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Multi-objective optimization and bio-inspired methods applied to machinability of stainless steel

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ABSTRACT

Nowadays, due to the growing needs of market, the simultaneous optimization of various responses is configured as a necessary strategy in real process. Machinability of stainless steel has always been considered a difficult task and any movement toward optimization of this process are really worthy. Traditionally, the treatment of this problem is done through the application of the desirability function that consists in transforming the original multi-response problem in a similar with one objective. In spite of various applications involving this methodology, the quality of the solution obtained is dependent on the choice of the inferior and superior limits and on goals for each one of the responses. To overcome this disadvantage, the present work proposes a methodology to solve the original multi-objective problem by using the Bio-inspired Optimization Methods (BiOM). The strategy proposed consists in the extension of the BiOM to problems with multiple objectives, through the incorporation of two operators into the original algorithm: (i) the rank ordering, and (ii) the crowding distance. The proposed algorithm is applied to the machinability of stainless steel AISI (ABNT) 420 using a model that considers the tool life and cutting forces responses in terms of cutting speed, feed per tooth and axial depth of cut, in end milling process. The effects of these variables in the responses were investigated crossing information contained in response surfaces of material removal rate and cutting forces. The results obtained showed that the methodology used represents an interesting approach to the treatment of the optimization problem formulated.

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1. Introduction

Naturally, real-world problems involve the simultaneous optimization of two or more (often conflicting) objectives, called multi-objective optimization problem (MOOP). The solution of such problems is different from that of a single-objective optimization problem.

The main difference is that multi-objective optimization problems normally have not one but a set of solutions, which may all be equally good [1].

Traditionally, the treatment of such problems is done transforming the original MOOP into one-objective problem. However, the development of specific methodologies allows the formulation of the optimization problem in a way that various objectives can be taken into account simultaneously. In addition, as a number of points that constitutes the optimal solution is found, it is possible to explore these solutions according to the practical application studied [1]. In the literature, several methods for solving MOOP can be found [1]. These methods follow a preference-based approach, in which a relative preference vector is used to scalarize multiple objectives. Since classical searching and optimization methods use a point-by-point approach, at which the solution is successively modified, the outcome of this classical optimization method is a single optimized solution. However, evolutionary algorithms (EA) can find multiple optimal solutions in one single simulation run due to their population-based search approach. Thus, EA are ideally suited for multi-objective optimization problems. A detailed account of multi-objective optimization using EA and some of the applications using genetic algorithms can be widely found in literatures [1,2].

In many engineering applications, it is necessary to find the conditions under which a certain process attains the optimal results. That is, they want to determine the levels of the design parameters at which the response reaches its optimum. The optimum could be either a maximum or a minimum of a function of the design parameters. One of the methodologies for obtaining the optimum is response surface technique (RS). This approach is a collection of

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statistical and mathematical methods that are useful for the modeling and analyzing engineering problems. The main objective is to optimize the response surface that is influenced by various process parameters.

Response surface also quantifies the relationship between the controllable input parameters and the obtained response surfaces. The design procedure of response surface methodology is as follows [3]: (i) designing of a series of experiments for adequate and reliable measurement of the response of interest; (ii) developing a mathematical model of the second order response surface with the best fittings; (iii) finding the optimal set of experimental parameters that produce a maximum or minimum value of response.

In this context, Pettersson et al. [4] proposed a genetic algorithm based multi-objective optimization technique for the training process of a feed forward neural network, using noisy data from an industrial iron blast furnace. Recently, Giri et al. [5] proposed a new bi-objective genetic programming (BioGP) for meta-modeling and applied in a chromatographic separation process using a simulated moving bed (SMB) process. The BioGP technique initially minimizes training error through a single objective optimization procedure and then a trade-off between complexity and accuracy is worked out through a genetic algorithm based bi-objective optimization strategy.

Associate with the MOOP, the multi-response surface technique is configured as good strategy to treatment of real-world problems. In this sense, the desirability function approach, originally developed by Harrington [6] and later modified by Derringer and Suich [7], to multi-response optimization is a useful technique for the analysis of experiments in which several responses have to be optimized simultaneously. The basic idea of the desirability function approach is to transform a multi-response problem into a single response problem by means of mathematical transformations.

