Modelling and Optimization of Alpha-set Sand Moulding System Using Statistical Design of Experiments and Evolutionary Algorithms

G. C. Manjunath Patel, Ganesh R. Chate and Mahesh B. Parappagoudar

Abstract The traditional trial-and error method applied to derive empirical relation and optimize the process is time consuming and results in reduced productivity, high rejection and cost. Hence, current research in foundries focussed towards development of statistical modelling and optimization tools. The present research work is focused on modelling and optimization of Alpha-set moulding sand system. The variables such as percent of resin and hardener, and curing time will influence the sand mould properties, namely, compression strength, permeability, mould hardness, gas evolution and collapsibility. Experimental data is collected as per CCD design matrix and non-linear models have been developed for all responses. The behaviour of all responses is studied by utilizing surface plots. The statistical adequacy of all models is tested with help of ANOVA. All responses are tested for their prediction capacity with the help of test cases. The predictive non-linear models, developed for the process resulted in average deviation of less than 5%. The optimization (GA, PSO, DFA and TLBO) tools are applied to optimize the process for conflicting requirements in sand mould properties. Six case studies with different combination of weight fractions assigned to sand mould properties are considered. The optimum solution correspond to highest composite desirability value is selected. TLBO outperformed other optimization tools (i.e. GA, PSO, and DFA) while determining the highest desirability value and resulted in optimized sand mould properties. Experiments are conducted for the optimized and normal (i.e. lowest desirability) sand mould conditions. Castings are prepared by pouring molten LM20 alloy to the prepared moulds. The casting obtained for the optimized sand mould condition resulted in a better casting quality.

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1 Introduction

In sand castings, parts and components are produced by pouring molten metal into the sand mould. The quality of casting is largely influenced by the moulding sand properties. Hence, attaining good moulding sand properties is of industrial relevance. Holtzer et al. reported that, approximately 103 million tonnes of metal was accounted for the production of cast parts throughout the year across the globe [1]. 80% production of cast parts were produced in sand moulds with either bentonite or organic resin binder. Resin bonded sand mould (that is, chemical binder) system offered better sand mould and casting properties as compared to green sand moulds (that is, clay binder or bentonite) [2]. Thoroughly mixed silica sand with chemicals (i.e. binder) will help to harden the mould using catalytic reaction [3]. Chemically mixed silica sand has the ability to prepare moulds with intricate shape and precise dimension at an ambient temperature [4]. However, chemical mixed sand moulds emit harmful toxic gases (i.e. chemical compounds) during the foundry processes, which causes environmental pollution and serious human health hazards. The emissivity of harmful compounds (benzene, toluene, ethylbenzene and xylene (BTEX) and polycyclic aromatic hydrocarbons (PAHs) group) to environment from alphaset resin is 2–5 times lesser than the furan resin sand moulds [5]. Further, smokeless, minimal erosion, better hot strength, good finishing and better collapsibility are the distinguished characteristics of alphaset binder [5, 6].

The molten metal poured into the mould cavity had released the undesirable gasses and resulted many surface defects in the casting produced [7–9]. Alphaset binder sand moulds offer excellent surface quality on ferrous castings, due to the absence of phosphorous and sulphur [6]. Further, absence of nitrogen restricts the formation of pinholes in the casting part [6]. Alphaset binder is found to be eco-friendly and keeps the foundry with a healthy working environment. Hence, working on Alphaset bonded sand moulding system to produce good quality castings is of industrial relevance.

The detailed analysis of moulding sand system with associated sand mould properties will provide good insight of a process and on casting quality. Chemical mix sodium silicate sand moulds will have low quantity of gas evolution (GE) as compared to the green sand moulding [7]. Sodium silicate binder is relatively cheap, but is limited to high residual stress, poor shake out property (that is, collapsibility) and difficult to sand reclamation [10]. The moulds with a poor collapsibility (CP) will result in casting defect, namely hot tear [11]. Casting dimensional accuracy and surface finish are primarily dependent on the mould compression strength and hardness. Correlation among sand mould properties were studied by researchers in the recent past. Strong third order non-linear regression relationship exists between the compression strength (CS) and mould hardness (MH) in sand moulds [12]. The

CS of sand moulds increased with the increase in MH, this was due to the existence of strong dependency relationship among themselves. Lower compression strength will yield rough casting surface, shrinkage porosity, sand erosion and dimensional inaccuracy etc. However, high compression strength moulds do not allow the generated gas to escape from mould (i.e. permeability, P). Casting defects (i.e. blowhole, misrun and porosity) in sand moulds might occur as a result of insufficient space for the trapped or generated gases inside the sand mould [13]. The casting quality in sand moulding process is affected largely by the moulding sand properties. The inappropriate combination of moulding sand properties will result in casting defects such as, blow holes, rat tails, misruns, dimensional in accuracies, rough surface, porosity, segregations and so on [14]. These defects can be minimized by selection of optimal levels of moulding sand variables (that is, grain fineness number, degree of ramming, percent of resin and hardener, curing time and so on). Observations made from the above literature, shows that the casting quality is dependent primarily on sand mould properties (GE, CS, MH, CP, and P). Further, studying the appropriate method to control the moulding sand properties is of significant scope for the researchers.

Research work on moulding sand system in the past few decades was more focused on classical engineering experimental (that is, varying one parameter at once after fixed the rest at middle values), analytical and numerical approaches. Numerical methods were applied to predict the gas evolution when the molten metal was poured into the furan bonded moulding sand system [15]. The chemically mixed sand moulds contain resin and hardener, however their impact in furan sand moulds on gas evolution was neglected and was limited to establish the input-output relationships. Classical experiments were conducted to study the influence of different quantity of furan resin and hardener on moulding strength, gas evolution, surface quality and casting microstructure [16–18]. However, interaction effects of furan resin and hardener quantity were not considered and no predictive equations were developed in their study. The optimized binder composition had yielded good casting surface features with dimensional accuracy and better mould collapsibility [19]. However, the effect of curing time was not considered during their experimental investigations. The effect of sodium silicate and bentonite binders on gas evolution was studied by conducting classical experiments [7]. The influence of size (that is, coarse or fine) of the sand particles and their impact on moulding sand permeability and casting surface finish studied [11, 20]. The coarse sand resulted in a high permeability with rough casting surface, whereas, smooth uniform casting surface was obtained with fine sand particles but resulted in low permeability. Gas porosity in castings occurred due to the generated pressure inside the mould as a result of low permeability [13]. High percent of resin was resulted in better mechanical properties in sand moulds, whereas it was difficult to extract the cores from the solidified metal cast [21]. Further, higher resin content resulted in evolving huge amount of gas due to resin decomposition during casting solidification. The evolved gases resulted in defects in the casting part [21]. The above literature confirmed that, the moulding sand variables (proportion of resin and hardener, curing time, grain fineness number and so on) will have large influence on sand mould properties and in-turn casting quality. The conflicting requirements (higher compression strength in moulds offer low permeability and vice versa) in sand mould are found to be complex (that is, non-linear). It is difficult to establish good control of a process with analytical, numerical and classical experiment approaches. To attain better casting quality through setting the sand mould properties at optimal level by utilizing appropriate method (that is, modelling and analysis) is the concern for foundry industries.

Early in 1964, the statistical methods were first applied to conduct foundry experiments and analysis [22]. Design of experiments (DOE) is an effective statistical tool used to study, analyse and establish the input-output relationships. DOE methods estimate both individual and combined factor effects by conducting minimum experimental trials. Taguchi method was applied to model and optimize the casting defects in green sand moulding process [23]. Computer aided simulation was performed to obtain the casting data (defects) for Taguchi parametric design. Taguchi method might fail to establish full quadratic (that is, linear, square and interaction) factor effects due to limitation in orthogonal array. DOE was applied to conduct analysis of moulding sand variables (proportion of resin, and hardener, and temperature) on moulding strength and sand inclusion defects in furan sand moulding system [24]. DOE and response surface methodology (RSM) were applied to get the full quadratic factor effects and develop predictive models for green sand moulding [25], phenol formaldehyde sand mould [26], sodium silicate, CO_2 gas hardened [27], and furan sand moulding processes [28]. Further, the models predicted the sand moulding properties with a better accuracy for test cases. It was observed from the above literature that, the design of experiments and response surface methodology is an ideal tool to study many variables, which are complex and highly non-linear. Further, the combined tools can be used to establish precise mathematical equation representing outputs as a function of inputs. Moreover, the derived empirical relationship can be used to determine optimal points for a process. Important to note that, not much of the research efforts were made in the recent past on modelling, analysis and optimization of Alphaset sand moulding system.

