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Review Article

Effective utilization of optimization algorithms on machining operations

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Optimization is ruling the entire field of machining and material processing technology from the time at which the revolution took place in machining processes. Various types of machining algorithms have been developed so far for optimizing the independent control factors in order to get the improved results of desirable output responses. Each algorithm has its own special features which made them useful in deriving the optimized solutions under different conditions. Suitable algorithm is chosen for the required case depending upon the nature of the problem, the requirement of the order of precision and the availability of optimization tools. In this review article, the general flow of few important algorithms has been explained in a simpler manner to be understood by the recent researchers. Also, required numbers of case studies for each algorithm have been provided extensively. This consolidated work will surely be helpful for the new researchers those who have entered into the domain of optimization.

Keywords: Optimization, Machining Processes, Fire-fly Algorithm (FA), Artificial Bee Colony (ABC) algorithm, Teacher learner based algorithm, Particle swam optimization technique

1 Introduction

Optimization is a widely used phenomenon in every technical sector in order to obtain the better desirable results over the processes. For performing the optimization process, several algorithms have been developed by various researchers for varieties of conditions. By understanding the logic and entire concept of each algorithm, one can select the suitable algorithm for their case[1].

In a general optimization problem, there will be a well-defined objective function for the chosen output factors of interest and a specified set of constraints for the considered input factors. Optimization algorithms have been broadly categorized into two types– (i) derivative based, and (ii) derivative free based types. Another one classification of optimization algorithms are as follows[2]:

- Deterministic optimization algorithms – In this type of algorithms, a defined rule has been followed for selecting the points in between the processes without randomization.
- Stochastic optimization algorithms – In this type, no definite rule has been followed for choosing the points between the working range; the points have been selected randomly. Hence, while performing the optimization process for a same case, one may obtain the solution with few slight changes in the second time.

Based on the nature of usage, optimization algorithms have been classified into the following types:

- Single variable optimization algorithms
- Multi variable optimization algorithms
- Constrained optimization algorithms
- Specialized optimization algorithms, and
- Non-traditional optimization algorithms.

One more classification of optimization algorithms based on the initial solution chosen has been presented below[2]:

i. Local search algorithms and
ii. Global search algorithms.

It is very important to correctly choose the suitable algorithm for the specified case in order to expect better results. That is the motivation behind this review work on various optimization algorithms.

2 Materials and Methods

A bulk of literatures related to the applications of optimization algorithms for different cases were considered for the study. If one can go through this review work, they can get a clear idea about how to choose the suitable algorithm for their case and the detailed methodology of such algorithm. Totally ten numbers of repetitive leading algorithms were selected and studied in detail, which are listed below.

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- Artificial Bee Colony (ABC) Algorithm
- Teaching – Learning Based Optimization (TLBO) Algorithm
- Particle Swarm Optimization Algorithm (PSOA)
- Grey Relational Analysis (GRA)
- Regression Analysis (RA)
- Genetic Algorithm (GA)
- Fire-Fly Algorithm (FA)
- Artificial Neural Network (ANN) Technique
- Integrated Genetic Algorithm And Artificial Neural Network
- Taguchi Optimization Algorithm

3 Results and Discussion

3.1 Artificial Bee Colony (ABC) Algorithm

ABC algorithm is too simple to follow. This algorithm has been utilized in many fields such as supply chain management, production scheduling, clustering, vehicle routing problem and large scale optimization cases in engineering discipline[3]. For complex cases, Genetic algorithm took more time to converge than ABC algorithm[4]. The methodology to be followed for ABC algorithm is presented in the flowchart shown in Fig. 1. Artificial Bee Colony algorithm is completely based on the combined behavior of the self-organized systems. It was initially used for optimizing multi variable continuous functions[5]. Researchers have reported that this algorithm provided comparatively better results among the population based optimization algorithms; also, it consumed very less amount of computation time in comparison with other algorithms[6,7]. ABC algorithm could be used for solving assignment problems, travelling salesman problem, job shop scheduling problem etc[8].

Ajorlou *et al.*[4] used ABC algorithm to predict the optimal work in process (WIP) inventory level and also the optimal sequence of processes to reduce overall processing time. They used a production line simulator developed in MATLAB to design a high degree nonlinear dynamics of the line of production and to assess the solutions. Rodriguez *et al.*[9] used ABC algorithm to optimize the weighted completion time in scheduling of unrelated parallel machine problems. The authors considered 12 identical instances for processing ‘n’ jobs on ‘m’ machines. The algorithm was implemented in C++; and the compilation of C++ source code with gcc 4.5 was performed. Pawar *et al.*[10] performed a multi-objective optimization work for minimizing the kerf width, minimizing the kerf taper, and maximize the depth of striation free surface during abrasive water jet machining process using ABC algorithm. Tang *et al.*[11] proposed a weighted extreme learning machine (WELM) based on hybrid artificial bee colony algorithm to obtain better performance than WELM, in which input weights and hidden bias of WELM and the weight assigned to training samples were optimized using hybrid artificial bee colony algorithm**.**. Wang *et al.*[8] proposed an efficient ABC algorithm to optimize the completion time of a flexible job shop scheduling problem. For that, the authors utilized different combination of strategies in the first step to form the initial solution as food sources. Further, they developed mutation and crossover operators to form the neighbor sources for employed bees. Followed by, a local search approach was proposed based on critical path to strengthen the

