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Optimization of Machining Processes Parameters

Manjulata Soni[1*], Mahesh Soni[2]
[1]Ph.D. Scholar, Department of Mechanical Engineering, Government Engineering College, Bilaspur, Chhattisgarh, India
[2]Student, Department of Computer & Communication Engineering, Manipal Institute of Technology, Udupi, Karnataka, India

Abstract*: Optimization of machining parameters is irreplaceable in modern productions since it is essential not only to achieve a high level of precision but also to increase productivity. The inherently bounded and non-linear nature of machining processes, their combining integer, discrete and continuum variables, further complicates this effort. Secondly, mathematical formulations of these systems are often discontinuous, implicit, or characterized by a non-differentiable (with regard to the design variables) nature. As a result, gradient-based non- linear optimization methods have rather limited usage. Genetic Algorithms (GA) have thus become an interesting choice, which can easily deal with complex and highly non-linear optimization issues of machining. In comparison with the other traditional approaches, GAs operate on a population of possible solutions and use both stochastic and deterministic search strategies to guide the search to solutions that meet feasible solution criteria and optimal solutions. Despite the strengths that GAs provide there are still some limitations that are inherent in the structure of the algorithm: (1) inefficiency of the way they encode continuous variables using ones and zeros, (2) lack of local-search functionality, (3) lack of self-adaptation and (4) poor handling of conveys. The article describes a new, structured evolutionary algorithm based on canonical genetic algorithms that was specifically designed to overcome the problems detected in current implementations. Discriminating improvements encompass a more efficient characterization of the nature of the problem-issues, the incorporation of selection procedures with an eye to population-level goals, specific genetic operators appropriate to variable groupings, competent constraint management measures and judicious initial population-setting regimes. Its efficacy and efficiency as provided by the proposed framework are empirically demonstrated with the help of two machining case studies, in which the framework proves better than the other established ones in terms of efficacy and efficiency.

***Keywords*: Genetic Algorithm, Production Cost, Crossover, Mutation, Constraints.**

1. Introduction

In the modern competitive manufacturing, meeting a product quality, confining the cost of production, as well as maximizing the efficiency of operations are key goals, specifically within the Computer Numerical Control (CNC) machining. When machine tools have been selected, the specific description of the machining parameters is unavoidable. The overall objective of machining is to produce components with high quality requirements and at the same time avoiding excessive spending. Since CNC machines are associated with large financial investments and maintenance costs, it is crucial to use the optimization techniques that provide good profit on investment.

A. Parameter Significance

Cutting speed, feed rate and depth of cut are the process parameters that significantly modulate the performance of any machining operation. These values are traditionally calculated by the assistance of personal experience and ordinary handbooks by the process planners. Although, these manual approaches hardly reach the level of optimality needed to minimize the costs. Conventional methods of optimization rely on robust mathematical studies drawn after making experimental observations but this information often tends to contain systematic and random errors thus hinders their accuracy.

B. Tools and Methods Tools and Methods

Several computation tools, algorithms and techniques have been created to overcome such limitations. Machine learning, such as support vector regression, artificial neural networks and other allied statistical models, has shown especially good prospects. The machine-learning methodologies include a number of benefits: they need little input of experimental data, presuppose small amounts of the a priori knowledge concerning the dynamics of the processes, and provide the creation of the predictions with the strong explanatory value. Moreover, they may be concatenated into the currently used optimization methods, giving probability of golden approaches that merge the powers of the two.

Summing up, sophisticated techniques of parameter optimization in the CNC machining cannot be overlooked when striving to achieve high quality increases, low operation expenses, and enhanced working efficiency. Such ambitions are possible to reach through the combination of machine learning with classic approaches to optimization.

The process of optimization is largely based on optimal decision making, which acts as the main process by which most operational decisions can be able to align to the overall strategic goals. Agapiou [1] tackled the subject in a multi-stage machining system, where they have used Nelder-Mead simplex algorithm to reduce the overall costs as well as raise in the tool

*Corresponding author: mohanharisoni3@gmail.com

life by the appropriate utilisation of idle time of succeeding machining stations. A second change combined the time and cost as bi-objectives, and weighted the objectives.

