Constrained Multi–Objective Optimization Problems in Mechanical Engineering Design Using Bees Algorithm

A. Mirzakhani Nafchi[1,*], A. Moradi[2]

[1]*Department of Mechanical Engineering, Payame Noor University, PO Box 19395-3697, Tehran, Iran*
[2]*Department of Mechanical Engineering, Chamran University, Ahvaz, Iran*

ABSTRACT

Many real-world search and optimization problems involve inequality and/or equality constraints and are thus posed as constrained optimization problems. In trying to solve constrained optimization problems using classical optimization methods, this paper presents a Multi-Objective Bees Algorithm (MOBA) for solving the multi-objective optimal of mechanical engineering problems design. In the present study, a satellite heat pipe design, a space truss design and pressure vessel problems are considered. Multi-objective optimization using the bees algorithm which is a new multi-object obtain a set of geometric design parameters, leads to optimum solve. This method is developed in order to obtain a set of geometric design parameters leading to minimum heat pipe mass and the maximum thermal conductance. Hence, a set of geometric design parameters, lead to minimum pressure total cost and maximum pressure vessel volume. Numerical results reveal that the proposed algorithm can find better solutions when compared to other heuristic or deterministic methods and is a powerful search algorithm for various engineering optimization problems.

© 2011 IAU, Arak Branch. All rights reserved.

Keywords: Bees Algorithm; Multi-objective optimization; Satellite heat pipe design; Pressure vessel design; Truss design

1 INTRODUCTION

THE goal of an optimization problem can be stated as finding the combination of parameters (independent variables) which maximizes or minimizes a given quantities or quantities, possibly subject to some restrictions on the allowed parameter ranges. The quantities to be optimized are called objective functions. If only one quantity has to be optimized, the problem is single function optimization and if more than one quantity are involved, the problem is multi-objective optimization. There is now increasing interest in constrained multi-objective function optimization as most engineering design problems involve multiple and often conflicting objectives. There are two ways of solving constrained multi-objective optimization problems. First, a linear combination could be formed of the different objective functions with different weights and could optimize the resulting function using methods developed for a single objective function problem. The other way of solving a multi-objective problem – the genuine - is to consider all objective functions simultaneously. There are two main drawbacks with converting a multi-objective function problem into a single objective function. First, not all the solutions are found second the weighting assigned to some criteria or objective functions may not be suitable and the resulting function may lack significance. In the multi-objective optimization, it is of interest to compute the Pareto optimal set or the set of non-dominated solutions, not to find a single optimal solution. A solution belonging to the Pareto set is not better than another one belonging to the same set. They are not comparable and each of them is called a feasible solution.

---

* Corresponding author. Tel.: +98 913 183 3292; fax: +98381 222 0201.
 E-mail address: amin.mirzakhani@yahoo.com (A.Mirzakhani).

Since multi-objective optimization problems give rise to a set of Pareto-optimal solutions, evolutionary optimization algorithms are ideal for handling multi-objective optimization problems [1]. A number of multi-objective optimization techniques using Evolutionary Algorithms (EAs) have been suggested since the pioneering work by Schaffer [2]. Other important developments are described in the works by Fonseca and Fleming [3], Horn et al. [4], Srinivas and Deb [5], Knowles et al. [6], Deb et al. [7], Zitzler et al. [8], [9], Farina et al. [10], Nebro et al. [11], Mainenti et al. [12], Copiello and Fabbri [13], Cuco et al. [14], Oliveira et al. [15], Khalkhali et al. [16], Szparaga et al. [17] and Shrivastava et al. [18].

The authors have developed a new optimization tool, called the Bees Algorithm [19], and have applied it to the constrained and unconstrained single objective function optimizations [20], [21]. An adapted version of this algorithm has been created to recognize and construct a Pareto set with as many non-dominated solutions as possible.

During the harvesting season, a colony of bees keeps a percentage of its population as scouts and uses them to explore the field surrounding the hive for promising flower patches. Honeybee foraging behavior consists of two types of behavior, i.e., (i) recruitment behavior and (ii) navigation behavior. In order to recruit members of the colony for food sources, honeybees inform their nest mates of the distance and direction of these food sources by means of a waggling dance performed on the vertical combs in the hive [22]. This dance (i.e., the bee language) consists of a series of alternating left-hand and right-hand loops, interspersed by a segment in which the bee waggles her abdomen from side to side. The duration of the waggle phase is a measure of the distance to the food, and the angle between the sun and the axis of the waggle segment on the vertical comb represents the azimuthally angle between the sun and the direction in which the recruit should fly to find the target [23], [24] (Fig. 1).

