Chapter 21

Multi-Objective Optimization of Manufacturing Processes Using Evolutionary Algorithms

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ABSTRACT

Recently evolutionary algorithms have created more interest among researchers and manufacturing engineers for solving multiple-objective problems. The objective of this chapter is to give readers a comprehensive understanding and also to give a better insight into the applications of solving multi-objective problems using evolutionary algorithms for manufacturing processes. The most important feature of evolutionary algorithms is that it can successfully find globally optimal solutions without getting restricted to local optima. This chapter introduces the reader with the basic concepts of single-objective optimization, multi-objective optimization, as well as evolutionary algorithms, and also gives an overview of its salient features. Some of the evolutionary algorithms widely used by researchers for solving multiple objectives have been presented and compared. Among the evolutionary algorithms, the Non-dominated Sorting Genetic Algorithm (NSGA) and Non-dominated Sorting Genetic Algorithm-II (NSGA-II) have emerged as most efficient algorithms for solving multi-objective problems in manufacturing processes. The NSGA method applied to a complex manufacturing process, namely plateau honing process, considering multiple objectives, has been detailed with a case study. The chapter concludes by suggesting implementation of evolutionary algorithms in different research areas which hold promise for future applications.

1. INTRODUCTION

Optimization refers to determining one or more feasible solutions from a set of available alternatives which may correspond to the maximum or minimum value of one or more objective functions. It implies choosing values for a variable from a set of real numbers such that the desired function takes one of the values. Finding an optimal solution for a given problem, which involves only one objective function is called single-objective optimization. Single-objective optimization generally attempts to find one good solution that is better than any

DOI: 10.4018/978-1-4666-1945-6.ch021

other feasible solutions in a set or search space. The input process parameters corresponding to such solution are called optimal parameters. For a single-objective problem, varieties of optimization methods ranging from classical to search methods have been used. Researchers have used the single-objective optimization techniques in several fields such as routing, scheduling, salesman, image processing, engineering design, parameter fitting, computer game playing, transportation, etc. (Goldberg, 1989; Srinivas and Deb, 1995).

A single-objective optimization involves maximizing or minimizing a chosen objective function without considering its effects on any other objective functions. Consider a hypothetical case, where the customer wants a product with the best possible surface finish irrespective of the cost/material removal rate. In such a scenario, the manufacturing engineer can choose the input process parameters that can yield the fine surface finish without considering the productivity or costs. On the other hand, if the desired outputs are more than one, for example when a customer demands for fine surface finish at lower cost, then it is considered as a multi-objective optimization problem. Therefore, the manufacturing engineer has to optimize two conflicting objectives i.e., fine surface finish and high material removal rate. If the manufacturing engineer chooses the first option based on the single-objective optimization considering only fine surface finish, then the productivity will suffer. Since, the fine surface finish results from lower material removal rate. If the manufacturing engineer chooses the input process parameters which provides only higher material removal rate, then it is very difficult to achieve the fine surface finish. Now the question arises, which is the best possible solution/solutions to achieve both fine surface finish and higher material removal rate together. In such a scenario, there is no single optimum solution or they cannot be solved through single-objective optimization techniques. Therefore, such problem is considered under the preview of multi-objective optimization.

Researchers made several attempts to solve multi-objective problems through different methods such as classical optimization, weighted sum, goal programming, min-max, etc. But these methods are not able to find multiple solutions in a single run. These methods change the multi-objective problem into a single-objective problem with the corresponding weights based on their relative importance and also suffer from a drawback that the decision maker must have a thorough knowledge of ranking of objective functions. These methods also fail when the objective functions become discontinuous. In contrast, evolutionary algorithms have been proved successfully for solving multi-objective problems because they operate with a population of individuals and also well suited to search for multiple solutions simultaneously. It is well proven that evolutionary algorithms can solve several conflicting objectives and also able to approximate the optimal solutions in a single run. Therefore, evolutionary algorithms have attracted a lot of research during the last two decades and it is still one of the hottest research areas in the field of evolutionary computation (Fonseca and Fleming, 1995; Sbalzariniy et al., 2000; Deb, 2001; Deb et al., 2002; Zitzler et al., 2004; Konak et al., 2006; Zhou et al., 2011).

In the view of the above, the following sections present the basic principles of multi-objective optimization as well as evolutionary algorithms and the working mechanisms of one of the efficient evolutionary algorithm has been detailed with a case study for ease in understanding. Finally the chapter is concluded with some potential directions for future research.

2. MULTI-OBJECTIVE OPTIMIZATION

In a multi-objective optimization problem there are more than one objective functions. The objective functions are often conflicting to each other and

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