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Resource efficiency optimization of manufacturing processes using evolutionary computation: A turning case

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Abstract

Most resource efficiency optimization measures being discussed in resent publications focus on component downsizing and adaptive control of components regarding the standard ISO 14955. Optimization of discrete manufacturing process parameter is a further approach to reduce resource consumption during operation. This paper presents a meta heuristic genetic algorithm approach which has been used to determine a pareto front of feasible machining parameter. The pareto front is used to select optimal solutions for the resource consumption integrated multi-dimensional optimization task. The results are presented for a turning process with respect to resource consumption, machining time and machining cost under product quality constrains and machine performance limits.

Keywords: Resource efficiency; multi-objective optimization; genetic algorithm

1. Introduction

The aspect of resource consumption gains more and more attention since resources are running short and the resulting costs per manufactured part are directly related with this development [1]. Manufacturing process optimization is usually performed on process level with the adaptation of process variables to find a reliable operation state. In the past, the aim was a reduction of manufacturing cost and cycle time. The preliminary definition of the process values is typically part of the process planning stage and often done as off-line process control. Selection of process variables is traditionally based on a machine book, tool manufacturer recommendation or the operator's experience [2].

Now the decrease of manufacturing process related resource consumption is taken into account as an additional target [3]. In metal cutting processes, optimization is typically done by adjusting three impact factors,

- cutting speed v_c
- feed rate f
- depth of cut a_p,

while maintaining the required product quality. Model supported process planning is therefore a step forward and provides better and faster results for a stable and a multi object oriented manufacturing of products. Off-line process planning uses process models to select process variables based on experimental results, e.g. the influence of cutting parameters on quality features like surface roughness. Measured values are used to determine the expected values according to an analytical model. Therefore, off-line process control depends on quality and accuracy of the data available for modeling, and the capability of the applied analytical model.

Venkata Rao [4] gives a detailed review of contemporary methodologies and practice on the modeling and optimization of manufacturing processes. Different optimization methodologies have been applied for solving constrained problems of determining manufacturing costs and cycle time in

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metal cutting processes, like regression analysis, ant colony optimization as well as genetic algorithms. For example, Bajić and Belajić [5] and Oktem et al. [6] used response surface methodology, while Jabri, Barkany and Khalfi [7] as well as Belloufi, Assas and Rezgui [8] used genetic algorithms for machining process optimization. Genetic algorithms were also used for optimization of emerging manufacturing processes like electro chemical machining [9] laser beam cutting [10], and rapid prototyping [11]. Braun and Heisel included energy consumption in process modeling and optimization [12]. Kara and Li as well as Winter derived empirical models for energy consumption of manufacturing processes [13,14].

Manufacturing and technological processes nowadays claim implementation of control systems using sophisticated mathematical methods for efficiency purposes. In particular the prior task is to determine those values of the process parameters that will allow achievement of the demanded product quality. A further task is to optimize manufacturing process performance regarding cost efficiency and resource consumption.

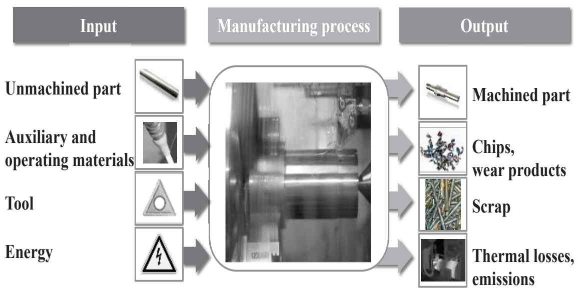

Fig. 1. Characteristic resource consumption of a turning processes

Due to the high number of different resources consumed on process and machine level shown in fig. 1, research is needed to get the mathematical approximations of machining processes and suitable optimization methods which are able to consider resource consumption as valid optimization target. The above mentioned approaches show the interest of selecting optimal cutting parameters in manufacturing process.

The aim of this research is to adapt a multi objective optimization algorithm that relates resource consumption of a machine with the manufacturing process time. Resources selected in this approach are the empirically determined process energy consumption and tool wear based on the three cutting parameters:cutting speed (v_c), feed per turn (f) and depth of cut (a_p), of the multi-pass surface turning process shown in fig. 3. The work piece surface roughness as quality determining feature has a significant impact on resource efficiency of the manufacturing process, since poor work piece quality demands reworking by additional resource consumption, or leads to scrap as material loss.

