ARCHIVE OF MECHANICAL ENGINEERING

Volume 67 2020 Number 3

DOI: 10.24425/ame.2020.131698

Key words: nanocomposites, epoxy, particle, swarm, Pareto front

Prakhar Kumar Kharwar [1], Rajesh Kumar Verma [1], Nirmal Kumar Mandal[2], Arpan Kumar Mondal[2]

Swarm intelligence integrated approach for experimental investigation in milling of multiwall carbon nanotube/polymer nanocomposites

In manufacturing industries, the selection of machine parameters is a very complicated task in a time-bound manner. The process parameters play a primary role in confirming the quality, low cost of manufacturing, high productivity, and provide the source for sustainable machining. This paper explores the milling behavior of MWCNT/epoxy nanocomposites to attain the parametric conditions having lower surface roughness (*Ra*) and higher materials removal rate (*MRR*). Milling is considered as an indispensable process employed to acquire highly accurate and precise slots. Particle swarm optimization (PSO) is very trendy among the nature-stimulated metaheuristic method used for the optimization of varying constraints. This article uses the non-dominated PSO algorithm to optimize the milling parameters, namely, MWCNT weight% ($Wt.$), spindle speed (N), feed rate (F), and depth of cut (D). The first setting confirmatory test demonstrates the value of *Ra* and *MRR* that are found as 1.62 µm and 5.69 mm^3/min, respectively and for the second set, the obtained values of *Ra* and MRR are 3.74 µm and 22.83 mm^3/min respectively. The Pareto set allows the manufacturer to determine the optimal setting depending on their application need. The outcomes of the proposed algorithm offer new criteria to control the milling parameters for high efficiency.

Nomenclature

ANOVA	Analysis of variance
CNC	Computer numeric control

✉ Rajesh Kumar Verma, e-mail: rkvme@mmmut.ac.in

[1]Department of Mechanical Engineering, Madan Mohan Malaviya University of Technology Gorakhpur, India, 273010.

[2]Department of Mechanical Engineering, National Institute of Technical Teachers' Training and Research, Kolkata, India,700106.

CNT	Carbon nanotube
DM	Decision maker
ECM	Electro-chemical machining
EDM	Electro discharge machining
f-MWCNT	functionalized multiwall carbon nanotube
GA	Genetic algorithm
MOPSO	Modified particle swarm optimization
MRR	Material removal rate
MWCNT	Multiwall carbon nanotube
PSO	Particle swarm optimization
Ra	Surface roughness

1. Intoduction

Polymeric materials play an important role in the development of lightweight structures [1, 2]. This is due to their exceptional chemical stability, excellent strength, electrical insulation, and low-cost processability [3, 4]. Polymeric composites lead to the design and production of a new range of structural material, which can provide a far-reaching modification in engineering and constructions. The composite material is a combination of two elements having their distinct properties. The strengthening of the polymer obtained by reinforcing various kinds of natural and synthetic reinforcement such as wood particles, carbon nanotube, nanorods, graphene [5–7]. MWCNT reinforced epoxy composites can fulfill the varying demand for the material society. Earlier, various scholars performed their work for the synthesis and characterization of carbon nanofiller materials. It has been observed that little addition of carbon nanofiller can enhance the material properties in a significant manner [8–10]. The imbalance addition of nanomaterials can lead to the tendency of agglomeration, in turn, reduce the strength and other properties of the composites [11–14]. Hence, there is an extreme need to understand the behavior of these nanomaterials. Szebe [15] performed mechanical characterization on MWCNT reinforced epoxy composites and found improvement in the tensile stress, Young's modulus, and flexural strength at up to 4 wt.% compared to pristine epoxy resin. Mittal et al. [16] reinforced functionalized multi-wall carbon nanotubes (f-MWCNTs) with the epoxy. They observed that the critical strain energy release rate improved by 57% in comparison to pristine epoxy at 0.1 wt.% reinforcement. Behzad et al. [17] reinforced epoxy polysulfide resin with pure and treated MWCNTs (0.1–0.3 wt.%), and investigation illustrated significant differences in mechanical properties of acid-treated and untreated CNTs reinforced epoxy polysulfide nanocomposites. Yu et al. [18] investigated the stress-life and fracture toughness in mode-I of MWCNT reinforced epoxy composites. The average fracture toughness was 1.29 and 1.62 times higher than pristine epoxy for

1 wt.% and 3 wt.%, respectively. Park et al. [19] used a thin sheet of entangled nanotubes and long MWCNTs to fabricate the composites for higher thermal conductivity and electrical conductivity. From the result, it was noticed that thermal conductivity increased up to 55 W/mK for long MWCNTs composites. For the complete utilization of any novel composites, it is highly required to understand its machining nature. Hence, the machining process, such as drilling, sinking, milling, turning, is the primary indispensable manufacturing process which is mainly used for the development and assembly of different machined samples. During manufacturing, the industrial requirements in the form of technical and economic facet play a vital part in the quality and productivity of the manufactured samples.The varying need for cutting factor is a judicious choice to achieve the machining objectives in terms of production rate, accuracy, and precision of developed components, cost-effectiveness. To achieve appropriate process conditions and simultaneously balance the conflicting responses, the optimization tools are widely utilized by scholars [20–24]. In many case studies, the multiple response optimization is preferred to afford a set of Pareto optimal values of the parameters for decision-makers (DM). In the optimization of multiple responses and varying parameters, the evolutionary algorithm (EA) is used as an effective alternative to conventional methods which have particular limitations [25].

Recently, the PSO algorithm was developed by Kennedy and Eberhart [26] to solve various complicated issues of multiple response optimization. It can find the solution in a unique exploring mechanism, conceptualized, computationally efficient, and straightforward in execution. The aforesaid evolutionary tools effectively deal with a set of solutions, and it seems natural to apply this algorithm in optimization issues for the search of Pareto values in a single run. PSO is significantly easy in use without complex computations, needs fewer constraints adjustment, provides efficient balancing among local and global solutions and requires less memory space. Recently, Sibalija [25] presented an exhaustive survey on the feasibility of the PSO and MOPSO modules. The outcome of the work demonstrates that the Swarm intelligence approach is more efficient than the Genetic algorithm [27], Desitrablity functions [24], Traditional Taguchi [20], ant colony optimization; cuckoo search, differential evolution; glow-worm swarm optimization, artificial bee colony [28]. Del Prete et al. [29] investigated the machining of AISI steel using MOPSO-based approach for parametric appraisal of process constraints. The outcomes of the work minimized the production time, which shows the application potential of MOSPO. Xu et al. [30] also used the MOPSO approach for injection molding procedure, and their results show that it is better than then Taguchi concept in optimization.

Some other potential works on process optimization, performed by the eminent scholars which related to PSO and other evolutionary tools, are summarized in this paper. Juan et al. [31] constructed the mathematical model for high-speed milling based on the polynomial network and found the optimal condition for lower production cost. Uros Zuperl et al. [32] constructed an artificial neural network for multiobjective optimization of machining conditions. Franci Cus et al. [33] explored the Genetic algorithm(GA) to assess cutting parameters for reducing the machining cost and time. Amiolemhen et al. [26] found that a GA is capable of optimizing single pass finishing operation and multi-pass roughing operation for drilling, turning, chamfering, and boring. Ezugwu et al. [34] established a PSO-based model to analyze and predict the relationship between process and cutting parameters for turning of nickel-based 718 alloys. Asokan et al. [35] optimized surface grinding parameters for minimizing production cost and maximizing productivity. Ramon et al. [36] used the metaheuristic approach and discussed the advantage of multiobjective optimization over single-objective optimization. Jia et al. [37] planned a new method for improving the efficiency of multiobjective PSO. Three classes of information derived from the population-based cultural algorithms can update the personal guide and the global guide. The epsilon domination criterion has improved the convergence and complexity of the estimated Pareto front. For verification of the competitive performance of the proposed algorithm, a comparative study with numerous algorithm has been performed. Carlos et al. [38] initiated the secondary repository based on the Pareto optimality in MOPSO for the non-dominated particles and with the adaptive grid. It was done for crowding distance-based CD-MOPSO selection based on crowding disitance [39] and in clustering MOPSO selection of global guide by clustering method [40]. Mostaghim and Teich [41] determined a local guide by sigma test method and their findings were confirmed by Branke and Mostaghim [42] by choosing different methods to select the local guide. Jegan et al. [43] investigated the chemical machining (ECM) parameters using PSO by developing the multiple regression model for varying input and responses. For feasibility evaluation, PSO was matched with the Genetic algorithm (GA) and it outperformed the GA in terms of mathematical analysis and estimation timing. Also, the outcome of the work has been validated by the confirmatory run, which gave accurate predictions with little error. Mohanty et al. [44] proposed optimal condition of Die-sinking EDM parameters of Inconel superalloys through a multiobjective PSO tool for the simultaneous analysis of machining performances. This study used the mutation operator of the GA tool to overcome the premature convergence in PSO.

