

BHARAT: A simple and effective multi-criteria decision-making method that does not need fuzzy logic, Part-2: Role in multi- and many-objective optimization problems

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ABSTRACT

A simple and effective multi-attribute decision-making method, named as BHARAT method, is proposed in Part-1 of this paper and the same method is used now as a multi- and many-objective decision-making method for evaluating the Pareto optimal solutions. The proposed BHARAT method is used to identify the best compromise Pareto solution. Based on their importance for the given optimization problem, the objectives are ranked, and the weights are assigned. The weights of the objectives and the normalized values of the objectives for different Pareto optimal solutions are used to compute the total scores. The total scores are used to differentiate the alternative optimal solutions and an alternative solution that gets the highest total score is suggested as the best compromise solution. Three case studies are presented to illustrate and validate the proposed BHARAT method. The case study 1 is a multi-objective optimization problem related to cloud manufacturing with 3 objectives and 20 alternative solutions; case study 2 is a many-objective optimization problem of electro-discharge machining process with 4 objectives and 50 alternative solutions; case study 3 is a many-objective optimization of milling process parameters with 4 objectives and 100 alternative solutions. The outcomes of the suggested BHARAT method are compared with those of the other popular decision-making approaches for each of the three case studies considered. The suggested simple and more logical BHARAT method can be used in multi- and many-objective optimization problems to select the best compromise solution.

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1. Introduction

Making decisions in the presence of several conflicting criteria is referred to as multi-criteria decision-making (MCDM). The two categories of MCDM problems are: (1) multi-objective decision-making (MODM) and (2) multi-attribute decision-making (MADM) (Rao, 2013). In MODM problems, a set of objective functions must be maximized or minimized within a domain containing acceptable variable values while meeting certain constraints. Many sets of variables that satisfy the stated constraints and maximize or minimize the objective functions may exist in the domain. The values of the corresponding objective functions make the Pareto front, and the trade-offs make the Pareto optimal set (Deb, 2001). There can be any number of objectives in the MODM problems. Many-objective optimization problems are MODM problems that have four or more objectives. The following provides an illustration of a MODM problem.

Maximize $f_1 = 3x_1 + 0.85x_2 + 1.56x_3 + 0.45x_4$

Minimize $f_2 = 0.73x_1 + 5x_2 + 2x_3 + 0.92x_4$

Subject to constraints: $x_1 + x_2 + 1.2x_3 + x_4 \leq 175$; $x_1 + 0.15x_2 + x_3 + 0.3x_4 \leq 200$; $3x_1 + 1.5x_2 + x_4 \leq 120$

Bounds of variables: $0 \leq x_1 \leq 40$, $0 \leq x_2 \leq 30$, $0 \leq x_3 \leq 46$, $0 \leq x_4 \leq 17$.

The objective functions f_1 and f_2 and the constraints are described in terms of the decision variables x_1 , x_2 , x_3 and x_4 . Both the constraints and the objective functions can generally be either linear or non-linear. The best option should meet the decision maker's preferences and constraints. In a continuous or integer domain, the decision variable values are chosen from an infinite

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or large number of choices. The MODM problems are solved by algorithms such as the multi-objective genetic algorithm (MOGA), non-dominated sorting genetic algorithm (NSGA)-II or NSGA-III, strength pareto evolutionary algorithm 2 (SPEA-2), multi-objective versions of particle swarm optimization (PSO), differential evolution (DE), artificial bee colony (ABC), ant colony optimization (ACO), teaching-learning-based optimization (TLBO), Jaya algorithm, etc.

Recently, a few researchers have started using the fuzzy logic for expressing the values of decision variables and the objective functions. However, these may be called as heedless attempts to apply fuzzy techniques anywhere there are numerical values, without scrutinizing the legitimacy of the methodology. Certain procedures view all numbers as amenable to fuzzy logic. When we proceed in that manner without questioning why, the modeling effort may turn into a misguided intellectual diversion intended only for publication, with little regard for the accuracy of our work. Many journal editors and reviewers approved the articles for publication without questioning the validity of the results. The idea that it is preferable to fuzzify the objective functions and the decision variables is, in fact, unsupported by data or mathematical reasoning.

All solutions in the Pareto front are non-dominated and hence these can be regarded as equivalent once a set of them is found. For every solution, there is a different trade-off between the objectives. Therefore, the best solution can be defined as the one that achieves the best compromise between the objectives. To find the best compromise, researchers have therefore been utilizing various MADM methods such as AHP, TOPSIS, GRA, PROMETHEE, WPM, etc. for the past few years. These methods have shown to be effective in a variety of decision-making scenarios. However, as Part-1 of this paper explains, each of these methods has advantages and disadvantages of its own. The recently proposed R-method (Rao and Lakshmi, 2021a, 2021b) developed an equation and a table that can be used to assign ranks to the objectives and the alternatives and then the ranks can be converted into corresponding weights. The weights proposed by the R-method are comparatively more stable and meaningful than the other ranking methods. However, even though R-method has simplified the decision-making process, assigning the ranks to the available quantitative values of objectives for different alternatives may not be much appropriate. It is because, if two alternative solutions have very close data for a particular objective, then they are assigned ranks 1 and 2 as per the R-method and the corresponding weights are assigned using a table developed for the purpose. This may make some difference in evaluation of alternatives, even though the values of the objective for the two alternatives do not differ significantly. To avoid this, a new MADM method named as BHARAT is presented in Part-1 of the paper. The BHARAT method uses R-method for assigning the ranks and weights to the objectives but not to the alternatives.

The next section describes how to make use of BHARAT methodology in multi- and many-objective optimization problems to evaluate the Pareto optimal solutions.

2. Proposed BHARAT methodology in multi- or many-objective optimization to evaluate the Pareto optimal solutions

2.1 BHARAT

In MODM methods, every decision table includes alternative solutions (which are called non-dominated solutions), objectives (just like attributes in MADM problems), performance measures of the objectives for different alternative solutions and the weights of the objectives. The decision maker's job is to evaluate each alternative and determine which is the best option based on the information in the decision table and the chosen decision-making technique. The steps of the proposed decision-making methodology using BHARAT are explained below.

Step 1: Identify the multi- or many-objective decision-making situation, pertinent objectives A_i ($i = 1, 2, \dots, m$) and the alternative solutions B_j (for $j = 1, 2, \dots, n$). The pertinent objectives include both beneficial and non-beneficial objectives. The beneficial objectives are those whose higher values are desirable, and non-beneficial objectives are those whose lower values are desirable. Create a decision table with the non-dominated alternative solutions obtained by using any advanced multi-objective optimization algorithm.

Step 2: To determine the objectives' weights w_i (for $i=1, 2, \dots, m$), order the objectives according to the decision-maker's assessment of their significance in terms of 1, 2, 3, 4, and so on. When two or more objectives are deemed to be equally significant, they are given an average rank. The R-method, which the author recently proposed (Rao and Lakshmi, 2021a, b), is used in the proposed BHARAT method. Table A1 or Eq. (1) given in Part-1 of this paper can be used for assigning the weights to the objectives. In a group decision-making scenario, compute the average value of the ranks given by the decision-makers for each objective as explained in Part-1 of the paper.

Step 3: Normalize the data of an objective for different alternative solutions with reference to the "best" value of the objective. Repeat this normalization procedure for all the objectives to get the normalized data. The word 'best' indicates the highest available value of the beneficial objective or the lowest available value of the non-beneficial objective. The performance measures of alternatives x_{ji} (for $j = 1, 2, \dots, n$; $i = 1, 2, \dots, m$) are to be normalized. The normalized value $(x_{ji})_{\text{normalized}}$ of an alternative corresponding to a beneficial objective is $x_{ji}/x_{ji, \text{best}}$, and it is $x_{ji, \text{best}}/x_{ji}$ in the case of non-beneficial objective. The $x_{ji, \text{best}}$ is the best value of i^{th} objective for j^{th} alternative. This type of normalizing the data with reference to the "best" values clearly shows the standing positions of the alternative solutions with reference to the "best" values of the objectives.

