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WEAR PERFORMANCE OPTIMIZATION OF SILICON NITRIDE USING GENETIC AND SIMULATED ANNEALING ALGORITHM

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Abstract

Replacing damaged joint with the suitable alternative material is a prime requirement in a patient who has arthritis. Generation of wear particles in the artificial joint during action or movement is a serious issue and leads to aseptic loosening of joint. Research in the field of bio-tribology is trying to evaluate materials with minimum wear volume loss so as to extend joint life. Silicon nitride (Si_3N_4) is non-oxide ceramic suggested as a new alternative for hip/knee joint replacement. Hexagonal Boron Nitride (hBN) is recommended as a solid additive lubricant to improve the wear performance of Si_3N_4. In this paper, an attempt has been made to evaluate the optimum combination of load and % volume of hBN in Si_3N_4 to minimize wear volume loss (WVL). The experiments were conducted according to Design of Experiments (DoE) – Taguchi method and a mathematical model is developed. Further, this model is processed with Genetic Algorithm (GA) and Simulated Annealing (SA) to find out the optimum percentage of hBN in Si_3N_4 to minimize wear volume loss against Alumina (Al_2O_3) counterface. Taguchi method presents 15 N load and 8% volume of hBN to minimize WVL of Si_3N_4. While GA and SA optimization offer 11.08 N load, 12.115% volume of hBN and 11.0789 N load, 12.128% volume of hBN respectively to minimize WVL in Si_3N_4.

Keywords: Silicon nitride, Hexagonal boron nitride, Alumina, Design of Experiments, Taguchi method, Genetic algorithm, Simulated annealing.

Nomenclatures

k	Scaling factor
X_i	Initial guess
X_{i+1}	Next guess
Δf	Difference in function value

Abbreviations

AISI	American Iron and Steel Institute
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ASTM	American Society for Testing and Materials
CoCr	Cobalt Chromium
DF	Degrees of Freedom
DoE	Design of Experiments
EDS	Energy Dispersive X-ray Spectroscopy
GA	Genetic Algorithm
hBN	Hexagonal Boron Nitride
PoD	Pin on Disc Tribometer
SA	Simulated Annealing
SEM	Scanning Electron Microscopy
S/N	Signal – to – Noise Ratio, dB
THR	Total Hip Replacement
THA	Total Hip Arthroplasty
UHMWPE	Ultra High Molecular Weight Polyethylene
WVL	Wear Volume loss, mm^3/m

1. Introduction

Biomaterials are applicable in the human body and hence need to be inert and mechanically stable enough to bear the load. These materials are used to develop parts and replace a body part or function of the body part in safe and reliable manner. It is estimated that every year approximately 1 million hip replacements and 250,000 knee replacements are carried out [1]. It is estimated that this number will double till 2025 as a result of ageing populations worldwide and growing demand for a higher quality of life [2, 3]. Biomaterials are expected to work satisfactorily in body environment, where the pH value of body fluid varies from 1 to 9. Friction, wear, and lubrication of artificial joints are an important consideration to optimize the performance of these human-made joints to improve its function and life. The first metal-on-metal (CoCr-CoCr) total hip replacement (THR) was unsatisfactory in terms of high friction forces and high rate of wear.

Titanium alloys and stainless steel are also frequently used in THR, but the main risk with metal alloy implants is the release of metal ions due to wear and creating a negative effect like aseptic loosening caused by adverse biological reactions due to wear products. Therefore metal-on-UHMWPE bearing became advantages or preferable to the metal-on-metal system. A lot of literature from hip simulator studies proved improvement in wear resistance of cross-linked UHMWPE [4, 5]. Since from last four decades, bio-inert alumina ceramic (aluminium oxide) have presented an attractive alternative for THR bearing surface in terms of improved wear resistance and extended joint life. In late 18th

century, the controlled implantation of bio-ceramic started in dental with the use of Plaster of Paris or gypsum for bone filling. Ceramic bearings were first introduced as an alternative to polyethylene (PE) bearings in THR about a decade after Sir John Charnley introduced the first durable THR with a metal-PE articulation. In 1965, the first Al_2O_3 material dedicated for hip joint was patented, and pioneering application of bio-ceramic was replacing traditional metallic femoral heads of hip prostheses. The Al_2O_3 and ZrO_2 like oxide have a lengthy history in the field of hip and knee joint replacement providing a tougher bearing surface with low wear rate.