The 'advertisement' for a food source can be adopted by other members of the colony. The decision mechanism for adopting an 'advertised' food source location by a potential recruit is not completely known. It is considered that the recruitment amongst bees is always a function of the quality of the food sources [25]. Different species of social insects, such as honeybees and desert ants, make use of non-pheromone based navigation. Non-pheromone- based navigation mainly consists of Path Integration (PI) which is the continuous update of a vector by integrating all angles steered and all distances covered [26]. A PI vector represents the insect's knowledge of direction and distance towards its destination. To construct a PI vector, the insect does not use a mathematical vector summation as a human does, but employs a computationally simple approximation [27]. Using this approximation the insect is able to return to its destination directly. More precisely, when the path is unobstructed, the insect solves the problem optimally. However, when the path is obstructed, the insect has to fall back on other strategies such as landmark navigation [28], [29] to solve the problem. Obviously, bees are able to fly and when they encounter an obstacle they can mostly choose to fly over it., Even, however, if the path is unobstructed, bees tend to use landmark navigation to minimize PI vector errors. The landmarks divide the entire path in segments and each landmark has a PI vector associated with it. In the remainder of this paper, we refer to a home-pointing PI vector as a Home Vector (HV). PI is used in both exploration and exploitation. During exploration, insects constantly update their HV. It is however, not used as an exploration strategy. During exploitation, the insects update both their HV and the PI vector indicating the food source, and use these vectors as guidance to a destination.

The Authors wrote an efficient algorithm for solving mechanical problems with Taking inspiration the life of bees based on finding optimal way for food search.
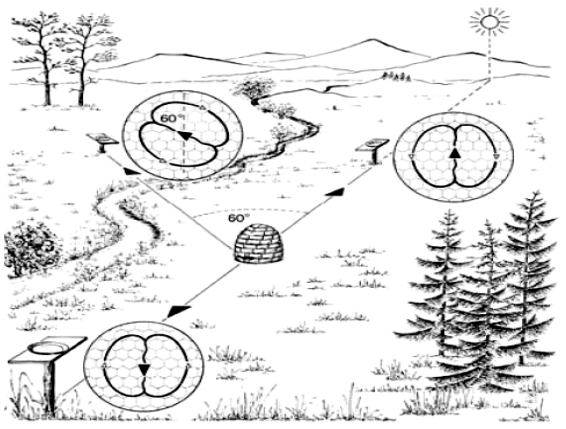

Fig. 1
Distance and direction by waggling dance [30].

2   MULTI-OBJECTIVE OPTIMIZATION PROBLEMS

This paper describes application of the Bees Algorithm to multi-objective optimization problems. Multi-objective optimization procedure yields a set of non-determinated solutions, called Pareto optimal set. Each of which is a trade-off between objectives and can be selected by the user, regarding the application and the project's limits. The Bees Algorithm is a search procedure inspired by the way honey bees forage for food. The general multi-objective optimization problem is posed as follows [1]:

$$
\begin{aligned}
\min imize\ & f_i(x) & i = 1, 2, ..., l \\
subject\ to\ & C_j(x) = 0 & j = 1, 2, ..., m \\
& h_k(x) \geq 0 & k = 1, 2, ..., p \\
& X = (x_1, x_2, ..., x_n)^T
\end{aligned}
\tag{1}
$$

where $f_i(x)$ are the objective functions, X is the column vector of the n independent variables, and $c_j(x)$ are equality constraints, and $h_k(x)$ are inequality constraints. Taken together, $f_i(x)$, $c_j(x)$ and $h_k(x)$ are known as the problem function. The word "minimize" means that we want to minimize all the objective functions simultaneously. If there is no conflict between the objective functions, then a solution can be found where every objective function reaches its optimum. To avoid such trivial cases, it is assumed that there is not a single solution that is optimal with respect to every objective function. This means that objective functions are at least partly conflicting. They may also have different units.

3   THE BEES ALGORITHM

The Bees Algorithm is a search procedure inspired by the foraging behavior of honey bees. This section summarizes the main steps of the Bees Algorithm. For more details, the reader is referred to references [31] to [33]. Table 1 shows the pseudo code for the Bees Algorithm in its simplest form which is dependent to some parameters:

n=Population
m=Number of selected sites
n_m=Number of bees recruited for m sites
n_{gh}=Initial patch size
i_{max}=Number of iteration

Table 1
Pseudo code of the bees algorithm

1. Initialize population with random solutions.
2. Evaluate fitness of the population.
3. While (stopping criterion not met) // forming new population.
4. Select sites for neighborhood search and determine the path size.
5. Recruit bees for selected sites (more bees for best e sites) and evaluate fitness
6. Select the fittest bee from each path.
7. Amend the Pareto optimal set.
8. Assign remaining bees to search randomly and evaluate their fitnesses.
9. End while.

4   MECHANICAL COMPONENT DESIGN

In this section we deal with the optimal design of a satellite heat pipe, a space truss design and pressure vessel which are important in aerospace industry, etc.