Milling is an essential process in the slot making and provides final shape polymer composites requisite for riveting/fastening final assembly of the finished products in various manufacturing industries. Metaheuristics can be an effective way which, in a reasonably practical time, provides acceptable solutions for complex problems through trial and error. It is a challenging task to find a possible solution or combination of possible solutions because of the complexity of the problem of interest, and the goal is to find a right and viable solution within a reasonable time scale.

From the above literature, one can observe that MWCNT reinforced nanocomposites play a vital role in the growth of a lightweight structure for various industrial applications. Scholars have made multiple attempts for the development of MWCNT polymer nanocomposites. However, very limited data is available on the machining of MWCNT/polymer nanocomposites using nature-inspired evolutionary tools. Nevertheless, these are broadly used in the manufacturing of various parts like sensors, PCB, battery application fuse-lag components. The machining and machinability aspects of epoxy nanocomposites are not sufficiently explored and require more attention for proper utilization in society's interest. PSO method is recently developed with evolutionary tools and successively employed in decision-making case studies [45–48], but limitedly used in machining of nanocomposites. Therefore, this article efficiently explores the modified PSO to achieve Pareto optimal values for multiobjective optimization of milling characteristics. This article aims to achieve a lower surface roughness and higher materials removal rate using limited memory space (archive) for the non-dominated values of PSO. The consequences of process constraints on milling characteristics (*MRR* and *Ra*) are evaluated through the Taguchi concept based designed experiments using ANOVA. An attempt has been made to overcome the drawback and limitations of the customary optimization tools. The outcomes of the PSO are validated by a confirmatory test to appraise the feasibility of the recommended module.

2. Material and methods

The MWCNT reinforced epoxy composites are developed with solution casting techniques. The average length of MWCNT is 15 μm and the average diameter is 10–15 nm. The mechanical properties of the fabricated MWCNT/Epoxy nanocomposites are specified in Table 1. The milling tool used for machining of composites was HSS-made parallel shank end mill. The assessment of surface roughness (*Ra*) was done by using roughness measurement setup Surtronic S128 supplied by Taylor Hobson Co., and the *MRR* was assessed by using expression (Eq. (1)):

$$MRR = \frac{(W_i - W_f)}{\rho t_m}, \tag{1}$$

W_i – the initial weight of the workpiece, W_f – final weight of the workpiece. ρ – density of the work material, t_m – machining time.

Table 1.
Mechanical properties of developed nanocomposites

Material	Uniaxial tensile testing	Flexural test		Impact strength (kJ/m^2)
	Tensile strength (MPa)	Flexural strength (MPa)	Flexural modulus (GPa)	
0.5 wt.% MWCNT/Epoxy	62.945	107.31	4.759	3.63
1.0 wt.% MWCNT/Epoxy	65.82	158.05	4.647	4.030
1.5 wt.% MWCNT/Epoxy	41.742	83.914	4.264	3.044

The MWCNT wt.%, spindle speed, feed rate, and depth of cut are measured as the milling parameters, as depicted in Table 2. As per the Taguchi concept, the favorable design for four factors at three levels is the L27 orthogonal array (Table 3). It is utilized to perform milling experiments on the CNC milling machine (Model: BMV35 TC20, Fig. 1), and their corresponding observed data are illustrated in Table 3. The fabricated MWCNT reinforced epoxy composites sample is shown in Fig. 2. After the fabrication, the sample was examined under the FE-SEM test as shown in Fig. 3. It revealed a good dispersion of MWCNT into the epoxy matrix. The dispersion of filler material/ reinforcing agent is highly desired for improved mechanical properties and it also provides a favorable machining interface during milling procedure [49–53].

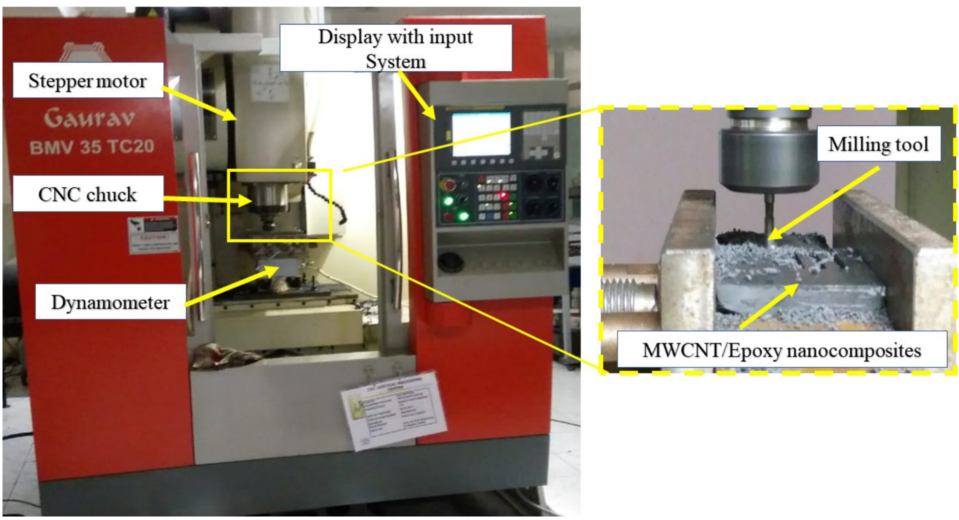

Fig. 1. Milling setup

Fig. 2. Fabricated MWCNT reinforced epoxy nanocomposite sample

Table 2.
Process parameters

	Process parameters			
	wt.% (Wt)	Spindle speed (N)	Feed rate (F)	Depth of cut (D)
Level 1	0.5	500	50	1
Level 2	1.0	1000	100	2
Level 3	1.5	1500	150	3

Table 3.
L27 orthogonal design

S. No.	MWCNT weight % ($Wt.$ %)	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	*Ra* (µm)	*MRR* (mm^3/min)
1	0.5	500	50	1	2.432	2.876
2	0.5	500	100	2	3.613	11.504
3	0.5	500	150	3	3.873	25.884
4	0.5	1000	50	1	1.908	2.907
5	0.5	1000	100	2	2.996	11.63
6	0.5	1000	150	3	3.596	26.16
7	0.5	1500	50	1	1.888	2.939
8	0.5	1500	100	2	2.906	11.75
9	0.5	1500	150	3	3.41	26.453
10	1	500	50	2	2.473	5.752
11	1	500	100	3	3.303	17.25
12	1	500	150	1	3.098	8.628
13	1	1000	50	2	1.996	5.815
14	1	1000	100	3	2.696	17.44
15	1	1000	150	1	2.859	8.72
16	1	1500	50	2	2.251	5.878
17	1	1500	100	3	2.81	17.635
18	1	1500	150	1	2.81	8.817
19	1.5	500	50	3	2.24	8.628
20	1.5	500	100	1	3.256	5.752
21	1.5	500	150	2	2.976	17.256
22	1.5	1000	50	3	2.068	8.723
23	1.5	1000	100	1	2.429	5.815
24	1.5	1000	150	2	2.77	17.446
25	1.5	1500	50	3	2.043	8.817
26	1.5	1500	100	1	2.722	5.878
27	1.5	1500	150	2	2.701	17.635

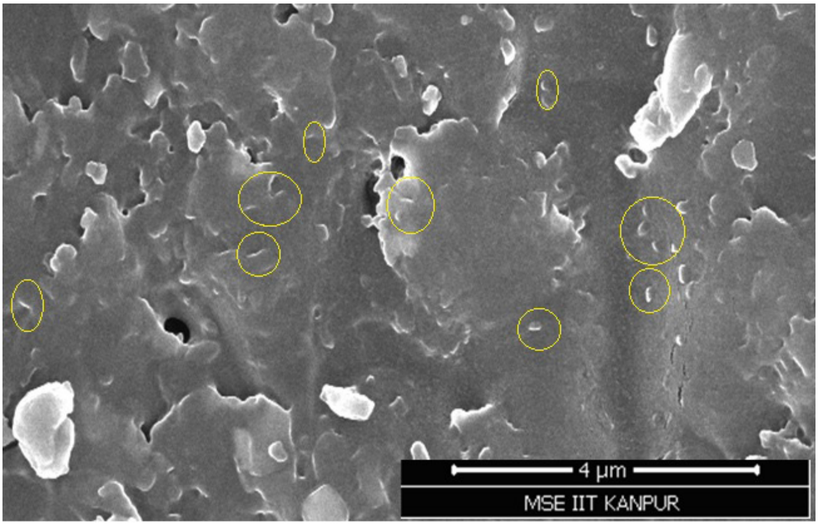

Fig. 3. FE-SEM image

3. Methodology

The evolutionary algorithm is mainly utilized to tackled the high-dimensional problems with multiple local optima. This article explores the feasibility of a nature-inspired metaheuristic algorithm, i.e., Particle swarm optimization (PSO). Firstly, Kennedy and Eberhart [26] suggested the PSO algorithm in the year 1995 by observing social behavior simulation. The PSO used the idea of information sharing between members who have some evolutionary advantage. Nowadays, the PSO effectively explores optimization case studies of the real-world such as job scheduling, power controller, agile and supply chain, weight spring method, energy optimizer, economic region studies, electric machining, routing of vehicles and control and inspection [43, 48, 54–63]. The PSO algorithm starts with the population (swarm) of random potential results (particles). Each particle is traveling iteratively through the search space and draws the best fitness obtained historically through the particle itself (local best) and the best among its neighbors (global best). Each particle adjusts its flying based on its flying skill and its companion's practice. Recently, the PSO tool is expanded to handle multi-criterion optimization studies. The distinctive approach of the Genetic Algorithm (GA) and the evolutionary approach is incorporated in the PSO. Once all the objectives function is considered, the solution is optimal in the logic that no other solution in the search field is particularly suitable for an alternative solution. These solutions are signified as Pareto optimal solutions. The non-dominance of each solution is matched with each solution and tested for satiating the rules provided for the solution. If the problem has two objective functions, one is for minimization and the second one for the maximization problem.

