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A multi-objective algorithm for optimization of modern machining processes

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ABSTRACT

Multi-objective optimization aspects of four modern machining processes namely wire-electro discharge machining process, laser cutting process, electrochemical machining process and focused ion beam micro-milling process are considered in this work. In WEDM process cutting velocity and surface quality are important objectives which are mutually conflicting in nature. Minimization of kerf taper is vital in the laser cutting process which increases with the increase in material removal rate. The ECM process is characterized by high material removal rate, but poor dimensional accuracy, high tool wear rate and high over cut. FIB micro-milling process is useful in applications where a nano-level surface finish is desired but this process is characterized by a very low material removal rate. All the above mentioned objectives are vital as they closely govern the performance of the machining processes considered in this work. Therefore, the aim of this work is to achieve these objectives through process parameter optimization. In order to handle multiple objectives simultaneously a new posteriori multi-objective optimization algorithm named as multi-objective Jaya (MO-Jaya) algorithm is proposed which can provide multiple optimal solutions in a single simulation run. The regression models for the above mentioned machining processes which were developed by previous researchers are used as fitness function for MO-Jaya algorithm.

In the case of WEDM process the optimization problem is an unconstrained, linear and parameter bounded. In the case of laser cutting process the optimization problem is a non-linear, unconstrained, quadratic and parameter bounded. In the ECM process the optimization problem is a non-linear, unconstrained, quadratic and parameter bounded. The second case study of ECM process the optimization problem is a non-linear, constrained, non-quadratic and parameter bounded. In the case of FIB micro-milling process, the optimization problem is a non-linear, unconstrained, quadratic and parameter bounded. In addition, the performance of MO-Jaya algorithm is also tested on a non-linear, non-quadratic unconstrained multi-objective benchmark function of CEC2009. In order to handle the constraints effectively a heuristic approach for handling constraints known as the constrained-dominance concept is used in MO-Jaya algorithm. In order to ensure that the newly generated solutions are within the parameter bounds a parameter-bounding strategy is used in MO-Jaya algorithm. The results of MO-Jaya algorithm are compared with the results of GA, NSGA, NSGA-II, BBO, NSTLBO, PSO, SQP and Monte Carlo simulations. The results have shown the better performance of the proposed algorithm.

1. Introduction

Determination of optimum combination process parameters of any machining process requires comprehensive knowledge of manufacturing process, empirical equations to develop realistic constraints, specification of machine tool capabilities, development of effective optimization criteria, and knowledge of mathematical and numerical optimization techniques. A human process planner selects proper machining process parameters using his own experience or machining tables. In most of the cases, the selected parameters are conservative and far from optimum. Selecting optimum combination of process parameters through experimentation is costly, time consuming and tedious. These factors have steered the researchers towards applying numerical and heuristics based optimization techniques for process parameter optimization of machining processes.

In order to determine the optimum combination of process parameters, researchers had applied various traditional optimization algorithms such as geometric programming, nonlinear programming,

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sequential programming, goal programming, dynamic programming, etc. (Mukherjee and Ray, 2006). Although these methods had performed well in many practical cases, they have certain limitations which are mainly related to their inherent search mechanisms. Search strategies of these traditional optimization methods are generally depended on the type of objective and constraint functions (linear, non-linear, etc.) and the type of variables used in the problem modeling (integer, binary, continuous, etc.), their efficiency is also very much dependent on the size of the solution space, number of variables and constraints used in the problem modeling and the structure of the solution space (convex, non-convex, etc.). They also do not provide generic solution approaches that can be used to solve problems where different types of variables, objective and constraint functions are used (Medina et al., 2014; Rao, 2015).

In order to predict the performance of machining processes the researchers had developed regression models based on the experimental data to map the relationship between the input and output parameters (Rao and Kalyankar, 2014). These regression models are often, quadratic equations with bounded values of input parameters. These regression models may be solvable using traditional optimization methods. However, traditional optimization methods are sensitive to the initial guess. Most of the machining processes involve several input parameters. An excellent guess of the initial solution in presence of several input parameters is difficult and an improper initial guess may cause the conventional optimization techniques to trap into local optima.

In order to overcome these problems and to search optimum solution, many population based heuristic algorithms had been developed by researchers in the past two decades. In the field of machining also, researchers had integrated the experimentally developed regression models with population based algorithms in order to obtain the optimum solution (Chandrasekaran et al., 2010; Yusup et al., 2012; Rao and Kalayankar, 2014). Depending on the nature of the phenomenon simulated by the algorithms, these population-based heuristic algorithms can be classified into two important groups: Evolutionary Algorithms (EA) and swarm intelligence based algorithms.

