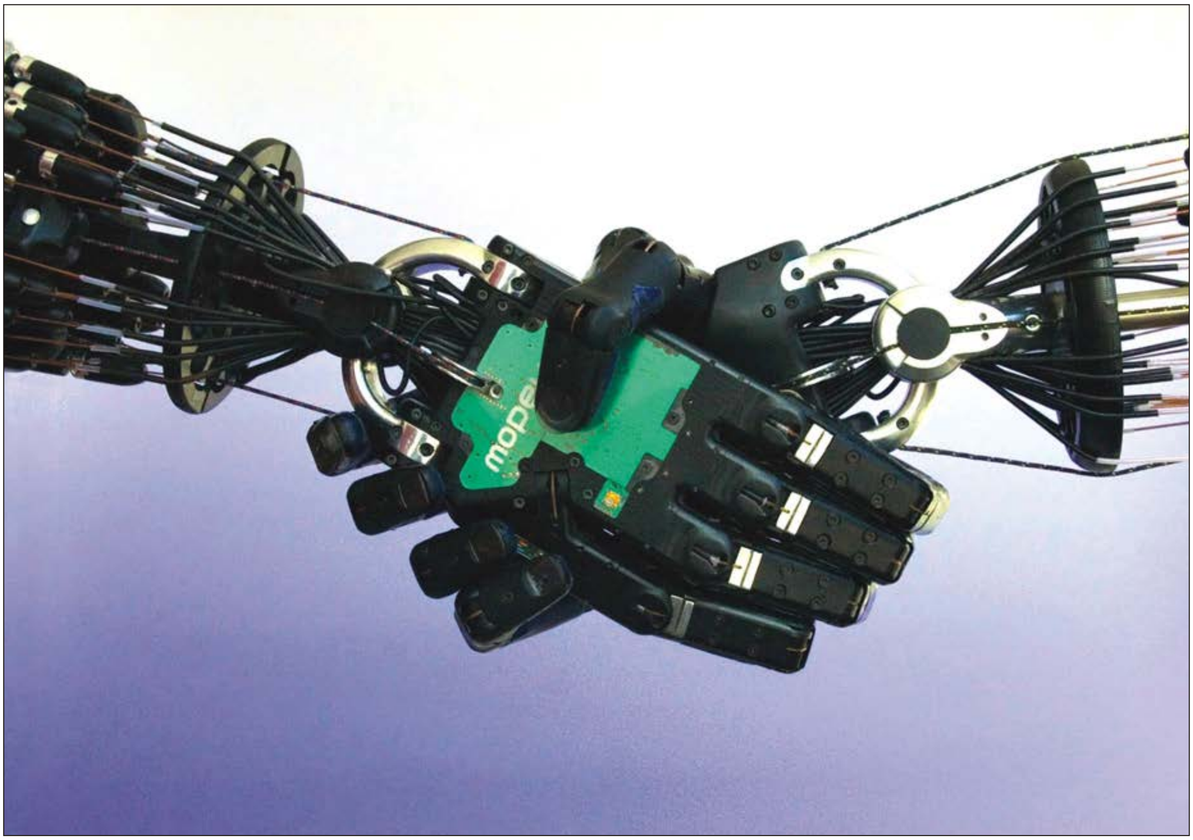

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Optimization of MEMS Accelerometer Parameter with Combination of Artificial Bee Colony (ABC) Algorithm and Particle Swarm Optimization (PSO)

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ABSTRACT

Optimizing the design of devices that belongs to Micro Electro Mechanical System (MEMS) technology is turning out to be a main area of research currently. Several algorithms are available to produce an optimized design of MEMS. The MEMS accelerometer may be scheduled using parameters that include Beam length, Beam width, Beam depth, Beam mass, proof mass and so on. This study is chiefly involved in the optimization of design parameters like die area and a novel parameter called as Force. Artificial Bee Colony (ABC) optimization and Particle Swarm Optimization (PSO) are the two algorithms that are used to optimize these parameters. The ABC performs the primary optimization and PSO does the optimization of the fitness solution resulting from the execution of ABC algorithm. Employing the two optimization algorithms in a combined way yields improved optimized parameters, which are engaged in the efficient design of MEMS accelerometer.