One very important manufacturing process is machining, which possesses a large number of variables. When measuring the way a material behaves under cutting one is determining its machinability. Therefore, machinability must be understood as a system of properties which depends on complex interactions among workpiece, tool material, cutting fluid and cut conditions. Trent [8] suggests that machinability is not only a property, but the "way" material behaves during machining. Therefore, machinability is much more than a test function, and it's improvement is characterized by, at least, one of the following factors: increase of tool life, higher rate of material removal, improvement of surface finishing, better chip control, reduction of cutting forces and power consumption, decrease of the cutting temperature, etc. According to its duration, the tests of machinability are classified in to short and long term duration. And the best example of long lasting test is the tool life test and their results, generally presented using Taylor's equation.

Stainless steel is one of the main materials employed in critical parts for installation of power plants and modern chemical industries due to combination of appropriate mechanical properties and high corrosion resistance. However, the composition required allowing such properties results in poor machinability of this steel, right below to that for the carbon steel. High rate of strain hardening, high toughness and low thermal conductivity are the main factors that cooperate for this. As a consequence, the machinability of stainless steel tends to present short tool life, especially in intermittent cut operations like milling, where thermal and mechanical shocks are observed [9]. Non-traditional machining has also many variables and process optimization is also challenging. Zhang et al. [10] analyzed the workpiece surface quality and the material removal rate on process parameters during machining a cold work die steel SKD11 (AISI D2) by medium-speed wire electrical discharge machining (MS-WEDM). The experimental data were utilized to material removal rate model and workpiece surface quality under optimal parameter condition by a backpropagation neural network combined with genetic algorithm (BPNN-GA) method. Another example of optimization within the area of machining was provided by Klancnik et al. [11] that proposed a system for the automatic programming of a CNC milling machine by particle swarm optimization (PSO). In the algorithm proposed, each individual swarm particle presents a possible numerical control (NC) program.

In this work, the machinability of AISI (ABNT) 420 stainless steel in end milling operation is analyzed using a model that foresees the responses of tool life and cutting forces in terms of cutting speed, feed per tooth and axial depth of cut. The effects of these variables in the responses were investigated crossing information contained in the bound surfaces of material removal rate and cutting force.

In this context, the main contribution of this paper is to introduce a systematic methodology for the solution of multi-objective optimization problems by using the bio-inspired optimization methods. These methodologies are based on strategies that seek to mimic the behavior observed in species found in the nature to update a population of candidates to solve optimization problems [12,13]. These systems have the capacity to notice and modify their environment in order to seek for diversity and convergence. In addition, this capacity makes possible the communication among the agents (individuals of population) that capture the changes in the environment generated by local interactions [14]. Among the most recent bio-inspired strategies stand the Bees Colony Algorithm – BCA [15], the Firefly Colony Algorithm – FCA [16], and the Fish Swarm Algorithm – FSA [17]. The BCA is based on the behavior of bees colonies in their search of raw materials for honey production. According to Lucic and Teodorovic [18], in each hive groups of bees (called scouts) are recruited to explore new areas in search for pollen and nectar. These bees, returning to the hive, share the acquired information so that new bees are indicated to explore the best regions visited in an amount proportional to the previously passed assessment. Thus, the most promising regions are best explored and eventually the least end up being discarded. Every iteration in this cycle repeats itself with new areas being visited by scouts. The FCA mimics the patterns of short and rhythmic flashes emitted by fireflies in order to attract other individuals to their vicinities. The corresponding optimization algorithm is formulated by assuming that all fireflies are unisex, so that one firefly will be attracted to all other fireflies. Attractiveness is proportional to their brightness, and for any two fireflies, the less bright will attract (and thus move to) the brighter one. However, the brightness can decrease as their distance increases and if there are no fireflies brighter than a given firefly it will move randomly. The brightness is associated with the objective function for optimization purposes [16]. Finally, the FSA is a random search algorithm based on the behavior of fish swarm observed in nature. This behaviors may be summarized as follows [17]: random behavior – in general, fish looks at random for food and other companion; searching behavior – when the fish discovers a region with more food, it will go directly and quickly to that region; swarming behavior – when swimming, fish will swarm naturally in order to avoid danger; chasing behavior – when a fish in the swarm discovers food, the others will find the food dangling after it; and leaping behavior – when fish stagnates in a region, a leap is required to look for food in other regions.

This work is organized as follows. Section 2 presents the desirability function concept. The mathematical formulation of multi-objective optimization is presented in Section 3. A review of the BiOM and its extension for multi-objective context are presented in Sections 4 and 5. Section 6 presents the methodology proposed in this work. The results and discussion are described in Section 7. Finally, the conclusions conclude the paper.

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