Then Obj.1$[l] \geqslant$ Obj.1$[m]$ and Obj.2$[l] \leqslant$ Obj.2$[m]$
where l and m are the solution number and Obj.1 and Obj.2 are the objective functions.

In modified PSO, each particle in the swarm population has a velocity $U_t(i)$, which allows it to pass through the problem region. A position then represents every particle $Y_t(i)$. The dimensions for velocity and position vector are described by the number of decision variables on the optimization problem. The update of the position and velocity of particles shall be affected by the use of information of its previous location and the current velocity.

Thus

$$(i) = \omega U_t(i) + C_1 R_1 \left(p_{best_t}(i) - Y_t(i)\right) + C_2 R_2 \left(g_{best_t}(i) - Y_t(i)\right), \tag{2}$$

$$Y_{t+1}(i) = Y_t(i) + U_t(i), \tag{3}$$

where: $U_t(i)$, $Y_t(i)$ is the velocity and current location of particle i^{th} at iteration t, $p_{best}(i)$ and $g_{best}(i)$ are the personal and global best of i^{th} particles, R is the random number in the range of [0, 1], ω, C_1 and C_2 are the weighting function, cognition learning rate and social learning rate, respectively. Such as a set of $g_{best}(i)$ is the externally archived 'At'. It is a repository where a non-dominated solution is stored so-far.

The crowding distance (CD) factor was calculated to make a well-dispersed set of non-dominated solutions. The CD factor was calculated for the solution k using Eq. (4).

$$CD_k = \frac{(f_{k+1} - f_{k-1})}{(f_{\max} - f_{\min})}. \tag{4}$$

The non-dominated solution in 'At' placed in the decreasing order of the CD factor and the top 10% among them are arbitrarily used as the best reference. The PSO usually converges reasonably quickly at the outset of the search and then declines due to the loss in variety inside the population. If the value of iteration is less than the product or the maximum number of repetitions and probability of mutation, then the mutation is done at the location of the particles. Given particles, a randomly chosen variables say mp is mutated to undertake a value mp' as given by the equation:

$$mp' = \begin{cases} mp + \Delta(t, UB - mp) & \text{if } \mathit{flip} = 0, \\ mp - \Delta(t, mp - LB) & \text{if } \mathit{flip} = 1, \end{cases} \tag{5}$$

where: UB and LB represent the upper bound and lower bound of the variables mp, respectively. The probability of $\Delta(t, x)$ being near and local to 0 increases as t amplifies.

$$\Delta(t, x) = x \times \left(1 - r^{\left(1 - \frac{t}{iter\max}\right)^b}\right), \tag{6}$$

where r is the random number created in the range [0, 1], $iter$ max is the highest number of iterations, and b is the dependency degree.

The parameter b estimates the mutation dependency degree on the iteration number. The pbest archives consist of the newest non-dominated position of a particle that has earlier encountered. The highest number of iterations is considered as the termination criteria. The proposed modified PSO algorithm for the multiobjective optimization problem is illustrated with a flow chart (Fig. 4).

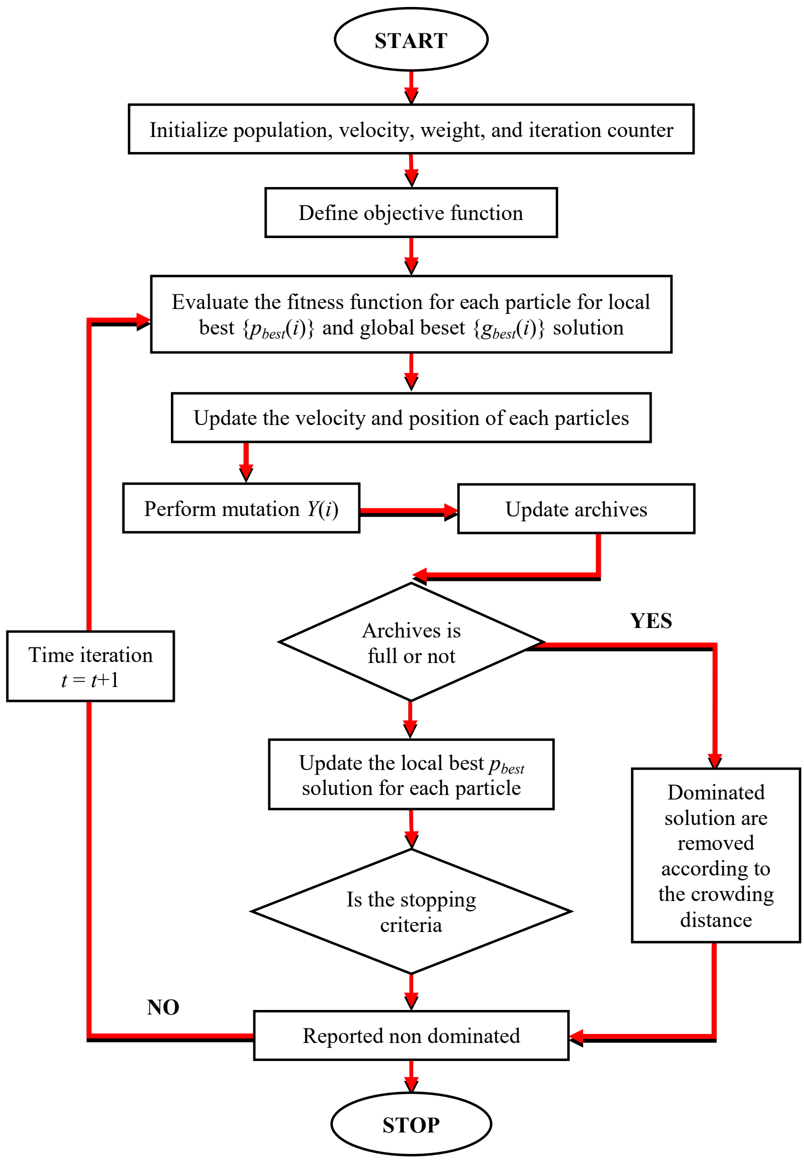

Fig. 4. Flow chart of the proposed PSO algorithm

4. Result and discussion

The execution of the PSO algorithm and the regression model are discussed to predict the values of *MRR* and *Ra*. ANOVA was presented to evaluate the importance of the parameters for milling responses, as mentioned in Table 4 and Table 5.

The R-square value of the established ANOVA model for *MRR* and *SR* are found as 99.91 and 96.83, respectively, which indicates the adequacy of the proposed regression model, and it can be used for further analysis and modeling of parameters. The second-order polynomial equation has been developed for both process response as represented in Eq. (7) and Eq. (8).

Surface roughness

$$\begin{aligned} Ra = {} & 2.44 - 0.22Wt. - 0.00252N + 0.0200F + 0.444D + 0.351Wt.\,Wt. \\ & + 0.00000N\,N - 0.000032F\,F - 0.023D\,D + 0.000203Wt.\,N \\ & - 0.00515Wt.\,F - 0.280Wt.\,D\,. \end{aligned} \tag{7}$$

Material removal rate

$$\begin{aligned} MRR = {} & 0.012 - 0.004Wt. - 0.000012N - 0.00014F - 0.125D + 0.004Wt.\,Wt. \\ & + 0.000N\,N + 0.000001F\,F - 0.0005D\,D - 0.0009Wt.\,D \\ & + 0.000128N\,D + 0.058149F\,D\,. \end{aligned} \tag{8}$$

Table 4.
ANOVA for surface roughness (*Ra*)

Source	DF	Seq SS	Adj SS	Adj MS	F-Value
Regression	11	7.52888	7.52888	0.684444	41.64
Wt.	1	0.64832	0.00012	0.000117	0.01
N	1	0.76963	0.51263	0.512628	31.19
F	1	4.29597	0.47910	0.479105	29.15
D	1	0.38623	0.11390	0.113904	6.93
Wt. Wt.	1	0.02819	0.02819	0.028195	1.72
N N	1	0.32202	0.32202	0.322017	19.59
F F	1	0.68209	0.30623	0.306231	18.63
D D	1	0.00011	0.01600	0.016003	0.97
Wt. N	1	0.04184	0.04184	0.041843	2.55
Wt. F	1	0.24970	0.07338	0.073383	4.46
Wt. D	1	0.10479	0.10479	0.104790	6.37
Error	15	0.24657	0.24657	0.016438	
Total	26	7.77545			
R-sq	96.83				

Table 5.

