Machining Quality Optimization by Goal Programming Method and Genetic Algorithm

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Abstract-*With the development of manufacturing technology, the precision machining has been widely used in aerospace, the military, the automobile manufacturing and other fields. Improving machine tools' machining accuracy is one of the most significant pursuits for industry manufactures.*

This paper presents manufacturing errors modeling and optimization for machining accuracy improvement. Firstly, cubic splines interpolation is used to describe machining errors by a set of cubic polynomials. Thermal -, table motion- and tool wear errors are taken into account in this study. Then, based on goal programming method, the optimization problem is established. In this paper, non-dominated sorting genetic algorithm (NSGA) is used to solve the goal programming problem; which makes the optimization problem free from using any weight factor. As a result, zero percent rejection of machining parts are obtained by this method.

Keywords: *Manufacturing tolerances; goal programming; Machining errors; cubic spline interpolation, genetic algorithm.*

I. introduction

Accuracy of CNC machined parts is affected by a combination of error sources such as tool deflection, geometric errors, thermal-induced and force-induced deformation errors. With the increasing demands of higher quality machined complex parts, improvement of machine tools precision is vital. J. Wang et al 2013; presented a modelization and compensation of thermal errors for nanopositioning systems, by using genetic algorithm (GA) a model is given to describe the relationship between temperature and deviation, a system for compensation of this errors is applied [1]. Y. X. Li et al 2008; based on grey system theory investigated and optimized thermal sensors placement on machine tools to select the most decisive temperature measuring points; for predicting a thermal error model with less variables and more effective [2]. Hui liu et al 2016; studied the thermal errors on CNC machine tool under different conditions, where the thermal error prediction model is established by using the ridge regression algorithm and an compensation of this errors is done by applying this method [3]. Junkang Guo et al (2015); proposed an analytical method to determine optimal tolerance design and assembly process planning. Using state space model, the variation propagation of machine tools is modeled, then tolerances of components can be optimally allocated. Zhiyong Chang et al (2018); developed a new mathematical model of the effective cutting edge to accurately estimate the surface quality and dimension errors in CNC turning. This model is used to tool path generation with high precision. Zhou-Long Li and Li-Min Zhu (2018); proposed a comprehensive approach for minimizing machining errors caused by tool and workpiece deformation by tool path optimization. The machined surface with the machining deformation errors is modeled, then the deviations between the machined surface and the design surface is determined. The machined surface are approximated to the design surface by tool path adjustment for machining errors compensation. Xiaojian Liu et al (2018); proposed an improved geometric error analysis method, geometric error model is established based on multi-rigid-body which include cutting tool's wear-out error and workpiece's clamping error by using HTM; screw mapping method is used to transform the geometric error model to screw form [7]. Xiaoyan Zuo et al (2013); proposed an integrated geometric error model based on Jacobian-Torsor theory for three axis machine tool. A novel compensation method is presented by modifying the corresponding NC codes according to the predicted errors [8]. De-ning Song et al (2017); proposed an effective method to estimate and compensate the trajectory error in high-feed-speed continuous- path machining. The continuous-path running trajectory error is valued by approximating the desired tool path with spline curves. The error compensation algorithm has been made by using mirror compensation and Taylor series expansion compensation [9]. Alexander Yuen and Yusuf Altintas (2018); developed a new methodology to compensate the deviation of the tooltip caused by geometric error of 3-axis gantry type micromill with rotary magnetic table of 6 degree of freedom. The geometric errors of each axis are measured and modeled with quintic polynomial functions. An ideal kinematic model is established, and modified to include the geometric errors; to get the tooltip position errors. The compensation of tooltip error in real time is done by changing the position of the rotary table using gradient descent algorithm [10]. Ryan Copenhaver et al. (2018); studied the stability of the modulated tool path (MTP) turning by a new periodic sampling approach, where the synchronicity of the sampled signal is evaluated numerically. The oscillation frequency of the spindle speed and the oscillation amplitude of the global feed per revolution is used to form discrete chips [11]. M. Salehi et al. (2019); proposed a probabilistic sequential prediction of cutting forces. Bayesian inference is used to Merchant and Kienzle cutting force models, to inspect the cutting force prediction. Markov chain Monte Carlo is used to determine the model uncertainties [12]. Chanda et al (2018); studied the influence of shape on tool path motion and developed a new methodology to characterize tool path motion that can be applied in any machine tool to enhance the efficiency and productivity of the manufacturing process. The characterization identifies the achievable set of kinematics for a tool path of a given shape without physical machining and a knowledge of the motion control algorithms [13]. Jian-wei Ma et al (2018); proposed a new method for machining errors minimizing by tool path modifying and feed-speed optimization for rapidly varied geometric features. The feed speed is optimized take into account jerk and acceleration limitations of the feed shafts. The compensated cutter locations is determined by machining errors estimation. Based on the optimized feed speed and the compensated toolpath, the NC codes is adapted [14]. Xing Zhang et al (2017); presented a new optimization approach of tool orientation in roughing and finishing milling in 5-axis ball-end milling in order to obtain high efficiency and accuracy machining. Firstly, a new precise cutter/workpiece engaging model based on enhanced analytical approach using Taylor formula is developed, taken into account tool orientation and cutter runout. Then, using cutting force prediction model, the exact tooth trajectory is established [15].

