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Hardware implementation of Monte Carlo and RSM method for the optimization of cutting force during turning of NiTi shape memory alloy

KOWALCZYK Małgorzata[1,a] *

[1]Chair of Production Engineering, Mechanical Faculty, Cracow University of Technology, Avenue Jana Pawła II 37, PL 31-864 Cracow, Poland

[a]malgorzata.kowalczyk@pk.edu.pl

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Abstract. This study was conducted to understand the exact turning of the NiTi shape memory alloy and consisted of four stages: experimental work, function modelling using RSM method, Monte Carlo method optimization and hardware implementation of Monte Carlo method . This article has the following main objectives: to develop a framework for solving machining optimization problems using the Monte Carlo method and hardware implementation of MC method. The solutions presented in this paper are important from the point of view of practical solutions related to the prediction and optimization of the cutting forces components F_c, F_p and F_f during turning of NiTi shape memory alloy.

Introduction

Cutting forces components which have an impact on the tool and on the workpiece causes a certain change in the position of the tool relative to the workpiece. Any displacement of the tool relative to of the workpiece occurring during machining, can adversely affect accuracy dimension of the machined surface. Prediction and optimization of cutting force before real machining can provide significant guidelines to the planning of turning process in particular such difficult to machine of NiTi alloys [1-4].

The shape memory materials are innovative materials with the high application potential. These materials can be used as the smart materials and multifunctional materials due to their memory shape and superelasticity properties [5-7]. But due to their specific properties NiTi alloys are known to be difficult-to-cut materials particularly by using conventional techniques. Their high ductility, high degree of strain hardening, poor thermal conductivity, very low “effective” elastic modulus and unconventional stress–strain behavior are the main properties responsible for their poor machinability [5,6,8,9].

In order to manufacture new products from difficult-to-machine materials, such as shape memory alloys, there is a need to search for more and more effective treatment methods that exceed technological barriers [10-12]. Therefore, an adapted process strategy, prediction and optimization of cutting force is very important when machining NiTi [2,3,13].

The ability to predict and optimization cutting force before machining has attracted great interest from many scientists, being the main goals of many research studies. The prediction and optimization of cutting force is currently determined by using various techniques such as theoretical models [14-15], FE method [4,15-17], the Taguchi procedure [1,2,11,17-20], response surface methodology (RSM) [13, 21-23], the Multi-Objective Ant Lion Optimizer MOALO [21] the multi-response TOPSIS method [3,19], artificial intelligence through the use of the artificial neural networks (ANNs) [15,2-25], genetic algorithms (GAs) [18] and fuzzy logic (FL) [26]. any research works show the use of these methods in the forecasting and also optimization of cutting force [13]. Researchers usually do not use only one modeling approach in their works, but look for a mutual compilation of the above strategies [18,21,23]. The benefits of using cutting force prediction methods include an increase in the productivity and competitiveness of the production process [1,2,27].

Analyzing the relevant literature regarding the prediction and optimization of machining processes, it can be easily noticed that the current trend is the use of RSM, ANNs, GAs, and the Taguchi procedure for these purposes. The author of this study note that despite the many application possibilities of the MC method [5,10], its application for solving the problems related to the prediction and optimization of machining has not been given much attention in the literature.

Taking into account the above literature review, this paper presents a procedure for model for prediction cutting components force (F_f– the feed force, F_p – the thrust force, F_c – the cutting force) in the turning of NiTi alloy (A_f =60ºC) with PCD tool. The main objective is to develop a model based on response surface methodology (RSM) to the cutting force in terms of machining parameters such as depth of cut (a_p), cutting speed (v_c) and feed rate (f). The computational model enabled to select optimal machining parameters for minimizing cutting forces values. The generation of mathematical models was necessary for the subsequent optimization with the Monte Carlo method, the purpose of which was to find for which cutting parameters the minimum values of the cutting force components are obtained. The algorithm consisted of performing random draws of input parameters from specified ranges for depth of cut, feed rate and cutting speed in a loop.

The next the hardware implementation of the Monte Carlo method was written in the form of code in the software environment, which was uploaded to the microcontroller.