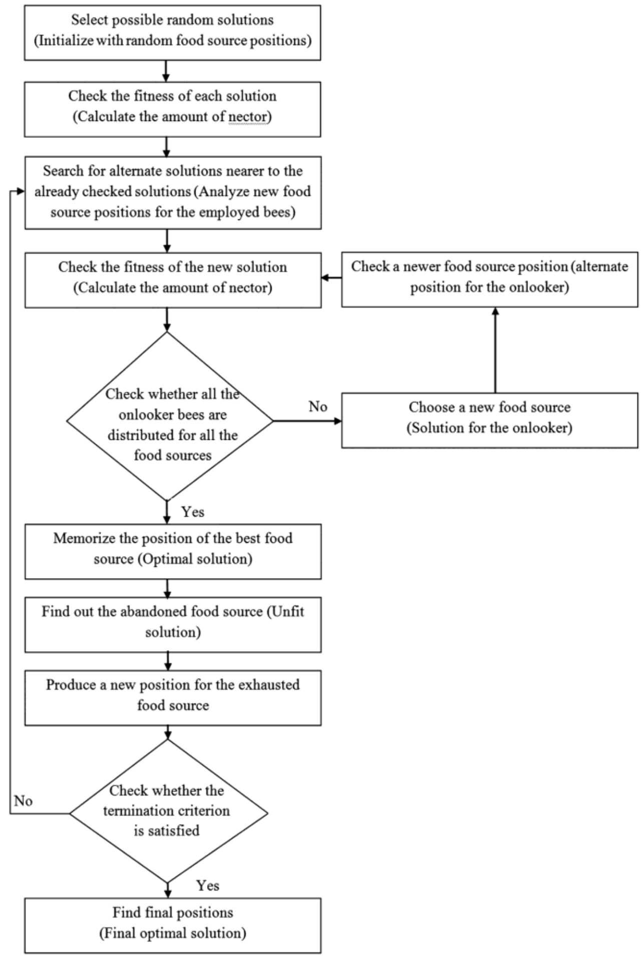

Fig. 1 — Methodology of ABC algorithm.

capability of the onlooker bees. In the mean time, a mechanism of population with the initial strategy was proposed to strengthen the searching behavior. Also, a left shift decoding method was used to transform solutions to an active schedule. Yusup *et al.*[6] used ABC algorithm to optimize the selective control factors such as water jet pressure, abrasive grit size, traverse speed, abrasive flow rate and standoff distance to get low value of surface roughness for Abrasive Water Jet machining process. The authors reported that the surface roughness values obtained by applying ABC algorithm were lower than that of the experimental analysis. It was observed that the output results obtained from ABC algorithm was completely fit with the input factors[6]. Penalty function is one of the efficient approaches to manage distinct constraints involved in an optimization problem. There are several kinds of penalty function methods such as static, dynamic, annealing, interior and exterior penalty functions. Jawad *et al.*[12] used exterior penalty function to eliminate the need of choosing the initial feasible solution while using ABC algorithm in optimizing the size and layout of truss structures.

3.2 Teaching – Learning Based Optimization (TLBO) Algorithm

Teaching – learning based optimization algorithm imitates the regular teaching – learning process happening in a regular classroom. This algorithm was proposed by Rao. The efficiency of this algorithm is based on the influence of the teacher on the results from the students. The researchers havedescribed this algorithmas accurate, efficient and nature inspired optimization tool[13]. This algorithm took very small amount of computational time with better satisfactory results.Two major phases are there in TLBO – Teacher phase and learner phase.

<u>Teacher phase</u> – As a normal teacher can be considered as the highest knowledgeable person in a classroom who tries to improve the efficiency of the students, the best results given by the sample is considered as teacher phase in TLBO[3,13].

<u>Learner phase</u> – How the learners in a class learn the things from the teacher and other students; in TLBO also, the results of the samples are compared with the best results and results of other samples and then updated. Then the optimal result is obtained by calculating the difference between the best result and the mean of the results of all other samples[3,13].

This algorithm has been used for analyzing many mechanical designs like pressure vessel, open coil and closed coil helical springs, welded beam structures, gear trains, etc.,; various machining processes like Wire-cut EDM, abrasive jet machining process, ultrasonic machining process, etc.,; and few casting processes like continuous casting, squeeze casting, die casting, etc.,[14]. The flow of process of TLBO is provided in a neat flow chart shown in the Fig. 2. In Fig. 2, ‘r’ refers to the random factor which lies between ‘0’ and ‘1’; ‘T_F’ refers to Teaching Factor. Dikshit *et al.*[15] used teaching – learning based algorithm for getting the optimal cutting parameters of ball – end milling process. In their work, the cutting parameters were considered as subjects; and population size was considered as learners.

The objective function for this case was set as

Minimize: Surface roughness, R_a (control factors – feed, cutting speed, axial depth of cut and radial depth of cut)[15].

Lin *et al.*[16] tried an attempt to quantify and optimize the cutting parameters of turning operations causing carbon emission. The researchers used TLBO for optimizing the operation time and cutting parameters causing carbon emission simultaneously. The major causes for the carbon emission during the machining operation were considered to be (i) energy conversion for the machining operation, (ii) energy conversion for the material processing, (iii) energy conversion for the removal of materials and (iv) energy conversion for the cutting tools. In the proposed work, different solutions were obtained by modifying the initial population values until the large difference between the initial and final solution occurred. With the help of pareto optimal frontier curves, the solutions for different attempts were compared. Patel *et al.*[17] used TLBO for optimizing the yield strength value, ultimate strength value and surface roughness value of the specimen produced by the hybrid squeeze casting process. Response function was chosen as,

$$Maximize\ Z = \{(W_1*YS)+(W_2*1/SR)+(W_3*UTS)\}.$$

where,

W_1, W_2 and W_3 represent the weight fractions of the responses,
YS – Yield Strength,