Key words: MEMS, artificial bee colony, particle swarm optimization, accelerometer, genetic algorithm

INTRODUCTION

While the microelectromechanical (MEM) switches are being designed, the two vital things that are to be considered are the reliability and longevity. A trade-off between response bandwidth and fatigue life arises when a switch is compelled to work in an environment that is closed to its operating limits. This is because of the impact force of the cantilever getting in touch with its corresponding contact point (Information from http://bura.brunel.ac.uk/bitstream/2438/5584/2/Fulltext.pdf). Microelectromechanical systems (MEMS) are systems that include a set of microseconds and actuators, which are capable of sensing its surroundings and responding to the variations in the surroundings using a microcircuit control. Besides the conventional microelectronics packaging, they also possess integrating antenna structures for giving control signals to micro electro mechanical structures to achieve desired sensing and actuating functions. Micro power supply, micro-relay and micro-signal processing units may constitute the other system requirements. Micro-components enable the system to function with more speed, reliability, low expense and allows incorporating more number of complex functions as well (Information from http://www.wiley-vch.de/vch/journals/2081/books/2081_rel_title_varadan.pdf).

MEMS technologies are the budding technologies that find varied applications in bioengineering, automotive engineering, telecommunications, environmental monitoring and space exploration (Zhang *et al.*, 2005). Micro mechanisms, also termed as Micro Electro Mechanical Systems (MEMS) (Rubio *et al.*, 2006) are infinitesimal mechanical systems, whose feature sizes vary from micrometers to millimeters. They use the same methods of building integrated circuits in their manufacturing processes and their size allows them to be incorporated into a broader classification of systems like micro sensors. Accelerometers for air-bag and micro pumps may be viewed as examples of MEMS.

The design optimization of Micro Electro Mechanical System (MEMS) technology devices is changing into an exciting and essential research problem. The MEMS accelerometers are widely used in air-bag deployment systems of modern automobiles. Plenty of studies are being carried out for designing accelerometers.

Benmessaoud and Nasreddine (2013) have designed a micro machined accelerometer that relies on an area variation capacitive sensing. This can be used in many applications to enhance the efficacy and sensitivity of a capacitive accelerometer. Here, the capacitive accelerometer depends on an area of variation capacitive sensing, regarded to be a Micro Electro Mechanical System (MEMS) that was existing and realizable. The MATLAB software was used for simulation. Optimization of some accelerometer parameters and a single direction, which possesses movable fingers and fixed fingers as two springs that ensures the system damping are carried out with MATLAB.

Sabouhi and Baghelani (2012) have suggested a capacitive micro machined MEMS acceleration sensor that was immune to normal-to-plane shock. When compared to the springs of the structure, the suspended cantilevers were more beneficial because it reduces the spring length for normal motion of the proof mass after covering certain distance. Thus, the springs were made even stronger to avoid normal movements and dangerous failures. Optimization of the consumed area, which was a significant parameter for determining the price associated with the on-chip device fabrication, was performed using genetic algorithm here.

Allen *et al.* (2008) has expressed the input waveform OUU for a highly nonlinear, electro statically actuated RF MEMS switch. The MCS, which helps in envisaging the maximum impact velocity experienced by an ensemble of switches subjected to an input waveform, utilizes a reduced-order model for the switch that incorporates an uncertainty model based on experimental data and expert's viewpoint. The contact velocity for the ensemble of switches can be decreased to a larger extent with the optimization of the shape of the waveform. On comparing the unshaped waveform, the overall contact velocity was minimized to 50% with the optimization in shape. The optimization steps aid in forecasting the amount of contact velocity reduction produced with the change in the design of the switch.

PROPOSED METHODOLOGY FOR DESIGNING THE MEMS ACCELEROMETER

MEMS denote the technology that includes both electrical and mechanical components of feature size ranging in microns. The enhanced techniques in designing have allowed the design of MEMS accelerometer to be a fascinating area of study. The functioning of the MEMS accelerometer is same as that of the spring mass system apart from the utilization of beam flexure system in accelerometers. In this study, the design of accelerometer is achieved by optimizing the design parameter like die area and a new parameter called as force (N). These design parameters are optimized by employing both the Artificial Bee Colony Optimization (ABC) algorithm and the Particle Swarm Optimization (PSO) algorithm. The ABC algorithm is used to handle the primary optimization and the resulting fitness solution from ABC algorithm is optimized again with PSO algorithm. The combination of these two optimization algorithms yield improved optimized parameters for designing the MEMS accelerometer efficiently.

Parameter selection for designing the accelerometer through optimization process: In general, the cost and the die area of the accelerometer are directly proportional. Thus, the cost associated with the design of accelerometer increases slowly with the increase in die area of the accelerometer. This behavior has lead to the need for minimizing the die area along the design parameter force (N) and thereby, optimization of these parameters comes into effect. The optimization algorithm is centered on objective function or fitness function. The proposed method uses a combination of Artificial Bee Colony Optimization algorithm and Particle Swarm Optimization algorithm to optimize the design parameters of MEMS accelerometer.

Beam length, Beam width, Beam depth, Beam mass, proof mass and so on are some of the parameters involved in the design of MEMS accelerometer. But the die area and force forms the main parameters of design. The flow diagram of the proposed methodology is shown in Fig. 1. Different design parameters of the accelerometer are chosen and for each of these parameters, the optimization process is performed by employing the ABC algorithm. The final solution will be nothing but the optimized parameters obtained from executing ABC algorithm.