Initially, in the engineering field, Si_3N_4 was proposed as a substitute for conventional materials in extreme operating conditions, due to its excellent chemical, and stability under a broad range of temperature, low density, and low friction [6]. Biocompatibility and material properties of Si_3N_4 have made it attractive alternative in the biomedical field also [7]. Bearings made of ceramics have low wear properties that make them suitable for total hip arthroplasty (THA) and total knee arthroplasty (TKA). When compared to cobalt chrome (CoCr)-on-polyethylene (PE) articulations, ceramics offer drastic reductions in bearing wear rates. Alumina and zirconia ceramics are familiar with the orthopaedic field in total joints for several decades [8]. As the search for the ideal total joint bearing material continues, currently Si_3N_4 is applicable in the biomedical field for various applications like bearing for spine disc surgery and prosthetic hip and knee joints also been developed with Si_3N_4 [9, 10]. Bal and Rahaman [11] covered scientific rationale for the use of Si_3N_4 in the orthopaedic application. Biomaterials with minimum WVL is need of orthopaedic field and research in this area trying to evaluate biomaterials with minimum WVL and consequently extending joint life. Si_3N_4 shows excellent wear resistance and Si_3N_4 bearing for arthroplasty applications are being investigated by Amedica Corporation (Salt Lake City, UT). Mode of failure in THR is related to the field of tribology i.e. wear of cup and head. Accumulation of wear at implant leads to aseptic loosening and failure of THR. Therefore it is desirable to reduce the generation of wear particle in the implant. Olofsson et al. [12] conducted sliding contact wear test using pin-on-disc tribometer with Si_3N_4 and CoCr disc against Si_3N_4 and Al_2O_3 ball in the presence of Phosphate Buffered Saline (PBS) and bovine serum. Si_3N_4 sliding against Si_3N_4 showed the formation of tribofilm on Si_3N_4 controlling friction and wear in both PBS and bovine serum comparable to other pairs. Low wear rate and biocompatibility of Si_3N_4 suggested it as a good candidate for hip joint replacement.

Hexagonal boron nitride (hBN) is well known solid situ lubricating material with biocompatibility [13 - 15]. Incorporation of the solid lubricant in Si_3N_4 can be considered to improve the tribological performance of Si_3N_4. Formation of an oxide of hydrated layers (H_3BO_3 and $BN(H_2O)_x$) has a significant effect on the tribological performance of Si_3N_4- BN composites, reducing the wear coefficient. Carrapichano et al. [16] conducted sliding wear test on pin-on-disc tribometer for Si_3N_4-BN composite in a self-mated pair, with 10, 18 and 25% vol. of BN in Si_3N_4. They concluded that addition of Boron up to 10% improved tribological properties of Si_3N_4 and further addition affect to mechanical properties of Si_3N_4. Chen et al. [17] investigated sliding wear behaviour of the Si_3N_4-hBN composite with 0, 5, 10, 20 and 30 volume % of hBN in Si_3N_4 against Si_3N_4 using pin-on-disc (PoD) tribometer. They reported that friction coefficient reduces up to 0.19 for 20% Volume of hBN in Si_3N_4.

To evaluate the performance of any process or system, it needs experimentation. In the field of experimentation Design of Experiment (DoE) - Taguchi method is efficient to plan and analyze results of the experiment [18]. Ficici et al. [19] investigated the wear behaviour of boronised AISI 1040 steel effectively using DoE-Taguchi design method. Results proved a very good agreement between experimental and predicted results. Patnaik et al. [20] implemented DoE-Taguchi design technique to evaluate the tribo-performance of polyester hybrid composites. The result presented that glass-polyester composite without any filler suffers greater erosion loss than the hybrid composite with alumina filling. Lastly, the results were optimized using a genetic algorithm. Asilturk and Suleyman [21] optimized turning parameters in CNC turning using Taguchi method and response surface analysis, presented efficiency and effectiveness of Taguchi method in the field of optimization. Sharma et al. [22] utilized response surface methodology and genetic algorithm to optimize the machining parameters of wire electric discharge machining for minimizing overcut. N. Rajasekar et al. [23] formulated an optimization problem for parameter extraction of the fuel cell and this problem further solved with GA. The results presented that GA is capable of extracting parameters accurately with less computational steps. Soleimani et al. [24] proposed ANN model for prediction of permeation flux and fouling resistance in the treatment of oily wastewater and further applied GA for optimizing operating conditions in the separation of oil from industrial oily wastewater, which presented optimal operating parameters with minimal computation. Simulated annealing is a general heuristic and one of the most well advanced iterative techniques. It is widely used for solving optimization problems. G. Rambabu et al. [25] implemented RSM for developing a mathematical model for corrosion resistance of friction stir welding as a function in terms of welding parameters and this mathematical model optimized using simulated annealing algorithm to maximize the corrosion resistance.

