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POSSIBILITIES OF USING THE MONTE CARLO METHOD FOR SOLVING MACHINING OPTIMIZATION PROBLEMS

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Abstract *Companies operating in today's machining environment are focused on improving their product quality and decreasing manufacturing cost and time. In their attempts to meet these objectives, the machining processes optimization is of prime importance. Among the traditional optimization methods, in recent years, modern meta-heuristic algorithms are being increasingly applied to solving machining optimization problems. Regardless of numerous capabilities of the Monte Carlo method, its application for solving machining optimization problems has been given less attention by researchers and practitioners. The aim of this paper is to investigate the Monte Carlo method applicability for solving single-objective machining optimization problems and to analyze its efficiency by comparing the optimization solutions to those obtained by the past researchers using meta-heuristic algorithms. For this purpose, five machining optimization case studies taken from the literature are considered and discussed.*

Key Words: *Machining, Optimization, Monte Carlo Method*

1. INTRODUCTION

In recent years, both high resource efficiency and machining processes optimization are vital for manufacturing companies to gain a competitive advantage and become market winners. The ultimate goal of machining optimization is to select machining factor values so that the overall machining performance is enhanced. Determination of optimal machining parameters is a continuous engineering task whose goals comprise production costs reduction as well as achievement of the desired product quality [1]. In general, the selection of optimal machining parameter values for a specific machine tool plays the most important role in manufacturing, as the process control parameters of a machine tool are not always precisely understood. Thus, it becomes increasingly difficult to recommend the optimum values with an enormous variety of expensive materials in the market [2].

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In the real production environment it is a common practice to select machining factor values based on the experience of the machinist (or production planner), machining handbooks and manufacturers recommendations. As a result, the user attempts to optimize the cutting operations by trial-and-error every time he needs to setup the existing equipment for a new different task [3]. The most adverse effect of such a not-very scientific practice is decreased productivity due to sub-optimal use of machining capability [4]. The advances in the machining technology and the developments in related areas (computing, statistics, artificial intelligence, etc.) have led to development of more sophisticated approaches including data storage and retrieval, expert systems, model-based approach, modeless approach based on the Taguchi method, etc. However, the non-availability of the required technological performance equation represents a major obstacle to the implementation of optimized cutting conditions in practice [4].

The model-based approach, very popular with researchers, integrates experimental, statistical, mathematical and artificial intelligence tools thus providing a means for better understanding of machining processes. Using the experimental data, with the help of regression analysis, artificial neural networks and fuzzy logic, different empirical equations for prediction of machining performance characteristic can be developed. Subsequently, the (near) optimal machining parameter values are determined by the application of an optimization algorithm such as gradient based, non-gradient, heuristic or meta-heuristic algorithms. In the field of machining process optimization, the current trend is the application of meta-heuristic algorithms such as genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO) algorithm, artificial bee colony algorithm and ant colony optimization algorithm [5].

Meta-heuristic algorithms perform an efficient and comprehensive exploration of the optimization search space using random the Monte-Carlo search guided by governing mechanisms which imitate certain strategies taken from nature, social behavior, physical laws, etc. Despite numerous capabilities of the Monte Carlo method, its application for solving machining optimization problems has been given less attention by researchers and practitioners. The present paper has three objectives: (*i*) to investigate the Monte Carlo method applicability for solving single-objective machining optimization problems, (*ii*) to develop a framework for solving machining optimization problems using the Monte Carlo method, and (*iii*) to analyze efficiency of the Monte Carlo method for solving machining optimization problems by comparing the optimization solutions to those obtained by the past researchers using meta-heuristic algorithms. For this purpose, five machining optimization case studies taken from the literature are considered and discussed.

2. Monte Carlo Method

Many numerical problems in science, engineering, finance, and statistics are solved nowadays by the Monte Carlo methods, that is, by means of random experiments on a computer [6]. The Monte Carlo is in fact a class of methods now widely used in computer simulations [7]. The "classical" Monte Carlo is used as an uncertainty analysis of the deterministic calculation because it yields distribution describing the probability of alternative possible values about the nominal (designed) point [8]. The idea of the Monte Carlo calculation is much older than the computer. The name Monte Carlo is relatively recent, and is connected to famous casinos in Monaco. It was coined by Nicolas Metropolis in 1949 under the name of "statistical sampling". Since the pioneer studies in 1940s and 1950s, especially the work by Ulam, von Newmann, and Metropolis, it has been applied in almost all area of simulations, from the Ising model to financial market, from molecular dynamics to engineering, and from the routing of the Internet to climate simulations [7].