The optimization task is generally carried out to determine the best results subjected to various resource (that is, input or design variable) constraints. Conventional optimization and nonconventional optimization are the two broad classifications of optimization techniques, distinguished based on search (that is, operating) mechanism employed to yield best results [29]. Conventional optimization algorithms are deterministic algorithms (such as, dynamic programming, non-linear programming, quadratic programming, geometric programming etc.) work with specific transition rules for moving solutions from one to another space during the optimal search [30]. For multi-modal optimization problems, the conventional optimization methods fail to locate the global optimal solutions. This is due to the difficulty in handling many variables with complex non-linear characteristics. The speed of convergence to locate the optimal solutions with conventional optimization tools is slow. Nonconventional optimization tools (that is, population based search methods include evolutionary and swarm intelligence algorithms) overcome the difficulties of conventional optimization tools by attaining the global solutions and rapid convergence that yield better results. Nonconventional optimization tools use heuristic search methods with definite set of probabilistic transition rules to get better solutions. The difference in the performance of evolutionary and swarm intelligence algorithms can be found for multi-modal and multidimensional optimization problems. This occur due to the different search mechanisms and different combination of employed rules to move population and associated solutions towards optimal. The population based algorithms [genetic algorithm (GA), particle swarm optimization (PSO), and teaching learning based optimization (TLBO)] are cost effective optimization tools in determining near optimal solutions through their heuristic search mechanism. Evolutionary GA, needs to set mutation rate and crossover parameters, and Swarm intelligence based PSO, needs to set inertia weight, social and cognitive parameters, at optimal level to yield best results [31]. Improper choice of genetic and swarm optimization parameters will affect both the computational efficiency and optimality of solutions [30]. Teaching learning based optimization (TLBO) do not require specific tuning parameters, thereby the probability to hit the global solutions are more [32]. GA and PSO were applied to optimize the green sand moulding [14] and squeeze casting process [33, 34] for better casting quality. PSO and GA had produced approximately similar results while locating global solution, and the computational effort and time was less for PSO. TLBO outperformed GA, PSO, and Taguchi optimization tools while performing optimization for different casting (that is, squeeze casting, die casting and continuous casting) and machining (wire electric discharge machining, abrasive jet machining and ultrasonic machining) processes [35, 36]. GA, PSO and TLBO tools can be applied to optimize the conflicting requirements (that is, maximize: CS, MH and P, and minimize: CP and GE) in sand mould properties. Further, use of optimization tools will minimize the requirements of practical experiments and analytical tools which are always costlier, tedious and time-consuming.

In the present work, the modelling of eco-friendly alphaset bonded sand mould system is conducted to understand the effect of sand moulding variables and moulding sand properties and to establish accurate relation between them. Statistical analysis will help the foundry personnel and researchers to study the full quadratic factors effects (linear, square and interaction) on sand mould properties. The statistical and 3D surface plot analysis will provide detailed insight of the physics of a process (i.e. process mechanics and dynamics). Further, sand mould properties (CP, CS, P, GE and MH) are expressed as a mathematical non-linear function of input variables. These predictive equations will help the foundry man to know the values of sand mould properties for the known set of moulding sand variables (that is, percent of resin, percent of hardener, and setting time). The conflicting requirements in moulding sand properties (minimize: GE and CP and maximize: CS, MH and P) are optimized by applying non-conventional optimization methods (that is, GA, PSO, and TLBO). Motivated by this, systematic study of modelling and optimization of alphaset bonded sand mould system would help the foundry personnel to obtain good quality castings, without much efforts, time and prior detailed knowledge of the process.

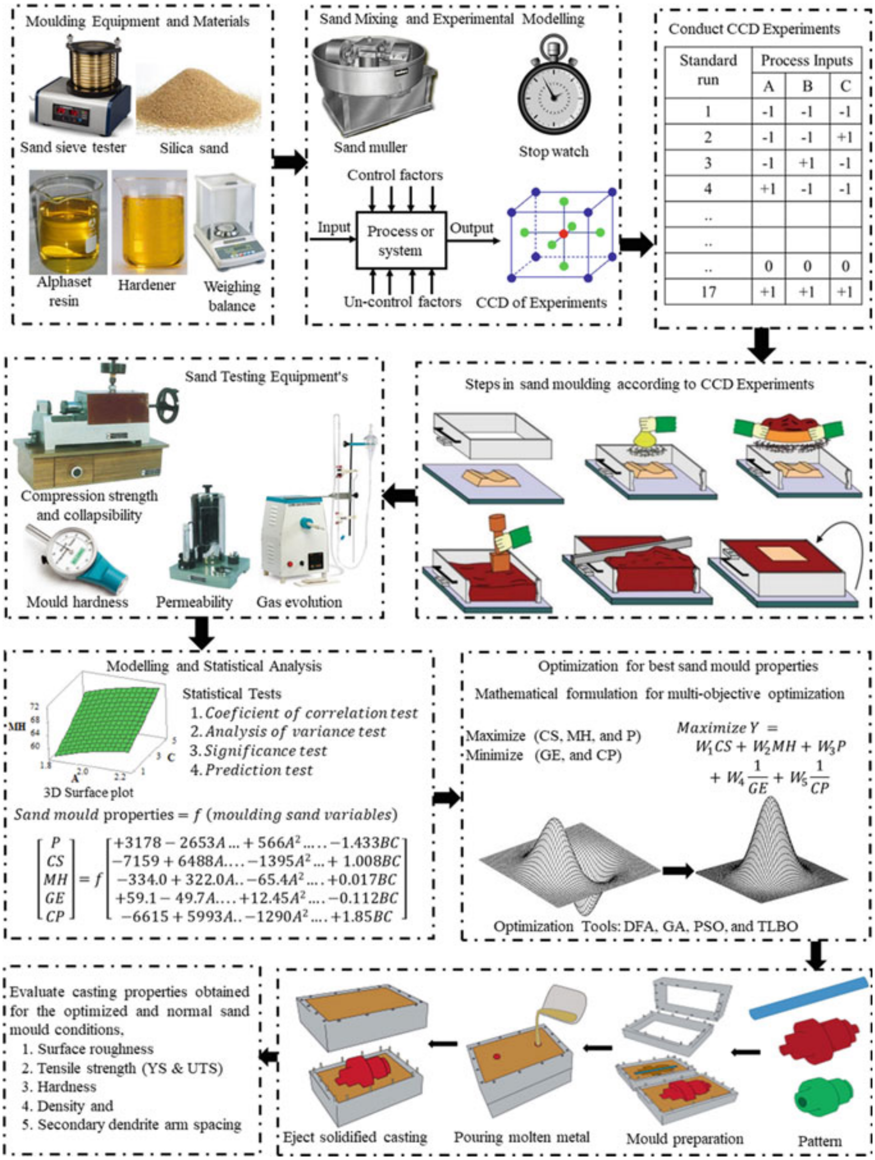

Fig. 1 Sequence of tasks performed during experimentation, modelling and optimization for better sand mould and casting properties

2 Experimentation, Modelling and Optimization

The experiments have been conducted in Alphaset sand moulding process. Further, the experimental data is used to develop non-linear models and optimize the process parameters. Figure 1 shows the sequence of various tasks with experimental setup during experimentation, modelling, and optimization of Alphaset sand moulding.