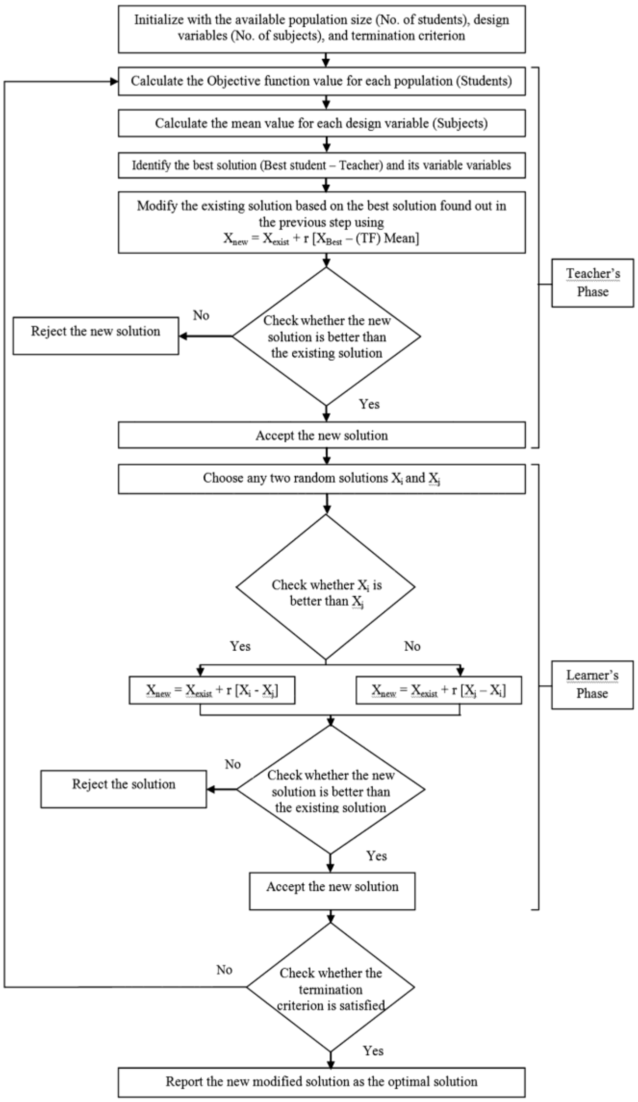

Fig. 2 — General steps in Teacher – learner based optimization algorithm.

SR – Surface Roughness,

UTS – Ultimate Tensile Strength.

Pawar *et al.*[18] explained the adaptability of TLBO for optimizing the independent control factors of abrasive water jet machining, grinding and milling processes.

(i) For the case of abrasive water jet machining process, the objective function was set as,

Maximize Z = material removal rate,

$= d_{awn} f_n (h_c + h_d)$

where, d_{awn} – diameter of abrasive water jet nozzle,
f_n – feed rate of nozzle,
h_c – indentation depth due to cutting wear, and
h_d – indentation depth due to deformation wear.

a Five control factors were considered as pressure of water jet at the exit of nozzle, nozzle feed rate, mass flow rate of water, diameter of abrasive water jet and mass flow rate of abrasive particles with the constraints.

b Similarly, for grinding process, the objective function was chosen as'minimize the production cost and maximize the rate of production' with the constraints of four process parameters as speed of work piece, depth of cut, speed of wheel and dressing lead.

c In case of optimizing the milling process parameters such as speed, feed and depth of cut to get optimal production time, constraints were fixed and the optimal results were obtained with the help of TLBO. Chen wang *et al.* proposed a modified teaching learning based algorithm for optimizing the weights and threshold of Direct Neural Networks. The authors performed the proposed operation by following the phases – (a) Algorithms initialization with the teaching formula, (b) From the results of teacher, update the results of students, (c) Learning phase, and (d) the termination condition[19]. In case of having more number of below average learners in a classroom, the convergence of getting optimal solutions took more time, where the need of some modifications arised. In this approach, number of students is allotted in number of groups. Number of teachers also may be more than one. By doing like this, the diversity of the algorithm gets improved.

3.3 Particle Swarm Optimization Algorithm (PSOA)

Particle Swarm Optimization Algorithm (PSOA) wasinitially used by Eberhart and Kennedy in 1995, which works out based on movement of intelligent swarms of birds in order to obtain the optimal objective function within the working space.[20] While following this algorithm, solutions of different possible trials are concurrently collaborated, which are termed as particles. Those particles will fly over the entire searching space to fit with the optimal solution by the experience of them as well as the experience of neighbor particles. The process gets continued till the iteration process gets converged. Usually, PSOA has been employed for optimization problem in three different phases: (i) PSOA – original[21], (ii) PSOA – Inertia Weight and (iii) PSOA – Constriction factor. Researchers haveexpressed that this algorithm is very easy to followand which provides comparably better results with other population algorithms[21-23]. Since this algorithm does not contain crossover and mutation operators, which converges the iteration faster than that of Genetic Algorithm[24].

The three different factors of PSOA are explained below:

PSOA – Cognitive: This constraint helps to faster the movement of the particle to the better location by its own skill and experience, which has been termed as 'pbest'.

PSOA – social: This constraint controls the movement of swarms followed by other neighbor swarms within the working space, and which has been denoted by 'gbest'.

PSOA – Inertia: This constraint is used to maintain the stability between the individual instants (pbest) with the overall investigation (gbest) within the search space[25].

PSOA has various factors such as range of particles, number of particles, local vs global values, learning factor and dimension of the particles[26]. The step by step procedure to be followed in Particle Swarm Optimization Algorithm has been presented in Fig. 3.

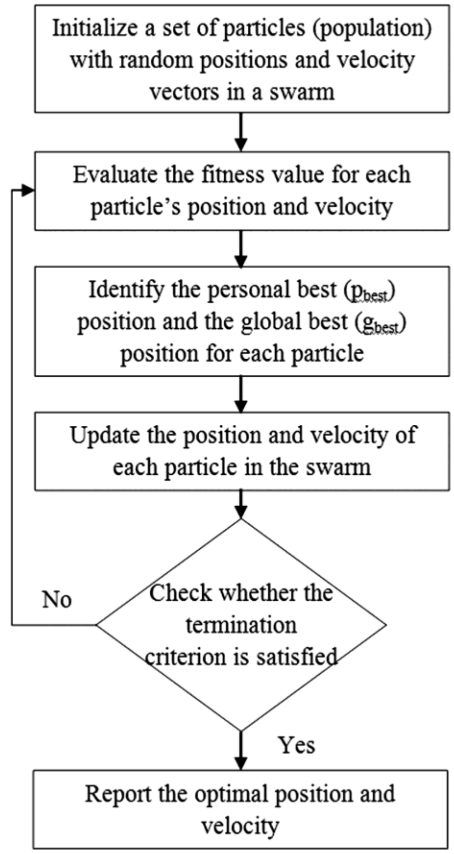

Fig. 3 — Particle swarm optimization algorithm – procedure

Majumder *et al.*[27] optimized the process parameters of EDM process for AISI 316LN stainless steel for getting the desirable output responses such as Material Removal Rate (MRR) and Electrode Wear Ratio (EWR) with the help of PSOA. Since the developed PSOA – original was with poor convergence ability, it could not be used for the efficient optimization process, where as PSOA – Constriction factor (CF) phase was fitted with better convergence capability, in turn the optimal solution was arrived with the help of particle swam optimization – Malghan *et al.*[25] tried an attempt on face milling process parameters optimization on AA6061 such as spindle speed, feed and depth of cut. The output responses considered in that work were cutting force, power consumption and surface roughness. For the validation purpose, the authors compared the solutions obtained from PSOA with the solutions of desirability approach, and it was reported that PSOA yielded better results over the desirability approach.

