An Application for Improved Bee Colony Algorithm on A Multi-Objective Real-World Optimization Problem

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***Abstract*—This paper presents an application of improved bee colony algorithm for multi-objective optimization (IBMO) on a real-world optimization problem known as welded beam design. IBMO is founded on the principle of single objective artificial bee colony algorithm (ABC). It also combines the nondominated sorting strategy of NSGAII and classical multi-objective optimization procedures such as Pareto-Dominance, crowding distance, external archive, and etc. Furthermore, IBMO has an improvement method to accelerate the convergence by considering the number of function evaluations. By using several benchmark problems, the running consistency and robustness of IBMO has been reported in a previous study of authors. In this study, IBMO determines the parameters of welded beam engineering problem which has several constraints and two objectives: (1) minimum cost and (2) minimum end deflection. The experimental results are compared with two algorithms. The results clearly show that IBMO reaches the better results easily and it is a capable tool to solve multi-objective real world optimization problems**

***IndexTerms*—Multi-objective optimization, IBMO, ABC, welded beam design problem**

I. Introduction

Many real-world engineering design problems contain multiple objectives to optimize simultaneously. Also these objectives are often conflicting with each other. So a multi-objective optimization problem differs from a single objective optimization problem. Optimizing a single decision or design in a search space is relatively an easier task. But evaluation of multiple objectives is a complicated task. Because multiple objectives mean that there is generally more than one optimal solution. Therefore, the decision maker needs to choose a solution from a feasible solution set [1, 2]. The general formulation of a multi-objective optimization problem can be defined as follows:

$$\text{Maximize/Minimize} \quad y = f(x) = \{f_1(x), f_2(x), \dots, f_M(x)\}$$

$$\text{Subject to} \quad g(x) = \{g_1(x), g_2(x), \dots, g_J(x)\} \leq 0$$

$$h(x) = \{h_1(x), h_2(x), \dots, h_K(x)\} = 0$$

$$\text{where} \quad x = \{x_1, x_2, \dots, x_N\} \in X$$

$$y = \{y_1, y_2, \dots, y_N\} \in Y$$

where x is set of the decision or feature vectors and X is the parameter space, y is the objective vector, Y is the objective space, g(x) and h(x) is the constraints imposed on the decision variables[13].

Recent studies have been showed that the hybrid approaches based on swarm intelligence can be used as an effective tool in this field [3, 4, 5, and 6]. Optimization algorithms based on swarm intelligence are multi-agent, robust and resilient methods, which are inspired by intelligent attributes of swarms. Their main advantage is the simple agents in communication that are capable of solving complex problems.

This paper focuses on improved bee colony algorithm for multi-objective optimization algorithm (IBMO) [7] for solving the welded beam design problem which is a real-world engineering problem. IBMO, which has been recently proposed by authors, is a hybrid algorithm to incorporate the main mechanism of NSGAII [8] with artificial bee colony optimization (ABC) [9]. It has been successfully applied on several benchmark problems and color image segmentation in previous studies [7, 10]. The aim of this study is to demonstrate the effectiveness of IBMO on a real-world engineering problem.

The rest of the paper is organized as follows. In section 2, the general outline of IBMO algorithm is explained. Then section 3 focuses on the problem of welded beam design in detail. The obtained experimental resultsare illustrated in section 4. The brief concluding remarks are given in section 5.

II. Improved Bee Colony Algorithm for Multi-Objective Optimization (IBMO)

The IBMO is a hybrid multi-objective optimization algorithm which has recently been proposed by authors [7]. It is developed as an adaptation of single objective ABC algorithm to multi-objective optimization. This algorithm takes the advantages of nondominated sorting strategy of NSGAII and principal concepts of Pareto-Optimal such as Pareto-dominancy, crowding distance (CD) and external archive (EXA). Also, an improvement procedure is implemented for the local search. The outline of algorithm is presented in Fig.1.

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The presented algorithm consists of four phases: (1) generating initial swarm by aid of a diversification technique, (2) employed bee phase, (3) onlooker bee phase, and (4) scout bee phase. In the diversification technique, the ranges of parameters in a candidate solution are divided into equal sized subranges. All subranges have a frequency value and it equals to zero at first. Then a subrange is selected inversely proportional to its frequency count. The parameter is produced in this range.

The next three phases are applied to swarm almost similarly to original ABC algorithm. But some modifications are added into each phases because of the nature of multi-objective optimization.

In the employed bee phase, neighbor solution which is used to generate new solution is selected from foods set just like in single objective ABC. But the parameter to change is randomly determined by using a frequency count assigned to all parameter like frequency approach used in diversification method.

In the onlooker bee phase, neighbors are selected from external archive (EXA) which stores the nondominated solutions obtained so far. The roulette wheel method is applied on the selection probabilities of nondominated solutions which are calculated by crowding distance (CD). The crowding distance guaranties a regular distribution in EXA.