Within a slightly different and yet same context, Shin et al. [2] developed a framework of multi-pass turning in which the depth of cut of every machining pass was established by the means of dynamic programming. The microcomputer-based optimization scheme of the surface grinding introduced in the paper by Wen et al. [3] took into consideration variables including the speed of the grinding wheel, the speed of the workpiece, the depth of dressing as well as the lead angle. Their model used quadratic programming to optimise a weighted objective term, where the constraint was to meet the thermal stresses, the wheel wear, the machine stiffness, and either a cost (rate of production) or surface quality.

White et al. [4] have put the traditional model of machining cost further by integrating cost penalties into surface roughness. In Chen et al. [5] the simulated annealing was used to optimize a single model featuring straight, taper, and circular turning. Kee [6] concerned himself with constrained optimization techniques in order to find the cutting parameters during multi-pass rough turning processes, in a conventional as well as a CNC lathe. Genetic algorithms were used by Bhaskara Reddy et al. [7] to optimize the depth of cut of multi-pass turning thus reducing cost of production.

Combined, these papers highlight the depth of the analytical methods to improve machining processes in terms of modelling approaches, constraint sets and objective functions.

Optimization of the machining processes using evolutionary techniques has been dealt upon by a number of researchers in the past. Importantly, Chen et al. [8] suggested rough turning by using multi-objective evolutionary algorithm. A mechanism-based model that was proposed by Cheol Lee and Yung Shin [9] to control the lead angle with minimized roughness and expense in single pass turning operations. Kennedy et al. [10] have implemented particle swarm optimization (PSO) a technique that has been observed as having global optima. Hui et al. [11] further expanded on this research and they extended it into coming up with a dynamic economical model that considered trade-offs between quality costs and other costs related to single-pass turning.

Expanding on such input, Onwubolu et al. [12], Choudhri et al. [13] and Suresh et al. [14] have used genetic algorithms to optimise multiple-objectives in turning processes involving surface roughness and cost simultaneously. Saravanan et al. [15] found out that GAs work better than quadratic programming in surface grinding model. In terms of multi-pass turning, Vijayakumar et al. [16] has employed ant colony optimization with results which performed better than those of GAs.

A more recent example of optimisation with the help of GAs has been applied by Venugopal et al. [17] in the case of grinding of silicon carbide using diamond grinding wheels and the major goal has been to maximize material removal rate with limitations on surface finish and damage. Gopal et al. [18] made some attempts to resolve comparable grinding problems using an existing mathematical model.

Another article by Saravanan et al. [19] gives the description of a hybrid scheme combining genetic algorithms and simulating annealing that is used to optimize turning operations. At the same time, Cus et al. [20] elaborate a genetic-algorithm-centered scheme, instrumental in the persistent optimization of cutting conditions, and experimentally proves it. Baskar et al. [21] then propose a simulated-annealing model of surface-grinding optimisation. According to Zhang et al. [22], the limitations of population size and velocity will have a significant impact on the performance of a particle swarm optimization used in the optimisation of machining parameters. In another version, Sardinas et al. [23] incorporate genetic algorithms to a multi-objective scenario where the two goals are maximizing tool life and decreasing operation time. The presentation furnished by Mukherjee and Ray [24] provides a thorough picture of optimization techniques in metal cutting. The work by Wang et al. [25] capitalizes on the combination of geometric programming and the use of interval analysis in obtaining bounds of unit production costs, with a view to enhancing accuracy of decisions made. The aim of research conducted by Lee [26] is the study of the robustness of the grinding process in order to achieve maximum amounts of material removal. Despite the fact that traditional methods of the dynamic programming, the geometric programming, and the branch and bound have been thoroughly researched, they often face the challenge of solving large, multidimensional search spaces, thus producing only locally optimal solutions. Comparatively, more advanced algorithms such as simulated annealing, genetic algorithms, particle swarm optimization have proved more flexible and applicable in practice in the field of machining. This review will focus on evaluating and contrasting the effectiveness of these methods examining the ability of techniques to be applied to different machining models to conclude a strong and versatile methods of optimization.

