DOI: 10.7763/IPEDR. 2013. V63. 20

Multiobjective Optimization of Cement-bonded Sand Mould System with Differential Evolution

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Abstract. Currently, most optimization cases in engineering and other heavy industries present themselves in a multi-objective (MO) setting. Thus, it would greatly aid the decision maker (DM) if a series of multiple solutions were at hand prior to selecting the suitable solution. In this work, the weighted sum scalarization approach is used in conjunction with the differential evolution (DE) algorithm. The DE approach was then applied to the cement-bonded sand mould system to construct the approximate Pareto frontier as well as to identify the best solution option. Some analysis was then performed on the produced computational results. Examination on the performance and the quality of the solutions obtained by the DE algorithm is presented here.

Keywords: Cement-bonded Sand Mould System, Multiobjective (MO) Optimization, Weighted Sum, Differential Evolution, Function Aggregation.

1. Introduction

In the manufacturing sector, many problems encountered by engineers and decision-makers present themselves in a multiobjective setting [1] [2]. In this work, the multiobjective (MO) optimization of the cement-bonded sand mould system is considered. The main idea behind these sorts of moulds is that a binder element (in this case cement) is used to enhance the mould strength, mould hardness and the casting accuracy. The primary constituents of the cement-bonded sand mould system are cement, silica sand and water [3]. However, a lot of time is taken for the production of cement-bonded sand moulds that respect the strength and hardness requirements. To rectify this issue, a constituent called an 'accelerator' (which is usually calcium formate) is introduced. For more detailed and comprehensive works on cement-bonded moulds see [4] [5] [6].

In this work, the cement-bonded mould sand system problem [3] was tackled using Differential Evolution (DE) [7] in conjunction with the weighted sum approach to generate a series of solutions that dominantly approximate the Pareto frontier. DE has been widely applied in many areas ranging from engineering and economics to operational research (for instance see [7], [8], [9], [10]). Analysis was then conducted to identify the individual best, median and worst solutions as well as the frontier approximations obtained in this work.

This paper is organized as follows. In section 2 of this paper, the problem formulation is presented. In section 3 the computational technique is discussed and this is followed by Section 4 which discusses the computational results. Finally, this paper ends with some concluding remarks and recommendations for future works.

2. Problem Formulation

In the cement-bonded mould sand system, the process parameters of the mould heavily influence the quality of the final product. In Surekha *et al* [3], these parameters were identified as the decision variables while the hardness (H) and the compression strength (CS) of the mould was used as the objective functions.

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The process parameters were; the ratio in terms of percentage of Portland cement (A), percentage of accelerator (B), percentage of water content (C) and the testing time in hours (D). The objective functions and the range of the decision variables are shown as follows:

$$\begin{aligned} H = {} & 13.5199 + 7.38194A + 11.6111B + 6.76042C + 0.113812D - 0.388889A^2 - 1.68056B^2 \\ & - 9.22222C^2 + 0.0493827D^2 - 0.289062AB + 1.57813AC + 0.0130208AD + 1.59375BC \\ & + 0.0989583BD + 0.30208CD \end{aligned} \tag{1}$$

$$\begin{aligned} CS = {} & 83.8913 - 3.59381A - 2.45386B + 135.424C - 18.6127D + 0.213865A^2 - 3.28139B^2 \\ & - 22.7782C^2 + 1.39739D^2 + 2.75252AB - 4.12608AC + 2.61247AD - 4.07222BC \\ & + 2.12947BD - 7.73506CD \end{aligned} \tag{2}$$

$$\begin{aligned} 8 \le A \le 12 \\ 2 \le B \le 4 \\ 3 \le C \le 8 \\ 2 \le D \le 8 \end{aligned} \tag{3}$$

The MO optimization problem statement for the green mould system problem is shown as follows:

$Max \quad (f_1, f_2)$ Subject to

$$\begin{aligned} 8 \le A \le 12 \\ 2 \le B \le 4 \\ 3 \le C \le 8 \\ 2 \le D \le 8 \end{aligned} \tag{4}$$

The DE algorithms used in this work was programmed using the C++ programming language on a personal computer (PC) with an Intel dual core processor running at 2 GHz.

3. Computational Technique

The weighted sum approach was used in conjunction with the DE method to solve this MO problem. The objective function (eqs. (1) and (2)) were aggregated to form a single weighted function (*F*) such as the following:

$$F = w_1 H + w_2 CS \quad \text{such that} \quad w_1, w_2 \in [0,1] \quad \& \quad w_1 + w_2 = 1 \tag{5}$$

where w_1 and w_2 are the scalar weights.

The DE algorithm is a class of evolutionary algorithms introduced in 1995 by Storn and Price [7]. This central concept of this technique is the incorporation of perturbative methods into evolutionary algorithms. DE starts by the initialization of a population of at least four individuals denoted as *P*. These individuals are real-coded vectors with some size *N*. The initial population of individual vectors (the first generation denoted *gen* = 1) are randomly generated in appropriate search ranges. One principal parent denoted x^p_i and three auxiliary parents denoted x^a_i is randomly selected from the population, P. In DE, every individual in the population, *P* would become a principle parent, x^p_i at one generation or the other and thus have a chance in mating with the auxiliary parents, x^a_i. The three auxiliary parents then engage in 'differential mutation' to generate a mutated vector, V_i. The algorithm for the DE approach is given in Algorithm 1:

Algorithm 1: Differential Evolution (DE)
Step 1: Initialize individual size N, P, CR and F
Step 2: Randomly initialize the population vectors, x^G_i.
Step 3: Randomly select one principal parents, x^p_i
Step 4: Randomly select three auxilary parents, x^a_i
Step 5: Perform differential mutation & generate mutated vector, V_i
Step 6: Recombine V_i with x^p_i to generate child trial vector, x^{child}_i
Step 7: Perform 'knock-out' competition for next generation survival selection
Step 8: If the fitness criterion is satisfied or t= T_{max} , halt and print solutions else proceed to step 3

4. Numerical Results

The solution sets (approximations of the Pareto frontier) were obtained using the DE method. The quality of these solutions was measured by simply by using the value of the aggregated function, *F*. Since this problem is a maximization problem, hence the higher the *F* value the more dominant the solution. For the approximation of the pareto frontier, 33 solutions for various weights were obtained. The approximate pareto frontiers obtained using the DE algorithm is shown in Fig. 1.