4.1 Multi-objective optimization of artificial satellite heat pipe

For a cooling system of an artificial satellite, heat pipes based isothermal radiator panels are generally employed. To maximize the fin efficiency of isothermal panels, the minimization of the temperature gradient between the lateral and header heat pipes becomes a very important design object. On the other hand, saving the total mass (weight) of the thermal control subsystem is highly important to reduce load (pay load cost) on a booster- rocket. The satellite panels contain many embedded aluminum heat pipes, which generally occupy over 50%of the total mass of the fundamental radiator panels. Thus, the thermal design of the artificial satellite requires both the fin efficiency and mass saving of the heat pipes at the same time.

The calculated value G is the thermal conductance across the thermal joint of the heat pipes, defined as [34]:

$$G = \frac{Q}{T_{con} - T_{eva}} \tag{2}$$

where T_{con} is condensing liquid temperature in the lateral heat pipe, T_{eva} is the evaporating vapor temperature in the header heat pipe, Q is the assumed quantity of the transported heat of the 2.5W per a thermal joint. The determined response surface equation of *G* is as follow [35]:

$$\begin{aligned}
G &= f(L_f, L_c, t_f, t_b, T_{OP}) \\
&= 0.3745378 - 0.9352909 t_b + 1.01612 t_b^2 + 0.02324128 L_c - 0.007209993 L_c^2 \\
&\quad + 0.001838379 L_f - 0.000053779707 L_f^2 + 0.02447391 t_f + 0.002304583 t_f^2 - 0.0006483411 T_{OP} \\
&\quad - 0.0000009232971 T_{OP}^2 - 0.02259702 t_b L_c - 0.009702533 t_b^2 L_c^2 + 0.005382211 t_b L_f \\
&\quad - 0.00009540484 t_b L_f^2 + 0.00515048 t_b^2 L_f - 0.0001232524 t_b^2 L_f^2 + 0.2972589 t_b t_f \\
&\quad - 0.1052935 t_b t_f^2 - 0.5422262 t_b^2 t_f - 0.1829687 t_b^2 t_f^2
\end{aligned} \tag{3}$$

The response surface equation for the total mass *M* also expressed in the following equation [35]:

$$\begin{aligned}
M &= f(L_f, L_c, t_f, t_b, T_{OP}) \\
&= (1313.877 - 75.5 L_c + 1.402597 L_f - 1.278314E - 15 L_f^2 + 62.38776 t_f \\
&\quad - 6.122449 t_f^2 - 380.8 t_b + 1120 t_b^2) \times 21
\end{aligned} \tag{4}$$

In the present heat pipe optimization, the 5-dimentional design parameter space is split in 2D and 3D subspaces, i.e., the 2D space of t_b, T_{OP} and the 3D space of L_f, L_c and t_f, respectively. The design parameters determined by the mechanical designers are as follow:

Length of fin (L_f)
Cutting length of adhesive attached area (L_c)
Thickness of fin (t_f)
Adhesive thickness (t_b)
Operation temperature (T_{OP})

These are illustrated in Fig. 2 and allowable range of design parameters are given in Table 2. (T_{OP}) and (t_b) are uncontrollable by mechanical designers but effect on the thermal performance of the heat pipes. Their ranges are given in Table 3.

Table 2
Design parameter bounds

Parameter	L_f	L_c	t_f
Lower Bound	10.0 mm	1.5 mm	1.0 mm
Upper Bound	25.4 mm	2.5 mm	1.7 mm

Table 3
Uncertain design parameter

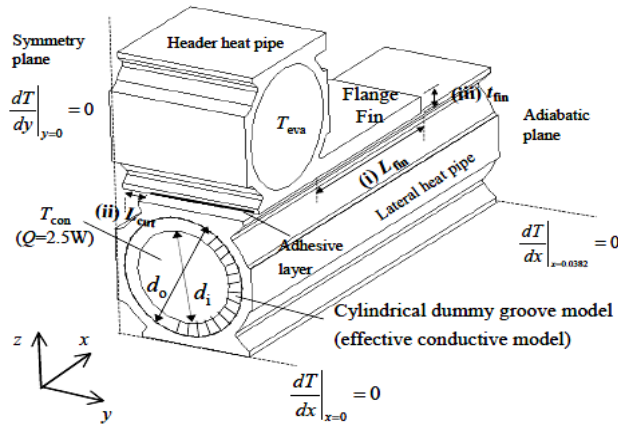| Parameter	t_b	T_{OP}
Lower Bound	0.12 mm	-20.0 0C
Upper Bound	0.22 mm	60.0 0C

Fig. 2
Schematic of heat pipe [34].

