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Genetic algorithm-based optimization of cutting parameters in turning processes

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Abstract

An optimization paradigm based on genetic algorithms (GA) for the determination of the cutting parameters in machining operations is proposed. In metal cutting processes, cutting conditions have an influence on reducing the production cost and time and deciding the quality of a final product. In order to find optimal cutting parameters during a turning process, the genetic algorithm has been used as an optimal solution finder. Process optimization has to yield minimum production time, while considering technological and material constrains.

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Keywords: Metal cutting; Cutting parameters optimization; Genetic algorithm

1. Introduction

In today's production systems, many industries have made an effort to introduce flexibility as their strategy to adapt to the ever-changing competitive market requirements. To ensure the quality of machining products, and to reduce the machining costs and increase the machining effectiveness, it is very important to select the machining parameters when the process parameters are selected in CNC machining. The traditional methods for solving this class of optimization problem include dynamic programming, random searches, and gradient methods whereas modern heuristic methods include, cognitive paradigms as artificial neural networks, simulated annealing [1] and Lagrangian relaxation approaches [2]. Some of these methods are successful in detecting the optimal solution, but they are usually slow in convergence and require much computing time.

Genetic algorithms (GA) approach, based on the principles of natural biological evolution will be used to tackle this kind of problem. Compared to traditional optimization paradigms, a GA is robust, global and may be applied generally without recourse to domain-specific heuristics. It can be used not only for general optimization problems, but also in indifferent optimization problems and unconventional optimization problems. So GAs are widely used for machine learning, function optimizing and system modeling [3 - 7]. Although GA is an effective optimization algorithm, it usually takes a long time to optimize machining parameters because of its slow convergence speed.

The main objective of this paper is to determine the optimal machining parameters during a turning process that minimize the production time without violating any imposed cutting constraints.

2. Genetic Algorithm

A GA is a paradigm that tries to mimic the genetic evolution of a species. Specifically, GA simulates the biological processes that allow the consecutive generations in a population to adapt to their environment. The adaptation process is mainly applied through genetic inheritance from parents to children and through survival of the fittest. Therefore, GA is a population-based search methodology [8, 9].

The GA starts with a randomly generated population of individuals, each one made by strings of the design variables, representing a set of points spanning the

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search space. Each individual is suitably coded into a chromosome made by a string of genes: each gene encodes one of the design parameters, by means of a string of bits, a real number or other alphabets.

In order to evaluates and rank chromosomes in a population, a fitness function based on the objective function should be defined. New individuals are then generated by using some genetic operators, the classical ones being the crossover, the selection and the mutation.

The selection operator cares with selecting an intermediate population from the current one in order to be used by the other operators, crossover and mutation. In this selection process, chromosomes with higher fitness function values have a greater chance to be chosen than those with lower fitness function values. Pairs of parents in the intermediate population of the current generation are probabilistically chosen to be mated in order to reproduce new individuals. In order to increase the variability structure, the mutation operator is applied to alter one or more genes of a probabilistically chosen chromosome. Finally, another type of selection mechanism is applied to copy the survival members from the current generation to the next one.

The crossover operator aims to interchange the information and genes between chromosomes. Therefore, crossover operator combines two or more parents to reproduce new children, then, one of these children may hopefully collect all good features that exist in his parents. Crossover operator is not typically applied for all parents but it is applied with probability which is normally set equal to 0.6.

The mutation operator alters one or more gene in a chromosome. Mutation operator aims to achieve some stochastic variability of GA in order to get a quicker convergence. The probability of applying the mutation operator is usually set to be small, normally 0.01.

The fitness function is a designed function that measures the goodness of a solution. It should be designed in the way that better solutions will have a higher fitness function value than worse solutions. The fitness function plays a major role in the selection process.

3. GA based optimization of turning parameters

3.1. Production model design

Intelligent manufacturing achieves substantial savings in terms of money and time if it integrates an efficient automated process-planning module with other automated systems such as production, transportation, assembly, etc.

Process planning involves determination of appropriate machines, tools for machining parts, cutting fluid to reduce the average temperature within the cutting zone and machining parameters under certain cutting conditions for each operation of a given machined part.