Step 4: Total score of an alternative solution is computed by $\sum w_i \cdot (x_{ji})_{\text{normalized}}$ which is the result of multiplying the normalized data of the objectives for the alternative solutions with the corresponding weights of the objectives.

Step 5: Sort the alternative solutions according to the total scores in decreasing order. For the particular decision-making scenario under consideration, the alternative solution with the highest total score is deemed optimal. The decision-maker can implement this best compromise optimal solution.

2.2 Second version of BHARAT

Another version of BHARAT is proposed in Part-1 of this paper and the *steps of this version are same as the steps of BHARAT except step-2*. In this version, the objectives are ranked in terms of 1, 2, 3, 4, etc., according to the decision-maker's assessment of their relative importance in determining the weights of the objectives. When two or more objectives are deemed to be equally significant, they are given an average rank. Table A2 or Eq. (2) or the appropriate procedure suggested to form Table 14 and Table 21 given in Part-1 of this paper can be used for assigning the weights to the objectives. In group decision-making scenario, compute the average value of the ranks given by the decision-makers for each objective as explained in Part-1 of the paper.

The next section demonstrates the applications of the proposed BHARAT method to three industrial case studies.

3. Demonstration of applications of the proposed BHARAT method for evaluating the Pareto optimal solutions

This section provides three case studies to illustrate the proposed BHARAT method and compare its performance with the other widely used MADM methods.

3.1 Case study 1: Multi-objective optimization of production planning in cloud manufacturing

Li et al. (2019) presented a multi-objective optimization case study that was related a Company A that received an order for the manufacturing and processing of automobiles. Owing to limited production capacity and elevated production costs, certain production duties were delegated to certain manufacturers via the cloud manufacturing platform. Using the modularization theory, the company broke down the automobile processing order and determined that three distinct types of modules—designated as Modules 1, 2, and 3—need to be produced and processed. Following that, the cloud manufacturing platform received specific module requirements from the company. Some candidate resources could be processed, some could not, and some could only be partially processed due to the wide variations in the module's functional requirements and type. The Company A's production planning for an order must take into account the unique demands of the customers as well as the company's and the manufacturers' manufacturing resources and capabilities in the cloud manufacturing platform. The optimization of production planning process was performed using NSGA-II based on the decision-makers' preferences. The detailed procedure is displayed in Fig. 1.

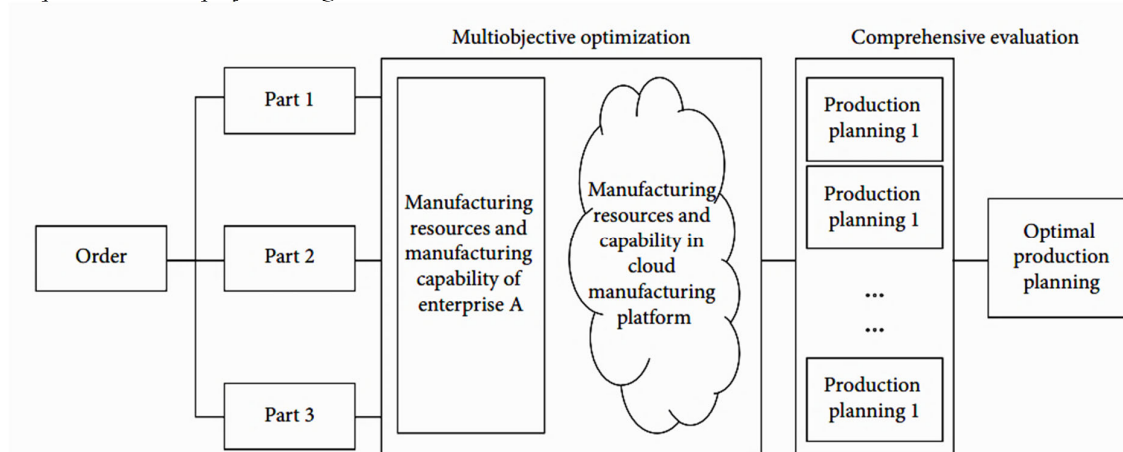


Fig. 1. Process of Production planning and optimization of Company A (Li et al., 2019)

After the processing module, the company A still needs to assemble the parts to form the product in the order for delivery, in compliance with the project order's requirements for quantity, delivery time, and product quality. As a result, company A adjusts the order's specific requirements to suit its own processing conditions. Twenty schemes of non-dominated solutions produced by NSGA-II were included in the calculation results, and each scheme of non-dominated solutions corresponds to a production planning. Table 1 displays the production planning schemes containing the non-dominating solutions derived from NSGA-II.

Table 1

Production planning schemes containing the non-dominating solutions derived from NSGA-II for case study 1

Alternative schemes	Modules	Company A	Cloud manufacturer					Product cost	Delivery time	Product quality (%)
			1	2	3	4	5			
Scheme 1	Module 1	251	1570	—	715	256	208	13581	58053	87.14
	Module 2	—	17	926	1150	549	858			
	Module 3	285	908	1892	172	—	773			
Scheme 2	Module 1	254	1571	—	715	255	205	14155	55959	89.06
	Module 2	—	17	926	1453	169	935			
	Module 3	1908	16	1863	174	—	39			
Scheme 3	Module 1	254	21	—	715	2556	1754	13453	62239	85.98
	Module 2	—	17	926	1455	170	932			
	Module 3	285	907	1863	172	—	773			
Scheme 4	Module 1	254	1571	—	715	256	204	14265	61662	90.38
	Module 2	—	1852	258	1150	170	70			
	Module 3	1908	16	1863	175	—	38			
Scheme 5	Module 1	254	1570	—	715	256	205	13915	59417	87.71
	Module 2	—	773	328	1454	169	776			
	Module 3	285	907	1863	172	—	773			
Scheme 6	Module 1	19	21	—	715	735	1510	14038	67404	88.90
	Module 2	—	1852	328	1150	170	—			
	Module 3	1908	16	1863	172	—	41			
Scheme 7	Module 1	251	1570	0	716	256	207	13751	60622	87.88
	Module 2	—	773	928	1453	169	177			
	Module 3	285	907	1863	172	—	773			
Scheme 8	Module 1	19	21	0	715	255	1990	13523	68547	87.10
	Module 2	—	1852	328	1150	170	—			
	Module 3	285	907	1862	174	—	772			
Scheme 9	Module 1	254	1570	—	715	256	205	13846	60305	87.65
	Module 2	—	773	925	1150	169	483			
	Module 3	286	907	1863	173	—	771			
Scheme 10	Module 1	254	1571	—	716	256	203	14246	61801	90.41
	Module 2	—	1852	328	1150	170	—			
	Module 3	1909	18	1863	175	—	35			
Scheme 11	Module 1	254	1570	—	715	256	205	14155	55964	89.06
	Module 2	—	17	926	1453	170	934			
	Module 3	1909	15	1863	174	—	39			
Scheme 12	Module 1	19	21	—	715	735	1510	13312	63953	85.88
	Module 2	—	17	928	1455	549	551			
	Module 3	284	908	1862	172	—	774			
Scheme 13	Module 1	19	21	—	715	256	1989	13431	62712	85.76
	Module 2	—	17	928	1454	170	931			
	Module 3	285	907	1863	172	—	773			
Scheme 14	Module 1	19	21	—	715	735	151	13486	69030	87.01
	Module 2	—	1852	328	1150	170	—			
	Module 3	284	908	1862	172	—	774			
Scheme 15	Module 1	254	21	—	173	256	1753	13371	63004	86.20
	Module 2	—	18	928	1455	549	550			
	Module 3	285	907	1863	716	—	772			
Scheme 16	Module 1	254	1571	—	715	255	205	14494	57565	89.52
	Module 2	—	774	258	1368	169	931			
	Module 3	1909	16	1863	174	—	38			
Scheme 17	Module 1	254	1570	—	715	256	205	13695	63430	88.51
	Module 2	0	1852	328	1150	170	—			
	Module 3	284	907	1863	174	—	772			
Scheme 18	Module 1	253	1571	—	715	255	206	14074	56722	89.28
	Module 2	—	18	926	1453	548	555			
	Module 3	1909	16	1863	174	—	38			
Scheme 19	Module 1	19	21	—	715	735	1510	14038	67404	88.91
	Module 2	—	1852	328	1150	170	—			
	Module 3	1908	16	1863	172	—	41			
Scheme 20	Module 1	20	21	—	715	735	1509	13313	63594	85.89
	Module 2	—	18	928	1455	549	550			
	Module 3	285	908	1862	172	—	773			