Monte Carlo methods have been used for a long time but only in the last few decades, they have gained the status of fully rounded numerical methods. In order to obtain reasonably accurate assessment, it is necessary to calculate a large number of special cases as well as to carry out a respective statistical analysis; that is why an effective application of the Monte Carlo methods begins with the emergence of fast computers.

At the heart of any Monte Carlo method is a random number generator: a procedure that produces an infinite stream of random variables that are independent and identically distributed according to some probability distribution. When this distribution is a uniform one (i. e. it has equal probability in the interval from 0 to 1), the generator is said to be a uniform random number generator [6]. Uniform distribution has a wide-ranging application in various problems in engineering modeling and optimization.

The Monte Carlo is not only used for estimation but also for optimization purposes. The optimization based on Monte Carlo methods can be useful for solving optimization problems with many local optima and complicated constraints, possibly involving a mix of continuous and discrete variables [6]. In order to enhance the accuracy of the method, the multistage approach may be applied in which the stochastic computations are repeated by diminishing the region of search after identifying a near optimal solution.

The basic steps in the Monte Carlo method implementation, illustrated in Fig. 1, are followed for solving machining optimization problems in this paper.

3. Case Studies

To investigate the efficiency of the Monte Carlo method for solving single-objective machining optimization problems, five conventional machining process research papers are considered. Although the Monte Carlo method has universal applicability, the selection of papers is restricted to only those dealing with the explicitly given mathematical models i.e. mathematical models in terms of polynomial equations, because optimization solutions can be readily checked and compared.

3.1. Case study 1

Sharma et al. [9] have conducted turning experiments on aluminum 6061 alloy and metal matrix composites of aluminum. For turning of Al-SiC (5%) the authors develop the following relationship between surface roughness and turning parameters:

$$\begin{gathered} R_{a|Al|SiC(5\%)} = -18.7 - 0.00122 \cdot v + 443 \cdot f + 10.4 \cdot d + 0.000001 \cdot v^2 \\ - 2541 \cdot f^2 - 4.71 \cdot d^2 - 0.0015 \cdot v \cdot f - 0.00229 \cdot v \cdot d + 40.7 \cdot f \cdot d \end{gathered} \tag{1}$$

where v is the cutting speed (m/min), f is the feed rate (mm/rev), and d is the depth of cut (mm).

The single-objective machining optimization problem is formulated as follows:

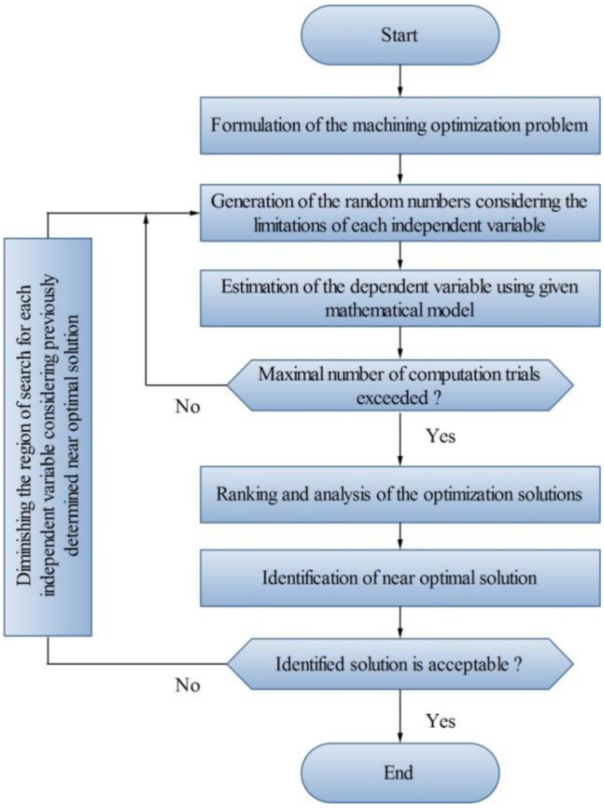

Fig. 1 Monte Carlo method flowchart for solving machining optimization problems

$$\begin{aligned} &\text{Minimize } R_a = f(v, f, d), \\ &\text{subject to: } 228 \le v \le 740 \text{ (m/min)} \\ &\qquad 0.05 \le f \le 0.1 \text{(mm/rev)} \\ &\qquad 0.4 \le d \le 1 \text{(mm)} \end{aligned} \tag{2}$$

In their attempt to obtain minimum surface roughness and corresponding optimal turning parameter values, the authors have applied PSO algorithm.