The machining economics problem consists in determining the process parameter, usually cutting speed, feed rate and depth of cut, in order to optimize an objective function.

A number of objective functions by which to measure the optimality of machining conditions include minimum unit production cost, maximum production rate, maximum profit rate.

Several cutting constraints that should be considered in machining economics include: tool-life, cutting force, power, stable cutting region, chip-tool interface temperature, surface finish, and roughing and finishing parameter relations.

The main objective of the present paper is to determine the optimal machining parameters that minimize the production time without violating any imposed cutting constraints. The entire development of planning of the machine processes is based on the optimization of the economic criteria by taking into account the technical and organizational limitations.

Several practical cutting constraints that were considered in the optimization of the production time in machining economics include: tool-life constraint, cutting force constraint, power, stable cutting region constraint, chip-tool interface temperature constraint, surface finish constraint, roughing and finishing parameter relations, and the number of passes.

Usually, the production time is measured as the time necessary for the fabrication of a product, T_p:

$$T_p = T_s + V(1 + T_c/T)/MRR + T_i \qquad (1)$$

where T_s, T_c, T_i, V and MRR are the tool set-up time, the tool change time, the time during which the tool does not cut, the volume of the removed material and the material removal rate. In some operations, the T_s; T_c, T_i and V are constants so that T_p is the function of MRR and T.

The material removal rate MRR is expressed by analytical starting point as the product of the cutting speed, v, feed rate, f, and depth of cut, a:

$$MRR = 1000*v*f*a \qquad (2)$$

The tool life, T, is measured as the average time between the tool changes or tool sharpenings. The relation between the tool life and the parameters is expressed with the Taylor's formula:

$$T = K_T/v^{\alpha}*f^{\alpha 1}*a^{\alpha 3} \qquad (3)$$

where K_T, α_1, α_2 and α_3, which are always positive constant parameters, are determined statistically.

The most important criterion for the assessment of the surface quality is roughness, R_a, calculated according to:

$$R_a = k*v^{x1}*f^{x2}*a^{x3} \quad (4)$$

where x_1, x_2, x_3 and k are the constants relevant to a specific tool-workpiece combination.

Due to the limitations on the machine and cutting tool and due to the safety of machining, the cutting parameters are limited with the bottom and top allowable limit.

Allowable range of cutting conditions are:

$$v_{min} < v < v_{max}, \quad f_{min} < f < f_{max}, \quad a_{min} < a < a_{max}$$

There are some other constraints related to the machine features. The cutting force, F, must not be greater than a certain maximum value, F_{max}, given by the strength and stability of the machine and the cutting tool. The cutting force is computed from empirical expressions in the form:

$$F (v, f, a) \leq Fmax$$

Another constraint related to machine is the maximum permissible value for cutting power, W, which must not exceed the machine motor power, W_{max}:

$$W (v, f, a) \leq W_{max}$$

The problem of the optimization of cutting parameters can be formulated by defining the goal function as the minimum production time, T_p:

$$\min T_p(v, f, a)$$

The mathematical model has been programmed in MATHLAB. As basis for GA development, Matlab's GA toolbox was used. For GA implementation, standard settings have been taken [10].

For each depth of cutting optimization process, the optimal cutting parameters have been given. GA converges until the stopping criteria are met.

Model output is presented with cutting parameters which satisfy constrain functions at the end of optimization process and give optimal value of goal function, which is a global minimum.

3.2. Illustrative example and results

On the NC lathe, the machining of a cast steel blank by means of the tool made from HSS was performed. The goal is to find optimum cutting conditions for the process of turning. The values of coefficients are statistically determined on the basis of the data measured experimentally:

T_s = 0.12 min
T_c = 0.26 min
Ti = 0.04 min
K = 1.001
K_T = 1686145.34
x_1 = 0.0088
x2 = 0.3232
x3 = 0.3144
α1 = 1.70
α2 = 1.55
α3 = 1.22
β1 = 0
β2 = 1.18
β3 = 1.26
V = 251378 mm^3
W = 4420,5