At the end of the both employed and bee phases, EXA is updated with new obtained solutions. Also a local search procedure is implemented after the generating a new solution. This procedure uses a greedy selection process based on constrained dominancy between new and current solutions. If new solution dominates the current, new solution is added to foods list instead of the current. Furthermore, same delta value is added to same parameter as long as new solution dominates the current, or until the number of iteration exceeds the predefined parameter limit_count. This process provides an accelerated convergence effect within selected parameter.

Later, the scout bee phase is executed. A trial value is incremented by one whenever related solution fails a greedy selection in both employed and onlooker bee phases. The solutions which exceed a predefined trial number limit are regenerated randomly and related trial values are set to zero.

Finally, the current Foods and EXA is combined and sorted according to nondomination level in order to fill the food set for next iteration. To find exactly N solutions, the last front is ordered by means of the crowded comparison in descending order, and the less crowded solutions are choosen to fill new food set[13].

The more detailed explanation and pseudo-codes of IBMO algorithm can be found in [7, 10].

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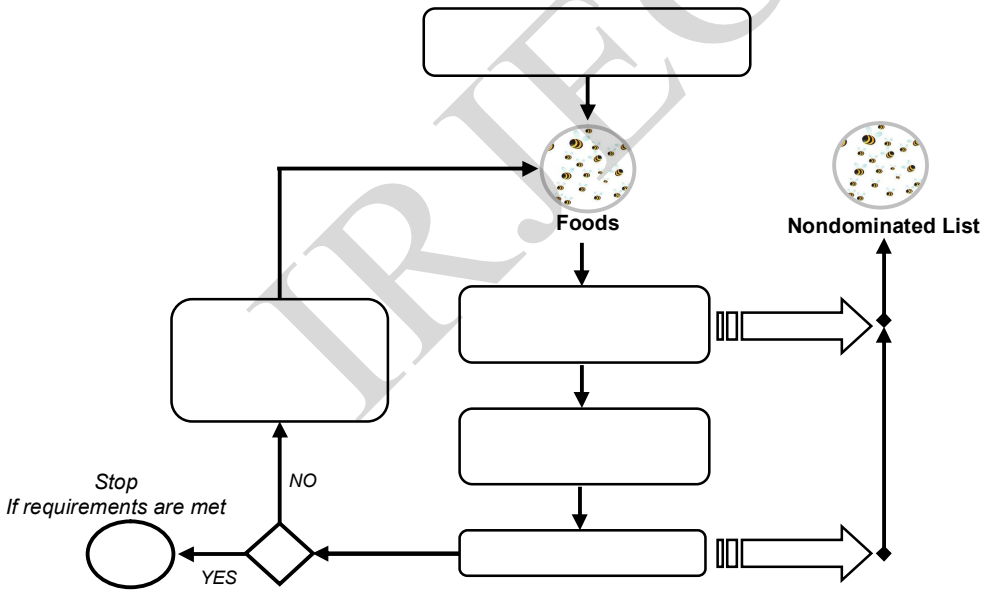


Fig. 1. The outline of IBMO algorithm

III. Design of a Welded Beam

The welded beam design problem is a well-known constrained optimization problem in the field of single objective optimization. The problem includes two conflicting objectives which are constructed for minimum cost and minimum end deflection. The constraints are shear stress, bending stress and buckling load. The four continuous design variables h, l, t and b are correspond to x_1,x_2,x_3 and x_4 as shown in Figure 2. To get smaller the beam dimensions causes

to get bigger end deflection. In order to obtain the feasible solutions, it should be taken into account both of the objectives simultaneously. Deb[11] solved the same problem using a real coded genetic algorithm with simulated binary crossover (SBX). Also Ray and Liew [12] deal with the problem using their proposed swarm algorithm. The formulation of the welded beam design problem is defined as:

Minimize $f_1(x) = 1.10471{x_1}^2 x_2 + 0.04811 x_3 x_4 (14.0 + x_2)$

Minimize $f_2(x) = \delta(x)$

Subject to

$$\tau(x) - \tau_{max} \le 0$$

$$\sigma(x) - \sigma_{max} \le 0$$

$$x_1 - x_4 \le 0$$

$$0.125 - x_1 \le 0$$

$$P - P_c(x) \le 0$$

where

$$\tau(x) = \sqrt{(\tau')^2 + \frac{2\tau'\tau'' x_2}{2R} + (\tau'')^2}$$

$$\tau'' = \frac{MR}{J}$$

$$M = P\left(L + \frac{x_2}{2}\right)$$

$$R = \sqrt{\frac{{x_2}^2}{4} + \left(\frac{x_1 + x_3}{2}\right)^2}$$

$$J = 2\left\{\frac{x_1 x_2}{\sqrt{2}}\left[\frac{{x_2}^2}{12} + \left(\frac{x_1 + x_3}{2}\right)^2\right]\right\}$$

$$\sigma(x) = \frac{6PL}{x_4 {x_3}^2}$$

$$\delta(x) = \frac{4PL^3}{E x_4 {x_3}^3}$$

$$P_c(x) = \frac{4.013\sqrt{\frac{E G {x_3}^2 {x_4}^6}{36}}}{L^2}\left(1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}}\right)$$

P= 6000 lb, L=14 in, δ_{max}=0.25 in, E=30 x 10^6 psi, G=12 x 10^6 psi, τ_{max}=13,600psi, σ_{max}=30,000 psi, $0.125 \le x_1 \le 5.0$, $0.1 \le x_2 \le 10.0$, $0.1 \le x_3 \le 10.0$ and $0.125 \le x_4 \le 5.0$.