Various researchers proposed different volume proportion of % volume of hBN in Si_3N_4 to minimize wear volume loss in a self-mated pair without consideration of the effect of load. In this work, we implemented DoE-Taguchi method to plan and analyze results to find an optimum combination of load and volume proportion of % Volume of hBN in Si_3N_4 to minimize wear loss against alumina. Taguchi method gives optimum combination of control factors at selected level only for required performance characteristic. Using experimental results mathematical model proposed for wear volume loss. In next step, this model is processed with Genetic Algorithm and Simulated Annealing to find the optimum combination of load and % volume of hBN for minimization of wear volume loss. The objective of this study was to investigate the interaction effect of load and % volume of hBN addition on volumetric wear loss of silicon nitride.

2. Experimentation

2.1. DoE-Taguchi method

Taguchi method is a form of DoE developed by Genichi Taguchi used for designing experiments and to investigate how different parameters affect the mean and variance of a process performance characteristic. The experimental design known as orthogonal arrays proposed by Taguchi involves the use of the parameters affecting the process and the levels at which they should be varied. It allows for the collection of the necessary data to determine which factors most affect product quality with a minimum amount of experimentation, thus saving time and resources. Knowing the number of parameters and the number of levels, the proper orthogonal array can be selected. The parameters /factors and their corresponding levels were chosen for the experiment as shown in Table 1.

Table 1. Designed experimental factors and levels.

Factors	Level 1	Level 2	Level 3	Level 4	Level 5
Load (N)	5	10	15	20	25
% Vol. of hBN	4	8	12	16	0

Load and % volume of hBN are two factors selected at five levels as shown in Table 1, therefore L_{25} orthogonal array selected for conduction of experiment. The orthogonal array provides a set of well-planned experiment with the minimum number.

2.2. Preparation of samples

Si_3N_4-hBN composites prepared with 4, 8, 12 and 16% volume of hBN mixed in Si_3N_4. The mixing of Si_3N_4 and hBN is performed with a ball mill. The samples were prepared at uniaxial hot-pressing at 30 MPa, 1600^0 C and 60 min dwell time with an additive of polyvinyl alcohol into a pin of the dimensions of 10 mm diameter and 15 mm long. Figures 1 and 2 show the prepared samples and alumina disc used for wear testing.

Fig. 1. Sintered Si_3N_4-hBN samples.

Fig. 2. Alumina wear disc.

Tables 2 and 3 show the density of sintered samples and properties of alumina disc respectively.

Table 2. Density of sintered samples*.

Sample	1 (4% Vol. hBN)	2(8% Vol. hBN)	3(12% Vol. hBN)	4(16% Vol. hBN)	5(0% Vol. hBN)
Density (kg/m^3)×10^3	1.96	1.96	1.93	1.84	2.04

*Testing at Central Glass and Ceramic Research Institute, Kolkata, India

Table 3. Typical properties of alumina disc.

Designation	Purity	Density (kg/m^3)	Max Service Temp. (^{0}C)	Avg. Surface roughness (μm)
Alumina (Al_2O_3)	99.8%	3.90×10^3	1800	1.791

2.3. Experimental setup

The wear tests were conducted on Ducom TRLE-PMH400 pin on disc tribometer having a maximum normal load capacity of 200 N. Tests were performed according to ASTM F732 standards [26]. During test composite used as pin specimen and alumina disc as counterface rotating at a speed of 200 rpm. The pin is stationary and sliding against alumina with applied load. Tests were conducted in a dry environment without lubricant and at atmospheric conditions.

