Beni-Suef University Engineering Journal
Contents lists available at Science Direct
Journal of Engineering Science and Sustainable Industrial Technology
Journal homepage: https://jessit.journals.ekb.eg/

Optimization of Wear Parameters for Glass Fabric-Epoxy Composites using Response Surface Methodology and Flower Pollination Algorithm

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ARTICLE INFO

Article history: March 2023
Accepted: March 2023
Online: May 2023

Keywords:
Glass fiber-reinforced epoxy; Abrasive wear performance; Response Surface Methodology (RSM); Filler weight; Abrading distance; Flower Pollination Algorithm (FPA).

ABSTRACT

The importance of glass fiber-reinforced epoxy lies in its physical and mechanical properties, making it suitable for various manufacturing applications. Additionally, it plays a significant role in enhancing the abrasive wear performance of materials. In this study, a Response Surface Methodology (RSM) was developed to optimize the control variables (including type and weight of filler, normal load, abrasive size, and abrading distance) for glass fabric-epoxy (G-E) composites with different organic (date seed (DS)) and inorganic (silicon carbide (SiC), aluminum oxide (Al2O3) fillers. The samples were prepared using a semi-automatic technique. The analysis of variance (ANOVA) was used to construct an empirical model to demonstrate the relationship between the control factors (filler weight, abrasive) and responses (specific wear rate) in glass fiber-reinforced epoxy. The results of the analysis showed that the filler weight, abrasive size, and their interaction have a significant effect on the specific wear rate. An integrated RSM and Flower Pollination Algorithm (FPA) approach was used to optimize the wear parameters. The results showed that the FPA approach demonstrated good agreement between the predicted and experimental values.

1. Introduction:

Composites are materials that are formed by combining two or more constituent materials with significantly different physical or chemical properties, resulting in a material with unique characteristics [1,2].

Glass Fiber Reinforced Plastics (GFRP) exhibit excellent properties such as high strength-to-weight ratio, high specific stiffness-to-weight ratio, and low weight, making them ideal for use in automotive and aerospace applications [3,4]. Due to these properties, GFRP composites have become preferred replacement materials for various industrial products and have found diverse applications in the industry [5].

In recent years, tribological research has focused on improving the wear resistance of GFRP composites and polymers [6-8]. Several studies have explored the effect of fillers on the wear behavior of GFRP composites. For instance, Youssef, A. H. et al. investigated date seed powder as a filler in poly (butylene adipate-co-terephthalate)

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composites, which demonstrated enhanced biodegradation compared to pure polymer [9-10]. Basavarajappa et al. studied the impact of SiC particles and graphite fillers on the tribological behavior of glass epoxy polymer composites and reported increased wear resistance in the composites [11-12]. Patnaik et al. and Suresha et al. investigated the use of Al2O3 fillers in glass fiber-reinforced epoxy composites and found that their introduction significantly improved the abrasive wear resistance of the composites [13-14].

Various statistical tools, such as full factorial design and response surface methodology (RSM), have optimized input parameters and responses of fillers-filled GFRP composites [15-16]. RSM has proven effective in identifying optimal machining variables for desired surface finish and maximum cutting speed using single-cut and multi-cut strategies [17]. In contrast, the flower pollination algorithm (FPA) is a new nature-inspired optimization algorithm inspired by flowering plant pollination, which has shown superior efficiency compared to other optimization engines in engineering optimization problems [18-19].

This study differs from previous research on woven fabric reinforced polymer composites by using two unidirectional angle-ply ([±45]4) s and a different type of fillers (SiC, Al2O3) and an organic filler (DS) to fabricate a new class of low-cost epoxy-based composites reinforced with glass fiber. Furthermore, this study utilized a semi-automatic technique for sample preparation (grinding), which has natural availability and hardness advantages. An integrated approach of RSM and FPA was used to optimize the wear parameters, which has not been previously used in similar studies. This approach provides significant benefits in optimizing wear parameters in GFRP composites.