Considering the result, without changing shape parameters L_f, L_c and t_f the design of heat pipes adopting thinner adhesive at lower operating temperature is expected to minimize the mass and to maximize conductance. However, it is very difficult to change the operating temperature because of the design limitation of an orbit and thermal control system. Moreover, controls over the thickness of adhesive involve great uncertainty in manufacturing. To improve heat pipe performance, therefore it is required to focus on the correlation of the shape parameters and the objective functions. For this purpose, the equation of G and M are regenerated to consider uncertainty of t_b and T_{OP} [34].

$$G = f(L_f, L_c, t_f)$$
$$= 0.2312513 + 0.0261369L_c - 0.008299937L_c^2 + 0.002905449L_f - 0.00007364545L_f^2 \tag{5}$$
$$+ 0.05925684t_f - 0.01028177t_f^2$$

$$M = f(L_f, L_c, t_f) = (1283.375 - 75.5L_c + 11L_c^2 + 1.4L_f - 380.8t_b + 1120t_b^2) \times 21 \tag{6}$$

4.2. Pressure vessel problem

A cylindrical vessel is capped at both ends by hemispherical heads as shown in Fig. 3. The objective functions are to minimize the total cost (f_1) and to maximize the storage capacity (f_2) of the vessel. The parameters that should be optimized are T_s (thickness of the shell, x_1), T_h (thickness of the head, x_2), R (inner radius, x_3) and L (length of cylindrical section of the vessel, not including the head, x_4). All parameters are continuous variable. By denoting the variable vector $x = (x_1, x_2, x_3, x_4) = (T_s, T_h, R, L)$ we write the two-objective optimization problem [36]:
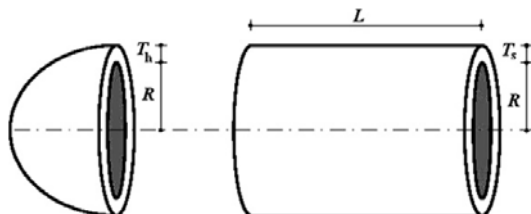

Fig. 3
Schematic of pressure vessel [35].

$$Minimize = f_1(x) = 0.6224T_sLR + 1.7781T_hR^2 + 3.1661T_s^2L + 19.84T_s^2R$$

$$Minimize = f_2(x) = -(\pi R^2 L + 1.333\pi R^3)$$

$$\begin{aligned} subject\ to \quad & g_1(x) = 0.0193R - T_s \leq 0 & g_2(x) = 0.00954R - T_h \leq 0 \\ & g_3(x) = 0.0625 - T_s \leq 0 & g_4(x) = T_s - 5 \leq 0 \\ & g_5(x) = 0.0625 - T_h \leq 0 & g_6(x) = T_h - 5 \leq 0 \\ & g_7(x) = 10 - R \leq 0 & g_8(x) = R - 200 \leq 0 \\ & g_9(x) = 10 - L \leq 0 & g_{10}(x) = L - 240 \leq 0 \end{aligned} \tag{7}$$

4.3 Multi-objective optimization of 120-bar truss design

The third structure considered is a 120-bar space truss whose members are collected in 7 groups as shown in Fig. 4. The problem is to find the cross-sectional area of each member such that the total structural weight and the vertical displacement are minimized concurrently. The loading of the truss and the upper bounds for the displacements of the restricted joints are given in Table 4. The modulus of elasticity and the minimum member cross-sectional area are taken as 2.06×10^4 (kN/cm^2) and 2 cm^2, respectively. In this case, objective functions are expressed as following [37]:

$$\min \begin{cases} w(x) = \sum_{i=1}^{120} \rho A_i l_i \\ \delta(x) = \sqrt{\delta_{ix}^2 + \delta_{iy}^2 + \delta_{iz}^2} \end{cases} \tag{8}$$

The design variables are bounded as

$$A_i^{(l)} \leq A_i \leq A_i^{(u)}, \qquad i = 1, 2, ..., 7 \tag{9}$$

where the limiting values are taken as

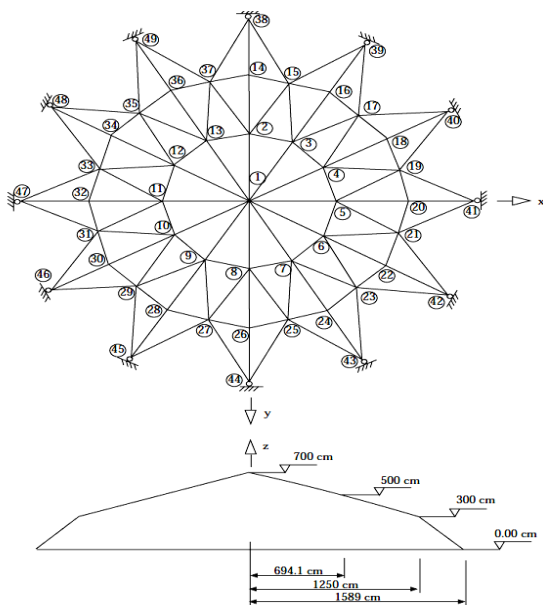$$A_i^{(l)} = 2.0\,\text{cm}^2, \qquad A_i^{(u)} = 10.0\,\text{cm}^2 \tag{10}$$

Fig. 4
120-bar space truss [37].

Table 4
The loading and displacement bounds for 120-bar space truss system [37].