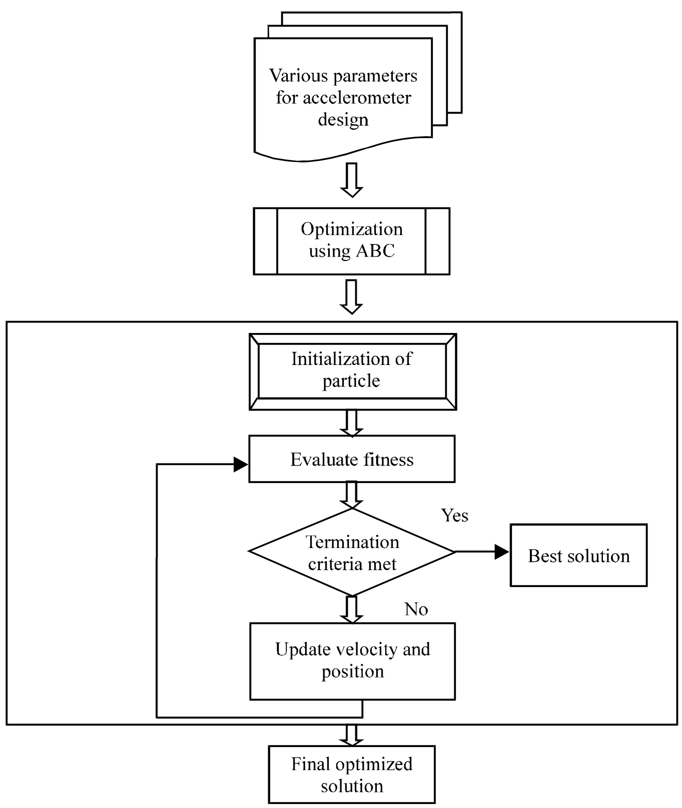

Fig. 1: Block diagram for our proposed design optimization of MEMS accelerometer

Design parameters of MEMS accelerometer: The proposed method of the MEMS accelerometer design is accomplished through the selection of various design parameters like Beam length, Beam width, Beam depth, Beam mass, proof mass etc. The process of MEMS designing will start with the approaching of the system and selection of concept domain (e.g., accelerometer design) by the MEMS designer because only then the design specifications can be formulated. The designer then inputs the design specifications for these various parameters. The parameters and its specifications can be represented as follows:

Beam length = $L\{L_1, L_2, L_3, L_j\}$
Beam width = $W\{W_1, W_2, W_3, W_j\}$
Beam depth = $G\{G_1, G_2, G_3, G_j\}$
Beam mass = $M\{a_M, b_M\}$
Proof mass = $f\{a_f, b_f\}$

The optimal designs of MEMS can be obtained with the optimization of parameters, L_1, L_2, L_3 and b_f. Figure 2 represents various parameters of MEMS accelerometer. The rest of the parameters are assigned with the constant values as follows using Eq. 1 and 2:

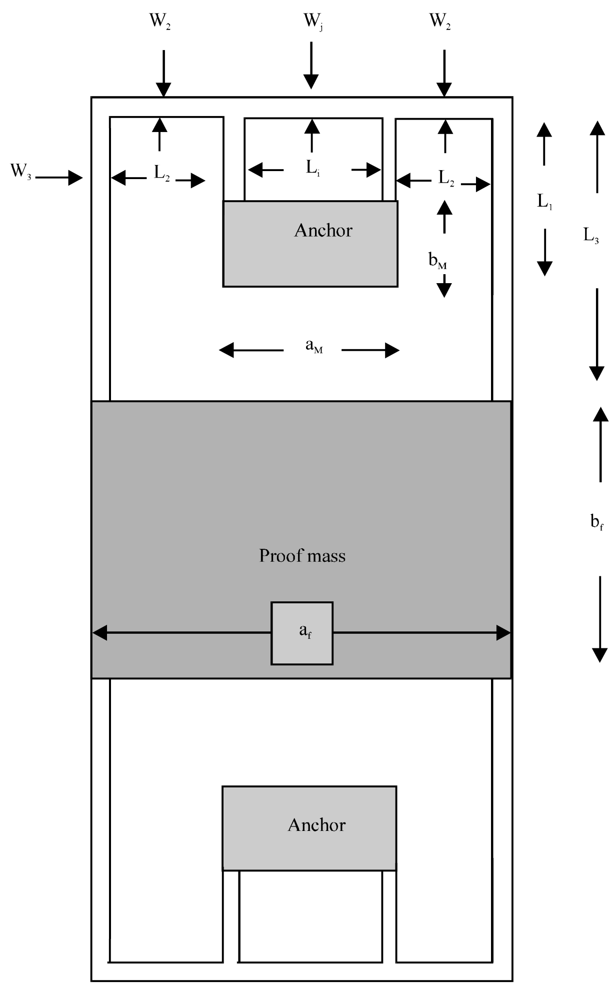

Fig. 2: MEMS accelerometer with design parameters

$$W_1 = W_2 = W_3 = W_j = P \tag{1}$$

$$G_1 = G_2 = G_3 = G_j = Q \tag{2}$$

Where:
P = Q = 1.8 μm

The MEMS accelerometer diagram indicates all the parameters that can be utilized to yield an optimal design of MEMS. A folded beam structure is available for use and the parameter values are described as in Eq. 3-6:

$$L_j = R \tag{3}$$

$$b_M = T \tag{4}$$

$$a_M = L_j+2W_1 \tag{5}$$

$$a_f = W_j+2L_2+2W_1+2W_3 \tag{6}$$

where, value of R is 150 μm and the value of T is 100 μm.

The other parameters like L_1, L_2, L_3 and b_f lie in the following ranges:

$$L_1 = B \tag{7}$$

$$L_2 = D \tag{8}$$

$$L_3 = E \tag{9}$$

$$b_f = F \tag{10}$$

where, 20 μm≤B≤500 μm, 20 μm≤D≤100 μm, 100 μm≤E≤500 μm, 100 μm≤F≤500 μm. Optimization of the parameters is done with both the ABC algorithm and PSO algorithm.

Artificial bee colony algorithm for optimization of design parameters: Artificial Bee Colony (ABC) is a new optimization algorithm, which is motivated by the natural behavior of honey bees in finding their best food resources. The colony of artificial bees in the ABC algorithm has three clusters of bees, namely, employed bees, onlookers and scouts. The initialization procedure consists of random generation of a set of food source positions as well as the assignment of values to the control parameters of the algorithm. The quantity of nectar obtained from the food source denotes the quality of solution embodied in that food source. Hence, the nectar amounts of the food sources available at the initial positions are determined. A bee that remains in the dance area to gather the information regarding food sources is termed as an onlooker. A bee that visits the food source is called as an employed bee. A scout bee is the one that performs random search (Krushnasamy and Juliet, 2014).

The bees in the ABC model aim at discovering the best solution. The location of a food source indicates a possible solution to the optimization problem and the amount of nectar specifies the quality (fitness) of the solution related to the food source. On delivering the information regarding the food source to the onlookers, the employed bee would visit the food source area that is visited by her previously in the past cycle using the food source information residing in her memory and then, continues to select a new food source that lies in the neighborhood of the previously visited food source through visual information and evaluates its nectar amount. The same process is repeated by the employed bee in the second stage after giving food source information resulting from first stage to onlookers, except that the new food source will now lie in the neighborhood of the food source visited at the first stage. During third stage, an onlooker uses the nectar information given by the employed bees in the dance area to choose the food source area. If the source gets discarded, the working bee becomes a survey bee and begins to hunt a novel starting place in the region seal to the colony.

The amount of working bees or the observer bees is corresponding to the number of results in the inhabitants. In the first cycle, ABC generates an arbitrarily spread early inhabitants of results. Sometimes ago compute gets finished, the inhabitants of the result will be subjected to frequent cycles of the hunt procedure handled by the working bees, the observer bees and the survey bees. A working bee is the one that modifies the solution in its memory with the help of area information and then, checks the quantity of nectar in the new solution. The employed bee would remember the new position, if the nectar quantity of the present food source is larger than in the previous food source and discards information regarding the previous food source. Else if the nectar quantity in the present food source is smaller than in the previous food source, the information of the previous food source is retained in the memory of the bee. On completion of the search process, the employed bees share the information related to the position of the food source and the nectar amount of the food source to the onlookers. The onlookers would then make an estimation of the information obtained from the employed bees and chooses a food source that has a probability identical to its quantity. If the solution achieved is satisfactory, memorize the solution and end up the process. Or else, continue the process until the new solution attains the suitable criteria. The working procedure of ABC algorithm relies on the fitness value of the solution and the flow diagram given in Fig. 3 depicts the entire processes involved in ABC algorithm.

Figure 3 reveals the complete process of ABC algorithm. Initialization of population forms the first stage of ABC algorithm, which is then followed by the fitness calculation. The fitness calculation process is done for both the employed bees and the onlooker bees. The algorithm gets ended only if the conditional criteria are satisfied. Through the usage of ABC algorithm, the intensity parameters are adjusted and an enhanced output image is obtained. The proposed ABC algorithm is explained as follows.

