Application of Multi-objective Genetic Algorithm (MOGA) Optimization in Machining Processes

Nor Atiqah Zolpakar, Swati Singh Lodhi, Sunil Pathak and Mohita Anand Sharma

Abstract Multi-objectives Genetic Algorithm (MOGA) is one of many engineering optimization techniques, a guided random search method. It is suitable for solving multi-objective optimization related problems with the capability to explore the diverse regions of the solution space. Thus, it is possible to search a diverse set of solutions with more variables that can be optimized at one time. Solutions of MOGA are illustrated using the Pareto fronts. A Pareto optimal set is a set of solutions that are non-dominated solutions frontier. With the Pareto optimum set, the corresponding objective function's values in the objective space are called the Pareto front. The conventional methods for solving multi-objective problems consist of random searches, dynamic programming, and gradient methods whereas modern heuristic methods include cognitive paradigm as artificial neural networks, simulated annealing and Lagrangian approcehes. Some of these methods are managed in finding the optimum solution, but they have tendency to take longer time to converge so that need much computing time. Thus, by implementing MOGA approach that based on the natural biological evaluation principle will be used to tackle this kind of problem. In this chapter authors attempts to provide a brief review on current and past work on MOGA application in few of the most commonly used manufacturing/machining processes. This chapter will also highlights the advantages and limitations of MOGA as compared to conventional optimization techniques.

Keywords Design-of-experiment · Machining · Genetic algorithm · Optimization

N. A. Zolpakar · S. S. Lodhi · S. Pathak (✉)
Faculty of Engineering Technology, Universiti Malaysia Pahang, Lebuhraya Tun Razak, 26300 Gambang, Kuantan, Pahang Darul Makmur, Malaysia
e-mail: sunilpathak@ump.edu.my; sunilpathak87@gmail.com

M. A. Sharma
IMS UNISON University, Mussoorie Diversion Road Makkawala Greens, Dehradun, Uttarakhand 248009, India

K. Gupta and M. K. Gupta (eds.), *Optimization of Manufacturing Processes*, Springer Series in Advanced Manufacturing, https://doi.org/10.1007/978-3-030-19638-7_8

1 Introduction

In the manufacturing field, the ultimate objectives are to produce high quality product with minimum cost and time constrains. In manufacturing field, the common step applied to produce a product is machining [1]. In some cases, a single product needs to undergo different types of machining processes to come into its final shape, size, and form. The success of machining operation in terms of best combination of productivity, machinability, cost and sustainability can only be achieved when perform under optimum set of process parameters. To accomplish this objective, one of the consideration methods is optimization techniques. For machining optimization, there are two main methods which are conventional or classical technique (Design of Experiment (DOE), and Mathematical Iterative Search) and modern or advanced Technique (Meta-Heuristic Search and Problem Specific Heuristic Search). Figure 1 presents various optimization tools and techniques used in the past research for optimization of machining parameters. A review of past work based on implementation of conventional techniques such as machining theory, experiment investigation (parametric study), and DOE etc. has been reported in [2]. For this chapter, the focus is on optimization of machining process using Genetic Algorithm (GA).

Genetic algorithms are exceptionally well known heuristic techniques which have been effectively utilised to address optimization issues of machining. Genetic algorithm approves the consistency of the numerical model. For example, when company gets a large order, planner in the company needs to schedule and come out with a gantt chart for the particular product. In the Gantt chart, the information related machining and process is stated. The Gantt chart also represents the connection activities, time, and cost to be spent by production line. This step involves a lot of parameters such

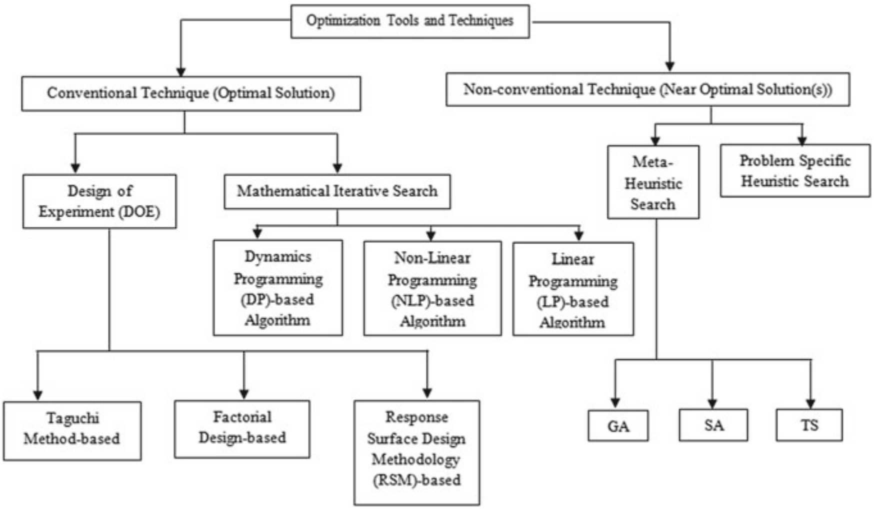

Fig. 1 Conventional (classical) and non-conventional (advanced) optimization techniques [3]