ANOVA for material removal rate (*MRR*)

Source	DF	Seq SS	Adj SS	Adj MS	F-Value
Regression	11	1318.84	1318.84	119.894	17567.37
Wt.	1	38.00	13.29	13.289	1947.13
N	1	0.29	0.01	0.008	1.11
F	1	608.60	8.66	8.663	1269.27
D	1	608.53	15.35	15.349	2248.93
Wt. Wt.	1	12.70	12.70	12.696	1860.30
N N	1	0.00	0.00	0.000	0.00
F F	1	0.00	9.53	9.532	1396.71
D D	1	0.00	9.50	9.503	1392.45
Wt. N	1	0.00	0.00	0.003	0.42
Wt. F	1	12.68	38.04	38.040	5573.70
Wt. D	1	38.05	38.05	38.051	5575.36
Error	15	0.10	0.10	0.007	
Total	26	1318.94			
R-sq	99.99%				

The contour plots between the combination of process parameters and process response, i.e., *MRR* and *Ra*, are developed to inspect the combined influence of process constraints on response. Figs. 5–9 demonstrate the contour plots for

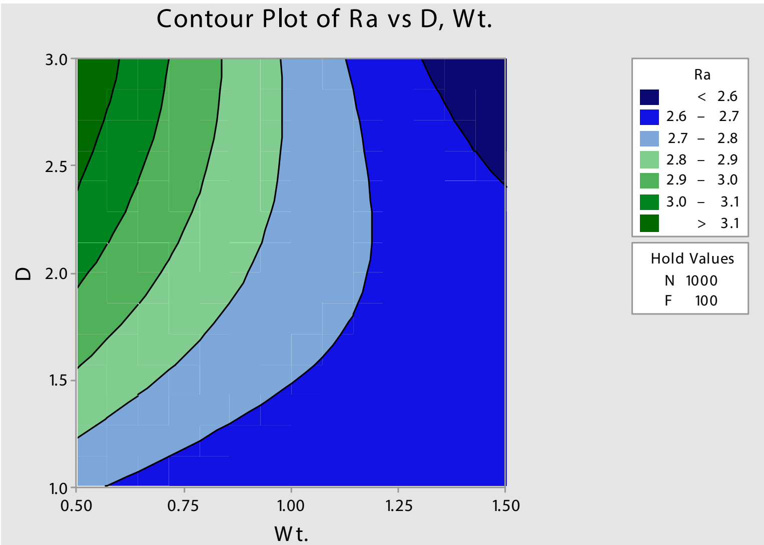

Fig. 5. Contour plot between *Ra* and combination of *Wt.* and *D*

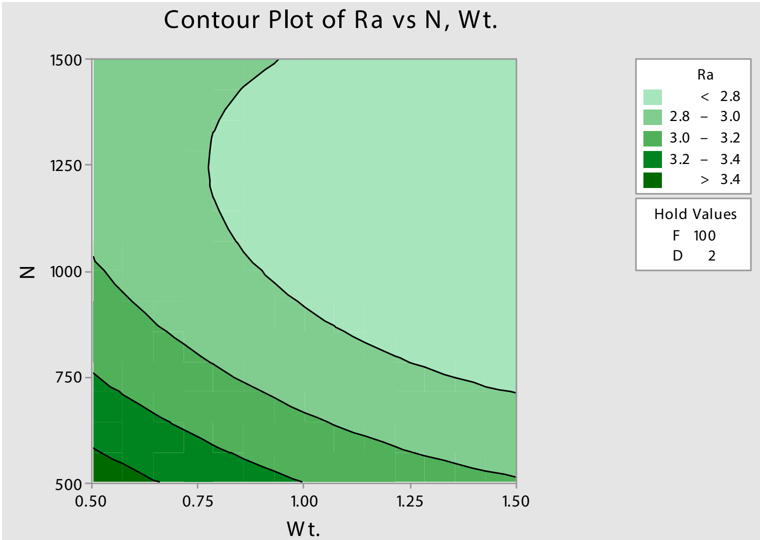

Fig. 6. Contour plot between *Ra* and combination of *Wt*. and *N*

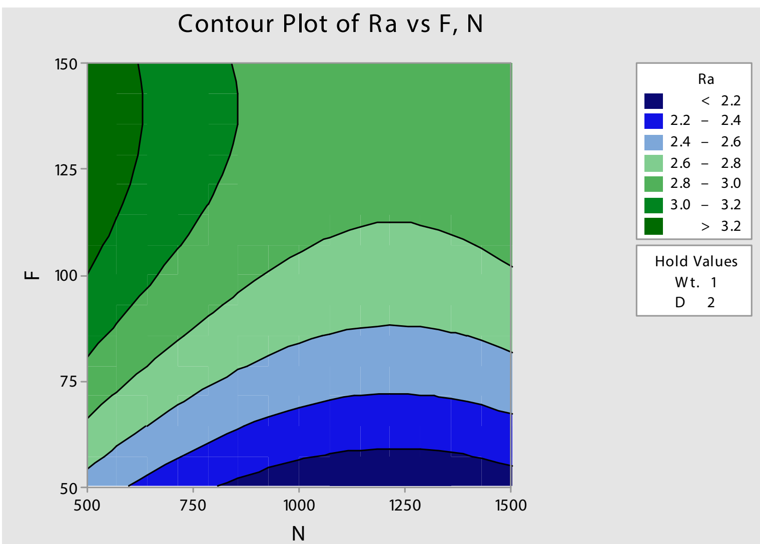

Fig. 7. Contour plot between *Ra* and combination of *F* and *N*

the surface roughness (*Ra*), and it has been noted that *Ra* decreases with the accumulation of MWCNT into the matrix, which is mainly due to the gap in the epoxy matrix, in turn, significantly demises with adding nano reinforcement [64]. The surface roughness reduces from 500 rpm to 1000 rpm, and after that increases with a rise in speed, which is due to the developed wear on a machined surface with high spindle speed [65, 66]. The surface roughness increased with feed rate due to strain hardening effect while machining with a higher feed rate [67, 68]. Surface roughness is also enhanced with a higher depth of cut due to large volume removal from the surface, which generates the rough surface of the machined sample. It has been noticed that lower surface roughness can be obtained by the combination of lower feed rate, lower depth of cut, higher spindle speed, and higher MWCNT wt.%.

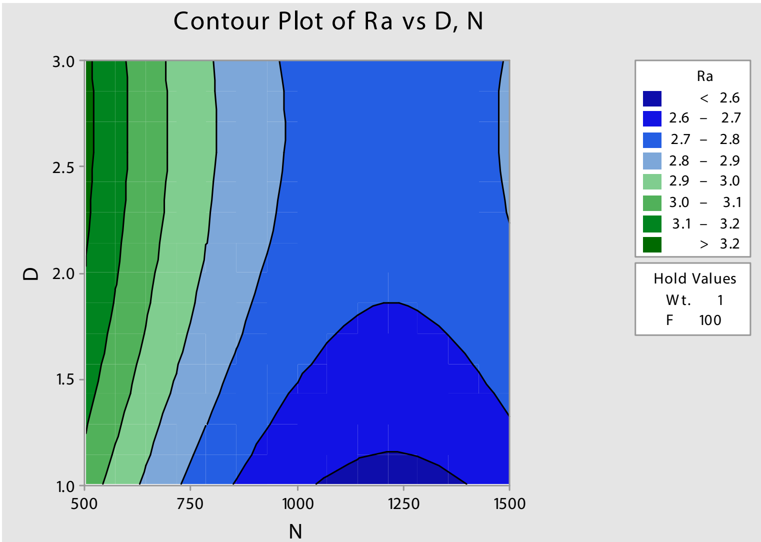

Fig. 8. Contour plot between *Ra* and combination of *N* and *D*

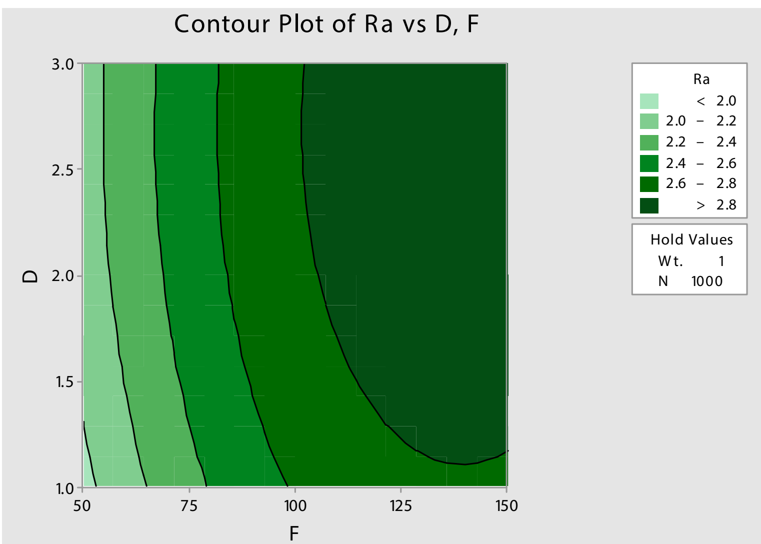

Fig. 9. Contour plot between *Ra* and combination of *F* and *D*

Figs. 10–14 display the contour plots for *MRR* against the combination of process parameters. From the contour plot, it is found that *MRR* reduces at higher MWCNT loading as the increased material removal rate decreases with *Wt*.% of MWCNT due to improving the machinability of thermoset epoxy by adding MWCNT, which causes the removal of small particles while machining [69, 70]. The *MRR* increases with a rise in spindle speed and the feed rate and the depth