3. Results and Discussion

3.1. Signal–to-Noise (S/N) ratio analysis

Experiments were performed on Pin-on-Disc tribometer with two input parameters and wear volume loss of a sample as output. Wear volume loss calculated for sliding distance covered by pin during 25 min duration and speed of disc 200 rpm at corresponding wear track diameter. Table 4 shows the average value of wear volume loss for all 25 experiments (each experiment conducted two times). The experimental results are further transformed into Signal-to-Noise (S/N) ratio. Taguchi's S/N ratios, which are logarithmic, the function of desired output and serves as an objective function for optimization. The standard S/N ratios used are: Smaller is Better (SB), Nominal is Better (NB), and Higher is Better (HB). The significance of controllable factor is investigated using S/N ratio approach. A smaller of wear volume loss is expected to extend joint life. Therefore in this study S/N ratio with Smaller the Better methodology was used for wear volume loss and calculated as follow:

$$(S/N)_{SB} = -10\log_{10}\left((y_1^2 + y_2^2 + y_3^2 + \cdots)/n\right) \quad (1)$$

where y_1, y_2 and so on = Experimental results/observation and n = Number of experiments (i ……… n).

Irrespective of the category of the performance characteristic, the higher value of S/N ratio corresponds to a better performance [27]. The maximization of S/N ratio signifies maximization of the desired effect against noise factor. In this study minimization of wear volume loss is a desirable characteristic. Observation of response table of S/N ratio gives an optimal combination of input parameters for required output characteristic. From Table 4, expt. 12 offers an optimal combination of 15 N load and 8% volume of hBN for minimum wear volume loss of 0.0111mm^3/m with corresponding S/N ratio of 39.09355 dB.

Table 4. Results for wear volume loss (WVL) and S/N ratio.

Expt. No.	Load (N)	% Volume of hBN	Avg. WVL (mm^3/m)	S/N ratio (dB)
1	5	4	0.3022	10.39411
2	5	8	0.199	14.02294
3	5	12	0.2444	12.23795
4	5	16	0.0338	29.43195
5	5	0	0.5055	5.92626
6	10	4	0.2007	13.94992
7	10	8	0.0156	36.12638
8	10	12	0.1438	16.84664
9	10	16	0.0205	33.78614
10	10	0	1.0867	-0.722194
11	15	4	0.314	10.06141
12	15	8	0.0111	39.09355
13	15	12	0.1029	19.75169
14	15	16	0.0953	20.41632
15	15	0	1.3473	-2.58929
16	20	4	0.2063	13.71002
17	20	8	0.5002	6.01662
18	20	12	2.2799	-7.15832
19	20	16	0.2035	13.82872
20	20	0	0.3169	9.98156
21	25	4	0.5142	5.77736
22	25	8	2.11	-6.48565
23	25	12	0.4144	7.65161
24	25	16	0.1551	16.18777
25	25	0	4.1178	-12.29331

3.2. Response plot

Interaction plot represents interaction effect of control factor on performance characteristic, showing the minimum value of WVL at the interaction of 15 N load and 8% volume of hBN in Fig. 3 and the maximum value of S/N ratio at same combination in Fig. 4 prepared with Minitab 17.

From interaction plot, for WVL and S/N ratio it is clear that WVL is affected by the interaction of load and % volume of hBN. Interaction plot in Fig. 3 also presents an optimal combination of 15 N load and 8% volume of hBN for minimum wear volume loss of 0.0111mm^3/m.

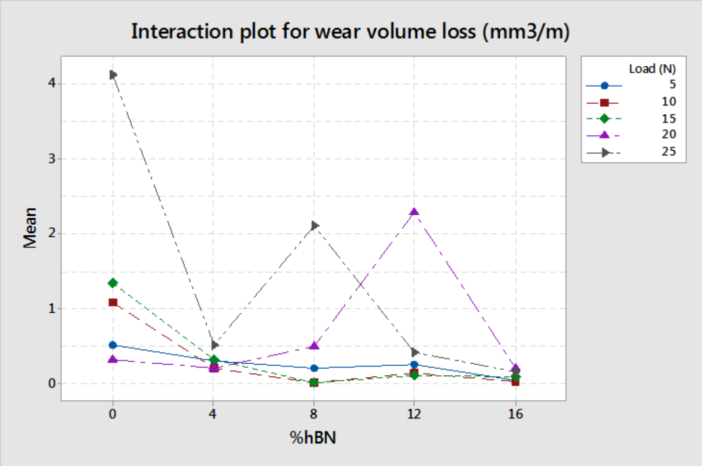

Fig. 3. Interaction plot for wear volume loss (mm^3/m).

