Grasshopper Optimization Algorithm With Crossover Operators for Feature Selection and Solving Engineering Problems

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ABSTRACT Feature selection (FS) is an irreplaceable phase that makes data mining more efficient. It effectively enhances the implementation and decreases the computational problem of learning models. The comprehensive and greedy algorithms are not suitable for the present growing number of features when detecting the optimal subset. Thus, swarm intelligence algorithms (SI) are becoming more common in dealing with FS problems. The grasshopper optimizer algorithm (GOA) represents a new SI; it showed good performance in different fields. Another promising nature-inspired algorithm is a salp swarm algorithm, denoted as SSA, an SI used to tackle optimization issues. In this paper, two phases are applied to propose a new method using crossover-salp swarm with grasshopper optimization algorithm (cSG). In this method, the crossover operators are used to maintain the population of the SSA then the improved SSA is used as a local search to boost the exploration phase of the GOA. Subsequently, this improvement prevents the cSG from premature convergence, high computation time, and being trapped in local minimum. To confirm the effectiveness of proposed cSG method, it is evaluated in different optimizations problems. Eventually, the obtained results are compared to a number of well-known algorithms over global optimization, feature selection datasets, and six real-engineering problems. Experimental results point out that the cSG is superior in solving different optimization problems due to the integration of crossover operators and SSA which enhances its performance and flexibility.

INDEX TERMS Grasshopper optimization algorithm, crossover operator, salp swarm algorithm, optimization problems, feature selection, engineering problems.

I. INTRODUCTION Recently, feature selection (FS) has acquired much attention from researchers working in machine learning and data mining domain. However, the increase in data size and dimensions causes different problems, such as the appearance of noisy, inconvenient and redundant data. Hence, it is hard to find optimal group of features and remove redundant ones. Dealing with datasets, some features are insignificant in the presence of irrelevancy and redundancy. Therefore, considering such features is not valuable and usually affects the classification accuracy [1]. FS attempts to enhance classification performance through selecting from the original enormous range of features just a small subset of suitable features [2]. The extraction of redundant and irrelevant features will, thus, minimize the data dimensionality, enhance the learning process by simplifying model learning and enhancing performance [3], [4]. Other benefits of FS are that: reducing overfitting minimizes redundant data, decreases chances for noise-based rulemaking, enhances precision and minimizes...
misleading data which means enhancing the precision of modeling. Furthermore, decreases training time, minimizes data points, reduces complexity of the algorithms, and accelerates the algorithm’s training [5], [6].

During the past few years, meta-heuristic algorithms have become very popular. They have been widely applied to find solutions for different complex problems in computer science and engineering. They are essentially utilized to obtain the optimal solution by getting different optimal values for producing a candidate value to completely solve the underlying issue [7], [8]. Generally, meta-heuristic optimization methods consider the optimal value by decreasing or increasing the objective function to get the optimal decision [9]. Most of them are inspired by evolution laws and intelligent behaviors of the natural animals [10]. For example, particle swarm optimizer (PSO) [11], monarch butterfly optimizer (MBO) [12], whale optimization (WO) [13], Grasshopper Optimization (GO) [14], salp swarm algorithm (SSA) [15], moth search (MS) [16], Harris hawks optimizer (HHO) [17], slime mould algorithm (SMA) [18], Gradient-based optimization (GBO) [19], Heap-based optimization (HBO) [20], hunger games search algorithm (HGS) [21], RUNge Kutta optimization (RUN) [22], as well as Colony Predation (CP) Algorithm [23].

These strong meta-heuristic algorithmic methods have been suggested, improved, or hybridized to solve different problems in several fields, such as, Mozaffari et al. [24] introduced a new inclined planes system optimization (IPO) algorithm to address optimization problems. Mozaffari & Lee [25] applied PSO to detect the optimal multilevel thresholds in image segmentation. Faris et al. [26] proposed an enhanced MBO with the aim of unconstrained global search as well as neural network training. Alweshah et al. [27] applied MBO with k-nearest neighbor (KNN) classifier for tackling feature selection problems. For image segmentation issues the MBO [28] was applied at multiple threshold values. Strumberger et al. [29] merged MSA with the algorithm of artificial bee colony, abbreviated as ABC, to handle constrained optimization issues. Elgamal et al., [2] improved HHO by the chaotic maps and simulated annealing (SA) algorithm and apply it to address feature selection issues in the medical field. Kundu & Garg [30] improved HHO by applying enhanced teaching–learning-based optimization to address engineering design and numerical optimization issues. Premkumar et al. [31] introduced GBO to address the multiobjective optimization problems. Helmi et al. [32] merged GBO with GWO for human activity recognition. To boost the optimization performance of SMA the authors of [33] hybridized SMA with inertia weight parameter, as well as reverse learning strategy for the best operation of cascade hydropower stations. Moreover, in [34] the SMA was hybridized with WOA adopting thresholding technique to address the image segmentation problem. Abdel-Basset et al. [35] improved HBO algorithms for parameters estimation of proton exchange membrane fuel cells model. Onay & Aydemir [36] proposed a chaotic HGS for handling real engineering problems and global optimizations. Devi et al. [37] proposed a binary HGSO algorithm relied on V- and S-shaped transfer functions to handle feature selection problems. Ahmadianfar et al. [22] proposed RUN optimizer to handle global optimization problems. Shi et al. [38] applied CPA with kernel extreme learning machine (KELM) for detecting COVID-19 from view of biochemical indexes. According to the good results of the previous studies in solving different types of problems, the improved and hybrid algorithms can effectively find the best solution compared to the ordinary algorithm. Consequently, in this work, the crossover operators are combined with SSA to enhance the search capability for the original GOA.