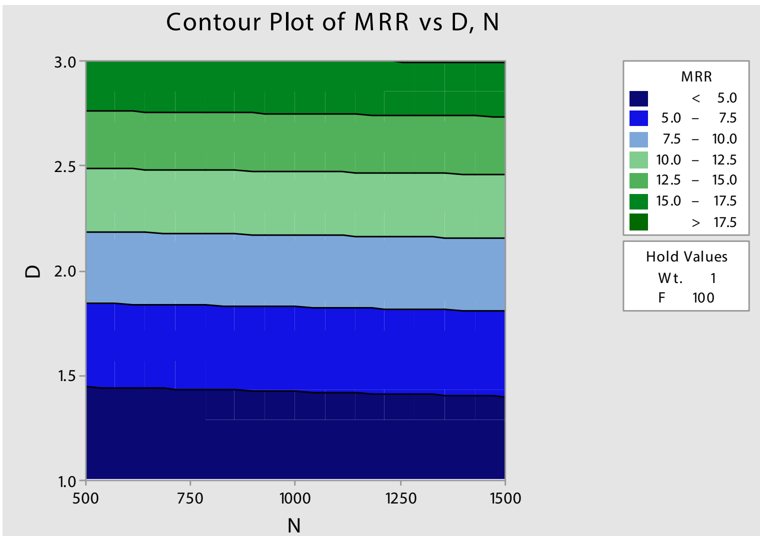

Fig. 10. Contour plot between *MRR* and combination of *N* and *D*

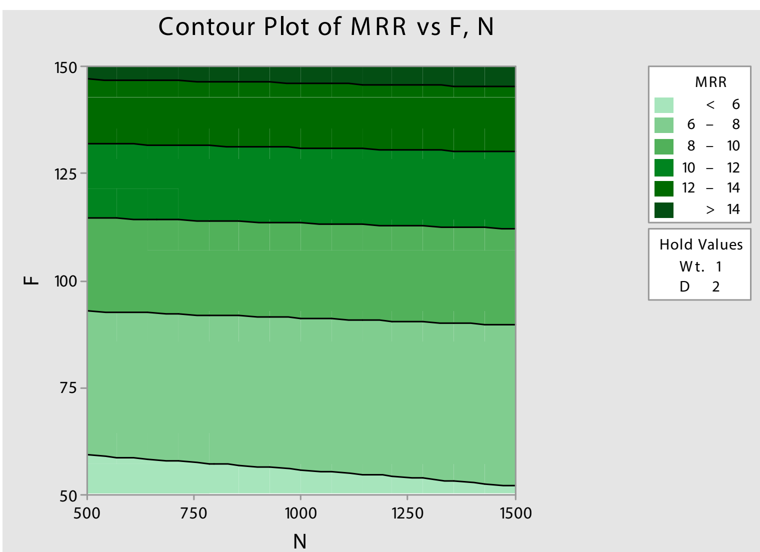

Fig. 11. Contour plot between *MRR* and combination of *N* and *F*

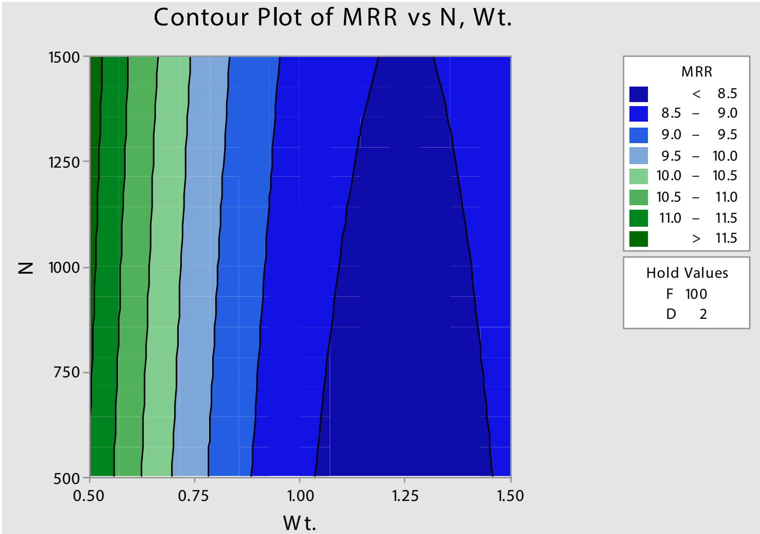

Fig. 12. Contour plot between *MRR* and combination of *Wt.* and *N*

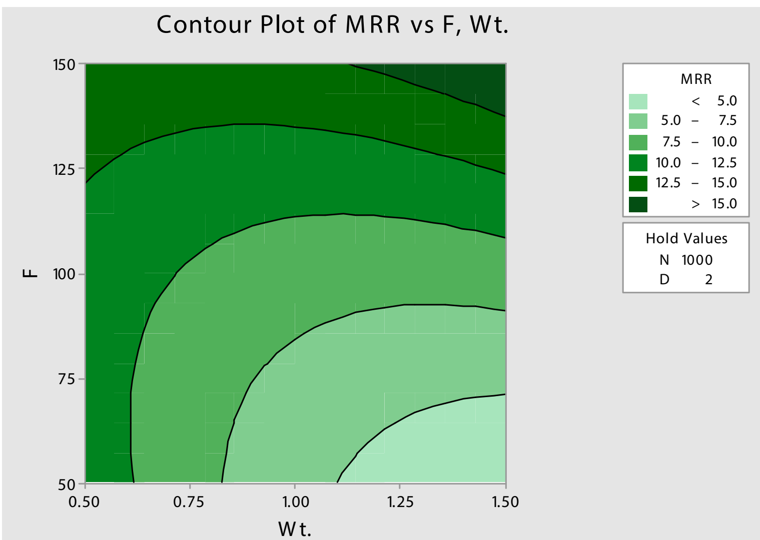

Fig. 13. Contour plot between *MRR* and combination of *Wt.* and *F*

of cut in a similar manner, because the high cutting depth is responsible for large chip thickness, and higher feed rate refers to the movement of the tool into the material [71–73].

To provide a set of non-dominated solution, an optimum Pareto front is generated, which can guide process engineers on how to determine the different combinations of weights for the output values. These values are actuality non-dominated

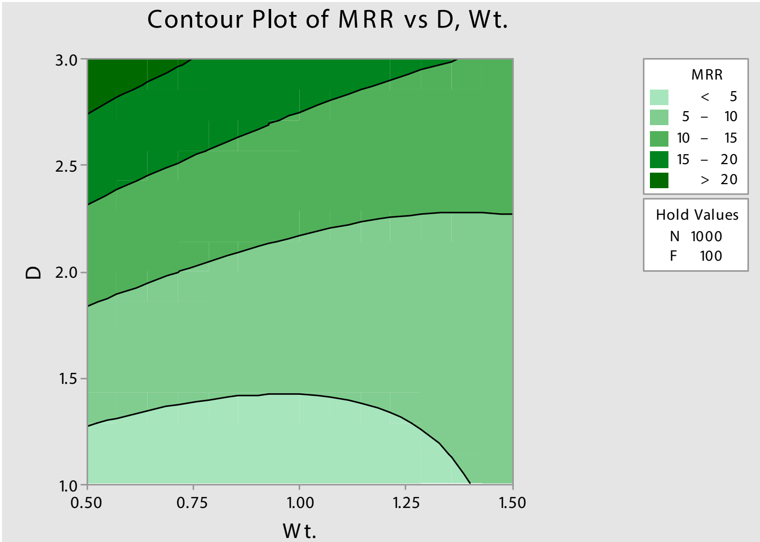

Fig. 14. Contour plot between *MRR* and combination of *Wt*. and *D*

and, in turn, confirm the outcomes as the optimally desired. In this paper, the simultaneous optimization of *Ra* and *MRR* using PSO has been performed. In the first run, surface roughness is minimized by generating all sets of all the points collected using iterations. The outcomes of all the collected points represent the convergence trends for reduced *Ra* values.

The second run of *MRR* is again separately maximized by a similar algorithm to obtain related sets of points towards the maximum *MRR* values. Afterward, both the datasets are clubbed, and optimal Pareto front is thus developed for *Ra* and *MRR*, i.e., a set of non-dominated solutions is designed, which simultaneously gives the desired values of *Ra* and *MRR* (Fig. 15). From the Pareto-optimal solution, two runs were picked randomly from an extreme range for *Ra* and *MRR* to validate the estimate of responses (Ra and MRR). The confirmatory experiment performed in the selected setting is detailed in Table 6. From the confirmation test, it is perceived that the *MRR* and *SR* attained in PSO demonstrates a satisfactory target value among the actual ones. The errors generated among experimental and prediction results of MRR and SR at two extreme ranges are observed as 3.1 and 1.4%, and 6.7 and 2.9%, respectively. The successful implementation of the population algorithm (PSO) must be tuned appropriately to maintain stability between global and local exploration for the estimation of actual optimum.