Step 1: The moulding materials (i.e. alphaset resin, hardener, and silica sand) are collected for experimentation. Sieve analysis test is conducted to determine the grain fineness number (GFN) as per American Foundry Society (AFS) standard. The required quantity of resin and hardener is measured with the help of digital weighing balance. The moulding materials and associated parameters used for the experimentation are selected based on trial experiments, consulting industrial expert's opinion, and available literature [12, 16–19, 25–28] (refer Table 1).
Step 2: Experiments are conducted with different set of sand mould variables as per Central Composite Design (CCD) matrix. The specimens (height of 5 cm and 3 cm in diameter) are prepared in accordance with American Foundry Society standard. The test specimens prepared as per CCD are used to determine the sand mould properties (that is, CS, P, MH, CP and GE).
Step 3: Moulding sand properties are expressed in terms of moulding sand variables by non-linear mathematical equations (regression models). Statistical tests (that is, coefficient of determination, significance test, analysis of variance and prediction tests) are carried out to determine statistical adequacy and to understand the behaviour of variables on mould properties.
Step 4: The derived empirical relationships for all sand mould properties are treated as an objective function for process optimization. Weight based method is employed to convert the conflicting objective function (maximize: CS, MH and P, and minimize: GE and CP) to a single objective function for maximization. GA, PSO, and TLBO algorithms are applied to optimize the sand mould properties in Alphaset sand moulding process. Further, the casting quality is evaluated for the different sand moulding conditions (that is, optimized and normal).

Table 1 Moulding materials and associated parameters

Parameters	Value
Grain fineness number or AFS number	55
Alphaset resin	1.8–2.2%
Ester cured	0.2–0.4%
Weighing balance accuracy	0.1 mg
Degree of ramming	3
Curing time	60–120 s
Mulling time	180 s

Table 2 Sand mould variables and associated operating levels

Input variables	Units	Un-coded levels		
		Low	Medium	High
[a]Resin	%	1.8	2.0	2.2
[a]Hardener	%	0.2	0.3	0.4
Curing time	min	60	90	120

[a]wt% of sand

3 Data Collection

The silica sand with 55 GFN is mixed with binder and catalyst for 3 min in sand muller and the test specimen are prepared by using this moulding sand mixture. The operating levels of moulding sand (input) variables used for conducting the experiments is presented in Table 2.

The following tests are conducted on the prepared test specimen to measure the sand mould properties. The height of the sand mould specimens are measured using standard height gauge and kept within the range of 5–5.1 cm. The permeability measurements are conducted using permeability meter. The compression strength and collapsibility (that is, retained strength) in the sand moulds are measured with the help of universal strength testing unit. The samples are kept in a muffle furnace maintained at 650 °C in for period of about 2 min and the collapsibility (that is, strength retained after heating) is determined by using universal strength testing machine. The harmful toxic compounds are emitted when the resin comes in contact with the molten metal. This will pollute the environment and cause serious threat to human health. 1 g of thoroughly mixed silica sand with alphaset binder and hardener, is taken in the ceramic boat and placed in the heated tube maintained at a temperature of 850 °C. The evolved gases as a result of burnt resin and hardener is measured by the displacement of water level in burette. The unit corresponding to gas evolution is ml/gm (Table 3).

4 Analysis, Modeling and Optimization

This section describes the modelling and optimization of Alphaset sand moulding process. The input-output data collected through experiment is used to develop surface plots for responses namely, GCS, CP, GE, MH, and P. The surface plots are the powerful graphical tool depicting the influence of linear and non-linear relation of the responses with input parameters. Statistical analysis is conducted to know the significance of full quadratic factor effects (that is, linear, square and interaction) of moulding sand variables on sand mould properties is tested by analysis of variance (ANOVA). Minitab (version 17) platform software is utilized for the said purpose. The prediction tests are also conducted to check the performance and practical utility

Table 3 CCD based experimental matrices for alphaset sand moulding

Exp. No.	Input variables			Sand mould properties				
	A	B	C	CS, KPa	CP, KPa	GE, ml/gm	MH	P
1	2.0	0.3	090	371.2	270.70	7.60	75.1	118.5
2	2.2	0.4	120	388.9	285.20	9.28	75.6	106.6
3	2.0	0.3	120	378.6	280.20	7.75	76.8	125.8
4	2.0	0.3	060	350.7	268.20	7.34	72.8	134.6
5	1.8	0.4	060	252.8	181.70	6.63	67.1	159.5
6	2.2	0.4	060	390.7	290.30	9.01	73.1	108.9
7	2.0	0.2	090	351.8	257.50	8.70	71.8	131.9
8	1.8	0.2	060	168.6	107.80	8.54	60.7	203.5
9	2.2	0.2	060	368.7	280.50	8.86	74.2	109.3
10	2.0	0.4	090	421.6	328.20	8.49	77.7	101.4
11	2.0	0.3	090	372.8	274.50	8.27	75.2	114.2
12	2.2	0.2	120	360.6	272.04	8.11	74.7	138.4
13	1.8	0.4	120	352.8	264.60	8.52	73.9	131.6
14	2.0	0.3	090	370.7	288.70	8.43	75.5	116.7
15	2.2	0.3	090	372.2	281.20	8.97	75.6	121.3
16	1.8	0.2	120	250.7	149.60	8.78	69.1	178.6
17	1.8	0.3	090	268.8	182.60	8.32	70.5	171.2

of the developed models. Castings are prepared by pouring the molten metal into the sand mould prepared with normal and optimized conditions and evaluated the casting quality.

4.1 Analysis and Modeling

4.1.1 Compression Strength

The compression strength, expressed as a non-linear mathematical function of moulding sand variables is as follows,

$$\begin{aligned} CS = {} & -7159 + 6488A + 1291B + 10.69C - 1395A^2 + 1040B^2 - 0.01294C^2 \\ & - 850AB - 4.0AC + 1.008BC \end{aligned} \quad (1)$$

Significance tests are carried out for the developed non-linear model to check the contributions of full quadratic (linear, square and interaction) effects of the factors on compression strength. The significance tests are conducted for the preset (P-value $\leq$ 0.05) confidence level of 95%. The significance test results obtained

Table 4 ANOVA test results for sand mould properties

Response		Compression strength				Collapsibility			
Source	DF	Adj. SS	Adj. MS	F	P	Adj. SS	Adj. MS	F	P
Model	9	68,492.5	07610.3	161.96	0.000	54,232.1	06025.8	062.71	0.000
Linear	3	47,896.0	15965.3	339.77	0.000	36,847.0	12282.3	127.81	0.000
Square	3	13,603.3	04534.4	096.50	0.000	11,306.6	03768.9	039.22	0.000
Interaction	3	06993.2	02331.1	049.61	0.000	06078.6	02026.2	021.09	0.001
Error	7	00328.9	0047.0			00672.7	00096.1		
Lack of fit	5	00326.5	0065.3	054.27	0.018	00492.6	00098.5	001.09	0.541
Pure error	2	00002.4	0001.2			00180.0	00090.0		
Total	16	68,821.4				54,904.8			
Response		Mould hardness				Gas evolution			
Model	9	272.419	30.269	29.55	0.000	6.85901	0.76211	12.04	0.002
Linear	3	179.606	59.069	58.45	0.000	1.72008	0.57336	09.06	0.008
Square	3	057.943	19.314	18.86	0.001	1.87379	0.62460	09.87	0.007
Interaction	3	034.870	11.623	11.35	0.004	3.26514	1.08838	17.19	0.001
Error	7	007.170	01.024			0.44309	0.06330		
Lack of fit	5	007.083	01.417	32.69	0.030	0.05529	0.01106	00.06	0.995
Pure error	2	000.087	00.043			0.38780	0.19390		
Total	16	279.589				7.30209			
Response		Permeability							
Model	9	12,869.1	1429.89	44.30	0.000				
Linear	3	09238.3	3079.42	95.40	0.000				
Square	3	02258.7	0752.89	23.32	0.001				
Interaction	3	01372.1	0457.37	14.17	0.002				
Error	7	00225.9	0032.28						
Lack of fit	5	00216.6	0043.32	09.29	0.100				
Pure error	2	00009.3	0004.66						
Total	16	13,095.0							