2. Experimental work

2.1. Materials

The materials used in this study consisted of unidirectional E-glass fiber reinforcement (ρ=1.15 g/cm^3) as reinforcement and epoxy resin PY1092 with HY1092 hardener as the matrix material. Additionally, organic filler Date seed (DS) with an average particle size of 175 µm, and inorganic fillers Silicon carbide (SiC) with an average particle size of 10 µm and aluminum oxide (Al2O3) with an average particle size of 15 µm were used. The mechanical properties of E-glass fiber/epoxy with the filler materials are shown in Table 1.

Table 1: Mechanical properties of E-glass fiber/epoxy with fillers specimen constituents

Material	Properties			
	Density, kg /m^3	Elasticity modulus E, GPa	Shear modulus G, GPa	Poisson ratio
Epoxy resin	1800	4.5	1.6	0.4
E-Glass fiber	1150	74	30	0.25
Date seed (DS)	1375	-	-	-
Silicon carbide (SiC)	3100	410	-	0.14
Aluminum oxide (Al2o3)	3690	300	124	0.21

2.2. Preparing Date seed

To prepare the Date seed filler material, fresh Date seeds were first cleaned with 50% H2SO4 for 5 hours to remove the surface layers. The seeds were washed with distilled water and dried in the air for 24 hours. After cleaning, the seeds were dried in an oven vacuum for 8 hours at 70 ºC to remove any remaining moisture. The seeds were then milled in a ball mill and sieved using a <175 µm.

2.3. Experimental procedure

In this study, three types of fiber-reinforced epoxy (GFRE) with angle-ply ([±45]4) s were produced, each containing different types of fillers: (0%, 5%, 10%) filler DS, (0%, 5%, 10%) filler SiC, and (0%, 5%, 10%) filler Al2O3. The composite specimens were prepared based on the weight of the different types of fillers, and the details of each specimen are presented in Table 2. The semi-automatic technique was used to prepare the composite laminates, following specific procedures. First, Araldite 1092 epoxy, the matrix material, was prepared by adding 50 parts of HY1092 as a hardener to 100 parts of PY1092 as a resin, with filled (SiC, Al2O3, and DS) fillers added separately for each type. The filler and epoxy mixture were stirred manually to ensure the particles were well distributed in the matrix.

A template was then fixed onto a table grinding with two pins, and all surfaces in direct contact with the epoxy were painted with a non-adhesive material (wax) to prevent their adhesion with composite materials after solidification. A glass plate was treated with a release agent, and a layer of epoxy resin was spread onto it. The first template with +45 oriented fibers was placed onto the resin using a grinding machine to control speed, as shown in Fig.1, using a digital gauge to determine the thickness of the specimen. The rolling motion was used to displace the perpendicular air wards. The layers were partially impregnated with the addition of epoxy, which was repeated to achieve full impregnation. The bundles were loosened from the template when the ply was fully impregnated. Finally, the specimen was covered with canson paper and pressed with normal load distributed uniformly on the glass plate for 72 hours at room temperature.

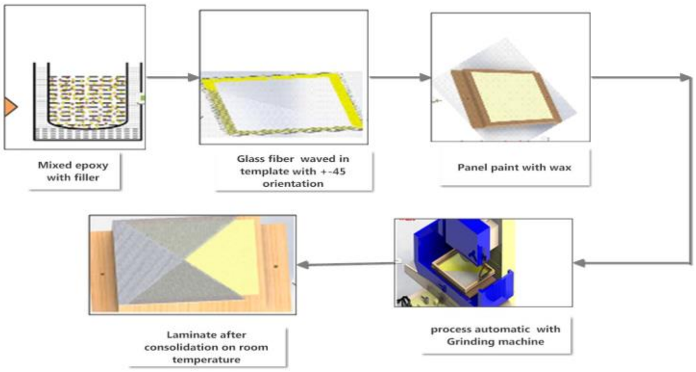


Figure 1. Schematic view of a process.

3. Optimization design

Response surface methodology (RSM) is a set of mathematical and statistical techniques for developing empirical models. The goal is to optimize a response or output variable affected by several independent input variables through a carefully designed experiment. An experiment consists of a series of tests called runs, where variations are made in the input variables to identify the causes for changes in the output response (21).