Low *et al.*[26] proposed a PSOA to solve the single-machine scheduling problem with periodic maintenance activities. The research results revealed that the proposed algorithm was quite satisfactory on both solution accuracy and efficiency to solve the addressed problem. Janahiraman & Ahmad[28] performed an optimization process on CNC turning process parameters using particle swarm optimization algorithm. In their proposed attempt, the authors coupled Extreme Learning Machine (ELM) technique with PSOA for having efficiently modeled process. By applying GUI (Graphical User Interface) in Matlab software pack, the optimization algorithm was implemented and the optimal results were obtained successfully.

3.4 Grey Relational Analysis (GRA)

Grey Relational Analysis (GRA) was developed and proposed by Deng[29]. GRA has been preferred for multi objective optimization cases in which optimal combination of independent factors is required for more than one dependent factor simultaneously[30,31]. Depending upon the nature of output responses required, the normalization of output responses are calculated under three criteria: larger – the better, smaller – the better and nominal – the better[32,33].In the calculation of Grey Relational Coefficient values, a specific constant value is defined, known as 'identification coefficient' or 'distinguishing coefficient', which is incorporated to express the relationship between the comparability and reference sequences whose value is normally set as 0.5[34,35]. Grey system refers the system which has very few data with incomplete details[36]. This approach has been used by various researchers in variety of fields for optimization problems even in medical field[37]. Figure 4 shows the step by step procedure to be followed for using GRA[38,39].

Angappan *et al.*[40] used GRA for predicting the better results for surface roughness, cutting power, cutting force and material removal rate for dry turning condition on CNC machine with Incoloy 800 H material. L27 orthogonal array tablewas used for performing the experimentations. Further, the authors performed Analysis of Variance to predict the influence of each input factors on the output responses. Gopalsamy *et al.*[41] dealt with an optimization study on hard machining and milling process with hardened steel. GRA results revealed the optimal combination of input factors such as speed, feed, width of cut and depth of cut. The maximum and minimum values of the Grey Relational Grade values revealed the significance level of the combination of input factors. The verification test results confirmed the results suggested by the Grey Relational Analysis technique. Pragadish *et al.*[42] analyzed the influence of the selected dry EDM process parameters on the desirable output responses such as material removal rate and surface finish. The results showed that 12 Ampere discharge current, 200 micro seconds pulse on time, 60 V voltage, 2.5 kilo Pascal pressure combination yielded the optimal solution corresponding to the highest grey relational grade.

Ranganathan *et al.*[43] performed a multi objective optimization with the hot turning process parameters on Type-316 Stainless Steel material using GRA. With the help of Grey Relational Analysis, the authors converted the multi objective phenomenon to single objective optimization; in turn, theyidentified the optimal combination as 113.1 m/min cutting speed, 0.381 mm/revolution feed rate, and 400^{0}C working temperature. Sindhu *et al.*[44] simplified a multi response problem by optimizing the process parameters of rotary ultrasonic machining process using Grey Relational analysis. The authors reported that main effect plots drawn followed by Taguchi

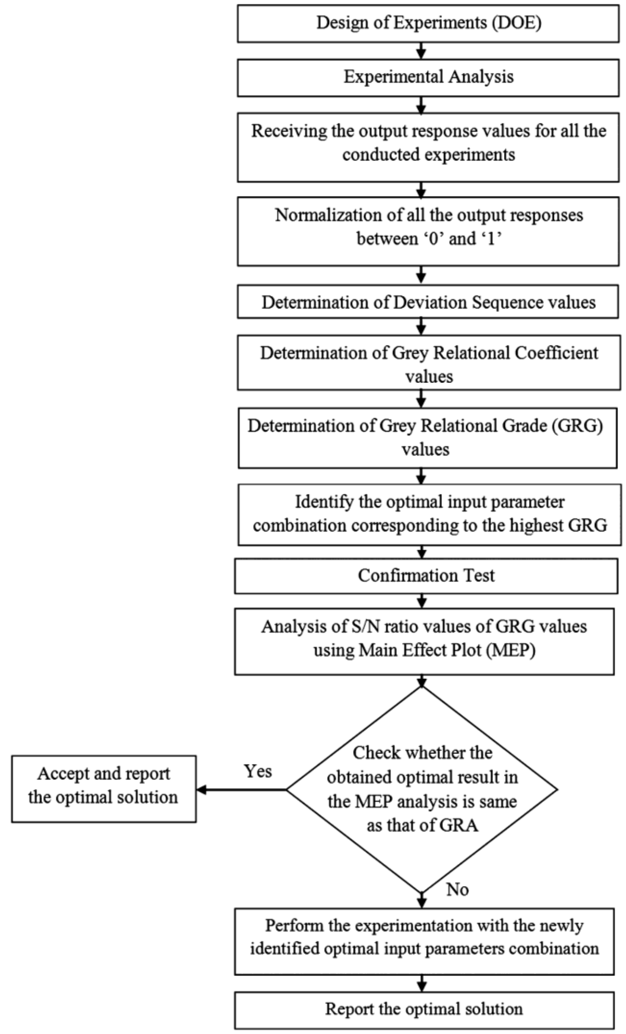

Fig. 4 — Grey Relational Analysis – Methodology.

method using Minitab software pack resembled the solution of GRA. ANOVA test also was used by the authors in order to view the effect of each individual factor on the output responses.

