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Technical Paper

Normal-boundary intersection based parametric multi-objective optimization of green sand mould system

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ABSTRACT

In manufacturing engineering optimization, it is often that one encounters scenarios that are multi-objective (where each of the objectives portray different aspects of the problem). Thus, it is crucial for the engineer to have access to multiple solution choices before selecting of the best solution. In this work, a novel approach that merges meta-heuristic algorithms with the Normal Boundary Intersection (NBI) method is introduced. This method then is used generate optimal solution options to the green sand mould system problem. This NBI based method provides a near-uniform spread of the Pareto frontier in which multiple solutions with gradual trade-offs in the objectives are obtained. Some comparative studies were then carried out with the algorithms developed and used in this work and that from some previous work. Analysis on the performance as well as the quality of the solutions produced by the algorithms is presented here.

1. Introduction

Most issues encountered when dealing with emerging technologies in engineering are multi-objective (MO) in nature [1,2]. Strategies in multi-objective optimization (MO) can be crudely classified into two classes. First being methods that use the concept of Pareto optimality to trace the non-dominated solutions at the Pareto curve (for instance, Zitzler and Thiele's [3] Strength Pareto Evolutionary Algorithm (SPEA) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) by Deb et al. [4]). The other type of methods is known as the weighted (or scalarization) techniques. In these methods, the objective functions in the problem are aggregated into a single objective function which is then solved for various scalar (weight) values. Some known scalarization techniques include the Weighted Sum method [5,6], Goal Programming [7] and Normal-Boundary Intersection (NBI) method [8]. Using these techniques, the scalars (or weights) are used to consign relative trade-offs to the objectives during the aggregation procedure. Hence, alternative near-optimal solution options are generated for various values of the scalars.

A unique and ideal solution that explains all the features of a MO problem in engineering are rarely encountered [9,10]. Nevertheless in more practical scenarios, the decision maker (DM) is only interested in a single optimal solution. To select this unique optimum, the DM utilizes some supplementary knowledge which is usually very heuristic and too complex to be represented mathematically [11]. Therefore, it is very useful for the DM to have access to numerous solution options with a variety of significance with respect to the objectives prior to the selection the best optimal solution. See [1,12,13] for more detail investigations and explanations on MO techniques in engineering optimization.

In optimization problems of this kind, it is required that the solution method caters for the multiobjective nature of the problem. Thus, in this work the MO issue is tackled using the NBI method for geometrical trade-offs of the weights while the GA-PSO is used to iteratively improve the solutions for each respective weight. This work aims to generate a series of Pareto-optimal solutions that obtain a near-complete trade-off among the objective functions for the green mould sand system. This problem was presented and solved in Surekha et al. [14] by the application of genetic algorithm (GA) and Particle Swarm Optimization (PSO) techniques in conjunction with the Weighted Sum approach.

The difference between sand mould and green sand mould is that green sand mould has green compression strength, permeability, hardness and bulk density requirements where as sand mould has the same properties without the green constraints. In green mould systems, the quality of the product obtained from the moulding process is very dependent on the physical properties of the

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moulding sand (such as hardness, permeability, green compression strength and bulk density). Incorrect proportions of the mentioned properties may lead to casting defects such as poor surface finish, blowholes, scabs and pinhole porosity. Controllable variables such as percentage of water, percentage of clay, grain fineness number and number of strokes heavily influence the physical properties of the moulded sand. Hence, by characterizing these parameters as the decision variables and the mould sand properties as the objective function, the MO optimization problem was formulated in Surekha et al. [14]. The purpose of this formulation is for the identification of best controllable parameters for optimal final-product of the moulding process. A more comprehensive study on the optimization and model formulation of mould systems can be seen in [15,16].

In this work, the green mould sand system is optimized further using genetic algorithms (GA), Particle Swarm Optimization (PSO) and a hybrid GA-PSO in conjunction with the Normal Boundary Intersection (NBI) method to generate a series of Pareto-optimal solutions. Comparison studies were then performed on the optimal solutions obtained in this work against those obtained in Surekha et al. [14].

Genetic algorithms (GA) were introduced by Holland in the nineties [17]. GAs belong to the group of stochastic search methods (such as simulated annealing [18] and some forms of branch and bound). While most stochastic search techniques operate on a distinct solution for a particular problem, GAs operates on a population of solutions. In recent times, GAs have been widely applied in engineering scenario (see [19,20]). For a more comprehensive text on GAs refer to [21]. Particle Swarm Optimization (PSO) is an optimization method developed based on the movement and intelligence of swarms. PSO was developed by Kennedy and Eberhart [22] in 1995. Lately, PSO has been applied to a variety of areas including optimization problems in engineering [23] as well as economic dispatch problems. Many works have done on the application of meta-heuristic techniques for modelling and optimization of manufacturing systems [24–26].