The number of swarms depends on the convolution of the optimization problem. It is noticed that a large number of swarms increase the performance PSO algorithm. In this study, there are four milling parameters studied; therefore, 200 population size is considered and 0.4 is inertia weight, which is used to limit the velocity because large velocity could miss out a suitable solution. Individual and

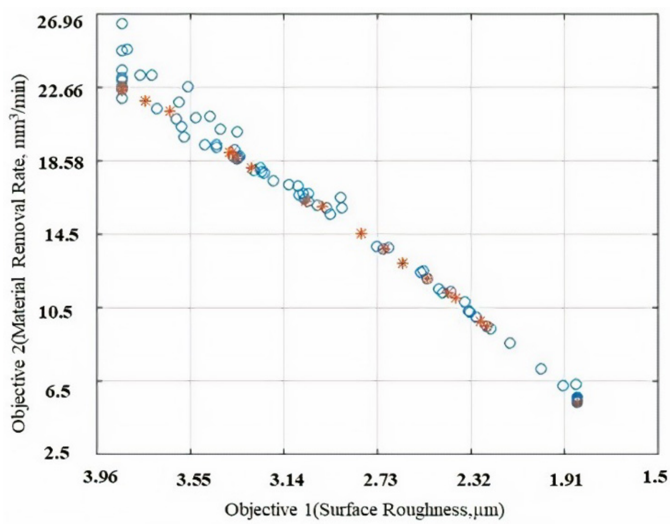

Fig. 15. Pareto optimal front

Table 6.

Confirmatory test

S. N	Optimal setting	Experimental results		Predicted results		Error %	
		Ra (µm)	*MRR* (mm^3/min)	*Ra* (µm)	*MRR* (mm^3/min)	*Ra* (µm)	*MRR* (mm^3/min)
1	1.5 Wt., 1000 rpm, 50 mm/min, 1 mm	1.62	5.69	1.73	5.51	6.7%	3.1%
2	1.5 Wt., 1500 rpm, 150 mm/min, 3 mm	3.74	22.83	3.85	22.51	2.9%	1.4%

swarm confidence factors, i.e., $C_1 = 2$ and $C_2 = 2$, respectively, have equal value, generally. Thus, the proposed PSO algorithm is effectual in deciding appropriate parametric settings during milling of MWCNT/Polymers. The outcomes of the validation test give satisfactory conformity with the predicted values of milling characteristics with very minute error, which is highly desired for a cost-effective and capable milling environment. The machining behavior of such a kind of polymeric material is less explored in previous works. The effect of process parameters and the obtained results show a similar trend [74–77]. Also, the present work demonstrates a significant improvement in the machining responses with acceptable errors in the results.

5. Conclusions

This article investigates the end-milling of MWCNT-based epoxy composites using Modified Particle Swarm Optimization (MOPSO). The potential of MWCNT into the epoxy matrix shows the exceptional properties for multifunctional applications. The machining nature of MWCNT polymers is significantly distinct from other materials and it can be controlled by proper selection of parameters using the PSO algorithm that can enrich the machining performance. The conclusion of this work can be outlined as follows.

A second-order polynomial equation was established for surface roughness and material removal rate. The contour plots were proposed to explore the influence of machine constraints on MRR and Ra. The MRR reduces at higher MWCNT loading as increased material removal rate decreases with Wt.% of MWCNT due to improving the machinability of thermoset epoxy by adding MWCNT. The surface roughness reduces from 500 rpm to 1000 rpm, and after that increases with a rise in spindle speed, which is due to developed wear on a machined surface caused by high spindle speed. The surface roughness increases with feed rate due to strain hardening effect and it also enhances with a higher depth of cut due to large volume removal from the surface, which generates the rough surface of the machined sample. MPSO was effectively used for multiobjective optimization problems associated with the machining (milling) performances of MWCNT nanocomposites. The proposed Pareto optimal graphics reveal sufficient information for a decision-maker to select the optimal parametric condition during milling of MWCNT polymers. The outcomes of the confirmatory test show a satisfactory agreement with a very small error. This research provided significant and beneficial information that could be helpful for machinists to improve quality indices and reduce milling time and cost. It is a generalized optimization module that can be modified for manufacturing and micro-manufacturing procedures like drilling, turning, etc.

This article effectively investigates the machining (milling) behavior of MWCNT epoxy nanocomposites using advanced PSO algorithm. The results of the confirmatory test show the prediction accuracy of the PSO algorithm in a machining environment. These nanocomposites possess a broad spectrum of applications in plastic manufacturing sectors. Therefore, consideration of some other factors like tool design, thermal behavior, chips mechanism, tool wear, temperature, etc., can be considered for different manufacturing methods, such as plastic forming, metal casting, heat treatment process, welding, etc. The modified PSO can be endorsed to other operational research case studies of industrial engineering as it gives very little error during the prediction of results.

Acknowledgments

The authors are very thankful to Madan Mohan Malaviya University of Technology Gorakhpur 273010 India for extending all possible help in carrying out this research work directly or indirectly.

Manuscript received by Editorial Board, April 19, 2020;
final version, August 16, 2020.

References

[1] M. Liu, H. Younes, H. Hong, and G.P. Peterson. Polymer nanocomposites with improved mechanical and thermal properties by magnetically aligned carbon nanotubes. *Polymer*, 166:81–87, 2019. doi: 10.1016/j.polymer.2019.01.031.

[2] S.K. Singh and V.K. Verma. Exact solution of flow in a composite porous channel. *Archive of Mechanical Engineering*, 67(1):97–110, 2020, doi: 10.24425/ame.2020.131685.

[3] N. Pundhir, S. Zafar, and H. Pathak. Performance evaluation of HDPE/MWCNT and HDPE/kenaf composites. *Journal of Thermoplastic Composite Materials*, 2019. doi: 10.1177/0892705719868278.

[4] N. Muralidhar, V. Kaliveeran, V. Arumugam, and I.S. Reddy. Dynamic mechanical characterization of epoxy composite reinforced with areca nut husk fiber. *Archive of Mechanical Engineering*, 67(1):57–72, 2020, doi: 10.24425/ame.2020.131683.

[5] F. Mostaani, M.R. Moghbeli, and H. Karimian. Electrical conductivity, aging behavior, and electromagnetic interference (EMI) shielding properties of polyaniline/MWCNT nanocomposites. *Journal of Thermoplastic Composite Materials*, 31(10):1393–1415, 2018. doi: 10.1177/0892705717738294.

[6] M.R. Sanjay, P. Madhu, M. Jawaid, P. Senthamaraikannan, S. Senthil, and S. Pradeep. Characterization and properties of natural fiber polymer composites: A comprehensive review. *Journal of Cleaner Production*, 172:566–581, 2018. doi: 10.1016/j.jclepro.2017.10.101.

[7] A.J. Valdani and A. Adamian. Finite element-finite volume simulation of underwater explosion and its impact on a reinforced steel plate. *Archive of Mechanical Engineering*, 67(1):5–30, 2020, doi: 10.24425/ame.2020.131681.

[8] A. Kausar, I. Rafique, and B. Muhammad. Review of applications of polymer/carbon nanotubes and epoxy/CNT composites. *Polymer-Plastics Technology and Engineering*, 55(11):1167–1191, 2016. doi: 10.1080/03602559.2016.1163588.

[9] E. Vajaiac, et al. Mechanical properties of multiwall carbon nanotube-epoxy composites. *Digest Journal of Nanomaterials and Biostructures*, 10(2):359–369, 2015.

[10] A.E Douba, M. Emiroglu, R.A Tarefder, U.F Kandil, and M.R. Taha. Use of carbon nanotubes to improve fracture toughness of polymer concrete. *Journal of the Transportation Research Board*, 2612(1):96–103, 2017. doi: 10.3141/2612-11.

[11] W. Khan, R. Sharma, and P. Saini. Carbon nanotube-based polymer composites: synthesis, properties and applications. In M.R. Berber and I.H. Hafez (eds.). *Carbon Nanotubes. Current Progress and their Polymer Composites*. chapter 1, pages 1-46. IntechOpen, Rijeka, Croatia, 2016. doi: 10.5772/62497.

[12] W.M. da Silva, H. Ribeiro, J.C. Neves, A.R. Sousa, and G.G. Silva. Improved impact strength of epoxy by the addition of functionalized multiwalled carbon nanotubes and reactive diluent. *Journal of Applied Polymer Science*, 132(39):1–12, 2015, doi: 10.1002/app.42587.