2. Multi-Objective Optimization

Genetic Algorithms (GA) are meta heuristic search algorithms based on the methods of natural selection and natural genetics [4,7,8]. A GA starts with an randomly generated initial population of individuals x_0. Each individual is represented by a string of design variables coded into series of bits or a real number. To get the ranking of the strings in a population, a fitness function based on the defined objective functions is evaluated. If the end condition is not reached new individuals are generated by using genetic operators like crossover, selection and mutation. In each generation the ranking is conducted. The fittest will be selected and new individuals will be created to get a conceivably better population of strings which are closer to the optimum solution to the problem. So in each generation, the GA creates a set of strings from the bits and pieces of the previous strings, occasionally adding random new data to keep the population from stagnating. The final result is a search strategy that is tailored for vast, complex, multi-modal search spaces. Fig. 2 shows a flow chart of the operation of a GA.

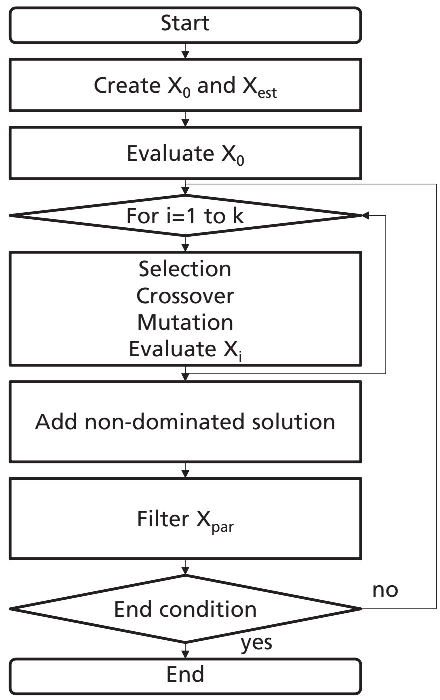

Fig. 2 Flow chart of the operation of the genetic algorithm

3. Resource Consumption Integrated Turning Process Model

In this work a hybrid approach has been used in order to generate the mathematical model for the resource consumption integrated turning process. The resource consumption process model will be the basis for the applied multi-objective optimization.

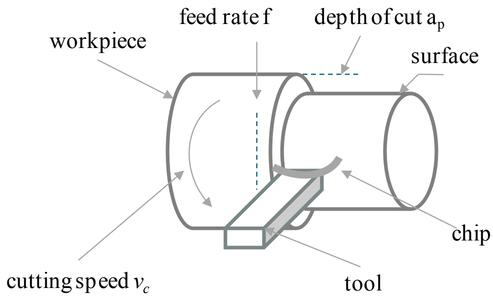

Fig. 3 Process parameters of the turning process

Fundamental for the modeling is an adaption of the works related to multi-pass turning process [15,16,17] including the energy consumption model as third objective.

Manufacturing process time

The first objective function is the total manufacturing process time t_m of actual operation. For multi-pass turning operation, total manufacturing time is the sum of the single cuts t_{sc} given by Eq. 1 [18]:

$$t_{sc} = \frac{\pi d_1 L}{1000 v_c f} \tag{1}$$

where:
d_1 = diameter before cutting
d_2 = diameter after cutting
L = length of cut

and the process adjusting and quick return time t_a.
The number of passes n is given as integer by:

$$n = \left(\frac{d_1 - d_2}{a_p}\right) \tag{2}$$

$$t_m = \sum_{k=1}^{n} (t_{a,k} + t_{sc,k}) \tag{3}$$

Tool wear

The second objective function is tool wear ξ. It is considered as the part of the whole tool life which is consumed in the multi-pass turning process [18]:

$$\xi = \left(\frac{t_{sc}}{\theta T_r}\right) 100\% \tag{4}$$

Where: T_r are the Taylor tool life of turning operations, with the constants C_0, p, q, r and θ as weight factor respectively [18]:

$$T_r = \frac{C_0}{v_c^p f^q a_p^r} \tag{5}$$

Process Energy

The third objective function is the corresponding process energy consumption. Due to the fact that the actual energy consumption depends on the components installed and varies from the analytical calculation by the cutting force, the model for energy consumption is gathered empirically by a design of experiments (DOE) based regression analysis related to [19,20,21]. This common and widespread parametric approach quantifies the impact of machining parameters on output parameters [22]. A central composite design (CCD) is applied to provide the necessary data points for the following empirical second-order polynomial model (6):

$$\boldsymbol{E_{Pr} = b_0 + \sum_{i=0}^{k} b_i \cdot X_i + \sum_{1 \le i < j}^{k} b_{ij} \cdot X_i \cdot X_j + \sum_{i=1}^{k} b_{ii} \cdot X_i^2} \tag{6}$$

where b0, bi, bij, bii are regression coefficients, and Xi, Xj are the coded values of input parameters. The required number of experimental points for CCD is determined as follows in (7):

$$\boldsymbol{N = 2^k + 2k + n_0 = n_k + n_\alpha + n_0} \tag{7}$$

where k is the number of parameters, n_0 is the repeated design number on the average level, and n_α is the design number on central axes. In total CCD of experiment demands 20 observed experiment conditions, 8 experiments with 3 factors on two levels, 6 experiments on the central axes and 6 experiments on the average level.