as machining time for every geometry, time for changing tools, surface roughness, and power consumtion. The function of GA is to find the combination of parameters to obtain a set of parameters that produces the optimum results. GA is one of the advanced techniques based on meta-heuristic search. One of the advantages of GA optimization including avoid converging into local minimum/maximum and instead this algorithm is able to find global minimum/maximum in the search space. Besides that, GA algorithm has capability to optimize more than one parameters in a single algorithm. This characteristic is important to apply in machining processes since machining process has a lot of parameters that need to be optimized such as spindle speed, feed rate, depth of cut, and axial angel of cutting etc.

Parameter selection is a critical part in optimizing the machining process in order to attain effective machining operation [4]. The selection of parameters typically based on the human judgement and experience. Due to that, most of the time, the selected process parameters does not provide an optimal result due to the fact that each of the parameters interrupt the process in getting optimum performance and quality. In fact, each machining parameter significantly affect other parameters as well. Based on that fact, a number of researchers used meta-heuristic search such as GA in their optimization (see Table 1). The following section will further discusses about application of GA optimization in machining process.

2 Genetic Algorithm (GA)

Genetic algorithm (GA) which was initially introduced by John Holland in 1975, is one of the classes for transformative algorithms that have been widely utilized in optimization problems. In spite of the fact that it is normal and conceivable to take care of issues with single target work, significant advantages of using GA are as follow:

- Real-life engineering problems usually demand for more than one objective functions and the GA is used to analyze various objective functions simultaneously.
- More than one parameter can be optimized.
- Optimization results are represented in the Pareto front form. It shows the combination of parameters with the values of objective function/s.
- Optimization results remain in the domain of the search area. Users have agility to define the size of the search area, and this avoids extreme results.

Today, due to the involvement of more complex engineering systems and processes, the optimum solutions are mainly trade-off based, where it is on the user description to select the appropriate and preferable decision criteria [37]. In GA optimization, if the algorithm has more than one objective functions, and one function is more important than the other, in that case the user needs to declare this by assigning weightage for every function. This new scheme of evaluating competing solutions without the necessity to determine relative importance weights, has given rise to multi-objective genetic algorithms (MOGA). In literature, MOGA has been

Table 1 Summary of past work based on GA optimization in machining process (2010–2018)

No.	Researcher	Process para meter	Machining process	Machining performance measure
1	Sekulic et al. [5]	Spindle speed, feed per tooth, axial depth, and radial depth	Ball-end milling	Surface roughness
2	Shukla and Singh [6]	Transverse speed, standoff distance, and mass flowrate	Abrasive wafer jet machining	Kerf top width and angle
3	Sangwan and Kant [7]	Cutting speed, feed, depth of cut	Turning	Energy consumption
4	Kumar et al. [8]	Cutting speed, feed rate, depth of cut, type of cutting tool	Turning	Surface finish
5	Kant and Sangwan [9]	Cutting speed, feed rate, depth of cut	Drilling milling	Surface roughness
6	Li et al. [10]	Speed, feed per tooth, width and depth of cut	Milling	Tool life, residual stress and surface roughness
7	Santos et al. [11]	Cutting speed, feed rate, depth of cut	Turning	Machining force, chip thickness ratio, and chip disposal
8	Manesh et al. [12]	Spindle speed, feed rate, axial depth of cut, and radial depth of cut	End milling	Surface roughness, MRR
9	Sahali and Serra [13]	Cutting speed, depth of cut	Turning	Production time
10	Sangwan et al. [14]	Cutting speed, depth of cut and feed rate	Turning	Surface roughness
11	Shivasheshadri et al. [15]	Speed and feed rate	Milling	Machining time
12	Agrawal and Varma [16]	Speed, feed	Milling	Surface roughness
13	Durairaja and Gowri [17]	Speed, feed, and depth of cut	Micro tuning	Surface roughness
14	Petkovic and Radovanovic [18]	Cutting speed and feed	Turning	Production cost
15	Selvam et al. [19]	Number of passes, cutting depth, spindle speed, and feed rate	Face milling	Surface roughness

(continued)

Table 1 (continued)