The wear test was performed on a G-E composite using the Box–Behnken Design (BBD) response surface methodology. The BBD is a type of response surface design that does not contain an embedded factorial or fractional factorial design. It is a three-level factorial design devoid of combinations from the 3k factorial design. Experimental data from 46 runs were collected according to the center point of the cube edges (41 positions) and the cube's center (5 repetitions). The design comprised data from 46 experiments, which were utilized to develop a model equation for the wear rate of G-E composites.

Table 2 presents the experimental values of the five factors under investigation at three levels of value designs (minimum, center, and maximum). The statistical significance level (P-value) was set at 0.05. The wear rate was the dependent response. The MINITAB17 statistical software was utilized to generate the order of the experiments randomly.

Table 2 : Parameters and level

symbols	Parameters	Levels		
		-1	0	1
T	**Type of material**	Sic	Al_2O_3	DS
F	**Filler wt (%)**	0	5	10
L	**Normal load(N)**	10	20	30
B	**Abrasive size (Grit size mesh or µm)**	400 (16 µm)	800 (8 µm)	1200 (3 µm)
D	**Abrading distance (m)**	420	840	1260

3.1. Development of empirical models and optimization

In response surface methodology, the quantitative form of the relationship between the desired response (specific wear rate) and independent input, including (type of material (a) can be represented in the following form:

$$Y = f\ (T, F, L, B, D)$$

Where Y is the desired response and F is the response function. In the analysis procedure, the polynomial regression model, a quadratic model of second-order type, was proposed to represent the relationship between the desired response and input parameters. The second-order polynomial regression (quadratic model) can be expressed as:

$$\mathrm{Y} = b_0 + \sum_{i=1}^{5} b_i x_i + \sum_{i=1}^{5} b_{ii}\ \ x_i{}^2 + \sum_{i=1}^{4}\sum_{J=1}^{5} b_{ij}\ x_i\ \ x_j \quad (1)$$

$$For\ \ i < j$$

where b_o is a constant and i, j are linear and quadratic coefficients, respectively; b is a regression coefficient, and X_i *and* X_j are the dimension less coded input variables. Eq. (1) was applied to convert input variables of the regression model into dimensionless coded variables and optimized in the experiments. When developing the quadratic equation, the test factors were coded according to the following equation:

$$X_i = \frac{x_{i-}x_0}{\Delta x_i} \quad (2)$$

X_i *and* x_i are the coded and actual values of the input variables, respectively; x_o is the actual value of the input variables at the central point; Δx_i is the step change value of the low and high levels of xi. A BBD with three levels of variables was used for the current study. A total of 46 experiments were conducted, encompassing a diverse range of sample compositions and wear tests. Using the quadratic mathematical models to ensure the wear rate of the analysis was abrasive. All the experimental data were checked through their residual plots to verify that the mathematical models displayed the standard normal distribution. The response surface plots can be produced by Minitab17 software and the optimization of the factors to reduce the wear rate.

3.2. Flower pollution algorithm approach

The Flower Pollination Algorithm (FPA) is an optimization algorithm classified as a meta-heuristic, originally introduced by Xin-She Yang. FPA is inspired by the pollination behavior of flowers in nature, and it is based on the idea that the pollination process can be used to generate new solutions to optimization problems.

The main steps of the FPA algorithm can be summarized as follows:

1. Initialization: Generate an initial population of solutions randomly.
2. Pollination: Generate new candidate solutions by combining the information from two parent solutions.
3. Selection: Select the best solutions from the population based on a fitness function.
4. Termination: Repeat steps 2-3 until a stopping criterion is met.

The pollination step in FPA is based on the concept of a "pollination vector, " representing the difference between two parent solutions. The pollination vector is then added to a third solution to generate a new candidate solution. The process is repeated for each member of the population, and the best solutions are retained for the next iteration.

The FPA algorithm can be expressed mathematically using the following equation:

$$x_{i(t+1)} = x_{i(t)} + \beta \odot \left(x_{j(t)} - x_{k(t)}\right) \tag{3}$$

Where $x_{i(t)}$ is the i^{th} solution at time t, β is a scaling factor, and $\odot$ represents element-wise multiplication. The indices j and k represent the two parent solutions that generate the pollination vector.