This paper is organized as follows. In Section 2 of this paper, the standard meta-heuristic techniques are presented, and this is followed by description on the Scalarisation Technique and Proposed Algorithms in Section 3. The real world application problem on green sand mould system is illustrated in Section 4. Section 5 discusses computational results and finally, the concluding remarks are given in Section 6.

2. Standard meta-heuristic techniques

2.1. Genetic algorithm (GA)

A genetic algorithm (GA) was applied in conjunction to the NBI approach for the MO optimization of the green sand mould system. GAs are categorized as a class of population-based search and optimization algorithms [27,28]. An N-point crossover operator was used to create new offspring for each successive generation. To avoid the solution from getting stagnant at the local minima, an N-bit flip mutation operator was used.

2.2. Particle Swarm Optimization (PSO)

The PSO algorithm introduced in 1995 (by Kennedy and Eberhart [22]) springs from two distinct frames of ideas. The first concept was based on the examination of swarming (or flocking) behaviours of certain species of organisms (such as birds, ants, bees and fireflies). The second idea was sprung from the study of evolutionary computations. The PSO algorithm searches the search space for candidate solutions and evaluates these solutions with respect to some (user specified) fitness condition. The candidate optimal solutions obtained by this algorithm are achieved as a result of particles which are in motion (swarming) through the fitness landscape. In the beginning, some candidate solutions are selected by the PSO algorithm. These solutions can be randomly selected or be established with the aid of some a priori facts. Next, the evaluation of the particles' position and velocity (which are also the candidate solutions) relative to the fitness function is carried out. Consequently, in conjunction with the fitness function a condition is introduced; where if the fitness function is not fulfilled, then the algorithm updates the individual and social terms by the aid of a user-specified update rule. Following this, the velocity and the position of the particles' are updated. This recursive course of action is iterated until the fitness function is satisfied by all candidate solutions and solutions have thus converged into a fix position. It is essential to note that the velocity and position updating rule is critical to the optimization capabilities of this method. The velocity of each particle in motion (swarming) is updated using the following equation.

$$v_i(t+1) = wv_i(t) + c_1r_1[\hat{x}_i(t) - x_i(t)] + c_2r_2[g(t) - x_i(t)] \tag{1}$$

where each particle is identified by the index i, $v_i(t)$ is the particle velocity and $x_i(t)$ is the particle position with respect to iteration (t). The parameters w, c_1, c_2, r_1 and r_2 are usually defined by the user.

3. Scalarisation Technique and Proposed Algorithms

3.1. Scalarisation technique: Normal Boundary Intersection (NBI) method

The NBI method was first introduced by Das and Dennis [8]. This method is a geometrically inspired scalarization approach for solving MO problems. In contrast to the Weighted Sum method, the NBI approach has the ability to find a near-uniform spread of Pareto-optimal solution options in the frontier. This makes the NBI approach a more interesting alternative as compared to the Weighted Sum method when solving non-convex MO problem.

The green mould system problem is presented as the following:

$$\begin{aligned} &Min \quad F(x) \quad subject \quad to \\ &X = \{x : g(x) = 0; h(x) \leq 0, 1 \leq x \leq 4\} \\ &F* = (f_1^*, f_2^*, f_3^*, f_4^*)^T \end{aligned} \tag{2}$$

where F^* is the utopia point for this MO problem. Let the individual minimum be denoted as x_i^* and be obtained for $i \in [1, 4]$. The convex hull of the individual minima is generated in this fashion. Thus, the representation of the simplex from the convex hull is as follows:

$$\Gamma = \{\phi \cdot Y : \phi = F(x_i^*); \quad Y = \beta_i : 1 \leq x \leq 4\} \tag{3}$$

where ϕ forms a 4 by 4 matrix and $\sum_{i=1}^{4} \beta_i = 1$. The formulation of the NBI β-sub problem is as the following:

$$\begin{aligned} &Max_{(X,t)} t \quad subject \quad to \\ &\phi \cdot Y + tn = F(x) \quad \text{and} \quad x \in X \end{aligned} \tag{4}$$

where t is some defined distance parameter, and n is the normal vector at the point towards the utopia point. The NBI scalarization method finds the maximum distance, t in the direction of the normal vector, n between a point on the simplex and the origin (or the utopia point). Next, the scalarization is carried out. The scalars, Y are varied thoroughly to generate a near-uniform spread of the Pareto frontier. The procedures of which this method is executed are as follows: