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Multi-Objective Optimization of Green Sand Mould System Parameters using Particle Swarm Optimization

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A B S T R A C T

This paper deals with multi-objective optimization of green sand mould system using Particle Swarm Optimization (PSO). It is important to note that the quality of cast products in green sand moulds is largely influenced by the mould properties (that is, responses), such as green compression strength, permeability, hardness and bulk density, which depend on the input (process) parameters (that is, grain fineness number, % clay, % water and number of strokes). In this study, non-linear regression equations developed between the control factors (process parameters) and responses have been considered for optimization utilizing PSO. An attempt is being made to form a single objective, after considering all the four individual objectives, to obtain a compromise solution, which satisfies all the four objectives. The results of this study show a good agreement with the experimental results

Introduction

The quality of the parts produced during moulding process depends on the properties (that is, green compression strength, permeability, hardness and bulk density) of moulding sand. It is important to note that improper levels of these properties leads to common casting defects, such as blow holes, pinhole porosity, poor surface finish, dimensional variation, scabs and rat tails, misruns etc. The properties of the mould are influenced by a large number of controllable parameters (that is, grain fineness number, % clay, % water and number of strokes). Hence, it is important to identify the levels of the input variables that provide required mould properties, which improves the quality of the parts produced by this mould. During 1960s and 70s, most of the research work on moulding sand was based on experimental and theoretical approaches. In [1], the relationship between permeability and transformation zones, mould pressure, void space control, etc., was developed through substantial mathematical equations. In addition to this, Frost and Hiller [2] established the pressure and hardness distributions in sand moulds. Later on, Wenninger [3] utilized the rigid water theory to explain sand-clay-water relationships. This approach was completely theoretical and not supported by a large number of experiments. Later on, statistical design of experiments (DOE) had been used by various investigators to study the effects of different variables on the green sand mould properties. In [4] Design of Experiments (DOE) technique was applied to study the effect of process variables on bulk density and green compression strength. Moreover, Casalino et al. [5] utilized Taguchi technique to establish third order model for permeability and compression strength in laser sintered sand moulds. Moreover, Parappagoudar et al. [6,7] developed linear and non-linear statistical models utilizing full factorial DOE, Central Composite Design (CCD) and Box-Bhenken design. In the above work, the authors had considered grain fineness number, % of clay, % of water and number of strokes as input parameters and green compression strength, permeability, hardness and bulk density as the responses. Among the non-linear regression equations developed by the above mentioned three approaches, CCD-based model was found to be the more accurate model for prediction of the responses. Optimization techniques are required to identify the optimal combination of parameters for achieving the desired performance of the green sand mould system. In single objective optimization, one attempts to obtain the best design or decision, which is usually the global maximum or minimum depending on the optimization problem. In green sand mould system, it is difficult to find a single optimal combination of parameters for green compression strength,

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permeability, hardness and bulk density. Hence, there is a need for a multi-objective optimization method to arrive at the solutions to this problem. This multi-objective optimization problem can be converted to a single objective problem after applying a suitable method. This type of problems can be best solved by utilizing Evolutionary Algorithms (EA), such as genetic algorithms (GA), particle swarm optimization (PSO), etc. It is important to note that PSO was used to solve multi-objective optimization problems related to grinding [8], electrochemical machining [9] and some other engineering problems.

In the present paper, the non-linear regression equations developed in [7] has been considered for multi objective optimization, utilizing the most popular evolutionary algorithm, PSO [10]. Green compression strength, permeability, hardness and bulk density are considered as responses (that is, objectives) and grain fineness number, % of clay, % of water and number of strokes are treated as inputs (that is, process variables). A single objective has been formed after combining the four responses. PSO algorithm has been used to optimize this single objective to obtain a compromise solution. The results obtained show a good agreement with the experimental results.