The grasshopper optimization algorithm (GOA) is a new algorithmic method inspired from lives of grasshoppers proposed in [14]. The search method of nature-inspired optimization algorithms contains two phases that are: exploration and exploitation, which appear during the search for food [39], [40]. GOA has many merits: simplicity, robustness, few parameters, ease in implementation, and strong potential exploratory ability [41]. It has been utilized for handling many optimization problems in various applications as feature selection [42], global optimization [43], power system stability [44], numerical optimization [45], and skin color segmentation [46]. Despite the advantages of GOA, it suffers from some shortcomings in exploiting the search space, premature convergence in a number of complex optimization techniques, and can get stuck into local optima. To overcome that, many improvements were proposed. Ewees et al. [47] introduced an opposition-based GOA for engineering problems and benchmark optimization functions. Bala et al. [48] presented an enhanced GOA for fault prediction in airplane engines. Huang et al. [49] proposed an improved GOA for enhancing the parameters of power filter (HAPF). Li et al. [50] integrated GOA with differential evolution (DE) to detect color differences of dyed fabrics. Motlagh & Foroud [51] proposed a hybrid GOA with SVM to recognize power quality disturbances.

Another promising nature-inspired algorithm is called the salp swarm algorithm, abbreviated as SSA, which is a new swarm intelligence algorithm proposed by [52]. It is based on gathering behavior, sailing the intellect of salp swarms [53]. SSA is simple to implement [54]. It confirmed its ability to settle large-and-small-scale issues [52]. SSA is characterized by its strength and flexible stochastic nature [15]. In recent years SSA has attracted attention of several researchers. One of the leading works on SSA was presented in [56], Sayed et al. suggested a new hybridization method relied on SSA and chaos theory to address feature selection issues. The outcomes of the suggested method showed that the CSSA is a good optimizer compared to several former methods. SSA was conducted
A. SALP SWARM ALGORITHM (SSA)
SSA is considered an optimization method. It was suggested by the authors of [52]. It imitates the existing salp chains which are: a swarm utilized to move and forage to get to the food source. Salp is distributed under the category of the Salpidae family. Also, the swarming salps are highly noticeable as they can construct cooperative chains through foraging actions in deep oceans. Such attitude makes salps gain more kinetic ability throughout tracking the food source [61]. The SSA method is based on the mechanism of swarming salps out of producing the salp chain, which assists SSA in relieving inertia to the native optima to several extents. However, SSA cannot constantly carry out an appropriate balance among exploration and exploitation stages. Subsequently, the premier method sometimes fails to acquire a high-quality, comprehensive optimum in several real-world issues [62]. The Salp chain is subdivided into two sets of salps: leader and followers. Accordingly, the first class represents the leader of a salp, whereas the second class is the followers. Leader salp leads the direction and movement of the swarm, whilst the followers benefit from other peers [63].

From this view, this behavior is transformed into a mathematical form to produce SSA. In SSA, the population is subdivided into two sets; the first set is the leader the second is the followers. The leader is set before the followers. To change the status of a set, the leader updates his status that can be denoted by,

\[ x_j^t = \begin{cases} 
F_j + c_1((u_b_j - l_b_j) \times c_2 + l_b_j), & c_3 \leq 0 \\
F_j - c_1((u_b_j - l_b_j) \times c_2 + l_b_j), & c_3 > 0 
\end{cases} \]  

where the position can be defined by \( x_j \), the boundaries of the upper and lower search area \( j \)-th represented by \( u_b_j \) and \( l_b_j \), the target is denoted by \( F_j \), \( c_2 \) and random parameters \([0, 1]\) is defined by \( c_3 \) where \( c_1 \) value is determined as,

\[ c_1 = 2e^{-\left(\frac{t}{t_{\text{max}}}\right)^2} \]  

where, the highest loop number is represented by \( t_{\text{max}} \) and the latest loop is indicated by \( t \).

The followers’ status is updated relied on Eq. 9.

\[ x_j^t = \frac{1}{2}(x_j^t + x_j^{t-1}) \]  

where \( i > 1 \), and the \( i \)-th follower status indicated by \( x_j^t \).

B. GRASSHOPPER OPTIMIZATION ALGORITHM (GOA)
GOA is a well-known optimization method in the last years. It was improved by the authors of [14]. It imitates the grasshopper insect’s nature. It is a harmful roach that eats crops, which affects the output of agriculture. The life cycle of grasshoppers contains three periods: firstly, the egg period; then comes the larval period; and at last, the adult period. The larval period is described as a slow movement besides small steps, while in the adulthood period, the grasshopper can move abruptly and rapidly. GOA relies on the following...
tactic: grasshoppers can form swarms in the larval and adulthood periods together [64]. These swarms are permanently searching for a food source. In general, in the first stage, the grasshoppers’ positions alter suddenly, while they are encouraged to proceed locally during the second stage. Grasshoppers essentially perform these two stages over the nymph and adulthood periods together, making grasshoppers the appropriate choice for mathematically resolving their swarming behavior as a robust optimization algorithm [39], [40]. And so, this attitude can be performed mathematically as,

\[ x_i = S_i + G_i + A_i, \quad i = 1, 2, \ldots, N \]  

where, the grasshopper status in \( i \)-th dimension indicated by \( x_i \). The social interaction indicated by \( S_i \), and can be determined as,

\[ S_i = \sum_{j=1 \atop j \neq i}^{N} s(d_{ij})\hat{a}_{ij}, d_{ij} = \left|x_i - x_j\right|, \quad \hat{a}_{ij} = \frac{x_j - x_i}{d_{ij}} \]  

where the distance among grasshoppers is denoted by \( d_{ij} \) and the unit vector among grasshoppers is defined by \( \hat{a}_{ij} \). The parameter \( s \) can be determined as,

\[ s(y) = fe^{\frac{y}{T}} - e^{-\gamma} \]  

Here, the attractive length scale is represented as \( l \) and the attraction intensity is represented as \( f \).

Besides, wind and gravity affect the small movements of the grasshoppers which can be determined as,

\[ \text{Wind advection} = A_i = u\hat{e}_w, \]  
\[ \text{Gravity force} = G_i = -g\hat{e}_g \]  

where, a drift constant is represented by \( u \) and the unit vector of wind direction represented by \( \hat{e}_w \), while \( g \) and \( \hat{e}_g \) denote the constant of the gravity and the unit vector across earth’s center, respectively.