Singh[45] used GRA to optimize the Electrical Discharge Machining process parameters for Al6061/Al_2O_3p/20P composite material. While normalizing the output responses for determining the Grey Relational Grade values, larger – the better criterion was preferred for Material Removal Rate and smaller – the better criterion was preferred for tool wear rate and Surface Roughness values. Tsao employed Taguchi based Grey Relational Analysis for optimizing the milling process parameters for Al6061/T651 alloy materials. The results yielded the precised optimized results which were ensured by conducting two numbers of confirmation tests. The author reported from the results that flank wear got reduced from 0.177 to 0.067 mm and surface roughness value from 0.44 to 0.24 μm by employing Taguchi based GRA[46].

3.5 Regression Analysis (RA)

Regression analysis is used to correlate the bond between the dependent and independent parameters of the considered process[47,48]. Hence, in simple regression analysis, two types of variables are used such as a single controllable variable and a single output variable, whereas with the help of Multiple Regression model, one can relate multiple input factors with the output responses[49,50]. The general regression model is as follows:

$$y_i = a_0 + a_1 x_i + a_2 y_i + a_3 z_i + a_4 x_i y_i + a_5 x_i^2 +$$

where,

y_i - Output response,

a_0, a_1, a_2,…… - Constant values,

x_i, y_i, z_i - input variables at their i[th] level.

The general procedure being followed in Regression analysis has been detailed below:

(i) Select the process parameters and complete the experimentation using Taguchi approach / full factorial design
(ii) Set the order of polynomial equation
(iii) Select the desirable pair of input factors
(iv) Check the regression model which has been generated
(v) If the generated regression model has its determination coefficient R^2 value nearer to '1', the model can be finalized and accepted.
(vi) Otherwise, go to step (ii)
(vii) The same process will get continued till the more accurate regression model getsgenerated

Many researchers have used Central composite design in Response Surface Methodology (RSM) for the purpose of developing multi regression models. The generated regression models will be more accurate if they are generated with more number of experimental data set[51].

Aydin *et al.*[52] used SPSS v17 software for performing multi regression analysis for the prediction of kerf angle with the input data for the variables traverse speed, mass flow rate of abrasive particles and standoff distance for water jet machining process. It was reported that the actual results obtained from the experimentation were perfectly matched with that of the results obtained from the proposed regression model. Kalidass & Palanisamy[53] developed an optimized regression model for surface roughness values for the end milling process against the proposed combinations of input parameters such as feed, helix angle, speed and depth of cut. The results obtained from the model were compared with the corresponding experimental results and reported that there was only 5% of deviation between the results. Kovac *et al.*[54] modeled a regression equation for the surface roughness value on the finished product out of the face milling process. Totally, 30 numbers of experiments were conducted and the results were presented. As the numbers of levels of the selected parameters were high, the regression model generated had 10.91% deviation from the actual results. Kuntal Maji *et al.*[55] performed a non-linear regression analysis on the EDM process for developing output-input relationships. The authors developed a second order optimized regression model with the R-squared value of 0.978. As the value of R-squared value was nearer to '1', the authors ensured the reliability and adaptability of the generated model. Palanisamy *et al.*[56] tried an attempt for predicting a relationship model for the output – input factors of end milling process by eliminating the least significant combinations. Maximum percentage of error noted between the results of actual experimentation and the regression model was about 4.37%. Radhakrishnan *et al*.[57] developed an empirical model for cutting force measurement in an end milling process. The author optimized the proposed model after crossing various trials. The final model was used for developing and training Artificial Neural Networks.

3.6 Genetic Algorithm (GA)

Genetic Algorithm was developed by John Holland which imitates the evolutionary process in solving the optimization problems. GA follows the functions of chromosomes for producing new populations or further generation. This recombination cum new production process will get continued until a same set of consequent baby chromosomes get produced[58]. GA is developed with different components such as,

- Chromosome encoding,
- Fitness function,
- Selection of chromosomes,
- Recombination of chromosomes, and
- Evolution of baby chromosomes[59].

The following step by step procedure is followed in a standard Genetic Algorithm problem[60].

(i) Generate a set of source populations randomly with the followings:

a) Crossover probability – which indicates the measure of the combination of chromosomes going to be made.

b) Mutation probability – which is the probability of selecting a chromosome randomly.

c) Offspring – which is the product of combining information of two parent chromosomes[61].

(ii) Estimate the fitness function for all the chromosomes in the source populations.

(iii) Generate a null successor population and iterate by following the below steps.

a) Choose a set of chromosomes (2 chromosomes) from the initial population with the help of fitness selection

b) Obtain the value of fitness function for the selected combination of chromosomes

c) Modify the successor population after arriving at the results of baby populations just by adding.

d) Continue the same procedure again and again till the iteration process gets converged, i.e., the values of consequent successor populations are the same[62].

Chan *et al.*[63] developed agenetic algorithm - based approach to machine assignment problem (MAP). Yu *et al.*[61] used genetic algorithm to solve the hybrid flow shop (HFS) scheduling problem and to minimize the total down time. In HFS, two or more machines can be kept at one stage which can introduce flexibility, increase capacity and avoid bottleneck. This work targeted the HFS with unrelated machines and machine eligibility constraints. The proposed algorithm considered practical uncertainties and it incorporated a new decoding method that was developed for total lateness objective, which enabled a tight scheduling and guaranteed the influence of the chromosome (Considered Parameters) on the schedule. A genetic algorithm involves encoding and decoding; in which decoding is a major factor that decides the solution quality[64]. Wu *et al.*[65] used modified genetic algorithm based on Boolean code for optimizing the layouts of turbines in the wind farm. As wind is the major renewable and reliable source of energy, wind farms are constructed in large scale and there is low power generation in downstream turbines when compared to upstream turbines that share higher wind speed which is called wake effect. Wake effect causes 10 – 20% losses in power generation[66]. Roychoudhri *et al.*[67] considered a manufacturing scheduling problem in automotive stamping operations, which is an essential element in modern day manufacturing process as it has high production rates and low labor cost. In this work, a mathematical program involving single machine problem was considered with known demand and production constraints. The chosen problems involved stamping dies and die set up with limited storage availability. Branch and bound (B&B) were shown to be inefficient in terms of computational time for relevant problem sizes. Hence, genetic algorithm was utilized with generalized earliest due dates (GAGEDD)[68]. Silva *et al.*[69] optimized the power loss in Poly-V belt transmissions which was majorly used in the front side of engines to transmit power from crankshaft to various accessories with the help of genetic algorithm. Optimization of the power loss has helped in reduction of fuel consumption. Recent regulations regarding automobiles have pushed all the car and truck manufacturers to reduce the loss in engine, which can be majorly done by reducing the belt transmission losses. This idea was first initiated by Gerbert. Lubarda[70] reported that several power losses regarding belt transmissions have been recorded by various researchers such as vibration, belt friction, etc., Robinson *et al.*[71] worked on the optimization of gerotors for kinematics and wear with the help of genetic algorithm.