The rest of the manuscript is organized as follows: Section 2 introduces the manufacturing process to be modeled. The proposed approach is explained in Section 3. Results are discussed and presented in Section 4. Section 5 provides with the concluding remarks of the present study

Formulation of the problem

The quality of the parts produced in green sand mould system mainly depends on the properties (responses) of the mould, such as green compression strength (GCS) kPa, permeability (P), hardness (H) and bulk density (BD) g/cm3, which in turn depends on the process variables (that is, grain fineness number, % of clay, % of water and number of strokes). The ranges of the process variables used in this study are given in Table 1.

The relation ship between the responses and the process variables available in the literature [7] are as given below:

Table 1: Process parameters and their ranges

Number	Parameters	Symbol	Range	
			High	Low
1	Grain fineness number	A	94	52
2	% clay content	B	12	8
3	% water content	C	3	1.5
4	Number of strokes	D	5	3

$$GCS = 17.2527 - 1.7384A - 2.7463B + 32.3203C + 6.575D + 0.014A^2 + 0.0945B^2 - 7.7857C^2 - 1.2079D^2 + 0.0468AB - 0.1215AC - 0.0451AD + 0.5516BC + 0.6378BD + 2.689CD. \quad (1)$$

$$P = 1192.51 - 15.98A - 35.66B + 9.51C - 105.66D + 0.07A^2 + 0.45B^2 - 4.13C^2 + 4.22D^2 + 0.11AB + 0.2AC + 0.52AD + 1.19BC + 1.99BD - 3.1CD. \quad (2)$$

$$H = 38.2843 - 0.0494A + 2.4746B + 7.8434C + 7.774D + 0.001A^2 - 0.00389B^2 - 1.6988C^2 - 0.6556D^2 - 0.0015AB - 0.0151AC - 0.0006AD - 0.075BC - 0.1938BD + 0.65CD. \quad (3)$$

$$BD = 1.02616 + 0.01316A - 0.00052B - 0.06845C + 0.0083D - 0.00008A^2 + 0.0009B^2 + 0.0239C^2 - 0.00107D^2 - 0.00004AB - 0.00018AC + 0.00029AD - 0.00302BC - 0.00019BD - 0.00186CD. \quad (4)$$

In this study, a weighted method is used for the optimization of the process with multiple mould performance outputs. The resultant weighted objective function to be maximized is:

$$\textit{Maximize } Z = (w_1 \times f_1 + w_2 \times f_2 + w_3 \times f_3 + w_4 \times f_4) \quad (5)$$

Subjected to constraints:

$52 \le A \le 94$,

$8 \le B \le 12$,

$1.5 \le C \le 3$,

$3 \le D \le 5$.

where f_1, f_2, f_3 and f_4 are the normalized functions for GCS, P, H and BD, respectively. Moreover, w_1, w_2, w_3 and w_4 are the weighted factors for the normalized GCS, P, H and BD, respectively, and A, B, C and D are the process variables. It is important to note that the weighted factors are selected in such a way that their sum will be equal to one. A higher weighing factor for an objective indicates more importance to that particular objective.

Tools and Techniques used

In the present work, particle swarm optimization algorithm has been employed to optimize the single objective function (refer to Eqn. (5)) of the green sand mould system. The descriptions of these algorithms are provided in the following sub section.

Particle Swarm Optimization

PSO is a population based stochastic optimization technique. Due to its easy implementation and quick convergence, PSO has gained much attention in solving many complex problems [8, 9]. PSO algorithm is a model that mimics the movement of individuals in a group. In the present study, MOPSO-CD [10], a variant of PSO has been utilized for the selection of optimum process parameters of green sand mould system. The schematic diagram showing he working cycle of the PSO is shown in