The objective function is fixed as the minimum production time, T_p:

$$\min T_p = T_s + V/(1000*v*f*a) + (V*T_c*(v^{(1/n-1)} * f^{(m/n-1)} * a^{(r/n-1)}))) / 1000*W^{(1/n)}) + T$$

where:

m = 0,9117 n = 0,5882 r = 0,7176

The limitation functions are:

$$v_{min} < v < v_{max}, \quad f_{min} < f < f_{max}, \quad a_{min} < a < a_{max}$$

The basic GA setup properties are: population size = 20 -100 individuals; genetic operators - those individuals that survive the selection step, undergo alteration by two genetic operators, crossover and mutation; probability for crossover = 0,8; mutation rate = 0,1.

The first step in the proposed GA is the generation of the individuals for the initial population.

The cutting conditions are generated at random inside the specific limits. The cutting conditions are generated at random inside the specified limits. The other values are calculated according to Eqs. 1 – 4 with selected cutting conditions. Initial population is produced either by making random changes to a single parent using the mutation operator or by combining the vector entries of a pair of parents using the crossover operator.

Table 1 contains the 10 initial individuals obtained by GA with 10 generations using (a) the crossover operator and (b) the mutation operator. In Fig. 1, the selected genes from the individuals in the initial population of T_p, v, f and a are plotted vs. # of generations using (a) crossover operator; (b) mutation operator.

Table 1. GA optimal cutting parameters for 10 generations and initial population = 20, obtained using (a) the crossover operator and (b) the mutation operator

# of generations	v (m/min)	f (mm/rev)	a (mm)	T_p (s)
1	72	1,8	3,2	0,724
2	75	1,5	2,3	1,364
3	88	1,1	4,1	0,744
4	71	1,4	2,1	1,195
5	87	1,8	4,1	0,521
6	88	1,1	4,1	0,744
7	87	1,8	1,9	0,885
8	70,6	1,1	3,8	0,930
9	88	1,1	4,1	0,744
10	87	1,8	1,9	0,883

(a)

# of generations	v (m/min)	f (mm/rev)	a (mm)	T_p (s)
1	76	1,8	4,6	0,516
2	71	1,4	2,1	1,174
3	83	1,8	3,8	0,550
4	71	1,7	4,6	0,574
5	88	1,1	4,1	0,744
6	86	1,7	4,1	0,530
7	87	1,8	4,3	0,487
8	88	1,1	4,1	0,744
9	88	1,1	4,1	0,744
10	86	1,7	4,1	0,538

(b)