In this study, first initialize the position of the employed bees by discovering the new solution. Here, contrast values are used as initial food source. Therefore, R_i is the initial food source (solution), where, (i = 1, 2, 3,..., n) is a D-dimensional vector. After finding the initial food source, calculate the fitness function for a new food source (new solution). The fitness function is calculated to yield the maximum fitness function. Therefore, the maximum fitness function can be obtained by Eq. 11.

The objective function or Fitness function for the MEMS design is represented by Eq. 11:

$$F(t) = DA+N \tag{11}$$

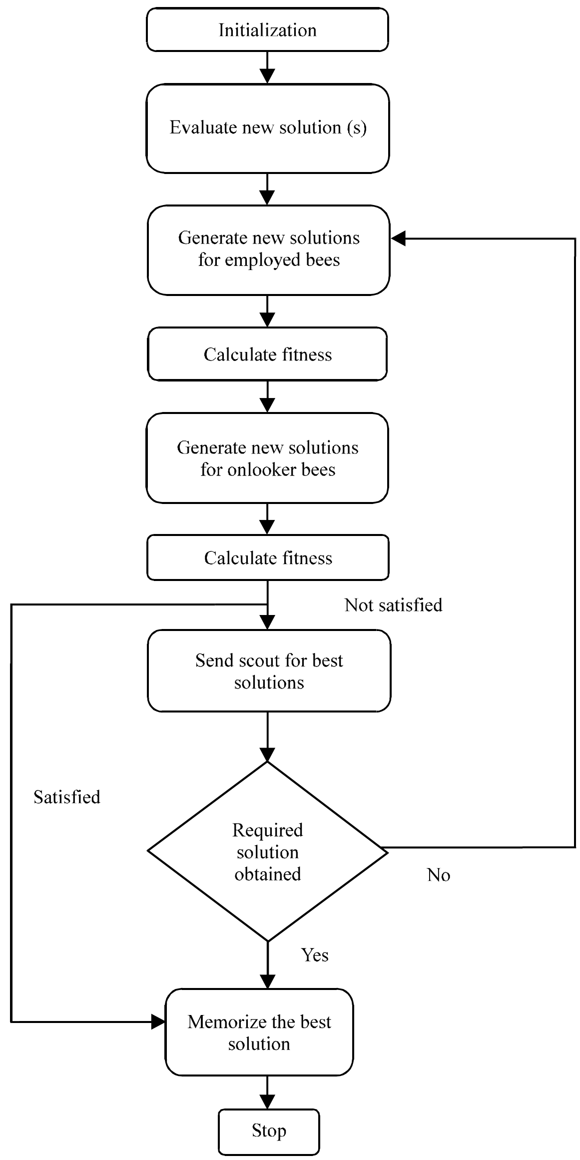

Fig. 3: Optimization process in ABC

where, DA is the die area and N is the force. The Die Area (DA) and the force (N) can be evaluated by Eq. 12 and 13, respectively:

$$DA = (p_m+2H_2+(H_3-H_1)+2G_2)q_m \tag{12}$$

$$N = ma \tag{13}$$

where, m is the beam mass and a is the acceleration.

Die area value can range between 90,000-160,000 μm^2 and it can be relaxed up to 240,000 μm^2. The food source with maximum fitness value is taken to be the best food source and by keeping this fitness function as initial stage, searching process that employs the employed bees, onlooker bees and scout is initiated. The initial stage of fitness function is calculated.

Employed bees: The employed bee search the neighborhood of its current food source (solution) to find out a new food source (new solution) using Eq. 14:

$$K_f = R_f + \phi_f (R_i - R_l) \tag{14}$$

where, l and f are the randomly chosen symbols. Here, l is the very next value of f or l is the next chance of f to find the new food source (solution). The ϕ_f is a random number between (-1, 1). After creating the new solution (food source), the quantity of it will be determined and a greedy choice process will be presented. If the quality of a new food source (solution) is better than the present position, the employed bee neglects that position and moves towards new solution (food source), or else the fitness of a new solution (food source) is equal or improved than that of R_i. Therefore, the new solution takes the place of R_i in the population and becomes a new solution.

Onlooker bees: The onlooker bees estimate the knowledge gathered from all of the employed bees to make a selection of the food source. The probability S_i for choosing the solution (food source) is evaluated by Eq. 15:

$$S_f = \frac{F(t)}{\sum_{f=1}^{n} F(t)} \tag{15}$$

where, F(t) is the fitness value of the solution (food source) R_i. After choosing a food source (solution), the onlooker bees generate a new food source using Eq. 14. Once the new food source is selected, a greedy selection will be applied in a similar way as that applied to employed bees. A food source is believed to be abandoned if a solution obtained a food source that cannot be improved by these trials and the employed bee associated with that solution (food source) will now turn out to be a scout. The scout creates a new food source in a random manner and hence in our proposed method, improved better food source (solution) is obtained prior to scout process. In this way, various optimal design parameters for the accelerometer are obtained for the purpose of improving the design process of the MEMS accelerometer. The obtained fitness values for the design parameters are optimized again using the PSO algorithm to get better optimized solution.

