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Determining optimal process parameters to increase the eco-efficiency of grinding processes

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ABSTRACT

Grinding processes aim to produce workpieces with high technological characteristics, such as: fine surface finish, great geometrical accuracy and specific material properties, and specific economic objectives. Despite these technological and economic objectives, it is more and more important to consider the environmental impact of grinding processes. Therefore, the process eco-efficiency needs to be addressed in relation to the aforementioned three objectives. This paper presents an approach to identify the process parameters that leads to Pareto-optimal solutions for advancing the eco-efficiency of grinding operations. An internal cylindrical grinding process is selected to demonstrate this approach. Empirical models are developed to characterise the grinding processes. Both single-objective and multi-objective optimisations are carried out, where geometric programming and a weighted max-min model are used respectively. Furthermore, sensitivity analyses are presented to reveal the trends of each process parameter in relation to the preference of technological, economic and environmental objectives.

1. Introduction

Manufacturing occupies a place of overwhelming importance in global economy. The traditional drivers of process development were solely focused on economic or technological advancement. Due to the resource scarcity and stringent environmental legislations, the environmental impact of manufacturing has also to be considered in conjunction with the traditional drivers. In the last years, international efforts have concentrated on improving the energy and resource efficiency from unit process level up to the system level (Duflou et al., 2012). At unit process level, the studies involve detailed investigation on process parameters and machine conditions. The outcome offers fundamental knowledge of the process towards better technological performances, lower manufacturing costs as well as less environmental impacts, namely, better eco-efficiency.

Grinding is used as one of the major manufacturing processes for the machining of hard-to-cut materials. Due to the simultaneous engagement of geometrically undefined cutting edge, the process shows a high stochastic behaviour and can only be empirically described. Furthermore, the undefined cutting edge enables the achievement of high surface quality but with the drawback of high energy intensity. Energy intensity and achieved surface roughness are influenced by various process parameters. It is challenging to identify the set of process parameters that meets the technological, economic and environmental objectives. The identification is further exacerbated as goal conflicts exist.

Eco-efficiency originally refers to the concept of creating more value with less environmental impact, and the concept has been adapted and defined for manufacturing processes at a unit process level (Li et al., 2012). Accordingly, the grinding process can be considered as three layers (see Fig. 1): on the upper layer, the grinding process transform the workpiece into a desired shape and surface finish; on the bottom layer, the process consumes energy and other auxiliary resources and induces environmental impacts; in the centre, the process parameters define the actual performance of the grinding process. Correspondingly, the input process variables (on the left side) can be categorised into three groups: workpiece properties, process parameters and enabling factors. The output eco-efficiency (on the right side) can be specified in terms of technological, economic and environmental objectives. The three objectives can be quantified by surface roughness (R_z), cost (C) and

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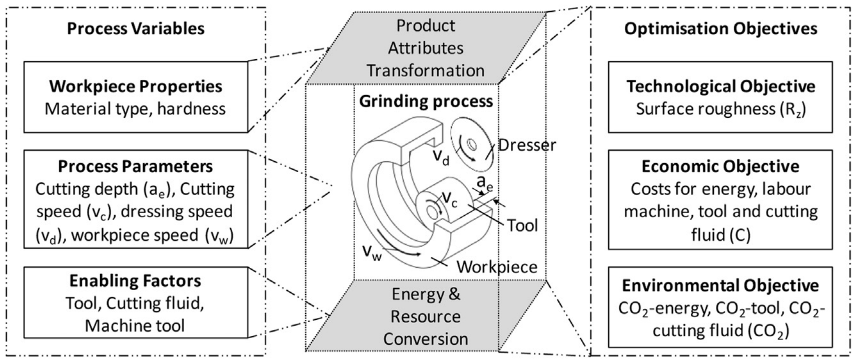

Fig. 1. Composition of a grinding process (adapted from Li et al., 2012).

carbon footprint (CO_2). For the case of grinding, improving the eco-efficiency means meeting the required surface roughness with minimal cost and environmental impacts.