Joint Number	Loading (kN)			Displacement Limitation (cm)
	X	Y	Z	Z
1	0	0	60	1
2	0	0	30	1
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
14	0	0	30	1
15	0	0	10	1
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
37	0	0	10	1

Table 5
Parameters of the Bees Algorithm for mechanical problems

Problems	n	m	n_m	n_{gh}	i_{max}
Heat pipe-3D	100	20	10	0.1	200
Heat pipe-5D	100	20	10	0.1	200
Pressure vessel	120	30	15	0.1	200
120 bar truss	100	20	15	0.1	100

Table 6
Results for heat pipe design obtained using the Bees Algorithm and other optimization methods

Objective function	Methods	Min (Total mass) (kg)	Max (Thermal conductance)(W/K)
Min(Total mass) Max(Thermal conductance)	BA	26.700	0.3818
Min(Total mass) Max(Thermal conductance)	BFGS [35]	26.854	0.3750
Min(Total mass) Max(Thermal conductance)	HS [35]	26.704	0.3810
Min(Total mass) Max(Thermal conductance)	GA [34]	26.714	0.3812

5 RESULTS AND DISCUSSION

The empirically chosen parameters for the Bees Algorithm are given in Table 5.

5.1 Multi objective optimization heat pipe with 5 dimensional parameters

It is assumed that the design optimization has two functions (G,M), two uncontrollable parameters (t_b , T_{op}), and three shape parameters of the satellite heat pipes (L_f , L_c , t_f). The empirically chosen parameters for the Bees Algorithm (BA) are given in Table 5. Figs. 5 and 6 show the non-dominated solutions obtained from using the Bees Algorithm. Other researchers have investigated this problem using the Genetic Algorithm (GA) [34], Harmony Search (HS) [35] and another different predecessor which is one of best mathematical techniques, called the Broyden—Fletcher—Goldfarb—Shanno (BFGS) [35] which searches the solution area based on mathematical gradients, for finding multiple Pareto optimal solutions. In comparison with other results, Bees algorithm shows most optimal results. This is illustrated in Table 6.
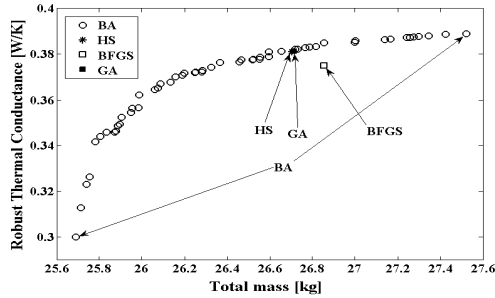
Fig. 5
Non-dominated solutions obtained for heat pipe design problem with 5D design parameter using the BA.
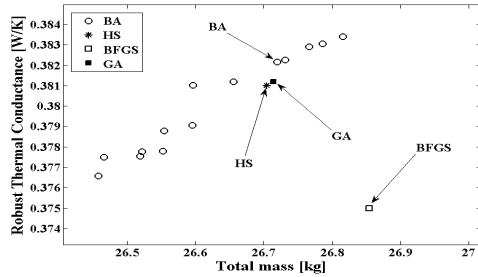

Fig. 6
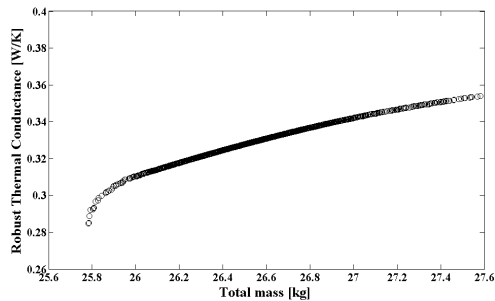Non-dominated solutions obtained for heat pipe design problem using the BA and other optimization methods.

Fig. 7
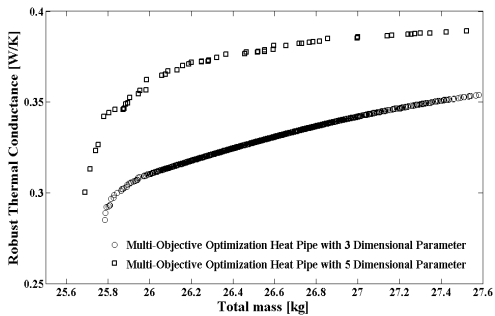Non-dominated solutions obtained for heat pipe with 3D design parameter using the Bees Algorithm.

Fig. 8
Non-dominated solutions obtained for heat pipe design problem with 3D design parameter and 5D design parameter using the Bees Algorithm.

5.2 Multi-objective optimization heat pipe with 3 dimensional parameter

It is assumed the design optimization has two functions (G,M), and three shape parameters of heat pipes of the satellite (L_f , L_c , t_f) .The empirically chosen parameters for the Bees Algorithm are given in Table 5. Fig. 7 shows the non-dominated solutions obtained from using the Bees Algorithm. Fig. 8 shows comparison between heat pipe optimization with 3 dimensional parameters and heat pipe optimization with 5 dimensional parameters. It can be seen that two uncontrollable parameters have slight effect on mass minimization but its effect on conductance maximization is further.