No.	Researcher	Process para meter	Machining process	Machining performance measure
16	Rai et al. [20]	Axial depth of cut, radial immersion, feed rate and spindle speed	Multi-tool milling	Machining time
17	Zeng et al. [21]	Rotate speed, speed and depth of cutting	N/A	Surface roughness
18	Gao et al. [22]	Bonding wear, feed per tooth and axial depth of cut	High speed machining	Cutting force, tool life
19	An et al. [23]	Speed, feed rate, depth of cut, and the number of passes	Multi-pass milling	Production cost
20	An [24]	Speed, feed rate and depth of cut	Multi-pass milling	Production cost
21	Kilickap et al. [25]	Cutting speed, feed rate, and cutting environment	Drilling	Surface roughness
22	Kuruvila and Ravindra [26]	Pulse-on and off duration, current, bed-speed and flushing rate	WEDM	Dimension error, surface roughness, volumetric MRR, production time
23	Ganesan et al. [27]	Depth of cut, cutting speed and cutting rate	Multi-pass turning	Production time
24	Xie and Guo [28]	Depth of cut, cutting speed and cutting rate	Multi-pass turning	Production cost
25	Zain et al. [29]	Cutting speed, feed rate, and radial rake angle	End milling	Surface roughness
26	Zain et al. [30]	Traverse speed, waterjet pressure, standoff distance, abrasive flow rate	Abrasive waterjet machining	Surface roughness
27	Zain et al. [31]	Cutting speed, feed rate and radial rake angle	End milling	Surface roughness
28	Zain et al. [32]	Radial rake angle, cutting speed and feed	End milling	Surface roughness

(continued)

Table 1 (continued)

No.	Researcher	Process para meter	Machining process	Machining performance measure
29	Sultana and Dhar [33]	Feed rate, pressure, flow rate and high pressure coolant	Turning	Chip reduction coefficient and surface roughness
30	Yongzhi et al. [34]	Axial depth-of-cut, radial depth-of-cut and helical angle	High speed milling	Cutting force, metal removal rate
31	Pasam et al. [35]	Ignition pulse current, short pulse duration, time between two pulses, servo speed, servo reference voltage, injection pressure, wire speed and wire tension	Wire electrical discharge machining	Surface roughness
32	Ansalam Raj and Narayanan Nambodiri [36]	Feed, speed rate, and depth of cut	NC milling	Surface roughness

reported superior compared to other classical algorithms [38]. In recent years, the GAs in machining application have been used by a number of researchers to find the optimal surface quality in various traditional and modern machining [5, 8, 9, 17]. Besides of surface roughness, many researchers applied GA optimization for minimize production cost and production time [13, 24, 27]. There are some variants of GA, some of the most commonly used in machining are as follows:

(a) ***Factual Coded Genetic Algorithm (FCGA)***: In FCGA, every gene signifies to a variable of the problem, and the extent of the chromosome is kept the same as the length of the response for the issue. In this way, FCGA can manage substantial areas without compromising with its accuracy as the binary execution. Moreover, FCGA has the ability with regards to the nearby tuning of the responses; it additionally permits integrating the domain knowledge in order to enhance the execution of Genetic Algorithm (GA).
(b) ***Binary coded Genetic Algorithm***: Binary coded Genetic Algorithm (BCGA) is a probabilistic search algorithm that iteratively changes a set (called as a population) of numerical items (typically settled length paired character strings), each associated with a fitness value, into another populace of posterity objects utilizing the Darwinian rule of regular choice and utilizing activities that are designed after normally happening genetic tasks, for example, hybrid (sexual recombination) and transformation. Following the model of development, they build up a population of individual, where every individual relates to a point in the hunt space. A target work is connected to every person to rate their wellness.

(c) ***Differential Evolution***: Differential Evolution (DE) tries to supplant the traditional hybrid and transformation plans of the genetic algorithm (GA) by elective differential administrators. The DE algorithm has as of late turned out to be very famous in the machine insight and computer science network. Much of the time, it has beaten the GA or the particle swarm enhancement (PSO). As in other developmental algorithms, two basic processes drive the advancement of a DE populace: the variety procedure, which empowers investigating the diverse districts of the inquiry space, and the determination process, which guarantees misuse of the obtained information about the wellness scene.
(d) ***Least Mean Square Algorithm***: Least mean squares (LMS) algorithms are utilized in versatile channels to discover the channel coefficients that identify with delivering the minimum mean squares of the blunder flag (difference between the desired and the actual signal). It is a stochastic inclination drop technique in which the channel is versatile in view of the blunder at the present time. The LMS algorithm can be actualized without squaring, averaging or separation and is a basic and effective process.
(e) ***Sawtooth Genetic Algorithm***: Various strategies have been produced to enhance the heartiness and computational proficiency of GAs. A straightforward GA utilizes a populace of consistent size and aides the development of an arrangement of haphazardly chose people through various ages that are liable to progressive determination, hybrid, and transformation, in view of the measurements of the age (standard GA). Population (data set) size is one of the principle parameters that influence the power and computational productivity of the GAs. Little populace sizes may result in untimely merging to non-ideal arrangements, while extensive populace sizes give a significant increment of computational exertion. A few strategies have been proposed in the writing that endeavors to build the decent variety of the populace and maintain a strategic distance from untimely merging.