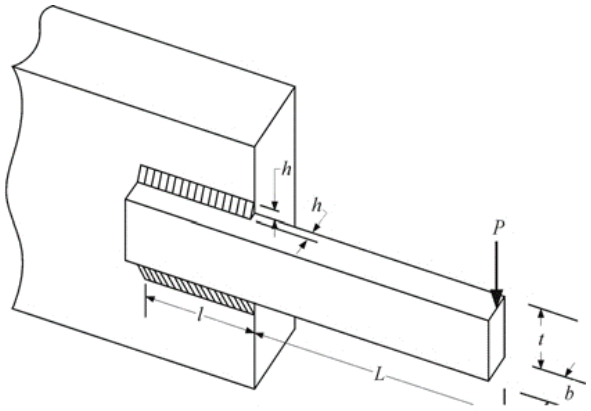


Fig. 2. Variables of the design of a welded beam

IV. Experimental Results

In this study, in order to prove the validity of IBMO, it is verified on a real-world multi-objective engineering problem. The IBMO is applied to determine the parameters of welded beam design problem. It is considered to be a candidate solution when the number of objective functions evaluation (maxFES) is reached at 5,000. The swarm size is set to 100 and external archive size is set to 100. Also the results of IBMO are compared with NSGAII which is the state-of-the-art algorithm in this field. NSGAII was previously applied to same problem with a population of 100 solutions for 500 generations. It means that the number of function evaluation is 50,000.

The Pareto front which is obtained by IBMO is presented in Fig. 3. It consists of 100 nondominated solutions.

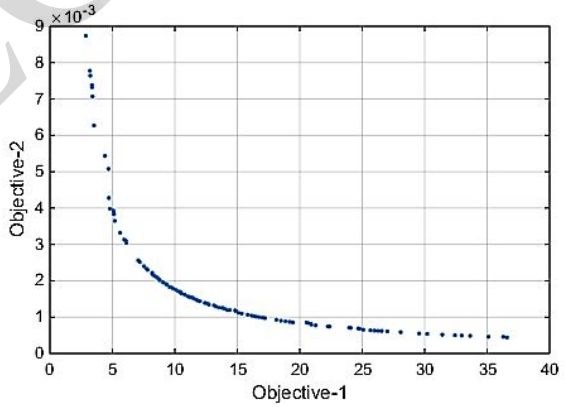


Fig.3. Pareto front obtained by IBMO for welded beam design problem

Two extreme nondominated solutions obtained by IBMO are shown in Table I. Also the results of same multi-objective of the welded beam problem obtained by Deb [11] and by Ray and Liew [12] are presented in Table I. These comparative results have been reported in the related references [11, 12]. It can be clearly seen that the IBMO has the better values than the other studies. Besides, IBMO was able to achieve these results by calculating much less function evaluations. Although the number of function evaluations for the welded beam design problem is 50,000 for NSGAII and 18,389 for Ray's swarm algorithm, respectively; the IBMO was able to obtain the better results after only 5,000 function evaluations.

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TABLE I TWO EXTREME PARETO OPTIMAL SOLUTIONS OBTAINED BY THREE ALGORITHMS

	Objective-1 Cost	Objective-2 Deflection	*h*	*l*	*t*	*b*
NSGAII (Deb)	3.944	0.005	0.422	2.465	9.990	0.439
	20.677	0.001	0.422	2.465	9.990	2.558
Swarm Alg. (Ray)	3.633	0.014	0.4532	3.71	7.0297	0.466
	55.202	0.0004	0.9366	6.5903	9.9965	4.9296
IBMO	2,876	0,008	0,2612	4,8208	9,5142	0,2917
	36,585	0,0004	1.2317	0.7126	10	5

V. CONCLUSIONS

In this study, the efficiency of IBMO was investigated by applying on an engineering problem known as welded beam design. IBMO depends on single-objective ABC and nondominated sorting strategy of NSGAII. Also it involves a local search strategy to expedite the convergence to Pareto front. The obtained experimental results were compared with two other multi-objective algorithms: first one is NSGAII which is a well-known state-of-the-art algorithm developed by Deb, and the second one is the swarm based multi-objective optimization algorithm proposed by Ray. The results demonstrate that IBMO is able to achieved better values than the other algorithms and it also reached the available solutions by making much less function evaluations. Finally it can be said that IBMO is a useful and reliable tool for real-word engineering problems which have multiple objectives to require optimization.

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