This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2017.Doi Number

MOSMA: Multi-objective Slime Mould Algorithm Based on Elitist Non-dominated Sorting

M. PREMKUMAR[1], PRADEEP JANGIR[2], R. SOWMYA[3], HASSAN HAES ALHELOU[4] (Senior Member, IEEE), ALI ASGHAR HEIDARI[5], HUILING CHEN[6] (Associate Member, IEEE)

[1] Department of Electrical and Electronics Engineering, GMR Institute of Technology, Rajam, Andhra Pradesh, 532127 India
[2] Rajasthan Rajya Vidyut Prasaran Nigam, Sikar, Rajasthan, 305001 India
[3] Department of Electrical and Electronics Engineering, National Institute of Technology, Tiruchirappalli, Tamil Nadu, 620015 India
[4] Department of Electrical Power Engineering, Faculty of Mechanical and Electrical Engineering, Tishreen University, 2230 Lattakia, Syria
[5] School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Tehran, Iran
[6] College of Computer Science and Artificial Intelligence, Wenzhou University, Wenzhou 325035, China

Corresponding author: Hassan Haes Alhelou (e-mail: alhelou@tishreen.edu.sy).

ABSTRACT This paper proposes a multi-objective Slime Mould Algorithm (MOSMA), a multi-objective variant of the recently-developed Slime Mould Algorithm (SMA) for handling the multi-objective optimization problems in industries. Recently, for handling optimization problems, several meta-heuristic and evolutionary optimization techniques have been suggested for the optimization community. These methods tend to suffer from low-quality solutions when evaluating multi-objective optimization (MOO) problems than addressing the objective functions of identifying Pareto optimal solutions' accurate estimation and increasing the distribution throughout all objectives. The SMA method follows the logic gained from the oscillation behaviors of slime mould in the laboratory experiments. The SMA algorithm shows a powerful performance compared to other well-established methods, and it is designed by incorporating the optimal food path using the positive-negative feedback system. The proposed MOSMA algorithm employs the same underlying SMA mechanisms for convergence combined with an elitist non-dominated sorting approach to estimate Pareto optimal solutions. As a posteriori method, the multi-objective formulation is maintained in the MOSMA, and a crowding distance operator is utilized to ensure increasing the coverage of optimal solutions across all objectives. To verify and validate the performance of MOSMA, 41 different case studies, including unconstrained, constrained, and real-world engineering design problems are considered. The performance of the MOSMA is compared with Multiobjective Symbiotic-Organism Search (MOSOS), Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D), and Multiobjective Water-Cycle Algorithm (MOWCA) in terms of different performance metrics, such as Generational Distance (GD), Inverted Generational Distance (IGD), Maximum Spread (MS), Spacing, and Run-time. The simulation results demonstrated the superiority of the proposed algorithm in realizing high-quality solutions to all multi-objective problems, including linear, nonlinear, continuous, and discrete Pareto optimal front. The results indicate the effectiveness of the proposed algorithm in solving complicated multi-objective problems. This research will be backed up with extra online service and guidance for the paper's source code at https://premkumarmanoharan.wixsite.com/mysite and https://aliasgharheidari.com/SMA.html. Also, the source code of SMA is shared with the public at https://aliasgharheidari.com/SMA.html.

INDEX TERMS Constrained, Multi-objective optimization problems, Multi-objective Slime Mould Algorithm (MOSMA), Real-World problems, Slime Mould Algorithm (SMA), Unconstrained.

I. INTRODUCTION

In any real-world case, a large set of solutions need to be determined precisely and estimated to minimize (or maximize) several objectives at hand. Such problems often happen when we need to advance a decision-making model [1-2]. These kinds of models and instances are not only limited to function optimization, but practitioners face them in any discipline, especially fuzzy optimization [3], location-based services [4], traffic management [5], neural networks [6], wireless sensor networks [7-9], honeynet potency [10], monitoring [11-12], computer-aided design [13], and Internet of things [14]. Real-world engineering design problems require optimization algorithms to be utilized and find the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

best possible solutions [3]. Optimization problems appear in many fields, and in most real-world cases, it is required to optimize several objectives together [15]. These problems can be multi-objective [16] or later; they can have many objective forms [17-18]. Before the popularity of computers, researchers used to make many trials and errors to find optimal solutions for such problems. Human involvement was essential but compromised the accuracy of the overall problem-solving process. Using computers to automate this process has always been a priority to mitigate manual optimization and design risk. In the area of computer-aided design [13, 19-20], computers assist practitioners in solving optimization problems. Therefore, designers need to focus on the setup and preparation of the problem more than the optimization process itself. This way of problem-solving is inherently faster and less prone to human errors. However, preparing the problem in a format readable and solvable by the machine requires relevant expertise.

In the optimization field, algorithms are designed and developed as 'recipes' for computers to solve problems [21]. They can be divided into two classes: deterministic [1] and stochastic [23]. Deterministic methods find the same solution in each run but suffer from trapping in locally optimal solutions. However, stochastic approaches find different solutions in each run due to the use of stochastic mechanisms. This assists them in avoiding sub-optimal solutions better. Most heuristic and meta-heuristics algorithms belong to the latter class. It is possible to generally classify meta-heuristic optimization methods into two types, such as single-objective and multi-objective. Single-objective methods aim to provide an optimal solution after improving the primary objective function. Some of the well-regarded algorithms are Genetic Algorithm (GA) [42], Differential Evolution (DE) [22], Particle Swarm Optimization (PSO) [48], Whale optimizer algorithm with Nelder-Mead [23], Harris hawks optimization algorithm with Nelder-Mead [24], spotted hyena optimization [25], Seagull optimization algorithm [26], Henry gas solubility optimization algorithm [27], Mine blast algorithm [28], and Butterfly optimization [29].

The algorithms mentioned above can estimate the global optimum for the optimization problem considering one objective. However, in a wide range of real-world problems, multiple objectives should be optimized simultaneously, often in conflict [30]. The sub-field of evolutionary computation to solve such problems is called Evolutionary Multi-Objective Optimization (EMOO) [31], which deals with the philosophy and submissions of multi-objective evolutionary algorithms [30-32]. Some of the most popular algorithms in EMOO are the Non-dominated Sorting Genetic Algorithm (NSGA) [44], Multi-objective PSO (MOPSO) [49], and Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D) [67]. Multi-objective EMOO algorithms can be divided into three classes based on decision-makers' involvement: a priori, posteriori, and interactive. In a priori method, a decision-maker provides us with preferences, and we can use them to combine the objectives into a single one. So, a single objective algorithm can be used in this case. In a posteriori algorithm, decision making is done after completing the optimization process. So, an algorithm finds a sub-set of Pareto optimal solutions for decision-makers. Finally, in an interactive method, decision-makers are involved during the optimization process. Multi-objective optimization (MOO) does not have a single solution, and many convergences among the different objectives. The reality that Pareto fronts (PF) have to come up with numerous points for good theories on the PF is particularly dreadful to every MOO problem [35]. Even still, it is not predicted that the MOO strategies on the PF are uniformly distributed on the front [36]. It is also tough to predict the solution to such multi-dimensional issues.

A well-known principle, called No Free Lunch theory, has claimed in this regard that there is no single algorithm to solve optimization problems altogether [33]. Because of this principle, there is no assurance that an optimization algorithm has the same efficiency in different problems. According to this fact, the multi-objective variant of a newer algorithm is being created, which has exciting results based on evolutionary computation compared to the state-of-the-art techniques. This work focuses on a posteriori algorithm by proposing the multi-objective version of a recently-proposed metaheuristic called Slime Mould Optimizer (SMA)[1] algorithm [34]. The algorithm is called Multiobjective SMA (MOSMA), which is designed using non-dominated sorting and crowding distance mechanisms. The proposed MOSMA is a popular MOO algorithm that consists of a random search with good search capabilities, a non-dominant sort maintains Pareto dominance, and a crowding distance increases the solution's diversity. The key contributions to this study can be summarized as follows.

- An archive component is applied to the basic version of SMA that can store all non-dominated Pareto solutions.
- The non-dominated sorting and the crowding distance mechanism is applied to handle the Pareto dominance and the solution diversity.
- The validity of MOSMA is verified for 41 case studies, including real-world engineering design optimization problems.
- The performance indicators are listed for all case studies to prove the effectiveness of the MOSMA.

The rest of the paper is planned as follows: Section 2 describes the structure of the multi-objective optimization problems with its basic definitions and the related works in

[1] https://aliasgharheidari.com/SMA.html

solving MOO problems. Section 3 presents the basic version of SMA and proposes the MOSMA algorithm. Section 4 represents the results/discussions/analysis of the proposed SMA. As a final point, Section 5 provides the conclusion of the work and future directions.

II. RELATED WORKS AND LITERATURE REVIEW

This section first introduces basic terminologies of MOO problems and their basic definitions, such as Pareto optimality, Pareto dominancy, Pareto optimality set, and Pareto optimality front. Further, the related works in solving MOO problems are discussed in detail.

A. MULTI-OBJECTIVE OPTIMIZATION

The structure of the multi-objective optimization problems can be represented as a maximization/minimization problem as follows:

$$\frac{\text{Min}}{\text{Max}}, \quad F(\vec{x}) = \{f_1(\vec{x}), f_2(\vec{x}), \dots, f_o(\vec{x})\} \tag{1}$$

Subject to:
$$g_i(\vec{x}) \geq 0, i = 1,2,\dots,m$$
$$h_i(\vec{x}) = 0, i = 1,2,\dots,p$$
$$Lb_i \leq x_i \leq Ub_i, i = 1,2,\dots,n$$

where *n* represent the number of design variables, *o* represents the number of objective functions, *m* represents the number of inequality constraints, *p* represents the number of equality constraints, g_i represent i^{th} inequality constraints, h_i indicates the i^{th} equality constraints, and $[Lb_i, Ub_i]$ represents the i^{th} variable's lower & upper boundaries. Relational operators are no longer adequate for comparing solutions to a problem with multiple objectives. In this case, a new operator called Pareto optimality is used. The essential definitions in this regard are as follows:

Def. 1. Pareto Dominance [35]:
Assume two vectors such as: $\vec{x} = (x_1, x_2, \dots, x_k)$ and $\vec{y} = (y_1, y_2, \dots, y_k)$. The vector $\vec{x}$ is said to dominate the vector $\vec{y}$ (denoted as $\vec{x} \prec \vec{y}$), if and only if:

$$\forall i \in \{1,2,\dots,k\}: f_i(\vec{x}) \leq f_i(\vec{y}) \wedge \exists i \in \{1,2,\dots,k\}: f_i(\vec{x}) < f_i(\vec{y}) \tag{2}$$

Def. 2. Pareto Optimality [35]:
A solution $\vec{x} \in X$ is called Pareto-optimum if and only if:

$$\nexists\, \vec{y} \in X \mid F(\vec{y}) \prec F(\vec{x}) \tag{3}$$

Def. 3. Pareto optimal set [35]:
The set of all Pareto-optimal solutions is called the Pareto set as follows:

$$P_s = \{x, y \in X \mid \exists F(\vec{y}) \succ F(\vec{x})\} \tag{4}$$

Def. 4. Pareto optimal front: A set containing the value of objective functions for Pareto solutions set [35]:

$$P_f = \{F(\vec{x}) | \vec{x} \in P_s\} \tag{5}$$

For solving a MOO problem using a posteriori method, we have to catch the Pareto optimal set. This set is the group of solutions on behalf of the Grade A trade-offs among objectives. This is illustrated in Fig. 1, in which the parametric space and objective space are visualized. The image of two solutions in both spaces is compared that clearly shows the circle is a better solution than the rectangle since it dominated the rectangle considering all objectives.

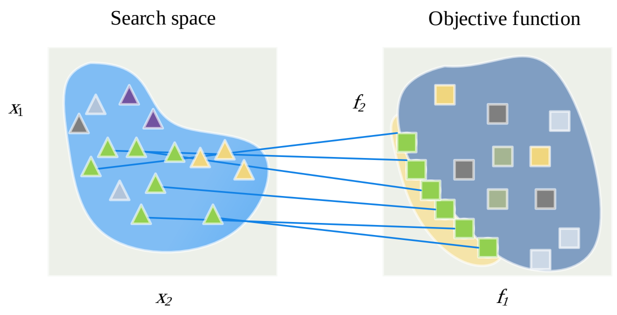


FIGURE 1. Parameter space and objective space in multi-objective optimization

B. RELATED WORKS

A multi-objective optimization methodology was introduced to evolutionary algorithms by Schaffer in 1984. The idea behind this was to use Pareto dominance operators, and optimum Pareto set instead of relational operators that give a single optimum solution. In the area of EMOO's famous multi-objective optimizers, the literature is MOEA/D, NSGA-II, MOPSO, Pareto Archived Evolutionary [36], and Prato-frontier Differential Evolution (PDE) [37]. As discussed above, such algorithms are divided into three classes: aggregation (*a priori*) method [38], *a posteriori* method [39], and interactive methods [40].

In aggregation-based, multi-objective problems can be converted into single optimization using different weights assigned to objectives. After converting the problem into one objective, an optimal solution can be found using a single-objective algorithm. The main advantage of a priori methods is that they do not require modifications in the algorithm. However, the disadvantage of a priori methods is the applicability to only convex parts failure in finding Pareto optimal solution in non-convex regions of the Pareto fronts [35]. There are several improvements in such techniques (e.g. [40]), but similar issues still exist. On the other hand, a posteriori approach does not need to convert the multi-objective problem into a single objective instead of an a priori approach. Such optimizers can get Pareto optimal front and solutions in one run, but they have to address multiple, often in conflict, objectives.

From detailed literature, it is observed that priori methods are faced with specific problems in tackling multi-objective difficulties, trapped in local optima, having high computational time, and problems emerging from priori method structures [41]. As a result of the initiative to establish various approaches, Posteriori approaches have been developed. The multi-objective meta-heuristic algorithms (MOMHAs) are among the posteriori techniques, and it has an essential feature, such as reduced computing time and good results irrespective of the nature of the problem. Each candidate solution produces a reliable

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

solution based on its closeness to PF and the spread (diversity) on PF while analyzing the MOO problems with MOMHAs. Throughout the evaluation of parents and the choice of the solutions that survive, such results are used. For counting, there are three fundamental methods used [40]:

- Pareto-based
- Indicator-based
- Decomposition-based

Pareto-based - Goldberg [42] first suggested in 1989, it was possible to use the Pareto-dominance principle to evaluate the optimal solution. Many MOMHAs also introduced several frameworks, motivated by this concept, that uses the Pareto-dominance principle to rate the proximity of optimal PF solution. For instance, Deb et al. rated the optimal solution using NSGA-II non-dominated-ranking mechanism [43, 44]. Multi-objective Seagull Optimization Algorithm [45], MOEAs [46], NSGA-III [47], bare-bones multi-objective particle swarm optimization [48], MOPSO [49], multi-swarm cooperative multi-objective particle swarm optimizer [50], MOWCA [51], incremental learning hybridized with adaptive differential evolution [52], MOSOS [53], and cooperative co-evolutionary optimization [54] are among the well-known Pareto-based MOMHAs in the literary works.

Indicator-based - A large number of quality metrics have been reported in the literature to measure the degree to which in terms of convergence and distribution, the PF achieved by a MOMHA for a problem shows the entire PF. A few of the indicators only measure the convergence performance (GD [53], etc.) or the diversity (Spacing [53], Spread [53], etc. of the PF collected, while others improve the impact of both convergence and diversity (Hyper Volume (HV) [54], IGD [55], etc.).

Decomposition-based - A Pareto-optimal response may be an appropriate choice to a scalar function obtained by integrating all of a multi-objective optimization problem's cost function. Therefore, a Pareto-optimal front can be broken down into various scalar optimization problems [54]. To enhance the decomposed fitness function created by the same weight vectors, decomposition-based strategies use this basic principle. Many decomposition-based algorithms are reported, and the following are the three optimizers adopting the proposed MOEA/D [67], MOMH/D [55], decomposition-based archiving approach [56], and Dynamic interval multi-objective optimization problems [57]. Therefore, in this work, a posteriori approach is applied in the SMA algorithm based on the elitist non-dominated approach similar to NSGA-II.

The next section first signifies the model of the SMA technique. Then, the novel multi-objective SMA is developed in this research.

III. MULTIOBJECTIVE SLIME MOULD ALGORITHM (MOSMA)

A. SLIME-MOULD ALGORITHM

The Slime Mould Algorithm [34] (SMA), proposed by Li et al. (2020), is a novel population-based metaheuristic inspired by the oscillation behaviors of slime mould in nature. The SMA algorithm is designed by incorporating the optimal food path using the positive-negative feedback system. According to the quality of food slime mould dynamically adjust their search path. The SMA algorithm mimics three fundamental principles, such as grabble, wrap, and approach phenomena. The grabble phenomena that avoid the collision among the slime mould while hunting for food. The wrap phenomena show the velocity matching of slime mould. Moreover, the approach phenomena, which states the learning of slime mould towards the food centre.