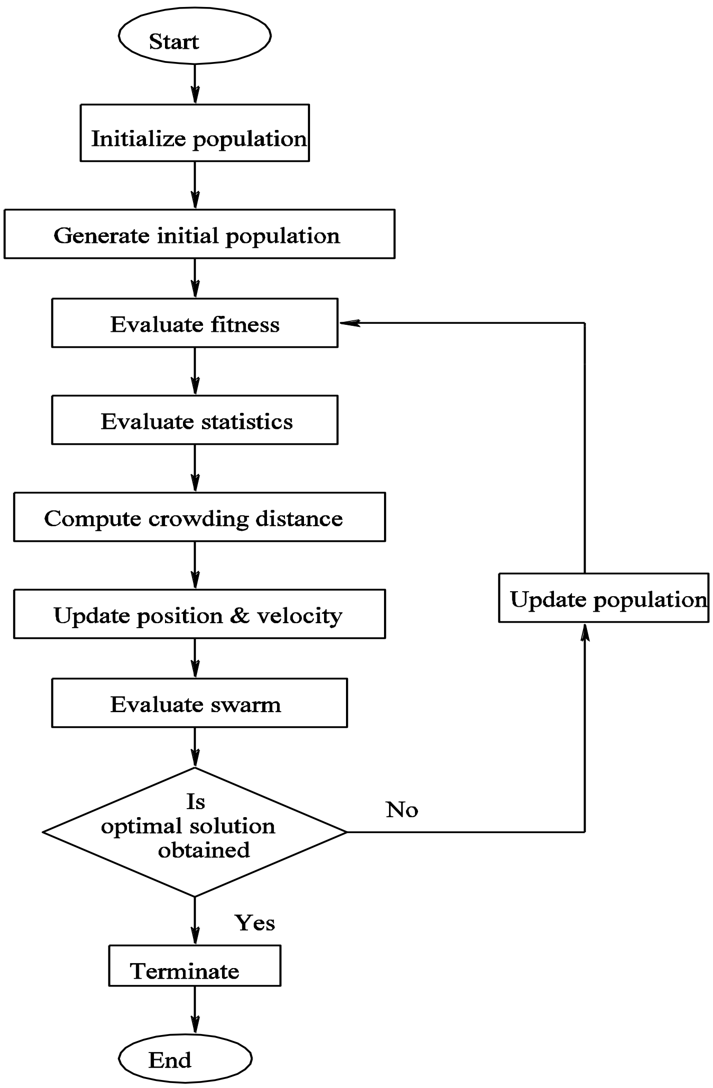


Figure: 1. Flowchart of the particle swarm optimization.

The present approach incorporates the crowding distance (that is, the average distance of its two neighboring solutions) and mutation operators into the simple PSO algorithm. This feature enhances the exploring capability of the algorithm by preventing the premature convergence problem of PSO algorithm. Instead of using evolutionary operators, such as selection and crossover, each particle in the population moves with velocity which is dynamically adjusted. The new position and velocity of the particles have been calculated using the formulation given below:

The new velocity: $V[i] = W \times V[i] + R_1 [P_{best}[i] - P[i]] + R_2 \times [A(G_{best}) - p[i]]$ (6)

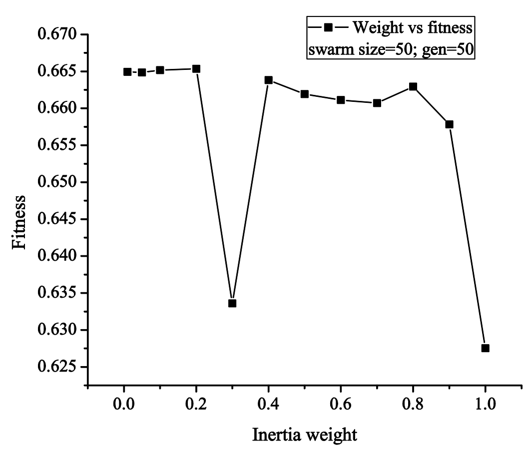
The new position: $P[] = P[i] + V[i]$ (7)

where W is the inertia weight, which is equal to 0.4, R_1 and R_2 are the random numbers in the range of [0, -1], $P_{best}[i]$ is the best population that the particle *I* reached and $A(G_{best})$ is the global best guide for each dominated solution. The parameters, namely swarm size, number of generations, inertia weight (W), social components R_1 and R_2 and repository size play an important role in the present approach.