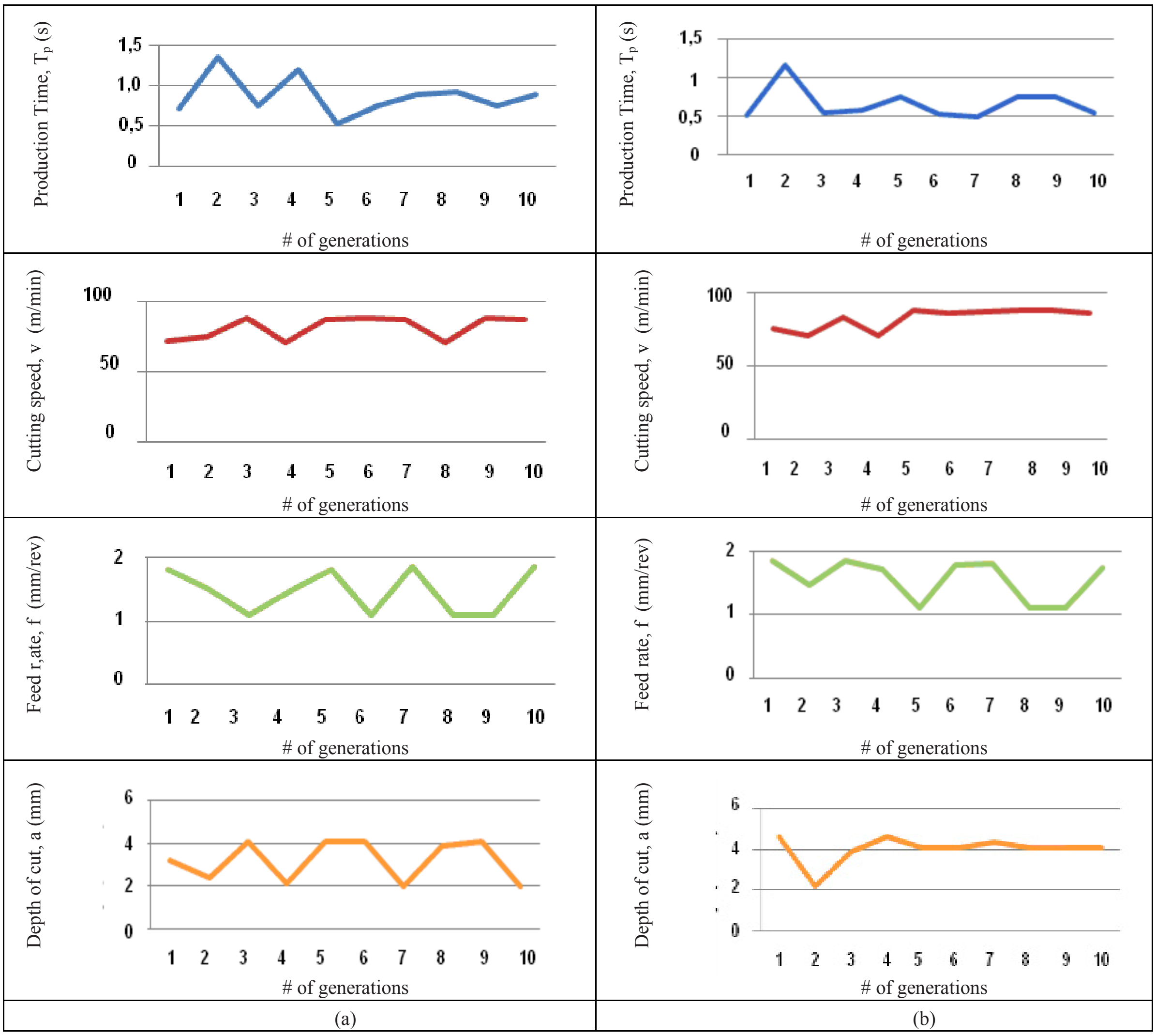

Fig. 1. GA optimal cutting parameters, from the individuals in the initial population = 20, plotted vs. # of generations using (a) crossover and (b) mutation operators

In Fig. 1a, it can be seen how the GA works when there is no mutation, set all individuals in the population are the same, namely, the best individual.

In this case, the algorithm selects genes from the individuals in the initial population and recombines them. The algorithm cannot create any new genes because there is no mutation and cannot generate the best individual as shown by plots that does not become level.

Fig. 1b shows the results of the application of mutation without crossover. While it improves the individual genes of other individuals, these improved genes are never combined with the genes of the best individual because there is no crossover. It can be seen that the best fitness plot is not level and the algorithm does not stall at generation number 10.

From Fig. 1, it can be seen that the initial value of the minimum production time, T_p, obtained by crossover operator is higher than the T_p values obtained applying the mutation operator. It can be note that the algorithm does not stall, but there is immediate improvement in the fitness function after generation 3 using the mutation operator.

It is worth noting that while the crossover enables the algorithm to extract the best genes from different individuals and recombine them into potentially superior children, the mutation adds to the diversity of a population and thereby increases the likelihood that the algorithm will generate individuals with better fitness values.

As result, both processes are essential to the GA.

To optimize the selected GA, the crossover operation is performed on the population obtained after selection. A two point crossover has been used with a high crossover probability = 0,8.

A two point crossover with the high crossover probability is used as it helps the diversity preservation better than the single point one.

After crossover, mutation of the population is performed. Bit wise mutation operator has been used with a mutation probability = 0,1.

Table 2 shows the minimum production time, T_p, for each iteration of the proposed GA and contains the 10 obtained optimal cutting parameters with 10 generations combining the crossover operator and the mutation operator and starting from an initial population = 100.