[13] S. Dixit, A. Mahata, D.R. Mahapatra, S.V. Kailas, and K. Chattopadhyay. Multi-layer graphene reinforced aluminum – Manufacturing of high strength composite by friction stir alloying. *Composites Part B: Engineering*,136: 63–71, 2018. doi: 10.1016/j.compositesb.2017.10.028.

[14] C. Kostagiannakopoulou, X. Tsilimigkra, G. Sotiriadis, and V. Kostopoulos. Synergy effect of carbon nano-fillers on the fracture toughness of structural composites. *Composites Part B: Engineering*, 129:18–25, 2017. doi: 10.1016/j.compositesb.2017.07.012.

[15] G. Romhány and G. Szebényi. Preparation of MWCNT reinforced epoxy nanocomposite and examination of its mechanical properties. *Plastics, Rubber and Composites*, 37(5-6):214–218, 2008. doi: 10.1179/174328908X309376.

[16] G. Mittal, V. Dhand, K.Y. Rhee, S.J. Park, and W.R. Lee. A review on carbon nanotubes and graphene as fillers in reinforced polymer nanocomposites. *Journal of Industrial and Engineering Chemistry*, 21:11–25, 2015. doi: 10.1016/j.jiec.2014.03.022.

[17] S. H. Behzad, M.J. Kimya, G. Mehrnaz. Mechanical properties of multi-walled carbon nanotube/epoxy polysulfide nanocomposite. *Journal of Materials & Design*, 50:62–67, 2013.

[18] N. Yu, Z.H. Zhang, and S.Y. He. Fracture toughness and fatigue life of MWCNT/epoxy composites. *Materials Science and Engineering: A*, 494(1-2):380:384, 2018. doi: 10.1016/j.msea.2008.04.051.

[19] J.G. Park, et al. Thermal conductivity of MWCNT/epoxy composites: The effects of length, alignment and functionalization. *Carbon*, 50(6):2083–2090, 2012. doi: 10.1016/j.carbon.2011.12.046.

[20] B. Singaravel and T. Selvaraj. Optimization of machining parameters in turning operation using combined TOPSIS and AHP method. *Tehnički Vjesnik*, 22(6):1475–1480, 2015. doi: 10.17559/TV-20140530140610.

[21] N. Kaushik and S. Singhal. Hybrid combination of Taguchi-GRA-PCA for optimization of wear behavior in AA6063/SiC_p matrix composite. *Production & Manufacturing Research*, 6(1):171–189, 2018. doi: 10.1080/21693277.2018.1479666.

[22] S.O.N. Raj and S. Prabhu. Analysis of multi objective optimisation using TOPSIS method in EDM process with CNT infused copper electrode. *International Journal of Machining and Machinability of Materials*, 19(1):76–94, 2017. doi: 10.1504/IJMMM.2017.081190.

[23] S. Chakraborty. Applications of the MOORA method for decision making in manufacturing environment. *International Journal of Advanced Manufacturing Technology*, 54(9-12):1155–1166, 2011. doi: 10.1007/s00170-010-2972-0.

[24] M.P. Jenarthanan and R. Jeyapaul. Optimisation of machining parameters on milling of GFRP composites by desirability function analysis using Taguchi method. *International Journal of Engineering, Science and Technology*, 5(4):23–36, 2013. doi: 10.4314/ijest.v5i4.3.

[25] T.V. Sibalija. Particle swarm optimisation in designing parameters of manufacturing processes: A review (2008–2018). *Applied Soft Computing*, 84:105743, ISSN 1568-4946, doi: 10.1016/j.asoc.2019.105743.

[26] J. Kennedy and R. Eberhart. Particle swarm optimization. In *Proceedings of the ICNN'95 – International Conference on Neural Networks*, pages 1942–1948, Perth, Australia, 27 Nov.–1 Dec. 1995. doi: 10.1109/ICNN.1995.488968.

[27] F. Cus and J. Balic. Optimization of cutting process by GA approach. *Robotics and Computer-Integrated Manufacturing*, 19(1-2):113–121, 2003. doi: 10.1016/S0736-5845(02)00068-6.

[28] M.N. Ab Wahab, S. Nefti-Meziani, and A. Atyabi. A comprehensive review of swarm optimization algorithms. *PLoS One*, 10(5): e0122827, 2015. doi: 10.1371/journal.pone.0122827.

[29] A. Del Prete, R. Franchi, and D. De Lorenzis. Optimization of turning process through the analytic flank wear modelling. *AIP Conference Proceedings*, 1960:070008, 2018.doi: 10.1063/1.5034904.

[30] G. Xu and Z. Yang. Multiobjective optimization of process parameters for plastic injection molding via soft computing and grey correlation analysis. *International Journal of Advanced Manufacturing Technology*, 78(1–4):525–536, 2015. doi: 10.1007/s00170-014-6643-4.

[31] H. Juan, S.F. Yu, and B.Y. Lee. The optimal cutting parameter selection of production cost in HSM for SKD61 tool steels. *International Journal of Machine Tools and Manufacturing*, 43(7):679–686, 2003. doi: 10.1016/S0890-6955(03)00038-5.

[32] U. Zuperl and F. Cus. Optimization of cutting conditions during cutting by using neural networks. *Robotics and Computer-Integrated Manufacturing*, 19(1-2):189–199, 2003. doi: 10.1016/S0736-5845(02)00079-0.

[33] P.E. Amiolemhen and A.O.A. Ibhadode. Application of genetic algorithms – determination of the optimal machining parameters in the conversion of a cylindrical bar stock into a continuous finished profile. *International Journal of Machine Tools and Manufacture*, 44(12-13):1403–1412, 2004. doi: 10.1016/j.ijmachtools.2004.02.001.

[34] E.O. Ezugwu, D.A. Fadare, J. Bonney, R.B. Da Silva, and W.F. Sales. Modeling the correlation between cutting and process parameters in high-speed machining of Inconel 718 alloy using an artificial neural network. *International Journal of Machine Tools and Manufacturing*, 45(12-13):1375–1385, 2005. doi: 10.1016/j.ijmachtools.2005.02.004.

[35] P. Asokan, N. Baskar, K. Babu, G. Prabhakaran, and R. Saravanan. Optimization of surface grinding operation using particle swarm optimization technique. *Journal of Manufacturing Science and Engineering*, 127(4):885–892, 2015. doi: 10.1115/1.2037085.

[36] R.Q. Sardinas, M.R. Santana, and E.A. Brindis. Genetic algorithm-based multio-bjective optimization of cutting parameters in turning processes. *Engineering Applications of Artificial Intelligence*, 19(2):127–133, 2006. doi: 10.1016/j.engappai.2005.06.007.

[37] C. Jia and H. Zhu. An improved multiobjective particle swarm optimization based on culture algorithms. *Algorithms*, 10(2):46–56, 2017. doi: 10.3390/a10020046.

[38] C.A. Coello Coello, G.T. Pulido, and M.S. Lechuga. Handling multiple objectives with particle swarm optimization. *IEEE Transactions on Evolutionary Computation*, 8(3):256–279, 2004. doi: 10.1109/TEVC.2004.826067.

[39] C.R. Raquel and P.C. Naval. An effective use of crowding distance in multiobjective particle swarm optimization. In: *Proceedings of the 7th Annual Conference on Genetic and Evolutionary Computation*, pages 257–264, Washington DC, USA, 2005. doi: 10.1145/1068009.1068047.

[40] G.T. Pulido and C.A. Coello Coello. Using clustering techniques to improve the performance of a multi-objective particle swarm optimizer. In: *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO)*, pages 225-237, Seattle, USA, 2004. doi: 10.1007/978-3-540-24854-5_20.

[41] S. Mostaghim and J. Teich. Strategies for finding good local guides in multi-objective particle swarm optimization (MOPSO). In: *Proceedings of the 2003 IEEE Swarm Intelligence Symposium (SIS'03)*, pages 26–33, Indianapolis, IN, USA, 26 April 2003. doi: 10.1109/SIS.2003.1202243.

[42] J. Branke and S. Mostaghim. About selecting the personal best in multi-objective particle swarm optimization. In *Proceedings of the Parallel Problem Solving From Nature (PPSN Ix) International Conference*, pages 523–532, Reykjavik, Iceland, 9–13 September 2006. doi: 10.1007/11844297_53.

[43] T.M. Chenthil Jegan and D. Ravindran. Electrochemical machining process parameter optimization using particle swarm optimization. *Computational Intelligence*, 33:1019–1037, 2017. doi: 10.1111/coin.12139.

[44] C.P. Mohanty, S.S. Mahapatra, and M.R. Singh. A particle swarm approach for multi-objective optimization of electrical discharge machining process. *Journal of Intelligent Manufacturing*, 27:1171–1190, 2016. doi: 10.1007/s10845-014-0942-3.

[45] U. Natarajan, V.M. Periasamy, and R. Saravanan. Application of particle swarm optimisation in artificial neural network for the prediction of tool life. *The International Journal of Advanced Manufacturing Technology*, 31:871–876, 2007. doi: 10.1007/s00170-005-0252-1.

[46] A.K. Gandhi, S.K. Kumar, M.K. Pandey, and M.K. Tiwari. EMPSO-based optimization for inter-temporal multi-product revenue management under salvage consideration. *Applied Soft Computing*, 11(1):468–476, 2011. doi: 10.1016/j.asoc.2009.12.006.