Consequently, the status of the grasshoppers is reformed applying the next equation.

\[ x_i^d = c \left( \sum_{j=1 \atop j \neq i}^{N} \frac{u_j - l_j}{2} s(|x_j^d - x_i^d|) \frac{x_j - x_i}{d_{ij}} \right) + \hat{T}_d, \]  

where the boundaries of the upper and lower search area are represented by \( u \) and \( l \), and the optimal solution value is represented by \( \hat{T}_d \). The problem dimension is denoted by \( D \) while the population size is denoted by \( N \), and the \( c \) parameter is determined as,

\[ c = c_{\text{max}} - t \frac{c_{\text{max}} - c_{\text{min}}}{t_{\text{max}}} \]  

where \( c_{\text{max}} \) and \( c_{\text{min}} \) equal 1 and 0.0001, respectively, the highest loop number is defined by \( t_{\text{max}} \), while, the actual loop is denoted by \( t \).

### C. CROSSOVER OPERATOR

Crossover is a genetic operator applied to change the chromosome or chromosome programming from one generation to another [65]. Crossover is sexual reproduction. Two chains are selected from the mating pool randomly to crossover for producing optimal offspring. The selected method relied on the Encoding Method. The crossover operator aims to select a middle to solve in a binary search space to imitate detecting a solution among two solutions. It transforms between two input vectors that have the same probability.

It can be categorized into three groups: the first is a single-point crossover in which a crossover point is chosen on the parent organism chain. All data behind that point in the organism chain, is exchanged between the two parent organisms. Positional Bias is used to characterize the strings. The second one is a two-point crossover which is a particular condition of an N-point Crossover tactic. Two points are selected randomly on the independent chromosomes, and the genetic substance is swapped at these points. The third one is a uniform crossover: every gene (bit) is chosen randomly from one of the identical chromosomes’ genes of the parent [65].

The crossover between two superior decisions may not consistently yield an optimum or a good decision. The better the parents are, the more expectation; that the child will be good. If children are not good (poor decision) during selection, it will be rejected in the upcoming iteration.

### III. PROPOSED METHOD

The proposed cSG method is detailed in this section. It stands for crossover SSA and GOA. In the proposed cSG the crossover operators are used to maintain the population of the SSA and enhance the exploration phase. Subsequently, the improved SSA is applied as a local search to the GOA. This improvement prevents the standard GOA version from premature convergence, the high computation time, besides trapping in local minima.

In the cSG the local search of the standard version of the GOA is supported by the enhanced SSA algorithm. The population of the SSA is improved by adding a new step to maintain the search domain; this step utilizes the crossover operator with the population of the SSA. Therefore, it selects two solutions to start the crossover operators; then it produces two new solutions, which helps maintain the search domain and avoid trapping in a local point.

The proposed cSG begins by providing a new random population \( X \) with \( N \) length and \( D \) dimension. This population contains the initial solutions of the problem. Each solution is evaluated using a fitness function. Eq. (10) shows the fitness function implemented in this study.

\[ f_i = er_i + (1 - \gamma) \left( \frac{ld}{d} \right) \]  

where \( er_i \) defines the error produced by the classification step, (this work applies the KNN classifier); whereas, the second part of this equation refers to the selected features number. \( ld \) and \( d \) is selected features, and the whole number of all
features, respectively. The parameter \( \gamma \in [0, 1] \) is applied in order to balancing the selected features number and the classification error.

Furthermore, each solution is updated. This update is applied by both the SSA and GOA based on a variable generated by using a probability formula \( sp \) as described in the following equation:

\[
sp_i = \frac{f_i}{\sum_{i=1}^{n} f_i} \tag{11}
\]

Here, \( f_i \) denotes the last obtained fitness value produced by Eq. 10. The \( sp \) value determines the updating algorithm by checking its value; therefore, if \( sp_i < 0.5 \), the solution will be updated using GOA by Eqs. 8-9, otherwise the enhanced SSA will be used to update the solution using Eqs. 1-3. Later, each solution’s quality is evaluated by using the fitness function (Eq. 10), and the best one is saved. This sequence is repeated until reaching the stop condition, which in this study set to 2500 fitness evaluations. The main phases of the proposed method are illustrated in Figure 1 and Algorithm 1.

The complexity of the cSG consists of the complexity of GOA, SSA and crossover operators as follows:

\[
O(cSG) = O(GOA) + (O(SSA) + O(Crossover)) \text{ where,} \ O(GOA) = O(t(N^2 \times D + N \times C)), \ O(SSA) = O(t(D \times N + C \times N)), \text{ and } O(Crossover) = O(t \times N); \text{ here, } (t) \text{ is the iterations number, } (N) \text{ is the solutions number, and } (D) \text{ dimension. } (C) \text{ denotes the cost of fitness function.}
\]

Algorithm 1 Pseudocode of the Proposed Method cSG

1. Determine the number of dimension \( (d) \), solutions \( (N) \), and number of fitness function evaluation \( (\text{stopCondition}) \).
2. Define the parameters for both SSA and GOA.
3. Generate the initial population \( X \).
4. While \((t <= \text{stopCondition})\)
5. Compute the fitness value for each solution \( X \) using Eq. (10).
6. Save the best solution based on the fitness value.
7. FOR \((i = 1 \text{ to } N)\)
8. Calculate the probability \( sp \) for each solution using Eq. (11).
9. If \((sp >= 0.50)\)
10. Normalize the distance between the solutions in \( X \) in the interval \([1,4] \).
11. Update \( X \) using operators of GOA (as in Eqs. 8-9).
12. Else
13. If \((\text{rand}() < 0.25)\)
14. Select randomly values from a solution.
15. Apply crossover to update the current solution.
16. End if
17. Update \( X \) using SSA equations as in Eqs. (1-3)
18. End if
19. End for
20. End while
21. Output the result.