The steps of the proposed BHARAT method are now followed as outlined below to determine which of the 20 alternative schemes is the best solution.

Step 1: There are 3 objectives (i.e., product cost, delivery time, and product quality) and it is a multi-objective decision-making situation. The 20 non-dominated alternative schemes obtained by NSGA-II algorithm for different schemes are shown in Table 1. The units of product cost and delivery time were not mentioned by Li et al. (2019). The objectives and lower values are desirable. Product quality is a beneficial objective, and product cost and delivery time are non-beneficial objectives.

Step 2: To determine the weights of the objectives w_i (for $i=1, 2, 3$), the objectives are ranked according to the decision-maker's assessment of their significance in terms of 1, 2, and 3. Li et al. (2019) considered AHP weights, entropy weights, and the combined weights of the objectives. The AHP weights for the product cost, delivery time, and the product quality were 0.369841, 0.297884, and 0.332275 respectively. The corresponding entropy weights were 0.246654, 0.303342, and 0.450004; and the corresponding combined weights were 0.275508, 0.272903, and 0.451589. In the present work, rank 1 is given to product quality, rank 2 is given to product cost, and rank 3 is given to the product quality. Using the BHARAT

methodology and Table A1 given in Part-1 of this paper, the weights of 0.30137, 0.24658, and 0.45205 are assigned to the product cost, delivery time, and product quality respectively.

Step 3: The data of the objectives for different alternative schemes is normalized with reference to the objectives' "best" values. The values of product quality are normalized as $x_{ji}/x_{ji.best}$, and the objectives of product cost and delivery time are normalized as $x_{ji.best}/x_{ji}$. This type of normalizing the data with reference to the "best" values clearly show the standing positions of the alternative schemes with reference to the "best" values of the objectives. The normalized data of the objectives is shown in Table 2.

Table 2

Normalized values of the objectives and the total scores of the alternative schemes for case study 1

Alternative schemes	Normalized values of the objectives			Total scores using BHARAT	Ranks of alternative schemes given by BHARAT
	Product cost	Delivery time	Product quality		
Scheme 1	0.980193	0.96393	0.963831	0.968786	5
Scheme 2	0.940445	1	0.985068	0.975302	1
Scheme 3	0.989519	0.899099	0.951001	0.949811	14
Scheme 4	0.933193	0.907512	0.999668	0.956911	10
Scheme 5	0.956665	0.941801	0.970136	0.95909	7
Scheme 6	0.948283	0.830203	0.983298	0.934996	19
Scheme 7	0.968075	0.923081	0.972016	0.958762	8
Scheme 8	0.984397	0.81636	0.963389	0.96972	4
Scheme 9	0.961433	0.927933	0.969472	0.956807	11
Scheme 10	0.934438	0.905471	1	0.956932	9
Scheme 11	0.940445	0.999911	0.985068	0.97528	2
Scheme 12	1	0.875002	0.949895	0.946528	17
Scheme 13	0.99114	0.892317	0.948568	0.947527	16
Scheme 14	0.987098	0.810648	0.962394	0.932421	20
Scheme 15	0.995587	0.888182	0.953434	0.950048	13
Scheme 16	0.918449	0.972101	0.990156	0.964094	6
Scheme 17	0.972034	0.882217	0.978985	0.953029	12
Scheme 18	0.945858	0.986548	0.987501	0.974716	3
Scheme 19	0.948283	0.830203	0.983409	0.935046	18
Scheme 20	0.999925	0.879942	0.950006	0.947773	15

Step 4: The weights of the objectives and the corresponding normalized data of the objectives for each of the 20 alternative schemes are multiplied to get the total scores of the alternative schemes. Table 2 also displays the total scores and the ranks of the alternative schemes.

Step 5: For the particular decision-making scenario under consideration, alternative scheme 2 has the highest total score. The second, third, and last choices are scheme 11, scheme 18, and scheme 14 respectively. The ranking of schemes is: 2-11-18-8-1-16-5-.....-14. Therefore, the decision-maker can select scheme 2 with the following details given in Table 3.

Table 3

Optimal production planning scheme suggested by BHARAT method for case study 1

Alternative schemes	Modules	Company A Cloud manufacturer						Product cost	Delivery time	Product quality (%)
		254	1571	—	715	255	205			
Scheme 2	Module 1	254	1571	—	715	255	205	14155	55959	89.06
	Module 2	—	17	926	1453	169	935			
	Module 3	1908	16	1863	174	—	39			

Li et al. (2019) used the combined weights in TOPSIS method (i.e., 0.275508, 0.272903, and 0.451589 for product cost, delivery time, and product quality respectively). These weights are also considered now by the BHARAT method for comparison purpose and applied to the same case study's normalized data of the objectives given in Table 2. It is observed that the ranking obtained by using the combined weights in BHARAT method also led to the same ranking of alternative schemes as given by BHARAT. It is because of the reason that the difference between the combined weights used in TOPSIS method are almost same as the weights used by BHARAT method in the computation of total scores. In fact, Li et al. (2019) carried out the AHP calculations and the TOPSIS calculations incorrectly. For example, the AHP matrix given in Eq. (31) of their paper is highly inconsistent and the consistency ratio is about 0.69 which is much more than the allowed value of 0.10. Hence AHP weights calculated by them were incorrect. Using such incorrect weights and the entropy weights, Li et al. (2019) calculated the combined weights and carried out the TOPSIS calculations which were, again, incorrect. Hence, the rankings given by them to the schemes as 3-13-20-15-12-....-10 is incorrect. Comparing the data of scheme 2 with the data of scheme 3, it is very clear that scheme 2 is better than scheme 3 in the case of delivery time and product quality whose combined weightage is 0.6986 (i.e., 69.86%). Hence, proposing scheme 2 as the first choice by BHARAT is logical. With the same logic, it can be said that proposing scheme 11 as second choice by BHARAT is more logical compared to scheme 13 proposed by Li et al. (2019) using TOPSIS method. Similarly, the differences in the other ranks of the schemes can be explained.

