genuine than that reported by Jahan et al. (2010). As a result, the proposed method is more logical and has ranked the alternative materials with less calculation. It is worthwhile to state that it does not matter the different methods results in different rankings for alternative materials, as long as the first choice material is consistent.

Table 13 Rankings of alternative materials of example 5

No.	*Comprehensive VIKOR*	*Proposed decision-making method*	
	Rank	*Performance index*	*Rank*
1	2	44.5747	2
2	9	17.5589	9
3	3	31.6469	3
4	1	50.9272	1
5	12	2.2373	12
6	4	21.5814	4
7	8	18.0518	8
8	5	19.5963	6
9	7	18.8494	7
10	10	16.3667	10
11	11	13.0694	11
12	6	19.6569	5

3.6 Example 6

Material selection for femoral component of knee prosthesis is considered as a six case to evaluate the efficiency of the proposed method in the biomedical material selection applications. The problem, which consists of ten alternatives and seven attributes, was solved by Bahraminasab and Jahan (2011) using comprehensive VIKOR method. The candidate materials, target values, criteria and their quantified values, which are obtained by using the fuzzy conversion scale proposed in Rao (2006), are listed in Table 14. Bahraminasab and Jahan (2011) used a combination of pair-wise and direct weight (i.e., revised Simos method (Figueira and Roy, 2002) to define the importance degree of criteria, we use the same values of direct weighting to specify constraints:

Minimise:

$$F(\vec{w})$$

Subject to:

$$g_1(\vec{w}) \equiv w_1 - w_4 \leq -0.01,\ g_2(\vec{w}) \equiv w_4 - w_2 \leq -0.01,$$
$$g_3(\vec{w}) \equiv w_2 - w_3 \leq -0.01,\ g_4(\vec{w}) \equiv w_3 - w_5 \leq -0.01,$$
$$g_5(\vec{w}) \equiv w_5 - w_7 \leq -0.01,\ g_6(\vec{w}) \equiv w_7 - w_4 \leq -0.01,$$
$$h(\vec{w}) = \sum_{j=1}^{7} w_j = 1,\ 0..051 \leq w_j \leq 0.256,\ j = 1, 2, \ldots, 7.$$

Table 14 Properties of candidate materials for femoral component

Objectives	*1.30*	*1,240.00*	*16.00*	*54.00*
Material	*Density(g/cc)*	*Tensile strength (MPa)*	*Modulus of elasticity (GPa)*	*Elongation (%)*
1	8	517	200	40
2	8	862	200	12
3	9.13	896	240	10–30
4	8.3	655	240	10–30
5	4.5	550	100	54
6	4.43	985	112	12
7	4.52	≥ 900	105–120	10
8	4.52	1,000–1,100	110	10–15
9	6.50	≥ 1240	≥ 48	12
10	4.3	1,000	15	12

Objectives	*0.96*	*0.96*	*0.96*
Material	*Corrosion resistance*	*Wear resistance*	*Osseointegration*
1	High (0.665)	Above average (0.59)	Above average (0.59)
2	High (0.665)	Very high (0.745)	Above average (0.59)
3	Very high (0.745)	Extremely high (0.865)	High (0.665)
4	Very high (0.745)	Extremely high (0.865)	High (0.665)
5	Exceptionally high (0.955)	Above average (0.59)	Very high (0.745)
6	Exceptionally high (0.955)	High (0.665)	Very high (0.745)
7	Exceptionally high (0.955)	High (0.665)	Very high (0.745)
8	Exceptionally high (0.955)	High (0.665)	Very high (0.745)
9	Extremely high (0.865)	Exceptionally high (0.955)	Average (0.5)
10	Very high (0.745)	Exceptionally high (0.955)	Exceptionally high (0.955)

Notes: Materials: (1) stainless steel L316 (annealed); (2) stainless steel L316 (cold worked); (3) Co-Cr alloys (wrought Co-Ni-Cr-Mo); (4) Co-Cr alloys (cast able Co-Cr-Mo);(5) Ti alloys (pure Ti); (6) Ti alloys (Ti-6Al-4V); (7) Ti-6Al-7Nb (IMI-367 wrought); (8) Ti-6Al-7Nb (protasul-100 hotforged); (9) NiTi shape memory alloy; (10) Porous NiTi shape memory alloy.