3.3. Abrasive wear test

The Abrasive Wear Test is a commonly used method for evaluating the wear resistance of materials. The test involves subjecting a material to a controlled abrasion process under specified conditions and then measuring the amount of material lost due to the abrasion. The test typically involves rubbing the surface of a material against a standardized abrasive material, such as sandpaper or a rotating grinding wheel, under controlled conditions of load, speed, and time. The amount of material lost is then measured by weighing the sample before and after the test or using a profilometer to measure the depth of the wear track.

Fig. 2 illustrates A pin-on-disc apparatus (as per ASTM: G-99-05 (2010), used for the sliding wear tests. The counter surface material for the wear testing is a steel disk 500 mm in diameter by 12 mm thick, hardness of 59–63 RC. The diameter of the pin collet ranges from 1.3 to 13 mm. The specimens are normally loaded against the SiC abrasive paper fixed on the hardened steel disk with the help of a cantilever mechanism.

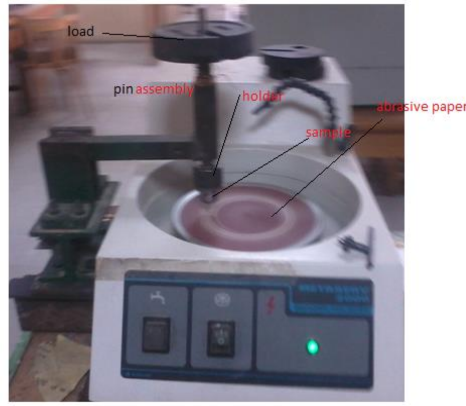


Figure 2. wear rate device

The Preliminary and final weights of the specimen are recorded using an electronic balance with an accuracy of 0.0001 gm. Where the difference in the recorded weights measures the abrasive wear loss, this difference in weight is converted into wear volume using the calculated density of the composite. Then the specific wear rate (Ks) is calculated as follows [10]

4. Results and decision

4.1. Effect of factors

Figure 3 depicts the relationship between the composite's specific wear rate (Ks) and the increase in abrasive particle size for an abrading distance of 420 m and a normal load of 20N. The Ks of the composite decrease with an increase in the abrasive particle size. It should be noted that abrasion against the abrasive paper with a large grit size (particle size of 400 mesh) was primarily characterized by a transfer of fine wear debris to the SiC counterpart, whereas abrasion against a small grit size (particle size of 1200 mesh) did not show this behavior.

Figure 3 shows the Ks of the composite as a function of filler weight percentage. The Ks of the unfilled G-E are larger than that of the filled composites, decreasing with an increase in the filler weight percentage. The order of abrasive performance of the composite is as follows: This ranking of performance indicates that including Al2O3) and DS fillers led to better abrasive resistance than SiC filler. The results suggest that the addition of lubricating filler, such as DS, into the G-E matrix leads to a significant improvement in abrasive resistance. Furthermore, the inclusion of inorganic filler, such as Al2O3) demonstrated a more effective lubricating effect when compared to the SiC filler.

These findings suggest that the choice of filler material is critical in designing composites with improved wear resistance. Including lubricating filler SiC into G-E demonstrated better abrasive resistance when compared to adding fillers (DS, Al2O3).

Furthermore, including lubricating filler organic filler, namely DS, into G-E exhibited better abrasive resistance when compared to the filler (Al2O3). Moreover, economically, it was found that the addition of DS filler into G-E exhibited better abrasive resistance when compared to other fillers, as shown in Figure 4. Additionally, it was found that the substitution of 6% SiC with 11% of DS is beneficial in reducing the material loss of these composites with a cheaper filler than other expensive fillers, as shown in the figures.