Second version of BHARAT method for case study 1

Second version of BHARAT method differs from BHARAT only in Step 2. The ranks assigned to the objectives are same as those given in BHARAT. Using Table A2 or Eq. (2) of Part-1 of the paper, the weights are assigned as 0.2727, 0.1818, and 0.5454 to product cost, delivery time, and product quality respectively. Using these weights, and the normalized data of the objectives, the total scores are computed which gives the ranking as 18-2-11-.....14. Here the scheme 18 is taking first place, scheme 2 is taking second place, scheme 11 is taking third place, and scheme 14 is taking the last place. It may be noted that the weights used in the second version of BHARAT are considerably different from the weights considered in BHARAT and hence the difference is there in ranking.

3.2 Case study 2: Many-objective optimization of electro-discharge machining process

Rao *et al.* (2016) carried out research on electro-discharge machining process and created models for maximizing the metal removal rate (*MRR*), minimizing the tool wear rate (*TWR*), minimizing the taper angle (θ), and minimizing the delamination factor (*DF*). The gap voltage (V_g), pulse current (I_p), pulse-on time (T_{on}) and tool rotation speed (N) were the process parameters taken into consideration for optimization. The four objective functions were then simultaneously optimized using a non-dominated sorting strategy by a multi-objective Jaya (MO-Jaya) algorithm. Table 1 lists the 50 non-dominated alternative solutions as well as the corresponding process parameter values. Each non-dominated alternative solution is made up of a set of values of *MRR*, *TWR*, θ and *DF* that match a set of V_g , I_p , T_{on} and N process parameters. Now, the steps of the suggested BHARAT method are followed as described below in order to select the best compromise solution.

Step 1: There are 4 objectives and hence it is a many-objective decision-making situation. The 50 non-dominated alternative solutions that the MO-Jaya algorithm produced for 50 sets of input parameters are shown in Table 4. The objectives *TWR*, θ and *DF* are non-beneficial and *MRR* is beneficial.

Table 4
Pareto optimal solutions generated by MO-Jaya algorithm for case study 2 (Rao *et al.*, 2016)

Solution no.	Process Parameters				Objectives			
	V_g (V)	I_p (A)	T_{on} (μ s)	N (rpm)	<i>MRR</i> (0.1 mg/s)	<i>TWR</i> (0.1 mg/s)	θ (degree)	<i>DF</i>
1	25	10	1913.724	200	1.2453	0.0965 $X_{ji,best}$	3.3476	1.1574
2	25.0495	10	1844.116	200	1.2865	0.0986	3.0562	1.1558
3	25	10	1757.623	200	1.3199	0.0996	2.7192	1.1536
4	26.2683	10	2000	200	1.4191	0.1162	3.7259	1.1603
5	25	10	300	200	1.4245	0.2215	0.0811 $X_{ji,best}$	1.079
6	31.7003	10	2000	200	2.5179	0.2405	3.8046	1.1629
7	28.5	10	932.73	212.1907	3.0999	0.2672	0.6472	1.1259
8	33.8835	10	980.8407	214.6995	5.0426	0.4827	0.7417	1.13
9	39.4565	10	1366.835	200	5.5058	0.5499	1.7016	1.1488
10	39.5125	10	893.006	200	6.1636	0.6041	0.6878	1.1325
11	43.1006	10	785.4233	214.3395	9.0452	1.0027	0.5488	1.1238
12	60.5423	10	300	200	9.4074	1.871	0.159	1.0949
13	50.252	10	951.2899	200	10.0145	1.1314	0.943	1.1347
14	50.4624	10	1094.945	209.8391	11.047	1.3154	1.1924	1.1359
15	95	10	300	370.8176	11.201	1.547	0.5758	1.0749 $X_{ji,best}$
16	53.9205	10	1193.568	203.7774	11.3644	1.3979	1.5711	1.1404
17	61.7591	10	417.817	200	11.776	1.8677	0.269	1.1054
18	52.3786	10	997.8612	216.286	12.7649	1.5735	0.9942	1.1302
19	59.0602	10	1199.503	212.3769	14.2355	1.9259	1.6368	1.1357
20	62.0647	10	782.3541	212.8126	16.3417	2.1735	0.7642	1.1214
21	57.6466	10	899.7264	241.1095	17.1198	2.3377	0.8244	1.1187
22	78.1695	10	300	303.9107	18.6777	3.184	0.3371	1.0817
23	63.9669	10	721.4555	233.2439	19.5525	2.7339	0.6496	1.1129
24	81.4454	10.4816	300	263.1196	20.3185	4.6091	0.3181	1.0889
25	82.047	10.242	300	276.3105	20.4793	4.1102	0.3279	1.0849
26	81.5354	10	407.3847	289.2469	22.0527	3.4706	0.4306	1.0863
27	93.3095	10	460.6347	290.8624	23.1194	3.5922	0.5781	1.0837
28	77.2987	10	847.0946	243.5197	23.7081	3.6683	1.0182	1.1097
29	84.271	11.0556	628.0503	247.9736	24.8563	5.7193	0.7768	1.1108
30	95	10	680.5518	230.7705	25.9749	4.2886	1.0235	1.101
31	95	10	726.217	247.0427	26.8204	4.4199	1.0638	1.0983
32	63.1759	35.7338	815.4502	250.6803	26.8784	141.1848	1.9473	1.2461
33	46.8665	45	704.2118	262.2001	26.8928	168.1049	2.1411	1.2377
34	66.0972	36.3491	644.0377	251.924	27.0320	153.657	1.8928	1.2522
35	63.4694	37.0986	865.4543	259.8581	27.2314	155.9124	2.0329	1.2489
36	65.7791	37.3432	876.1797	259.7034	27.5357	164.2039	2.1005	1.2531
37	48.7786	45	750.8355	259.6498	27.6576	176.157	2.1703	1.2431
38	53.8153	45	571.8286	249.4247	27.9858	200.6127	2.1753	1.2581
39	55.3277	45	591.4365	277.3743	28.3591	208.3648	2.2865	1.2568
40	52.1831	45	875.1416	246.9805	28.454	185.9188	2.3039	1.254
41	55.6714	45	867.8184	251.2169	29.5533	205.7847	2.3407	1.2608
42	56.978	45	895.9178	245.2088	29.6352	208.5368	2.4141	1.265
43	59.1992	45	664.6343	264.8876	29.8885	224.7545	2.3068	1.2662
44	58.1049	45	835.4176	253.878	30.121	218.1782	2.3559	1.2653
45	60.3879	45	738.0855	255.0349	30.420	228.327	2.3521	1.27
46	62.1815	45	846.2731	248.4064	30.6445	233.4057	2.473	1.2745
47	64.936	45	937.1024	251.8109	30.7501	246.4366	2.577	1.278
48	64.7866	45	770.7681	249.6904	30.8257	243.3128	2.4831	1.2792
49	69.817	45	810.0259	259.0902	30.8293	260.9632	2.5826	1.2849
50	68.0958	45	836.1816	252.7234	31.0207 $X_{ji,best}$	256.4056	2.5864	1.2836
Ranks assigned to the objectives→					1.5	1.5	3.5	3.5

Step 2: The objectives are ranked according to the decision-maker's assessment of their significance in terms of 1, 2, 3, and 4. The two attributes *MRR* and *TWR* are considered equally significant. Hence, *MRR* and *TWR* are given an average rank of 1.5 (i.e., $(1+2)/2$) and both objectives are assigned the weight of 0.309545 (i.e., $(0.3714543 + 0.2476362)/2$) using Table A1 from Part 1 of this paper. Furthermore, the objectives Θ and *DF* are also considered equally significant. Thus, both Θ and *DF* are given an average rank of 3.5 (i.e., $(3+4)/2$) and both are assigned average weight of 0.190454 (i.e., $(0.202611436 + 0.178298064)/2$).