Material Properties

The NiTi alloy used for the experiment was 57.88Ni-42.12Ti (wt%) obtained from Baoji Hanz Metal Material Co.,Ltd. (China). The diameter of the workpiece was 20 mm. The austenite finish temperature was, A_f =60º C. Table 1 shows the chemical composition (wt. %) of NiTi. The physical, thermal and mechanical properties of the materials of β-TiNi: Tensile Strength, Ultimate, 1364 MPa, Tensile Strength, Yield, 649 MPa, Modulus of Elasticity, 28 GPa, Thermal conductivity, 18 W/m·°C, Hardness, 231 HV, Density, 6500 kg/m^3 , Structure (phase), hi-temp B2 [28-29].

Table 1. The spectroscopy (EDS) analysis results.

β-TiNi		
Element	wt.%	at.%
TiK	42.12	47.15
NiK	57.88	52.85
Total	100	100

Cutting tool

The 80º rhombic insert of PCD with single-top corner, brazed tip and a positive rake angle was selected for turning of NiTi. The symbol of insert: CCMT 060202 ID5. The new cutting edge was used for each test sample. Each cutting insert was attached to the designated tool holder SCACR 1616K – 06S. The recommends cutting conditions for insert: depth of cut a_p = 0.08- 3.0 mm, feed f = 0.05 – 0.3 mm/rev;. The literature recommends cutting conditions during precise turning of NiTi alloy; cutting speed v_c = 10-50 m/min; feed rate f <0.2 mm/rev; depth of cut a_p<0.5 mm [6-9].

Experimental design

Turning tests were performed in according Taguchi experiment design at three different cutting parameters (feed f, cutting speeds v_c and depth of cut a_p); Taguchi L9 orthogonal array. For the cutting parameters in turning of NiTi, three factors and three levels, as shown in Table 2 [11]. The parametric design of Taguchi is a very useful technique for elastic design since it provides a simple and systematic empirical effective design at a low cost. It is a method to design an experiment, as it creates the set of arrays with variable factors arranged in such a way that only significant variation is pointed out and the rest insignificant set of variations are neglected thus reducing the number of experiments [2].

Table 2. Cutting parameters.

Parameters	**Code**	**Levels**		
		1	**2**	**3**
Feed rate, *f* [mm/rev]	A	0.038	0.058	0.077
Depth of cut, a_p [mm]	B	0.03	0.08	0.13
Cutting speed, v_c [m/min]	C	30	40	50

The following testing equipment was prepared: precise lathe (Masterturn 400), the workpiece (NiTi alloy), CCMT 060202 PCD insert, tool holder SCACR 1616K – 06S, Kistler dynamometer with DynoWere software to visualize measurements [Fig. 1].

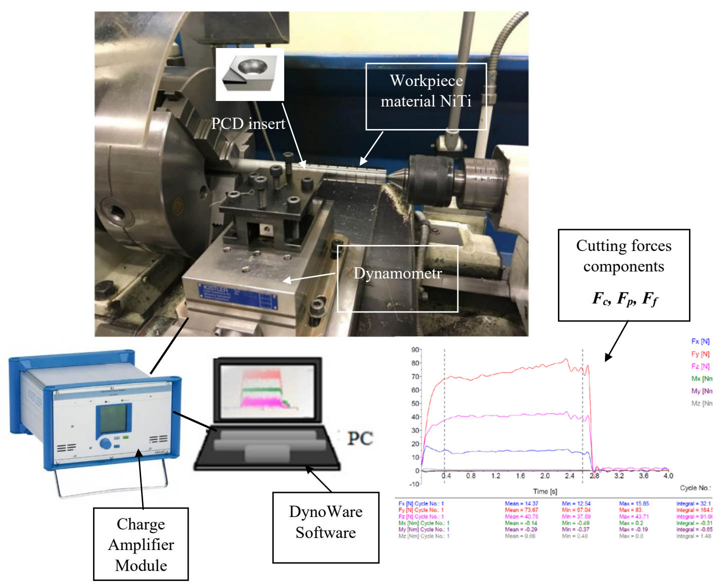

Fig. 1. Experimental set-up for turning of NiTi.

Method

This study was worked out in order to optimize the cutting forces components F_c, F_p and F_f during turning of NiTi shape memory alloy and includes four main stages: experimental work, function modelling using RSM method, Monte Carlo method optimization and hardware implementation of Monte Carlo method. Fig. 2 shows the flow chart which constitutes the overall representation of the methodology developed in the paper. This research has the following main objectives: to develop a framework for solving machining optimization problems using the Monte Carlo method and hardware implementation of MC method.