In Fig. 2, the GA optimal cutting parameters (cutting speed, feed rate, depth of cut) and the best fitness values (production time, T_p) are plotted vs. # of generations.

Table 2 and Fig. 2 show that the production time function is quasi-constant as from the 4th generation.

Table 2. GA optimal cutting parameters obtained for 10 generations and initial population = 100

# of generations	v (m/min)	f (mm/rev)	a (mm)	T_p (s)
1	86	1,1	4,8	0,663
2	86	1,5	4,1	0,584
3	86	1,6	4,1	0,571
4	86	1,7	4,6	0,496
5	86	1,6	4,6	0,520
6	86	2,0	5,0	0,430
7	87	1,8	4,1	0,498
8	71	2,0	5,0	0,487
9	98	1,2	4,5	0,572
10	70	1,6	5,0	0,555

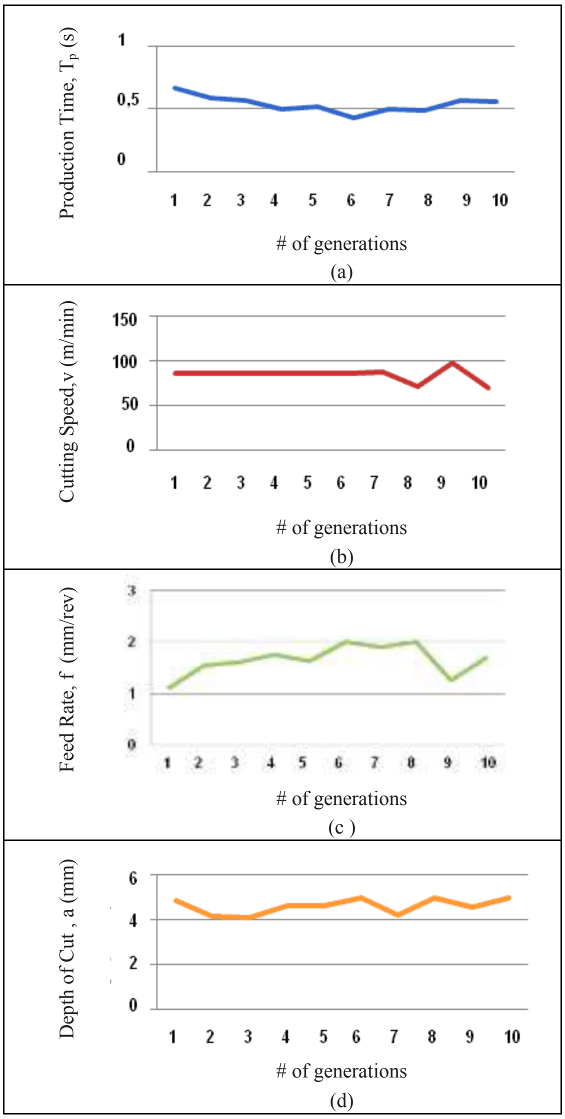

Fig. 2. GA optimal cutting parameters from the individuals in the initial population = 100 plotted vs. # of generations

4. Conclusion

This paper deals with a novel approach to optimize the machining parameters during turning process, by basing on the use of cognitive paradigms.

In metal cutting processes, cutting conditions have an influence on reducing the production cost and time and deciding the quality of a final product. In order to find optimal cutting parameters during a turning process, the genetic algorithm has been used as an optimal solution finder.

Process optimization has to yield minimum production time, while considering technological and material constrains.

Since the genetic algorithm-based approach can obtain near optimal solution, it can be used for machining parameter selection of complex machined parts that require many machining constraints. Integration of the proposed approach with an intelligent manufacturing system will lead to reduction in production cost, reduction in production time, flexibility in machining parameter selection, and improvement of product quality.

The main advantage of proposed methodology is the capability to perform multi-object optimization, minimum machining time while considering technological and material constrains. The results obtained from the simulation model have presented a fast and suitable solution for automatic selection of the machining parameters.

This research definitely indicates some directions for future work. The first priority is the application of the genetic algorithm-based approach in complex machining systems and automated process planning system. The second is comparing the genetic algorithm based approach with a number of other emerging optimization-techniques.

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