Step 3: The data of the objectives for different alternative solutions is normalized with reference to the “best” values of the objectives. The values of *MRR* are normalized as $x_{ji}/x_{ji.best}$, and the objectives *TWR*, Θ , and *DF* are normalized as $x_{ji.best}/x_{ji}$. The normalized values of the objectives for 50 alternative solutions are shown in Table 5.

Table 5

Normalized values of the objectives and the total scores of the alternatives for case study 2

Solution no.	Normalized values of the objectives				Total scores (BHARAT)
	<i>MRR</i>	<i>TWR</i>	Θ	<i>DF</i>	
1	0.040144	1	0.024226	0.92872	0.503464
2	0.041472	0.978702	0.026536	0.930005	0.497967
3	0.042549	0.968876	0.029825	0.931779	0.496223
4	0.045747	0.830465	0.021767	0.926398	0.451809
5	0.045921	0.435666	1	0.9962	0.529257
6	0.081168	0.401247	0.021316	0.924327	0.329431
7	0.09993	0.361153	0.125309	0.954703	0.348418
8	0.162556	0.199917	0.109343	0.951239	0.314194
9	0.177488	0.175486	0.047661	0.935672	0.296541
10	0.198693	0.159742	0.117912	0.949139	0.314176
11	0.291586	0.09624	0.147777	0.956487	0.330361
12	0.303262	0.051577	0.510063	0.981733	0.393957
13	0.322833	0.085293	0.086002	0.947299	0.323129
14	0.356117	0.073362	0.068014	0.946298	0.326123
15	0.361081	0.062379	0.140848	1	0.348359
16	0.366349	0.069032	0.05162	0.942564	0.324116
17	0.379617	0.051668	0.301487	0.972408	0.376121
18	0.411496	0.061328	0.081573	0.951071	0.343032
19	0.458903	0.050106	0.049548	0.946465	0.347256
20	0.5268	0.044398	0.106124	0.958534	0.37958
21	0.551883	0.04128	0.098375	0.960847	0.385344
22	0.602104	0.030308	0.240581	0.993714	0.430836
23	0.630305	0.035298	0.124846	0.965855	0.413762
24	0.654998	0.020937	0.254951	0.987143	0.445794
25	0.660182	0.023478	0.247332	0.990783	0.447427
26	0.710903	0.027805	0.188342	0.989506	0.452989
27	0.745289	0.026864	0.140287	0.99188	0.454642
28	0.764267	0.026306	0.07965	0.96864	0.444369
29	0.801281	0.016873	0.104403	0.967681	0.457438
30	0.837341	0.022502	0.079238	0.976294	0.46719
31	0.864597	0.021833	0.076236	0.978694	0.475306
32	0.866467	0.000684	0.041647	0.862611	0.440642
33	0.866931	0.000574	0.037878	0.868466	0.441149
34	0.871418	0.000628	0.042847	0.858409	0.441585
35	0.877846	0.000619	0.039894	0.860677	0.443442
36	0.887656	0.000588	0.03861	0.857793	0.445675
37	0.891585	0.000548	0.037368	0.864693	0.447957
38	0.902165	0.000481	0.037282	0.854384	0.449231
39	0.914199	0.000463	0.035469	0.855267	0.452773
40	0.917258	0.000519	0.035201	0.857177	0.45405
41	0.952696	0.000469	0.034648	0.852554	0.464019
42	0.955336	0.000463	0.033594	0.849723	0.464094
43	0.963502	0.000429	0.035157	0.848918	0.466756
44	0.970997	0.000442	0.034424	0.849522	0.469055
45	0.980636	0.000423	0.03448	0.846378	0.471445
46	0.987873	0.000413	0.032794	0.84339	0.472792
47	0.991277	0.000392	0.031471	0.84108	0.473147
48	0.993714	0.000397	0.032661	0.840291	0.473979
49	0.99383	0.00037	0.031402	0.836563	0.473057
50	1	0.000376	0.031356	0.83741	0.475122

Step 4: The normalized data of the objectives for the alternative solutions is multiplied by the corresponding weights of the objectives to obtain the total scores of the alternative solutions. . The last column of Table 5 shows the total scores.

Step 5: The optimal alternative solution is the one with the highest total score. Since the alternative solution no. 5 has the highest total score, it is regarded as the best option. The second, third, and the last choices are solution nos. 1, 2, and 9

respectively. Therefore, for the electro-discharge machining process under consideration, the decision-maker (i.e., process planner) can choose the process parameters that match the solution no. 5.

Four different MADM methods are used on the same case study to study the efficacy of the the suggested BHARAT, using Table 5 and the same weights given to the objectives. The MADM methods are: (i). Weighted product method (WPM), (ii). PROMETHEE, (iii). R-method, and (iv). TOPSIS. Based on the total scores given by these MADM methods and the proposed BHARAT method, the rankings of alternative solutions are given below.

BHARAT:	5-1-2-3-----9
WPM:	5-12-7-17-----49
PROMETHEE:	5-22-25-26-----6
R (Rao and Lakshmi, 2021b):	5-1-50-15-----33
TOPSIS:	29-31-30-27-----49

When faced with a decision-making situation, the decision-maker is always curious to know what the first best option is. It should be noted that the solution no. 5 is recommended as the first best option in the current example by the suggested BHARAT method, WPM, PROMETHEE, and R-method. Based on the proposed BHARAT method and R-method, the second option is the alternative solution no. 1. The first option recommended by the TOPSIS method is solution no. 29. Nevertheless, a detailed examination of the *MRR*, *TWR*, Θ , and *DF* values of alternative solutions 5 and 29 reveals that, out of the four objectives, solution no. 5 is superior to solution no. 29 in *TWR*, Θ , and *DF*. Furthermore, because the three objectives - *TWR*, Θ , and *DF* – have a combined weight of 0.690453 (i.e., $0.309545 + 0.190454 + 0.190454$), solution no. 5 outperforms solution no. 29 of TOPSIS by a significant margin.

Second version of BHARAT method for case study 2

Second version of BHARAT method differs from BHARAT only in Step 2. The ranks assigned to the attributes are the same as those given in BHARAT. Using the appropriate procedure suggested to form Table 14 and Table 21 given in Part-1 of the paper, the weights are assigned as 0.35 to both *MRR* and *TWR*, and 0.15 to both Θ and *DF*. Using these weights, and the normalized data of the objectives, the total scores are computed which gives the ranking as 1-2-3-50-48-.....-9. Of course, it is to be noted that in this second version the weights of the objectives are somewhat different from the weights considered in BHARAT and hence the difference is there in ranking.

3.3 Case study 3: Many-objective optimization of machining process parameters

A case study by Wu et al. (2022) is used to further illustrate the suggested BHARAT method. The authors proposed a data driven genetic algorithm based on deep learning. The TOPSIS method was then used to optimize the machining process parameters for multiple objectives and find the ultimate solutions. The authors used deep learning to automatically generate the data-driven prediction function of various optimized objectives. The Pareto set was then created by combining the genetic algorithm and a surrogate model that was created from the optimized objective prediction function. Lastly, from the produced Pareto set, the TOPSIS method was used to automatically search for the best optimum processing parameters. The tests were carried out on a milling machine. The process input parameters were cutting speed v (m/min), feed f (mm/rev.), width a_c (mm), and depth of cut a_p (mm). The four objectives considered were: energy consumption E_c (kW-h), maximum cutting force C_f (N), material removal rate *MRR* (E-03), and surface roughness R_a (μm). The 100 Pareto optimal solutions obtained by using NSGA-III showing 4 process parameters and 4 objectives are shown in Table 6.