However, all evolutionary and swarm intelligence based optimization algorithms require common control parameters like population size, number of generations, elite size, etc. for their working. Besides the common control parameters, different algorithms require their own algorithm-specific parameters. For example, genetic algorithm (GA) uses mutation rate and crossover rate; particle swarm optimization (PSO) algorithm uses inertia weight, social cognitive parameters, maximum velocity; artificial bee colony(ABC) algorithm uses number of bees (scout, onlooker and employed) and limit; biogeography based optimization (BBO) algorithm requires habitat modification probability, mutation probability, maximum species count, maximum immigration rate, maximum emigration rate, maximum mutation rate, generation count limit and number of genes in each population member; etc. The improper tuning of algorithm-specific parameters either increases the computational effort or yields to local optimal solution. In addition to the tuning of algorithm-specific parameters the common control parameters need to be tuned which further enhances the effort. Considering this fact, Rao et al. (2011) introduced the teaching-learning-based optimization (TLBO) algorithm which does not require any algorithm-specific parameters. The TLBO algorithm requires only common controlling parameters like population size and number of generations for its working. The TLBO algorithm has gained wide acceptance among the optimization researchers (Rao, 2015).

Keeping in view of the success of the TLBO algorithm, another algorithm-specific parameter-less algorithm is proposed very recently by Rao (2016). However, unlike two phases (i.e. teacher phase and the learner phase) of the TLBO algorithm, the proposed algorithm has only one phase and it is comparatively simpler to apply. The working of the proposed algorithm is much different from that of the TLBO algorithm. The Jaya algorithm is simple and has also proved its effectiveness in solving a number of constrained and unconstrained benchmark functions (Rao, 2016).

Most of the machining processes involve more than one machining process performance characteristic. This gives rise to the need to formulate and solve multi-objective optimization problems. There are basically two approaches to solve a multi-objective optimization problem and these are: a priori approach and a posteriori approach (Collette and Siarry, 2003). In a priori approach, multi-objective optimization problem is transformed into a single objective optimization problem by assigning an appropriate weight to each objective. This ultimately leads to a unique optimum solution. However, the solution obtained by this process depends largely on the weights assigned to the objective functions. This approach does not provide a set of Pareto points. Furthermore, in order to assign weights to each objective the process planner is required to precisely know the order of importance of each objective in advance which may be difficult when the scenario is volatile or involves uncertainty (Abbas et al., 2016). This drawback of a priori approach is eliminated in a posteriori approach, wherein it is not required to assign the weights to the objective functions prior to the simulation run.

The major advantage of a posteriori approach over a priori approach is that, a posteriori approach provides multiple tradeoff (Pareto-optimal) solutions for a multi-objective optimization problem in a single simulation run. The process planner can then select one solution from the set of Pareto optimal solutions based on the requirement or order of importance of objectives. On the other hand, as a priori approach provides only a single solution at the end of one simulation run, in order to achieve multiple trade-off solutions using a priori approach the algorithm has to be run multiple times with different combination of weights. Thus, a posteriori approach is very suitable for solving multi-objective optimization problems in machining processes wherein taking into account frequent change in customer desires is of paramount importance and determining the weights to be assigned to the objectives in advance is difficult.

Researchers had already proposed various multi-objective versions of the existing algorithms. Shang et al. (2014) proposed artificial immune system (AIS) based multi-objective algorithm for change detection in synthetic aperture radar images. Medina et al. (2014) developed multi-objective version of teaching-learning-based optimization algorithm (TLBO) and artificial bee colony algorithm (ABC) for solving multi-objective optimal power flow problem. Gonzalez et al. (2015) developed multi-objective version of TLBO algorithm based on Pareto-tournament for software requirements selections. Li et al. (2015) developed a discreet multi-objective TLBO algorithm for realistic flow shop rescheduling problems. Chen et al. (2015) proposed a multi-objective version of AIS for design of heat treated alloy steels. Paniagua et al. (2015) proposed multi-objective shuffled frog leaping (SFL) algorithm for mobile robot path planning. Sudeng and Wattanapongsakorn (2015) developed post Pareto-optimal pruning algorithm for multi-objective optimization using specific extended angle dominance. Ma et al. (2015) proposed ensemble multi-objective biogeography based optimization (BBO) algorithm for automated warehouse scheduling. Khalesian and Delavar (2016) proposed a constrained Pareto-based multi-objective evolutionary approach for wireless sensors deployment optimization.

In this work a posteriori population based multi-objective version of the Jaya algorithm is proposed to solve the multi-objective optimization problems of modern machining processes and is named as “Multi-objective Jaya algorithm (MO-Jaya)” algorithm. The optimization case studies of four modern machining processes namely wire-electric discharge machining (WEDM) process, laser cutting process, electrochemical machining (ECM) process and focused ion beam (FIB) micro-milling process are considered in this work.

The multi-objective optimization problem formulated in the case of WEDM process is an unconstrained, linear and parameter bounded problem. The multi-objective optimization problem formulated in the

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