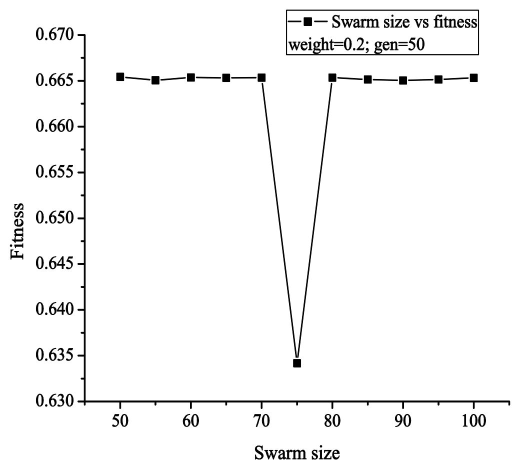
Results and Discussion

A parametric study (that is, by varying one parameter of PSO, namely swarm size, inertia weight and generations at a time) has been conducted to determine the combination of PSO parameters that are responsible for the optimal mould performance. It is also important to note that the selection of the weighting factor for each objective is also important and it should be selected based on the requirement of the decision maker. In this study, five different cases (refer to Table 1) have been considered after varying the weighing factors of the multiple objectives. The results of the parametric study are shown in Figure. 2, and the procedure for conducting the systematic study is as follows.

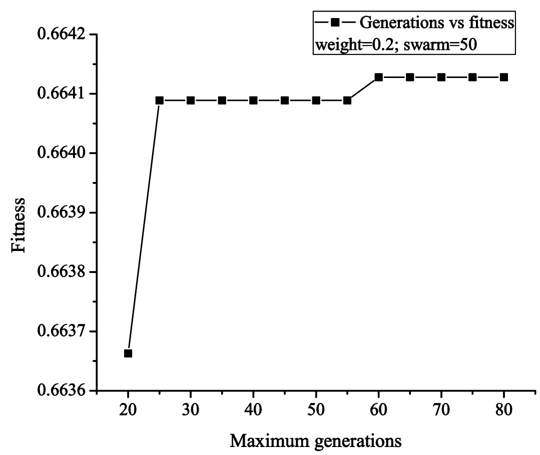
Figure 2 (a) shows the variation of fitness with the change in the values of inertia weight. During this process, the other two parameters, such as swarm size and generations are kept at the fixed level. In this case, the inertia weight value (W*), corresponding to the maximum fitness is identified. Figure. 2 (b) shows the study related to the swarm size. In this case, inertia weight is set at W* and maximum generations are set at the same level as discussed in Figure. 2(a). In this study, the swarm size (SS*) that is responsible for maximum fitness has been found. Figure. 2(c) shows the convergence of the solution over number of generations. The number of generations (G*) that are responsible for maximum fitness has been obtained in this study.



(a)



(b)



(c)

Figure: 2. PSO parametric study: (a) inertia weight vs fitness; (b) swarm size vs fitness; (c) maximum generational vs fitness.

Thus, the parameters of PSO that are responsible for the better performance are as follows:

inertia weight (W^*) = 0.2

swarm size (SS^*) = 50

number of generations (G^*) = 60

In this case, five different cases have been considered after varying the weight factors of the objectives. Table 2 shows the optimum conditions of the mould parameters for multiple performance outputs with different combinations of the weight factors. It is interesting to note that the maximum fitness values for Cases 1 through 5 are found to be equal to 0.6647, 0.7609, 0.8719, 0.7630 and 0.6066, respectively. In this method also, Case 3 is recommended, as it has produced maximum fitness.