2. Proposed Methodology

Non-conventional search and optimization methods, mainly evolutionary algorithms, have lately been acknowledged as a feasible approach of tackling an extensive scope of engineering current optimization issues. They are based on the biological law of the survival of the fittest and these methods work under a set of population where there is constant evolutionary process through transfer of information. The optimization of machining processes was conducted by using several evolutionary methods in the current study.

A. *Concept of Genetic Algorithm*

Genetic algorithms may be described as adaptive search methods that are monopolized of evolutionary theory, and classical genetics. Unlike the traditional optimization processes that evaluate one solution at a time, genetic algorithms only optimize a population of possible designs. They obey laws of natural selection according to which the most fit people get more chance to procreate and transfer the beneficial properties to their descendants.

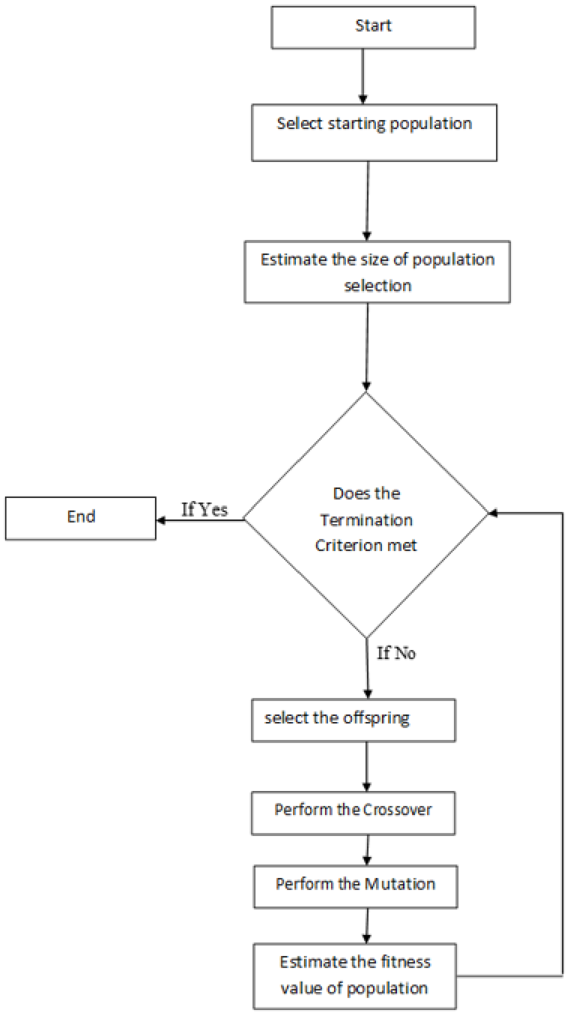

Fig. 1. Flow chart of working of genetic algorithm

B. *Parameters of GA*

Table 1

Number of iteration performed	1,000
Population	100
Cross-over probability	0.80
Mutation probability	0.05

The process starts by producing in random a set of initial populations. A particular design is encoded by each member of this population as a binary string with each bit representing a distinct design variable. The fitness is measured against pre-specified denominator called the objective function that measures the performance within the optimization context.

The selection follows their individual fitness value, where those that score well stand higher chances of becoming parents. After selection, the genetic operations, which are crossover as well as mutation, apply to the generation of the next generation. Crossover is used to mix bits of two parent strings and give birth to new strings, whereas mutation causes random changes to ensure the diversity of population.

The genetic algorithm does not use any new crossover, mutation, selection or evaluation, but is repeated until either an arbitrary limit on the number of iterations of the algorithm is reached, or the algorithm converges to a solution which performs as well as possible. All these phases may be outlined as follows:

1. *Population initialization*: A cohort of people is randomly produced initially.
2. *Fitness calculation*: In the objective function, every person will be considered based on the objective function.
3. *Termination check*: The algorithm quits when the maximum number of iterations has been attempted or the performance offered by the current solution is satisfactory.
4. *Parent selection*: Reproduction individuals are selected based on their fitness; most of the time, the reproduction involves individuals who are in the best part of the population.
5. *Operator usage*: The acceptable pairs undergo crossover and mutation, thus giving birth to future generations.
6. *Fitness assessment*: The actual children are also tested and the procedure is repeated again starting at step 2 until the process is stopped.