Table 5 Summary of significance test results for sand mould properties

Output	Coefficient of correlations		Parameters	
	All terms	Exclude insignificant terms	Significant terms	Insignificant terms
GE	0.9393	0.8613	A, C, AA, BB, CC, AB, AC, BC	B
CS	0.9952	0.9821	A, B, C, AA, BB, CC, AB, AC	BC
CP	0.9877	0.9720	A, B, C, AA, AB, AC	BB, CC, BC
MH	0.9744	0.9414	A, B, C, AA, AB, AC	BB, CC, BC
P	0.9827	0.9606	A, B, AA, AB, AC	C, BB, CC, BC

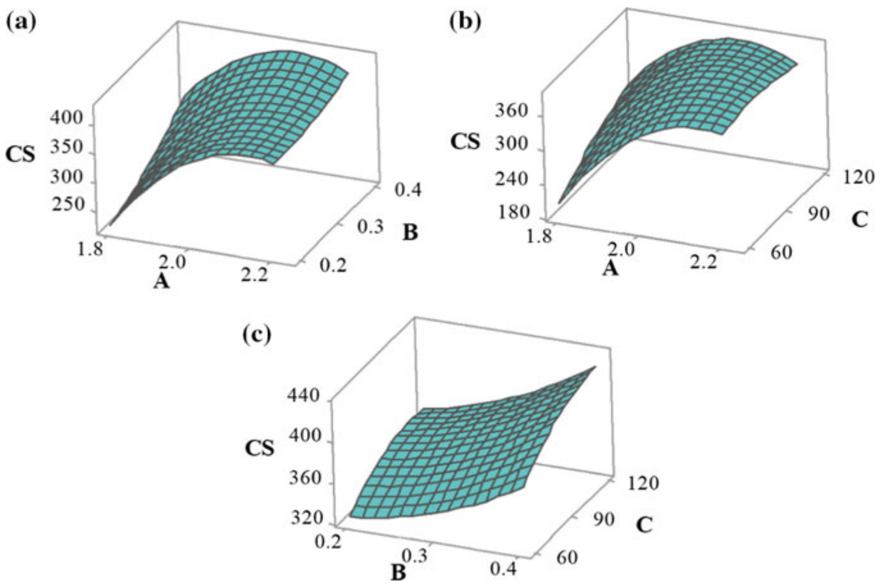

Fig. 2 3D surface graphs of compression strength with: **a** percent of resin and percent of hardener, **b** percent of hardener and curing time and **c** percent of hardener and curing time

for the compression strength is presented in Table 4. All linear, corresponding square and combined interaction terms (excluding the interaction among percent of hardener and curing time) are found to be significant for the response, CS (refer Table 5). Insignificant term depict there is no significant change in the output value when the independent variables are varied simultaneously within their operating levels. The *P*-values of all square terms are found to be significant (as their corresponding *P*-value is found to be less than 0.05), indicating all sand mould variables (that is, percent of resin, percent of hardener and curing time) are found to have non-linear relation with the response, CS. The results of statistical tests are found to be in line with the 3D surface plots (refer Fig. 2).

Figure 2 shows the 3-dimensional response surface plots drawn to know the impact of experimental (input) factors on the compression strength, when two variables are varied simultaneously within their operating range and keeping the remaining parameters at fixed center level. The observations made from the surface plots are as follows:

1. Figure 2a shows the interaction factors effect between the percent of resin and percent of hardener on the response, CS. It is observed that, the compression strength tends to increase with percentage of resin and hardener. The results showed that the resin tends to contribute more in comparison with hardener for the CS. Lower resin quantity might not be sufficient enough to coat the sand grains, will not develop strong bonding action between the sand grains. Further,

low quantity of hardener might not be sufficient enough to stimulate the available resin. The results are in line with the experiments conducted earlier by Bargaoui et al. [21].

2. High values of compression strength are seen with the increased values of percent of resin (refer Fig. 2b). Further, CS is found to have a negligible impact when the curing time is varied from low to high values. This implies high values of hardener content support polymerization that develops strong bonding action between the molecules of resin to coat on sand grains.
3. CS is found to increase linearly with an increase in hardener and curing time simultaneously. This indicates high quantity of hardener might not provide strong bonding strength with low curing time. Increase in curing time will provide sufficient time for the resin to undergo polymerization and develop strong bonding action between the sand grains which improves the mould compression strength.

The multiple correlation coefficient established for the compression strength is found to be close to 1, which indicates the model fits to the assumed regression equation with good precision. The ANOVA result shows that, the model developed for the response, CS is statistically adequate. The combined effect of linear, square and 2-term interactions and lack-of-fit was found significant. Further, the model needs to be tested for its accuracy in prediction by utilizing test cases with randomized combination of variable parameter values. However, it is to be noted that, the variable parameters should be within their operating range.

4.1.2 Permeability

The relationship of the response permeability with the sand mould variables (percent of resin, curing time and percent of hardener) is represented mathematically as follows,

$$\begin{aligned} \mathrm{P} = {} & 3178 - 2653\mathrm{A} - 342\mathrm{B} - 4.320\mathrm{C} + 566.0\mathrm{A}^2 - 696\mathrm{B}^2 + 0.00732\mathrm{C}^2 + 367\mathrm{AB} \\ & + 1.658\mathrm{AC} - 1.433\mathrm{BC} \end{aligned} \tag{2}$$

The significance of moulding sand variables, their curvature, and two-term interactions are tested at 95% confidence interval. The obtained significance test results are discussed below (refer Table 5).

1. The variable, curing time (that is, C) is not having significant contribution towards this response.
2. The quadratic terms of variables, namely, percent of hardener and curing time are not significant towards the response, permeability. This indicates that, the existence of strong dependent linear relationship of these parameters with permeability.
3. Although percent of hardener alone has showed a significant impact, their interaction with curing time is found insignificant. This indicates the permeability

does not depend much on the interaction of curing time and percent of hardener (i.e. BC).

The combined effect of all linear (A, B, C), corresponding square (A^2, B^2 and C^2), and combined two-term interaction (AB, AC, and BC) term effects is found to be significant at 95% confidence level (refer Table 4). Excluding insignificant terms will result in imprecise input-output relationship and might reduce the prediction accuracy. The multiple correlation coefficient obtained for the response permeability is found equal to 0.9827 (refer Table 5). Hence, the models are statistically adequate to make use for prediction of permeability for known set of sand mould variables.

4.1.3 Mould Hardness

Mould hardness, expressed as a mathematical non-linear function of percent of resin, percent of hardener and curing time is shown below-

$$\begin{aligned} \mathrm{MH} = & -334.0 + 322.0\mathrm{A} + 213.0\mathrm{B} + 0.751\mathrm{C} - 65.4\mathrm{A}^2 - 91.8\mathrm{B}^2 - 0.000964\mathrm{C}^2 \\ & - 71.2\mathrm{AB} - 0.2542\mathrm{AC} + 0.017\mathrm{BC} \end{aligned} \tag{3}$$

The result of significance test for the response-mould hardness shows that, the combined effect of all linear, quadratic, two-factor terms and lack-of-fit are statistically significant at 95% confidence level (refer Table 4). The terms (i.e. B^2, and C^2) are found insignificant, indicating percentage of hardener and curing time have strong linear relationship with the response, mould hardness. Although hardener and curing time are found to have significant contribution, its interaction (i.e. BC) is insignificant towards this response. Percent of resin has maximum contribution, followed by hardener and curing time towards the response, mould hardness. The model found to be statistically adequate with good fit of response surface and resulted in a better correlation coefficient value equal to 0.9744 (refer Table 5). Therefore, the model can be used to make mould hardness prediction for known combination of sand mould variables.