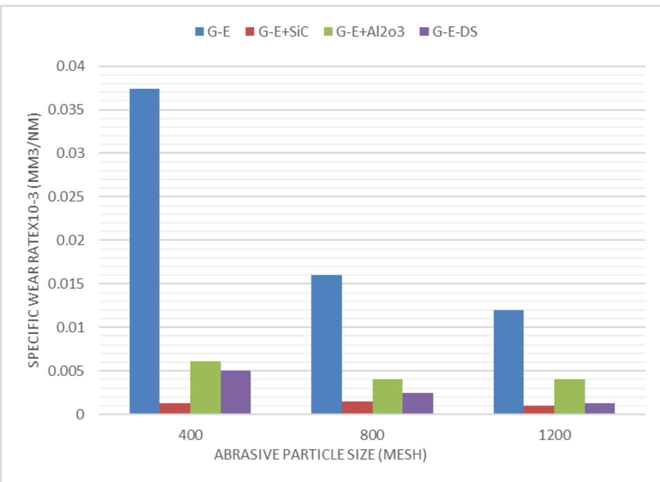


Figure 3. specific wear rate function of filler type at load 20N abrasive size 400 mesh

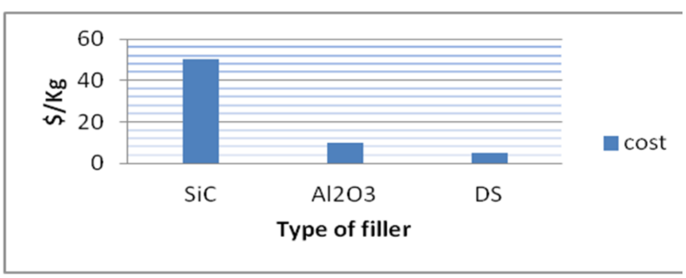


Figure 5. The cost function of type filler.

4.2. Empirical Models and Optimization

The estimated regression coefficient and analysis of variance (ANOVA) for the Ks of G-E with supplements are shown in Table 3. According to the results, the p-value for Ks was 0.0001, and the p-value for the lack of fit was 0.032. The analysis was conducted at a significant level of 5% with a confidence level of 95%, indicating that the model terms significantly influenced the response variable. There was a strong correlation between the experimental values and the model's R2 value of 0.89, indicating that the model's predicted specific wear values were close to the experimental values.

Objective

$$K_s^{0.5} = 4.227e^{-1} - 7.0e^{-4}C1 - 2.254e^{-2}C2 - 1.1081e^{-2}C3 - 2.8e^{-4}C4 - 1.50e^{-4}C5 + 1.997e^{-2}\,C2^2 \quad (4)$$

The models generated regression equation Box-Cox transformation λ = 0.5Eqs [2].

Table 3: Analysis of variances

source	DF	Adj SS	Adj MS	F	P
Model	20	0.034774	0.001887	9.11	0.000 significant
Linear	5	0.022256	0.004451	21.5	0.000
C1	1	0.000035	0.000035	0.17	0.685
C2	1	0.012916	0.012916	62.38	0.000
C3	1	0.000456	0.000456	2.20	.0.15
C4	1	0.006812	0.006812	32.90	0.000
C5	1	0.002037	0.002037	9.84	0.004
Square	5	0.011018	0.002204	10.64	0.000
C1*C1	1	0.003481	0.003481	16.81	0.000
C2*C2	1	0.007293	0.007293	35.22	0.000
C3*C3	1	0.004162	0.004162	20.1	0.000
C4*C4	1	0.004202	0.004202	20.29	0.000
C5*C5	1	0.000874	0.000874	4.22	0.05
2-way Interaction	10	0.004458	0.000446	2.15	0.058
C1*C2	1	0.000068	0.000068	0.33	0.571
C1*C3	1	0.002373	0.002373	11.46	0.002
C1*C4	1	0.000045	0.000045	0.22	0.646
C1*C5	1	0.001606	0.001606	7.76	0.010
C2*C3	1	0.000238	0.000238	1.15	0.294
C2*C4	1	0.000008	0.000008	0.04	0.843
C2*C5	1	0.000067	0.000067	0.32	0.576
C3*C5	1	0.000051	0.000051	0.25	0.623
C4*C5	1	0.000002	0.000002	0.01	0.931
Error	25	0.005177	0.000207		
Lack-of-Fit	20	0.005167	0.000258	143.29	0.000
Pure terror	5	0.000009			
Total	45	0.042909			

