

Chapter XIX

Artificial Neural Network and Metaheuristic Strategies: Emerging Tools for Metal Cutting Process Optimization

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ABSTRACT

Application of optimization tools and techniques is necessary and an essential requirement for any metal cutting-based manufacturing unit to respond effectively to severe competitiveness and increasing demand of quality product in the global market. However, both problem types and techniques employed are diverse. Often the context of the problem involves building nonlinear inferential response surface model(s) of the process(s), and then determine levels of inputs and in-process parameters that result in best (or significantly improved than existing) measures of process quality improvement and effectiveness. Selecting the appropriate levels or settings of inputs and in-process variables is a typical example of desired process effectiveness. However, determination of optimal process conditions, using appropriate solution methodology through cost-effective inferential nonlinear response surface model(s) is a challenging and continual research endeavour for researchers and practitioners. In this context, artificial neural network (ANN) and metaheuristic strategies, such as genetic algorithm (GA), simulated annealing (SA), and tabu search (TS), either in its original form or its variant, has been shown to yield promising outcomes for solving nonlinear response surface optimization problems in metal cutting process(s). The goal of this chapter is to assess the status and scope of artificial neural network-based inferential model, GA, SA, and TS-based metaheuristic search strategies in metal cutting processes. Subsequently, a solution methodology for nonlinear response surface optimization in metal cutting processes is proposed for the

benefits of selection of an appropriate technique. Specific application in a multiple response grinding process optimization problem using ANN, real-valued genetic algorithm, simulated annealing, and a modified tabu search is also provided for a clearer understanding of the settings, where the proposed methodology is being used.

INTRODUCTION

Modelling an abrasive metal cutting process and determining its optimal process conditions with respect to a particular component or part with a desired quality to be manufactured are the two main objectives in the context of process parameter optimization. These two objectives are to be achieved in two successive stages. In the first stage, modelling of the cutting process is to be carried out. In the second stage, an appropriate optimization methodology needs to be developed and used. However, modelling and optimization is considered to be a formidable and challenging task in almost all situations, particularly in a complex abrasive metal cutting process (Chen & Kumara, 1998; Krajnik, Kopac, & Sluga, 2005; Petri, Billo, & Bidanda, 1998; Sathyanarayanan, Lin, & Chen, 1992; Shaji & Radhakrisnan, 2003; Shin & Vishnupad, 1996).

In this context, in order to produce a wide variety of components or parts having different shapes, sizes, and surface texture, a large number of metal cutting processes have been developed. These processes are classified into traditional and nontraditional categories (El-Hofy, 2005) on the basis of the types of machining and machine tools or mechanical tool(s) or abrasives used. The metal cutting processes are grouped into several categories as shown in Figure 1. In a typical metal cutting process, materials are removed by plastic deformation of the work materials by harder tool materials, such as SiC and diamond. However, producing shapes of the tools with a hard material may be uneconomical because of

tool wear. Grains or grits or abrasives are the only viable alternatives in such a situation (Farago, 1976; Ghosh & Mallik, 1999). As the parts and components are hardened to extend their service life, abrasive cutting is generally the only way that can readily cut hardened materials to achieve required dimensional accuracy and surface texture (Waters, 1996).

The use of abrasives, which are bonded in wheels, for machining a high quality part or component at low cost represents one of the important and emerging areas of metal cutting (Farago, 1976; Shin & Vishnupad, 1996). Grinding, a bonded-abrasive based metal cutting process, is the only possible practical and economic means of shaping parts into finished products with required surface finish, acceptable surface integrity, and high geometric accuracy (Feng, Wang, & Yu, 2002; Maksoud & Atia, 2004). In case of grinding, metal is removed in the form of small chips produced by plowing, rather than conventional cutting mechanism, using geometrically undefined abrasive cutting edges (El-Hofy, 2005; Farago, 1976; Waters, 1996). The term “grinding” has been defined as removing either metallic or other materials by the use of a solid grinding wheel, and includes processes such as honing and lapping (King & Hahn, 1986). In a typical grinding process, a hard bonded abrasive surface is pressed against a workpiece, resulting in the removal of material from both the work piece and the abrasive. Material removal rate in a typical grinding process is usually low, with chip thickness varying between 0.002 to 0.05mm (Stephenson & Agapiou, 1997). Whereas, for turning, drilling, boring, and milling, chip thickness is generally greater than 0.05mm (King & Hahn, 1986; Stephenson & Agapiou, 1997).

Inferential modeling and optimization have been conceived as important means to control and improve the complex grinding process, which attempts to mimic the jobs earlier performed by human workers based on their knowledge and experience (Gupta, Shishodia, & Sekhon, 2001;

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