The SMA approach starts with a randomly generated population within its upper and lower boundary, where 'N' population size (i.e., slime mould) and 'dim' is the dimension of a problem. Next, the population is evaluated using an objective function. In the following stage, the population is updated by grabbling, wrapping, and approaching phenomena in each iteration. Moreover, the SMA algorithm's progression is controlled by various parameters such as fitness weight (W) of slime mould that can provide faster convergence and avoid local solutions. The vibration parameter (V_b) ensures early exploration or later exploitation accuracy of individual slime mould. The detailed stepwise process of the SMA algorithm, which includes grabbling food, wrap food, and approach food, which can be mathematically detailed as below [34]:

$$\begin{cases} \overrightarrow{X^*} = rand \cdot (Ub - Lb) + Lb, & if\ (rand < 0.03) \\ \overrightarrow{X^*} = \overrightarrow{X_b(t)} + \overrightarrow{vb} \cdot \left(W \cdot \overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}\right) & ,if\ (r < p) \\ \overrightarrow{X^*} = \overrightarrow{vc} \cdot \overrightarrow{X(t)}, & if\ (r \geq p) \end{cases} \tag{6}$$

where,

$$\begin{cases} \overrightarrow{W(SmellIndex(\iota))} = \begin{cases} 1 + r \cdot log\left(\frac{bF - S(i)}{bF - wF} + 1\right), & condition \\ 1 - r \cdot log\left(\frac{bF - S(i)}{bF - wF} + 1\right), & others \end{cases} \\ SmellIndex = sort(S) \\ \overrightarrow{vb} = [-a, a] \\ a = \operatorname{arctanh}\left(-\left(\frac{t}{Max\_t}\right) + 1\right) \\ p = \tanh|S(i) - DF| \end{cases} \tag{7}$$

where $\overrightarrow{vb}$ is vibration parameter, t represents the current iteration, $\vec{X}$ represents the location of slime mould, $\vec{W}$ represents the weight of slime mould. DF represents the best fitness obtained in all iterations, $S(i)$ ranks first half of the population, r denotes the random value in the interval of $[0,1]$, bF denotes the optimal, wF denotes the worst fitness, $SmellIndex$ denotes the sequence of fitness values sorted (ascends in the minimum value problem, Lb and Ub denote the lower and upper boundaries of the search range, $rand$ and r denote the random value in [0,1]. The vibration parameter $\overrightarrow{vb}$ and fitness weight $\vec{W}$ balances between exploration and exploitation. The procedure of the SMA is given in *Algorithm-I*.

Algorithm-I: Pseudocode of SMA

Initialize the parameters *population size and Maximum number of iterations*
Initialize the positions of slime mould, $X_i (i = 1,2, \dots, n)$;
While ($t \le Max\_t$)
    Calculate the fitness of all slime mould
    Update best fitness, X_b
    Calculate the W by Eq.(7);
    For each search portion
        Update p, vb, vc;
        Update positions by Eq.(6);
    End For
    $t = t + 1$;
End While
Return the best fitness, X_b

Step I: **Provide the input Data**
No of Search Agent(N), No of decision variable(dim), lower boundary (Lb), upper boundary (Ub), objective function (fobj, and Maximum Iteration (Max_t)
Step II: **Initialize the set of random solutions**
X=rand(N,dim)*(Ub-Lb)+Lb;
Step III: **Main Optimization loop start**
while t <= Max_t
Step IV: **Check if solutions go outside the search space bring them back**
AllFitness = fobj(Lb < X > Ub);
Step V: **Sort the calculated fitness**
[SmellOrder,SmellIndex] = sort(AllFitness);
worstFitness = SmellOrder(N); bestFitness = SmellOrder(1);
S=bestFitness-worstFitness+eps;
Step VI: **Update the best fitness value and best position**
if bestFitness < Destination_fitness
    bestPositions=X(SmellIndex);
    Destination_fitness = bestFitness;
end if
a = atanh(-(t/Max_t)+1); b = 1-t/Max_t;
Step VII: **Update the Position of search agents**
for each search portion
Step VIII: **Calculate the fitness weight of each slime mould (Wrap Food)**
if rand()<=half search portion
    weight=1+rand()*log10((bestFitness-smellOrder)/(S)+1);
else
    weight = 1-rand()*log10((bestFitness-SmellOrder)/(S)+1);
end if
if rand<0.03
    X=(Ub-Lb)*rand+Lb;
else
    p=tanh(abs(AllFitness - Destination_fitness));
    vb=unifrnd(-a,a,1,dim); **(Grabble Food)**
    vc=unifrnd(-b,b,1,dim); r=rand();
Step IX: **Two positions randomly select from search agent (Approach Food)**
A = randi([1,N]);
B = randi([1,N]);
if r<p
    X=bestPositions+vb*(weight*X(A)-X(B));
else
    X=vc*X;
end if
end if
end for
    t=t+1;
end while
Step X: **Return Destination_fitness (*P_j*)**

FIGURE 2. Step by step approach of the slime-mould optimizer.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

A detailed description of the SMA algorithm is given in Fig. 2. In the SMA optimizer's leading paper, it has been proved that this algorithm solves different real-world problems effectively and is competitive compared to the existing algorithms. This motivated us to design a new multiple-objective version of the slime mould optimizer in the following subsection.

B. Multi-Objective Slime Mould Algorithm (MOSMA)

The proposed MOSMA algorithm uses an elitist non-dominated sorting and a diversity preserving crowding distance mechanism [36]. Non-dominated sorting includes the following steps:

- First, calculating the non-dominated solution
- Second, applying non-dominated sorting (NDS)
- Calculating non-dominated ranking (NDR) of all non-dominated solutions.

Fig. 3 presents the non-domination ranking (NDR) process, in which two fronts are given. The solutions in the first front give the index of *0* since they are not dominated by any solutions, while the solutions in the second front are dominated by at least one of the solutions in the first front. Such solutions' NDR is equal to the number of solutions that dominate them. The crowding distance mechanism is shown in Fig. 4 used to maintain diversity among the acquired solutions. Crowding distance (CD) as follows.

$$CD_j^i = \frac{f_j^{i+1} - f_j^{i-1}}{f_j^{max} - f_j^{min}} \tag{8}$$

where, f_j^{min} and f_j^{max} are the minimum and maximum values of j^{th} objective function. The schematic representation of a non-dominated sorting-based algorithm is depicted in Fig. 5.

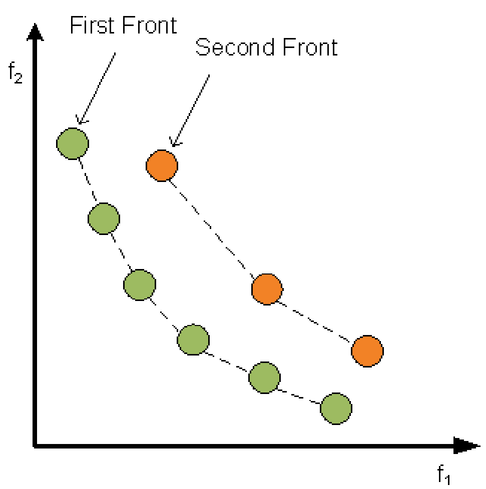


FIGURE 3. Diagram of non-dominated sorting

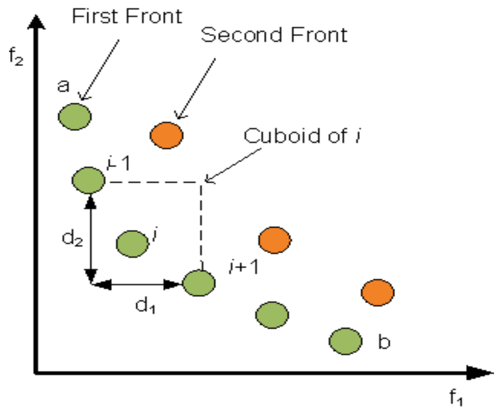


FIGURE 4. **Diagram of crowding distance approach**

The pseudocode of MOSMA is shown in *Algorithm-II*. Firstly, the algorithm starts with defining the controlling parameters, including search agent/population size (N_{pop}), loop terminated criteria, and maximum iteration/maximum number of generation (*Max_t*) to run the MOSMA algorithm. Secondly, a random generated parent's population P_o in feasible search space region S is generated, and every objective function of the objective space vector F for P_o is evaluated. Thirdly, the elitist-based *NDS* and *CD* are applied to P_o. Fourthly, a new population of P_j, is created and merged with P_o to get population P_i. This P_i is sorted based on elitism non-domination and the resulted data of *NDR* and *CD*. The best N_{pop} solutions are revised to create a new parent population. Finally, this process is repeated until the end condition is met. The flowchart of MOSMA is depicted in Fig. 6.

Algorithm-II: Pseudocode of MOSMA

Step I	Initially Generate population (P_o) randomly in solution space (S)
Step II	Evaluate objective space (F) for the generated population (P_o)
Step III	Sort the based on the elitist non-dominated sort method and find the non-dominated rank (NDR) and fronts
Step IV	Compute crowding distance (*CD*) for each front
Step V	Update solutions (P_j) using **Algorithm-I**
Step VI	Merge P_o and P_j to create $P_i = P_o \cup P_j$
Step VII	For P_i perform **Step II**
Step VIII	Based on *NDR* and *CD* sort P_i
Step IX	Replace P_o with P_i for N_{pop} first members of P_i

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

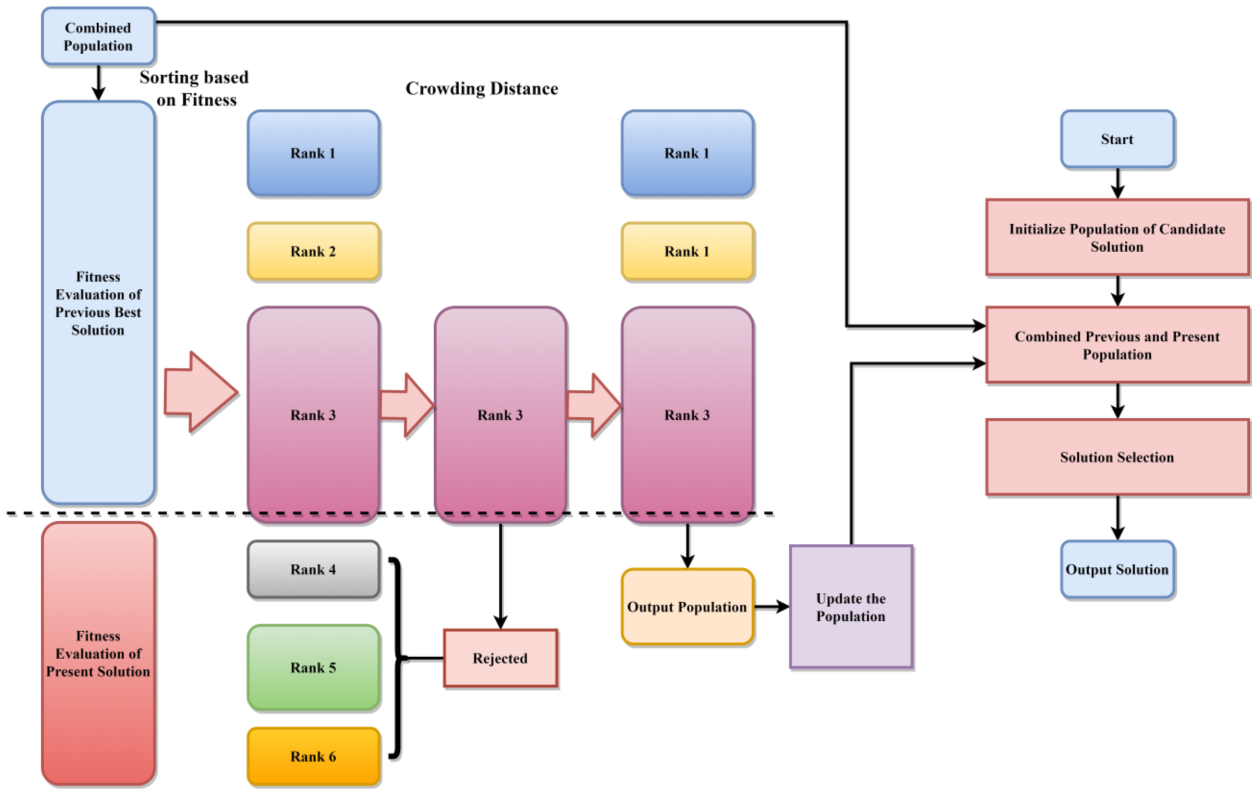


FIGURE 5. Schematic representation of a non-dominated sorting-based algorithm

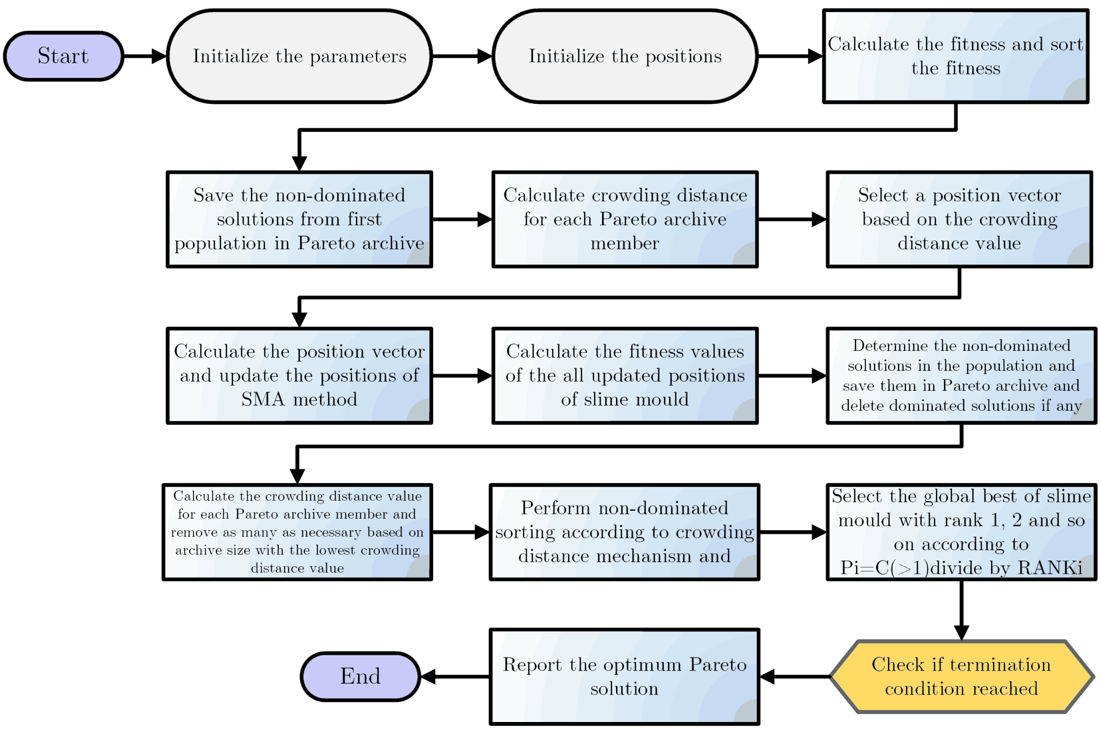


FIGURE 6. Flowchart of Multi-objective SMA

C. COMPUTATION COMPLEXITY OF MOSMA

The computation complexity of the proposed MOSMA is given in terms of space complexity and time complexity. As discussed earlier, the proposed MOSMA uses the same operators of NSGA-II. Since the NDS and CD assignment of MOSMA are adopted from NSGA-II, the computational space complexity of MOSMA is $O(MN_{pop}^2)$, where M is the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

total number of objective functions, and N_{pop} is the number of search agents/population size. The computational time complexity of the MOSMA is presented for each iteration. For the first iteration, the computational time complexity is equal to $O(dim*N_{pop}+Cost(f_{obj})*N_{pop})$. After the first iteration, the computational time complexity is equal to $O(dim*N_{pop}+Cost(f_{obj})*N_{pop}+(NDS+CD)*dim)$. In addition, the overall computational time complexity of the MOSMA is given for the maximum number of iteration which is equal to $time=O(M)|M=(dim*Max\_t*N_{pop}+Cost(f_{obj})*Max\_t*N_{pop}+(NDS+CD)*(Max\_t-t)*dim+(NDS+CD)*(Max\_t-t)*Cost(f_{obj}))$. Where, current iteration is denoted as t, maximum number of iterations is denoted as Max_t, the objective function is represented by f_{obj}, cost of the objective function is denoted as $Cost(f_{obj})$, and the number of variables in objective function is denoted as dim.

IV. RESULTS AND DISCUSSIONS

In this section, the performance validation of the proposed MOSMA is discussed. In order to prove the validity of the MOSMA, a comprehensive set of benchmark functions, including constrained, unconstrained, and real-world problems are considered.