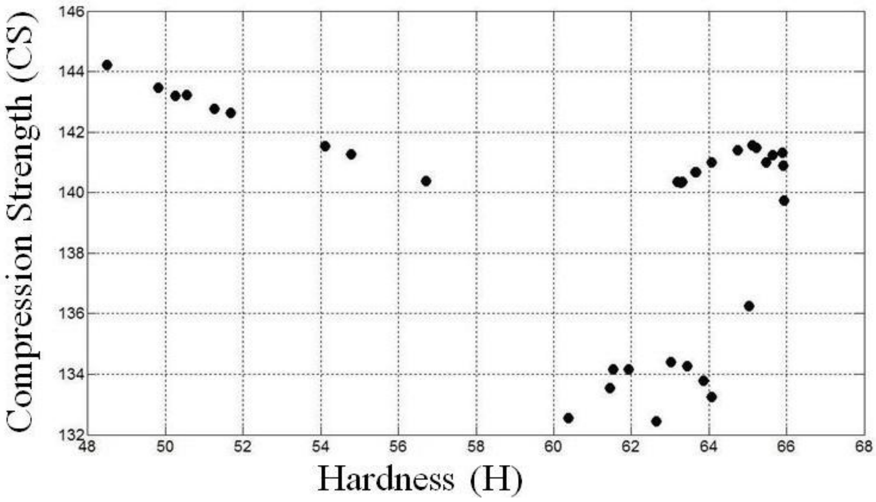

Fig. 1: Approximate Pareto frontiers obtained using the DE algorithm

The maximum, median and the minimum values of the aggregated objective function, *F* is 141.481, 97.1386 and 20.4328 respectively. Based on these values the best, medium and worst individual solutions were identified. These values are shown in Table 1:

Table 1: The best, medium and worst individual solutions

Description	Best	Median	Worst
CS	143.203	134.156	140.669
H	50.2467	61.5384	63.6605
A	8.32593	10.8081	11.9524
B	2.24948	3.20532	2.51011
C	3.01115	3.12692	3.05565
D	2.01115	2.12692	2.05565
Number of iterations	75	73	20

The best, median and worst individual solutions were obtained at the weights (w_1, w_2) of (0.97, 0.03), (0.49, 0.51) and (0.01, 0.99) with the computational time of 0.6, 2.25 and 2.19 seconds respectively. The values of the aggregated function, *F* with respect to the weights in given in Fig. 2:

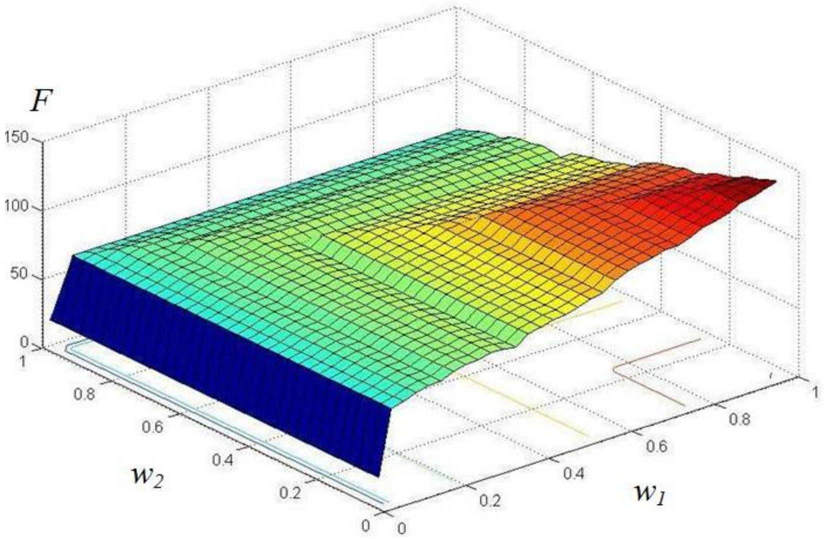

Fig. 2: Values of the aggregated function, F with respect to the weights.

It can be seen from Fig. 2 that the values of F increases sharply as $w_1 \rightarrow 1$ and as $w_2 \rightarrow 0$. Hence, it can be said that the more the second objective (CS) is compromised and the first objective (H) is given importance, the higher the value of F obtained. In this work, the DE algorithm performed stable calculations during the program executions. All pareto-efficient solutions produced by the algorithms developed in this work were feasible and no constraints were compromised. Besides, a local optimum was discovered in this work by the implementation of the DE method (see Table 1).

5. Conclusions & Recommendations

A new local maximum and an efficient construction of the pareto frontier was done using the DE approach. The aggregated function (F) was used to gauge the individual solutions produced by the DE algorithm. For future works, other meta-heuristic algorithms such as NSGA-II and other hybrid algorithms should be applied to the Cement-bonded Sand Mould System.

6. Acknowledgement

The author thanks the Department of Fundamental and Applied Sciences and Universiti Teknologi PETRONAS for providing financial support for presenting this research work.

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