Machining Constraints:

The decision variables constraints are the allowed cutting parameter values. Typically the boundaries are given either by the tool manufacturer or by common engineering reference tables.

$$v_{c,min} \le v_c \le v_{c,max} \tag{8}$$

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

$$a_{p,min} \le a_p \le a_{p,max} \tag{10}$$

The major constraint which is affecting the optimization process is the maximum cutting power available on the machine. The cutting power must not surpass the machine main spindle power.

$$P_{El} \leq P_{spindle} \tag{11}$$

The product related limitation will be taken into account by the obtained surface roughness [23] regarding the tool radius R which is given by Eq. 12

$$R = \frac{f^2}{8R} \leq R_{max} \tag{12}$$

4. Experimental Set Up and Results

The type of machine tool used for the turning process was the universal lathe TC 300 manufactured by Spinner. The test sample used in experiments was a cylinder made of steel 42CrMo4 with dimensions 150 mm length and a diameter of 60 mm. The turning experiments were executed by the tool TP2500 MF5390, produced by Seco. Each run was executed with a new and unused cutting tool. Process energy consumption was measured by utilizing the Beckhoff three phase power measuring terminal EL3403 and the Janitza cable split core current transformer 400 A/1A at the Siemens Sinumerik 840D frequency converter of the Spinner turning lathe. Process energy consumption data was then passed via bus coupler to a SQL database each 5 ms. All measuring instruments were calibrated before testing. The experiments were carried out with 6 % cooling and lubrication agent concentration at 3 bar application pressure. Twenty experiments from the CCD setup were performed in order to allow the regression analysis (equation 6). For modeling the DOE regression equation the MATLAB statistics toolbox [24] and for the GA implementation the MATLAB global optimization toolbox was applied [25].

Machining Parameter

The design variables constraints are given by table 1. The boundaries are the tool manufacturer recommendation from Seco.

Table 1: Design variables value range

Coded values	Levels	-1	-0.5	0	0.5	1
Physical values	$X1=v_c$ [m/min]	310	337	365	393	420
	$X2=a_p$ [mm]	0.35	0.525	0.7	1.05	1.4
	X3=f [mm/turn]	0.3	0.338	0.375	0.413	0.45

The energy values are determined by a numerical integration of the individual CCD experiment load curve. Fig. 4 shows the load curve for the experiment with the decision variable values **X**=[0,0,0]. Quick return time is const. 1 sec per pass.

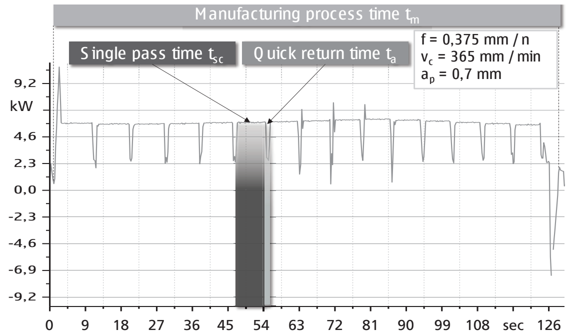

Fig. 4 Process parameters of the turning

The empirical energy regression model is determined as follows:

$$E_{Pr} = 18027.3 - 28123.1 * x(1) - 26.9 * x(2) - 9092.3 * x(3) + 24659 * x(1)^2 + 2840.8 * x(3)^2 + 6.4 * x(1) * x(2) + 5016.6 * x(1) * x(3) + 1.9 * x(2) * x(3) \tag{13}$$

Testing of the DOE E_{pr} model was performed with 5 additional experiment data that had not been used in the modelling process. The resulting model prediction error is given as mean square percentage error in table 2.

Table 2: Relative prediction error for Epr

Exp. Numb.	Epr [%]
I	12.04%
II	13.22%
III	20.44%
IV	8.26%
V	14.17%
Average	13,63%

The constraints for power and surface roughness are:

$$P_{spindle} = 11\,kW \tag{14}$$

$$R_{max} \leq 16 \tag{15}$$

Genetic algorithm parameters

For determining the pareto front for the multi-objective optimization problem the GA based non dominated sorting algorithm-II (NSGA-II) [24] is applied. All objectives are simultaneously considered. Table 3 shows the search options used.

Table 3: Applied GA-Parameter

GA-Parameter	value
Solution space size (population)	500
Maximum number of iterations	100
Crossover probability	70 %
Mutation probability	5 %

The randomly distributed initial population X_0 is shown in fig. 5.