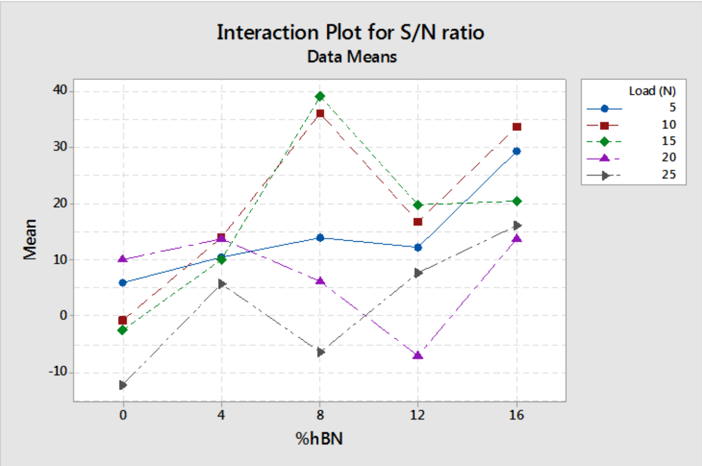

Fig. 4. Interaction plot of S/N ratio for wear volume loss.

Confirmation experiment

The optimal combination of control factors has been presented in S/N ratio, response plot, and ANOVA analysis. The final step in any design of experiment approach is to predict and verify improvements in characteristic performance values through the use of the optimal combination level of control factors [20]. Table 5 shows experimental conditions and results for confirmation experiment; tests were conducted as per earlier conditions.

Table 5. Experimental conditions and results.

Expt. No.	Load (N)	% Vol. of hBN	Expt. Result-WVL (mm^3/m)
1	50	8	4.01204
2	100	8	5.0456
3	150	8	5.0498

Confirmation experiments were conducted for 8% volume of hBN sample for 50 N, 100 N, and 150 N load. The average value of WVL found to be 4.70248mm^3/m. It shows there is a slight increase in wear loss with an increase in load, indicating wear loss as a function of both parameters.

3.3. Material characterization

The microstructures of sintered specimens were observed after wear testing at 200rpm and a normal load of 15 N using SEM along with energy-dispersive X-ray spectroscopy (EDS). In Fig. 5, a consequence of adhesive wear can be observed as there was a pulling material from the contact area of the composite material in the form of irregular cavities.

3.4. Mathematical modeling

A second order polynomial equation used to fit the experimental data using Minitab 17 statistical software. From the experimental data obtained from Taguchi orthogonal array experimentation the final equations obtained in terms of control factors for wear volume loss as follow:

$$WVL\ (\mathrm{mm^3/m}) = 0.656 - 0.049\times load\ (N) - 0.062 * \%\ Volume\ of\ hBN + 0.00484\times load(N)\times load(N) + 0.00479\times \%\ Volume\ of\ hBN \times \%\ Volume\ of\ hBN - 0.00501\times load\ (N)\times \%\ Volume\ of\ hBN \qquad (2)$$

Analysis of Variance (ANOVA) is a statistical technique that subdivides the total variation in a set of data parts associated with the specific source of variation for the purpose of testing hypotheses on the parameters of the model. Table 6 shows ANOVA for model performed at 90% of confidence level.

From ANOVA Table, the model P-Value is 0.042 which is less than 0.05, presenting model is significant. Variance Inflation Factor (VIF) =1, stating that the predictors are correlated, and there is no multicollinearity.

Table 6. Analysis of Variance (ANOVA).