The constrained optimum solution after 400 generation is w^* = (0.0751, 0.1033, 0.1123, 0.0841, 0.1213, 0.256, 0.247) with a function value equal to F^* = –25.0420. Table 15 demonstrates the performance index for each of the candidate materials and compares ranking orders with the comprehensive VIKOR approach (Bahraminasab and Jahan, 2011). According to Spearman's rank correlation coefficient there is 0.8909 agreement between two approaches. The similarities of the first five choices for the application by two methods verify the stability of the proposed method with regard to different material selection problems. The reason this material selection problem is chosen is to challenge the applicability of the presented method with regard to medical material problems which the result validate the potential of the GA approach in this field.

Table 15 Ranking of materials

No.	*Comprehensive VIKOR*	*Proposed decision-making method*	
	Rank for λ = 0	*Performance index*	*Rank*
1	10	1.5924	10
2	6	3.5854	9
3	8	7.5673	6
4	9	6.8683	7
5	7	6.0214	8
6	4	7.9103	4
7	5	7.5879	5
8	3	8.0924	3
9	2	8.8050	2
10	1	25.0420	1

3.7 Example 7

The seventh example is related to the selection of suitable material for mass produced non-heat-treatable cylindrical sheet, which was considered by several researchers (Shanian and Savadogo, 2006c, 2009; Shanian et al., 2008; Rao and Davim, 2008; Jahan et al., 2012). Table 16 demonstrates objectives, eight alternative sheet materials and 12 material selection attributes for this case. To define constraints in our optimisation model the same subjective weights are determined by those Rao and Davim (2008) applied. The constrained optimum solution after 400 generation is w^* = (0.0275, 0.0636, 0.0456, 0.1577, 0.1425, 0.0546, 0.0726, 0.0715, 0.0185, 0.0366, 0.1335, 0.1748) with a function value equal to F^* = –30.7053 Table 17 compares the ranking orders of alternative materials obtained by the reported method with those suggested in Rao and Davim (2008). This example reveals that as the number of attributes increases, the amount of calculations that GA algorithm requires to assign the weight of attributes rises quite rapidly. Also, there is some illogical ranking for the alternative materials 7 and 8 in our method which is due to the large number of attributes and weight assignment process. However, from Table 17, it is understood that the material designated as four is the first right choice for the given design application which matches well with that suggested by Rao and Davim (2008) and Jahan et al. (2012).

Table 16 Alternatives for example 7

Objectives	*Min*	*Max*	*Max*	*Min*	*Min*	*Max*
Material's no.	*D*	*CS*	*UT*	*SB*	*BF*	*SL*
1	8.25	560	940	0.78	15,183	2,916
2	8.65	460	600	0.71	12,472	2,395
3	8.94	50	210	0.08	1,355	260
4	8.95	340	380	0.48	9,218	1,770
5	2.67	190	295	0.25	2,0317	1,966
6	8.06	690	1030	1.55	5,909	2,174
7	8.63	95	270	0.17	2,711	520
8	7.08	267	355	0.48	1,957	720
Objectives	*Max*	*Max*	*Max*	*Max*	*Max*	*Min*
Material's no.	*H*	*YS*	*EM*	*TD*	*TC*	*C*
1	380	560	138	465	105	18.64
2	220	460	125	465	205	13.99
3	45	50	122	460	398	3
4	115	340	135	460	390	3.46
5	87	191	73.59	741	152	2.81
6	350	800	190	189	17	5.99
7	63	100	116	174	185	3.32
8	110	265	205	329	50	1.04

Notes: Material selection attributes: D density (milligram per cubic meter), CS compressive stress (megapascal), UT ultimate tensile stress (megapascal), SB spring back index, BF bend force index, SL static load index, H hardness (Vickers), YS yield stress (megapascal), EM elastic modulus (gigapascals), TD thermal diffusivity (square centimeters per hour), TC thermal conductivity (Watts per meter Kelvin), C cost of base material (Canadian dollars per kilogram). Materials: 1 copper-2beryllium (cast), 2 copper-cobalt-beryllium (cast), 3 electrolytic tough-pitch, h.c. copper, soft (wrought), 4 electrolytic tough-pitch, h.c. copper, hard (wrought), 5 wrought aluminium alloy, 6 wrought austenitic stainless steel, 7 commercial bronze, CuZn10, soft (wrought), 8 carbon steel (annealed).

Table 17 Ranking orders of the materials for example 7

No.	*Rao and Davim (2008)*	*Jahan et al. (2012)*	*Proposed decision-making method*	
	Rank	*Rank*	*Performance index*	*Rank*
1	8	8	9.7727	8
2	7	7	13.9694	5
3	3	2	24.0326	2
4	1	1	30.7053	1
5	6	6	13.3177	6
6	5	5	12.7998	7
7	4	4	19.7756	3
8	2	3	18.2057	4
Correlation coefficient	0.8333	0.8810		

Figure 3 Feasible solutions for test problem 2

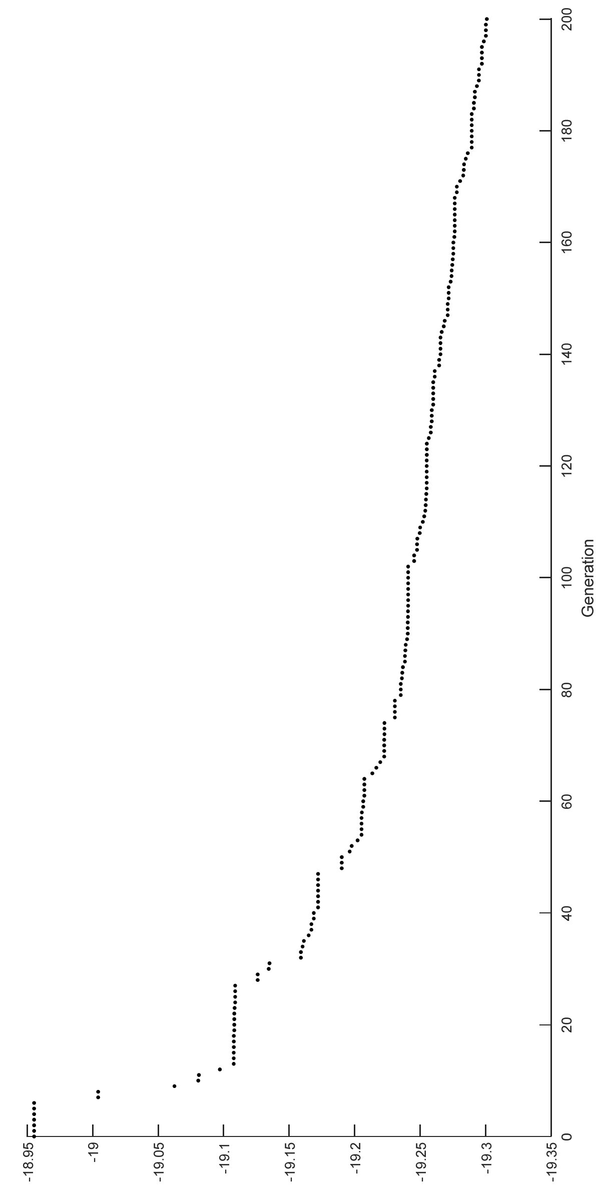


Figure 4 Feasible solutions for test problem 3

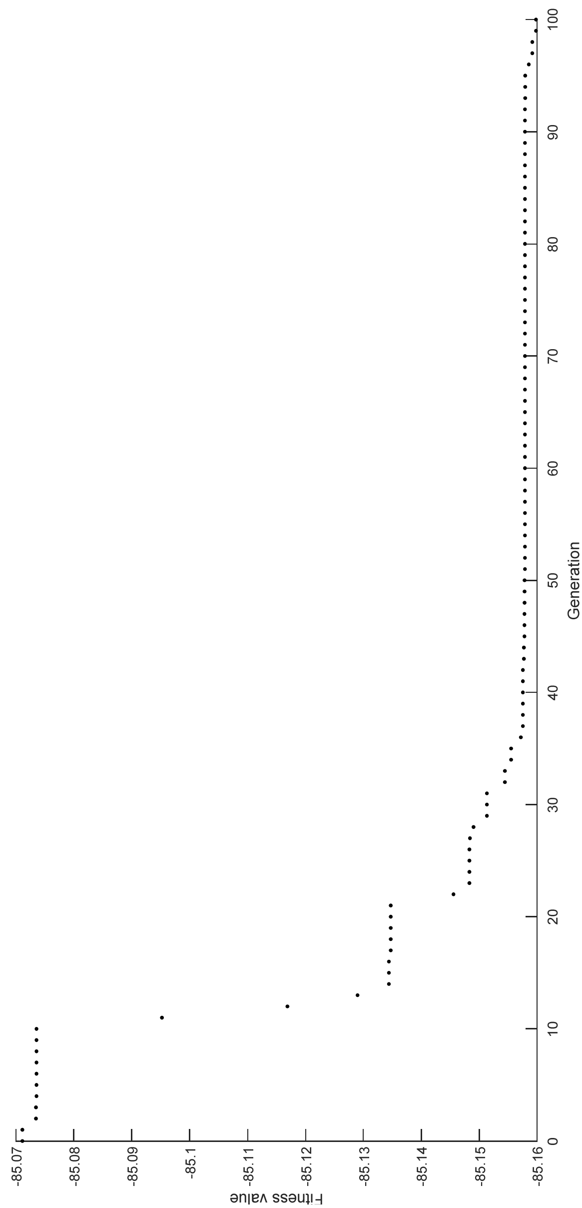


Figure 5 Feasible solutions for test problem 4

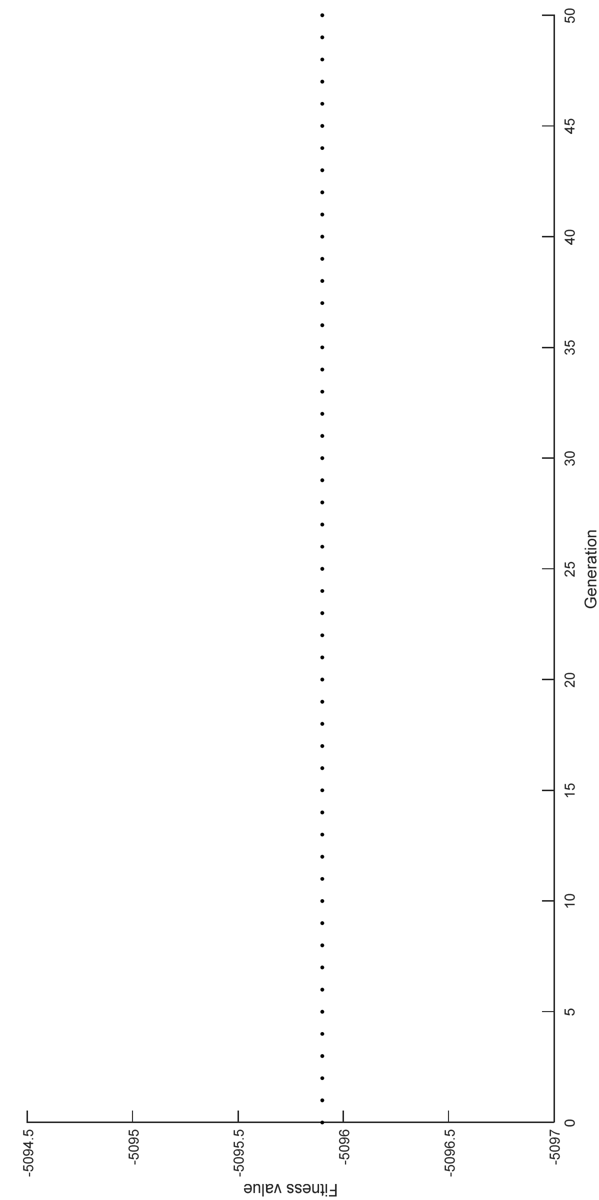


Figure 6 Feasible solutions for test problem 5

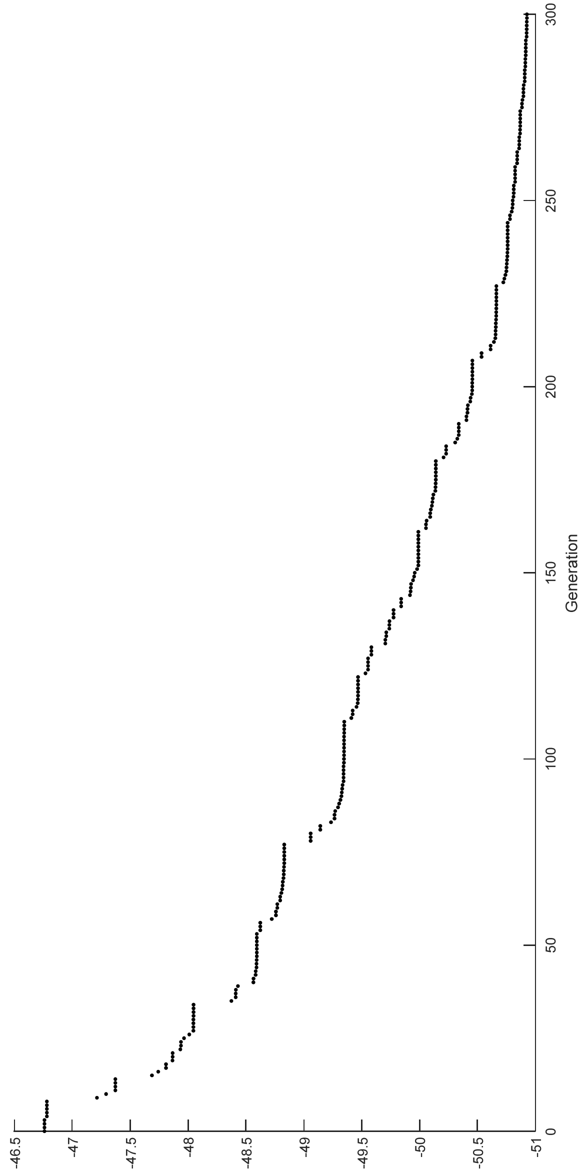


Figure 7 Feasible solutions for test problem 6

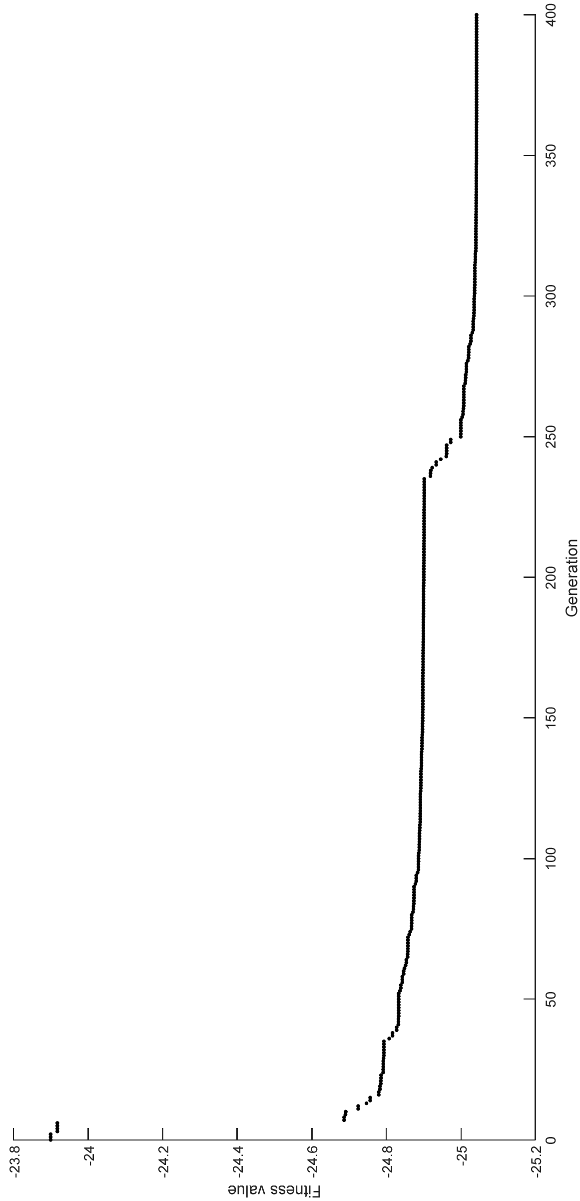
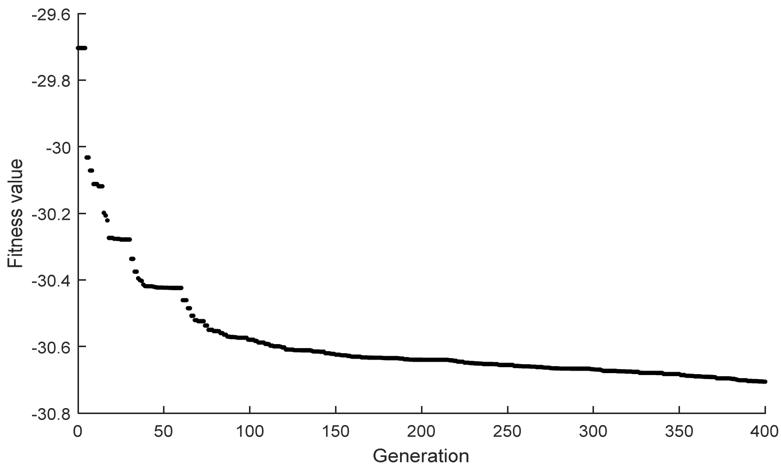


Figure 8 Feasible solutions for test problem 7



Results of the applied examples demonstrated the potentiality of the proposed procedure for selecting an optimum material in any type of decision-making situations. Figure 3 to 8 show feasible solutions in each iteration obtained by using GA for each example mentioned above.

4 Conclusions

A novel method for evaluating weights of criteria and selecting optimal materials from any numbers of available alternative materials is proposed in this paper. The GA is exploited to measure the relative closeness of each alternative and ranks them according to their selection index. The ranking results produced by using the reported method are consistent with the previous material selection methods and show that the proposed procedure is feasible for selecting materials under uncertainty. The suggested methodology is effective for situations where the information regarding weight of the criteria is incomplete and can simultaneously consider any numbers of quantitative and qualitative material selection attributes. Also, our approach lessens the inadvertent human errors for assigning attributes weight.

The GA would, also, be useful for cases where both material selection and topology optimisation should be considered simultaneously. So this paper should be of value to researchers who work on multi objective optimisation technique in materials and design applications.

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