4.1.4 Gas Evolution

The mathematical model established between gas evolution and sand mould variables (i.e. percent of resin, percent of hardener and curing time) using experimental data is shown below,

$$\begin{aligned} \mathrm{GE} = & \; 59.1 - 49.7\mathrm{A} - 81.6\mathrm{B} + 0.2026\mathrm{C} + 12.45\mathrm{A}^2 + 44.8\mathrm{B}^2 - 0.000669\mathrm{C}^2 \\ & + 21.81\mathrm{AB} - 0.0544\mathrm{AC} + 0.1112\mathrm{BC} \end{aligned} \tag{4}$$

Table 4 shows the significance test results obtained for GE. The percent of hardener is not found to be significant, because their *P*-value is more than 0.05. The analysis of variance values of full quadratic (linear, square, and two term interaction) terms for the gas evolution is shown in Table 5. The *P*-values of full quadratic terms are found to be lower than 0.05, indicating good fit of response surface for GE. Further, the coefficient of determination value obtained for gas evolution is found to be equal to 0.9393, indicating the mathematical models are capable to predict accurately the response, GE. Excluding non-significant terms from the derived response Eq. (4), will make the lack-of-fit significant.

4.1.5 Collapsibility

The second order response surface model between the moulding sand variables and collapsibility is expressed as follows:

$$\begin{aligned} \mathrm{CP} = & -6615 + 5993\mathrm{A} + 1630\mathrm{B} + 7.48\mathrm{C} - 1290\mathrm{A}^2 + 934\mathrm{B}^2 - 0.01034\mathrm{C}^2 \\ & - 1037\mathrm{AB} - 2.880\mathrm{AC} + 1.85\mathrm{BC} \end{aligned} \tag{5}$$

The significance of linear factors (i.e. sand mould variables), their nonlinearity (i.e. curvature), and two term interactions are evaluated for the confidence level of 95%. It is important to note that the collapsibility and mould hardness identified similar significant and insignificant terms (refer Table 5). This might have happened due to the existence of strong dependency between the mould hardness and collapsibility. The coefficient of determination for the response, collapsibility was found equal to 0.9877 (refer Table 5). Since, the coefficient of correlation is close to 1, prediction ability by the response equation will be close the actual values of collapsibility.

4.1.6 Prediction Test for the Developed Non-linear Models

The discussion from previous section indicates, all non-linear regression models developed for the responses, namely CS, P, MH, GE and CP are statistically adequate at 95% confidence level. These models are tested towards their prediction capability by conducting 14 experiments (test cases), which will be treated as target values. It is to be noted that these experiments are conducted with different set of variable combination generated at random. The values of variables are generated at random within their operating range (Appendix 1). The percent deviation in predicting the sand mould properties (i.e. CS, P, MH, GE and CP) for 14 test cases are presented in Appendices 2 and 3. The Percentage deviation in predicting the response value is found to vary in the ranges between −6.58 and +6.26% for CS, −9.53 and +5.34% for CP, −4.05 and +4.29% for GE, −4.86 and +3.29% for MH, and −8.38 and + 6.18% for P (Appendices 2 and 3). It is important to mention that, the % deviation is found to vary on both positive and negative sides and vary within the acceptable

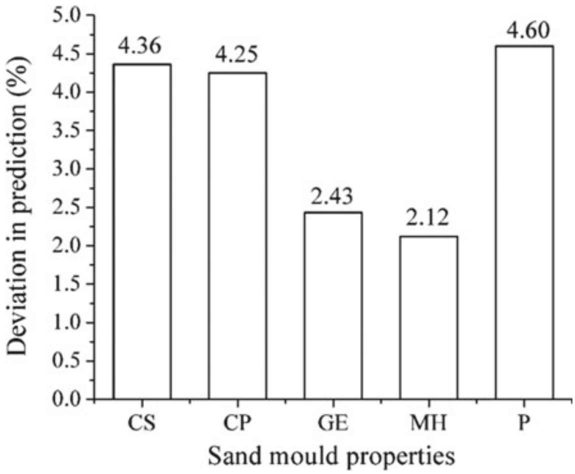

Fig. 3 Mean absolute percent error in prediction of sand mould properties

range for all the responses (refer Appendices 2 and 3). This shows that, the model has accurately captured the process physics, mechanics and dynamics. Further, the mean absolute percent deviation in prediction for CS, CP, GE, MH and P is found equal to 4.36, 4.25, 2.43, 2.12 and 4.6%, respectively (refer Fig. 3). The mean absolute percent deviation in prediction of all sand mould properties (i.e. CS, CP, GE, MH and P) is found equal to 3.55%. This depicts the developed non-linear models can be used by any novice user to predict the sand mould properties without the requirement of prior knowledge and conducting trial experiments.

4.2 Multi-response Optimization

Accurate control of moulding sand properties with conflicting requirements is a tedious task in foundry industries. A situation might arise in shop floor such that a set of sand mould variables might results in better permeability, but not offer the desired strength and hardness of moulds. This is due to the fact that, the response permeability has inverse relation with mould hardness and compression strength. Multi-objective optimization would solve this complex situation by determining an optimal set of sand mould variables (that is, percent of resin, percent of hardener and curing time) for the conflicting requirements in sand mould properties (that is, minimize: GE and CP, and maximize: CS, MH and P). The upper and lower constrained values of sand mould variables could define the three-dimensional solution spaces, which will help optimization tools (DFA, GA, PSO, and TLBO) to conduct search for the best sand mould properties. Optimal sand moulding properties for the conflicting objective functions (simultaneous, maximization and minimization) in alphaset sand moulding system will need a suitable mathematical formulation. Weight average method is employed to convert multiple conflicting objective functions to a single objective function either for maximization or minimization [14, 34]. The present work require optimization of five conflicting objective functions. Six different case studies are considered by assigning equal importance (i.e. 20 wt%) to all outputs and maximum importance to one output at a time (that is, 60%), with the rest at low and equal weights (that is, 10%). The optimal search is conducted. Accurate control of moulding sand properties with conflicting requirements is treated as a tedious task in shop floor foundry. A situation might arise in shop floor such that a set of sand mould variables might results in better permeability, but not offer the desired strength and hardness of moulds due to permeability pose inverse relation with mould hardness and compression strength. Multi-objective optimization would solve this complex situation by determining optimal set of sand mould variables (that is, percent of resin, percent of hardener and curing time) for the conflicting requirements in sand mould properties (that is, minimize: GE and CP, and maximize: CS, MH and P). The upper and lower constrained values of sand mould variables could define the three-dimensional solution spaces, which help optimization tools (DFA, GA, PSO, and TLBO) to conduct optimal search for best sand mould properties. Optimal sand moulding properties for the conflicting objective functions (simultaneous, maximization and minimization) in alphaset sand moulding system require suitable mathematical formulation. Weight average method is employed to convert multiple conflicting objective functions to single function either for maximization or minimization [14, 34]. The present work require optimization of five conflicting objective functions, six different case studies are considered after assigning equal importance (i.e. 20 wt%) to all outputs and maximum importance to single output (that is, 60%), with the rest at low and equal weights (that is, 10%). Optimization tools are used to obtain the best set of mould properties. Optimization of mathematically formulated weighted objective (output) function for maximization is discussed as follows,

Output function (Y_1) = CS
Output function (Y_2) = P
Output function (Y_3) = MH
Output function (Y_4) = 1/GE
Output function (Y_5) = 1/CP

$$Maximize\ (Y) = W_1Y_1 + W_2Y_2 + W_3Y_3 + W_4Y_4 + W_5Y_5$$

Terms W_1Y_1, W_2Y_2, W_3Y_3, W_4Y_4, and W_5Y_5 are the weight fraction combination for the objective function CS, P, MH, GE and CP, respectively. Weight factors (W_1–W_5) combination are selected such that their cumulative value must be equal to one. In Alphaset sand moulding process, the sand mould properties are imposed by parameter upper and lower bound constraints which cover percent of resin, percent of hardener and curing time. These variable constraints are listed in Table 6.

Table 6 Upper and lower bound of constrained variables

Parameters	Lower bound	Upper bound
Percent of resin, %	1.8	2.2
Percent of hardener, %	0.2	0.4
Curing time, s	60	120

4.2.1 Desirability Function Approach (DFA)

In 1980, Derringer and Suich had proposed the desirability function approach for multi-response optimization [37]. Reduced gradient approach was employed to locate the optimal solutions, which initiate with multiple solution and end with global solution (i.e. highest desirability) [38]. The desirability (D) value could vary between the ranges of 0 and 1. The solutions are completely acceptable (i.e. output function value is perfectly the target or global value) when the D = 1 or close to 1. The present work is focussed to optimize the conflicting objective functions which have both maximizing and minimizing the individual desirability functions.