Experimental work.

The following testing equipment was prepared: precise lathe, work piece (NiTi alloy), tool holder and insert, Kistler dynamometer. Turning tests were carried out in according to Taguchi experiment design (with different feed, cutting speeds and depth of cut). The values of the cutting force components were recorded by the dynamometer and then the cutting force components were in DynoWere software processed (Table 3).

Modelling.

The mathematical relationships between input data and the output parameter-response i.e. cutting force components (F_f , F_p, F_c) Taguchi design was selected. The model for finding parameters of cutting force was appointed using the Response Surface Methodology algorithm.

Monte Carlo Method.

The generation of mathematical models was necessary for the subsequent optimization with the Monte Carlo method, the purpose of which was to find for which cutting parameters the minimum values of the cutting force components are obtained. The algorithm consisted of performing draws of input parameters from specified ranges for depth of cut, feed rate and cutting speed, in a loop.

Hardware implementation.

the Monte Carlo method was written in the form of code in the software environment, which was uploaded to the microcontroller.

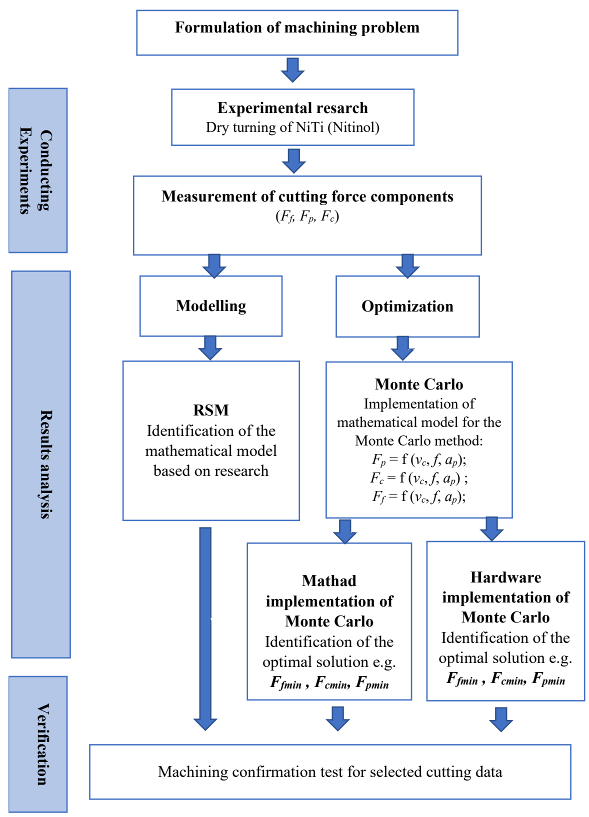

Fig. 2. Flow chart for overall representation of the work methodology.

Results and Discussion

Response surface methodology (RSM).

Response Surface Methodology (RSM) is a series of statistical and mathematical techniques useful for optimizing processes [1,30]. This method is a very effective tool for prediction and modeling the manufacturing problems. It provides more information with a small number of investigations. It is a research strategy to study the limits of input parameters and the emerging experimental statistical model for the measured response, by approximating the existing correlation between the response surface and input process parameters. The limit of the process parameters has to be defined in response surface method, and the first set of experiments was performed to identify machining parameters, which have an impact on the cutting force and to find selected range of cutting parameters [30]. In this study, the cutting speed v_c , depth of cut a_p and the feed f were considered as cutting parameters for monitoring cutting conditions, and the cutting forces components are measured as a response variable (Table 3).

The mathematical model suitable for predicting suitable value is Quadratics model (Eq. 1) where y is a parameter value, describing the investigated physical phenomenon, i.e., the cutting force F_c; b1, b2, …, bi are constant coefficients; and x1, x2, …, xi are factors, which influence the investigated parameter, by considering the full quadratics model as shown in Eq. 2 (F_f – the feed force), Eq. 3 (F_c – the cutting force) and Eq. 4 (F_p – the thrust force).

$$y = bo + b1x1 + b2x2 + b3x3 + b4x4 + b11x12 + b22x22 + b33x32 + b44x42 + b12x1x2 + b13x1x3 + b14x1x4 + b23x3x3 + b24x2x4 + b34x3x4 \quad (1)$$