3.2. Case study 2

Sanjeev et al. [10] have investigated the turning process of polymeric material (polytetrafluoroethylene – PTFE, teflon). The authors have developed regression model for predicting surface roughness in the following form:

$$\begin{aligned} R_a = &-0.309 + 0.675 \cdot v + 0.87 \cdot f + 0.175 \cdot d \\ &- 0.234 \cdot v \cdot f - 0.002 \cdot f \cdot d - 0.143 \cdot v \cdot d \end{aligned} \tag{3}$$

The single-objective machining optimization problem is formulated as follows:

$$\begin{aligned} &\text{Minimize}\, R_a = f(v, f, d), \\ &\text{subject to}: 150 \le v \le 275\,(\text{m/min}) \\ &\qquad 0.1 \le f \le 0.3\,(\text{mm/rev}) \\ &\qquad 0.5 \le d \le 2.5\,(\text{mm}) \end{aligned} \tag{4}$$

In their attempt to obtain minimum surface roughness and corresponding optimal turning parameter values, the authors have applied GA.

3.3. Case study 3

Saravanakumar et al. [11] have investigated turning process of the Inconel 718. Using the experimental data, the authors have developed regression equation for prediction of material removal rate (MRR) in the following form:

$$\begin{aligned} \text{MRR} = 19158 - 298 \cdot v - 112136 \cdot f + 91493 \cdot d + 1749 \cdot vf \\ + 1417 \cdot vd + 537343 \cdot fd - 7880 \cdot vfd \end{aligned} \tag{5}$$

The single-objective machining optimization problem is formulated as follows:

$$\begin{aligned} &\text{Maximize}\, \text{MRR} = f(v, f, d), \\ &\text{subject to}: 60 \le v \le 80\,(\text{m/min}) \\ &\qquad 0.15 \le f \le 0.25\,(\text{mm/rev}) \\ &\qquad 0.1 \le d \le 0.25\,(\text{mm}) \end{aligned} \tag{6}$$

In their attempt to obtain maximal MRR and corresponding optimal turning parameter values, the authors have applied GA.

3.4. Case study 4

Bhushan et al. [12] have investigated turning of Al alloy SiC particle composite material using carbide inserts. On the basis of the experimental results, the authors have developed the following regression equation for the prediction of surface roughness:

$$\begin{aligned} R_a = 0.72412 + 0.00324 \cdot v - 0.19694 \cdot f + 4.19915 \cdot d - 0.18753 \cdot r - \\ - 0.0000174 \cdot v^2 - 3.42419 \cdot d^2 + 3.33125 \cdot fd - 0.56484 \cdot dr \end{aligned} \tag{7}$$

where r is the tool nose radius (mm).

The single-objective machining optimization problem is formulated as follows:

$$\begin{aligned} &\text{Minimize}\, R_a = f(v, f, d, r), \\ &\text{subject to}: 90 \le v \le 210\,(\text{m/min}) \\ &\qquad 0.15 \le f \le 0.25\,(\text{mm/rev}) \\ &\qquad 0.2 \le d \le 0.6\,(\text{mm}) \\ &\qquad 0.4 \le r \le 0.8\,(\text{mm}) \end{aligned} \tag{8}$$

In order to obtain minimum surface roughness and corresponding optimal turning parameter values, the authors have applied GA.