[47] J.J. Yang, J.Z. Zhou, W. Wu, and F. Liu. Application of improved particle swarm optimization in economic dispatching. *Power System Technology*, 29(2):1–4, 2005.

[48] T. Sibalija, S. Pentronic, and D. Milovanovic. Experimental optimization of nimonic 263 laser cutting using a particle swarm approach. *Metals* 9:1147, 2019. doi: 10.3390/met9111147.

[49] X. Luan, H. Younse, H. Hong, G.P. Peterson. Improving mechanical properties of PVA based nano composite using aligned single-wall carbon nanotubes. *Materials Research Express*, 6(10):1050a6, 2019. doi: 10.1088/2053-1591/ab4058.

[50] H. Younes, R.A. Al-Rub, M.M. Rahman, A. Dalaq, A.A. Ghaferi, and T. Shah. Processing and property investigation of high-density carbon nanostructured papers with superior conductive and mechanical properties. *Diamond and Related Materials*, 68:109–117, 2016. doi: 10.1016/j.diamond.2016.06.016.

[51] G. Christensen, H. Younes, H. Hong, and G.P. Peterson. Alignment of carbon nanotubes comprising magnetically sensitive metal oxides by nonionic chemical surfactants. *Journal of Nanofluids*, 2(1): 25–28, 2013. doi: 10.1166/jon.2013.1031.

[52] H. Younes, M.M. Rahman, A.A. Ghaferi, and I. Saadat. Effect of saline solution on the electrical response of single wall carbon nanotubes-epoxy nanocomposites. *Journal of Nanomaterials*, 2017: 6843403, 2017 doi: 10.1155/2017/6843403.

[53] H. Younes, G. Christensen, L. Groven, H. Hong, and P. Smith. Three dimensional (3D) percolation network structure: Key to form stable carbon nano grease. *Journal of Applied Research and Technology*, 14(6):375–382, 2016. doi: 10.1016/j.jart.2016.09.002.

[54] J. Jerald, P. Asokan, G. Prabaharan, and R. Saravanan. Scheduling optimization of flexible manufacturing systems using particle swarm optimization algorithm. *The International Journal of Advanced Manufacturig Technology*, 25:964–971, 2005. doi: 10.1007/s00170-003-1933-2.

[55] M. Ghasemi, E. Akbari, A. Rahimnejad, S.E. Razavi, S. Ghavidel, and L. Li. Phasor particle swarm optimization: a simple and efficient variant of PSO. *Soft Computing*, 23:9701–9718, 2019. doi: 10.1007/s00500-018-3536-8.

[56] M.R. Singh and S.S. Mahapatra. A swarm optimization approach for flexible flow shop scheduling with multiprocessor tasks. *The International Journal of Advanced Manufacturing Technology*, 62(1–4), 267–277, 2012. doi: 10.1007/s00170-011-3807-3.

[57] H. Yoshida, K. Kawata, Y. Fukuyama, S. Takayama, and Y. Nakanishi. A particle swarm optimization for reactive power and voltage control considering voltage security assessment. *IEEE Transactions on Power Systems*, 15(4):1232–1239, 2000. doi: 10.1109/59.898095.

[58] F. Belmecheri, C. Prins, F. Yalaoui, and L. Amodeo. Particle swarm optimization algorithm for a vehicle routing problem with heterogeneous fleet, mixed backhauls, and time windows. *Journal of Intelligent Manufacturing*, 24(4):775–789, 2013. doi: 10.1007/s10845-012-0627-8.

[59] M. Bachlaus, M.K. Pandey, C. Mahajan, R. Shankar, and M.K. Tiwari. Designing an integrated multi-echelon agile supply chain network: a hybrid taguchi-particle swarm optimization approach. *Journal of Intelligent Manufacturing*, 19(6):747–761, 2008. doi: 10.1007/s10845-008-0125-1.

[60] B. Brandstatter and U. Baumgartner. Particle swarm optimization – mass-spring system analogon. *IEEE Transactions on Magnetics*, 38(2):997–1000, 2002. doi: 10.1109/20.996256.

[61] B. Kim and S. Son. A probability matrix-based particle swarm optimization for the capacitated vehicle routing problem. *Journal of Intelligent Manufacturing*, 23(4):1119–1126, 2012. doi: 10.1007/s10845-010-0455-7.

[62] C.H. Wu, D.Z. Wang, A. Ip, D.W. Wang, C.Y. Chan, and H.F. Wan. A particle swarm optimization approach for components placement inspection on printed circuit boards. *Journal of Intelligent Manufacturing*, 20(5):535–549, 2009. doi: 10.1007/s10845-008-0140-2.

[63] S.B. Raja and N. Baskar. Application of particle swarm optimization technique for achieving desired milled surface roughness in minimum machining time. *Expert Systems with Applications*, 39(5):5982–5989, 2012. doi: 10.1016/j.eswa.2011.11.110.

[64] N. Yusup, A.M. Zain, and S.Z.M. Hashim. Overview of PSO for optimizing process parameters of machining. *Procedia Engineering*, 29:914–923, 2012. doi: 10.1016/j.proeng.2012.01.064.

[65] R.L. Malghan, K.M.C. Rao, A.K. Shettigar, S.S. Rao, and R.J. D'Souza. Application of particle swarm optimization and response surface methodology for machining parameters optimization of aluminium matrix composites in milling operation. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 39(9):2541–3553, 2017. doi: 10.1007/s40430-016-0675-7.

[66] A. Hadidi, A. Kaveh, B. Farahmand Azar, S. Talatahari, and C. Farahmandpour. An efficient optimization algorithm based on particle swarm and simulated annealing for space trusses. *International Journal of Optimization in Civil Engineering*, 3:377–395, 2011.

[67] T. Chaudhary, A.N. Siddiquee, A.K. Chanda, and Z.A. Khan. On micromachining with a focus on miniature gears by non conventional processes: a status report. *Archive of Mechanical Engineering*, 65(1):129–169, 2018. doi: 10.24425/119413.

[68] D. Kumar and K.K Singh. An experimental investigation of surface roughness in the drilling of MWCNT doped carbon/epoxy polymeric composite material. *IOP Conference Series: Materials Science and Engineering*, 149:012096, 2016. doi: 10.1088/1757-899X/149/1/012096.

[69] Niharika, B.P. Agrawal, I.A. Khan, and Z.A. Khan. Effects of cutting parameters on quality of surface produced by machining of titanium alloy and their optimization. *Archive of Mechanical Engineering*, 63(4):531–548, 2016. doi: 10.1515/meceng-2016-0030.

[70] N.S. Kumar, A. Shetty, Ashay Shetty, K. Ananth, and H. Shetty. Effect of spindle speed and feed rate on surface roughness of carbon steels in CNC turning. *Procedia Engineering*, 38:691–697, 2012. doi: 10.1016/j.proeng.2012.06.087.

[71] E.T. Akinlabi, I. Mathoho, M.P. Mubiayi, C. Mbohwa, and M.E. Makhatha. Effect of process parameters on surface roughness during dry and flood milling of Ti-6A-l4V. In: *2018 IEEE 9th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT)*, pages 144–147, Cape Town, South Africa, 10-13 February 2018. doi: 10.1109/ICMIMT.2018.8340438.

[72] J.P. Davim, L.R. Silva, A. Festas, and A.M. Abrão. Machinability study on precision turning of PA66 polyamide with and without glass fiber reinforcing. *Materials & Design*, 30(2):228–234, 2009. doi: 10.1016/j.matdes.2008.05.003.

[73] J. Cha, J. Kim, S. Ryu, and S.H. Hong. Comparison to mechanical properties of epoxy nanocomposites reinforced by functionalized carbon nanotubes and graphene nanoplatelets. *Composites Part B: Engineering*, 162:283–288, 2018. doi: 10.1016/j.compositesb.2018.11.011.

[74] R.V. Rao, P.J. Pawar, and R. Shankar. Multi-objective optimization of electrochemical machining process parameters using a particle swarm optimization algorithm. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 222(8):949–958, 2008. doi: 10.1243/09544054JEM1158.

[75] R. Farshbaf Zinati, M.R. Razfar, and H. Nazockdast. Surface integrity investigation for milling PA6/ MWCNT. *Materials and Manufacturing Processes*, 30(8):1035–1041, 2014. doi: 10.1080/10426914.2014.961473.

[76] I. Shyha, G.Y. Fu, D.H. Huo, B. Le, F. Inam, M.S. Saharudin, and J.C. Wei. Micro-machining of nano-polymer composites reinforced with graphene and nano-clay fillers. *Key Engineering Materials*, 786:197–205, 2018. doi: 10.4028/www.scientific.net/kem.786.197.

[77] G. Fu, D. Huo, I. Shyha, K. Pancholi, and M.S. Saharudin. Experimental investigation on micro milling of polyester/halloysite nano-clay nanocomposites. *Nanomaterials*, 9(7):917, 2019. doi: 10.3390/nano9070917.