The mathematical model was established by neglecting the insignificant coefficients of the cuttings forces components (Eq. 2-4):

$$F_f(f, a_p, v_c) = 1.6 + 60.15 \cdot f + 494.26 \cdot a_p - 0.82 \cdot v_c - 5596.04 \cdot f^2 - 3783.73 \cdot a_p^2 \cdot 0.003593 \cdot v_c^2 + 4826.64 \cdot f \cdot a_p + 10.27 \cdot f \cdot v_c \quad (2)$$

$$F_c(f, a_p, v_c) = -381 - 900.2 \cdot f + 2460.6 \cdot a_p + 19.4 \cdot v_c - 14727.8 \cdot f^2 + 7257.6 \cdot a_p^2 - 0.4174 \cdot v_c^2 - 55636.6 \cdot f \cdot a_p + 214.6 \cdot f \cdot v_c \quad (3)$$

$$F_p(f, a_p, v_c) = -24.2 + 1045.5 \cdot f + 1318.1 \cdot a_p - 1.228 \cdot v_c - 17431.4 \cdot f^2 - 4092.9 \cdot a_p^2 \, 0.01768 \cdot v_c^2 - 3756.8 \cdot f \cdot a_p + 39.46 \cdot f \cdot v_c \quad (4)$$

The mathematical model was used to for prediction cutting components force (F_f– the feed force, F_p – the thrust force, F_c – the cutting force) in the turning of NiTi alloy (A_f=60ºC) with PCD tool by replacing the values of the machining parameters. The impact of cutting cutting parameters was examined using the developed model.

The information in Table 3 shows the result from the comparison between actual value and forecasting value which found that the forecasting values of mean of the feed force F_f has the maximum error of only 1.67%, for mean of the cutting force F_c – 3,93% and for mean of thrust force F_p – 0.23%.

Table 3. Experimental results.

Test no.	Control factors			Measured value (Mean)			Predicted value RSM			% Error		
	f [mm/rev]	a_p [mm]	v_c [m/min]	F_f [N]	F_c [N]	F_p [N]	F_{fRSM} [N]	F_{cRSM} [N]	F_{pRSM} [N]	F_f	F_c	F_p
1	0.038	0.03	30	3.10	32.70	14.20	3.07	31.42	14,17	0.92	3.90	0.23
2	0.038	0.08	40	14.40	73.70	40.80	14.36	72.01	40,76	0.26	2.29	0.09
3	0.038	0.13	50	7.50	67.50	43.40	7.45	65.41	43,36	0.63	3.09	0.10
4	0.058	0.03	40	2.90	108.50	21.30	2.86	106.81	21,26	1.39	1.56	0.18
5	0.058	0.08	50	21.80	53.30	48.50	21.75	51.20	48.46	0.23	3.93	0.09
6	0.058	0.13	30	19.50	121.30	67.60	19.47	119.98	67.56	0.16	1.09	0.05
7	0.077	0.03	50	3.20	169.00	26.50	3.15	166.89	26.45	1.67	1.25	0.17
8	0.077	0.08	30	20.50	66.30	47.50	20.47	64.98	47.46	0.16	1.99	0.07
9	0.077	0.13	40	26.30	118.80	61.70	26.26	117.06	61.66	0.17	1.46	0.07

Monte Carlo method.

The Monte Carlo method is often used in engineering, finance, statistics and other fields of science. Fig. 3 shows a block diagram of the applied MC method for determining the optimal (minimum) values of the factors as shown in Eq.2 (F_f – the feed force), Eq. 3 (F_c – the cutting force) and Eq. 4 (F_p – the thrust force). The optimization task was solved using Mathcad software and hardware implementation. After optimization using the Monte Carlo method, the optimization results were verified experimentally.