2.1 GA Methodology

The GA algorithm start with randomly created initial population. Initial population is created by randomly form binary number. Every set of binary code that represent the solution is called chromosome. The length of the chromosome, L, is equal to the number of the bit in the string. There are $2^L - 1$ possible solution for selection and each solution is presented by L-bit binary code of chromosome, C. The optimization began with initialisation of a chromosome that contains the parameters to be optimized. A general representation is shown below:

$$C_k = [X_{k1},\ X_{k2}, \ldots X_{kn}]$$

$$C_k = [\underbrace{|110 \ldots 00|}_{X_1}\underbrace{|101 \ldots 1|}_{X_2}\underbrace{|001 \ldots 11|}_{X_3}\underbrace{|110 \ldots 11|}_{X_4}]$$

Where X is represent the parameters that need to be optimized. From this initial population, a population that has a better representation of the strong species generated through selection process.

In GA, the selection process is based on the best individual performance on fitness function. The performance evaluation is depended on the fittest objective function. For minimization optimization problem, individual's chromosome with a smaller value of the fitness function will have higher possibilities selected for producing offspring. In the aforesaid explanation, the selection process is one in which the individuals that undergo genetic operations and come out with the offspring solutions. The selection has two primary objectives:

1. To choose the fittest individuals chromosome that can be directly copied for the next generation (elitism).
2. To give a chance to individual's chromosome with the fitness function that relatively bad value to partake in the process of the subsequent generations. To accomplish this, the observation of the global character of the search process is needed by not allowing a single individual dominate the population.

The selection process will create the intermediate population. The intermediate population is allowed to mate through cross-over and to modify through mutation and thus produce the next set of population. In the crossover operator, two solutions (parent) are chosen in the mating pool and at random point of string and some portion of the string are switched between the two solutions to create a new solution or offspring.

Parents	Offspring
0 1 1 0 | 0 1 1 1 | 0 1 0	0 1 1 1 | 0 1 1 1 | 0 1 0
0 0 1 1 | 0 1 1 1 | 0 0 0	0 0 1 0 | 0 1 1 1 | 0 0 0

Meanwhile, the mutation operator modifies a string locally to expectantly generate a better string. The bit-wise mutation process necessitates the construction of a random number for every bit. This procedure is repeated until the termination condition is reached [39]. Population is a collection of chromosomes that randomly initialized. The population get more fit with the search progress. The two operators that improve the population fitness are crossover and mutation. The flowchart of GA algorithm is shown in Fig. 2. The step-by-step procedure to apply GA in optimizing machining processes are listed as follow:

i. The selected parameters are encoded from real number to binary by binary encoding.
ii. A chromosome is performed by combination of a set of genes which this set is used to perform crossover and mutation.

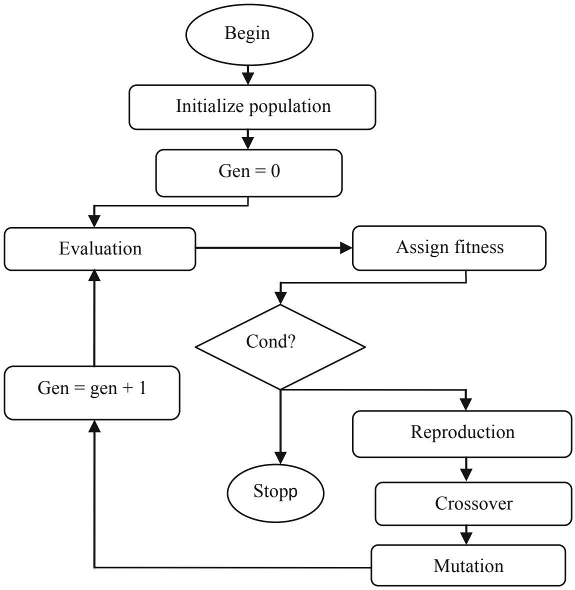

Fig. 2 Flowchart of GA optimization

iii. Crossover operator will combine two chromosomes from population to form new chromosome that called offspring. The offspring chromosome expected to have better genes compared to the parent. As the crossover operator applied, the good chromosome will appear in the population and provide an overall good solution.
iv. Mutation is the process that applied after crossover operation. The mutation operator will apply random changes into a string of chromosome. The mutation process will help to overcame trapping at local minima.
v. The evaluation of chromosome is determinate by encoding from binary codes of chromosome to machining parameters values that can be used to estimate the machining performance.
vi. Objective function or fitness function is the function that needs to be maximize/minimize in the machining operation. This function must contain all the parameters that need to be optimized. The values of fitness function can be used as indication whether the parameters to be optimized or not.
vii. The iteration of the algorithm will continue until certain stopping criterion is made. One of the stopping criteria usually used is when value of fitness function of previous generation is less than 1×10^{-7} with the subsequent generation.