The values of the four objectives are normalized. *MRR* is a beneficial one and the other objectives are of non-beneficial type. The best values of E_c , C_f , *MRR*, and R_a are 5.03kW-h, 46.33N, 1324.45×10^{-3} , and $0.08 \mu\text{m}$. Using these values, the values of the objectives for the 100 alternative solutions (i.e., alternative process input parameters) are normalized and given in Table 6. For space reasons, a separate table is not produced here to show the normalized values of the objectives.

Wu et al. (2022) considered equal importance to the four objectives (i.e., $w_i = 0.25$ for $i=1,2,3,4$) and then carried out the TOPSIS procedure for finding the best alternative solution corresponding to the best combination of process input parameters. Hence, for fair comparison, same equal weights are considered in the BHARAT method. The four objectives are assigned an average rank of 2.5 (i.e., $(1+2+3+4)/4$). Using Table A1 of Part-1 of this paper, the average equal weight is computed as 0.25 (i.e., $(0.3714543+0.2476362+0.2026114+0.1782980)/4$). The total scores are calculated using the equal weights and the normalized values of the objectives given in Table 6, and are given in the last column of Table 6 (for space reasons, a separate table is not produced here). From the total scores, it can be understood that the alternative solution no. 6 with a total score of 0.425964 is considered as the first choice and solution no. 2 as the second choice. However, TOPSIS method used by Wu et al. (2022) proposed solution no. 75 as the first choice and solution no. 92 as the second choice. The original performance data of the alternative solutions (and the corresponding normalized values) of E_c , C_f , *MRR*, and R_a reveal that proposing solution no. 6 is logically better than solution no. 75. Similarly, solution no. 2 is better than solution no. 92 in case of 3 objectives out of 4 objectives. Therefore, it makes sense to suggest solution no. 2 as the second choice. Using the second version of BHARAT leads to the same total scores given by BHARAT because of the equal weight consideration for each objective.

Table 6

Pareto optimal solutions with the sets of process input parameters, objectives along with their normalized values, and the total scores for case study 3