3.5. Case study 5

Poornima and Sukumar [13] have investigated turning of martensitic stainless steel. On the basis of the experimental results, the authors have developed the following regression equation for the prediction of surface roughness:

$$R_a = 1.51539 - 0.01518\cdot v - 1.30442\cdot f - 0.47976\cdot d - 0.00002\cdot v^2 \\ - 6.80272\cdot f^2 - 0.02333\cdot d^2 + 0.07857\cdot vf + 0.00575\cdot v\cdot d + 2.142\cdot fd \tag{9}$$

The authors have formulated the following single-objective machining optimization problem:

$$\begin{aligned} &\text{Minimize } R_\text{a} = f(v, f, d),\\ &\text{subject to}: 80 \le v \le 120 \text{ (m/min)}\\ &\qquad 0.15 \le f \le 0.22 \text{ (mm/rev)}\\ &\qquad 0.5 \le d \le 0.5 \text{ (mm)} \end{aligned} \tag{10}$$

Minimum surface roughness and corresponding optimal turning parameter values are determined by using GA.

4. Results and Discussion

In previous research studies the machining optimization problems are solved by using meta-heuristic algorithms such as the GA and PSO. In this section the optimization solutions obtained by the past researchers are compared to those obtained by applying the Monte Carlo method. All calculations are accomplished by the proposed optimization procedure given in Fig. 1 by using Excel spreadsheet package. The generation of random numbers is done by using function RAND(). In this paper for solving the machining optimization problems formulated in previous section, a two-stage Monte Carlo approach is applied.

In the first stage, random numbers for each independent variable (machining parameter) are generated by considering the interval ranges for each variable. Subsequently, 5000 estimations of dependent variable (performance characteristic) are calculated by using the given mathematical model. After ranking all solutions, the best solution with extreme (minimal or maximal) value of dependent variable along with corresponding values of independent variables is identified. In the second stage, on the basis of the analysis of the previously identified best solution, the range for each independent variable is modified. Subsequently, the stochastic computations are repeated again for 5000 estimations, and the best solution is recorded.

The comparison of obtained optimization solutions for the case studies is summarized in Table 1.

Table 1 Comparison of machining optimization solutions

Case study	Method		Machining parameters				Objective function	
			v (m/min)	f (mm/rev)	d (mm)	r (mm)		
1	IHSA[****]		740	0.05	0.4	---	R_a (µm)	0.22936
	PSO		233	0.05	0.4	---		1.2883[*]
								0.8745[**]
	Monte Carlo method	I stage	609.928	0.051	0.421	---		0.639
		II stage	739.367	0.05	0.4	---		0.2298
2	GA		158.065	0.164	1.719	---	R_a (µm)	61.92
	Monte Carlo method	I stage	151.813	0.291	2.494	---		38.3504
		II stage	150.016	0.3	2.5	---		37.5009
3	SA[****]		80	0.25	0.1	---	MRR (mm^3/min)	2124.275
	GA		79.99	0.25	0.1	---		2122.23
	Monte Carlo method	I stage	79.928	0.25	0.133	---		2071.87
		II stage	80	0.25	0.1	---		2124.06
4	GA		207.055	0.151	0.201	1.199	R_a (µm)	1.039[***]
								1.0650[**]
	Monte Carlo method	I stage	209.293	0.187	0.207	1.108		1.1077
		II stage	209.968	0.15	0.2	1.2		1.0499
5	GA		119.93	0.15	0.5	---	R_a (µm)	0.74
	Monte Carlo method	I stage	119.051	0.151	0.5	---		0.7424
		II stage	119.979	0.15	0.5	---		0.7315

[*] Results reported by Sharma et al. [9]
[**] Corrected values
[***] Results reported by Bhushan et al. [12]
[****] Results reported by Madić et al. [14]; IHSA – improved harmony search algorithm

The analysis of the machining optimization solutions presented in Table 1 indicates that: (*i*) the optimization solutions obtained by the Monte Carlo method after first stage are comparable to those obtained by past researchers using meta-heuristic algorithms such as GA and PSO, and (*ii*) solutions obtained by Monte Carlo method after second stage are better than those obtained by past researchers using meta-heuristic algorithms.

The optimization solutions presented in this paper indicate that few thousand Monte Carlo computation runs are efficient for solving multi-dimensional and complex machining single-objective optimization problems. The efficiency of the Monte Carlo method is assessed by calculating the percentage improvement of the optimization solution for each case study. The comparisons are graphically illustrated in Fig. 2.

The entire optimization time when using Monte Carlo method consists of the time needed to formulate machining optimization problem, the time needed to generate random numbers for each independent variable considering interval ranges, the time for Monte Carlo computation runs i.e. evaluation of dependent variable values, the time needed for ranking the optimization solutions and the time needed for the identification of the best solution.