2.2 GA in Machining Applications

GA algorithm has the ability to optimize more than one parameter and more than one objective function simultaneously. This characteristic is very crucial in machining performance by optimizing several machining parameters to satisfy one or more objective functions. Moreover, in machining processes, machining conditions have an effect on diminishing the production cost and time and choosing the nature of the end product. To discover ideal cutting parameters amid a turning/milling/drilling/advanced machining procedure, the genetic algorithm has been successfully implemented. Process optimization needs to yield the least production time while thinking about innovative and material limitations. Target work is to decide the ideal machining parameters amid a machining procedure that limits the production time without disregarding any forced cutting imperatives. In the present work authors have tried to summarize few of the articles where MOGA has been used as optimization tool for machining application. From the review it was observed that majority of the work in machining was done to optimize the surface quality in terms of finish by optimizing machining conditions (almost 56%), production cost and time (almost 28%) and others such as cutting tool life span and energy consumption takes the stake of 16% as presented in Fig. 3.

Various researchers have done work using artificial intelligence for optimization of manufacturing and machining processes. This includes optimization of conventional machining such as turning, milling, cutting and drilling, and advanced machining techniques which includes electrochemical machining, electrical discharge machining, wire-electrical discharge machining and many more. The optimization has been used either to optimize the performance or improve the production cost and productivity. Aggarwal and Singh [2] have presented a detailed review on optimization of machining techniques using advanced optimization techniques including details of methodology and implementation of genetic algorithm (GA). Evolutionary algorithm and its comparison with various optimization techniques have been presented by Alberto et al. [39]. They have also developed new pareto rankings and compared them with the conventional methods.

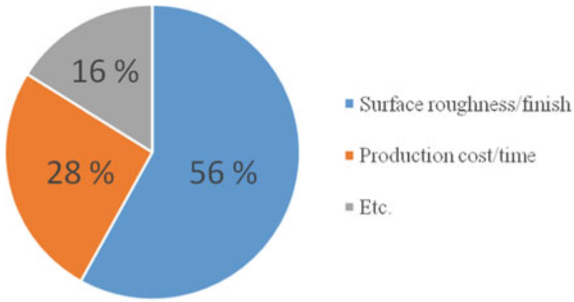

Fig. 3 Distribution of the research objectives in the previous study (2010–2018)

In the most recent work Sekulic et al. [5] have used response surface methodology (RSM), genetic algorithm (GA) optimization and grey wolf optimizer (GWO) algorithm for optimization of in ball end milling for prediction of surface roughness of hardened steel. They used predefined reduced-quadratic model as a benchmark model to develop GA and GWO algorithm. There results suggest 89.58% accuracy for GA model for training and testing data. Shukla and Singh [6] have used Taguchi method and Evolutionary optimization techniques in abrasive jet machining to optimize the transverse speed, stand-off distance and mass flow rate for attaining optimum values of kerf-top width and taper angle. They also used regression analysis to correlate the data of experimental findings. Sangwan and Kant [7, 14] have used integrated response surface methodology with genetic algorithm to optimize the energy efficiency in machining of AISI steel in turning, they also used GA to optimize the surface finish of the workpiece in turning operation. Sangwan and Kant [9] found experimental values and predicted results quite close with mean relative error is 4.11% showing fine accurateness in predicting the surface roughness values in ANN model joined with GA.

Kumar et al. [8] used GA to optimize the surface finish of the aluminum alloy composite. They praise the capabilities of GA in optimization of independent process parameters of machining methods. Multi-objective study on turning operation to find optimum cutting conditions for aluminium alloy using GA was done by Santos et al. [11]. Their study involves optimization of cutting speed, feed rate, and depth of cut on various inter related responses namely machining force, chip thickness ratio (CTR), and chip disposal. Durairaja and Gowri [17] had obtained the optimized cutting conditions for both surface roughness and tool wear by optimization of process parameters and statistical modeling using the multi objective genetic algorithm with valid experimental results. Petkovic and Radovanovic [18] obtained with minimal cost for the turning process, optimal parameters of machining (cutting speed and feed) were determined. Similar outcome was obtained during the use of GA checked by SQP (Sequential Quadratic Programming) algorithm and of machining cost, cutting speed and feed found with the GA.