Solution no.	Process input parameters				Objectives (process output parameters)				Normalized values of the objectives				Total scores
	v (m/min)	f (mm/rev)	a _c (mm)	a _p (mm)	E _c (kW-h)	C _r (N)	MRR (10 ⁻³)	Ra (μm)	E _c	C _r	MRR	Ra	
1	32.34	4.07	2.11	0.52	42.08	143.2	3.86	0.16	0.11953	0.323534	0.002914	0.5	0.236496
2	99.99	4	10	0	9.49	449.08	0.01	0.08	0.53003	0.103166	7.55E-06	1	0.408301
3	40.12	4.01	0.79	0	35.05	69.83	0	0.12	0.14350	0.663468	0	0.666667	0.368411
4	98.2	12.5	6.84	3.99	6.38	844.03	889.34	1.83	0.788401	0.054891	0.671479	0.043716	0.389622
5	99.99	12.49	9.4	2.94	10.99	1211.48	916.29	1.11	0.457689	0.038242	0.691827	0.072072	0.314958
6	30	4	1.58	0.03	38.02	46.33	0.17	0.14	0.132299	1	0.000128	0.571429	0.425964
7	99.99	12.5	10	3.99	13.09	1025.41	1324.45	1.15	0.384263	0.045182	1	0.069565	0.374752
8	99.98	12.5	8.99	0	5.03	618.8	0.02	0.62	1	0.074871	1.51E-05	0.129032	0.30098
9	99.41	10.48	6.56	3.98	6.66	799	722.4	1.63	0.755255	0.057985	0.545434	0.04908	0.351938
10	99.99	11.7	7.05	3.98	6.5	858.24	871.41	1.75	0.773846	0.053983	0.657941	0.045714	0.382871
11	34.72	4.02	1.12	0.16	35.26	72.97	0.67	0.14	0.142655	0.634918	0.000506	0.571429	0.337377
12	35.42	4	1.58	0.03	30.06	56.68	0.2	0.13	0.167332	0.817396	0.000151	0.615385	0.400666
13	99.4	11.79	7.05	0.18	5.34	287.07	38.52	0.9	0.941948	0.161389	0.029084	0.088889	0.305327
14	40.12	4.01	0.96	0	33.23	77.15	0	0.12	0.151369	0.600518	0	0.666667	0.354639
15	94.73	11.72	7.31	2.68	7.36	1011.67	577.52	1.46	0.683424	0.045798	0.436045	0.054795	0.305015
16	99.98	12.46	8.94	2.37	10.33	1093.77	700.63	1.18	0.486931	0.042358	0.528997	0.067797	0.281521
17	99.98	12.41	8.93	2.63	10.66	1163.42	772.53	1.22	0.471857	0.039822	0.585284	0.065574	0.290134
18	96.15	11.24	7.51	2.68	6.58	999.8	560.72	1.42	0.764438	0.046339	0.423361	0.056338	0.322619
19	95.12	5.42	2.8	3.71	17.69	473.01	142.02	0.5	0.284341	0.097947	0.107229	0.16	0.16238
20	99	12.36	9.86	3.67	12.17	1069.91	1174.59	1.08	0.413311	0.043303	0.886851	0.074074	0.354385
21	79.76	4.12	2.49	3.55	18.26	420.26	77.1	0.43	0.275465	0.110241	0.058213	0.186047	0.157492
22	69.34	12.25	9.58	2.4	15.75	664.65	517.93	0.98	0.319365	0.069706	0.391053	0.081633	0.215439
23	100	11.87	9.69	3.06	11.4	1144.19	933.73	0.95	0.441228	0.040492	0.704995	0.084211	0.317731
24	98.67	12.4	7.43	0.03	5.26	350.74	8.24	0.92	0.956274	0.132092	0.006221	0.086957	0.295386
25	99.92	6.27	9.81	3.97	13.54	885.32	646.38	0.59	0.371492	0.052331	0.488037	0.135593	0.261863
26	95.3	5.19	1.63	3.89	40.27	432.3	83.18	0.52	0.124907	0.107171	0.062803	0.153846	0.112182
27	98.28	4.54	6.55	2.75	6.24	714.4	213.16	0.63	0.80609	0.064852	0.160942	0.126984	0.289717
28	97.38	6.27	7.76	3.97	9.76	747.57	498.88	0.82	0.515369	0.061974	0.37667	0.097561	0.262893
29	80.1	4.74	9.88	2.53	15.12	493.83	251.53	0.55	0.332672	0.093818	0.189913	0.145455	0.190464
30	97.56	4.12	9.65	3.74	13.7	776.43	384.59	0.53	0.367153	0.059671	0.290377	0.150943	0.217036
31	94.31	10.4	7.37	0.13	5.53	316.27	24.6	0.62	0.909584	0.146489	0.018574	0.129032	0.30092
32	99.86	12.04	9.64	3.43	11.46	1111.63	1056.75	1.05	0.438918	0.041678	0.797878	0.07619	0.338666
33	97.93	4.72	7.13	3.5	6.96	787.98	306.06	0.69	0.722701	0.058796	0.231085	0.115942	0.282131
34	94.93	11.76	7.05	3.98	7.68	813.59	831.61	1.71	0.654948	0.056945	0.627891	0.046784	0.346642
35	72.62	11.18	7.03	3.92	13.36	872.63	593.4	1.3	0.376497	0.053092	0.448035	0.061538	0.234791
36	99.82	11.45	2.58	3.55	16.32	556.04	277.79	0.79	0.308211	0.083321	0.20974	0.101266	0.175634
37	99.98	10.74	7.55	3.96	7.53	868.13	852.59	1.56	0.667995	0.053368	0.643731	0.051282	0.354094
38	97.8	5.67	8.02	3.99	10.7	750.81	470.67	0.7	0.470093	0.061707	0.35537	0.114286	0.250364
39	89.48	6.36	6.12	3.93	6.91	648.02	363.63	1.16	0.727931	0.071495	0.274552	0.068966	0.285736
40	35.22	4.01	2.17	0.04	28	61.85	0.32	0.14	0.179643	0.74907	0.000242	0.571429	0.375096
41	99.98	12.41	8.99	2.75	10.81	1178.69	815.3	1.22	0.46531	0.039306	0.615576	0.065574	0.296442
42	96.1	9.93	9.96	3.94	14.29	929.71	993.73	0.81	0.351994	0.049833	0.750296	0.098765	0.317222
43	44.2	4.02	1.12	0.16	30.51	88.77	0.85	0.12	0.164864	0.521911	0.000642	0.666667	0.338521
44	99.2	12.43	7.88	3.96	8.79	913.78	1020.89	1.69	0.572241	0.050701	0.707803	0.047337	0.360271
45	99.99	12.41	8.64	3.95	10.64	965.07	1123.85	1.52	0.472744	0.048007	0.848541	0.052632	0.355481
46	96.15	11.24	8.15	2.68	10.11	1062.92	625.19	1.24	0.497527	0.043587	0.472037	0.064516	0.269417
47	99.94	4.32	7.55	3.98	8.39	727.77	344.09	0.66	0.599523	0.06366	0.259798	0.121212	0.261048
48	99.99	12.5	9.23	4	11.49	985.65	1222.92	1.39	0.437772	0.047005	0.923342	0.057554	0.366418
49	99.87	12.5	8.08	3.51	8.88	1022.01	939.02	1.6	0.566441	0.045332	0.708899	0.05	0.342691
50	95.11	5.19	8.28	3.89	11.17	737.49	422.56	0.57	0.450313	0.062821	0.319046	0.140351	0.243133
51	99.95	4.13	1.95	4	38.7	439.57	85.24	0.48	0.129974	0.105398	0.064359	0.166667	0.1166
52	33.53	4.1	3.18	0.15	19.29	100.36	1.79	0.12	0.260757	0.461638	0.001352	0.666667	0.347603
53	99.99	5.73	7.65	0.18	5.43	264.41	20.44	0.29	0.926335	0.17522	0.015433	0.275862	0.348213
54	40.17	4.19	3.12	0.49	22.02	130.55	6.79	0.18	0.228429	0.354883	0.005127	0.444444	0.258221
55	99.86	12.41	8.92	1.85	9.6	940.44	544.24	1.09	0.523958	0.049264	0.410918	0.073394	0.264384
56	76.93	12.5	9.99	2.6	15.31	684.44	663.58	0.96	0.328543	0.06769	0.501023	0.083333	0.245148
57	33.09	4.03	3.32	0.05	18.74	103.32	0.63	0.1	0.26841	0.448413	0.000476	0.8	0.379325
58	89.95	12.25	9.98	3.56	14.57	931.39	1037.17	0.93	0.34523	0.049743	0.783095	0.086022	0.316022
59	99.86	12.11	7.95	3.99	8.85	912.12	1018.56	1.65	0.568362	0.050794	0.769044	0.048485	0.359171
60	99.66	4.29	9.08	3.96	11.67	808	408.12	0.46	0.43102	0.057339	0.308143	0.173913	0.242604
61	34.68	4.03	2.89	0.58	22.87	148.24	6.19	0.17	0.219939	0.312534	0.004674	0.470588	0.251934
62	99.98	10.09	7.55	3.96	7.61	853.34	800.8	1.49	0.660972	0.054293	0.604628	0.053691	0.343396
63	99.78	12.29	7	3.97	6.36	868.64	904.58	1.81	0.790881	0.053336	0.682985	0.044199	0.39285
64	96.68	11.16	2.24	2.67	14.35	578.52	171.4	0.72	0.350523	0.080084	0.129412	0.111111	0.167782
65	99.94	4.13	7.55	3.96	8.39	727.02	327.62	0.63	0.599523	0.063726	0.247363	0.126984	0.259399
66	41.44	4.21	3.1	0.49	24.79	118.41	6.99	0.2	0.202904	0.391268	0.005278	0.4	0.249862
67	97.42	12.5	9.41	3.99	12.53	964.07	1214.58	1.27	0.401437	0.048057	0.917045	0.062992	0.357383
68	99.78	12.06	9.84	3.97	12.77	1009.1	1247.66	1.12	0.393832	0.045912	0.942021	0.071429	0.363131
69	95.36	5.16	2.83	3.82	17.85	478.06	141.19	0.5	0.281793	0.096913	0.106603	0.16	0.161327
70	35.22	4.02	2.17	0.04	28	61.81	0.32	0.14	0.179643	0.749555	0.000242	0.571429	0.375217
71	97.93	4.15	6.73	3.26	6.35	766.26	236.16	0.65	0.792126	0.060463	0.178308	0.123077	0.288493
72	40.33	4.15	2.46	0.34	26.3	82.86	3.68	0.16	0.191255	0.559136	0.002779	0.5	0.313292
73	66.19	11.64	9.95	3.89	16.79	820.72	790.22	1.37	0.299583	0.05645	0.59664	0.058394	0.252767
74	97.93	4.1	2.91	3.4	16.31	441.25	105.34	0.39	0.3084	0.104997	0.079535	0.205128	0.174515
75	97.85	11.15	9.98	3.99	13.94	966.13	1151.22	0.97	0.360832	0.047954	0.869206	0.082474	0.340117
76	100	12.44	9.38	2.5	10.98	1118.5	772.84	1.04	0.458106	0.041422	0.583518	0.076923	0.289992
77	93.78	4.49	6.56	0.71	5.98	238.36	52.17	0.2	0.841137	0.19437	0.03939	0.4	0.368724
78	99.99	12.5	9.23	3.85	11.43	1015.91	1179.03	1.37	0.44007	0.045604	0.890203	0.058394	0.358568
79	94.97	9.93	6.55	2.67	6.24	906.6	438.86	1.34	0.80609	0.05			

Wu et al. (2022) considered a second case consisting of four groups with only three objectives, i.e., E_c , C_f , and MRR. Different weight combinations of E_c , C_f , and MRR were attempted using TOPSIS method. For fair comparison, the same weight combinations are now used in the BHARAT method and the rankings are given in Table 7.

Table 7

Total scores for different weight combinations of E_c , C_f , and MRR using BHARAT method for case study 3