A. EXPERIMENTAL SETUP

The case studies used to benchmark the performance of MOSMA are as follows:

- Unconstrained ZDT & CEC-2009 benchmarks with 2-objectives (ZDT1-ZDT4, ZDT6) & (UF1-UF10) [58-68].
- Constrained benchmark with 2-objectives (TNK, KITA, CONSTR, OSY & SRN) [69-73].
- Real-world highly nonlinear constraint, discrete, continuous & mix-integer design MOO problems, including 2-bar truss design, 3-bar truss design, 4-bar truss design, disk brake design, CNC machine tool design, discrete-gear train design, bar vessel design, welded beam design, I-beam design, C-beam design, multiple disk clutch brake design, car crash design, car side impact design, metal cutting tool design, rolling element bearing design, helical spring design, satellite heat pipe design, speed reducer design, BLDC motor design, and isolated safety transformer design [74-86].

The authors established an environment that ensures fairness, reliability, and justice among the methods we compared to avoid any accidental bias toward a better condition for any algorithm. This condition is a constraint in experiments to ensure that the superiorities are not due to the testing advantages.

In general, the performance of all multi-objective algorithms is measured using the performance indicators. Therefore, to compare the MOSMA with other competitive algorithms, the following performance indicators are used, and the expressions for the same have been stated in Eq. 9-Eq. 12.

$$\mathrm{GD} = \frac{\sqrt{\sum_{i=1}^{no} d_i^2}}{n} \tag{9}$$

$$\mathrm{IGD} = \frac{\sqrt{\sum_{i=1}^{nt} (d_i')^2}}{n} \tag{10}$$

$$\text{Spacing (SP)} \triangleq \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\bar{d}-d_i\right)^2} \tag{11}$$

$$\text{Maximum Spread (MS)} = \sqrt{\sum_{i=1}^{o} \max\left(d(a_i, b_i)\right)} \tag{12}$$

where nt is the number of true Pareto optimal solutions, no is the number of True Pareto optimal set (P_s), d_i and d_i' indicates the Euclidean distance (ED), $\bar{d}$ is the average of all d_i, n is the number of obtained P_s, and $d_i = \min_j\left(|f_1^i(\vec{x}) - f_1^j(\vec{x})| + |f_2^i(\vec{x}) - f_2^j(\vec{x})|\right)$ for all $i, j=1,2,\ldots,n$, o is the number of objectives, a and b is the maximum and minimum value in the i^{th} objective. The first two performance measures quantify the convergence and the last two measures the coverage of Pareto optimal solutions estimated by the algorithms.

B. CONSTRAINT HANDLING APPROACH

Some potential applications of the proposed MOSMA may also have constraints, and they are not limited to landslide prediction, dealing with modelling in the environmental concerns, enhancing the target tracking systems, design of the equipment tracking systems, supply chain management and related multi-objective models, improving the productivity of hydrothermal systems, solving several objectives in order-picking systems, and many applications in the image enhancement, and image segmentation. To solve constrained multi-objective problems, it is needed to put in place a mechanism to avoid violating constraints. This paper uses a static penalty approach to handle constraints in the MOSMA algorithm because its convert constrained problem into an unconstrained problem. In this approach, if any constraint is violated, a large penalty (P_i) is added to the returned objective value. The static penalty function is presented as follows:

$$f_j(X) = f_j(X) + \sum_{i=1}^{p} P_i \max\{g_i(X), 0\} + \sum_{i=p}^{NC} P_i \max\{|h_i(X)| - \delta, 0\} \tag{13}$$

$f_j(X), j = 1,2 \ldots n$, (Objective function to be optimized)
$X = \{x_1, x_2, \ldots x_m\}$ are design variables
$g_i(X) \leqslant 0, i = 1,2 \ldots p$ are inequality constraints
$h_i(X) = 0, i = p+1 \ldots NC$ are equality constraints,
δ is tolerance inequality constraint

To observe the outcomes qualitatively, the best Pareto optimal fronts attained by the proposed MOSMA technique on the considered case studies are demonstrated in Figs. 7 - Fig. 9. The performance of the proposed MOSMA is compared with the other well-known competitive algorithms, such as MOWCA, MOSOS, and MOEA/D. The control parameters of all algorithms are listed in Table 1.

TABLE 1.
CONTROL PARAMETERS OF ALL ALGORITHMS

Parameters	MOWCA [51]	MOEA/D [67]	MOSOS [69]	MOSMA
Number of Runs	30	30	30	30
Population Size /Search agent (N_{pop})	100	100	100	100
Maximum Number of Iterations (Max_t)	1000	1000	1000	1000
Number of Function Evaluations (FES_{max})	1,00,000	1,00,000	1,00,000	1,00,000
Other Related Parameters	Number of rivers+sea, N_{sr} =4; Evaporation condition constant, D_{max}=1e-16.	Distribution Index, $\eta = 30$; Crossover Rate, $CR = 0.5$; Probability of selecting parents from the neighbourhood, $\delta = 0.9$; Maximal copies of a new child in the update, $n_r = 1$; The number of neighbours, $T = 10$.	Number of Pareto archive=100	-

C. SIMULATION RESULTS

Based on the non-dominated sorting mechanism to illustrate the effectiveness of the developed MOSMA algorithm, four types of analysis are discussed in this section to evaluate the effectiveness of the MOSMA.

The analysis-I, therefore, aims to evaluate MOSMA optimizer's convergence with MOWCA, MOSOS, and MOEA/D, which all concentrate on enhancing the convergence in the NDS technique. In order to evaluate the convergence output of MOSMA, MOWCA, MOSOS, and MOEA/D concerning GD metrics, the simulation is carried out for 30 individual runs of all algorithms on ZDT1-6, UF1-10 and the constrained benchmark functions, such as TNK, KITA, CONSTR, OSY and SRN, and instead of measuring the mean and standard deviation, the optimal GD (including both mean and standard deviation (SD)) values are listed for all selected problems in Table 2 and Table 7. Boldface highlights the best outcome for each test problem. In Table 2 and Table 7, with more than 78.57% of benchmark functions, the GD value of MOSMA is higher than other algorithms. The GD value of MOSMA has improved 80 % over the other algorithms, specifically for the ZDT test problem with unimodal, convex, and separable variables.

The purpose of analysis-II is to demonstrate the efficacy of the proposed MOSMA. In order to compare the diversity success of MOSMA, MOWCA, MOSOS, and MOEA/D with respect to Spacing and Spread metrics, the study runs 30 times individually on ZDT1-6, UF1-10, the constrained benchmark functions, such as TNK, KITA, CONSTR, OSY and SRN, and real-world engineering design constrained optimization problems and then found the optimal values of Spacing, Spread. The values are listed in Table 3, Table 4, Table 8 and Table 9. The value of spacing/spread for the proposed MOSMA is better than other algorithms for more than 79.76 % of all test problems. In fact, MOSMA diversity has increased by 39% relative to MOEA/D and over 36.5% compared to the other two algorithms. The MOSMA Spacing/Spread values are 86.66 %, mostly on UF and constrained design test problems with discrete PF, demonstrating that the MOSMA has a substantial diversity of discrete test problems. It has a uniform solution spread in local PF on ZDT, UF and constrained benchmarks, so it performs well in the Spacing/Spread metric.

Analysis-III aims to demonstrate the robust output of the MOSMA for balancing convergence and diversity compared to MOWCA, MOSOS, and MOEA/D. By running 30 times on ZDT1-6, UF1-10, and the constrained benchmark functions, such as TNK, KITA, CONSTR, OSY, and SRN independently, the IGD metric of all algorithms are listed in Table 5 and Table 10. For each algorithm, the best outcomes are displayed in boldface. The IGD metric is used to calculate each algorithm's quantitative efficiency, both considering convergence, and distribution. Tables 5 and 10 show that the proposed MOSMA ranks first, followed by MOWCA, MOSOS, and MOEA/D.

The purpose of analysis-IV is to demonstrate the efficacy of the proposed MOSMA in terms of run time. In order to compare the time complexity of all algorithms concerning run time metrics, the run time of all algorithms is listed in Table 6 and Table 11. For each problem, the best run-time outcomes are displayed in boldface. The run-time metric is used to calculate each algorithm's quantitative efficiency, considering reduced time complexity. Table 6 and Table 11 show that MOSMA convergence speed ranks first, followed

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

by MOSOS, MOWCA, and MOEA/D. The obtained Pareto front using the MOSMA optimizer is shown in Fig. 7, and Fig. 8 are concerning the true Pareto front for ZDT1-6, UF1-10, and the constrained benchmark functions, such as TNK, KITA, CONSTR, OSY, and SRN.

TABLE 2.
RESULTS OF THE MULTI-OBJECTIVE ALGORITHMS (USING GD) ON THE SELECTED UNCONSTRAINED TEST FUNCTIONS

Problem	N	M	D	FEs	MOWCA	MOSOS	MOEA/D	MOSMA
ZDT1	100	2	30	100000	8.6012e-5 (9.88e-7)	1.4501e-4 (1.87e-5)	3.3766e-4 (1.02e-4)	**6.5167e-5 (4.94e-5)**
ZDT2	100	2	30	100000	7.9115e-5 (3.78e-5)	1.0994e-4 (2.01e-6)	2.3756e-4 (7.69e-5)	**5.3235e-5 (3.30e-5)**
ZDT3	100	2	30	100000	7.0276e-5 (3.44e-5)	6.6463e-5 (1.64e-5)	3.9059e-4 (2.05e-4)	**5.5405e-5 (1.47e-5)**
ZDT4	100	2	10	100000	3.7541e-2 (1.74e-2)	2.9834e-5 (1.92e-5)	6.6765e+0 (2.60e+0)	**2.1453e-5 (1.45e-5)**
ZDT6	100	2	10	100000	**3.2558e-6 (4.54e-10)**	3.6187e-6 (1.10e-7)	9.3319e-3 (1.32e-2)	3.5879e-6 (9.17e-8)
UF1	100	2	30	100000	1.1192e-2 (6.80e-3)	2.8623e-4 (5.63e-7)	4.2068e-3 (5.97e-4)	**1.2106e-4 (1.33e-5)**
UF2	100	2	30	100000	6.8119e-3 (5.16e-3)	1.7227e-3 (4.84e-5)	4.0264e-3 (8.95e-4)	**9.0028e-4 (4.13e-4)**
UF3	100	2	30	100000	1.6268e-2 (4.66e-5)	**3.4180e-3 (1.72e-3)**	1.0230e-2 (2.03e-3)	3.6240e-3 (2.61e-3)
UF4	100	2	30	100000	9.5131e-3 (4.22e-4)	4.8177e-3 (7.55e-5)	7.3641e-3 (7.13e-4)	**4.5816e-3 (6.08e-5)**
UF5	100	2	30	100000	1.1327e-1 (7.36e-2)	7.1955e-2 (1.07e-2)	1.5841e-1 (6.43e-2)	**1.9155e-2 (2.22e-2)**
UF6	100	2	30	100000	2.5554e-3 (1.28e-3)	1.7334e-2 (4.61e-3)	4.4733e-2 (8.69e-3)	**1.8613e-3 (2.61e-3)**
UF7	100	2	30	100000	2.7197e-3 (1.57e-3)	3.7810e-4 (3.94e-4)	1.5920e-3 (5.97e-5)	**2.4601e-4 (1.88e-4)**
UF8	100	3	30	100000	5.9513e-1 (2.02e-1)	1.1753e-1 (9.12e-2)	2.5970e-1 (5.69e-2)	**8.4872e-2 (1.02e-1)**
UF9	100	3	30	100000	5.5881e-1 (7.56e-2)	1.4329e-1 (4.02e-2)	4.4996e-1 (6.81e-3)	**3.1003e-2 (3.91e-3)**
UF10	100	3	30	100000	2.8066e-1 (5.25e-2)	2.9269e-1 (1.85e-1)	4.4664e-1 (1.15e-1)	**9.1754e-4 (1.93e-4)**

TABLE 3.
RESULTS OF THE MULTI-OBJECTIVE ALGORITHMS (USING SPREAD) ON THE SELECTED UNCONSTRAINED TEST FUNCTIONS

Problem	N	M	D	FEs	MOWCA	MOSOS	MOEA/D	MOSMA
ZDT1	100	2	30	100000	3.9745e-1 (4.57e-3)	3.3274e-1 (1.28e-3)	2.7283e-1 (3.74e-3)	**1.3250e-1 (4.96e-3)**
ZDT2	100	2	30	100000	3.4926e-1 (3.56e-2)	4.4948e-1 (1.10e-3)	1.4480e-1 (4.32e-3)	**1.3701e-1 (2.78e-3)**
ZDT3	100	2	30	100000	3.7856e-1 (3.04e-2)	4.7548e-1 (4.33e-2)	6.0592e-1 (4.87e-2)	**1.6694e-1 (3.11e-2)**
ZDT4	100	2	10	100000	8.8436e-1 (1.12e-1)	4.4169e-1 (2.90e-2)	2.7807e-1 (1.11e-2)	**9.7080e-2 (4.00e-3)**
ZDT6	100	2	10	100000	4.2211e-1 (5.33e-2)	4.1330e-1 (3.61e-2)	1.4134e-1 (2.16e-3)	**1.2754e-1 (5.53e-3)**
UF1	100	2	30	100000	8.5200e-1 (2.29e-1)	8.7564e-1 (9.62e-2)	1.0154e+0 (1.36e-2)	**3.8568e-1 (9.79e-2)**
UF2	100	2	30	100000	4.0331e-1 (4.84e-2)	5.5838e-1 (1.12e-2)	6.6444e-1 (6.80e-2)	**2.3911e-1 (7.40e-3)**
UF3	100	2	30	100000	**3.7250e-1 (2.75e-2)**	1.1412e+0 (2.04e-1)	9.9457e-1 (7.76e-3)	1.1007e+0 (2.10e-2)
UF4	100	2	30	100000	3.4252e-1 (2.35e-2)	4.5371e-1 (6.30e-2)	5.5955e-1 (4.29e-2)	**1.8376e-1 (1.44e-3)**
UF5	100	2	30	100000	9.9502e-1 (8.74e-3)	1.1885e+0 (2.01e-1)	1.0001e+0 (1.34e-4)	**8.7244e-1 (6.18e-3)**
UF6	100	2	30	100000	1.0162e+0 (1.22e-2)	1.2426e+0 (2.42e-1)	1.0000e+0 (3.88e-7)	**8.0721e-1 (5.06e-2)**
UF7	100	2	30	100000	4.9296e-1 (6.02e-3)	8.3903e-1 (2.23e-1)	1.0046e+0 (6.51e-3)	**1.8959e-1 (3.15e-2)**
UF8	100	3	30	100000	5.9951e-1 (2.06e-2)	5.9378e-1 (1.08e-2)	5.8554e-1 (1.82e-1)	**1.6357e-1 (4.05e-3)**
UF9	100	3	30	100000	6.2083e-1 (2.17e-2)	6.1360e-1 (7.51e-2)	8.2358e-1 (5.84e-2)	**2.9605e-1 (2.01e-2)**
UF10	100	3	30	100000	6.1987e-1 (2.65e-2)	6.7163e-1 (7.71e-2)	1.0000e+0 (2.77e-6)	**2.8938e-1 (1.30e-1)**

TABLE 4.
RESULTS OF THE MULTI-OBJECTIVE ALGORITHMS (USING SPACING) ON THE SELECTED UNCONSTRAINED TEST FUNCTIONS

Problem	N	M	D	FEs	MOWCA	MOSOS	MOEA/D	MOSMA
ZDT1	100	2	30	100000	6.6033e-3 (5.41e-4)	6.3174e-3 (3.06e-4)	**2.6868e-3 (2.84e-4)**	3.1446e-3 (2.82e-4)
ZDT2	100	2	30	100000	6.5610e-3 (5.13e-4)	7.1819e-3 (1.92e-4)	3.8111e-3 (1.35e-3)	**3.0210e-3 (1.00e-4)**
ZDT3	100	2	30	100000	7.2519e-3 (9.33e-5)	8.3539e-3 (4.41e-4)	**3.7316e-3 (3.67e-4)**	4.1650e-3 (6.29e-4)
ZDT4	100	2	10	100000	2.9875e-2 (2.75e-3)	7.4689e-3 (2.41e-4)	8.1050e-1 (1.90e-1)	**2.5587e-3 (2.49e-5)**
ZDT6	100	2	10	100000	6.1549e-3 (2.92e-4)	6.0501e-3 (3.45e-4)	9.4197e-2 (1.29e-1)	**2.3385e-3 (3.67e-5)**
UF1	100	2	30	100000	1.7612e-2 (6.66e-3)	1.0518e-3 (1.17e-4)	1.3582e-2 (1.34e-2)	**4.6609e-4 (1.32e-4)**
UF2	100	2	30	100000	5.6148e-3 (1.89e-3)	8.9811e-3 (4.21e-3)	5.0599e-3 (1.06e-3)	**4.0469e-3 (8.04e-4)**
UF3	100	2	30	100000	7.0326e-3 (5.17e-4)	2.2867e-2 (3.22e-2)	8.7684e-3 (2.99e-3)	**4.3421e-3 (6.12e-3)**
UF4	100	2	30	100000	5.4915e-3 (7.82e-4)	6.7493e-3 (6.12e-4)	3.7108e-3 (2.21e-4)	**3.5166e-3 (9.52e-6)**
UF5	100	2	30	100000	6.4018e-3 (3.30e-3)	4.2152e-2 (2.92e-2)	7.4955e-2 (2.34e-2)	**1.6083e-5 (2.27e-5)**
UF6	100	2	30	100000	2.8014e-3 (2.61e-3)	5.2434e-2 (3.96e-2)	1.7419e-2 (2.37e-3)	**4.3918e-8 (6.21e-8)**
UF7	100	2	30	100000	8.0963e-3 (5.25e-3)	2.8185e-3 (2.90e-3)	3.9495e-3 (1.24e-3)	**2.6846e-3 (3.79e-3)**
UF8	100	3	30	100000	2.5775e-1 (1.19e-1)	1.2244e-1 (2.98e-2)	1.4901e-1 (5.49e-3)	**6.5931e-2 (7.99e-3)**
UF9	100	3	30	100000	3.8672e-1 (5.90e-2)	1.1187e-1 (1.35e-2)	2.3874e-1 (1.45e-2)	**7.7053e-2 (4.00e-4)**
UF10	100	3	30	100000	1.5654e-1 (4.16e-4)	2.1179e-1 (6.98e-2)	3.0916e-1 (9.03e-2)	**1.3305e-5 (7.75e-6)**

