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Super-Nickel Orthogonal Turning Operations Optimization

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Abstract

The machining processes simulation are commonly used by manufacturing industries in order to produce high quality and very complex products in a short time. These machining processes simulation include large number of input parameters which may affect the cost and quality of the products. Selection of optimum machining parameters in such machining processes is very important to satisfy all the conflicting objectives of the process. There are two options to choose the optimal cutting parameters for a given economic objective. The first one is concerned with the need of a machine expert that manually selects the machining parameters on the basis of its own experience and by means of a proper machining handbook. That way generates many uncertainties and drawbacks in terms of efficiency of solutions and time/cost requirements. As an alternative to the above mentioned approach, many research efforts have been made to state a comprehensive mathematical model of a turning process that, in practice, entails a set of cutting constraints to be handled. Machining optimization problems become tricky whenever a given objective function must be optimized with respect to a large number of constraints. This paperwork is focused about the generation of an automated optimization procedure, for turning processes of nickel superalloys, under certain process conditions. For the automated optimization procedure the response surface methodology (RSM) has been used to detect the influence of the process variables on its performances.

Keywords: Optimization, Nickel superalloys, Turning

1. Introduction

General machining of nickel superalloy materials is more difficult compared to normal steels or even stainless steels. The same elements (Ni, Co, Cr, Ti) that give these materials their high strength and corrosion resistance also give trouble when machining. The poor machinability of the nickel superalloys in fact is due to the various inherent properties such as: low thermal conductivity, rapid work hardening, ability to react with tool materials under atmospheric conditions, formation of built-up edge, weld to the cutting edges presence of abrasive carbides in their microstructure. A significant improvement in process efficiency may be obtained with a process parameters optimization that identifies and determines areas of critical process control factors. Usually, small variation in one parameter causes notable changes in other one. Moreover, some variables, such as: cutting forces, machining time and tool wear, heavily depend upon the cutting conditions [1]. Optimization is an important task in machining processes, allowing selection of the most convenient cutting conditions in order to obtain desired values in some variable, which usually has a direct economic impact (such as tool life or total operation cost). In obtaining optimal solutions for these problems, a number of heuristic algorithms including: genetic algorithms (GA), simulated annealing (SA), as well as a recently developed optimization algorithm called particle swarm optimization (PSO) are successfully applied for prediction and optimization of cutting parameters. Karpat and Özel [2] proposed a Neural Network models integrated with the Particle Swarm Optimizer in order to obtain a group of optimal process parameters for turning processes. Venkata Rao and Pawar [3] investigated the performance of three non-traditional optimization algorithms, Artificial Bee Colony (ABC), Particle Swarm optimization (PSO) and Simulated Annealing (SA), in minimization time problem (i.e. maximization of production rate) subjected

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to the constraints of spindle strength, spindle deflection and cutting power. Azlan Mohd Zain et al. [4] compared the result of the GA with the result of the conventional approach known as the Response Surface Roughness Methodology (RSRM) technique to observe the optimal effect of the radial rake angle of the tool, combined with speed and feed rate cutting conditions in influencing the surface roughness result. Soleymani Yazdi and Khorram [5] used the Response Surface Methodology (RSM) and the Artificial Neural Networks (ANN) to investigate optimal machining parameters (i.e., spindle speed, depth of cut and feed rate) for face milling operations in order to minimize the surface roughness and to maximize the material removal rate. Ganesan et al. [6] used a Genetic Algorithm (GA) and a Particle Swarm Optimization (PSO) in order to investigate the optimal machining parameters with respect to the minimum production time, subject to a set of practical constraints: cutting force, power and dimensional accuracy and surface finish. Bharathi Raja and Baskar [7] used a Particle Swarm Optimization (PSO) technique to find the optimal machining parameters for minimizing machining time subjected to desired surface roughness. Senthilkumaar [8] used the genetic algorithm coupled with Artificial Neural Network (ANN) as an intelligent optimization technique for machining parameters optimization of Waspaloy.

In this paper authors have developed an automated optimization procedure, in iSight® environment interfaced with AdvantEdge®, for turning processes of nickel superalloys. In fact it has been developed a methodology that allows to determine and compare the optimal machining parameters: feed, cutting speed and rake angle (f, S and α), to maximize the Material Removal Rate (MRR) using Genetic Algorithm (GA) and Simulated Annealing (SA) optimization algorithms. A FE model, able to predict the cutting interactions between tool and workpiece (cutting forces and cutting edge temperature), of Waspaloy experimentally characterized, has been considered. Optimal Latin Hypercube DOE methodology, to evaluate the design space for process parameters, has been used. A comparative analysis of second, third and fourth order response surface models (RSM) for approximating deterministic computer FEM analyses results has been made.

Finally, a preliminary experimental campaign has been carried out in order to obtain a numerical-experimental comparison of the cutting forces.

2. Material model development

Compression testing at various temperatures has been used to generate the strain hardening and thermal softening curves for Waspaloy material. Samples have been heated to different temperatures (20°C, 250°C, 550°C, 750°C, 850°C, and 1050°C) to cover the effective strength of the material at different temperatures. This data have been then replicated to allow for comparisons in the event that a sample failed early or the data was corrupted, and to allow for an average curve to be created for each temperature. As expected, as temperature increased, material yielded at a progressively lower stress. The strain/stress curve for the material is shown Fig. 1 for each temperature. As expected, as temperature increased, material yielded at a progressively lower stress.

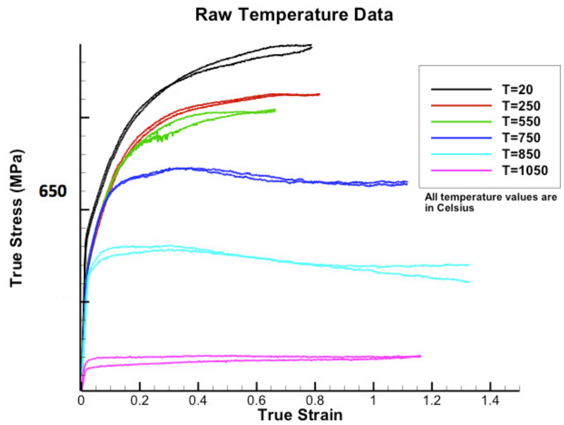

Fig. 1. True Stress – True Strain curve at different temperature

2.1. Constitutive Model

Material flow stress is governed by the following equation [9]:

$$\sigma(\varepsilon^p, \dot{\varepsilon}^p, T) = g(\varepsilon^p) * \Gamma(\dot{\varepsilon}^p) * \Theta\,(T) \tag{1}$$

where σ is the flow stress, g is the strain hardening function, Γ is the strain rate sensitivity function, and Θ is the thermal softening function.

Equations (2) and (3) report the functions and conditions for strain hardening:

$$g = \sigma_0 \left(1 + \frac{\varepsilon^p}{\varepsilon_0^p}\right)^{\frac{1}{n}} \quad \forall\, \varepsilon^p < \varepsilon_{cut}^p \tag{2}$$

$$g = \sigma_0 \left(1 + \frac{\varepsilon_{cut}^p}{\varepsilon_0^p}\right)^{\frac{1}{n}} \quad \forall\, \varepsilon^p \geq \varepsilon_{cut}^p \tag{3}$$

where σ_0 is the initial yield stress, ε_0^p is the reference plastic strain, n is the strain hardening exponent, and ε_{cut}^p is the cutoff strain.

The constitutive equations and conditions for rate sensitivity are reported in Equations (4) and (5):