Solution no.	Total scores for different weight combinations of E_c , C_f , and MRR using BHARAT			
	0.2, 0.2, 0.6	0.3, 0.3, 0.4	0.5, 0.4, 0.1	0.6, 0.2, 0.2
1	0.090362	0.134086	0.189472	0.13701
2	0.126644	0.189962	0.306283	0.338654
3	0.161396	0.242093	0.337142	0.218799
4	0.571546	0.521579	0.483305	0.618315
5	0.514282	0.42551	0.313324	0.420627
6	0.226537	0.339741	0.466162	0.279405
7	0.685889	0.528833	0.310204	0.439594
8	0.214983	0.322467	0.52995	0.614977
9	0.489908	0.462146	0.455365	0.573837
10	0.56033	0.511525	0.47431	0.606692
11	0.155818	0.233474	0.325345	0.212678
12	0.197036	0.295479	0.410639	0.263909
13	0.238118	0.342635	0.538438	0.603263
14	0.150378	0.225566	0.315892	0.210925
15	0.407471	0.393184	0.403635	0.506422
16	0.423256	0.370386	0.313309	0.40643
17	0.452306	0.386817	0.310186	0.407736
18	0.416172	0.412577	0.443091	0.552603
19	0.140795	0.157578	0.192073	0.21164
20	0.623434	0.491725	0.312662	0.434018
21	0.112069	0.138997	0.187651	0.19897
22	0.312446	0.273142	0.22667	0.283771
23	0.519341	0.426514	0.30731	0.413834
24	0.221406	0.328998	0.531596	0.601427
25	0.377587	0.322362	0.255482	0.330969
26	0.084098	0.094745	0.111602	0.108939
27	0.270754	0.325659	0.44508	0.528813
28	0.34147	0.323871	0.320141	0.39695
29	0.199246	0.203912	0.222854	0.256349
30	0.259591	0.244198	0.236483	0.290302
31	0.222359	0.324251	0.515245	0.578763
32	0.574846	0.46333	0.315918	0.431262
33	0.29495	0.326883	0.407977	0.491597
34	0.519113	0.464724	0.413041	0.529936
35	0.354739	0.308091	0.254289	0.326124
36	0.20415	0.201356	0.208408	0.243539
37	0.530511	0.473901	0.419718	0.540217
38	0.319582	0.301688	0.295266	0.365471
39	0.324616	0.349648	0.420018	0.505968
40	0.185888	0.278711	0.389474	0.257648
41	0.470269	0.397615	0.309935	0.410162
42	0.530543	0.420667	0.27096	0.371222
43	0.13774	0.206289	0.29126	0.203429
44	0.58707	0.495204	0.383481	0.507646
45	0.613275	0.495642	0.340429	0.462956
46	0.391445	0.351149	0.313402	0.401641
47	0.288516	0.302874	0.351206	0.424406
48	0.65096	0.51477	0.330022	0.456732
49	0.547748	0.467128	0.372252	0.490729
50	0.294054	0.281559	0.28219	0.346561
51	0.08569	0.096355	0.113582	0.111936
52	0.14529	0.217259	0.315169	0.249052
53	0.229571	0.33664	0.534799	0.593932
54	0.119738	0.177044	0.25668	0.209059
55	0.361195	0.336334	0.322777	0.406411
56	0.379861	0.319279	0.24145	0.310869
57	0.14365	0.215237	0.313618	0.250824
58	0.548851	0.43173	0.270822	0.373706
59	0.585257	0.493364	0.381403	0.504984
60	0.282558	0.269765	0.26926	0.331708
61	0.109299	0.161611	0.23545	0.195405
62	0.50583	0.456431	0.412666	0.528368
63	0.578635	0.526459	0.485073	0.621793
64	0.163769	0.180947	0.220236	0.252213
65	0.281068	0.29792	0.349988	0.421932
66	0.122001	0.180363	0.258487	0.201052
67	0.640126	0.501666	0.311645	0.433882
68	0.653174	0.50875	0.309513	0.433922
69	0.139703	0.156253	0.190322	0.209779
70	0.185985	0.278856	0.389668	0.257745
71	0.277502	0.3271	0.438079	0.52303
72	0.151745	0.226229	0.31956	0.227136
73	0.429191	0.345466	0.232036	0.310368
74	0.1304	0.155833	0.204152	0.221946
75	0.603281	0.470318	0.286518	0.399931
76	0.450016	0.383265	0.303973	0.399851
77	0.230735	0.326408	0.502255	0.551434
78	0.631257	0.501784	0.327297	0.451204

Table 7Total scores for different weight combinations of E_c , C_f , and MRR using BHARAT method for case study 3 (Continued)

Solution no.	Total scores for different weight combinations of E_c , C_f , and MRR using BHARAT			
	0.2, 0.2, 0.6	0.3, 0.3, 0.4	0.5, 0.4, 0.1	0.6, 0.2, 0.2
79	0.37025	0.389699	0.456621	0.560145
80	0.362037	0.376382	0.431801	0.526331
81	0.1159	0.143415	0.195702	0.214988
82	0.613075	0.483318	0.306639	0.425387
83	0.254064	0.267053	0.307684	0.364635
84	0.658256	0.513689	0.314947	0.441558
85	0.119407	0.176491	0.256935	0.212848
86	0.153021	0.229267	0.321258	0.216
87	0.155513	0.232031	0.32823	0.234237
88	0.343605	0.318779	0.302305	0.377013
89	0.508126	0.420733	0.310366	0.416223
90	0.115094	0.170391	0.249479	0.210258
91	0.563781	0.505376	0.45181	0.583139
92	0.555348	0.440836	0.285509	0.392086
93	0.678606	0.524791	0.311314	0.439959
94	0.153727	0.22894	0.358144	0.369686
95	0.662738	0.509781	0.296069	0.419714
96	0.474345	0.450602	0.449639	0.565464
97	0.152571	0.228	0.355762	0.361907
98	0.25072	0.247004	0.257553	0.307778
99	0.160098	0.239067	0.338708	0.242789
100	0.288933	0.334683	0.439778	0.526312

From the total scores given in Table 7 using BHARAT method, it can be observed that solution no. 7 is the first choice for the weight combinations of (0.2, 0.2, 0.6) as well as (0.3, 0.3, 0.4); solution no. 13 is the first choice for the weight combination of (0.5, 0.4, 0.1) and solution no. 4 is the first choice for the weight combination of (0.6, 0.2, 0.2). However, comparison of these results with those given by Wu et al. (2022) is not possible, as it seems that they had generated Pareto solutions for these four groups of weights separately and then carried out the TOPSIS procedure. The correct procedure is: Once the non-dominated Pareto optimal solutions are generated by any multi-objective optimization algorithm, then the application of any MADM method such as TOPSIS can be used for a specific set of weights of the objectives decided by the decision-maker. If the decision-maker wants to see the results for different specific sets of weights of the objectives, he or she must apply those different sets of specific weights of the objectives on the same non-dominated Pareto optimal solutions. That makes him/her clear of the effect of assigning different sets of weights to the objectives. It is not clear whether Wu et al. (2002) followed this correct procedure or not. This ambiguity is because the results shown by them in Table 5 of their paper for the four groups of weights do not appear at all in the generated Pareto solutions shown in Table 4 of their paper.

The second version of BHARAT also gives the same choices as the weights of the objectives considered are same for both the first and second case.

The BHARAT method allows the decision-makers to directly assign the numerical weights to the objectives rather than the ranks. For instance, in all three of the case studies, the decision-maker is free to assign the numerical weights to the objectives directly based on his or her understanding of them, i.e., without designating ranks such as 1, 2, etc. This feature is proved in second case of case study 3 of this paper. The numerical weights of the objectives (assigned based on the decision-maker's opinion) can be multiplied with the corresponding normalized values of the objectives for various alternative solutions to get the total scores of the alternative solutions.

4. Conclusions

In Part-1 of this paper, the BHARAT method—a novel and straightforward multi-attribute decision-making technique—is proposed. The current paper employs the BHARAT method as a multi- and many-objective decision-making method for evaluating and ranking Pareto optimal solutions in industrial optimization problems. All that is needed for the BHARAT method is the ranking of objectives, assigning weights to them, and normalizing the objectives after the Pareto optimal solutions are found by any advanced optimization algorithm. It is simpler and more convenient to rank order the objectives' importance. Three case studies are provided to potential of the suggested methodology. The three case studies demonstrate how straightforward the suggested BHARAT method is, and how easily the decision-maker can use it to select the best solution among the Pareto optimal options. Furthermore, the BHARAT method enables the decision-makers to directly assign the numerical weights to the objectives rather than the ranks and compute the total scores for the alternatives as demonstrated in the second case of case study 3.

The outcomes showcased in this study are highly valuable for industrial process planners and designers. The suggested BHARAT method's concept is clear-cut, uncomplicated, and efficient; it can tackle many- and multi- objective optimization issues in a variety of scientific and engineering domains.

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