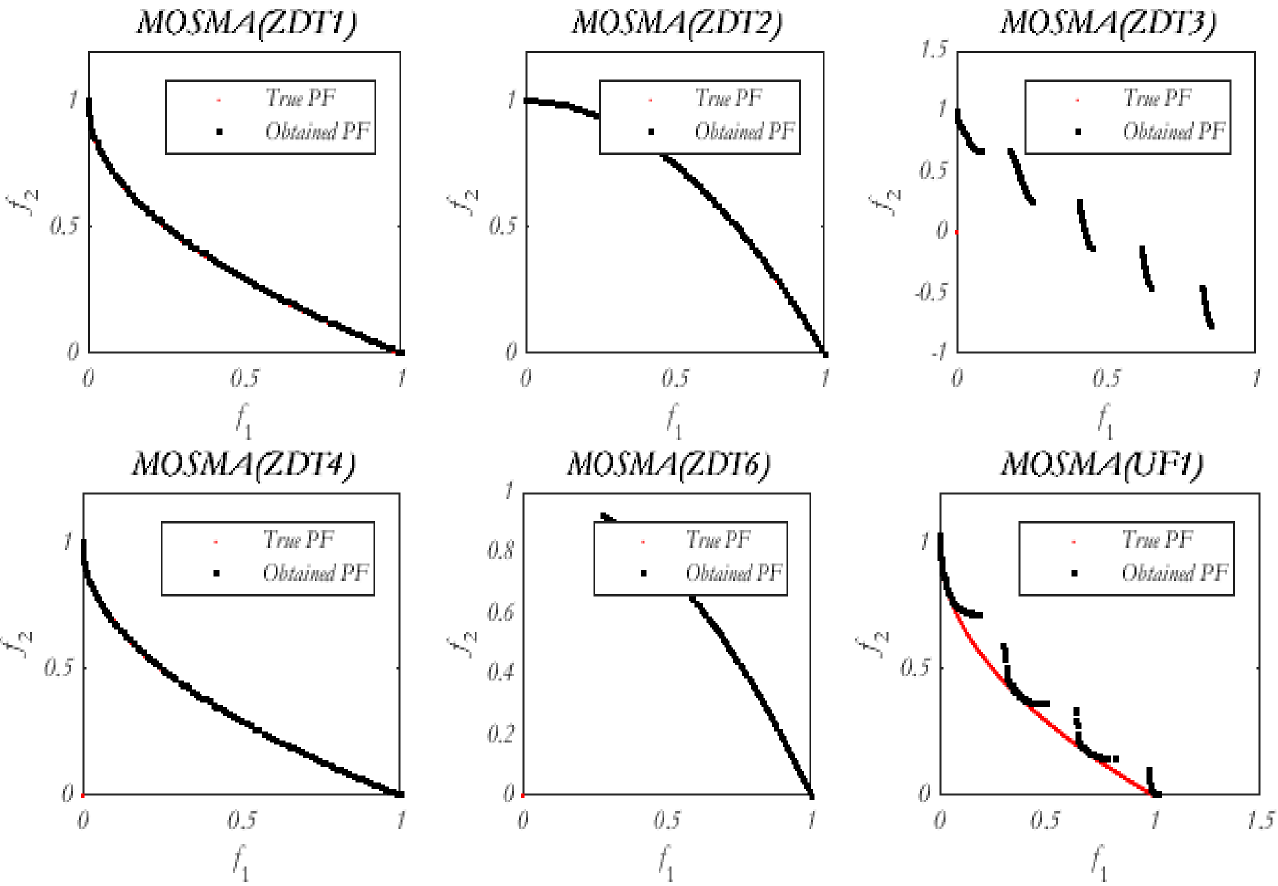
TABLE 5.
RESULTS OF THE MULTI-OBJECTIVE ALGORITHMS (USING IGD) ON THE SELECTED UNCONSTRAINED TEST FUNCTIONS

Problem	N	M	D	FEs	MOWCA	MOSOS	MOEA/D	MOSMA
ZDT1	100	2	30	100000	5.0230e-3 (1.76e-4)	4.4742e-3 (1.64e-4)	4.0711e-3 (1.27e-4)	**3.8898e-3 (4.00e-5)**
ZDT2	100	2	30	100000	4.7842e-3 (8.05e-6)	4.9289e-3 (1.08e-4)	3.9485e-3 (5.36e-6)	**3.9120e-3 (6.10e-5)**
ZDT3	100	2	30	100000	5.2151e-3 (9.64e-5)	5.8920e-3 (1.05e-4)	1.2191e-2 (4.45e-4)	**4.9243e-3 (8.56e-5)**
ZDT4	100	2	10	100000	2.3998e-1 (8.52e-2)	4.5570e-3 (5.95e-5)	5.6804e-3 (2.25e-3)	**3.7941e-3 (1.45e-5)**
ZDT6	100	2	10	100000	3.9688e-3 (1.80e-4)	3.5883e-3 (1.44e-5)	3.6873e-3 (5.27e-4)	**3.0782e-3 (2.24e-5)**
UF1	100	2	30	100000	1.0483e-1 (2.13e-2)	9.9124e-2 (1.27e-2)	2.4081e-1 (8.08e-3)	**4.2432e-2 (2.42e-3)**

UF2	100	2	30	100000	5.1495e-2 (1.68e-2)	2.9975e-2 (3.56e-3)	1.7568e-1 (3.16e-2)	**2.8347e-2 (1.56e-3)**
UF3	100	2	30	100000	1.4627e-1 (5.94e-4)	2.6595e-1 (3.65e-2)	2.7174e-1 (8.69e-2)	**8.6610e-2 (1.28e-2)**
UF4	100	2	30	100000	8.4065e-2 (7.35e-3)	4.5618e-2 (1.84e-3)	7.2472e-2 (4.76e-3)	**4.4336e-2 (7.79e-4)**
UF5	100	2	30	100000	9.5235e-1 (5.23e-1)	**3.7642e-1 (5.34e-2)**	4.4809e-1 (2.99e-2)	3.9080e-1 (1.02e-1)
UF6	100	2	30	100000	4.0697e-1 (5.52e-2)	2.5032e-1 (2.22e-1)	3.7607e-1 (3.07e-2)	**1.1596e-1 (2.22e-2)**
UF7	100	2	30	100000	4.5630e-2 (3.84e-3)	1.9885e-1 (2.11e-1)	5.0500e-1 (1.79e-1)	**1.7391e-2 (2.01e-3)**
UF8	100	3	30	100000	5.4477e-1 (1.49e-1)	2.5311e-1 (5.03e-2)	**2.1728e-1 (1.08e-1)**	2.9876e-1 (1.28e-2)
UF9	100	3	30	100000	5.5320e-1 (3.19e-2)	3.5805e-1 (1.97e-2)	2.8886e-1 (4.47e-3)	**2.5876e-1 (2.29e-3)**
UF10	100	3	30	100000	2.0011e+0 (1.35e-1)	6.1812e-1 (7.49e-2)	7.7617e-1 (1.23e-1)	**3.9607e-1 (9.47e-2)**

TABLE 6.
RESULTS OF THE MULTI-OBJECTIVE ALGORITHMS (USING RUN-TIME) ON THE SELECTED UNCONSTRAINED TEST FUNCTIONS

Problem	N	M	D	FEs	MOWCA	MOSOS	MOEA/D	MOSMA
ZDT1	100	2	30	100000	7.3996e+0 (5.61e-1)	1.1043e+1 (1.25e-1)	1.0296e+2 (7.00e-3)	**6.4451e+0 (2.03e-1)**
ZDT2	100	2	30	100000	7.1364e+0 (1.52e-1)	1.0234e+1 (8.44e-2)	1.0209e+2 (4.82e-1)	**6.4050e+0 (8.97e-2)**
ZDT3	100	2	30	100000	7.1249e+0 (1.30e-1)	8.2029e+0 (1.99e-1)	1.0347e+2 (8.40e-1)	**6.3871e+0 (1.26e-1)**
ZDT4	100	2	10	100000	6.3961e+0 (5.95e-2)	6.5345e+0 (5.94e-3)	9.8113e+1 (1.92e-1)	**5.7882e+0 (5.78e-2)**
ZDT6	100	2	10	100000	6.6024e+0 (2.06e-2)	1.5461e+1 (3.69e-1)	1.0148e+2 (1.58e-1)	**5.7655e+0 (7.01e-2)**
UF1	100	2	30	100000	7.2423e+0 (3.53e-2)	6.9220e+0 (2.19e-1)	1.1198e+2 (5.54e-3)	**6.6655e+0 (1.10e-3)**
UF2	100	2	30	100000	7.6719e+0 (9.65e-2)	7.3445e+0 (9.56e-3)	1.2559e+2 (2.51e-1)	**7.0879e+0 (2.62e-1)**
UF3	100	2	30	100000	7.7473e+0 (3.20e-2)	7.5837e+0 (2.11e-1)	1.1254e+2 (3.66e-1)	**7.2740e+0 (5.59e-2)**
UF4	100	2	30	100000	7.4830e+0 (3.41e-2)	7.8831e+0 (5.84e-2)	1.1204e+2 (3.99e-2)	**6.7603e+0 (2.50e-2)**
UF5	100	2	30	100000	7.0822e+0 (3.94e-2)	**6.5804e+0 (3.83e-2)**	1.1176e+2 (3.62e-1)	7.4078e+0 (2.61e-1)
UF6	100	2	30	100000	7.1753e+0 (2.62e-2)	**7.0189e+0 (1.58e-1)**	1.1175e+2 (5.68e-1)	7.3742e+0 (2.59e-1)
UF7	100	2	30	100000	7.3207e+0 (4.56e-2)	8.0319e+0 (1.47e-1)	1.1166e+2 (4.39e-1)	**6.6519e+0 (1.93e-2)**
UF8	100	3	30	100000	7.8605e+0 (8.37e-2)	1.0288e+1 (8.07e-1)	1.1664e+2 (1.00e-1)	**7.2731e+0 (1.04e-1)**
UF9	100	3	30	100000	7.9181e+0 (7.77e-4)	1.0308e+1 (7.79e-1)	1.1635e+2 (3.66e-1)	**7.4040e+0 (2.71e-1)**
UF10	100	3	30	100000	7.9672e+0 (6.00e-2)	7.9995e+0 (3.24e-1)	1.1624e+2 (2.27e-1)	**7.4225e+0 (5.74e-3)**



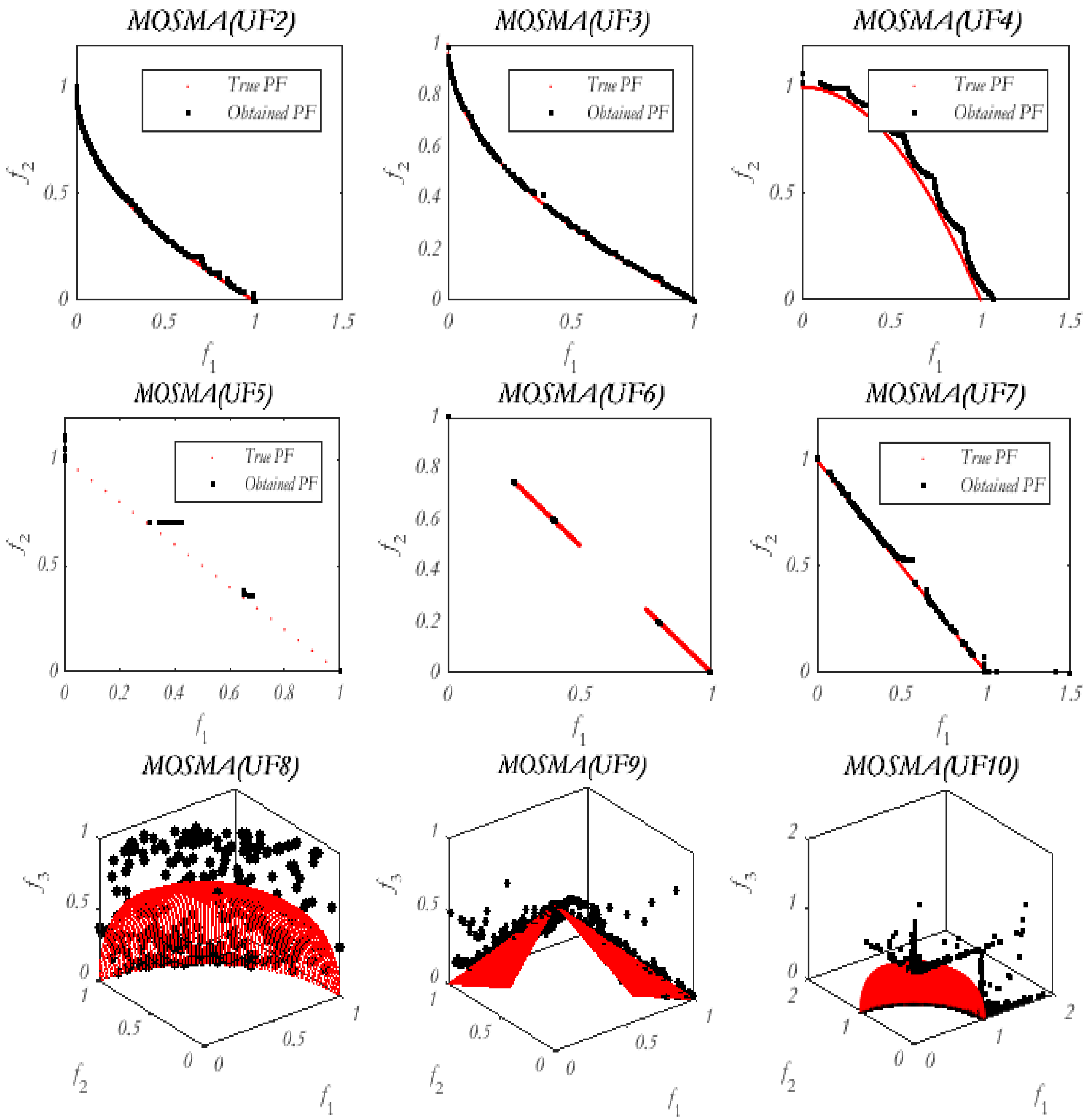


FIGURE 7. Results of Pareto optimal front realized by the MOSMO algorithm on ZDT1, ZDT2, ZDT3, ZDT4, ZDT6, UF1, UF2, UF3, UF4, UF5, UF6, UF7, UF8, UF9, and UF10 cases.