IV. EXPERIMENTS

The performance of suggested cSG method is assessed in this section by using four experiments. Accordingly, the first one evaluates the components of the proposed method. Whereas, the second one tests the performance of cSG using CEC2017 functions. The third experiment aims to test the cSG in solving the general feature selection problems. Whereas, the fourth one tests the performance of the cSG in solving six common engineering problems design. The implementation of the experiments was applied using “MATLAB 2014b” and “Windows 10” over “CPU Core i5” with “8GB of RAM”. The compared methods and the parameter settings are listed in the next subsection.

A. PARAMETER SETTINGS

The proposed method is compared with eleven algorithms, namely salp swarm algorithm (SSA) [52], grasshopper optimization algorithm (GOA) [14], particle swarm optimization (PSO) [11], genetic algorithm (GA) [66], multi-verse optimizer (MVO) [67], opposition-based learning GOA [47], Harris hawks optimizer (HHO) [17], Gradient-based optimizer (GBO) [19], slime mould optimization algorithm (SMA) [18], RUNge Kutta optimizer (RUN) [22], hunger games search algorithm (HGS) [21], Differential evolution based upon learning the covariance matrix and setting the bimodal distribution parameter (CoBiDE) [68], enhanced SSA based upon particle swarm optimizer (SSAPSO) [53], and LSHADE with semi-parameter adaptation hybrid with CMA-ES (LSHADSP) [69].

Table 1 records the parameter settings of the algorithms for all experiments. In addition, the population size for all algorithms was set to 25 and the fitness value evaluation was set to 2500; each experiment was implemented 30 times for a statistical purpose.

![FIGURE 1. Phases of the proposed cSG method.](image-url)
TABLE 1. Parameter settings for all methods.

| Algorithm | Settings |
|-----------|----------|
| cSG       | $C_2$ and $C_1 \in [0, 1], C_{mix} = 1, C_{max} = 0.00004, pm = 0.2$ |
| GOA       | $C_{max} = 1, C_{min} = 0.00004$ |
| SSA       | $C_1 \in [0, 1], C_2 \in [0, 1]$ |
| CoBiDE    | $p = 0.4, p_1 = 0.5$ |
| SSAPSO    | $C_2 \in [0, 1], C_3 \in [0, 1], \ w_{Damp} = 0.99, w = 1, C_1 = 1$ |
| LSHADSP   | $L_{Rate} = 0.8, a_{rate} = 1.4, p_{best} = 0.11, \ first$ |
| OBLOGA    | $C_{max} = 1, C_{min} = 0.00004, OBL_{ratio} = 0.5$ |
| HHO       | $E \in [0, 2]$ |
| SMA       | $z = 0.03$ |
| RUN       | $r \in [1, 1], L \in [0, 1], g \in [0, 2]$ |
| GBO       | $p = 0.5$ |
| HGS       | $V_{C2} = 0.03$ |
| MVO       | $W_{EPr} = 0.2, W_{EP_{max}} = 1$ |
| GA        | $pc = 0.8, beta = 8, \ gamma = 0.2, \ mu = 0.02, pm = 0.2$ |
| PSO       | $C_1 = 1, w_{Damp} = 0.99, w = 1, C_2 = 2$ |

B. EXPERIMENT 1: COMPARISON WITH CSG, CROSSOVER SSA, AND GOASSA

This experiment compares the cSG to two other models which formed the proposed methods to show the effectiveness of each model on the cSG in solving global optimization problems. These models are: crossover SSA and GOASSA. The first model is the improved version of the SSA algorithm by using the crossover operator, whereas the second model improves the local search of the GOA with the SSA algorithm without using the crossover operators. Ten different functions: (1) unimodal, (2) multimodal, (3) hybrid, and (4) composition, were selected for this evaluation from the CEC2017 benchmark. All results are recorded in Table 2.

By inspecting these results, we can show that the cSG outperformed the two other models with regard to average of fitness function values by showing the optimal results over 8 functions which are F1, F2, F5, F6, F15, F16, F24, and F25, whereas the GOASSA reached the best values across only two functions, which are F14 and F23. In this regard, the crossover SSA failed to fulfill the optimal values over all functions. Moreover, the cSG had been noticed as the most stable algorithm since it succeeded in achieving the smallest values over eight functions, whereas the GOASSA showed a smaller standard deviation over two functions, and the crossover SSA was ranked third in all functions in terms of the stability behavior.

From the above results, we can conclude that, the combination of both crossover operators and SSA adds a significant improvement and enhances the searching behavior of the original GOA. Therefore, in the following experiments we evaluate and compare the performance of the cSG over different problems and some recently meta-heuristics algorithms.

C. EXPERIMENT 2: SOLVING GLOBAL OPTIMIZATION PROBLEMS

This experiment evaluates the proposed method over the CEC2017 benchmark [70] and compares the results of the cSG with some recently meta-heuristic algorithms from the literature including: the SSA, HHO, GBO, SMA, RUN, HGS, CoBiDE, OBLOGA, SSAPSO, and LSHADSP (it was named in the following tables as LSHADSP). We reported the results of: (1) the average fitness, (2) the standard deviation, and (3) the computational time across 29 test functions of the CEC2017 benchmark in Tables 3-5. The experiment settings were 200 iterations and 30 population size. The dimension was set to 50 with 9000 fitness function evaluations.

As far as the unimodal functions, denoted as F1-F2, the cSG fulfilled the best values respecting average fitness as demonstrated in Table 3, whereas the other competitors failed to achieve the optimal values. Furthermore, the cSG was ranked first concerning standard deviation, as it was the most stable algorithmic method over the two functions F1 and F2, followed by the RUN and LSHADSP algorithms, whereas the GPO was ranked third in the stability measure as in Table 4.

In the multimodal functions, denoted as F3-F9, the LSHADSP was ranked first by reaching the best average fitness over three functions that are F4, F5 and F9, whereas the cSG, HHO, GPO, RUN, and HGS were ranked second by showing the optimal values on F8 and F9. The SMA and CoBiDE ranked third by performing well across both F9 and F7. Moreover, the LSHADSP was also observed to be the most stable method as it attained the smallest standard deviation across three functions, F5, F7 and F9, which is followed by the cSG, HHO, GPO, RUN, and HGS, respectively.