According to Gao et al. [22], it was very essential to logically optimize cutting parameters prior to machining while the cutting force and tool wear have significantly reduced and cutting efficiency improved.

Training, testing and application subsequent to optimized 300 steps was adapted by Zeng et al. [21] resulting with the test error less than 2.6% with average relative error tended to saturation training was 4.0%.

Similarly, Sahali and Serra [13], Sultana and Dhar [33] and various other researchers have used GA as primary optimization tool to optimize the machining condition and responses in turning operations. The non-traditional algorithms were formulated by Ganesan et al. [27] where the optimal machining parameters for the continuous profile, GA and PSO have been employed. PSO produces better results with minimized time and Xie and Guo [28] have used GA to optimize the parameters in multi-pass turning for different materials, the complexity of optimization if multi-pass turning has been effectively eased by using GA.

Genetic Algorithm has been effectively used in optimization of milling parameters, many researchers have used to identify the optimum combination of parameters of milling using GA to obtain best results. Santos et al. [11] showed significant effect on the responses by the results of the input parameters acting both individually or in combination with each other. Li et al. [10] solved the multi-objective optimization problem by non-dominated sorting genetic algorithm-II (NSGA-II) and the Pareto-optimal solutions was obtained. The relative errors of surface roughness, tool life, and residual stress were less than 7, 5, and 5%, respectively after comparison of optimized results and experimental results.

Machining time was reduced by minimizing the negative effect to the part quality by Shivasheshadri et al. [15]. Initially required machining parameters (speed, feed and depth of cut) were given and 3D model was created which was undergone by five milling operations (facing, cornering, pocketing and two slot milling). Agrawal and Varma [16] proposed that GA can attain better-quality solutions to other metaheuristics to optimize the parameters of other machining processes (drilling and unconventional machining). By using RSM within the specified limits the optimal surface roughness value can be attained. The genetic algorithm (GA) model was trained and tested in MATLAB by Manesh et al. [12] to discover the best possible cutting parameters leading to least surface roughness (recommended 0.25 μm). Selvam et al. [19] used Taguchi technique that was fine-tuned with Genetic algorithm for finding Optimum machining parameter combination. The surface roughness evaluated through genetic algorithm it was 0.88 μm with 4.625% error from the predicted value and for Taguchi technique was 0.975 μm with 4.308% error from the predicted value. The different methods (integer programming, genetic algorithms and nonlinear programming) were used by An et al. [24] for obtaining optimal values of machining parameters. They match up the results from the literature and machining data handbook. Approximation algorithms used by An [23] developed the methods useful to optimize grinding and drilling type processes. The optimal cutting conditions were analyzed and obtained by Zain et al. [29] that yielded 0.138 μm as the minimum surface roughness value. The GA technique has reduced 27% of the least surface roughness value of the experimental sample data, 26% of regression modeling and 50% of response surface methodology technique. The R_a value was compared by Zain et al. [31] at about 26.8% to the experimental, 25.7% regression, 26.1% ANN and 49.8% response surface method in the reduced ANN–GA integration system. It was as well establish in comparison to the conventional GA result that integrated ANN–GA reduced the mean R_a value at about 0.61% and the number of iterations in searching for the optimal result at about 23.9%. Zain et al. [30] proposed that by means of the integrated SA–GA, the time for penetrating the optimal solution can be made quicker. A full-factorial experimental design and multi-linear regression technology were used by Yongzhi et al. [34] for developing the predictive model of surface roughness, for obtaining minimum cutting force and reasonably good metal removal rate it was possible to select optimum axial depth-of-cut, radial depth-of-cut and helical angle. Rai et al. [20] also have used multi-objective genetic algorithm (MOGA) for optimization of parameters of milling namely Speed, feed rate, depth of cut, radial rake angle and the number of passes on surface quality of different materials. Ansalam and Nambodiri [36] used MOGA for optimization of surface roughness in numerical control milling machines, they considered effects of feed, speed rate, and depth of cut for multi-objective optimization techniques. MOGA has also been used to optimize advanced machining processes such as abrasive jet machining (AJM), EDM, WEDM, ECM, ECH and PECH [40, 41] etc. In AJM traverse speed, waterjet pressure, standoff distance, abrasive flow rate was considered as most frequently used input parameter while surface roughness has been selected as response [32]. Kuruvila and Ravindra [26] and Pasam et al. [35] have used MOGA to analyze and optimize the pulse current, pulse duration, pulse interval, servo speed, servo voltage, wire speed and wire tension during wire-EDM. Simultaneous optimization of such variety of parameters were possible at same time due to the use of genetic algorithm.