The behaviour of the algorithm is regulated by five primary parameters:

- *Population size*: Solution diversity is directly dependent on the numerical magnitudes of the population.
- *Crossover probability*: Crossover probability influences the severity with which genetic material is recombined, a factor which may influence convergence paths.
- *Mutation probability*: In the same way, mutation probability defines the degree of diversification that takes place.
- *Number of generations*: This is one of the parameters of the schedule and they can be predetermined a priori to represent the maximum computation time that will be allocated to the algorithm.
- *Termination criteria*- The convergence criterion may be performance criterion or iteration criterion.

Versions of canonical genetic algorithm (GA) have been suggested to handle constraints. One of the vectors of changes is selection procedures, especially when it comes to changes in persons in the population. There are three paradigmatic approaches that include generational replacement (GR), steady-state replacement (SSR), and elitism (EL). In GR, the population is immediately replaced as a whole, in SSR, only a portion of it is restored. EL retains certain discrete elite in its nature.

Crossover is a second theory of variability. It can be performed as single-point crossover (SPC) and multi-point crossover (MPC). The operators can be combined and it is possible to have SPC applied in some loci and MPC in others.

Convergence is affected by fitness normalization schemes too. Linear scaling is the most common one. The mean fitness may be scaled to the fitness range such that, prior to selection, the mean fitness = unity maximizing the diversity of the population.

Since GA has many different variants, it does not exist such a panoptic configuration that would help in any kind of optimization in the best way. The practitioners, instead, are supposed to refine each of the parameters to the setting of the particular problem.

A genetic algorithm was used in the current investigation such that the control parameters were as follows:

Total iterations: 1, 000

- Population size 100

Crossover probability: 0.80

- Probability of mutation: 0.05

3. Single-Pass Turning Operation

A. Mathematical Model

In this section, one has addressed the single-pass turning and studied that mathematical model developed by Agapiou [1] is adopted to ensure the best choice of three basic parameters namely the cutting speed, feed rate and depth of cut. The variables have significant impacts on the cost of production, cycle time, quality of products as well as productivity in general. It is thus a prerequisite in optimization of them to achieve efficient use of machines. The current study aims at the minimization of an integrated optimization goal that includes production cost and production time.

B. Formulation of Objective Function

In the framework of the example with the single-pass turning operation, the parameters adopt values that have been fixed according to the machine specification and conventional handbooks. The work piece material is high-carbon steel and the cutting tool is tungsten carbide. The details of the particular machining parameters used are in Table 2.

Table 2
Values of machining parameters

Parameters	Values	Parameters	Values
L	203 MM	Fmax	1,100 N
D	152 mm	SRmax	8 µm
vmin	30 m/min	HPmax	5 KW
vmax	200 m/min	tmax	500°C
fmin	0.254 mm/rev	a1	0.29
fmax	0.762 mm/rev	a2	0.35
dmin	2.0 mm	a3	0.25
dmax	5.0 mm	K	193.3
tcs	0.5 min/edge	Co	0.1/min
tR	0.13 min/pass	Ct	0.5/ed

The overall expense incurred in the machining of one unit of part includes the cost due to cutting tool, cutting process, replacement of blunt parts, work piece handling, and the additional movements due to the tool contact used to bring the tool back. It would be possible to calculate the cost of tool replacement by dividing the time taken to machine with the observed instances by the life expectancy of the tool encountered according to expected tool running time to produce multiple pieces before one tool finishes its returning to the Unrepeated life or prime and another tool is required.

1) Production Cost

The production cost per component for a machining operation consists of the sum of the costs for tooling, machining, tool changing time; handling time, and quick return time. Tool changing cost for each part is calculated based on the machining time of the part to the tool life. This is because a single tool may be used to machine several parts before it needs to be replaced by a sharp one.