5.3 Multi objective optimization pressure vessel

The empirically chosen parameters for the Bees Algorithm are given in Table 5. Figs 9 to 11 show the non-dominated solutions obtained using the Bees Algorithm. Deb has investigated this problem [36] using the NASGA-II for finding multiple Pareto optimal solution. In comparison with the number of solution found by non-dominated sorting genetic algorithms, it can be seen that the Bees Algorithm can find more non dominated solutions.

According to Table 7, the solutions are spread in the following range: [(37.545 $, 7330.383 in^3) , (3.215e+005 $, 6.367e+007 in^3)] respectively, which indicates the superiority of the Bees Algorithm compared to other optimization methods.

5.4 Multi-objective optimization of 120-bar truss design

The empirically chosen parameters for the Bees Algorithm are given in Table 5. Fig. 12 shows the non-dominated solutions obtained using the Bees Algorithm. Kelesoglu has investigated this problem [37] using the Genetic Algorithm (GA) for finding optimal solution. In comparison with the number of solution found by non-dominated sorting genetic algorithms, it can be seen that the Bees Algorithm can find more non dominated solutions.
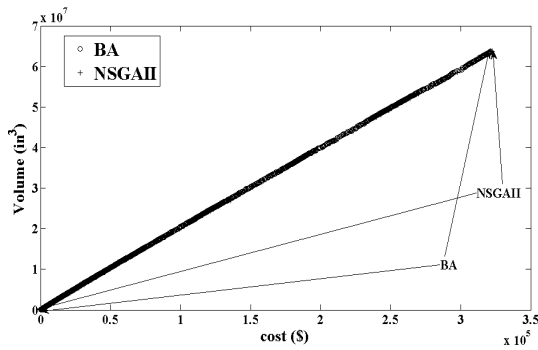
Fig. 9
Non-dominated solutions obtained for the pressure vessel design problem using the BA and other optimization methods.
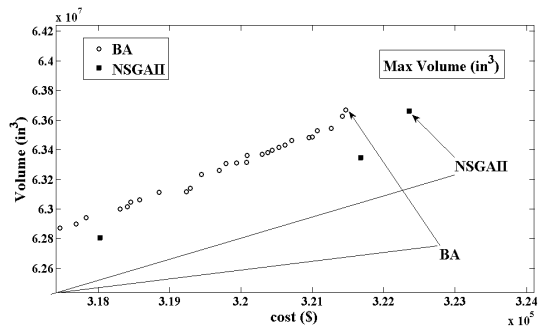
Fig. 10
Non-dominated solutions obtained for max volume pressure vessel design problem using the BA and other optimization methods.
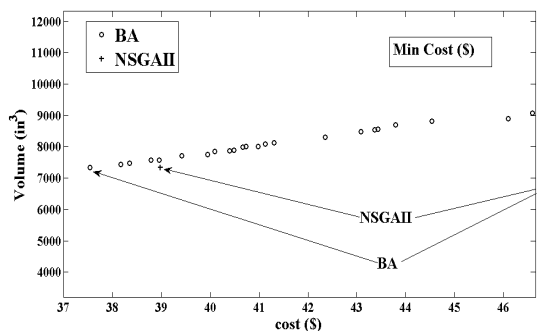
Fig. 11
Non-dominated solutions obtained for min cost pressure vessel design problem using the BA and other optimization methods.

Table 7
Results for the pressure vessel design problem obtained using the Bees Algorithm and other optimization methods

Method	X_1	X_2	X_3	X_4	Min Cost ($)	Max Volume (in³)
BA	0.193	0.0954	10	10	37.545	7330.383
BA	3.860	1.9080	200	240	3.215 e+005	6.367 e+007
NSGAII [36]	0.200	0.0973	10	10	38.982	7329.341
NSGAII [36]	3.871	1.9100	200	240	3.223 e+005	6.366 e+007

Table 8
Results for 120-bar truss design obtained using the Bees Algorithm and other optimization methods

Variables	Methods		
	Fuzzy-Linear by GA [37]	Fuzzy-Non-Linear by GA [37]	BA
A1 (cm²)	36.17	34.44	21.52
A2 (cm²)	50.00	26.68	26.37
A3 (cm²)	27.81	40.11	26.52
A4 (cm²)	34.99	32.70	15.23
A5(cm²)	28.40	39.73	49.17
A6 (cm²)	40.15	33.44	17.43
A7 (cm²)	34.87	32.73	9.62
Min W (cm³)	2,175,715	2,134,888	1,604,695
Min δ (cm)	0.52	0.33	0.3137
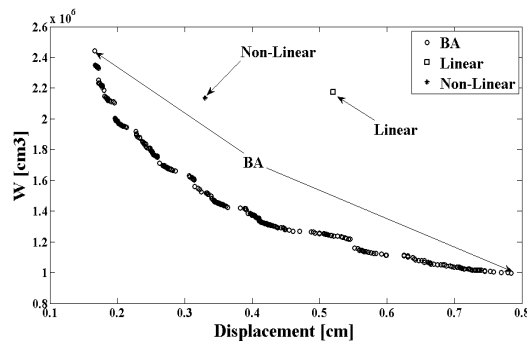
Fig. 12
Non-dominated solutions obtained for the 120-bar truss design problem using the BA other optimization methods.