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	5	9.333	43.24%	9.333	1.866	2.89	0.042
Linear	2	6.892	31.93%	6.892	3.446	5.34	0.014
Load (N)	1	3.972	18.40%	3.972	3.972	6.16	0.023
% Vol. of hBN	1	2.920	13.53%	2.920	2.920	4.53	0.047
Square	2	1.438	6.66%	1.438	0.719	1.12	0.348
Load (N) ×Load (N)	1	1.026	4.76%	1.026	1.026	1.59	0.222
% Vol. of hBN × % Vol. of hBN	1	0.41	1.91%	0.411	0.411	0.64	0.434
2-Way Interaction	1	1.0024	4.64%	1.0024	1.0024	1.55	0.228
Load (N) ×% Vol. of hBN	1	1.002	4.64%	1.002	1.002	1.55	0.228
Error	19	12.25	56.76%	12.25	0.644		
Total	24	21.58	100%				
S= 0.803083, **R-sq**=43.24%, **VIF** (all factors)=1							

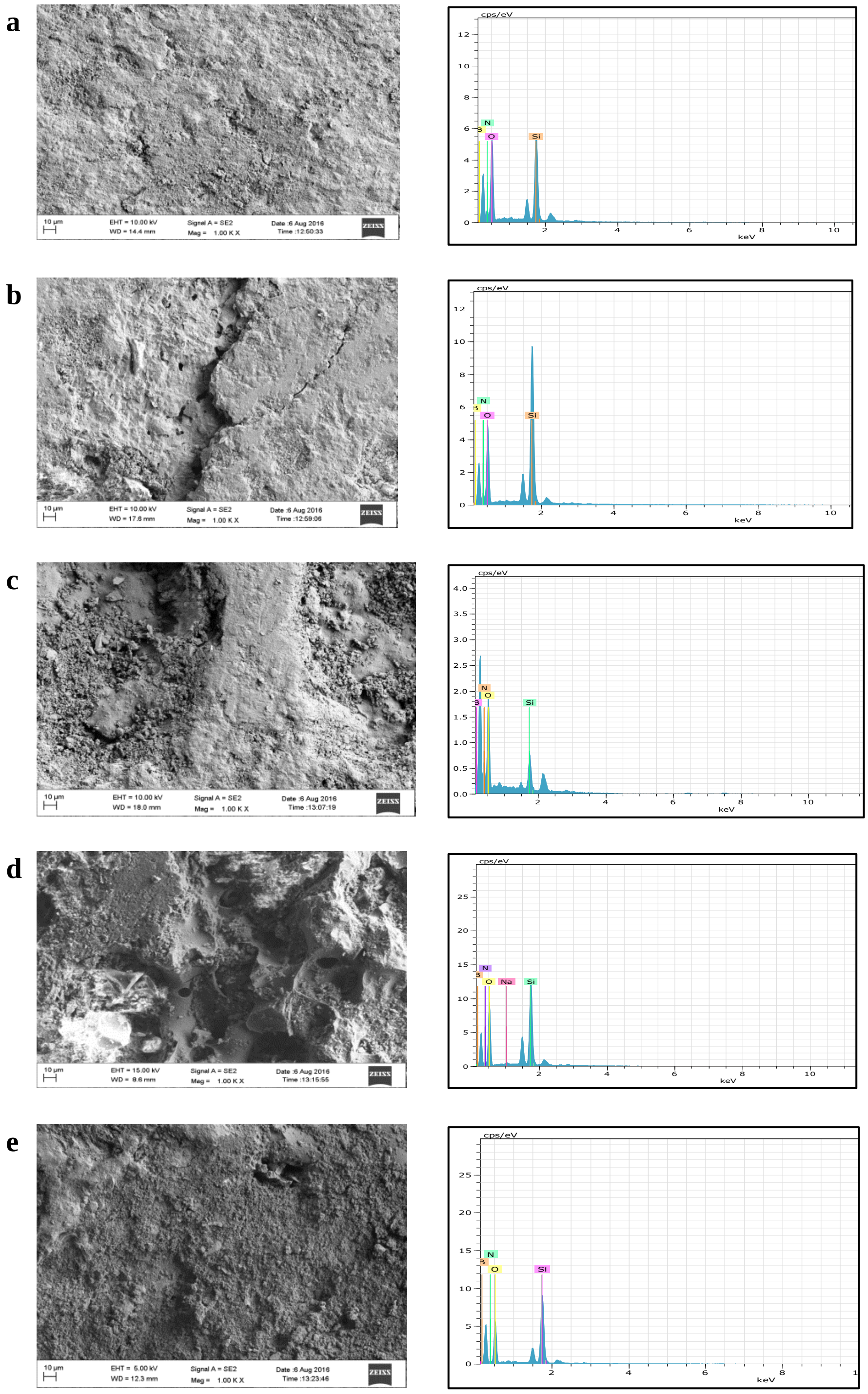

Fig. 5. SEM image and EDS of sintered pin sample 1 to 5.