In the hybrid functions, denoted as F10-F19, the cSG was the best-performing method concerning the average of the fitness function values. It was superior with regard to the best average fitness of the best solutions so far over four functions, F12, F15, F16, and F19. The RUN was ranked second by showing the optimal fitness values in three out of ten functions (F10, F13, and F17), while the HGS and SMA were ranked third by achieving good performance in only two hybrid functions. The obtained results over the F10 and F14 functions were the best ones with regard to HGS, while the SMA showed the optimal values in both F10 and F18. Additionally, the GBO came in the first rank respecting
the standard deviation, where it outperformed the other metaheuristics with respect to stability in four out of ten functions namely F10, F11, F14 and F17, followed by the cSG, HHO, SMA, RUN, HGS, and SSAPSO which gained the second rank.

In the composition functions, denoted as F20-F29, the cSG showed dominant performance over this group by realizing the best average fitness values over most functions, i.e., F21, F22, F24, F25, F27, and F25. The HGS was the second best-performing method by achieving the optimal values across two functions (i.e., F20 and F29), whereas the SSA and RUN gained the third rank, which showed the best performance over F23 and F26, respectively. In addition, the cSG was also dominant across this group and superior to the other competitors in achieving a low standard deviation over eight out of ten functions.

Furthermore, in terms of computational time of all methods, the cSG showed acceptable computational time in all
functions, as recorded in Table 5, whereas, the HGS was faster than the compared methods and it was ranked first followed by the SSA, CoBiDE, SSAPSO, and GBO, respectively. However, the cSG was considered as a faster algorithm, it obtained the best fitness values and showed good stability in most cases.

Moreover, the convergence behaviors for all methods are illustrated in Figure 2. This figure shows and compares
convergence curves to evaluate the behavior of each method in reaching the optimal values. From the figure, we can see that the cSG showed fast convergence (the black curve) to the optimal value and improved its behavior in the course of iterations than the compared methods, especially in F19 and F28. The LSHADSP also showed good convergence in most of the functions. In function F23, the SMA and HGS showed fast convergence at the beginning of the iterations; then, they did not show any convergence until the last quarter of iterations; they also showed good convergence in F29.

In general, all algorithms were able to update their search domains during the process, except the original GOA took a long time to update its populations; therefore, the proposed cSG effectively improved the local search of the original GOA.

**D. EXPERIMENT 3: SOLVING FEATURE SELECTION PROBLEMS**

In this experiment, eleven datasets, including Wine, Breast-cancer, Glass, Lymphography, Waveform, Spect, Zoo, Ecoli, Vote, Breastw, and Ionosphere, were used to evaluate the proposed cSG method. These benchmark datasets were chosen...
from the UCI Repository Machine Learning Database [71], which all have distinct properties as shown in Table 6. In order to prove the performance of suggested cSG algorithm in solving the general feature selection problems, we compared
it to some recent and well-known competitive optimizers, including: SSA, GOA, GA, PSO, and MVO.

The experimental results are discussed based on some performance measures, namely: 1) The fitness function value as in Eq. (10). 2) The number of selected features formulated in Eq. 12. 3) The classification accuracy as in Eq. (13). 4) The computation time. 5) The Wilcoxon rank-sum test as a statistical test.

The number of selected features is calculated as:

$$NF = \left[1 - \frac{\sum_{i=1}^{S} e_i}{S}\right], \quad e_i \left\{ \begin{array}{ll} 1 & \text{if } e_i \text{ is selected} \\ 0 & \text{if } e_i \text{ is neglected} \end{array} \right. \quad (12)$$

where, $S$ is the feature number. $e_i$ denotes the selected attribute.

The accuracy ($ACC$) is calculated as:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

Here $TP$ symbolizes the true positive instances, $FP$ indicates the false positive instances, $FN$ symbolizes the false negative instances, $TN$ indicates the true negative instances.

In terms of the fitness function values, according to Table 7, the cSG method achieved the lowest fitness values in 8 datasets out of 11: Glass (0.1266), Lymphography (0.2605), Waveform (0.6325), Spect (0.3120), Ecoli (0.2077), Vote (0.1274), Breastw (0.1009), and Ionosphere (0.1620). Furthermore, the PSO ranked second in three datasets namely Wine (0.0042), Breastcancer (0.1682), and ZOO (0.0037). It is also noted that the cSG algorithm similarly acts with PSO in Breastcancer and Zoo datasets, achieving RMSE of 0.1898 and 0.0047, respectively. It is observed that the GOA realized the last rank by showing the highest error rates across all the tested datasets. These results reflect the stability of the cSG algorithm over the different runs. Figure 3 illustrates the average results of fitness function value.

In terms of classification accuracy, as observed in Table 8, the cSG method realized the highest accuracy over 9 datasets: Breastcancer (0.9705), Glass (0.7862), Lymphography (0.9305), Spect (0.8972), Zoo (1), Ecoli (0.8492), Vote (0.9833), Breastw (0.989), and Ionosphere (0.9735). These results reveal the general capability of the algorithm to effectively search the promising regions within the search space. Furthermore, the classification accuracy results of cSG are very close to these of PSO in two datasets that are Wine and Waveform, respectively. Accordingly, the PSO algorithm took the second rank after the proposed method with respect to classification accuracy, while the GOA also achieved the last rank between the other compared models. Moreover, the F-measure for all methods was also calculated and presented in Table 9. It is observed from this table that the proposed cSG method obtained the best F-measure results in 8 out of 11 datasets. Whereas, the PSO ranked second, it realized the best results over 3 datasets with a slight difference from cSG. The SSA and MVO were ranked third and fourth, respectively followed by the GA and GOA.

| Dataset   | Classes number | Instances number | Features number |
|-----------|----------------|------------------|-----------------|
| Wine      | 3              | 178              | 13              |
| Breastcancer | 2              | 699              | 9               |
| Glass     | 7              | 214              | 9               |
| Lymphography | 2              | 148              | 18              |
| Waveform  | 3              | 5000             | 40              |
| Spect     | 2              | 267              | 22              |
| Zoo       | 6              | 101              | 16              |
| Ecoli     | 8              | 336              | 7               |
| Vote      | 2              | 300              | 16              |
| Breastw   | 2              | 569              | 30              |
| Ionosphere| 2              | 351              | 34              |