TABLE 7.
RESULTS OF THE MULTI-OBJECTIVE ALGORITHMS (USING GD) ON THE SELECTED CONSTRAINED BENCHMARK FUNCTIONS

Problem	M	D	MOWCA	MOSOS	MOEA/D	MOSMA
CONSTR	2	2	3.2591e-4 (1.16e-5)	8.9109e-4 (1.12e-4)	2.9091e-4 (1.10e-5)	**1.1898e-4 (8.08e-6)**
TNK	2	2	NaN (NaN)	5.1706e-3 (1.41e-4)	3.8768e-4 (7.97e-5)	**2.3780e-4 (2.93e-5)**
SRN	2	2	2.3699e+0 (1.05e+0)	2.4729e+0 (9.06e-1)	**3.5219e-2 (8.63e-3)**	3.9666e-2 (1.04e-2)
OSY	2	6	NaN (NaN)	2.0741e-1 (4.85e-1)	7.9047e-1 (1.06e-1)	**7.4260e-2 (7.67e-2)**
KITA	2	2	1.3891e-3 (2.18e-4)	1.3444e-3 (1.26e-5)	1.1501e-3 (3.72e-7)	**6.7687e-4 (2.69e-5)**

TABLE 8.
RESULTS OF THE MULTI-OBJECTIVE ALGORITHMS (USING IGD) ON THE SELECTED CONSTRAINED BENCHMARK FUNCTIONS

Problem	M	D	MOWCA	MOSOS	MOEA/D	MOSMA
CONSTR	2	2	2.4239e+0 (7.05e-3)	2.8962e-2 (1.78e-5)	5.1573e-2 (4.13e-3)	**2.1763e-2 (1.62e-4)**

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

TNK	2	2	NaN (NaN)	**5.3874e-3 (1.09e-4)**	3.6941e-2 (1.00e-3)	5.4946e-3 (3.48e-4)
SRN	2	2	8.6545e+1 (4.16e+1)	1.0267e+0 (2.23e-2)	1.0042e+1 (1.60e+0)	**8.4934e-1 (1.17e-2)**
OSY	2	6	NaN (NaN)	**2.5710e-1 (1.63e-1)**	5.8349e+1 (8.76e+0)	2.8411e+1 (1.57e+0)
KITA	2	2	1.5436e-1 (2.88e-3)	1.2441e-1 (1.24e-2)	9.5856e-2 (1.10e-3)	**3.7949e-2 (2.86e-3)**

TABLE 9.
RESULTS OF MULTI-OBJECTIVE ALGORITHMS (USING SPACING) ON THE SELECTED CONSTRAINED BENCHMARK FUNCTIONS

Problem	M	D	MOWCA	MOSOS	MOEA/D	MOSMA
CONSTR	2	2	4.3773e-2 (1.79e-4)	4.8466e-2 (3.00e-3)	7.0009e-2 (5.43e-4)	**1.6387e-2 (2.35e-4)**
TNK	2	2	NaN (NaN)	6.6992e-3 (3.89e-4)	3.9180e-2 (1.79e-2)	**4.7473e-3 (4.61e-4)**
SRN	2	2	5.5793e+1 (0.00e+0)	1.6470e+0 (1.24e-1)	9.1999e+0 (2.49e+0)	**6.7313e-1 (7.85e-2)**
OSY	2	6	NaN (NaN)	**1.3342e+0 (7.18e-1)**	3.6409e+1 (4.28e-1)	2.9570e+0 (9.69e-1)
KITA	2	2	2.0851e-1 (1.94e-2)	1.9471e-1 (2.40e-2)	1.2398e-1 (1.69e-3)	**4.4449e-2 (5.17e-3)**

TABLE 10.
RESULTS OF MULTI-OBJECTIVE ALGORITHMS (USING SPREAD) ON THE SELECTED CONSTRAINED BENCHMARK FUNCTIONS

Problem	M	D	MOWCA	MOSOS	MOEA/D	MOSMA
CONSTR	2	2	9.8042e-1 (7.68e-3)	9.0790e-1 (7.06e-2)	6.5204e-1 (3.68e-3)	**5.5468e-1 (2.49e-2)**
TNK	2	2	NaN (NaN)	7.0373e-1 (1.21e-1)	5.6547e-1 (1.02e-1)	**3.6133e-1 (4.60e-2)**
SRN	2	2	1.2307e+0 (0.00e+0)	3.9230e-1 (1.29e-2)	5.4803e-1 (2.01e-2)	**1.5201e-1 (1.49e-2)**
OSY	2	6	NaN (NaN)	7.9908e-1 (2.33e-2)	1.1393e+0 (1.14e-1)	**7.1835e-1 (1.09e-1)**
KITA	2	2	4.9916e-1 (2.09e-2)	6.3628e-1 (9.51e-2)	4.3132e-1 (1.97e-2)	**3.0704e-1 (8.20e-3)**

TABLE 11.
RESULTS OF MULTI-OBJECTIVE ALGORITHMS (USING RUN-TIME) ON THE SELECTED CONSTRAINED BENCHMARK FUNCTIONS

Problem	M	D	MOWCA	MOSOS	MOEA/D	MOSMA
CONSTR	2	2	9.7004e-1 (3.13e-2)	7.2160e-1 (1.03e-1)	1.9045e+1 (4.05e-2)	**6.0797e-1 (7.46e-2)**
TNK	2	2	7.1118e-1 (1.26e-1)	6.8539e-1 (5.78e-2)	1.1364e+0 (2.96e-1)	**6.2697e-1 (1.19e-2)**
SRN	2	2	1.1762e+0 (2.42e-2)	6.3965e-1 (5.65e-3)	1.0239e+0 (2.46e-1)	**6.2826e-1 (8.97e-2)**
OSY	2	6	6.7079e-1 (3.74e-3)	**6.5131e-1 (2.65e-3)**	8.9023e-1 (1.89e-3)	6.5641e-1 (6.51e-3)
KITA	2	2	1.5538e+0 (1.90e-2)	6.4419e-1 (5.44e-3)	1.9708e+1 (2.53e-1)	**5.5940e-1 (1.16e-2)**

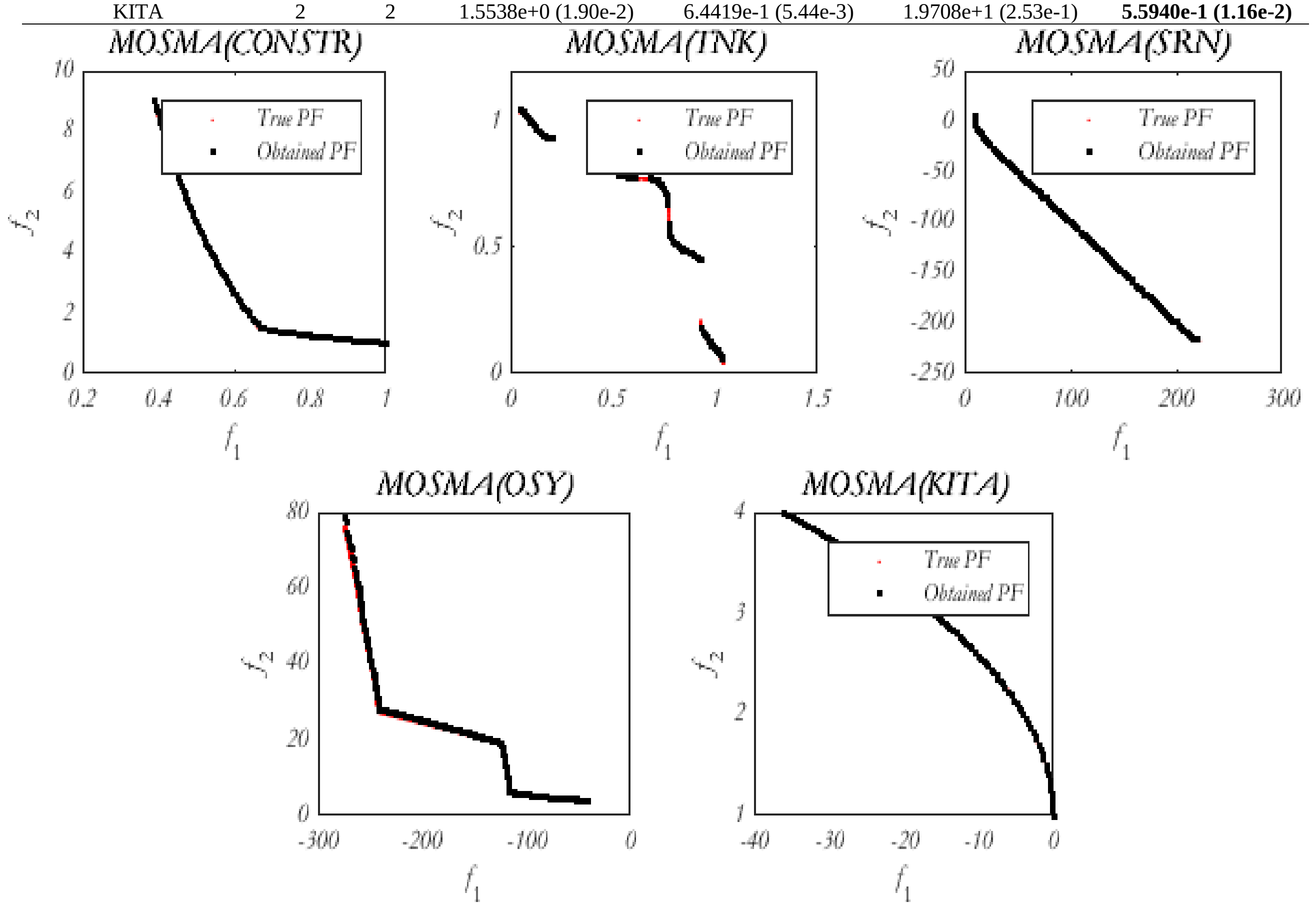


FIGURE 8. **Results of Pareto optimal front attained by the MOSMO technique on CONSTR, TNK, SRN, OSY, and KITA benchmark functions.**

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

As similar to the previous discussion, the proposed MOSMA and other selected algorithms are applied to 21 real-world engineering design optimization problems, such as 2-bar truss, I-beam, 3-bar truss, 4-bar truss, pressure vessel, helical spring, disk brake, welded-beam, gear-train, speed reducer, tool spindle, CNC machine tool, cantilever beam, car crash, car side-impact, metal cutting tool, multiple disk clutch break, rolling-element bearing, satellite heat pipe, BLDC motor, and isolated safety transformer.

In order to evaluate the convergence output of MOSMA, MOWCA, MOSOS, and MOEA/D about GD metrics, the simulation is carried out for 30 individual runs of all algorithms on all selected real-world engineering design constrained optimization problems, and the optimal GD values are listed for all selected problems in Table 12. The bold letter indicates the best outcome for each problem. In Table 12, with more than 66.66 % of benchmark functions, the GD (including both mean and SD) value of MOSMA is higher than other algorithms. To compare the diversity success of all algorithms concerning Spacing and Spread metrics, the study runs 30 times individually on all selected real-world engineering design constrained optimization problems and then finds the optimal values of Spacing, Spread. The values are listed in Table 13 and Table 14. The value of spacing/spread for the proposed MOSMA is better than other algorithms for more than 69.04 % of all test problems. The robust output of the MOSMA for balancing convergence and diversity is demonstrated by finding the optimal values of the IGD indicator.

By running 30 times on selected engineering design optimization problems independently, the IGD metric of all algorithms is listed in Table 15. Table 15 shows that the proposed MOSMA ranks first, followed by MOEA/D, MOSOS, and MOWCA. To compare the time complexity of all algorithms for run-time metrics, the run time of all algorithms is listed in Table 16. The results in Table 16 shows that MOSMA convergence speed ranks first, followed by MOSOS, MOWCA, and MOEA/D. The obtained Pareto front using the MOSMA optimizer is shown in Fig. 9 concerning the true Pareto front for all engineering design problems.

TABLE 12.
RESULTS OF THE MULTI-OBJECTIVE ALGORITHMS (USING GD) ON THE SELECTED ENGINEERING DESIGN OPTIMIZATION PROBLEMS

Problem	M	D	MOWCA	MOSOS	MOEA/D	MOSMA
2-bar truss	2	3	NaN (NaN)	3.3323e-2 (9.59e-1)	3.5380e-2 (4.78e-1)	**3.2059e-3 (6.30e-2)**
3-bar truss	2	2	1.8401e-1 (4.85e-2)	7.0519e-2 (1.48e-2)	9.7862e-2 (3.26e-3)	**3.0046e-2 (2.98e-2)**
4-bar truss	2	4	1.7518e-2 (2.09e-3)	1.8080e-2 (1.03e-3)	1.8325e-2 (2.95e-4)	**8.6231e-3 (5.27e-4)**
Gear train continues	2	4	**4.2244e-3 (4.42e-3)**	4.9797e-3 (4.16e-3)	1.4774e-1 (2.01e-1)	1.0799e-1 (1.51e-1)
Pressure vessel	2	4	NaN (NaN)	1.9465e-2 (2.30e-2)	1.9839e-2 (7.04e-1)	**1.8707e-3 (1.26e-2)**
Helical spring	2	3	NaN (NaN)	1.6518e-1 (2.01e-1)	1.0486e-1 (1.19e-1)	**5.2544e-2 (2.81e-1)**
Welded beam	2	4	NaN (NaN)	1.3619e-2 (3.21e-3)	**1.2633e-3 (8.33e-5)**	1.4868e-2 (7.52e-4)
Disk break	2	4	NaN (NaN)	1.9960e-1 (2.78e-1)	1.1817e-3 (1.29e-4)	**9.7573e-4 (2.18e-4)**
Speed reducer	2	7	NaN (NaN)	8.7950e-1 (9.83e-3)	1.1938e+0 (1.14e+0)	**2.4403e-2 (6.26e-2)**
CNC machine tool	2	3	NaN (NaN)	2.9554e-3 (5.59e-4)	8.4012e-4 (5.01e-4)	**5.7586e-4 (6.35e-5)**
Tool spindle	2	4	3.3456e-1 (9.96e-1)	8.0571e-1 (2.75e-1)	4.0519e-1 (4.62e-1)	**3.6258e-2 (4.96e-1)**
I-beam	2	4	4.6108e-2 (1.35e-3)	3.0865e-2 (2.77e-3)	2.6579e-2 (1.57e-3)	**2.5868e-2 (2.90e-3)**
Cantilever beam	2	2	1.6999e-4 (2.53e-6)	**2.9175e-5 (2.08e-6)**	8.9222e-5 (1.40e-6)	9.3549e-5 (5.00e-6)
Multiple disk clutch brake	2	5	**7.1320e-16 (0.0e+0)**	3.2259e-3 (6.51e-4)	1.8308e-4 (7.45e-5)	3.7185e-4 (3.89e-5)
Car crash	3	5	4.7609e-2 (2.02e-3)	1.3663e-2 (8.02e-4)	1.1774e-2 (3.93e-3)	**1.1583e-2 (3.68e-4)**
Car side impact	3	7	1.4822e-2 (6.10e-4)	1.0529e-2 (5.39e-4)	1.1673e-2 (1.62e-3)	**7.5748e-3 (2.48e-4)**
Metal cutting tools	3	3	3.7644e-4 (4.30e-5)	5.1346e-4 (3.79e-5)	**2.8105e-4 (6.60e-5)**	4.2866e-4 (8.82e-5)
Rolling element bearing	2	10	NaN (NaN)	7.6563e+3 (6.77e+3)	1.6349e+4 (2.10e+3)	**1.9544e-1 (9.43e-3)**
Satellite heat pipe	2	5	6.0230e-2 (5.96e-3)	**3.3275e-2 (1.10e-4)**	5.8838e-2 (1.99e-3)	5.3992e-2 (2.11e-4)
BLDC motor	2	5	NaN (NaN)	3.8237e-4 (6.39e-5)	2.2000e-4 (1.14e-5)	**2.0761e-4 (6.69e-6)**
Isolated safety transformer	2	7	NaN (NaN)	1.1027e-3 (2.82e-4)	1.5591e-2 (2.10e-2)	**9.5552e-4 (5.64e-5)**

TABLE 13.
RESULTS OF MULTI-OBJECTIVE ALGORITHMS (USING SPACING) ON THE SELECTED ENGINEERING DESIGN OPTIMIZATION PROBLEMS

Problem	M	D	MOWCA	MOSOS	MOEA/D	MOSMA
2-bar truss	2	3	NaN (NaN)	5.6314e+2 (4.96e+1)	1.0362e+3 (2.50e+2)	**5.3497e-2 (1.67e-1)**
3-bar truss	2	2	1.4458e+1 (3.09e+0)	1.1279e+1 (7.31e-1)	NaN (NaN)	**8.6652e+0 (7.39e-1)**
4-bar truss	2	4	2.5331e+0 (1.10e-1)	2.5981e+0 (2.23e-1)	**6.6241e-1 (8.95e-4)**	2.4435e+0 (4.37e-2)
Gear train continues	2	4	**1.2608e-1 (8.45e-3)**	7.7423e-1 (9.19e-1)	2.0588e-1 (1.06e-1)	1.0873e+0 (1.35e+0)
Pressure vessel	2	4	NaN (NaN)	2.4354e+5 (2.79e+3)	3.0925e+5 (6.43e+4)	**1.4955e-1 (4.37e-3)**
Helical spring	2	3	NaN (NaN)	**6.6984e+2 (1.29e+2)**	2.1515e+3 (3.27e+1)	1.3150e+3 (1.68e+2)
Welded beam	2	4	NaN (NaN)	2.1206e-1 (1.75e-2)	NaN (NaN)	**1.7504e-1 (3.67e-2)**
Disk break	2	4	NaN (NaN)	8.4921e-2 (6.11e-3)	9.1869e-1 (1.20e+0)	**7.6673e-2 (2.86e-4)**
Speed reducer	2	7	NaN (NaN)	2.2968e+1 (3.89e+0)	1.1661e+2 (3.42e+1)	**1.7183e-1 (7.40e+0)**
CNC machine tool	2	3	NaN (NaN)	1.0020e-1 (5.29e-2)	2.0963e-1 (2.52e-2)	**2.7147e-2 (5.78e-4)**
Tool spindle	2	4	**0.0000e+0 (0.00e+0)**	6.0450e-3 (3.88e-2)	3.6905e-4 (3.10e-4)	4.6720e-3 (9.19e-1)
I-beam	2	4	5.9204e+0 (4.12e-1)	4.1204e+0 (4.36e-2)	3.0342e+1 (1.11e+1)	**3.7523e-1 (9.55e-1)**
Cantilever beam	2	2	2.1082e-2 (2.76e-3)	1.8812e-2 (1.38e-3)	5.7855e-2 (2.69e-2)	**1.5684e-2 (5.25e-4)**
Multiple disk clutch brake	2	5	**0.0000e+0 (0.00e+0)**	4.5865e-2 (5.02e-4)	4.8525e-2 (1.23e-2)	4.7535e-2 (1.21e-4)
Car crash	3	5	2.2391e-1 (5.17e-2)	2.2740e-1 (2.14e-2)	2.9360e-1 (9.00e-2)	**1.8536e-1 (2.35e-2)**