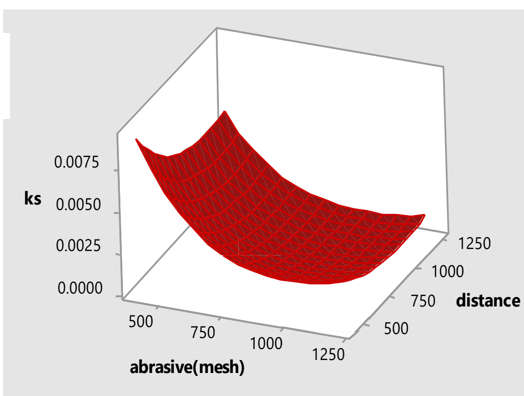
4.3. Effect signification parameters

4.3.1. Effect control parameters

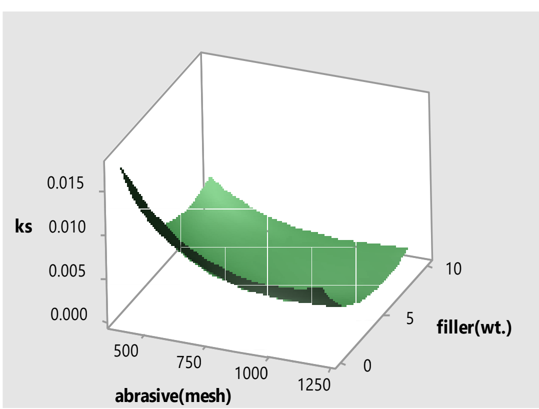
The effects of control parameters such as type of filler, filler weight, normal loading, abrasive size, and abrading distance on the wear rate of G-E composites were analyzed using a three-dimensional response surface, as shown in Figure 5a. The results demonstrate that Ks of G-E were reduced as filler weight and distance increased, as observed in Figure 3. This may be attributed to the fact that with more paths, the pores of the SiC paper become filled with wear debris, reducing the effectiveness of abrasive grit in penetrating, or cutting the surface. Additionally, the plot of filler weight and abrasive size in Figure 3b shows that Ks drops sharply with increasing abrasive size from 400 (16µm) to 1200 (3µm) grit size, possibly due to the decreased penetration ability of the specimen surface. Notably, filler weight is more significant than abrasive size and distance (20).

Figure 5 (b and c) illustrates the plot between the type of filler and normal load. As shown, Ks of G-E were reduced as the normal load increased. This could be due to the deposition of small, soft parts of wear debris between the counter face of the abrasive asperities that had broken off from the softer materials. Moreover, adding filler, particularly SiC, lowered the Ks of the G-E composite. SiC is the best type of filler, followed by DS, but the latter is inferior to SiC in terms of reducing Ks. The lowest Ks was observed at G-E with a filler weight of 10%, abrasive size of 1200 mesh, normal load of 30, a distance of 1280, and type of filler SiC.

(a)



(b)



(c)

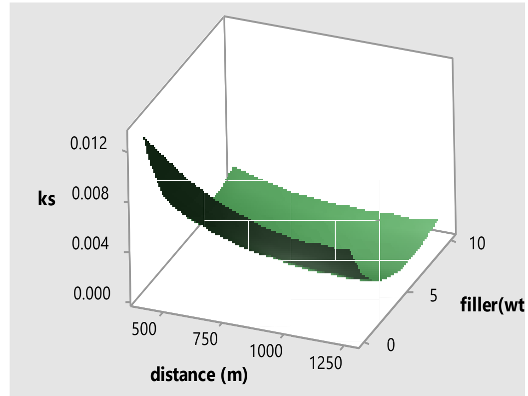


Fig.5. responses surface as specific wear rate

5. Optimization of wear

5.1. Optimization RSM

RSM is useful because its response may be optimized by adjusting the input parameters. This is a significant advantage. The Minitab 17 program takes into consideration five variables to create approbation indices. These parameters are called the lower, upper, and goal factors. The outcomes of the trials will serve as the basis for the goal.