The responses (CS, MH, and P) are of maximizing type and the individual desirability function is presented by Y_{CS}, Y_P, and Y_{MH}.

$$y_{CS} = \frac{CS - CS_{\min}}{CS_{\max} - CS_{\min}}, \quad y_P = \frac{P - P_{\min}}{P_{\max} - P_{\min}}, \quad \text{and} \quad y_{MH} = \frac{MH - MH_{\min}}{MH_{\max} - MH_{\min}}$$

where,

P_{max} and P_{min} is the maximum and minimum value of P
CS and CS_{min} is the maximum and minimum value of CS
MH_{max} MH_{min} is the maximum and minimum value of MH.

The responses (GE, and CP) are of minimizing type and the individual desirability function is presented by Y_{GE}, and Y_{CP}.

$$y_{GE} = \frac{GE\text{max} - GE}{GE\text{max} - GE_{\text{min}}} \quad \text{and} \quad y_{CP} = \frac{CP\text{max} - CP}{CP\text{max} - CP_{\text{min}}}$$

where,

GE_{max} and GE_{min} is the maximum and minimum value of GE
CP_{max} and CP_{min} is the maximum and minimum value of CP.

For multi-objective functions the highest composite desirability value obtained from six different case studies is treated as an optimal choice for Alphaset sand moulding process. The single composite desirability value, satisfying all conflicting requirements in sand mould properties is computed as shown below

$$D_0 = \sqrt[5]{y_{CS}^{w_1} \times y_P^{w_2} \times y_{MH}^{w_3} \times y_{GE}^{w_4} \times y_{CP}^{w_5}} \tag{6}$$

4.2.2 Genetic Algorithm (GA)

In 1975, Holland introduced the concept of genetic algorithm which mimic the natural selection of living organisms based on Charles Darwin theory of survival of fittest [14, 34]. The process starts with initialization of genetic operators (mutation, crossover and selection) and generation of population to produce local solutions. To obtain global solutions the decision on optimum selection of genetic operators are of primary importance. There are no universal standards or methods established to obtain the global solutions for optimum choice of GA parameters (i.e. genetic operators, population size and generation or iteration number). Thereby, parameter study is conducted to ensure the highest desirability (D_0) values correspond to GA parameters. Tournament selection method is employed to rank the obtained solutions by balancing the diversity of new population and enhance the current solution. The optimum GA parameters correspond to highest desirability (D_0) value is decided by conducting parameter study is presented in Table 7.

4.2.3 Particle Swarm Optimization: PSO

In 1995, Dr. Eberhart and Dr. Kennedy presented the concept of particle swarm optimization at the Congress on Evolutionary Computation (Kennedy and Eberhart 1995). PSO imitate the cooperation among individuals and in the team utilizing swarm intelligence and share experiences from one generation to other. PSO pose technical advantage over GA, as PSO requires few tuning (inertia weight, swarm size, mutation rate and generation) parameters [14, 34], and do not require sorting of fitness values and the solution lead to fast convergence. Mutation operator is introduced to simple PSO to enlarge the search space to avoid local minima, if any [14]. Systematic study results of optimization of particle swarm optimization parameters for highest composite desirability (D_0) value correspond to the sand moulding properties and sand mould variables are presented in Table 7.

Table 7 Parameter study results of GA and PSO

GA parameter study			PSO parameter study		
Parameters	Levels	Optimum value	Parameters	Levels	Optimum value
Cross over rate	0.3–1.0	0.5	Inertia weight	0–1	0.55
Mutation rate	0.03–0.3	0.15	Mutation rate	0.03–0.3	0.09
Population size	20–180	150	Swarm size	20–180	100
Generations	20–1000	500	Generations	20–1000	200

4.2.4 Teacher Learning Based Optimization (TLBO)

Rao introduced the concept of teaching learning-based optimization algorithm. TLBO is also a population-based algorithm [30], wherein the group of learners or class of learners is treated as populations. TLBO algorithm is considered to be more efficient for solving the non-linear optimization problem, and do not require algorithm specific tuning parameters. Thus, TLBO algorithm converge solutions at faster rate and avoids local minima solution due to improper choice of tuning parameters. The algorithm works in two phases (i.e. teacher and learner phase) to locate optimal solutions. In teacher phase, teacher is the highly trained professional who motivate the students to acquire greater knowledge and always focussed to improve the mean result of a class. In learner phase, apart from acquire knowledge in teacher phase, the learner's mutual interaction could also help to improve the mean result of a class. Although there are no algorithm specific tuning parameters, the size of population and generations are required to be optimized in TLBO. TLBO parameters are optimized for highest desirability (D_0) value as below:

Number of population = 60
Number of generation = 100.

4.2.5 Comparison of Performance of Optimization Models: DFA, GA, PSO, and TLBO

Table 8 shows the different optimization tools (DFA, GA, PSO, and TLBO) used to locate extreme values of sand mould properties and corresponding sand mould variables for six case studies. The values with highest global desirability will define the best sand mould conditions (percent of resin, percent of hardener, and curing time) and properties. The optimum set of sand mould properties, located with the help of fine-tuned GA, PSO and TLBO parameters is used to determine the global desirability value for six different case studies. The choice of best sand moulding conditions from six different case studies is obtained with the help of highest desirability (D_0) value. The composite desirability value obtained for case 1–6 are found to be {0.8826, 0.8873, 0.8881, 0.8947}, {0.9073, 0.9076, 0.9109, 0.9122}, {0.9033, 0.9098, 0.9185, 0.9152}, {0.9199, 0.9138, 0.9275, 0.9297}, {0.9099, 0.9146, 0.9351, 0.9382}, and {0.9031, 0.9059, 0.9117, 0.9096} for DFA, GA, PSO, and TLBO, respectively (refer Table 8). Important to note that, TLBO outperformed PSO, DFA, and GA to locate the highest composite desirability (D_o) value. TLBO determined case 5 (that is, highest importance assigned to GE) is recommended as an optimum choice for Alphaset-sand moulding system, as their corresponding desirability function value found to be maximum compared to other cases studied. Further, TLBO optimizes the sand mould properties with less population size and generation {60 and 100} number as compared to GA {150, 500} and PSO {100, 200} (refer Table 7). Further, TLBO does not require algorithm specific tuning parameters unlike in GA (crossover, and mutation) and PSO (inertia weight, social and cognitive leader) and lead to faster

Table 8 Optimum sand moulding conditions for multiple outputs with different combination of weight factors via DFA, GA, PSO, and TLBO