Final optimization of parameters using PSO: Consider swarm of particle is flying the parameter space and searching for optimum. Each particle is characterized by a position vector $X_j(t)$, velocity vector $V_j(t)$. During the process, each particle will have its individual knowledge pbest and social knowledge gbest. The velocity, position update can be done by Eq. 16 and 17:

$$V_j(t+1) = \alpha\, V_j + d1*rand*(pbest(t) - X_j(t)) + d2*rand*(gbest(t) - X_j(t)) \tag{16}$$

$$X_j(t+1) = X_j(t) + V_j(t+1) \tag{17}$$

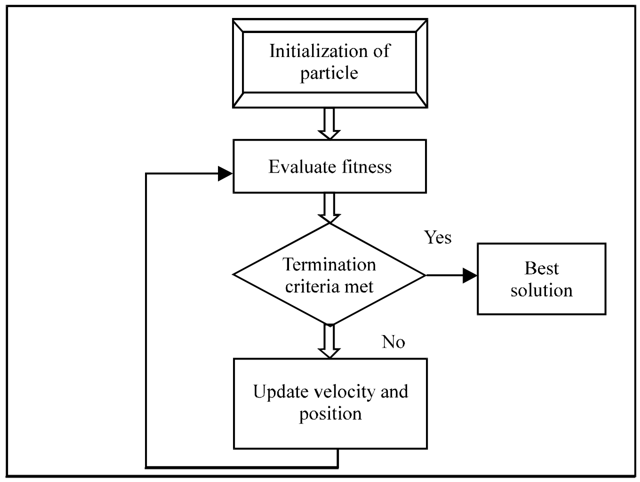

Fig. 4: General flow diagram for particle swarm optimization

where, α is the inertia weight and d1, d2 are acceleration constants, rand is a random number between 0 and 1. The above process is repeated for each and every particle considered in the computation and the best optimal solution is obtained. The general steps involved in the Particle Swarm Optimization are shown in Fig. 4.

The basic operation of particle swarm optimization is given by:

Step 1: Initializing the swarm from the solution space
Step 2: Evaluating fitness of individual particles
Step 3: Modifing pbest, gbest and velocity
Step 4: Moving each particle to a new position
Step 5: Go to step 2 and repeat until convergence or stopping condition is satisfied

RESULTS AND DISCUSSION

MATLAB is used for implementing the proposed technique. The application of ABC and PSO algorithms has produced optimal values for L1, L2, L3 and b_f. A total of thousand iterations were used to accomplish the optimal design. The optimization process has minimized the die area along with force parameter, represented by the objective or fitness function F, through the satisfaction of design criteria. The best performing design was saved for each successive starting population for converging to the optimum values. The results had been displayed for the each and every iteration and the optimum values obtained by the optimization algorithms have also been described in the tables.

Table 1-5 depicts the optimal values obtained for 100th, 200th, 300th, 400th and 500th iteration, respectively. Five optimal values for each of the iterations are found out and tabulated. The corresponding graphical representations are shown in Fig. 5-9 with the minimized objective function.

Table 6 shows the comparison of the fitness value that is obtained using our proposed method and the existing method that utilizes ABC alone for optimization. It is apparent that the fitness value has improved in the proposed method.

Table 1: Five optimal values obtained in the 100th iteration after optimization

Iteration rank	L1	L2	L3	b_f	F
1	2.283e-05	5.174e-05	4.805e-04	1.019e-04	111089.42430
2	2.500e-05	5.777e-05	4.727e-04	1.017e-04	111751.39832
3	2.500e-05	5.777e-05	4.727e-04	1.017e-04	111751.39832
4	2.500e-05	5.777e-05	4.727e-04	1.017e-04	111751.39832
5	3.786e-05	5.071e-05	4.866e-04	1.003e-04	112075.01720

Table 2: Five optimal values obtained in the 200th iteration after optimization

Iteration rank	L1	L2	L3	b_f	F
1	3.015e-05	4.464e-05	4.925e-04	1.020e-04	111922.60829
2	3.015e-05	4.464e-05	4.925e-04	1.020e-04	111922.60829
3	3.863e-05	4.527e-05	4.914e-04	1.015e-04	112584.34912
4	3.863e-05	4.527e-05	4.914e-04	1.015e-04	112584.34912
5	3.863e-05	4.527e-05	4.914e-04	1.015e-04	112584.34912

