Chapter 8
Optimization of Drilling Process via Weightless Swarm Algorithm

T. O. Ting
Xi'an Jiaotong-Liverpool University, China

ABSTRACT

In this chapter, the main objective of maximizing the Material Reduction Rate (MRR) in the drilling process is carried out. The model describing the drilling process is adopted from the authors' previous work. With the model in hand, a novel algorithm known as Weightless Swarm Algorithm is employed to solve the maximization of MRR due to some constraints. Results show that WSA can find solutions effectively. Constraints are handled effectively, and no violations occur; results obtained are feasible and valid. Results are then compared to previous results by Particle Swarm Optimization (PSO) algorithm. From this comparison, it is quite impossible to conclude which algorithm has a better performance. However, in general, WSA is more stable compared to PSO, from lower standard deviations in most of the cases tested. In addition, the simplicity of WSA offers abundant advantages as the presence of a sole parameter enables easy parameter tuning and thereby enables this algorithm to perform to its fullest.

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INTRODUCTION

The drilling optimization is the utilization of an existing model to predict an unknown parameter aiming to assist in decision-making. In the manufacturing, drilling has been crucial process as it consumes significant costs in drilling tools. Therefore, an accurate model is crucial in the manufacturing process. However, the model would not have been useful without the presence of a reliable algorithm to seek for unknown parameters in this model. As drilling is an extremely common process in manufacturing industry, the materials removing due to degraded or wear out drills, which are frequent events in the manufacturing process. It is by no doubt that one-third of the material removal process is due to drilling operations.

Hence, the maximization of the so-called Material Removal Rate is done in this work. The drilling operation is a basic operation for many processes such as boring, tapping, and reaming. This complex cutting operation holds a substantial portion for all metal cutting operations, and the largest amount of money spent on any class of the cutting tool (Ting & Lee, 2012). In short, drilling is crucial from the viewpoint of cost, productivity and manufacturing. As a matter of fact, effective drilling also significantly reduces the down-time of the manufacturing processes. In order to overcome this inevitable drawback, constant monitoring is performed in the cutting process to determine the right time to change the relevant tool. Alternatively, one can optimize the relevant parameter in the drilling process. This improves the tool life and apparently increases the cutting period in the prolonged lifetime. Hence, is the motivation of the work being done here.

Many methods were introduced in the past. For instance, Li and Wu (1998) have introduced a new approach for online monitoring of drill wears by using a fuzzy approach, which was known as fuzzy c-means algorithm. From their results, the wear conditions can be categorized into a few fuzzy grades. Dutta et al. (2000) proposed machining features in tool condition monitoring during the drilling process, in which process parameters are related to the machining responses and experimental observations provide a basis for monitoring the tool wear. Yao et al. (1999) have proposed tool wear detection by fuzzy classification and wavelet fuzzy network. In the work done by El-wardany et al. (1996), vibration analysis is carried out to predict the conditions of drills.

More interestingly, drilling wear prediction and monitoring based on current signals was proposed by Li and Tso (1999). Thangaraj and Wright (1998) used change rate of thrust force for drilling failure monitoring. Liu and Wu (1990) applied sensor fusion methods in estimating drill wear. Further, Singh et al. (2006) used an artificial neural network to learn the drilling process based on experimental data in order to predict drill wear. The results from the ANN is found to be satisfactory and reliable. The ant algorithm was applied by Ghaiebi and Solimanpur (2007) to optimize drill-making operation using tool airtime and tool switch time as the objective function. On the other hand, Lee et al. (1998) used the abductive network for modeling and optimization of the drilling process. Once the process parameters such as drill diameter, cutting speed and feed are given, the drilling performance such as tool life, removal rate and thrust force can be predicted by the proposed network. This was successfully done in the work by Ting and Lee (2012).

In terms of process optimization related to machining processes, many methods were applied in the literature. These are the deterministic optimization approaches (Wang, Kuriyagawa, Wei, & Guo, 2002) (Armarego, Smith, & Wang, 1993) which were applied to turning and peripheral milling processes. For turning process, Gopalakrishnak (1991) and Fang (1994) introduced the polynomial geometric programming for turning process. Subsequently, Gopal and Rao (2003) applied the genetic algorithm to tackle grinding process optimization. Subsequently, Lee, Ting, Lin, & Than (2006) solved the similar problem

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