4. Optimization

4.1. Genetic algorithm (GA)

The genetic algorithms (GAs) are numerical optimization technique based on natural selection mechanism, used for solving both constrained and unconstrained optimization problems that are based on natural selection, the process that drives biological evolution. GA follows Darwin's principle of 'survival of the fittest.' GA use biologically inspired techniques such as genetic inheritance, natural selection, mutation, and recombination or crossover [28]. The genetic algorithm repeatedly modifies a set population for individual solutions. At each step, the genetic algorithm selects individuals at random from the current population state to be work as parents and uses them to produce the modified children for the next generation. Over successive generations, the population "moves" toward an optimal solution.

The genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

i. Selection rules: select the individuals, called parents that contribute or go for reproduction to the population to the next generation.

ii. Crossover rules: combine two parents and exchange of genetic material to form children for the next generation.

iii. Mutation rules: apply random changes or modification of chromosomes to individual parents to form children.

The equation number 2 is further processed with a genetic algorithm to find out optimum value of variables load and & % volume of hBN to minimize wear volume loss of composite. The GA algorithm is simulated with MATLAB. The upper and lower bound of control factors are given in Eqs. (3) and (4).

$$5 \leq Load\ (N) \leq 25 \tag{3}$$

$$0 \ \leq \%\ volume\ of\ hBN\ \leq 16 \tag{4}$$

For GA simulation selected initial population size of 60. GA is simulated, and results of the optimum value of the individual factor are shown in Table 7 with best fitness plot in Fig. 6. The value of fitness function goes on decreasing with increase in a number of iteration or generation as illustrated in Fig. 6. Further, it observes to be constant.

Table 7. Optimum factor value and objective function value.

Load (N)	% Vol. of hBN	Objective function value-WVL(mm^3/m)
11.08	12.115	0.00898

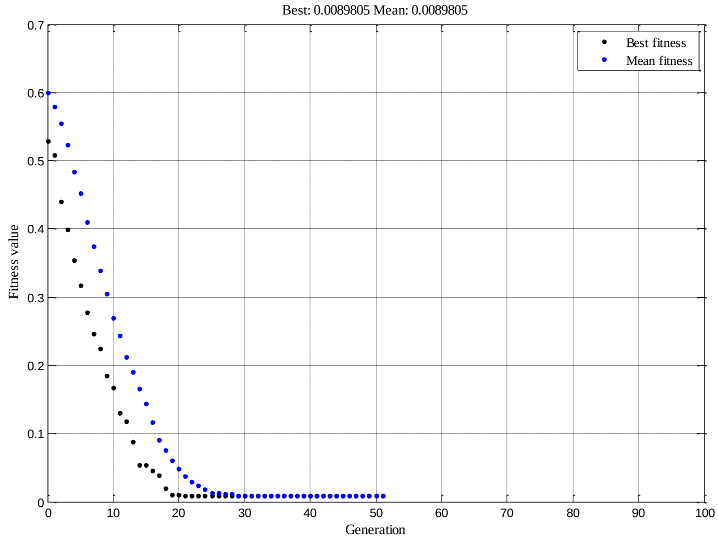

Fig. 6. Best fitness plot.

4.2. Simulated Annealing (SA)

Simulated annealing (SA), name and inspiration come from the annealing process in metallurgy, a technique involving heating and controlled cooling of the material to increase the size of its crystal and reduce their defects. Simulated annealing is a method for finding a good (not necessarily perfect) solution to an optimization problem. If you're in a situation where you want to maximize or minimize something, your problem can likely be tackled with simulated annealing. The first use or idea of SA derived from a paper by Metropolis et al. [29] in 1953. If you heat a solid past melting point and then cool it, the structural properties of the solid depend on the rate of cooling. If the liquid is cooled slowly enough, large crystals will be formed. However, if the liquid is cooled quickly (quenched), the crystals will contain imperfections. Metropolis's algorithm simulated the material as a system of particles. The algorithm simulates the cooling process by gradually lowering the temperature of the system until it converges to a steady, frozen state.

The algorithm for SA as follows [30, 31]:

1. Start with an initial guess (X_i) and high temperature.
2. Generate a new design point (X_{i+1}) in the vicinity of current point randomly and find the difference in function values.