Table 3: Five optimal values obtained in the 300th iteration after optimization

Iteration rank	L1	L2	L3	b_f	F
1	2.904e-05	4.905e-05	4.901e-04	1.001e-04	110549.75521
2	2.422e-05	4.210e-05	4.948e-04	1.022e-04	110855.15497
3	2.412e-05	4.954e-05	4.922e-04	1.014e-04	111783.11165
4	2.414e-05	3.907e-05	4.975e-04	1.045e-04	112838.48265
5	3.009e-05	5.555e-05	4.876e-04	1.006e-04	112843.14634

Table 4: Five optimal values obtained in the 400th iteration after optimization

Iteration rank	L1	L2	L3	b_f	F
1	2.151e-05	4.177e-05	4.939e-04	1.037e-04	111898.38770
2	2.151e-05	4.177e-05	4.939e-04	1.037e-04	111898.38770
3	2.044e-05	7.413e-05	4.514e-04	1.019e-04	112987.58026
4	2.044e-05	7.413e-05	4.514e-04	1.019e-04	112987.58026
5	2.315e-05	3.750e-05	4.885e-04	1.066e-04	113109.55355

Table 5: Five optimal values obtained in the 500th iteration after optimization

Iteration rank	L1	L2	L3	b_f	F
1	2.754e-05	4.534e-05	4.919e-04	1.014e-04	111053.33436
2	2.754e-05	4.534e-05	4.919e-04	1.014e-04	111053.33436
3	2.754e-05	4.534e-05	4.919e-04	1.014e-04	111053.33436
4	2.169e-05	5.984e-05	4.793e-04	1.004e-04	111468.25048
5	3.417e-05	5.371e-05	4.862e-04	1.001e-04	112047.32099

Table 6: Comparison of fitness value using the existing and proposed method

Methods	Fitness function
Existing method	112369.1602
Proposed method	115826.6054

The graphical representation for the comparison of two methods is given in Fig. 10. As revealed by the graph, the fitness value of the proposed method is improved using the incorporation of PSO along with the ABC algorithm.