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

Car side impact	3	7	4.3241e-1 (7.26e-2)	2.1379e-1 (8.19e-3)	1.9393e-1 (3.07e-2)	**1.1403e-1 (3.61e-3)**
Metal cutting tools	3	3	2.5127e-2 (4.35e-4)	2.3003e-2 (2.24e-3)	1.5102e-1 (5.95e-3)	**1.7021e-2 (2.64e-6)**
Rolling element bearing	2	10	NaN (NaN)	**1.3662e+1 (6.84e+0)**	5.4522e+3 (0.00e+0)	4.9352e+3 (1.45e+3)
Satellite heat pipe	2	5	9.9518e+0 (2.50e-1)	9.9008e+0 (5.94e-1)	**2.6746e-1 (1.69e-3)**	9.2570e+0 (1.64e-1)
BLDC motor	2	5	NaN (NaN)	1.9306e-2 (1.58e-3)	4.1656e-2 (3.74e-3)	**1.2685e-2 (1.23e-3)**
Isolated safety transformer	2	7	NaN (NaN)	4.5027e-1 (4.45e-1)	2.3096e-1 (2.17e-3)	**9.2953e-2 (5.98e-2)**

TABLE 14.
RESULTS OF MULTI-OBJECTIVE ALGORITHMS (USING SPREAD) ON THE SELECTED ENGINEERING DESIGN OPTIMIZATION PROBLEMS

Problem	M	D	MOWCA	MOSOS	MOEA/D	MOSMA
2-bar truss	2	3	NaN (NaN)	8.3285e-1 (3.52e-3)	1.0798e+0 (1.94e-1)	**6.1586e-1 (1.71e-2)**
3-bar truss	2	2	6.1883e-1 (2.56e-2)	8.4752e-1 (4.05e-3)	NaN (NaN)	**5.6165e-1 (3.99e-2)**
4-bar truss	2	4	5.1085e-1 (3.14e-2)	5.4429e-1 (4.73e-2)	6.2192e-1 (5.40e-3)	**4.1710e-1 (1.54e-2)**
Gear train continues	2	4	**7.0458e-1 (3.14e-2)**	1.0302e+0 (3.19e-1)	1.0343e+0 (1.81e-2)	9.5399e-1 (4.19e-1)
Pressure vessel	2	4	NaN (NaN)	5.4976e-1 (2.60e-2)	8.2592e-1 (2.39e-2)	**2.3942e-1 (8.74e-3)**
Helical spring	2	3	NaN (NaN)	1.5754e+0 (1.30e-1)	7.6712e-1 (1.21e-1)	**7.5119e-1 (2.09e-1)**
Welded beam	2	4	NaN (NaN)	7.5816e-1 (5.64e-2)	NaN (NaN)	**5.4629e-1 (1.04e-1)**
Disk break	2	4	NaN (NaN)	6.7509e-1 (6.37e-2)	1.0576e+0 (6.04e-1)	**5.2227e-1 (1.60e-3)**
Speed reducer	2	7	NaN (NaN)	8.3379e-1 (4.73e-4)	1.3657e+0 (1.19e-1)	**6.9187e-1 (1.19e-2)**
CNC machine tool	2	3	NaN (NaN)	**9.6555e-1 (9.76e-2)**	1.1709e+0 (5.60e-2)	1.0636e+0 (1.59e-1)
Tool spindle	2	4	1.0000e+0 (0.00e+0)	6.7538e-1 (2.19e-2)	1.0380e+0 (4.93e-2)	**3.7136e-1 (3.97e-3)**
I-beam	2	4	5.6545e-1 (1.73e-2)	7.5217e-1 (2.67e-2)	1.0762e+0 (2.00e-2)	**4.4907e-1 (2.94e-2)**
Cantilever beam	2	2	6.2294e-1 (9.06e-3)	8.6279e-1 (1.24e-1)	1.4518e+0 (1.81e-2)	**4.8883e-1 (4.49e-2)**
Multiple disk clutch brake	2	5	1.0000e+0 (0.00e+0)	1.3878e+0 (5.77e-2)	6.2063e-1 (7.82e-3)	**5.7265e-1 (5.58e-2)**
Car crash	3	5	5.1697e-1 (2.63e-2)	6.7946e-1 (4.08e-2)	7.3413e-1 (5.05e-2)	**4.6747e-1 (1.31e-1)**
Car side impact	3	7	7.4408e-1 (8.90e-2)	5.0136e-1 (4.72e-2)	4.3655e-1 (2.20e-2)	**3.7426e-1 (1.01e-2)**
Metal cutting tools	3	3	4.4303e-1 (4.41e-2)	4.8807e-1 (4.39e-2)	1.0956e+0 (9.47e-4)	**2.2487e-1 (2.73e-2)**
Rolling element bearing	2	10	NaN (NaN)	1.0637e+0 (3.62e-2)	1.0626e+0 (0.00e+0)	1.1180e+0 (9.51e-2)
Satellite heat pipe	2	5	6.9109e-1 (1.62e-2)	7.0590e-1 (1.11e-1)	7.5193e-1 (3.80e-2)	5.3056e-1 (1.11e-2)
BLDC motor	2	5	NaN (NaN)	9.2617e-1 (8.90e-3)	9.6090e-1 (1.36e-2)	8.5440e-1 (2.44e-3)
Isolated safety transformer	2	7	NaN (NaN)	8.3822e-1 (2.21e-2)	9.4306e-1 (1.06e-1)	9.1019e-1 (1.18e-1)

TABLE 15.
RESULTS OF THE MULTI-OBJECTIVE ALGORITHMS (USING IGD) ON THE SELECTED ENGINEERING DESIGN OPTIMIZATION PROBLEMS

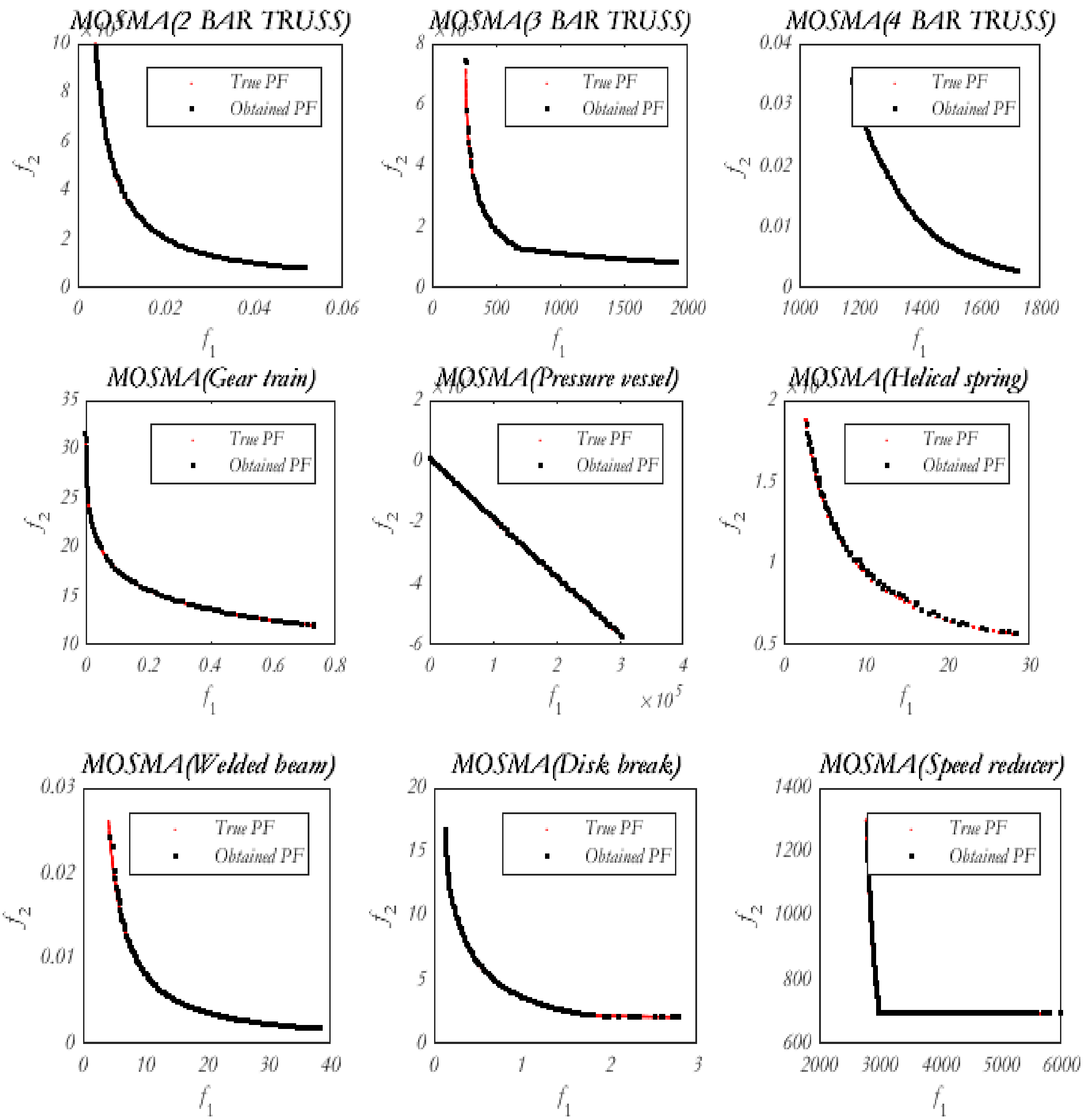
Problem	M	D	MOWCA	MOSOS	MOEA/D	MOSMA
2-bar truss	2	3	NaN (NaN)	2.9788e+2 (1.31e+1)	7.6272e+2 (4.57e+1)	**2.4611e-2 (4.42e-3)**
3-bar truss	2	2	1.9681e+2 (1.26e+1)	5.0124e+0 (4.10e-1)	4.7261e+2 (2.42e-2)	**4.1086e-2 (4.12e-1)**
4-bar truss	2	4	1.7570e+0 (8.06e-2)	1.7645e+0 (7.77e-2)	**4.9818e-1 (3.48e-3)**	1.4684e+0 (1.50e-3)
Gear train continues	2	4	7.1468e-2 (9.06e-3)	7.1763e-2 (2.54e-3)	1.0610e-1 (7.79e-3)	**5.9599e-2 (8.53e-3)**
Pressure vessel	2	4	NaN (NaN)	2.0306e-4 (1.12e-4)	2.8128e-3 (6.79e-3)	**1.6118e-5 (3.91e-2)**
Helical spring	2	3	NaN (NaN)	**9.5295e-2 (4.29e-1)**	2.9251e+3 (1.17e+3)	1.5846e-1 (1.18e+-)
Welded beam	2	4	NaN (NaN)	1.1635e-1 (2.60e-3)	1.0831e+1 (6.15e-1)	**9.2482e-2 (6.76e-4)**
Disk break	2	4	NaN (NaN)	6.7926e-2 (9.55e-3)	9.0921e-2 (1.26e-2)	**4.5821e-2 (2.98e-4)**
Speed reducer	2	7	NaN (NaN)	8.2716e+1 (9.73e+1)	9.8328e+1 (9.58e-1)	**1.1985e-1 (2.04e-2)**
CNC machine tool	2	3	NaN (NaN)	1.9219e-1 (1.88e-1)	1.2926e-1 (2.13e-2)	**4.7609e-2 (2.35e-2)**
Tool spindle	2	4	6.6314e-2 (3.35e-4)	4.0499e-2 (1.39e-2)	2.9660e-2 (5.65e-3)	**3.1374e-3 (1.86e-1)**
I-beam	2	4	5.5490e-1 (5.43e-2)	7.5335e+0 (7.09e+0)	1.4232e-1 (1.57e-1)	**1.8313e-2 (1.09e-2)**
Cantilever beam	2	2	1.6809e-2 (1.54e-3)	9.0251e-3 (1.09e-3)	4.5101e-2 (2.76e-2)	**6.8705e-3 (3.84e-5)**
Multiple disk clutch brake	2	5	6.7811e-1 (0.00e+0)	6.5230e-3 (1.52e-5)	2.8682e-2 (4.53e-3)	**2.8565e-3 (2.26e-5)**
Car crash	3	5	7.3726e-1 (4.03e-1)	1.2131e+0 (9.99e-1)	1.7669e+0 (1.14e-2)	**3.1731e-1 (1.28e-1)**
Car side impact	3	7	8.0912e-1 (4.67e-2)	2.5525e-1 (1.20e-2)	**1.6045e-1 (5.28e-3)**	2.4546e-1 (6.63e-3)
Metal cutting tools	3	3	1.6564e-2 (9.54e-4)	2.1968e-2 (6.83e-3)	1.8009e-1 (2.39e-5)	**1.3620e-2 (1.13e-4)**
Rolling element bearing	2	10	NaN (NaN)	1.2554e-3 (3.78e-1)	4.6399e-2 (8.59e-2)	2.4967e-2 (3.99e-3)
Satellite heat pipe	2	5	5.2999e+0 (3.17e-1)	5.2066e+0 (3.78e-1)	1.0023e+1 (5.91e+0)	4.2736e+0 (1.12e-2)
BLDC motor	2	5	NaN (NaN)	3.1337e-2 (3.64e-3)	3.1474e-1 (2.57e-3)	3.1435e-1 (1.12e-2)
Isolated safety transformer	2	7	NaN (NaN)	6.0325e-1 (4.51e-1)	2.0043e+0 (2.63e+0)	1.6970e-1 (6.46e-3)

TABLE 16.
RESULTS OF MULTI-OBJECTIVE ALGORITHMS (USING RUN-TIME) ON THE SELECTED ENGINEERING DESIGN OPTIMIZATION PROBLEMS

Problem	M	D	MOWCA	MOSOS	MOEA/D	MOSMA
2-bar truss	2	3	9.0140e-1 (1.27e-2)	6.4696e-1 (3.75e-3)	1.4945e+1 (8.76e-2)	**5.6025e-1 (9.89e-3)**
3-bar truss	2	2	1.1119e+0 (5.06e-2)	6.4244e-1 (3.64e-3)	1.0242e+1 (6.80e-2)	**5.5248e-1 (5.77e-3)**
4-bar truss	2	4	1.1303e+0 (1.12e-2)	6.4722e-1 (7.47e-3)	1.9182e+1 (2.07e-2)	**5.5629e-1 (1.25e-3)**
Gear train continues	2	4	9.6741e-1 (3.75e-3)	6.4441e-1 (4.81e-3)	1.9032e+1 (2.04e-1)	**5.7630e-1 (8.35e-3)**
Pressure vessel	2	4	8.3633e-1 (4.79e-3)	6.5245e-1 (9.63e-4)	2.0083e+1 (7.79e-2)	**5.6579e-1 (2.01e-3)**

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

Helical spring	2	3	**6.1667e-1 (1.16e-2)**	6.5142e-1 (4.91e-3)	1.6444e+1 (1.60e-1)	7.0801e-1 (5.38e-3)
Welded beam	2	4	7.0200e-1 (5.87e-3)	6.5404e-1 (1.91e-3)	1.7988e+1 (1.86e-2)	**5.7651e-1 (5.21e-3)**
Disk break	2	4	8.0508e-1 (4.32e-3)	6.6086e-1 (9.83e-5)	1.9519e+1 (3.96e-1)	**5.8525e-1 (6.80e-3)**
Speed reducer	2	7	7.3675e-1 (3.18e-2)	**6.7976e-1 (7.25e-3)**	1.9829e+1 (9.74e-2)	7.0924e-1 (2.41e-2)
CNC machine tool	2	3	6.2314e-1 (1.02e-2)	6.6234e-1 (3.83e-3)	1.8570e+1 (5.98e-3)	**6.0503e-1 (1.86e-3)**
Tool spindle	2	4	1.0218e+0 (9.13e-3)	6.7015e-1 (2.84e-3)	1.2695e+1 (5.76e-3)	**6.0432e-1 (6.45e-3)**
I-beam	2	4	1.2065e+0 (8.39e-2)	6.5322e-1 (1.74e-3)	1.8650e+1 (1.56e-1)	**5.7401e-1 (3.92e-3)**
Cantilever beam	2	2	1.4981e+0 (1.39e-2)	6.5634e-1 (5.25e-3)	1.8497e+1 (6.49e-2)	**5.7275e-1 (8.61e-3)**
Multiple disk clutch brake	2	5	9.1096e-1 (3.18e-2)	6.6418e-1 (1.66e-3)	2.0413e+1 (1.92e-1)	**5.9028e-1 (2.78e-4)**
Car crash	3	5	1.2549e+0 (3.80e-2)	7.0231e-1 (4.23e-3)	1.4819e+1 (8.23e-2)	**6.2795e-1 (4.27e-3)**
Car side impact	3	7	1.7124e+0 (1.61e-2)	7.2202e-1 (5.94e-3)	1.5853e+1 (9.25e-2)	**6.5690e-1 (4.33e-3)**
Metal cutting tools	3	3	2.1953e+0 (3.47e-2)	7.5626e-1 (7.98e-5)	1.0991e+1 (8.31e-2)	**6.6335e-1 (8.94e-3)**
Rolling element bearing	2	10	3.5236e+1 (2.21e+0)	**5.3167e+0 (3.43e-2)**	1.9173e+1 (6.37e-2)	1.2646e+2 (7.55e-1)
Satellite heat pipe	2	5	1.0723e+0 (1.21e-2)	6.7581e-1 (6.60e-3)	1.9344e+1 (6.35e-2)	**5.9721e-1 (6.95e-3)**
BLDC motor	2	5	2.8470e+0 (2.42e-1)	**2.5737e+0 (7.93e-3)**	3.9219e+1 (4.48e-1)	2.5931e+0 (4.48e-2)
Isolated safety transformer	2	7	**2.9997e+0 (9.02e-3)**	3.0260e+0 (2.46e-2)	4.4632e+1 (2.87e-1)	3.1593e+0 (1.45e-2)