The optimization of the responses obtained from G-E and the filler, as displayed in figure 6. The predicted operating conditions for the input parameters to obtain the minimum wear rate G-E composites in this study were a load of 7.7N approximately(10N) abrasive size and 1006.6(mesh) approximately (1200 mesh), and dreading distance1260m. SiC Type of wear (-1) and filler (wt) of 7.8%pproximately.

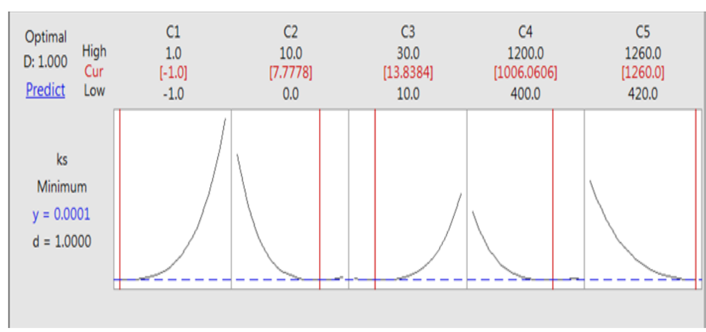


Figure 6. Optimization of flower pollution

5.2. Optimization of flower pollution

The MATLAB implementation of FPA was executed 15 times with a fixed number of iterations of 100. The parameters used in all runs were n = 25, β = 1.5, p = 0.8, and γ 0.1. The first step of the FPA algorithm involved defining the objective function and initializing the population of flowers (n) with random solutions. The best solution in the initial population was then computed. A switching probability (p ∈ (0, 1)) was defined to control local or global pollination selection. The choice between global pollination and local pollination was determined by generating a random number, and if this random number was less than the switching probability (p), then global pollination was performed. Otherwise, local pollination was carried out using the mathematical representation of global pollination.

5.3. Conformation test

A conformation wear test was performed with the result obtained from FP as SiC Type of wear (-1)(filler (wt) of 9 .2 % approximately(10%), a load of 10N approximately(10N) abrasive size and 1250(mesh) approximately(1200 mesh) and dreading distance 1233 m approximately(1260 m) t was found that experimental s under this conditions was 0.0001 mm3/Nm as shown in table 4 FP can be effusively used to predict the optimum wear characteristics of G-E.

Table 4: Conformation test

	Parameters					
	Type filler	**Filler wt(%)**	**Load (N)**	**Abrasive size (mesh)**	**Abrading(m)**	**Wear rate**
RSM	**SiC**	**7.7**	**13.7**	**1006**	**1260**	0.0001
FP	**SiC**	**9.2**	**10**	**1223**	**1260**	0.0051
Experimental	**SiC**	**10**	**10**	**1260**	**1260**	0.0001

6. Conclusion

The study investigated the impact of control parameters, including the type of filler, filler weight, normal loading, abrasive size, and abrading distance, on the wear rate of G-E composites with different organic and inorganic fillers. The following conclusions were drawn from the results obtained:

1. The Ks of unfilled G-E are larger than that of composites with fillers and reduce with increased filler weight. The abrasive performance of composites is in the order of the first SiC, second, DS, and third Al_2O_3.
2. The surface of G-E-SiC is harder than that of soft unfilled G-E, and filler particles in G-E serve as a medium to bear part of the stress exerted on G-E directly.
3. A good correlation was observed between the mathematical model (R2 = 0.88) and experimental values, indicating that the predicted specific wear values were close to the experimental values.
4. The exchange of 6% SiC with 11% DS is beneficial for reducing material loss in these composites with cheaper filler than other expensive ones.
5. DS filler successfully reduced the wear rate in G-E and provided a smoother surface compared to unfilled composites.
6. The Flower Pollination Algorithm (FPA) was implemented on MATLAB and executed in 0.52 minutes, with several iterations set to 100. The FPA showed effectiveness in a wide range of optimization problems, and its main steps include initialization, pollination, selection, and termination, based on the concept of a pollination vector.

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