II. Goal programming

Goal programming is a practical tool to solve optimization problems with conflicting objectives with a wide variety of fields of application. Goal programming (GP) method is used for the optimization problem. The principle of this method is given by the system (1):

$$\begin{cases} \textbf{Minimize} \sum_{i=1}^{P} |f_i(x) - g_i| \\ C(x) \leq c \quad (\textbf{constraints}) \end{cases} \tag{1}$$

$f_i(x)$: Objectives

g_i:The goal set for the i-th goal (for i = 1,2, ..., p);

$C(x)$:Manufacturing tolerance interval

c :Design tolerance interval

By introducing the negative and positive deviations $\delta^- \ and \ \delta^+$ respectivelly. The system (1) can be written as:

$$min\ Z = \sum_{i=1}^{p}(\delta^+ - \delta^-)$$

Subject to (2)

$$\begin{cases} \sum_{i=1}^{p} a_{ij}x_j - \delta^+ + \delta^- = g_i & (for\ i = 1,2, \dots \dots p) \\ x_j \geq 0 \quad (for\ j = 1,2, \dots \dots n) \\ \delta_i^+ et\ \delta_i^- \geq 0 \quad (for\ j = 1,2, \dots \dots n) \end{cases}$$

III. Genetic Algorithm

A GA is based on the mechanics of natural selection and natural genetics and Darwinian survival of the fittest. Detailed discussion of the mechanisms of GA can be found in [16], Figure present the flowchart of NSGA.

Non-dominated sorting genetic algorithm (NSGA) differs from simple genetic algorithm only in the selection operation. The crossover and mutation operators work the same way. NSGA used in this study is a real parameters GA.

The first step is to sort the population P randomly created according to the non-domination. This classifies the population into a number of non-dominated sets P_k.

The next step is to assign to each solution in these classes a fitness value. Because all the solutions belong to the first front are the best and equally important, the large fitness value is assigned to these solutions. And then, assign progressively worse fitness value to solution in the higher classes.

In order to maintain diversity, theses sorted individuals are then shared with their dummy fitness values. Sharing is achieved by performing selection operation using degraded fitness which are obtained by dividing the original fitness value of an individual by a quantity proportional to the numbers of individuals around it [16].

After all solutions are assigned a shared fitness. The population is then reproduced according to the dummy fitness value. A stochastic remainder proportionate selection is used in this study; this assigns copies in the mating pool proportional to the shared fitness.

For crossover operation, two solutions are picked from the mating pool at random, and crossed with a probability $p_c = 0.8$, in order to create to new children solutions. In this study simulated binary crossover (SBX) operator is used.

The need for mutation operator is to keep diversity in the population. Polynomial mutation [16] is used in this study to create a new solution from the parent solution with mutation probability $p_m = 0.1$.