Table 6. Description of the benchmark datasets.

| Dataset   | cSG  | SSA  | GOA  | GA   | PSO  | MVO  |
|-----------|------|------|------|------|------|------|
| Wine      | 0.0131 | 0.0487 | 0.1506 | 0.0168 | 0.0042 | 0.0209 |
| Breastcancer | 0.1898 | 0.2112 | 0.3240 | 0.2152 | 0.1682 | 0.2113 |
| Glass     | 0.1266 | 0.1484 | 0.2229 | 0.1499 | 0.1394 | 0.1471 |
| Lymphography | 0.2605 | 0.2952 | 0.5109 | 0.3558 | 0.2776 | 0.3249 |
| Waveform  | 0.6325 | 0.6500 | 0.7285 | 0.6516 | 0.6333 | 0.6564 |
| Spect     | 0.3120 | 0.3519 | 0.4710 | 0.3642 | 0.3284 | 0.3578 |
| Zoo       | 0.0047 | 0.0471 | 0.1155 | 0.0157 | 0.0037 | 0.0143 |
| Ecoli     | 0.2077 | 0.2284 | 0.3363 | 0.2249 | 0.2192 | 0.2242 |
| Vote      | 0.1274 | 0.1871 | 0.3350 | 0.2017 | 0.1682 | 0.1841 |
| Breastw   | 0.1009 | 0.1056 | 0.2164 | 0.1229 | 0.1042 | 0.1279 |
| Ionosphere| 0.1620 | 0.2221 | 0.3173 | 0.2276 | 0.1831 | 0.2199 |

Table 7. Results of fitness function value.

In terms of computational time, as seen in Table 10, the MVO method ranked first based on the average of all datasets, whereas the PSO, cSG, and SSA methods showed similar times to some extent followed by GOA and GA, respectively. That means the cSG is faster than the original version of the GOA due to the effective balance of the SSA and the GOA operators. Figure 4 illustrates the average results of the classification accuracy for all methods.

In terms of the selected attributes number, checking the results of Table 11, the cSG method was capable of selecting the significant features over 2 datasets out of 11 (namely Spect and Breastw) and acts like the ISSALD approach in one dataset (named Exactly2 dataset). Although the GOA method realized the last rank in terms of RMSE and classification accuracy, it comes in the first place with regard to the number of selected attributes by realizing the best results over 5 datasets (namely Wine, Glass, Waveform, Zoo, and Ecoli). In addition, the PSO model achieved the third rank by showing the best results over 3 datasets (namely Breastcancer, Breastw, and Ionosphere). Moreover, the SSA model took the fourth rank by achieving the least number of selected attributes in only 1 dataset (namely Lymphography).

Furthermore, Table 12 records the statistical results of all methods using the Wilcoxon rank-sum test for inspecting if there is a significant difference between the cSG and the other algorithms or not at p-value < 0.05. The Wilcoxon rank-sum is a statistical test implemented for assessing the performance significance. It is non-parametric test that sets
ranks for the scores. It ranks all the scores in one group then it sums the ranks of the groups. In this two-sample test, the null assumption assumes that the samples are from the same population. Accordingly, if there is a difference in two rank sums, the sampling error will be the reason of that. From Table 12 we can notice that, the cSG has a significant difference to the compared algorithms in most cases namely: 64% with SSA and GA, 100% with GOA, 45% with PSO, and 55% with MVO.

The results of this experiment indicate that the cSG is a strong algorithm in solving the global optimization problems. The superiority of the algorithm above all the other applied algorithms is due to the integration of both genetic crossover operator and SSA which enhanced the exploitation and exploration of both algorithms. This hybridization added more flexibility for both algorithms and ensured finding the best solution for the optimization problem quickly and efficiently.

### E. EXPERIMENT 4: SOLVING DIFFERENT PROBLEMS OF ENGINEERING APPLICATIONS

This experiment evaluates the proposed cSG using six popular engineering problems including: (1) Welded beam design. (2) Pressure vessel design. (3) Three-bar truss. (4) Tension/compression spring. (5) Rolling element bearing. (6) Multi-plate disc clutch brake. These problems were solved by the proposed cSG and some meta-heuristic methods formerly...

#### TABLE 9. F-measure results for all methods.

| Dataset     | cSG   | SSA   | GOA   | GA    | PSO   | MVO   |
|-------------|-------|-------|-------|-------|-------|-------|
| Wine        | 0.9925| 0.9738| 0.9038| 0.9952| 0.9988| 0.9937|
| Breastcancer| 0.9764| 0.9647| 0.9211| 0.9638| 0.9786| 0.9651|
| Glass       | 0.9742| 0.7280| 0.5885| 0.6726| 0.7263| 0.6945|
| Lymphography| 0.9473| 0.9248| 0.6715| 0.8455| 0.9328| 0.8701|
| Waveform    | 0.7932| 0.7863| 0.7425| 0.7825| 0.7933| 0.7813|
| Spect       | 0.7427| 0.6518| 0.4377| 0.6284| 0.7004| 0.6673|
| Zoo         | 1.0000| 0.8841| 0.6277| 0.9478| 0.9940| 0.9662|
| Ecoli       | 0.6202| 0.5509| 0.3793| 0.5529| 0.5689| 0.5827|
| Vote        | 0.9785| 0.9520| 0.8511| 0.9472| 0.9636| 0.9557|
| Breastw     | 0.9848| 0.9809| 0.9328| 0.9765| 0.9839| 0.9749|
| Ionosphere  | 0.9798| 0.9600| 0.9228| 0.9588| 0.9724| 0.9599|