Case studies	Models	Desirability (D_0)	Responses							
			A	B	C	CS, KPa	P	MH	GE, ml/gm	CP, KPa
Case 1: equal importance to all outputs (W_1, W_2, W_3, W_4 and $W_5 = 0.2$)	DFA	0.8826	1.87	0.27	79.3	283.6	157.7	70.44	8.09	204.7
	GA	0.8873	1.88	0.24	114.4	312.3	154.3	72.85	8.30	218.5
	PSO	0.8881	1.83	0.32	066.6	252.6	169.0	68.42	7.35	182.7
	TLBO	0.8947	1.86	0.35	60.42	277.7	157.8	69.22	6.90	207.5
Case 2: highest importance to CS ($W_1 = 0.6$, W_2, W_3, W_4 and $W_5 = 0.1$)	DFA	0.9073	2.17	0.23	118.7	363.5	131.8	75.99	8.00	273.7
	GA	0.9076	1.96	0.27	112.5	360.4	132.4	75.76	8.00	266.7
	PSO	0.9109	2.04	0.22	119.3	368.7	131.5	75.73	7.85	274.2
	TLBO	0.9122	2.04	0.27	119.4	375.9	127.5	76.75	7.75	281.5
Case 3: highest importance to P ($W_2 = 0.6$, W_1, W_3, W_4 and $W_5 = 0.1$)	DFA	0.9033	1.8	0.23	83.6	222.42	184.0	66.59	8.82	144.9
	GA	0.9098	1.83	0.32	66.6	252.6	169.0	68.42	7.35	182.7
	PSO	0.9185	1.81	0.32	60.8	219.9	182.4	66.39	7.06	155.7
	TLBO	0.9152	1.82	0.29	63.9	230.8	178.2	67.01	7.4	163.4
Case 4: highest importance to MH ($W_3 = 0.6$, W_1, W_2, W_4 and $W_5 = 0.1$)	DFA	0.9199	2.14	0.31	118.7	382.6	120.9	77.23	8.14	289.9
	GA	0.9138	1.91	0.33	91.3	348.93	130.5	74.57	8.07	262.3
	PSO	0.9275	1.91	0.32	118.6	363.02	130.4	76.29	7.92	269.5
	TLBO	0.9297	1.94	0.29	119.4	359.3	134.1	76.06	7.82	264.8
Case 5: highest importance to GE ($W_4 = 0.6$, W_1, W_2, W_3 and $W_5 = 0.1$)	DFA	0.9099	1.87	0.36	72.4	315.1	142.1	71.74	7.51	237.5
	GA	0.9146	1.98	0.30	61.3	332.1	135.2	72.28	7.34	253.4
	PSO	0.9351	1.86	0.37	61.7	296.2	149.2	69.95	6.93	224.1
	TLBO	0.9382	1.84	0.38	60.8	285.7	153.2	69.21	6.84	215.8
Case 6: highest importance to CP ($W_5 = 0.6$, W_1, W_2, W_3 and $W_4 = 0.1$)	DFA	0.9031	1.84	0.24	62.3	226.95	178.8	65.88	7.85	159
	GA	0.9059	1.8	0.28	81.2	239.57	176.4	68.4	8.21	164.3
	PSO	0.9117	1.81	0.32	60.8	219.92	182.4	66.39	7.06	155.7
	TLBO	0.9096	1.81	0.29	69.9	226.69	180.4	67.17	7.72	157.4

Table 9 Validate the optimization models with experimental sand mould conditions

D_0	Condition	Sand mould variables (inputs)			Sand mould properties (outputs)				
		A	B	C	CS, KPa	P	MH	GE, ml/gm	CP, KPa
0.9382	Optimized	1.84	0.38	60.8	285.7	153.2	69.21	6.84	215.8
0.7861	Normal	2.20	0.40	120	388.9	106.6	75.60	9.28	285.2

convergence. Confirmation experiments are conducted for the determined optimal sand mould conditions with highest composite desirability value of Case 5 by TLBO. TLBO results are compared with experimental values to confirm their practical utility. The results are found to be more useful for a foundry personal as their deviation is found to be less than 8% with enhanced sand mould properties. The experiments are also conducted for the lowest desirability value obtained from Table 9 (that is, Experiment No. 2) for the normal sand moulding condition. This experiment is done to know the importance of optimization methods in achieving the casting quality. Important to note that, although normal sand moulding condition (refer Table 9) provide better strength, but affects the mould permeability, gas evolution and collapsibility. Low permeable moulds and high gas evolution increase the mould pressure which create inadequate space for the generated gases during metal pouring and will result in gas porosity in the castings [13]. Further, poor collapsibility requires additional equipment to break the moulds, which might induce the residual stresses and hot tear defects in castings [11].

5 Casting Quality Assessments for Different Sand Mould (Optimized and Normal) Conditions

The Alphaset resin bonded sand mould prepared with optimized and normal sand mould condition is used to cast the automotive bushing (refer Table 10). The castings are subjected to different tests according to reference standards to evaluate the quality characteristics. LM20 molten metal is poured to the prepared mould cavity. The mould cavity is prepared with the help of aluminium pattern.

The casting, automotive bushing part is tested for different quality (density, SR, YS, UTS, SDAS, and BHN) characteristics (refer Fig. 4a) and evaluated the difference in quality for the castings obtained from optimized and normal moulding sand conditions. The outer casting surface structure is evaluated with the help of Mitutoyo Surftest SJ301. Gas porosity was observed on the tensile fracture surface for the castings prepared by normal sand mould condition (refer Fig. 4d).

Homogeneous texture with increased amount of fine dimples on the fractured intergranular surface is observed on tensile specimens (refer Fig. 4e). This indicates relatively large amount of plastic deformation occurs before fracture (refer

Table 10 Casting quality characteristics under different moulding conditions

Casting quality characteristics	Notation	Testing Standards	Optimized condition	Normal condition
Surface roughness, μm	SR	JIS 2001	4.88	5.63
Yield strength, MPa	YS	ASTM E8	112	104
Ultimate tensile strength, MPa	UTS	ASTM E8	183	158
Hardness	BHN	ASTM E10	61	58
Density, g/cm3	ρ	Archimedes	2.62	2.59
Secondary dendrite arm spacing, μm	SDAS	ASTM E112	49.0	55.0

Fig. 4e). The resulted microstructure is dendritic structure with fine α-aluminium grains. The refined silicon particles have appeared in the matrix between the dendrites and resulted in a low value of secondary dendrite arm spacing (refer Fig. 4c).

Segregations are formed between the dendrites for the castings obtained by normal sand mould condition (refer Fig. 4b). The surface finish, dendritic structure, and fracture mechanism obtained for highest desirability value (i.e. 0.9382) is found to be better as compared to low values of global desirability (i.e. 0.7861). Three replicates are considered for each casting condition and the average value of different quality characteristics (i.e. 9 SR, 3 YS and UTS, 9 BHN, and 3 SDAS) at different section on the casting samples are presented in Table 10. The casting quality obtained for the optimized sand mould condition experiment is found to be better compared to that obtained with the normal sand mould condition (refer Table 10). That is, the casting quality made in mould with highest desirability value is found to be better than the casting made in mould with lower desirability value.

6 Conclusion

The main objective of the present research work is to apply statistical modelling and optimization tools in Alpha-set moulding sand system to improve the quality of mould and thereby the quality of casting. The research work will help the foundry personnel to produce good quality castings with lower cost. Modelling has been carried out by conducting experiments, as per CCD matrix with different combination of sand mould variables (i.e. percent of resin, percent of hardener and curing time). The responses considered in the study include sand mould properties, namely CS, P, MH, GE, and CP. Statistical (significance, analysis of variance, and prediction) tests, and 3-dimensional response surface analysis are carried out to know the behaviour of