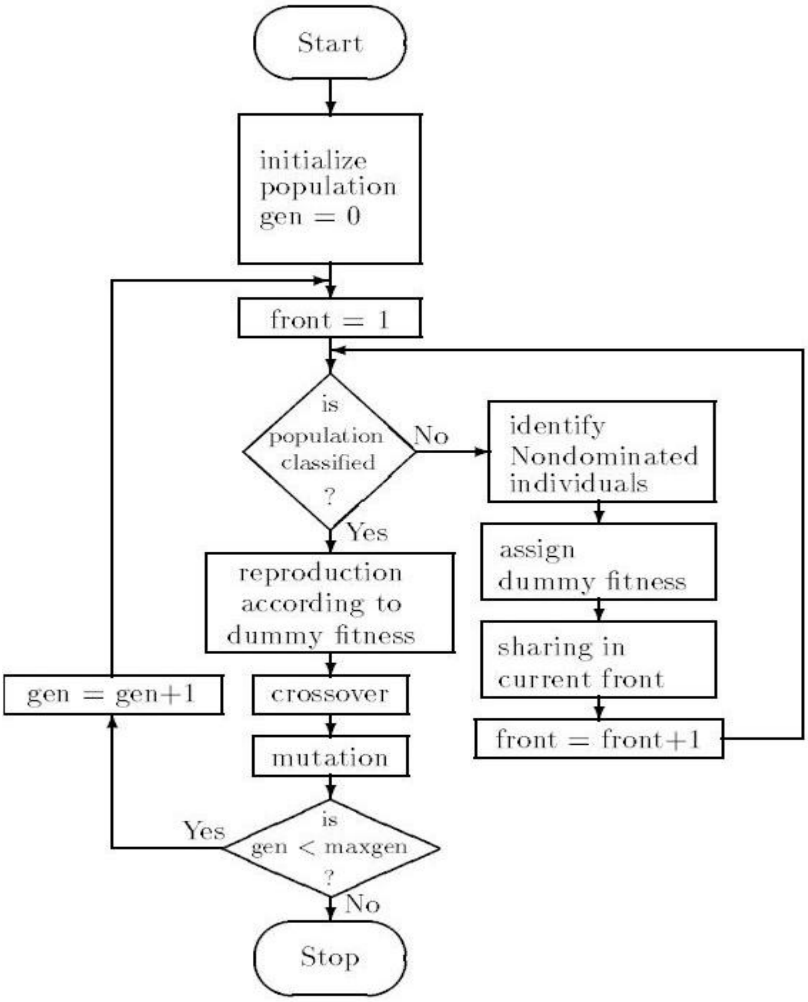

Fig 1. Flow chart of NSGA [17]

IV. Application

In this paper, a test piece is machined represented in the next figure, and three errors are measured and modeled.

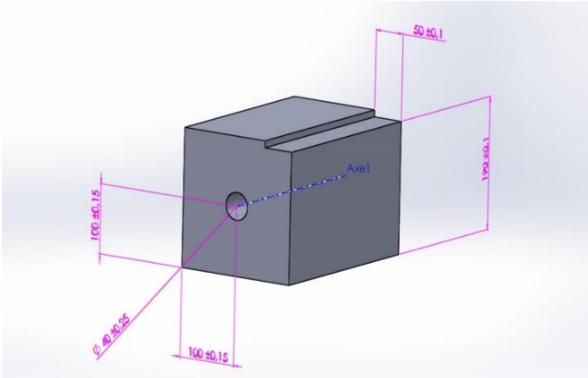

Fig 2. Test piece.

In this paper, three sources of machining errors are considered; thermal induced errors, table motion errors and tool wear errors are modeled based on cubic spline interpolation in the next figures.