This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

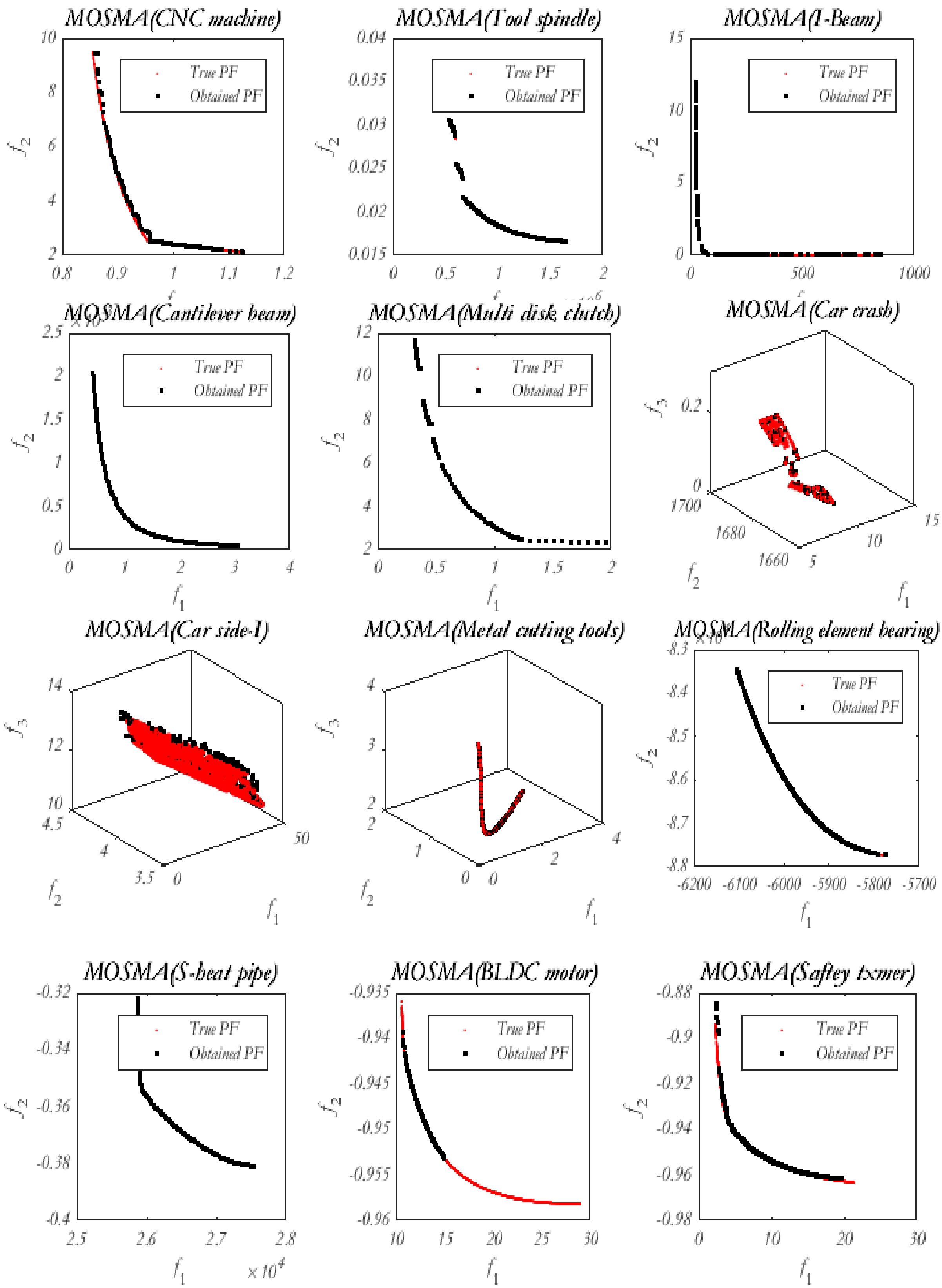


FIGURE 9. **Results of Pareto optimal front achieved by the MOSMO method on 2-bar truss, 3-bar truss, 4-bar truss, gear train, pressure vessel, helical spring, welded beam, disk brake, speed reducer, CNC machine tool, tool spindle, I-beam, cantilever beam, multiple disk clutch break, car crash, car side-impact, metal cutting tool, rolling-element bearing, satellite heat pipe, BLDC motor, and isolated safety transformer design problems.**

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

Inspecting the results in Table 2 – Table 16 and the optimal Pareto fronts obtained in Fig. 7 – Fig. 9, it is evident that the proposed MOSMA can provide a relatively accurate estimation of the true Pareto optimal solutions for all constrained, unconstrained, and engineering design optimization problems. The high coverage can be seen in Figs. 7-9. Note that NaN in all tables stands for Not a Number, which refers to the algorithms that the results are not available for the respective problem.

D. BRIEF DISCUSSIONS

In summary, findings and analyses demonstrate that MOSMA has a very high speed of convergence. This comes from the fact that the best solution often leads significantly to the enhancement of other solutions. This section discusses MOSMA optimizer benefits, such as high accuracy (convergence) and high coverage on most case studies. The former is an indication of high exploitation by MOSMA. Since MOSMA uses the same methodology as SMA, it inherently benefits from high exploitation. However, this is not enough for a posteriori algorithm. The MOSMA optimizer also represents exploration positively due to the SMA's operator and MOSMA's crowding distance. Sudden changes in Eq. 1 results in high exploratory behaviour. The non-dominated sorting mechanism and crowing distance operators also contribute to the exploration of MOSMA. The high coverage of Pareto optimal solutions achieved by MOSMA on many of the benchmark problems would be another finding. This probably originated from the processes of leader selection and archive maintenance.

V. CONCLUSION AND FUTURE DIRECTIONS

This paper introduced a multiple-objective version of the SMA optimizer. Motivated from the main idea of NSGA-II, a non-dominated ranking and crowding distance approach were integrated into conventional SMA to design the MOSMA algorithm. The proposed method was tested on 41 case studies, including unconstrained/constrained/real-world engineering design problems. The result proves that the MOSMA optimizer can estimate Pareto optimal solutions for all types of discrete/continuous Pareto front problems. All the PF obtained were highly distributed across all objectives. The analysis of the metrics, such as GD / IGD / Spread / Spacing / RUNTIME, showed the superiority and balance between the exploration phase and exploitation phase in MOSMA. As per the obtained results and comparative study on different optimizers, it is concluded that the MOSMA has merits among the recent competitive algorithms. The proposed MOSMA is acceptable for two and three objective problems. The proposed MOSMA can be directly applied to any engineering design problems due to its local front avoidance and high exploration capability.

The authors are planning to apply the proposed MOSMA and its enhanced variants to practical problems such as developing the solar models, realizing and developing the structural health assessment, modelling wireless sensor networks and deployment cases, and problems and concerns in power engineering. For future works, the method's proposal to handle many objectives optimization using MOSMA is also recommended. Also, the binary and mixed-integer version on MOSMA is worth of investigation.

REFERENCES

[1] L. Liu and S. Liu, "Integrated Production and Distribution Problem of Perishable Products with a Minimum Total Order Weighted Delivery Time," Mathematics, vol. 8, no. 2, p. 146, 2020.

[2] S. Liu, F. T. Chan, and W. Ran, "Decision making for the selection of cloud vendor: An improved approach under group decision-making with integrated weights and objective/subjective attributes," Expert Systems with Applications, vol. 55, pp. 37-47, 2016.

[3] H. Chen, H. Qiao, L. Xu, Q. Feng, and K. Cai, "A Fuzzy Optimization Strategy for the Implementation of RBF LSSVR Model in Vis–NIR Analysis of Pomelo Maturity," IEEE Transactions on Industrial Informatics, vol. 15, no. 11, pp. 5971-5979, 2019.

[4] X. Li, Y. Zhu, and J. Wang, "Highly Efficient Privacy-Preserving Location-Based Services with Enhanced One-Round Blind Filter," IEEE Transactions on Emerging Topics in Computing, pp. 1-1, 2019.

[5] Y. Liu, C. Yang, and Q. Sun, "Thresholds Based Image Extraction Schemes in Big Data Environment in Intelligent Traffic Management," IEEE Transactions on Intelligent Transportation Systems, pp. 1-9, 2020.

[6] T. Ni et al., "Non-Intrusive Online Distributed Pulse Shrinking-Based Interconnect Testing in 2.5D IC," IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 67, no. 11, pp. 2657-2661, 2020.

[7] X. Fu, P. Pace, G. Aloi, L. Yang, and G. Fortino, "Topology Optimization Against Cascading Failures on Wireless Sensor Networks Using a Memetic Algorithm," Computer Networks, p. 107327, 2020.

[8] X. Fu, G. Fortino, P. Pace, G. Aloi, and W. Li, "Environment-fusion multipath routing protocol for wireless sensor networks," Information Fusion, vol. 53, pp. 4-19, 2020.

[9] X. Fu, G. Fortino, W. Li, P. Pace, and Y. Yang, "WSNs-assisted opportunistic network for low-latency message forwarding in sparse settings," Future Generation Computer Systems, vol. 91, pp. 223-237, 2019/02/01/ 2019.

[10] J. Ren, C. Zhang, and Q. Hao, "A theoretical method to evaluate honeynet potency," Future Generation Computer Systems, 2020.

[11] D. Wen, X. Zhang, X. Liu, and J. Lei, "Evaluating the consistency of current mainstream wearable devices in health monitoring: a comparison under free-living conditions," Journal of medical Internet research, vol. 19, no. 3, p. e68, 2017.

[12] J. Xie, D. Wen, L. Liang, Y. Jia, L. Gao, and J. Lei, "Evaluating the validity of current mainstream wearable devices in fitness tracking under various physical activities: comparative study," JMIR mHealth and uHealth, vol. 6, no. 4, p. e94, 2018.

[13] V. Singh, N. Gu, and X. Wang, "A theoretical framework of a BIM-based multi-disciplinary collaboration platform," Automation in construction, vol. 20, no. 2, pp. 134-144, 2011.

[14] Z. Lv and W. Xiu, "Interaction of Edge-Cloud Computing Based on SDN and NFV for Next Generation IoT," IEEE Internet of Things Journal, vol. 7, no. 7, pp. 5706-5712, 2020.

[15] B. Cao, J. Zhao, Y. Gu, Y. Ling, and X. Ma, "Applying graph-based differential grouping for multi-objective large-scale optimization," Swarm and Evolutionary Computation, vol. 53, p. 100626, 2020.

[16] B. Cao, S. Fan, J. Zhao, P. Yang, K. Muhammad, and M. Tanveer, "Quantum-enhanced multi-objective large-scale optimization via parallelism," Swarm and Evolutionary Computation, vol. 57, p. 100697, 2020/09/01/ 2020.

[17] B. Cao, X. Wang, W. Zhang, H. Song, and Z. Lv, "A Many-Objective Optimization Model of Industrial Internet of Things Based on Private Blockchain," IEEE Network, vol. 34, no. 5, pp. 78-83, 2020.

[18] B. Cao, W. Dong, Z. Lv, Y. Gu, S. Singh, and P. Kumar, "Hybrid Microgrid Many-Objective Sizing Optimization with Fuzzy Decision," IEEE Transactions on Fuzzy Systems, 2020.

[19] J. Zhu, X. Wang, P. Wang, Z. Wu, and M. J. Kim, "Integration of BIM and GIS: Geometry from IFC to shapefile using open-source technology," Automation in Construction, vol. 102, pp. 105-119, 2019.

[20] J. Zhu, X. Wang, M. Chen, P. Wu, and M. J. Kim, "Integration of BIM and GIS: IFC geometry transformation to shapefile using enhanced open-source approach," Automation in Construction, vol. 106, p. 102859, 2019.

[21] J. Liu, C. Wu, G. Wu, and X. Wang, "A novel differential search algorithm and applications for structure design," Applied Mathematics and Computation, vol. 268, pp. 246-269, 2015.

[22] G. Sun, G. Xu, and N. Jiang, "A simple differential evolution with time-varying strategy for continuous optimization," Soft Computing, vol. 24, no. 4, pp. 2727-2747, 2020.

[23] A. Riza Yildiz, "A novel hybrid whale Nelder mead algorithm for optimization of design and manufacturing problems," The International Journal of Advanced Manufacturing Technology, vol. 105, pp. 5091–5104, 2019.

[24] A. Rıza Yıldız, B. Sultan Yıldız, S. M. Sait, S. Bureerat, and N. Pholdee, "A new hybrid Harris hawks Nelder-Mead optimization algorithm for solving design and manufacturing problems", Materials Testing, vol. 61, pp. 735-743, 2019.

[25] B. Sultan Yıldız, "The spotted hyena optimization algorithm for weight-reduction of automobile brake components," Materials Testing, vol. 62, pp. 383-388, 2020.

[26] N. Panagant, N. Pholdee, S. Bureerat, A. Rıza Yıldız, and S. M. Sait, "Seagull optimization algorithm for solving real-world design optimization problems, Materials Testing, vol. 62, no. 6, pp. 640-644, 2020.

[27] B. Sultan Yıldız, A. Rıza Yıldız, N. Pholdee, S. Bureerat, S. M. Sait, and V. Patel, "The Henry gas solubility optimization algorithm for optimum structural design of automobile brake components261- .62no. 3, pp , .Materials Testing, vol ", .264,2020

[28] B. Sultan Yıldız, "The mine blast algorithm for the structural optimization of electrical vehicle components, Materials Testing, vol. 62, no. 5, pp. 497-501, 2020.

[29] B. Sultan Yıldız, A. Rıza Yıldız, E. İsa Albak, H. Abderazek, S. M. Sait, and S. Bureerat, "Butterfly optimization algorithm for optimum shape design of automobile suspension components," Materials Testing, vol. 62 no. 4, pp. 365-370, 2020.

[30] S. Mirjalili, J. Pradeep, S. Zahra Mirjalili, S. Saremi, and I. N. Trivedi, "Optimization of problems with multiple objectives using the multi-verse optimization algorithm," Knowledge-Based Systems, vol. 134, pp. 50-71, 2017.

[31] Pradeep Jangir, Narottam Jangir, "A new Non-Dominated Sorting Grey Wolf Optimizer (NS-GWO) algorithm: Development and application to solve engineering designs and economic constrained emission dispatch problem with integration of wind power," Engineering Applications of Artificial Intelligence, vol. 72, pp. 449-467, 2018.

[32] S. Mirjalili, P. Jangir, and S. Saremi, "Multi-objective ant lion optimizer: a multi-objective optimization algorithm for solving engineering problems," Applied Intelligence, vol. 46, pp. 79-95, 2017.

[33] D. H. Wolpert and W. G. Macready, "No Free Lunch Theorems for Optimization," IEEE Trans. Evol. Comput., vol. 1, no. 1, pp. 67–82, 1997.

[34] S. Li, H. Chen, M. Wang, A. A. Heidari, and S. Mirjalili, "Slime mould algorithm: A new method for stochastic optimization," Future Generation Computer Systems, vol. 111, pp. 300-323, 2020.

[35] P. Ngatchou, A. Zarei, and M. El-Sharkawi, "Pareto multi-objective optimization," in Intelligent Systems Application to Power Systems, 2005. Proceedings of the 13th International Conference on, 2005, pp. 84-91: IEEE.

[36] J. Knowles and D. Corne, "The Pareto archived evolution strategy: A new baseline algorithm for Pareto multi-objective optimisation," in Evolutionary Computation, 1999. CEC 99. Proceedings of the 1999 Congress on, 1999, vol. 1: IEEE.

[37] H. A. Abbass, R. Sarker, and C. Newton, "PDE: a Pareto-frontier differential evolution approach for multi-objective optimization problems," in Evolutionary Computation, 2001. Proceedings of the 2001 Congress on, 2001, vol. 2, pp. 971-978: IEEE.

[38] I. Y. Kim and O. De Weck, "Adaptive weighted-sum method for bi-objective optimization: Pareto front generation," Structural and multidisciplinary optimization, vol. 29, no. 2, pp. 149-158, 2005.