Production cost is given by:

$$c_u = C_o\, t_m + (t_m/T)\, C_o\, tcs + C_t + C_o\, (th + t_R) \tag{1}$$

The machining time per pass in turning is given by:

$$t_m = (\pi DL)/(1000\ vf\,) \tag{2}$$

Tool life is given by:

$$T = (K/v\ f^{a1}\ d^{a2})^{(1/a3)} \tag{3}$$

2) Production Time

The total time required to produce a part is the sum of the times necessary for machining, tool changing, tool quick return time, and work piece handling time that includes loading and unloading of work piece in the machine. This is given by:

$$t_u = t_m + t_{cs}(t_m/T) + t_h + t_R \tag{4}$$

3) Combined Objective Function

The objective function consists of the combination of the production time and the production cost using different weight coefficients for each criterion.

$$\mu(v, f, d) + w_1.c_u + w_2.\lambda.t_u \tag{5}$$

where, w_1 and w_2 are the weight coefficients, which indicates the relative importance of the production time and production cost. It has been assumed that these weight coefficients should satisfy the condition given below. When both weight coefficients w_1 and w_2 are set equal to 0.5, the objective functions moves closer to the higher profit rate.

$$w_1 + w_2 = 1,\ 0 \leq w_1 \leq 1 \text{ and } 0 \leq w_2 \leq 1 \tag{6}$$

The optimum function is normalized through the use of a constant multiplier.

$$\lambda = c_u \min/t_u \min \tag{7}$$

where, c_u min and t_u min are the minimum production cost and minimum production time, respectively, under the defined process constraints.

C. Machining Parameters

Although there are many machining parameters which affect the machining operation, cutting speed, feed, and depth of cut have the greatest effect on the success of a machining operation. Therefore, only these machining parameters are considered in this work. Moreover, these machining parameters also considered as the practical constraints.

1) Cutting Speed

When compared to depth of cut and feed rate, cutting speed has a greater effect on tool life. Certain combinations of speed, feed, and depth of cut are usually selected for easy chip removal, which are directly proportional to the type of tool and work piece material. Thus, the range of cutting speed can be written as:

$$v_{min} \leq v \leq v_{max} \tag{8}$$

2) Feed

By increasing the feed and decreasing the cutting speed, it is always possible to obtain much higher metal removal rates without reducing tool life. Thus, the range of feed can be written as:

$$f_{min} \leq f \leq f_{max} \tag{9}$$

3) Depth of Cut

Selection of depth of cut should counter balance between the tool life and metal removal rate to obtain highest permissible level of depth of cut. Thus, the range of depth of depth of cut can be written as:

$$d_{min} \leq d \leq d_{max} \tag{10}$$

D. Physical Constraints

There are always many constraints that exist in the actual cutting condition for the optimization of the objective function. For a given pass, an optimum cutting speed, feed, and depth of cut is chosen and, thus, balancing the conflict between the metal removal rate and tool life. The following constraints are considered in optimizing the machining parameters. On satisfying these constraints, the optimum machining parameters are arrived.

1) Parameter Constraints

$$v_{min} \leq v \leq v_{max},\ f_{min} \leq f \leq f_{max}\ \&\ d_{min} \leq d \leq d_{max} \tag{11}$$

2) Power Constraint

$$0.0373\ v^{0.91}\ f^{0.78}\ d^{0.75} \leq HP_{max} \tag{12}$$

3) Surface Finish Constraint

$$14785\ v^{-1.52} f^{1.004} d^{0.25} \leq SR_{max} \tag{13}$$

4) Temperature Constraint

$$74.96\ v^{0.4}\ f^{0.2}\ d^{0.105} - 17.8 \leq T_{max} \tag{14}$$

5) Cutting Force Constraint

$$844\ v^{-0.1013}\ f^{0.725}\ d^{0.75} \leq F_{max} \tag{15}$$

4. Surface Grinding

A. Mathematical Model

The mathematical model proposed by Anne Venugopal et al. [17] is considered in this work. This work is concerned with the optimal selection of machining parameters such as feed rate and depth of cut. Since these parameters strongly affect the cost, time, productivity, and quality of the machined

parts, determining the optimal machining parameters is an essential step in machining operation. Maximizing the material removal rate is the objective function of the proposed model. Table 3 shows the machining parameter values for surface grinding.