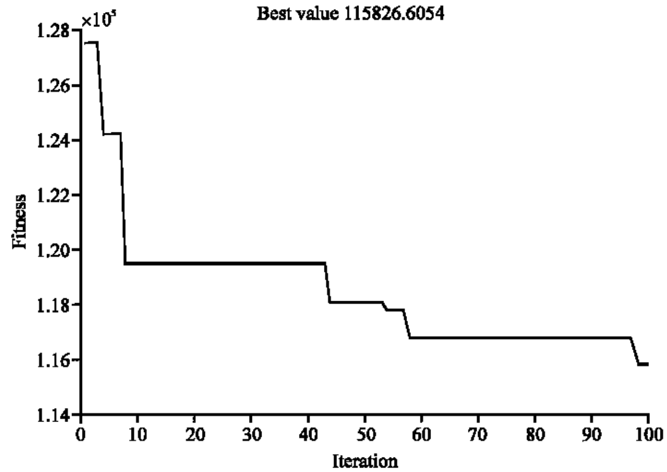

Fig. 5: Minimization of objective function in the 100th iteration

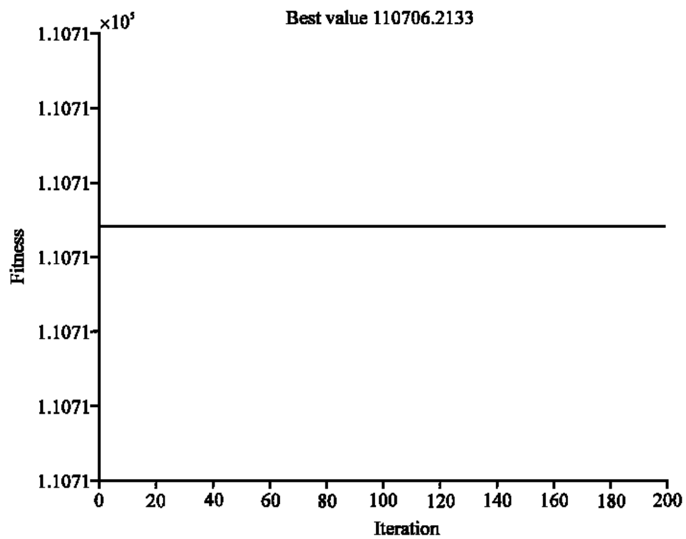

Fig. 6: Minimization of objective function in the 200th iteration

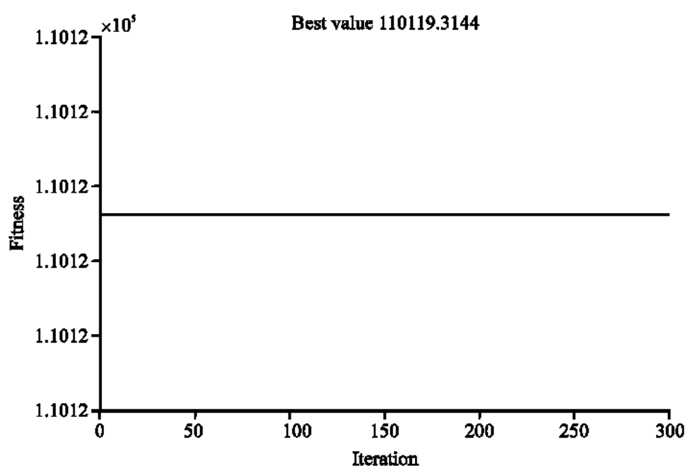

Fig. 7: Minimization of objective function in the 300th iteration

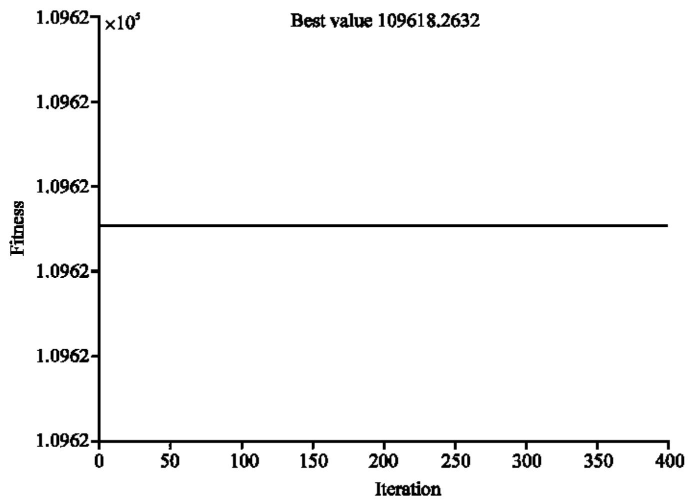

Fig. 8: Minimization of objective function in the 400th iteration

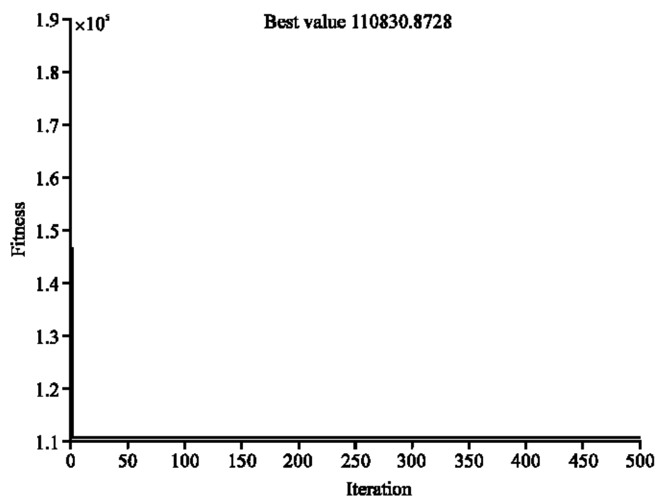

Fig. 9: Minimization of objective function in the 500th iteration

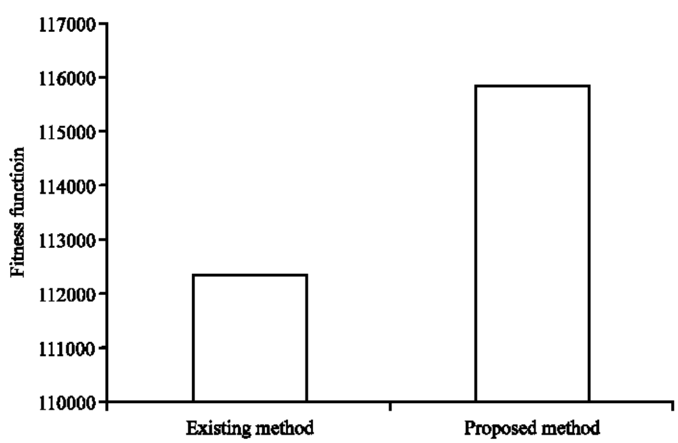

Fig. 10: Fitness value by using the existing and proposed method

CONCLUSION

This study deals with a system that optimizes the design parameters of MEMS accelerometer. Highly efficient optimization is obtained with the proposed method, which incorporates both Ant Bee Colony Optimization algorithm and Particle Swarm Optimization algorithm to produce optimal design parameters. It is evident from the results that the proposed method outperforms other optimization techniques like Genetic Algorithm in terms of fitness values and hence, provides improved optimization. Some of the shortcomings of utilizing GA can be eliminated with the proposed method and serves good for designing MEMS accelerometer architecture. The fitness is based on two design parameters, namely, die area and force that lie within a particular range.

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