   $\Delta E = \Delta f = f_{i+1} - f_i = f(X_{i+1}) - f(X_i)$

   If Δf is negative accept the X_{i+1} as the next design point.
3. If Δf is positive, accept the X_{i+1} as the next design point only with a probability $e^{-\Delta E / kT}$. Otherwise reject the point X_{i+1}., where k is a scaling factor, called Boltzmann's constant.
4. When the X_{i+1} is rejected, then repeat the steps 2 and 3. To simulate the attainment of thermal equilibrium at every temperature, a predetermined number (n) of new points X_{i+1} are tested for any specific value of

temperature *T*. If 'Metropolis equilibrium' is reached go to step 5, else go to step 2.

5. If the current value of *T* is sufficiently small or even when the change in the function values (Δf) are to be sufficiently small, the solution has converged.

Using this algorithm code developed and simulated with MATLAB for equation 2, objective function wear volume loss to be minimized. The upper and lower bound of control factors are given in equation 3 and 4. Results of the optimum value of the individual factor are shown in Table 8 with best fitness plot illustrated in Fig. 7.

Table 9 shows optimum values for load and % volume of hBN obtained by Taguchi analysis, GA optimization and SA optimization for minimization of wear volume loss in Si_3N_4 against alumina counterface.

Table 8. Optimum factor value and objective function value.

Load (N)	% Vol. of hBN	Objective function value-WVL(mm^3/m)
11.079	12.128	0.00898

Table 9. Optimum parameters and corresponding WVL.

Parameter	Taguchi Analysis	GA Optimization	SA Optimization
Load (N)	15	12.115	12.128
% Vol. of hBN	8	11.08	11.079
WVL (mm^3/m)	0.0111	0.00898	0.00898

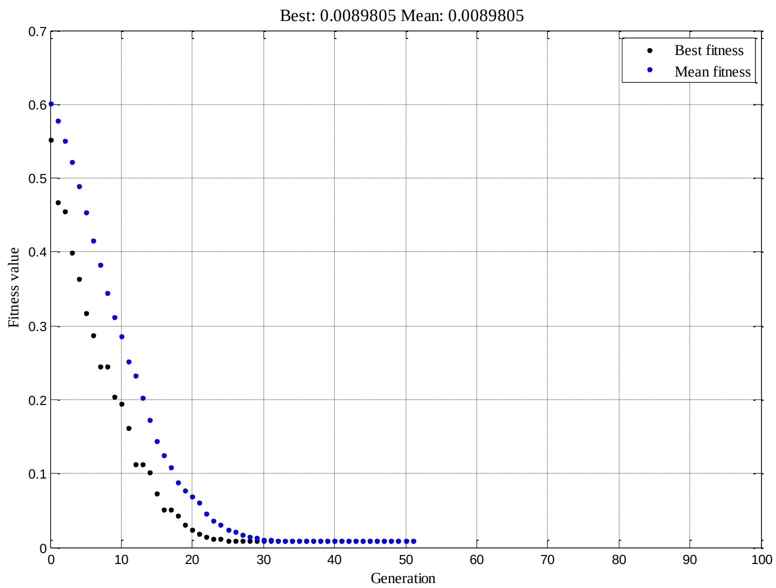

Fig. 7. Best fitness plot.

5. Conclusions

Experiments were conducted using DoE-Taguchi method at five levels of load and % volume of hBN in Si_3N_4. The objective function was to minimize wear volume loss and find interaction effect on wear loss. All three methods present different combination of load and % volume of hBN in Si_3N_4, to minimize wear volume loss, which signifies that wear volume loss is a function of both control factors. From the results, the following is concluded:

- The result of GA and SA optimization is very close to each other, so this may be considered as a suitable combination of load and % volume of hBN to minimize wear volume loss in Si_3N_4-hBN composite against alumina counterface. It proves effectiveness and applicability of GA and SA in the field of modeling and optimization**.**
- Silicon nitride- hexagonal boron nitride composite against alumina is proposed combination for hip/knee joint replacement. Minimizing wear volume loss in this pair is a prime requirement. From Table 9 it is clear that wear volume loss is a function of load and % volume of hBN. So for minimizing wear loss of silicon nitride, selecting the optimum proportion of hBN in Si_3N_4 corresponding load value must be considered.

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