According to Fig. 12, the solutions are spread in the following range: [(0.1666 cm, 2,441,573 cm³) , (0.7834 cm , 995,963cm³)] respectively, which indicates the superiority of the Bees Algorithm compared to other optimization method. Table 7 shows comparison between BA and another algorithm.

6   CONCLUSIONS

We have presented a novel approach to solve engineering design problems based on a simple evolution strategy. The proposed approach has described a modified version of the Bees Algorithm and its application to the search for multiple Pareto optimal solutions in mechanical engineering problems. We compared our results with respect to those obtained by two algorithms that had been previously found to perform well in the same problems. The Bees Algorithm found many trade-off solutions compared to the number of solutions obtained using non-dominated sorting genetic algorithms. Also, the computational cost of our approach (measured in terms of the number of evaluations of the objective function) is very low. Furthermore, the proposed approach is very simple and easy to implement. Hence, the Bees Algorithm is a computationally fast multi-objective optimizer tool for complex engineering multi-objective optimization problems.

REFERENCES

[1]   Deb K., 2001, *Multi-Objective Optimization using Evolutionary Algorithms*, First edition, Wiley, Chichester, UK.

[2]   Schaffer J.D., 1985, Multiple objective optimization with vector evaluated genetic algorithms and their applications, in: *Proceedings of the first international conference on Genetic Algorithms*, Pittsburgh, PA, USA, 93-100.

[3]   Fonseca C.M., Fleming P.J., 1993, Genetic algorithms for multi-objective optimization: Formulation, discussion, and generalization, in: *Proceedings of the 5th international conference on Genetic Algorithms*, University of Illinois at Urbana-Champaign, July 17-21, 416-423.

[4]   Horn J., Nafploitis N., Goldberg D.E., 1994, A niched Pareto genetic algorithm for multi-objective optimization, in: *Proceedings of the First IEEE Conference on Evolutionary Computation,* IEEE World Congress on Computational Intelligence, June 27-29, Orlando, Florida, USA, 82-87.

[5]   Srinivas N., Deb K., 1995, Multi-objective function optimization using non-dominated sorting genetic algorithms, *Evolutionary Computation Journal* **2**: 221-248.

[6]   Knowles J., Corne D., 1999, The Pareto archived evolution strategy: A new baseline algorithm for multi-objective optimization, in: *Proceedings of the Congress on Evolutionary Computation*, New Jasery, IEEE Service Center, 98-105.

[7]   Deb K., Pratap A., Agrawal S., Meyarivan T., 2000, A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II, in: *Proceedings of the 6th International Conference on Parallel Problem Solving from Nature*, Paris, France, 846-858.

[8]   Zitzler E., Theiele L., 1999, Multi-objective evolutionary algorithm: a comparartive case study and the strength Pareto approach, *Evolutionary Computation Journal* **3**(4): 257-271.

[9]   Zitzler E., Deb K., Thiele L., 2000, Comparison of multi-objective evolutionary algorithms: Empirical results, *Evolutionary Computation Journal* **8**(2): 173-195.

[10]   Farina M., Deb K., Amato P., 2004, Dynamic multi-objective optimization problems: test cases, approximations, and applications, *IEEE Transactions On Evolutionary Computation* **8**(5): 425-442.

[11]   Nebro A.J., Durillo J.J., Luna F., Dorronsoro B., Alba E., 2009, A cellular genetic algorithm for multiojective optimization, *International Journal of Intelligent Systems* **14**(7):726-746

[12]   Mainenti I., DeSouza L., Sousa F., Kuga H., Galski R., 2007, Satellite attitude control using the generalized extremal optimization with a multi-objective approach, in: *Proceedings of the 19th International Congress of Mechanical Engineering*, DF, Brazil.

[13]   Copiello D., Fabbri G., 2008, Multi-objective heat transfer optimization in corrugated wall channels by hybrid genetic algorithms, in: *Proceedings of the 5th European Congress on Computational Methods in Applied Sciences and Engineeering (ECCOMAS)*, Venice, Italy, 81-88..

[14]   Cuco A., Sousa F., Vlassov V., Neto v., 2008, Multi-Objetive Design Optimization of a New Space Radiator, in: *Proceedings of the International Conference on Engineering Optimization*, Rio de Janeiro, Brazil, 201-209.

[15]   Oliveira L., Saramago S., 2010, Multi-objective optimization techniques applied to engineering problems, *Journal of the Brazilian Society of Mechanical Sciences and Engineering* **32**(1): 94-105.