A multi-objective optimization was performed using Genetic algorithm to effectively minimize the size, flow ripple, adhesive wear, and subsurface fatigue wear of circular-toothed gerotor gears. Call[58] explained how to use Genetic Algorithm for solving certain medical problems relevant with immunology field. Various components used in GA and the standard methodology for performing GA for general case were detailed. In addition to that, the author described the way in which the artificial immune system will be generated in order to solve the specific optimization problems.

3.7 Fire-Fly Algorithm (FA)

Fire-fly algorithm follows the way of the attractive flashing nature of fire flies[72]. FA has two significant advantages over the relevant algorithms – (i) automatic subdivision capacity and (ii) capacity of processing with multi-modality. This approach is completely based on a physical law that the emitting light intensity of two flies is inversely proportional to the second order of the distance between those flies[73]. Johari *et al*.[74] and his colleagues worked on a review paper on applications of firefly algorithm (FA) in various domains of optimization problems. FA is the most commonly used algorithm to solve computer science and engineering problems. Some of them have been enhanced or hybridized to arrive at better solutions. FA was developedby getting inspired from the flashing behaviour of the fireflies and bio-luminescent communication between them.

- FA was developed by Yang in 2008 is a very efficient method to solve NP-hard problems and constrained optimization problems[75].
- Luthra *at al.*[76] introduced a hybrid algorithm by combining FA and genetic algorithm to solve mono alphabetic substitution cipher.
- Falcon *et al.*[77] used a hybrid algorithm known as Harmony-Seeking Firefly Algorithm (HSFA) which was developed by hybridizing FA with Harmony Search (HS) to obtain nearly-optimal solution.
- Horng *et al.*[78] introduced FA in Radial Basis Function (RBF) Network and the results werefound to be comparable with that of the Gradient Descent (GD), Particle Swarm Optimization and ABC algorithms.
- The results obtained using hybridized FA techniques were of more efficient and consumed less processing time than simple FA[74].

The common methodology of FA is represented in detail in the following table 1.

Table 1 — Methodology to be followed in Fire-fly algorithm

Steps	Description
I	Specify the desirable objective function for the considered case.
II	Initialize the number of fire-flies and their exact location within the specified constraints.
III	Determine the value of objective function of each fire-fly (i.e., the intensity of light)
IV	Select the fire-fly which has maximum value of intensity.
V	Determine the distance of all the fire-flies from the fire-fly which is having maximum value of light intensity; Also, the positions of each fire-fly need to be modified correspondingly.
VI	Again, calculate the intensity value of all the fire-flies within the field.
VII	Ranke of the position of fire-flies based on the intensity of emitted light.
VIII	Choose the best fire-fly from the previous step.
IX	Iteration process should be continued till the maximum limit is reached.

Shukla and Singh[79] used firefly algorithm for selecting the parameters for advanced machining processes. High precision machining is the demand of the day and hence manufacturers opt for advanced machining processes which are also the only possible way to machine complex geometries and intricate profiles. The objective of this work was set to arrive at the optimum parameters for two advanced machining processes viz. Electric Discharge Machining (EDM) and Abrasive Water Jet Machining (AWJM). The firefly algorithm (FA) was attempted to the considered processes to obtain optimized level of parameters and the results obtained were compared with the results reported by previous researchers[80].In both the processes, the obtained results showed a significant improvement in the responses. The applicability and effectiveness of FA can be extended to other advanced machining processes to get the optimal results. Yang[81] proposed that Firefly algorithm (FA) is the most efficient algorithm among the metaheuristic algorithms for multi model optimization problems. The author performed an optimization study using FA and also compared the results with that of the other few algorithms such as genetic algorithm and PSO. On comparison, Firefly algorithm was proven to be the most effective one for optimization problems in both effectiveness and success rate. It was reported that it is possible to improve the quality of the solution by reducing the randomness.

Zhang *et al.*[82] proposed an improved firefly algorithm for collaborative manufacturing chain optimization. Cloud manufacturing (CMfg) is a new service oriented manufacturing system which can provide on-service demand for producers and can deploy online machining resources. In CMfg, distributed resources are enclosed into a cloud platform as service providers. The concept of collaborative manufacturing chain (CMC) was proposed to conduct the sharing and deployment of service resources. CMC is inter-enterprise resource integration proposed to reduce production cost, shorten production cycle and improve product quality. Fuzzy analytical hierarchy process was adapted to add the above multi-criteria model to a single objective problem. Then, an improved firefly algorithm was used to solve a reasonable collaborative manufacturing chain scheme. Particle swarm optimization (PSO) was alsoincorporated with firefly algorithm to make it even more effective. Compared with the genetic algorithm, numerical results suggested that the improved firefly algorithm has more advantages in convergence speed and solving efficiency Xu *et al.*[83] proposed an improved firefly algorithm (FA) for feature selection in classification[83].

Guyon *et al.*[84] proposed an improved firefly algorithm. An improved FA wasemployedas opposition-based learning in population initialization and opposition strategy in the searching process which fastened the convergence rate to obtain the global optima. Pan *et al.*[85] proposed a new and efficient version of Firefly algorithm (FA)since the conventional firefly algorithm had slow convergence rate and less precised solutions. In the new efficient fire-fly algorithm (NEFA),an adaptive parameter strategy was employed to eliminate the problems that arise due to step factor α. In NEFA, three modified strategies were employed. First, a new attraction model that is used to determine the number of attracted fireflies was developed. Second, a new search operator was designed for some better fireflies. Third, the step factor was dynamically updated during the iterations. Hence it was concluded that NEFA will outperform all other forms of FA[85].