The afore discussed literature review is summarized in Table 1.

3 Conclusion

Multi-objective genetic algorithm technique has widely been employed for optimization of machining parameters to secure the best possible values of various machinability indicators such as surface roughness, material removal rate, and surface integrity etc.

GA optimization in optimizing machining parameters showed positive results based on literature review. Based on the review, most of the researchers used single-objective GA in their optimization scheme. By doing this, the other outcomes of machining is ignored even thought the same parameters will contribute to that outcome. Thus, as suggestion for the future researchers, Multi-Objective GA (MOGA) can be implemented in optimizing machining process without neglecting other properties. For now, the main concern is surface roughness and production cost, by making one of this as objective function, another function need to be sacrificed. To obtain maximum quality of surface roughness, production cost gets higher. Due to that fact, implementation of MOGA techniques will balance out the objective function and produces high quality surface roughness within the cost limitation.

In terms of machining, every different setup of machining with different type of workpiece, type of machining work and coolant used, and other parameters will provide unique solution set of optimization for particular setup when apply GA optimization. This showed that GA optimization is capable to provide technologist the required parameters for optimum machining processes.

References

1. Gupta K, Gupta MK (2019) Developments in non-conventional machining for sustainable production: a state of art review. Proc Inst Mech Eng C J Mech Eng. https://doi.org/10.1177/0954406218811982
2. Aggarwal A, Singh H (2005) Optimization of machining technique—a retrospective and literature review. Sadhana-Acad Proc Eng Sci 30: 699–711
3. Mukherjee I, Ray PK (2006) A review of optimization techniques in metal cutting processes. Comput Ind Eng 50:15–34
4. Magabe R, Sharma N, Gupta K, Davim JP (2019) Modeling and optimization of wire-EDM parameters for machining of $Ni_{55.8}$-Ti shape memory alloy using hybrid approach of Taguchi and NSGA-II. Int J Adv Manuf Technol. https://doi.org/10.1007/s00170-019-03287-z
5. Sekulic MA, Pejic VB, Brezocnik MC, Gostimirović MA, Hadzistevic MA (2018) Prediction of surface roughness in the ball-end milling process using response surface methodology, genetic algorithm, and grey wolf optimizer algorithm. Adv Prod Eng Manag 13:18–30
6. Shukla R, Singh D (2016) Experimentation investigation of abrasive water jet machining parameters using Taguchi and evolutionary optimization technique. Swarm Evol Comput 32:167–183
7. Sangwan KS, Kant G (2017) Optimization of machining parameters for improving energy efficiency using integrated response surface methodology and genetic algorithm approach. Procedia CIRP 61:517–522
8. Kumar KP, Manikandan K, Nandhakumar M, Rajendran KL (2015) Optimisation of machining parameters in aluminium alloy composite using genetic algorithm. Int J Sci Eng 1(1)
9. Kant G, Sangwanb KS (2015) Predictive modelling and optimization of machining parameters to minimize surface roughness using artificial neural network coupled with genetic algorithm. Procedia CIRP 31:453–458
10. Li J, Yang X, Ren C, Chen G, Wang Y (2015) Multiobjective optimization of cutting parameters in Ti-6Al-4V milling process using nondominated sorting genetic algorithm-II. Int J Adv Manuf Technol 76:941–953
11. Santos MC Jr, Machado MR, Barrozo MAS, Jackson MJ, Ezugwu EO (2015) Multi-objective optimization of cutting conditions when turning aluminum alloys (1350-O and 7075-T6 grades) using genetic algorithm. Int J Adv Manuf Technol 76:1123–1138
12. Mahesh G, Muthu S, Devadasan SR (2014) Prediction of surface roughness of end milling operation using genetic algorithm. Int J Adv Manuf Technol 77:369–381
13. Sahali MA, Belaidi I, Serra R (2015) Efficient genetic algorithm for multi-objective robust optimization of machining parameters with taking into account uncertainties. Int J Adv Manuf Technol 77:677–688
14. Sangwan KS, Saxenaa S, Kanta G (2015) Optimization of machining parameters to minimize surface roughness using integrated ANN-GA approach. Procedia CIRP 29:305–310
15. Shivasheshadri M, Arunadevi M, Prakash PS. Simulation approach and optimization of machining parameters in CNC milling machine using genetic algorithm. Int J Eng Technol 1(10):1–10
16. Agarwal A, Varma SN (2015) Optimization of machining parameters for milling operations using a genetic algorithm approach. Int J Eng Technol Res 3(1)
17. Durairaja M, Gowri S (2013) Parametric optimization for improved tool life and surface finish in micro turning using genetic algorithm. Procedia Eng 64:878–887
18. Petkovic D, Radovanovic M (2013) Using genetic algorithms for optimization of turning machining process. J Eng Stud Res 19(1):47–55
19. Selvam MD, Shaik Dawood AK, Karuppusami G (2012) Optimization of machining parameters for face milling operation in a vertical CNC milling machine using genetic algorithm. Eng Sci Technol Int J (ESTIJ) 2(4):2250–3498
20. Rai JK, Brand D, Slama M, Xirouchakis P (2011) Optimal selection of cutting parameters in multi-tool milling operation using a genetic algorithm. Int J Prod Res 49(10):3045–3068
21. Zeng HY, Qiang EJ, Yang XP, Li HM (2011) Soft-sensing model on the roughness of machining surface under the numerical control and its application. Appl Mech Mater 48–49:1077–1085