#### TABLE 10. Results of the computational time.

| Dataset     | cSG   | SSA   | GOA   | GA    | PSO   | MVO   |
|-------------|-------|-------|-------|-------|-------|-------|
| Wine        | 6.005 | 6.413 | 6.732 | 7.182 | 6.455 | 6.436 |
| Breastcancer| 6.302 | 6.032 | 6.690 | 6.752 | 6.040 | 6.065 |
| Glass       | 5.902 | 6.672 | 6.787 | 7.327 | 6.577 | 6.587 |
| Lymphography| 5.728 | 6.122 | 6.145 | 6.672 | 5.734 | 5.623 |
| Waveform    | 18.40 | 18.15 | 18.41 | 20.33 | 18.18 | 18.13 |
| Spect       | 6.066 | 6.071 | 6.471 | 6.679 | 6.039 | 6.017 |
| Zoo         | 6.408 | 6.373 | 6.462 | 7.286 | 6.172 | 6.314 |
| Ecoli       | 5.286 | 5.231 | 5.265 | 5.838 | 5.220 | 5.234 |
| Vote        | 6.209 | 6.448 | 6.717 | 7.276 | 6.559 | 6.515 |
| Breastw     | 6.697 | 6.355 | 6.951 | 7.069 | 6.304 | 6.333 |
| Ionosphere  | 6.416 | 6.183 | 6.809 | 6.859 | 6.171 | 6.154 |

#### TABLE 11. Results of the selected features by each algorithm.

| Dataset     | cSG   | SSA   | GOA   | GA    | PSO   | MVO   |
|-------------|-------|-------|-------|-------|-------|-------|
| Wine        | 8.7   | 7.0   | 6.5   | 7.6   | 7.6   | 7.3   |
| Breastcancer| 15.9  | 15.1  | 16.3  | 15.8  | 14.9  | 15.6  |
| Glass       | 5.8   | 5.4   | 4.9   | 5.3   | 5.0   | 5.5   |
| Lymphography| 10.8  | 8.7   | 9.4   | 10.1  | 9.2   | 9.8   |
| Waveform    | 16.0  | 13.5  | 11.7  | 13.2  | 13.9  | 13.1  |
| Spect       | 10.3  | 11.0  | 11.6  | 11.0  | 10.4  | 11.1  |
| Zoo         | 10.1  | 9.2   | 8.4   | 9.2   | 9.4   | 9.4   |
| Ecoli       | 5.2   | 4.9   | 3.6   | 4.9   | 5.0   | 5.3   |
| Vote        | 7.2   | 7.2   | 8.3   | 7.9   | 7.7   | 7.5   |
| Breastw     | 17.7  | 15.8  | 15.4  | 15.8  | 15.3  | 15.7  |
| Ionosphere  | 17.3  | 14.6  | 17.2  | 15.7  | 14.0  | 15.7  |
TABLE 13. Results of the proposed method for solving the problem of welded beam design.

| Algorithm | Optimal values for the variables | Optimal cost |
|-----------|----------------------------------|--------------|
|           | $h$ | $l$ | $tt$ | $bb$ |               |
| Proposed cSG | 2.05044 | 3.48701 | 9.03768 | 2.0572 | 1.72586 |
| MVO [67] | 2.0546 | 3.47319 | 9.04450 | 2.0569 | 1.72645 |
| GSA [67] | 0.18212 | 3.85697 | 10.05 | 0.20237 | 1.87995 |
| GA [72] | 0.24890 | 6.17300 | 8.17890 | 0.25330 | 2.43312 |
| WOA [13] | 0.20539 | 3.48429 | 9.03742 | 0.20627 | 1.73049 |
| HHO [17] | 0.20403 | 3.53106 | 9.07246 | 0.20614 | 1.731991 |
| GWO [73] | 0.20567 | 3.47837 | 9.03681 | 0.20577 | 1.72624 |

TABLE 14. Results of the proposed method for solving the problem of pressure vessel design.

| Algorithm | Optimal values for the variables | Optimal cost |
|-----------|----------------------------------|--------------|
|           | $T_s(t_1)$ | $T_h(t_2)$ | $R_s(t_3)$ | $L(t_4)$ |               |
| Proposed cSG | 0.830556 | 0.41064 | 43.0358 | 165.9827 | 5995.783 |
| MVO [67] | 0.8125 | 0.4375 | 42.09074 | 176.7387 | 6060.807 |
| GSA [67] | 1.125 | 0.625 | 55.98865 | 84.4542 | 8538.835 |
| GA [72] | 0.8125 | 0.4375 | 42.0974 | 176.6541 | 6059.946 |
| WOA [13] | 0.8125 | 0.4375 | 42.09827 | 176.639 | 6059.741 |
| HHO [17] | 0.817558 | 0.40729 | 42.09715 | 176.7196 | 6000.463 |
| GWO [73] | 0.8125 | 0.4345 | 42.08818 | 176.7857 | 6051.564 |

implemented in the literature. The following subsections compare the solutions reached by cSG and the other methods to solve these optimization problems.

1) PROBLEM OF WELDED BEAM DESIGN
This problem tries to minimize fabrication cost for welded beam as shown in Figure 5. There are four variables to be optimized namely the weld’s thickness ($h$), the bar’s thickness ($bb$), length of an attached part ($l$), and the bar’s height ($tt$).

The results in Table 13 point out that the cSG algorithm obtained the best result among the compared methods for the welded beam structure through finding the lowest cost namely 1.72586; this cost represents the minimum optimum cost among all other compared algorithms. The GWO, MVO, and WOA achieved 1.72624, 1.72645, and 1.73049 and were ranked as second, third, and fourth, respectively. The highest cost was reported by the GA which reached 2.43312. It is apparent that the cSG significantly outperforms the aforementioned techniques in solving this problem.

2) PROBLEM OF PRESSURE VESSEL DESIGN
This experiment is intended to minimize the cylindrical pressure vessel’s cost. Figure 6 shows the design of this problem. Four variables in this experiment need to be optimized namely: both thickness of a shell ($T_s$) and head ($T_h$), the cylindrical section length ($L$), and the inner radius ($R$).