[39] J. Branke, T. Kaußler, and H. Schmeck, "Guidance in evolutionary multi-objective optimization," Advances in Engineering Software, vol. 32, no. 6, pp. 499-507, 2001.

[40] W. S. Shin and A. Ravindran, "Interactive multiple objective optimization: Survey I-Continuous case," Computers & Operations Research, vol. 18, no. 1, pp. 97-114, 1991.

[41] R. T. Marler and J. S. Arora, "The weighted sum method for multi-objective optimization: new insights," Structural and multidisciplinary optimization, vol. 41, no. 6, pp. 853-862, 2010.

[42] Goldberg D.E. "Genetic Algorithms in Search, Optimization, and Machine Learning," In: Addison-Wesley Longman Publishing Co., Inc., United States, 1989, pp. 25-68.

[43] X. Sun, L. Zhao, P. Zhang, L. Bao, and Y. Chen, "Enhanced NSGA-II with evolving directions prediction for interval multi-objective optimization," Swarm and Evolutionary Computation, vol. 49, pp. 124-133, 2019.

[44] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A Fast and Elitist Multi-objective Genetic Algorithm: NSGA-II," IEEE Transactions On Evolutionary Computation, vol. 6, no. 2, pp. 182-197, 2002.

[45] G. Dhiman, K. Kant Singh, A. Slowik, V. Chang, A. Riza Yildiz, A. Kaur, and M. Garg, "EMoSOA: a new evolutionary multi-objective seagull optimization algorithm for global optimization," International Journal of Machine Learning and Cybernetics, pp. 1-26, 2020, DOI: 10.1007/s13042-020-01189-1.

[46] R. Sarangkum, K. Wansasueb, N. Panagant, N, Pholdee, S. Bureerat, A. R. Yildiz, and S. M. Sait, "Automated design of aircraft fuselage stiffeners using multi-objective evolutionary optimisation .International Journal of Vehicle Design, vol ",80, no. 2-4 pp. 162-175,2019.

[47] R. H. Bhesdadiya, I. N. Trivedi, P. Jangir, N. Jangir, and A. Kumar, "An NSGA-III algorithm for solving multi-objective economic/environmental dispatch problem," Cogent Engineering, vol. 3, no. 1, pp. 1269383, 2016.

[48] Y. Zhang, D.W. Gong, and Z. Ding, "A bare-bones multi-objective particle swarm optimization algorithm for environmental/economic dispatch," Information Sciences, vol. 192, pp. 213-227, 2012.

[49] Y. Zhang, D. Gong, and J. Cheng, "Multi-objective Particle Swarm Optimization Approach for Cost-Based Feature Selection in Classification," IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 14, no. 1, pp. 64-75, 2017.

[50] Y. Zhang, D.W. Gong, and Z.H. Ding, "Handling multi-objective optimization problems with a multi-swarm cooperative particle swarm optimizer," Expert Systems with Applications, vol. 38, no. 11, pp. 13933-13941, 2011.

[51] A. Sadollah, H. Eskandar, and J. Hoon Kim, "Water cycle algorithm for solving constrained multi-objective optimization problems," Applied Soft Computing, vol. 27, pp. 279-298, 2015.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3047936, IEEE Access

[52] N. Panagant, N. Pholdee, K. Wansasueb, S. Bureerat, A. R. Yildiz, and S. M. Sait, "Comparison of recent algorithms for many-objective optimisation of an automotive floor-frame," International Journal of Vehicle Design, vol.80, no.2/3/4, pp.176-208, 2019.

[53] H.V.H. Ayala, C.E. Klein, V.C. Mariani, and L. dos Santos Coelho, "Multi-objective symbiotic search algorithm approaches for electromagnetic optimization," IEEE Conference on Electromagnetic Field Computation, Miami, FL, 2016, pp. 1-1, DOI: 10.1109/CEFC.2016.7815989.

[54] D. Gong, B. Xu, Y. Zhang, Y. Guo, and S. Yang, "A Similarity-Based Cooperative Co-Evolutionary Algorithm for Dynamic Interval Multiobjective Optimization Problems," IEEE Transactions on Evolutionary Computation, vol. 24, no. 1, pp. 142-156, Feb. 2020.

[55] P. Champasak, N. Panagant, N. Pholdee, S. Bureerat, and A. R. Yildiz, "Self-adaptive many-objective meta-heuristic based on decomposition for many-objective conceptual design of a fixed-wing unmanned aerial vehicle," Aerospace Science and Technology, vol. 100, pp. 105783, 2020.

[56] Y. Zhang, D.W. Gong, J.Y. Sun, and BY Qu, "A decomposition-based archiving approach for multi-objective evolutionary optimization," Information Sciences, vol. 430-431, pp. 397-413, 2018.

[57] B. Xue, M. Zhang, W. N. Browne and X. Yao, "A Survey on Evolutionary Computation Approaches to Feature Selection," IEEE Transactions on Evolutionary Computation, vol. 20, no. 4, pp. 606-626, 2016.

[58] M. Karakoyun, A. Ozkis, and H. Kodaz, "A new algorithm based on gray wolf optimizer and shuffled frog leaping algorithm to solve the multi-objective optimization problems," Applied Soft Computing, vol. 96, pp. 106560, 2020.

[59] M. Abdel-Basset, R. Mohamed, and M. Abouhawwash, "Balanced multi-objective optimization algorithm using improvement-based reference points approach," Swarm and Evolutionary Computation, vol. 60, 100791, 2021.

[60] E. Zitzler, K. Deb, and L. Thiele, "Comparison of multi-objective evolutionary algorithms: Empirical results," Evolutionary computation, vol. 8, no. 2, pp. 173-195, 2000.

[61] K. Deb, L. Thiele, M. Laumanns, and E. Zitzler, Scalable test problems for evolutionary multi-objective optimization. Springer, 2005.

[62] Q. Zhang, A. Zhou, S. Zhao, P. N. Suganthan, W. Liu, and S. Tiwari, "Multi-objective optimization test instances for the CEC 2009 special session and competition," University of Essex, Colchester, UK and Nanyang technological University, Singapore, special session on performance assessment of multi-objective optimization algorithms, technical report, vol. 264, 2008.

[63] L. Nguyen, L. T. Bui, and H. A. Abbass, "DMEA-II: the direction-based multi-objective evolutionary algorithm-II," Soft Computing, vol. 18, no. 11, pp. 2119-2134, 2014.

[64] G.-Q. Zeng et al., "An improved multi-objective population-based extremal optimization algorithm with polynomial mutation," Information Sciences, vol. 330, pp. 49-73, 2016.

[65] L. T. Bui, K. Deb, H. A. Abbass, and D. Essam, "Interleaving guidance in evolutionary multi-objective optimization," Journal of Computer Science and Technology, vol. 23, no. 1, pp. 44-63, 2008.

[66] L. T. Bui, J. Liu, A. Bender, M. Barlow, S. Wesolkowski, and H. A. Abbass, "DMEA: a direction-based multi-objective evolutionary algorithm," Memetic Computing, vol. 3, no. 4, pp. 271-285, 2011.

[67] H. Li and Q. Zhang, "Multi-objective optimization problems with complicated Pareto sets, MOEA/D and NSGA-II," IEEE Transactions on Evolutionary Computation, vol. 13, no. 2, pp. 284-302, 2009.

[68] M. Li, S. Yang and X. Liu, "Pareto or Non-Pareto: Bi-Criterion Evolution in Multi-objective Optimization," in IEEE Transactions on Evolutionary Computation, vol. 20, no. 5, pp. 645-665, Oct. 2016, doi: 10.1109/TEVC.2015.2504730.

[69] A. Panda and S. Pani, "A Symbiotic Organisms Search algorithm with adaptive penalty function to solve multi-objective constrained optimization problems," Applied Soft Computing, vol. 46, pp. 344-360, 2016.

[70] X. Zhang, Y. Tian, and Y. Jin, "A knee point-driven evolutionary algorithm for many-objective optimization," IEEE Transactions on Evolutionary Computation, vol. 19, no. 6, pp. 761-776, 2015.

[71] N. Srinivasan and K. Deb, "Multi-objective function optimisation using non-dominated sorting genetic algorithm," Evolutionary Comp, vol. 2, no. 3, pp. 221-248, 1994.

[72] T. T. Binh and U. Korn, "MOBES: A multi-objective evolution strategy for constrained optimization problems," in The Third International Conference on Genetic Algorithms (Mendel 97), 1997, vol. 25, p. 27: Citeseer.

[73] A. Osyczka and S. Kundu, "A new method to solve generalized multicriteria optimization problems using the simple genetic algorithm," Structural optimization, vol. 10, no. 2, pp. 94-99, 1995.

[74] M. Li, S. Yang, K. Li, and X. Liu, "Evolutionary algorithms with segment-based search for multi-objective optimization problems," IEEE transactions on cybernetics, vol. 44, no. 8, pp. 1295-1313, 2014.

[75] A. Sadollah, H. Eskandar, A. Bahreininejad, et al. "Water cycle algorithm for solving multi-objective optimization problems," Soft Computing, vol. 19, pp. 2587-2603, 2015.

[76] C. C. Coello and G. T. Pulido, "Multi-objective structural optimization using a microgenetic algorithm," Structural and Multidisciplinary Optimization, vol. 30, no. 5, pp. 388-403, 2005.

[77] T. Ray and K. M. Liew, "A swarm metaphor for multi-objective design optimization," Engineering Optimization, vol. 34, no. 2, pp. 141-153, 2002.

[78] F. Moussouni, S. Brisset, and P. Brochet, "Some results on the design of brushless DC wheel motor using SQP and GA," International Journal of Applied Electromagnetics and Mechanics, vol. 26, no. 3, 4, pp. 233-241, 2007.

[79] K. Deb and R. Datta, "Hybrid evolutionary multi-objective optimization and analysis of machining operations," Engineering Optimization, vol. 44, no. 6, pp. 685-706, 2012.

[80] K. Deb and A. Srinivasan, "Monotonicity analysis, evolutionary multi-objective optimization, and discovery of design principles," Indian Institute of Technology, Kanpur Genetic Algorithm Laboratory (KanGAL), Report, no. 2006004, 2006.

[81] K. Deb and A. Srinivasan, "Innovization: Discovery of innovative design principles through multi-objective evolutionary optimization," in Multi-objective Problem Solving from Nature: Springer, 2008, pp. 243-262.

[82] M. J. Jeong, T. Kobayashi, and S. Yoshimura, "Extraction of design characteristics of multi-objective optimization–its application to design of artificial satellite heat pipe," in International Conference on Evolutionary Multi-Criterion Optimization, 2005, pp. 561-575: Springer.

[83] M. Kotinis, "A particle swarm optimizer for constrained multi-objective engineering design problems," Engineering Optimization, vol. 42, no. 10, pp. 907-926, 2010.

[84] A. M. Nafchi and A. Moradi, "Constrained Multi-objective Optimization Problems in Mechanical Engineering Design Using Bees Algorithm," Journal of Solid Mechanics Vol, vol. 3, no. 4, pp. 353-364, 2011.

[85] T. Ray, K. TAI, and K. C. SEOW, "Multi-objective design optimization by an evolutionary algorithm," Engineering Optimization, vol. 33, no. 4, pp. 399-424, 2001.

[86] C.-L. Yu, Y. Lu, and J. Chu, "Multi-objective optimization with combination of particle swarm and extremal optimization for constrained engineering design," WSEAS Trans Syst Control, vol. 4, no. 7, pp. 129-138, 2012.

M. PREMKUMAR was born in Coimbatore, Tamil Nadu, India. He received the B.E. degree in Electrical and Electronics Engineering from Sri Ramakrishna Institute of Technology, Coimbatore, India, in 2004; and the M.E. degree in Applied Electronics from Anna University of Technology, Coimbatore, India, in 2010. He received his Ph.D. degree from Anna University, Chennai, India, in 2019. Currently, he is working as an Assistant Professor at GMR Institute of Technology, Rajam, India. He has more than twelve years of experience in teaching, and he has published more than 65 technical papers in various National/International peer-reviewed a journal such as IEEE, Elsevier, Springer, etc. with over 250 citations and H-index of 10. He is serving as an Editor/Reviewer in leading journals, such as IEEE, IET, Wiley, Taylor & Francis, Springer, etc. His current research field includes optimization techniques, including single, multi and many objectives, Solar PV Microinverter, Solar PV Parameter Extraction, Modern Solar PV MPPTs (Optimization Technique Based), PV array faults, and Non-isolated/Isolated DC-DC converters for PV systems. For more info and guidance, please refer to https://premkumarmanoharan.wixsite.com/mysite.

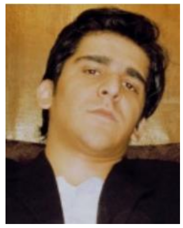
PRADEEP JANGIR is the co-director of the Zero Lab Optimization at Gujarat and Power Engineer at RVPN Jaipur, Rajasthan. He is internationally recognized for his advances in Swarm Intelligence and Optimization. He has published over 76 publications with over 1,000 citations and an H-index of 15.

His research interests include many-objective, Robust Optimization, Power System Engineering Optimization, Multiobjective Optimization, Swarm Intelligence, Evolutionary Algorithms, and Artificial Neural Networks. He is working on the applications of multiobjective, many-objective and robust meta-heuristic optimization techniques as well.

R. SOWMYA received her BE degree in Electrical and Electronics Engineering from Saranathan College of Engineering, Tiruchirappalli, India in 2013 and M.Tech. degree in Energy Engineering from National Institute of Technology, Tiruchirappalli, India, in 2015. She worked as an Assistant Professor in the Department of Electrical and Electronics Engineering at KPR Institute of Engineering and Technology, Coimbatore, India for the academic year 2015-2016 and worked as an Assistant Professor in the Department of Power Engineering at GMR Institute of Engineering and Technology, Rajam, India during the academic year 2016-2017. Currently, she is pursuing a PhD at National Institute of Technology, Tiruchirappalli, India. Her research interest includes control systems, Electric vehicle and Renewable Energy.

HASSAN HAES ALHELOU (Senior Member) is a faculty member at Tisheen University, Lattakia, Syria.

He is included in the 2018 Publons list of the top 1% best reviewer and researchers in the field of engineering in the world. He was the recipient of the Outstanding Reviewer Award from many journals, e.g., Energy Conversion and Management (ECM), ISA Transactions, and Applied Energy. He was the recipient of the best young researcher in the Arab Student Forum Creative among 61 researchers from 16 countries at Alexandria University, Egypt, 2011. He has published more than 100 research papers in high-quality peer-reviewed journals and international conferences. He has also performed more than 600 reviews for high prestigious journals including IEEE Transactions on Industrial Informatics, IEEE Transactions on Industrial Electronics, Energy Conversion and Management, Applied Energy, International Journal of Electrical Power & Energy Systems. He has participated in more than 15 industrial projects. His major research interests are Power systems, Power system dynamics, Power system operation and control, Dynamic state estimation, Frequency control, Smart grids, Micro-grids, Demand response, and Load shedding.



ALI ASGHAR HEIDARI, a researcher, qualified at the School of Computing, National University of Singapore (NUS), is an exceptionally talented researcher at the University of Tehran, and he is an elite researcher of Iran's National Elites Foundation (INEF). He is an outstanding researcher with an impressive deep-rooted record of cooperation on many international research projects with different top researchers from the optimization and artificial intelligence community. His research interests include advanced machine learning, evolutionary computation, optimization, prediction, solar energy, information systems, and mathematical modeling. He has authored more than 70 journal articles with over 3100 citations (i10-index of 49 and H-index of 30) and over 85000 readers in prestigious international journals, such as Information Fusion, Information Sciences, Future Generation Computer Systems, Renewable, and Sustainable Energy Reviews, the Journal of Cleaner Production, Energy, Energy Conversion and Management, Applied Soft Computing, Knowledge-Based Systems, IEEE Access, and Expert Systems with Applications. He is awarded and recognized by Iran's National Elites Foundation (INEF). He has been recognized by (publons.com/a/1397783) as the top 1% peer reviewers in computer science and cross-field. He has several highly cited and hot cited papers. For more info and guidance, please refer to http://aliasgharheidari.com.

HUILING CHEN is currently an associate professor in the college of computer science and artificial intelligence at Wenzhou University, China. He received his Ph.D. degree in the department of computer science and technology at Jilin University, China. His present research interests center on evolutionary computation, machine learning, and data mining, as well as their applications to medical diagnosis, bankruptcy prediction, and parameter extraction of the solar cell. He is currently serving as an associate editor of IEEE ACCESS and the editorial board member of Computational and Mathematical Methods in Medicine. He is also a reviewer for many journals such as Applied Soft Computing, Artificial Intelligence in Medicine, Knowledge-based Systems, Future Generation Computer System. He has published more than 100 papers in international journals and conference proceedings, including Information Sciences, Pattern Recognition, Future Generation Computer System, Expert Systems with Applications, Knowledge-based Systems, Neurocomputing, PAKDD, and among others. He has more than 10 ESI highly cited papers and 2 hot cited papers.