22. Gao DQ, Li ZY, Mao ZY (2011) Study of high speed machining parameters on nickel-based alloy GH2132. Adv Mater Res
23. An I, Feng I, Lu C (2011) Cutting parameters optimization for multi-pass milling operations by genetic algorithms. Adv Mater Res 160–162:1738–1743
24. An I (2011) Optimal selection of machining parameters for multi-pass turning operations. Adv Mater Res 156–157:956–960
25. Kilickap E, Huseyinoglu M, Yardimeden A (2011) Optimization of drilling parameters on surface roughness in drilling of AISI 1045 using response surface methodology and genetic algorithm. Int J Adv Manuf Technol 52:79–88
26. Kuruvila N, Ravindra HV (2011) Parametric influence and optimization of wire EDM of hot die steel. Mach Sci Technol 59:142–145
27. Ganesan H, Mohankumar G, Ganesan K, Ramesh Kumar K (2011) Optimization of machining parameters in turning process using genetic algorithm and particle swarm optimization with experiment verification. Int J Eng Sci Technol (IJEST) 3:1091–1102
28. Xie S, Guo Y (2011) Intelligent selection of machining parameters in multi-pass turning using a GA-based approach. J Comput Inf Syst 7(5):1714–1721
29. Zain AM, Haron H, Sharif S (2010) Application of GA to optimize cutting conditions for minimizing surface roughness in end milling machining process. Expert Syst Appl 37:4650–4659
30. Zain AM, Haron H, Sharif S (2011) Integration of simulated annealing and genetic algorithm to estimate optimal solutions for minimizing surface roughness in end milling Ti-6Al-4V. Int J Comput Integr Manuf 24(6):574–592
31. Zain AM, Haron H, Sharif S (2012) Integrated ANN-GA for estimating the minimum value for machining performance. Int J Prod Res 50(1):191–213
32. Zain AM, Haron H, Sharif S (2011) Estimation of the minimum machining performance in the abrasive waterjet machining using integrated ANN-SA. Expert Syst Appl 38:8316–8326
33. Sultana I, Dhar NR (2010) GA based multi-objective optimization of the predicted models of cutting temperature, chip reduction co-efficient and surface roughness in turning AISI 4320 steel by uncoated carbide insert under HPC condition. Paper presented at the proceedings of 2010 international conference on mechanical, industrial, and manufacturing technologist, MIMT, 2010, pp 161–167
34. Yongzhi P, Jun Z, Xiuli F, Xing A (2010) Optimization of surface roughness based on multilinear regression model and genetic algorithm. Adv Mater Res 97–101:3050–3054
35. Pasam VK, Battula SB, Valli PM, Swapma M (2010) Optimizing surface finish in WEDM using Taguchi parameter design method. J Braz Soc Mech Sci Eng 32(2):107–113
36. Ansalam Raj TG, Namboothiri VN (2010) An improved genetic algorithm for the prediction of surface finish in dry turning of SS 420 materials. Int Adv Manuf Technol 47:313–324
37. Zolpakar NA, Ghazali NM, Hassan El-Fawal M (2016) Performance analysis of the standing wave thermoacoustic refrigerator, review. Renew Sust Energ Rev 54:626–634
38. Deb K (2001) Multi-objective optimization using evolutionary algorithm. Wiley, London
39. Alberto I, Azcarate C, Mallor F, Mateo PM (2003) Multiobjective evolutionary algorithms. Pareto rankings. Monogfias del Senim. Matem. Gracia de Galdeano. 27:27–35
40. Pathak S, Jain NK, Palani IA (2016) Investigations on surface quality, surface integrity and specific energy consumption in finishing of straight bevel gears by PECH process. Int J Adv Manuf Technol 85 (9–12):2207–2222
41. Pathak S, Jain NK, Palani IA. (2014) On use of pulsed-electrochemical honing to improve micro-geometry of bevel gears. Mater Manufact Process 29 (11–12):1461–1469