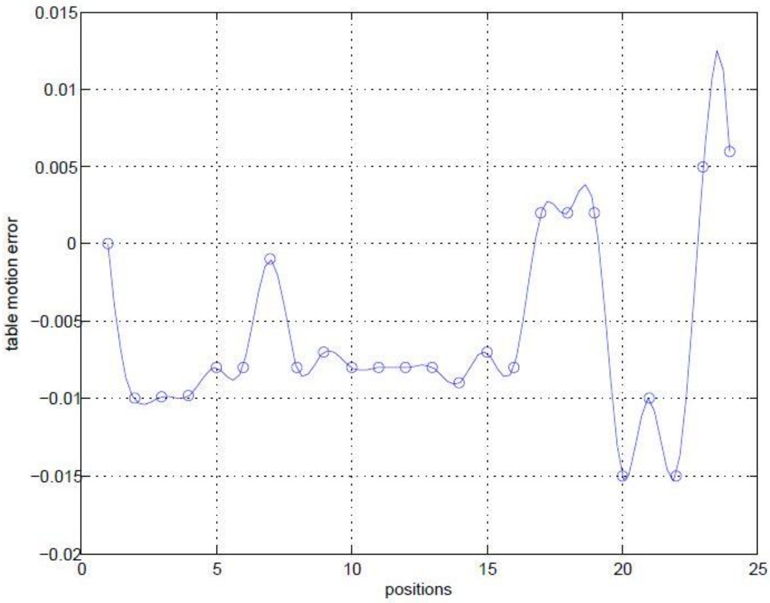

Fig 3. Table motion errors

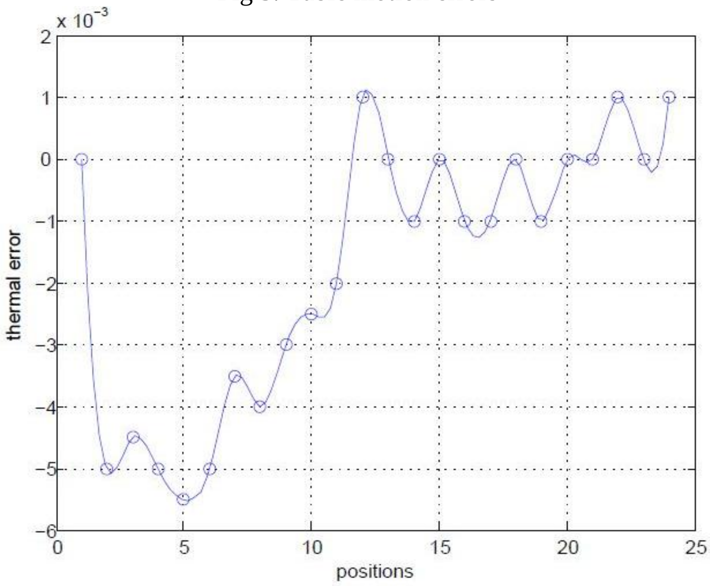

Fig 4. Table motion errors

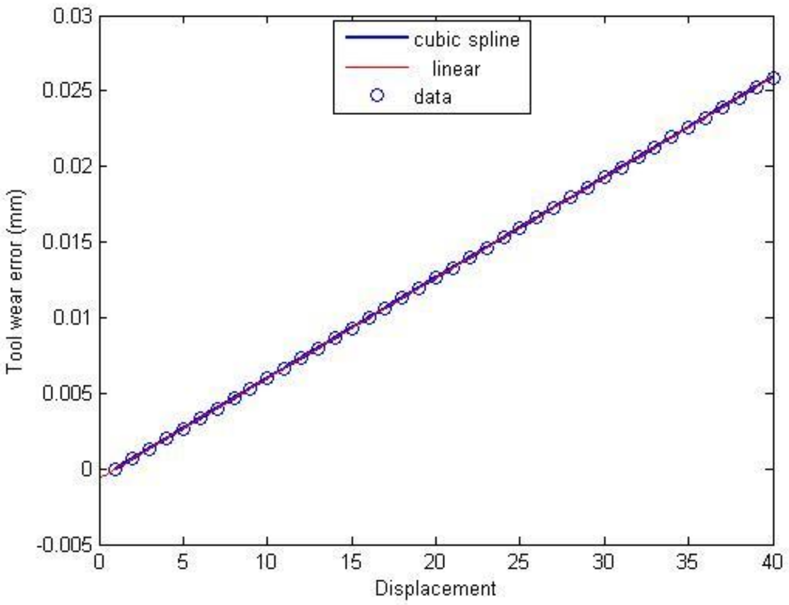

Fig 5. Tool wear error

The cubic spline $f_1(x)$, $f_2(x)$, and $f_3(x)$ is composed of a set of cubic polynomials smoothly connected:

$$f_1(x) = \begin{cases} S_0 & 0 \le x \le 1 \\ S_1 & 1 \le x \le 2 \\ \vdots & \\ \vdots & \\ S_{24} & 24 \le x \le 25 \end{cases} \tag{3}$$

Based on GP, the optimization problem is constructed. Positive deviations are minimized in order to not violate the tolerance interval. Which lead us to rewrite the equation (2) to the next system

$$min \sum_1^4 \sigma_i^+$$

Subject to

$$\begin{aligned} & f_1(x) - \sigma_1^+ = IT \\ & f_2(x) - \sigma_2^+ = IT \\ & f_3(x) - \sigma_3^+ = IT \\ & \sum_1^3 f_i(x) - \sigma_i^+ = IT \\ & \sigma_i^+ \ge 0 \end{aligned} \tag{4}$$

In order to use NSGA to solve goal programming problem, the goals are converted to objective functions of minimizing the deviations.

We can reformulate system 4 as:

$$min < f_i(x) - IT > \tag{5}$$

With the bracket operator < > returns the operand value if it is positive, otherwise returns 0. We use a population of size 50 and run NSGA for 50 generations.

The result founded are listed in the table. 1.

Table. 1 Results

x_1	x_2	x_3	$f_1(x_1)$	$f_2(x_2)$	$f_3(x_3)$	$\sum_1^3 f_i(x_i)$
2	3	1	-0.005	-0.005	0	-0.01
8	5	7	-0.0035	-0.0055	0.01	0.001
12	10	15	-0.007	-0.0025	0.012	0.0025
17	15	24	0.003	0	0.015	0.018
21	19	33	-0.007	0.001	0.025	0.019

Based on the results listed on the table above; it's clear that all the result are less then tolerance interval IT = 0.02 fixed in the design. More on that, the sum of the machining errors are less than the IT.

V. Conclusion

This paper present manufacturing errors modeling and optimization for machining accuracy enhancement by considering tool wear-, table motion-, and thermal induced errors. A new procedure is presented in this article for optimizing the machining errors of multi-axis machine tools. This was accomplished by optimizing the machining errors and taken the design tolerance as hard constraint in order to achieve zero percent rejection. Based on cubic spline interpolation The machining errors considered in this study are modeled; then based on goal programming the optimization problem is established. Finally, NSGA is used to solve this problem.

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