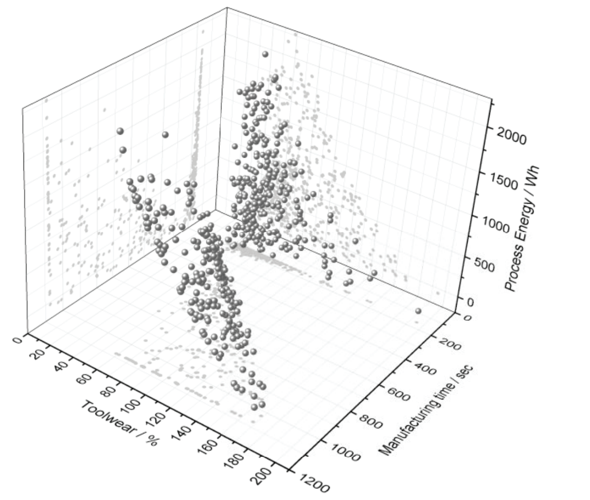

Fig. 5 Initial population of the GA

After the 100 iterations the final determined pareto front is shown in fig. 6. The corner points 1;2;3 indicate the local optimal point for the single objectives within the pareto solution space. The related process parameters for the three characteristic points are shown in table 4. All other points represent possible compromise solutions regarding the multi-dimensional optimization, each with a different focus on the three single objective functions.

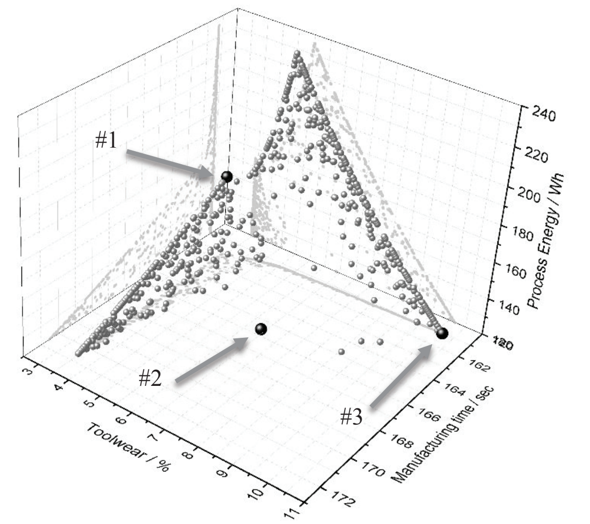

Fig. 6 Pareto front of the multi-pass turning processs

For the manufacturing task a order-related specific solution can be chosen from the pareto set.

Table 4: Design variables for the identified optima

Decision Vector	#1	#2	#3
X1=f [mm/turn]	0.3	0.44	0.5
X2=v_c [m/min]	300	325.11	358.06
X3= a_p [mm]	2	1.95	2
E_{Pr} [Wh]	164.42	120.01	120.03
ξ [%]	3.41	6.38	10.17
t_m [sec]	162.09	165.6	161.06

5. Conclusion

The purpose of this study was to analyze the capability of a genetic algorithm based on a posteriori multi-objective resource consumption optimization of a multi-pass turning process. The application example gives an answer regarding optimal combinations of input process parameters for simultaneously minimizing energy consumption, minimizing tool wear and minimizing manufacturing process time. Because it is a meta heuristic approach, the search results can only be specified in relation to the initial population. The results were positively evaluated for their behavior with respect to the valid fundamentals of machining. Regarding the results, the approach is found to be capable of identifying a pareto front including predictions on single optimization goals and of finding simultaneously multi-dimensional optimization solutions. The range of possible solutions suiting the derived pareto front varies 6.5 % for t_m from min 161.06 to max 171.5 sec; 96.6 % for $E_{Pr\ from}$ min 120.01 to max 235.6 Wh; 297,4 % for ξ min 3.41 to max 10.17 %.

Due to the fact that accurate predictions are substantial to improve off-line process control resulting in significant reduction of machining cost and resource consumption, the approach is considered to be suitable for this purpose. For further detailing a comparison of the absolute optima results of additional optimization algorithms needs to be performed.

Today only a small amount of modern evolutionary computation technology has been transferred to manufacturing. Therefore, off-line process control as an approach that demonstrates its capabilities to be applied in practice and easily integrated in existing conditions represents a key for successful and resource efficient machining. For complex manufacturing tasks a feature division application is recommended.

In addition to the comparison with different optimization algorithms a next step to advanced manufacturing processes, the established approach has to be applied into a closed methodology to determine suitable process models and parameters for cost-, time- and resource- efficient operating points.

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