[16]   Khalkhali A., Sadafi M., Rezapour J., Safikhani H., 2010, Pareto based multi-objective optimization of solar thermal energy storage using genetic algorithms, *Transactions of the Canadian Society for Mechanical Engineering* **34**(4): 463-474.

[17]   Szparaga L., Ratajski J., Zarychta A., 2011, Multi objective optimization of wear resistant TiAlN and TiN coatings deposite by PVD techniques, *Achievements in Materials and Manufacturing Engineering Journal* **48**(1): 33-39.

[18]   Shrivastava R., Singh S., Dubey G.C., 2012, Multi-objective optimization of time cost quality quantity using multi colony ant algorithm, *International Journal of Contemporary Mathematical Sciences* **7**(16): 773-784.

[19]   Pham D.T., Ghanbarzadeh A., Koc E., Otri S., Rahim S., Zaidi M., 2005, Technical Note: Bees Algorithm, Technical Report No MEC 0501, Manufacturing Engineering Centre, Cardiff University, Cardiff.

[20]   Pham D. T., Ghanbarzadeh A., Koc E., Otri S., Rahim S., Zaidi M., 2006, The Bees Algorithm. A novel tool for complex optimization problems, in: *Proceedings of the Second International Conference on Intelligent Production Machines and Systems*, 454–459.

[21]   Pham D.T., Ghanbarzadeh A., Koc E., Otri S., 2006, Application of the bees algorithm to the training of radial basis function networks for control chart pattern recognition, in: *Proceedings of 5th CIRP International Seminar on Intelligent Computation in Manufacturing Engineering*, Ischia, Italy, 711-716.

[22]   Frisch K., 1967, *The Dance Language and Orientation Of Bees*, First edition, Harvard University Press, Massachusetts, USA.

[23]   Michelsen A., Andersen B., Storm J., Kirchner W., Lindauer M., 1992, How honeybees perceive communication dances, studied by means of a mechanical model, *Behavioral Ecology and Sociobiology Journal* **30**(3-4): 143-150.

[24]   Dyer F., 2002, When it pays to waggle, *Nature Journal* **419**(6910): 885-886.

[25]   Camazine S., Sneyd J., 1990, A model of collective nectar source by honey bees: self-organization through simple rules, *Journal Theoretical Biology Journal* **149**: 547-571.

[26]   Lambrinos D., Möller R., Labhart T., Pfeifer R., Wehner R., 2000, A mobile robot employing insect strategies for navigation, *Robotics and Autonomous Systems Journal* **30**(1-2): 39-64.

[27]   Müller M., Wehner R., 1988, Path integration in desert ants, Cataglyphis Fortis, *Experimental Biology Journal* **85**(14): 5287-5290.

[28]   Collett P., Graham T.S., Durier V., 2003, Route learning by insects, *Current Opinion in Neurobiology Journal* **13**(6): 718-725.

[29]   Collett T., Collett M., 2004, How do insects represent familiar terrain, *Journal of Physiology* **98**:259-264.

[30]   Barth F. G., 1982, *Insects and Flowers: The Biology of a Partnership*, First edition, Princeton University Press, Princeton, NJ, USA.

[31]   Pham D.T., Otri S., Ghanbarzadeh A., Koc E., 2006, Application of the bees algorithm to the training of learning vector quantization networks for control chart pattern recognition, in: *Proceedings of Information and Communication Technologies Conference*, Syria, 1624-1629.

[32]   Pham D.T., Koç E., Ghanbarzadeh A. Otri S., 2006, Optimization of the weights of multi-layered perceptions using the Bees Algorithm, in: *Proceedings of the 5th International Symposium on Intelligent Manufacturing Systems*, Turkey, 38-46.

[33]   Pham D.T., Castellani M., Ghanbarzadeh A., 2007, Preliminary design using the bees algorithm, in: *Proceedings of the International Conference on Laser Metrology, CMM and Machine Tool Performance, LAMDAMAP*, Cardiff: euspan Ltd, UK, 420-429.

[34]   Jeong M.J., Kobayashi T., Yoshimura Sh., 2005, extraction of design characteristics of multi-objective optimization-Its application to design of artificial satellite heat pipe, *Lecture Notes in Computer Science Journal* **3410**: 561-575.

[35]   Geem Z.W., Hwangbo H., 2006, Application of harmony search to multi-objective optimization for satellite heat pipe design, *US-Korea Conference on Science, Technology, and Entrepreneurship*, Teaneck, NJ, 157-165.

[36]   Deb K., Srinivasan A., 2006, Monotonicity analysis, evolutionary multi-objective optimization, and discovery of design principles, in: *Proceedings of the Bio-Inspired Computing: Theory and Applications*, Wuhan, China, 89-96.

[37]   Kelesoglu O., Ulker M., 2005, Fuzzy optimization of geometrical nonlinear space truss design, *Engineering Turkish Journal* **29**: 321- 329.