To achieve an eco-efficient or Pareto-optimal grinding process, the process variables have to be varied. In most cases the workpiece material is predetermined by the product design. Therefore the three objectives can be influenced by changing the process parameter or the enabling factors. However, the feasible range of process parameter and the chosen enabling factors is constrained by the technological, economic and environmental objectives. The enabling factors therefore influence the energy and resources conversion process.

This paper presents an approach to identify the process parameters in conjunction with different cutting fluids, which leads to Pareto-optimal solutions for advancing the eco-efficiency of grinding operations.

2. Research background

2.1. Process models for grinding processes

Different researchers have developed models for predicting technological results of grinding processes. A very comprehensive overview on this topic was presented by Brinksmeier et al. regarding different modelling and simulation approaches in grinding (Brinksmeier et al., 2006) and by Tönshoff et al. especially regarding the application of regression models to describe the grinding process using physical/empirical models (Tönshoff et al., 1992). In general, models for the description of a grinding process are categorised into physical, empirical and heuristic models (Brinksmeier et al., 2006). The physical models are compiled on the basis of physical laws, under the condition where full knowledge and understanding of the physical processes exists. Measured and known input and output variables of a process are the basis for empirical models. The modelling is based on explicit functional relationships (e.g. physical/empirical models or artificial neural networks). The heuristic models are also based on measured and known input and output variables, and they apply knowledge based systems or fuzzy logic systems (Brinksmeier et al., 2006). By using this approach the grinding process can be described for example by modelling of grinding forces (Foeckerer et al., 2012), the grinding energy (Singh et al., 2012) the residual stress (Tönissen et al., 2012) or the surface roughness (Dzebo et al., 2012).

Especially in grinding, empirical models are often used to characterise the relationship between input and output variables (Tönshoff et al., 1992). The regression analyses are conducted by using the measured experimental data. In this context linear or non-linear regression models can be developed. The interactions in grinding processes are mostly fitted with non-linear equations.

For example, a model of the specific normal force is presented in equation (1). The force is dependent on the machining process parameters (speed ratio q, cutting depth a_e and equivalent workpiece diameter d_{eq}) and the regression parameters (c_{wg}, c_{gw}, e_1, e_2 and e_3) (Tönshoff et al., 1992).

$$F_n' = c_{wp} \cdot c_{gw} \cdot \left(\frac{1}{q}\right)^{e_1} \cdot a_e^{e_2} \cdot d_{eq}^{e_3} \tag{1}$$

2.2. Mathematical optimisation of grinding processes

Mathematical optimisation is a procedure of identifying the optimal or close to optimal solution of a given task regarding constrains and a set of given functions. The tasks can be generally classified as single-objective or multi-objective optimisation. For the former one, the aim is to solve a single-objective function by identifying the minimum or maximum value. In comparison, the latter one identifies a best solution of conflicting objectives, which is not a single optimal solution but rather a set of compromised solutions, also known as Pareto-optimal or non-dominated solutions (Savic, 2007).

The mathematical optimisation in machining processes with geometrical defined cutting edge, such as turning or milling, is commonly used to identify process parameter that lead to specific technological or economic impact. Bhushan presented a multi-response optimization regarding the technological parameters tool life and power consumption. Aim was the identification of the optimal turning parameters when machining metal matrix composite material. The mathematical optimization approach was performed by using desirability function analysis (Bhushan, 2013). In the study of Kuram et al. the technological influence of cutting fluid type on an end milling process was evaluated. The authors defined their multi objective optimisation problem in the context of an implicitly constrained optimization. Objective was the identification of the optimal combination of process parameters and cutting fluid type to achieve low process energy, a high tool life and good surface roughness. The study focused only on technological impact and not on the economic and environmental impact of the investigated cutting fluid (Kuram et al., 2013). The study of Yan and Li focuses on a multi response optimisation to identify the optimal milling process parameter to evaluate the trade-offs between the technological, economic and environmental impact. For this purpose a multi-objective optimisation based on weighted grey relational analysis and response surface methodology (RSM) was performed (Yan and Li, 2013).

When using mathematical optimisation in machining process with geometrical undefined cutting edge, such as grinding