This subsection gives a comparison on the optimal results taken for the problem of pressure vessel design by cSG and the other previously mentioned models. As shown in Table 14, the lowest cost was reported by the cSG algorithm which is 1.72586. It is also seen that the GWO, MVO, and WOA came in the second, third, and fourth rank with the cost of 1.72624, 1.72645, 1.73049, respectively. In this regard, the GA reported the highest cost of 2.43312 among the other algorithms. These results demonstrate the merits of cSG algorithm in solving this design problem.

3) PROBLEM OF THREE-BAR TRUSS
The aim of this experiment is minimizing the truss weight. Two variables in this experiment need to be optimized namely $A_1$ and $A_2$. Variable $A_3 = A_1$ as shown in Figure 7.

The results of the cSG algorithm for solving the design problem of three-bar truss in comparison to some algorithms are provided in Table 15. It can be noticed that the algorithm of cSG is competitive. It achieved the lowest cost of 263.896. It is also clear that the MVO is competitive to the GOA and MFO by reporting lower cost of 263.896 while the two other algorithms reported 263.896 and 263.896, respectively. The highest cost was reached by the CS algorithm which achieved a value of 263.972. From these results, it is apparent that cSG
significantly outperforms the other compared meta-heuristic algorithms when solving this design problem.

4) PROBLEM OF TENSION/COMPRESSION SPRING
The objective of this experiment is to minimize the tension/compression spring weight. Three variables in this experiment need to be optimized namely the mean coil diameter (D), the active coils number (NN), and the wire diameter (dd). These variables are illustrated in Figure 8.

The problem of tension/compression spring design problem was extensively addressed through various bio-inspired optimization algorithms including: MVO, GSA, PSO, WOA, GWO, MFO, SSA and RO. Table 16 presents the comparison results between the proposed cSG and the other competitors’ algorithms with regard to the values of design variables and the cost value for this problem. Accordingly, the results in Table 16 shows that the proposed cSG is capable of finding the optimal design for this problem achieving a minimum cost of 0.012665. Such cost is slightly lower than those given by other algorithms. The WOA and SSA showed similar cost of 0.01268 whereas the MVO algorithm showed the highest cost of 0.01279. These results confirm that cSG performs better than other meta-heuristic optimization methods in reaching the optimum solution for solving this design problem.

5) PROBLEM OF ROLLING ELEMENT BEARING
The aim of this experiment is maximizing the ability of the dynamic load carrying. In this experiment, ten variables used for assembling and restrictions of geometric, need to be obtained. Figure 9 illustrates an overview of this problem.

A comparison between the cSG and the HHO, MVO, PVS, and TLBO, for solving the rolling element bearing design problem is illustrated in Table 17. Regarding the optimal costs in Table 17, cSG presented the best value for that design problem with 85446.7489. The MVO came in the second rank by reporting a cost value equals 83535.147 followed by the HHO which showed a cost equals 83011.883. On the other side, the PVS and TLBO algorithmic models reported almost similar cost values. These results reflect that the cSG outperforms the other meta-heuristic optimization techniques in reaching the best optimal solution for this design problem.

6) PROBLEM OF MULTI-PLATE DISC CLUTCH BRAKE
The aim of this experiment is minimizing the multiple disc clutch brake weight. Five variables in this experiment need to be optimized namely outer radius, discs thickness, inner radius, actuating force, and friction surfaces. Figure 10 illustrates an overview of this problem.

The cSG algorithm is used to solve multi-plate disc clutch brake problem and compared to MVO, PVS, WCA, and TLBO. Table 18 reports the results of this comparison to get the best cost found by such meta-heuristics. The findings report that the proposed cSG algorithm outperformed all other methods in finding the optimum minima solution of this design. It showed the lowest cost of 0.2598 followed by
TABLE 17. Results of the proposed method for solving the design problem of rolling element bearing.

| Variable | Proposed cSG | HHO [17] | MVO [77] | PVS [78] | TLBO [78] |
|----------|--------------|----------|----------|----------|----------|
| $D_{ax}$ | 125.5126     | 125.000  | 126.1035 | 125.719  | 125.719  |
| $D_{b}$  | 21.4233      | 21.000   | 21.03794 | 21.42559 | 21.42559 |
| $Z$      | 10.98428     | 11.092   | 11.13977 | 11.0000  | 11.0000  |
| $f_1$    | 0.51500      | 0.51500  | 0.51500  | 0.51500  | 0.51500  |
| $f_2$    | 0.51500      | 0.51500  | 0.52286  | 0.51500  | 0.51500  |
| $K_{max}$| 0.49385      | 0.40000  | 0.44355  | 0.40043  | 0.424266 |
| $K_{ext}$| 0.613865     | 0.60000  | 0.67521  | 0.68016  | 0.635948 |
| $e$      | 0.300329     | 0.30000  | 0.30108  | 0.30000  | 0.30000  |
| $c$      | 0.078389     | 0.05050  | 0.08852  | 0.07999  | 0.068858 |
| $\xi$    | 0.635913     | 0.60000  | 0.61468  | 0.70000  | 0.799498 |
| Max cost | 85446.748    | 83011.88 | 83535.14 | 81859.74 | 81859.74 |

V. CONCLUSION

In this work, an improved grasshopper optimization algorithm (GOA) is proposed by applying the crossover operators to maintain the population of the salp swarm algorithm (SSA), then the improved SSA is applied as local search to the original GOA. This improvement prevents the proposed method from premature convergence, the high computation time, besides getting trapped in local minima. The proposed method was applied to solve 29 global optimization problems, feature selection (FS) tasks, and real-engineering problems. For FS problems, eleven well-known benchmark datasets and four performance measures were selected for the experiment. Additionally, the performance of the proposed cSG method was compared with several algorithms in the state-of-the-art. The experimental results demonstrated the superiority of the proposed method compared to other optimization algorithms in all metrics. Moreover, the results showed that using crossover operators with SSA improved the performance of GOA effectively and enhanced the exploration behavior. In future, it would be attractive to examine the performance of cSG method on more advanced science, machine learning tasks in dealing with other datasets, and further improve its complexity with no effect on the performance.

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