It is interesting to note that confirmation experiments are conducted for the Case 3, as it has given better performance compared to other four cases. The percentage errors associated with GCS, P, H and BD are found to be equal to 3.22, 5.78, 4.95 and 2.25%, respectively. It is important to note that other optimization algorithms, such as genetic algorithms (GA) and differential evolution (DE) can also be used to optimize the sand moulding system. The difference between PSO and the above mentioned algorithms is that PSO is computationally less expensive and produce better resultswhen compared with GA and DE.

Conclusions

In the present work, an attempt has been made to search for the optimal process parameter values for the multiple objectives, namely green compression strength, permeability, hardness and bulk density utilizing particle swarm optimization. Five different cases have been considered by varying weighting factor of each objective. It is interesting to note that Case 3 has given better performance when compared with the other approaches. Confirmation experiments have been conducted for with the optimal process parameters obtained in Case 3. The percent deviations of the objective function values between the values obtained through PSO and experiments are found to be in the acceptable range.

Table 2: Optimum mould parameters for multiple responses with different weighing factors using PSO

Process parameters and responses	Optimum values of mould parameters and responses				
	Case 1: (w1=0.25; w2=0.25;w3=0.25; w4=0.25)	Case 2: (w1=0.70; w2=0.10;w3=0.10; w4=0.10)	Case 3: (w1=0.10; w2=0.70;w3=0.10; w4=0.10)	Case 4: (w1=0.10; w2=0.10;w3=0.70; w4=0.10)	Case 5: (w1=0.10; w2=0.10;w3=0.10; w4=0.70)
A: GFN	52.00	52.02	52.00	93.99	93.99
B: %C	11.99	8.00	11.99	12.00	11.99
C: %W	2.91	2.67	2.85	3.00	2.31
D: NS	5.00	3.00	5.00	5.00	5.00
GCS	55.43	20.89	55.41	53.87	54.13
P	107.72	214.20	107.89	54.96	51.40
H	84.86	77.61	84.79	86.99	85.89
BD	1.51	1.47	1.51	1.58	1.59

References

1. C.T. Marek, Green sand permeability – its significance and control, AFS Trans., Vol. 74, 1966, pp. 70-81.
2. J. Frost and J.M. Hiller, The mechanics of green sand moulding, AFS Trans., Vol. 74, 1966, pp. 177-186.
3. E.C. Wenninger, Green sand processing: an introduction to current fundamental thinking, AFS Trans., Vol. 76, 1968, pp. 101-111.
4. K.B. Dhindaw and M. Chakraborty, Study and control of properties and behavior of different sand systems by application of statistical design of experiments, in Proc. of 41st International Foundry Congress, 1974, pp. 9-14.
5. G. Casalino, L.A.C. De Filippis and A. Ludovico, A technical note on the mathematical and physical characterization of selective laser sintered sand for rapid casting, Journal of Material Processing Technology, Vol. 166, 2005, pp. 1-8.
6. M. B. Parappagoudar, D.K. Pratihar and G.L. Datta, Linear and non-linear statistical modeling of green sand mouldsystem, International Journal of Cast Metals Research, Vol. 20, No.1, 2007, pp. 1-13.
7. M. B. Parappagoudar, D.K. Pratihar and G.L. data, Non-linear modeling using central composite design to predict green sand mould properties, Proc. of IMechE., Part B: Journal of Engineering Manufacture, Vol. 221, 2007, pp. 881--894.
8. T. S. Lee, T.O. Ting and Y.J. Lin, An investigation of grinding process optimization via evolutionary algorithms, Proc. Of the 2007 IEEE Swarm Intelligence Symposium, 2007.
9. R.V. Rao, P.J. Pawar and R. Shankar, Multi-objective optimization of electrochemical machining process parameters using a particle swarm optimization, Proc. of IMechE-Part B: Journal of Engineering Manufacture, Vol. 222, 2008.
10. C. Raquel and P. Naval, An effective use of crowding distance in multi objective particle swarm optimization, in Proc. of the 2005 conference on genetic and evolutionary computation, Washington DC, USA, 2005, pp.257-262