3.8 Artificial Neural Network (ANN) Technique

ANN is an optimization tool which imitates the function of neurons of human brain[86]. The technique carries three different layers such as input layer, hidden layer and output layer. The relationship between the input factors and output factors are provided through the hidden layer. The updated output results are received at the output layer. The artificially developed Neural Networks improve their skills by learning from the surrounding. Neuron is the basic unit of ANN, which has the function resembling a biological neuron. The input conditions given to neurons are consolidated and conveyed to the neighbor neuron by the activation functions addressed. The level of the knowledge transferred to a neuron is represented by a weight function[87].

It was observed that the recent researchers have utilized ANN approach for analyzing the effect of control factors of machining processes on surface roughness of the final product.ANN technique holds many advantages such as easily adaptable capability, robustness, generalization, etc., Several factors influence the effective function of artificially developed Neural Networks like selection of proper control factors, assortment of quantum of hidden layers, weight function, etc., ANN will train up themselves from the provided input factor details[88].

This technique is best suitable for non – linear problems. Palavar *et al.*[89] used ANN tool for the computation of aging effects on the wear rate of 706 Inconel alloy material; and reported that ANN provided excellent results. Rao and Murthy[90] investigated the effect of cutting factors on surface roughness with stainless steel and exclaimed about the results that ANN tool provided better response over Response Surface Methodology model.

3.9 Integrated Genetic Algorithm And Artificial Neural Network

GA and ANN concepts have been widely used for optimization purpose by various researchers. Few research works have been done with integrating both of them in order to get efficient optimization results. Researchers have mentioned that this integration of GA and ANN methodology is more efficient than Response Surface Methodology (RSM) especially for complex models. This sort of integration models have been developed and utilized for various machining operations such as face milling, cutting and turning. Amit Kumar Gupta *et al.*[91] made an attempt to optimize the dominant turning process parameters with the help of integrated genetic algorithm with ANN. The authors reported that this type of analysis could be used in any sort of industrial sector to get the optimal results for surface roughness and tool wear. The results revealed that Genetic algorithm provided improved results when it was integrated with ANN which trained the data in a proper manner. Sedighi *et al.*[92] developed an integrated GA – ANN model for optimizing the creep feed grinding process parameters to obtain better results for Material Removal Rate and Surface Roughness. For integrating Genetic algorithm and Artificial Neural Network concepts for this case, sequence of program instructions was created by the authors. The authors reported from the research results that the integrated GA – ANN concept is preferable in obtaining the optimal combination of process parameters for creep feed grinding process. Also, they revealed that their integrated system could be modified to use for other few metal cutting processes such as grinding, turning, etc. The authors integrated GA and ANN for their work by following the step by step processes as explained in the flow chart presented in the Fig. 5.

Zhao *et al.*[93] proposed a new approach of hybridizing Genetic algorithm and ANN for job shop scheduling problem. The authors exclaimed that the searching efficiency of GA and parallel computability

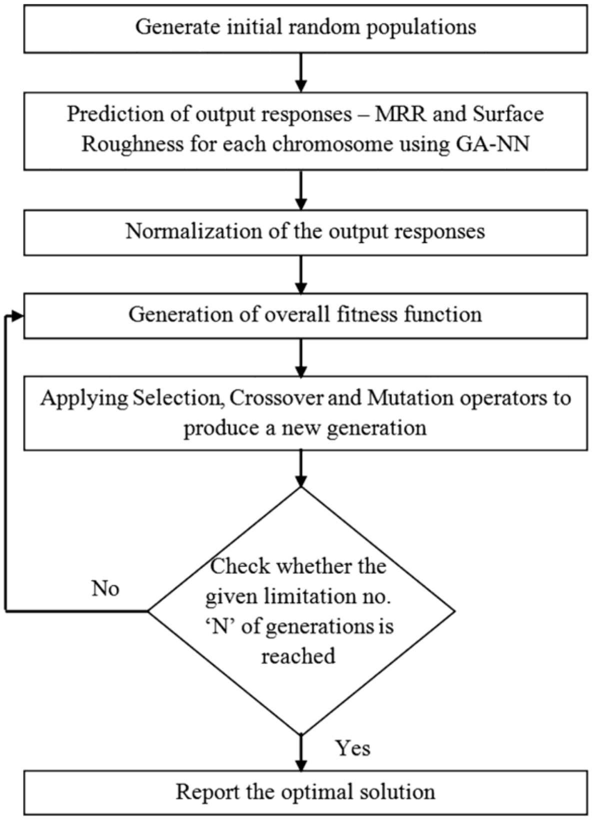

Fig. 5 — Methodology followed for integrating GA and ANN for creep feed grinding process[92]

of ANN makes this integration more efficient. Also it wasreported that the operational time consumed by this integration approach was less in comparison with that of the ANN approach. The methodology followed by the authors for the integration of GA and ANN is provided in the flowchart shown in the Fig. 6.

3.10 Taguchi Optimization Algorithm

Researchers havereported that Taguchi method – integrated with Grey Relational Analysis yielded better results for multi – objective optimization problems[94]. Taguchi method uses an orthogonal array table which reduces the number of experiments to be actually conducted and leads to fractional factorial experimentation[95]. Kopac *et al.*[96] used Grey based Taguchi method for optimizing the flank milling parameters on machining of Aluminium alloy casting plates for injection moulds. Tsao[46] employed grey based Taguchi optimization method on milling parameters optimization with A6061P-T651 alloy for multi objective optimization.