The program implementing the assumptions of the Monte Carlo algorithm was written in the Arduino IDE environment, and then uploaded to the Arduino UNO board with the Atmega 328P microprocessor, which is responsible for performing the calculations necessary to carry out the optimization process. In the first part of the program code ‘string’ and ‘int’ variables were initialized. They were used to send numbers (in the form of characters) to the microprocessor, which will define the ranges of input parameters (depth of cut a_p, cutting speed v_c, feed rate f, and number of MC draws). Then ‘float’ values are declared, which will determine the output values (cutting components force F_f– the feed force, F_p – the thrust force, F_c – the cutting force and the values of optimal cutting parameters (v_c, a_p, f). Auxiliary variables have also been introduced, i.e. m - number of MC draws and time - variable responsible for calculating the time program duration. The ‘random’ function is responsible for generating pseudo-random numbers from a specific range. The program initialization was included in the void setup() function. The void loop function is defined in the following part( ) in which the main part of the code was placed. It contains the way in which the microcontroller reads character type values entered into its memory. The functions responsible for displaying the ranges of input parameters on the terminal were generated. Next a loop implementing the algorithm was placed in the function void loop() Monte Carlo in the final part. The code contains functions responsible for displaying the results received from the microcontroller on the terminal.

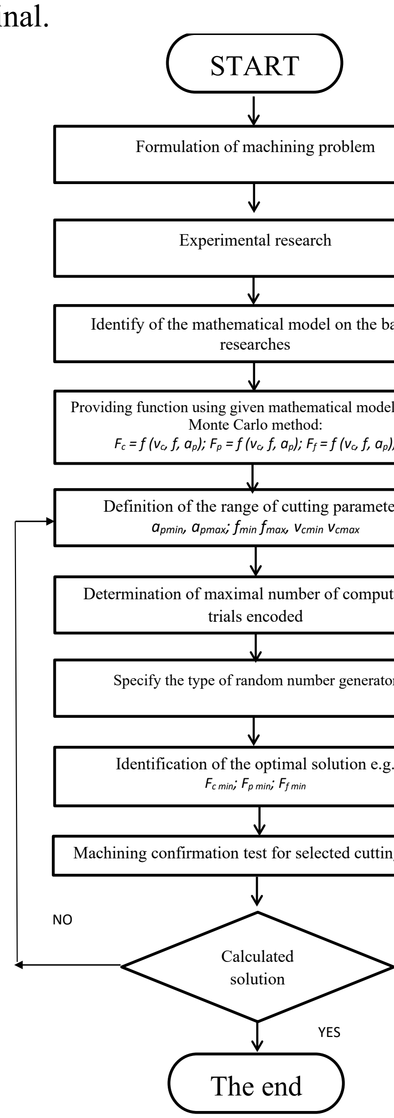

Fig. 3. Monte Carlo method algorithm for solving machining optimization problems [10].
Monte Carlo optimization result.

Table 4 summarizes the results of the calculations of the minimum values (rows 2, 9 and 16) of the functions described by Eq. 2, 3 and 4 and defined by F_f MC min, F_c MC min and F_p MC min for the case of three different numbers of MC draws (the first row): 10^4, 10^5, and 10^6 for Mathcad software and hardware implementation. For the values of the functions F_f MC min, F_c MC min and F_p MC min for all Monte Carlo trials, the corresponding drawing number m (rows 3,10 and 17), the values of parameters f, a_p, and v_c (rows 4–6, 11-13 and 18–20), the measure values of F_f, F_p and F_c (rows 7, 14 and 21) and error of method are determined for Mathcad software and hardware implementation.

Table 4. Calculation results of the minimum value of Eq. 2, Eq. 3 and 4 by using the MC method.

No.	Parameters/Factors	Results MC (Mathcad)			Hardware implementation		
1	MC[no.]	10^4	10^5	10^6	10^4	10^5	10^6
2	$F_f{}^{MC}{}_{min}$	1.028	1.608	1.859	1.037	1.698	1.889
3	m [no.]	4.3	4.787	9.326	4.3	4.787	9.326
4	f [mm/rev]	0.077	0.077	0.077	0.077	0.077	0.077
5	a_p [mm]	0.031	0.03	0.03	0.031	0.03	0.03
6	v_c [m/min]	32.64	30.064	30.042	32.64	30.064	30.042
7	$F_{f\ measure}$	1.81	1.81	1.81	1.81	1.81	1.81
8	*%Error*	43.20	11.16	2.71	42.71	6.19	4.36
9	$F_c{}^{MC}{}_{min}$	71.697	72.503	82.307	71.89	72.78	82.205
10	m [no.]	3.876	8.194	1.169	3.876	8.194	1.169
11	f [mm/rev]	0.038	0.039	0.038	0.038	0.038	0.038
12	a_p [mm]	0.031	0.034	0.032	0.03	0.03	0.03
13	v_c [m/min]	49.285	49.55	49.967	48.94	48.49	48.87
14	$F_{c\ measure}$	79.25	79.25	79.25	79.25	79.25	79.25
15	*%Error*	9.53	8.51	3.86	9.29	8.16	3.73
16	$F_p{}^{MC}{}_{min}$	6.229	6.13	7.75	6.34	6.18	7.83
17	m [no.]	3.876	1.291	4.492	3.876	1.291	4.492
18	f [mm/rev]	0.038	0.039	0.038	0.038	0.038	0.038
19	a_p [mm]	0.031	0.03	0.03	0.03	0.03	0.03
20	v_c [m/min]	49.285	49.766	49.792	48.83	48.26	48.95
21	$F_{p\ measure}$	7.71	7.71	7.71	7.71	7.71	7.71
22	*%Error*	19.21	20.49	0.52	17.77	19.84	1.56