B. Objective Function

Material removal rate is the objective function of the proposed model. It is the rate at which the material is removed from the work piece during the machining process.

$$MRR = f, d \tag{16}$$

C. Machining Parameters

1) Feed

The maximum allowable feed greatly affects the production rate. It has a significant effect on tool life. By increasing the feed and decreasing the cutting speed, it is always possible to obtain much higher metal removal rates without reducing tool life. Surface finish determines the maximum feed in finish operation. Thus, the range of feed can be written as:

$$f_{min} \leq f \leq f_{max} \tag{17}$$

Table 3
Values of machining parameters

Parameters	Values	Parameters	Values
f_{min}	5 M/MIN	R_{min}	50
f_{max}	15 m/min	R_{max}	100
d_{min}	5 µm	Ra_{min}	0.155 µm
d_{max}	30 µm	Ra_{max}	0.4 µm
M_{min}	120	$\%D_{min}$	1.5
M_{max}	500	$\%D_{max}$	4.0

Table 4
Results of GA

Machining Parameter	**Optimum value of Machining Parameter**		
	N rpm	**f mm/rev**	**d mm**
	125.6659	0.132	0.4
Unit Production Cost except material cost			
Unit Production Cost	**in turning in Rs/piece**	**in facing in Rs/piece**	**in grinding in Rs/piece**
	142.2627	9.779692	40.23723
Total Unit Production Cost except material cost turning, in facing and in grinding in Rs/piece			192.2797

2) *Depth of Cut*

By changing the depth of cut, tool life is less affected. So, there should be a counter balance between the tool life and metal removal rate to obtain highest permissible level of depth of cut. The selection of maximum depth of cut is dependent on (1) tool material, (2) cutting force, (3) available horsepower, (4) stability of the tool work machine, (5) dimensional accuracy, and (6) surface finish required. Thus, the range of depth of depth of cut can be written as:

$$d_{min} \le d \le d_{max} \tag{18}$$

D. *Physical Constraints*

1. *Feed*: optimum feed must be in the range determined by the minimum and maximum feed rates of the machine and can be written as:

$$f_{min} \le f \le f_{max} \tag{19}$$

2. *Depth of cut*: optimum depth of cut must be in the range determined by the minimum and maximum depth of cut of the machine and can be written as:

$$d_{min} \le d \le d_{max} \tag{20}$$

3. *Grain size*: grain size is the size of the abrasive grain in the grinding wheel which should be within the given range.
4.

$$M_{min} \le M \le M_{max} \tag{21}$$

5. *Grain density*: grain density is the closeness of packing of abrasive grains on the grinding wheel which should be within the given range.

$$R_{min} \le R \le R_{max} \tag{22}$$

6. *Surface roughness*: it refers to the smoothness of machined surface which should be within the range is given by:

$$Ra = 0.36(d)^{0.1843}(f)^{0.5253}(M)^{-0.2866}(R)^{-0.2444} \le Ra_{max} \tag{23}$$

7. *Surface damage*: surface damage should be within the range is given by:

$$\%D = 24.44\,(d)^{0.2857}(f)^{-0.3}(M)^{-0.4140} \le D_{max} \tag{24}$$

E. *Computational Result of GA*

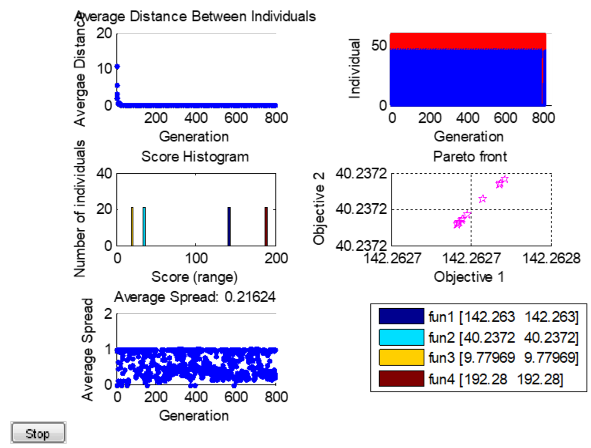

Fig. 2. Display of plot on using MATLAB software for optimization using genetic algorithm toolbox