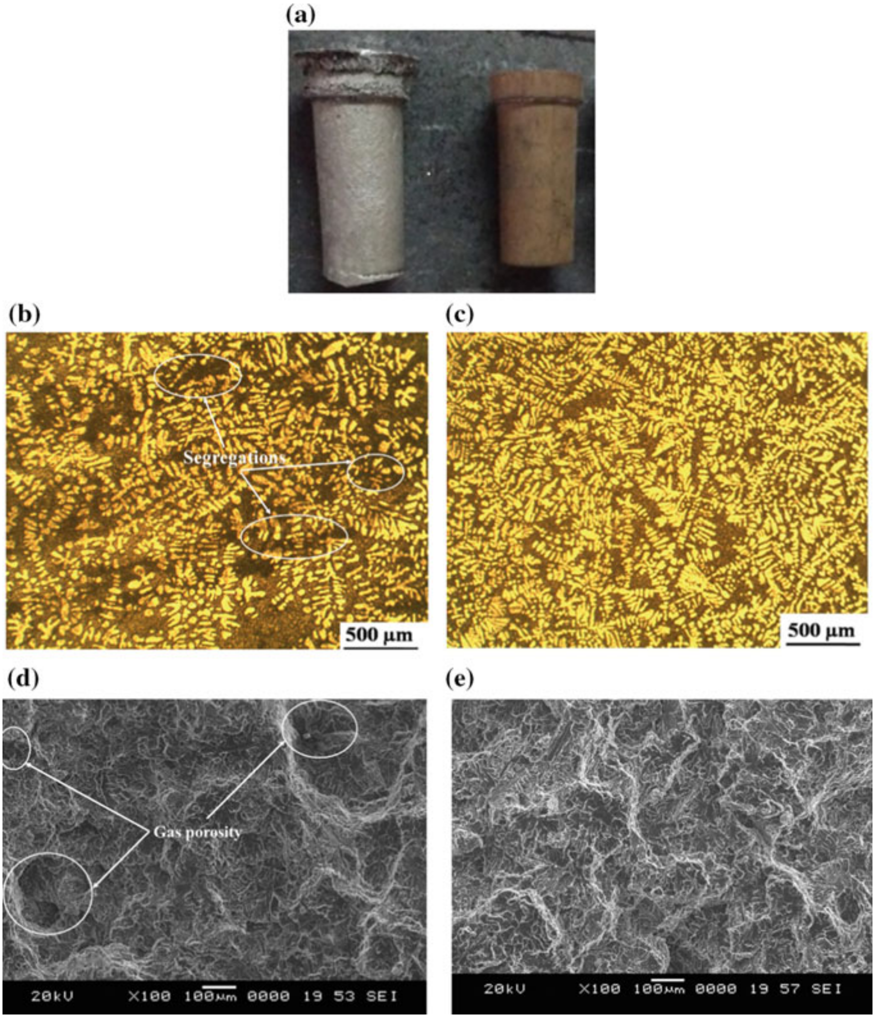

Fig. 4 **a** Photograph of cast samples, dendrite structure of **b** normal sand mould and **c** optimized sand mould, fracture surface of **d** normal sand mould and **e** optimized sand mould

variables, physics and mechanics of a process accurately. Optimization tools, namely DFA, GA, PSO and TLBO are applied to optimize the multiple outputs (maximize: CS, P, and MH, and minimize: GE, and CP). The following conclusions are drawn from the present work:

1. All linear factors (i.e. percent of resin, percent of hardener and curing time) are found to have significant contribution towards all sand mould properties (excluding, curing time for permeability).

2. The quadratic effects of percent of hardener and curing time is found insignificant (as *P*-values > 0.05) for the responses, namely collapsibility, mould hardness and permeability. This indicates CS, MH and P relationship with percent of hardener and curing time is linear in nature. Important to note that, the interaction among percent of hardener and curing time is insignificant for all the sand mould properties (excluding, GE).
3. Non-linear models developed for all sand mould properties are found to be statistically adequate with good fit of response surfaces. The prediction accuracy of all non-linear models is found to be less than 5%. The better prediction accuracy might be due to the fact that, model captured the physics, mechanics and dynamics of a process accurately. Further, the developed models help any novice user to predict the sand mould properties without conducting the practical experiments.
4. The sand mould properties are complex, non-linear and conflicting (maximize: CS, P, and MH, and minimize: GE and CP) in nature. The optimum solutions are many due to multiple objective functions with conflicting requirements. Weight based method is used to determine the optimal solutions after assigning different combination of weight fractions (importance) to each individual output. The highest desirability (D_0) value corresponds to the different cases is studied and treated as an optimal condition for sand mould properties. Confirmation experiments revealed that, the optimized sand mould properties will produce the casting with better quality characteristics compared to normal sand moulding conditions.

Appendix 1: Test Case Data for Sand Moulding Variables and Moulding Sand Properties

Test no.	Moulding sand variables			Moulding sand properties				
	% of resin	% of hardener	Curing time	CS, KPa	P	MH	CP, KPa	GE, ml/gm
1	1.85	0.20	064	212.4	187.3	62.04	142.2	8.40
2	2.20	0.25	118	376.8	138.6	76.74	256.8	8.34
3	1.90	0.30	106	360.7	134.3	73.28	258.9	7.82
4	1.95	0.35	074	367.3	120.2	71.20	256.3	7.73
5	1.80	0.35	089	271.8	159.9	72.48	216.0	8.02
6	2.10	0.30	102	414.0	108.4	79.84	290.4	8.72
7	1.95	0.25	096	332.2	142.8	76.23	260.6	8.21
8	2.20	0.40	063	381.6	100.7	74.03	286.7	9.45
9	2.15	0.20	074	361.1	121.3	75.32	292.4	9.20
10	2.05	0.35	096	428.8	99.8	78.13	289.7	8.63
11	1.85	0.30	088	276.3	164.3	72.38	218.9	8.04
12	2.20	0.25	112	350.8	132.4	75.30	280.1	8.80
13	1.80	0.25	092	247.8	182.7	65.23	151.5	8.38
14	2.05	0.35	078	402.5	101.4	76.40	278.7	8.08

Appendix 2: Summary Results of Model Predicted Test Cases of Sand Mould Properties (CS, P, MH, GE and CP)

Test no.	Compression strength, KPa				Permeability			
	Exp. value	Model prediction	Deviation (%)	Absolute deviation (%)	Exp. value	Model prediction	Deviation (%)	Absolute deviation (%)
1	212.4	225.17	−6.01	−6.01	187.3	178.10	4.91	4.91
2	376.8	355.63	5.62	5.62	138.6	134.00	3.32	3.32
3	360.7	342.85	4.95	4.95	134.3	137.19	−2.15	2.15
4	367.3	356.35	2.98	2.98	120.2	124.92	−3.93	3.93
5	271.8	282.86	−4.07	−4.07	159.9	157.17	1.71	1.71
6	414.0	389.05	6.03	6.03	108.4	115.54	−6.59	6.59
7	332.2	343.86	−3.51	−3.51	142.8	135.50	5.11	5.11
8	381.6	390.71	−2.39	−2.39	100.7	106.22	−5.48	5.48
9	361.1	374.83	−3.80	−3.80	121.3	114.94	5.24	5.24
10	428.8	401.94	6.26	6.26	99.8	107.21	−7.43	7.43
11	276.3	294.49	−6.58	−6.58	164.3	154.15	6.18	6.18
12	350.8	360.63	−2.80	−2.80	132.4	130.08	1.75	1.75
13	247.8	239.59	3.31	3.31	182.7	178.71	2.18	2.18
14	402.5	391.30	2.78	2.78	101.4	109.90	−8.38	8.38
	Mould hardness				Collapsibility			
1	62.04	64.69	−4.27	4.27	142.2	155.8	−9.53	9.53
2	76.74	75.92	1.06	1.06	256.8	267.1	−4.02	4.02
3	73.28	74.88	−2.18	2.18	258.9	252.3	2.56	2.56
4	71.20	73.98	−3.91	3.91	256.3	272.5	−6.33	6.33
5	72.48	71.16	1.82	1.82	216.0	204.5	5.34	5.34
6	79.84	77.21	3.29	3.29	290.4	296.2	−2.01	2.01
7	76.23	74.05	2.86	2.86	260.6	254.5	2.34	2.34
8	74.03	74.40	−0.50	0.50	286.7	292.5	−2.03	2.03
9	75.32	74.40	1.22	1.22	292.4	290.4	0.67	0.67
10	78.13	77.23	1.15	1.15	289.7	308.5	−6.47	6.47
11	72.38	71.68	0.97	0.97	218.9	212.7	2.84	2.84
12	75.30	76.08	−1.03	1.03	280.1	271.7	2.98	2.98
13	65.23	68.40	−4.87	4.87	151.5	158.3	−4.48	4.48
14	76.40	76.01	0.52	0.52	278.7	300.8	−7.94	7.94

Appendix 3: Summary Results of the Test Cases for the Responses—GE

Test no.	Exp. value	Model prediction	Deviation (%)	Absolute deviation (%)
1	8.40	8.52	−1.37	1.37
2	8.34	8.16	2.12	2.12
3	7.82	8.14	−4.05	4.05
4	7.73	7.70	0.41	0.41
5	8.02	8.13	−1.34	1.34
6	8.72	8.38	3.88	3.88
7	8.21	8.33	−1.43	1.43
8	9.45	9.11	3.60	3.60
9	9.20	8.97	2.55	2.55
10	8.63	8.43	2.35	2.35
11	8.04	8.15	−1.36	1.36
12	8.80	8.42	4.29	4.29
13	8.38	8.72	−4.04	4.04
14	8.08	8.18	−1.27	1.27

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