Based on the mathematical model, cutting components force F_f– the feed force, F_p – the thrust force, F_c – the cutting force were optimized using Monte Carlo method. The optimal solution is the following for :
For the feed force F_f *(Mathcad)*: number Monte Carlo trials: 9.326 x10^6, F_f = 1.859 N, f = 0.077 mm/rev, a_p = 0.03 mm, v_c = 30.042 m/min, %error of method: 2.71% .
For the feed force F_f *(hardware implementation)*: number Monte Carlo trials: 9.326 x10^6, F_f = 1.91 N, f = 0.077 mm/rev, a_p = 0.03 mm, v_c = 30.042 m/min, %error of method 4.36% .
For the thrust force F_p *(Mathcad)*: number Monte Carlo trials: 4.492 x10^6, F_p= 7.75N, f = 0.038 mm/rev, a_p = 0.03 mm, v_c = 49.766 m/min, %error of method: 0,52%
For the thrust force F_p *(hardware implementation)*: number Monte Carlo trials: 4.492 x10^6, F_p= 7.82N, f = 0.077 mm/rev, a_p = 0.03 mm, v_c = 48.95 m/min, %error of method: 1.56%
For the cutting force F_c *(Mathcad)*: number Monte Carlo trials: 1.169 x10^6, F_c= 82.307 N, f = 0.038 mm/rev, a_p = 0.032 mm, v_c = 49.967 m/min, %error of method: 3.86%
For the cutting force F_c *(hardware implementation)*: number Monte Carlo trials: 1.169 x10^6, F_c= 81.95 N, f = 0.038 mm/rev, a_p = 0.03 mm, v_c = 48.87 m/min, %error of method: 3.73%

Summary
This paper proposes the Monte Carlo method to predicted and optimized cutting forces based on cutting parameters (cutting speed, feed rate and depth of cut).
The procedure presented in this paper, which is devoted use of Monte Carlo Method for optimization of the cuting forces components (F_c, F_f, F_p) during turning of NiTi alloys , allows for an easy and quick assessment of the obtained results related to the prediction and optimization carried out in the process of conventional machining of NiTi alloys.
The work demonstrates that this method is a quick and effective tool, that enables defining optimal cutting parameters to minimize the cutting force during turning of NiTi alloys.
The important findings are summarized as follows:
1) Prediction accuracy of cutting forces by MC method developed models is efficient both for implementation of MC method in Mathcad software like and hardware implementation of MC method.
2) Comparison of experimental and predicted values of the cutting forces show that a good agreement has been achieved between them (Table 4). The maximum method error was 4.36% for MC draws 10^6. The method is more effective for more MC draws.
3) The Monte Carlo optimization show that the optimal combination of cutting parameters are found to be cutting speed of 50 m/min, feed rate of 0.038 mm/rev, cutting depth of 0.03 mm for the thrust force F_p and the cutting force F_c *and* cutting speed of 30 m/min, feed rate of 0.077 mm/rev, cutting depth of 0.03 mm for feed force F_f .
In this study, the optimization methodology proposed is a powerful approach and can offer to scientific researchers as well industrial metalworking a helpful optimization procedure for various combinations of the workpiece and the cut material tool. The procedure for the cutting force optimization during the turning proposed in this paper can be used to optimize costs and ensure maximum efficiency during applications of turning for NiTi alloy.

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