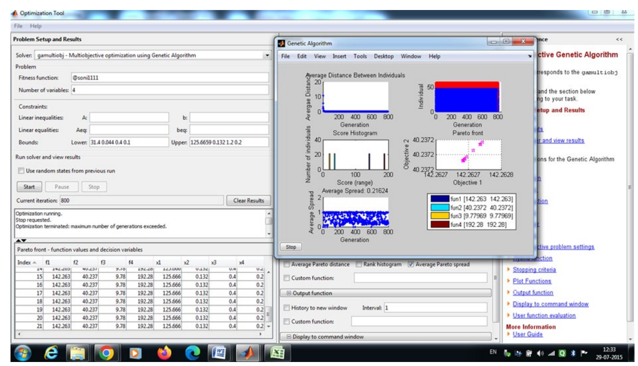

Fig. 3. Display of results on using MATLAB software for Optimization using genetic algorithm toolbox

5. Results and Discussions

The current study uses MATLAB software to bring about implementation and evaluation of optimization models and algorithms related to turning and grinding operations. Types of all computational trials that are conducted using the same experimental setup take a size of 100 and 1,000 runs per genetic algorithm (GA running).

Evaluation of genetic algorithms as a performance tuning of a multi-modular flexible manufacturing system was carried out. The major goal was to decrease the overall objective function (COF). It has used a two-stage experimental design. The first phase informed the optimisation of single-pass turning processes with 15-second computation time and the COF minimum of 0.6896. At the second stage, optimisation of ground surface operations was performed, with a computation time of 6 seconds, and maximum of 179.8 mm c 2 /min material removal rate (MRR). These findings implied that a genetic algorithm would be an efficient optimisation tool of a flexible manufacturing system.

The genetic algorithm (GA) has proved successful in both the studied applications, single-pass turning and surface grinding because of its robustness and efficiency in relation to both applications. In single-pass turning the GA was used to minimize the overall objective function (time and cost). This success shows that the algorithm has ability to trade off many goals in constrained machining problem setting.

In case of surface grinding, the GA was applied to maximize the metal removal rate (MRR) under parametric limitation of surface roughness and surface damage. The results indicate that, to some extent of acceptability, an increment in the surface roughness and surface damage consequently implies greater values of MRR. Here, it implies a sacrifice of productivity against the surface integrity, which was successfully addressed with the help of the GA.

These findings reveal that genetic algorithm is practical as means of resolving multi-variable, constrained optimization problem within the machining process. The algorithm is fast converging and provides astonishing performance terms.

6. Conclusion

In this analysis, the mathematics of how the parameters involved in various machining processes are optimized through the mathematical modelling of each operation by designing of unique laws derived by the machining process objective functions and constraints is addressed. Specifically, these two relatively essential machining processes are considered:

1. Single-pass turning, in which the goal is to optimise a sum total of goals that included production time and production cost.
2. Surface grinding, in which the aim is to maximize the material removal rate (MRR) subject to surface finish and damage related constraints.

These optimisation tasks are solved by means of non-traditional inherent population-based evolutionary technique: genetic algorithm (GA). This strategy is the same throughout all models making, hence showing its nature of flexibility and adaptability.

These findings are affirmative that GA is effective tool of optimising machining operations under wide range of real constraints and economic considerations. Among the most significant benefits of the suggested framework, it is possible to state that the GA-based software, designed herein is problem-independent and general-purpose, which enables its easy conversion or adaptation to other machining processes or other optimisation constraints. Moreover, the given methodology does not apply only to the issues that have been outlined: the same GA framework can be applied to numerous engineering problems that involve multi-objective optimisation in constrained settings.

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