Haq *et al.*[97] performed optimization on drilling parameters with Al/SiC composites with the help of

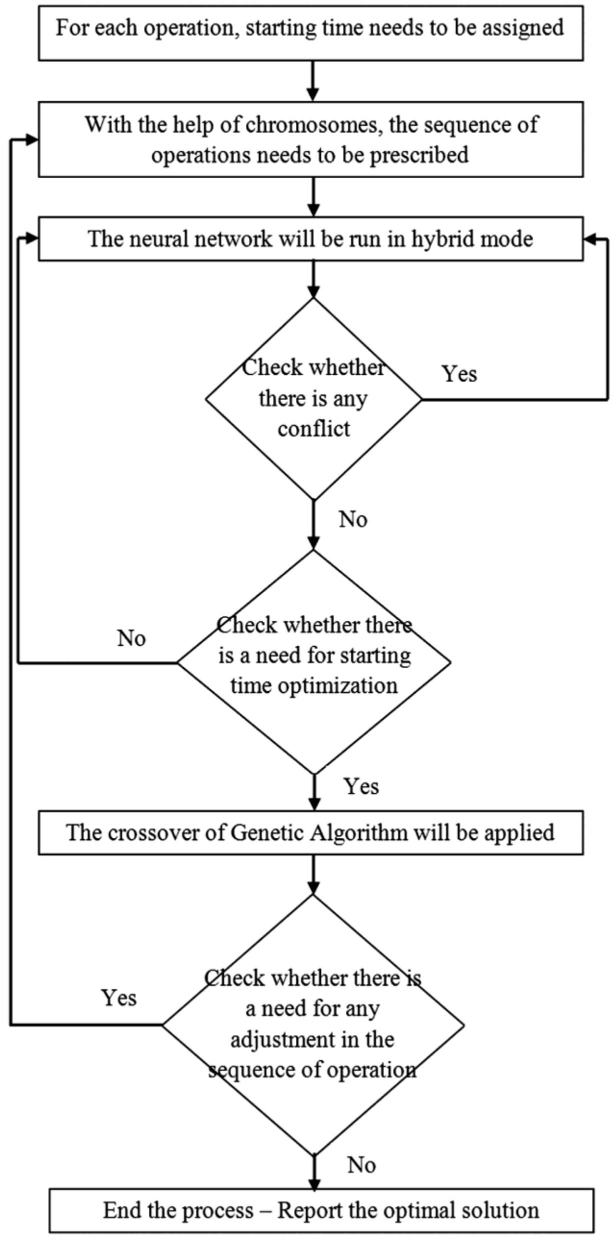

Fig. 6 — Integration of GA and ANN for job shop scheduling problem[93]

GRA cum Taguchi method. Okl¨u[98] carried out multi objective optimization work with the continuous cylindrical grinding process on AISI 4140 steel using grey-based Taguchi method. Kurt *et al.*[99] applied Taguchi method for the optimization of dry drilling process parameters. By employing Taguchi technique, Kuram *et al.*[100] optimized surface roughness, cutting force and tool wear of micro milling process on AISI 304 stainless steel. The general methodology of Taguchi method is presented in Fig. 7.

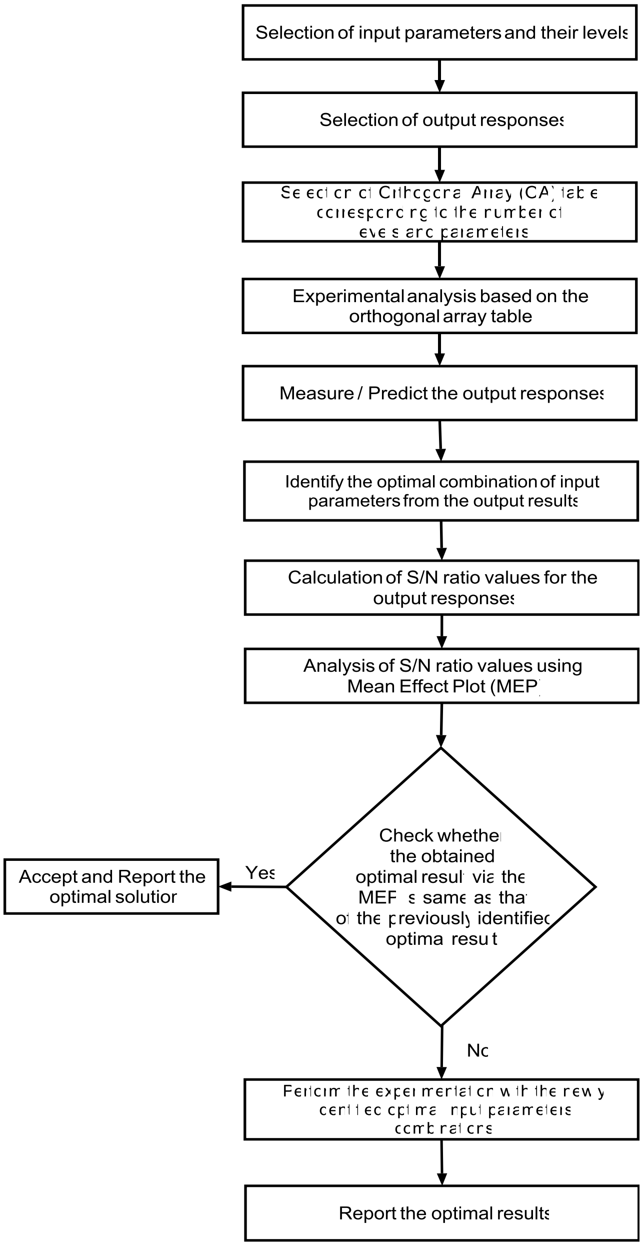

Fig. 7 — Taguchi optimization technique – Methodology

4 Conclusion

This extensive review work has detailed different kinds of optimization algorithms so far repetitively used by various researchers, the general methodologies of those algorithms, and the hybridization of such algorithms with other algorithms. The various application areas of different optimization algorithms have been elaborated. Further, the significant points given by the researchers after the interpretation of their results have been provided under specific conditions. The comparison of accuracy of results obtained by different algorithms for the similar machining operations will yield better understanding and guidance to the researchers to follow appropriate algorithms for their cases. Definitely, this collective work will be helpful to the future researchers those who need to choose suitable optimization algorithms for their research investigations on distinct machining operations.

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