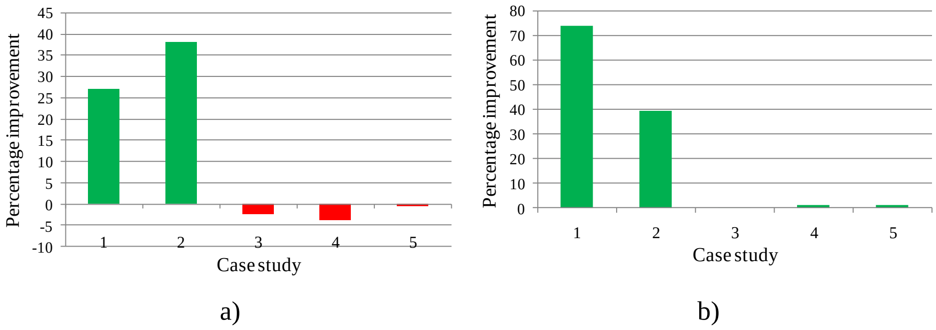

Fig. 2 Percentage improvement of the optimization solutions: a) results of Monte Carlo method after I stage, and b) results of Monte Carlo method after II stage

When the entire optimization time is considered, the Monte Carlo method application for solving single-objective machining optimization problems requires only few minutes. The salient advantage of the Monte Carlo method application is that it is possible to obtain a majority of optimization solutions, which can be particularly advantageous in machining practice considering different machine/tool constraints. Furthermore, the Monte Carlo based optimization approach requires no expert knowledge, setting of algorithm parameters and/or defining an initial solution as in the case of using classical mathematical and meta-heuristic optimization algorithms.

5. CONCLUSION

In this paper, an attempt has been made to investigate the Monte Carlo method applicability for solving single-objective machining optimization problems. Five single-objective machining optimization case studies are considered. In order to analyze the Monte Carlo efficiency, the optimization solutions obtained are compared to those determined by past researches using meta-heuristic algorithms. On the basis of the analysis of the obtained results the following conclusions related to the Monte Carlo capabilities for solving single-objective machining optimization problems can be made:

- Optimization procedure based on the Monte Carlo method consists of only few steps and it is very easy to implement without the need to write programming code or use specialized software packages,
- Monte Carlo is a parameter-free universal method in which optimization search based on random numbers is independent of initial conditions,
- When the computational time is considered, the Monte Carlo method provides an efficient determination of solutions,
- The application of the Monte Carlo method is well suited for solving machining optimization problems and the quality of solutions is comparable or even better than those obtained by meta-heuristics. Using a multiple-stage procedure one could expect further enhancement of the optimization search,
- With increasing computational runs, the Monte Carlo method can be more efficient by avoiding being trapped in local minima,
- Monte Carlo method enables determination of a majority of solutions,

- Monte Carlo method has the capability for solving multi-objective machining optimization problems thus marking the scope of future research.

On the basis of obtained results this study proposes the wider usage of the Monte Carlo method for solving machining optimization problems because of its simplicity, efficiency and wide-ranging capabilities.

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MOGUĆNOSTI PRIMENE MONTE CARLO METODE ZA REŠAVANJE PROBLEMA OPTIMIZACIJE PARAMETARA OBRADE

U savremenim tržišnim uslovima kompanije su fokusirane na povećanje kvaliteta proizvoda, smanjenje troškova i vremena izrade. Za postizanje ovih ciljeva optimizacija parametara obrade je od izuzetnog značaja. Pored klasičnih metoda optimizacije, poslednjih godina za rešavanje problema optimizacije se sve češće koriste meta-heuristički algoritmi. Uprkos brojnim mogućnostima Monte Carlo metode, primena ove metode za rešavanje problema optimizacije parametara obtrade nija dovoljno istražena. Cilj ovog rada je da se istraži mogućnost primene Monte Carlo metode za rešavanje jednokriterijumskih problema optimizacije parametara obrade. U ovom radu dobijeni rezultati optimizacije su upoređeni sa rezultatima optimizacije dobijenih primenom raličitih meta-heurističkih algoritama. U radu su razmatrane pet studije slučaja jednokriterijumske optimizacije procesa mašinske obrade.

Ključne reči: *mašinska obrada, optimizacija, Monte Carlo metod*