Teaching learning based optimization of squeeze casting process for quality castings

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Abstract: The hybrid squeeze casting method combines the immense features of forging and casting processes. Ultimate tensile strength (UTS), surface roughness (SR), and yield strength (YS) are the important casting quality characteristics influenced mainly by input variables. Determining the set of optimal input variables (pressurized duration, squeeze pressure, pouring and die temperature) for conflicting requirement in casting quality (maximize: YS and UTS and minimize: SR) is considered to behave complex and non-linear. Multiple objective functions with conflicting requirements are modified suitably to single fitness function with different set of weight fractions for maximization to solve the optimization problem. Four scenarios are selected with different sets of weight fractions by assigning equal weights for all outputs, followed by assigning maximum weight fraction for each individual output function, after keeping the rest at fixed low equal weights. Teaching learning based optimization (TLBO) is selected to optimize the squeeze casting input-output parameters. TLBO results are found to be comparable with evolutionary algorithms (i.e. GA, PSO and MOPSO-CD). TLBO has outperformed the evolutionary algorithms with regard to computation time.

1. Introduction

In 1878, D. K. Chernov introduced the concept of pressurized solidification popularly now referred as squeeze casting process. Pressurized solidification idea is the coined to integrate the immense features of strength and integrity by forging process and design flexibility and economy of gravity and pressure die casting processes [1]. The possible likely squeeze casting defects are extrusion, underfilling/overfilling, segregations, cold laps, oxide inclusion, poor surface finish, die sticking, hot tear, debonding etc. [1-3]. The appropriate choice of control variables (namely, squeeze pressure, die temperature, time delay, compression holding time and pouring temperature, and so on) might eliminate most of the squeeze casting defects [1].

Many research efforts are made to enhance properties (i.e. reducing defects) throughout the globe utilizing numerical, analytical and trial-and-error experimentation methods during the 1990s to 2000s. Analytical and numerical studies are conducted to study the casting parameters (namely, pouring temperature and applied pressure) that enhance the casting density and some mechanical properties [4].
and solidification time [5] of different casting alloys. Increased squeeze pressure resulted in reduced solidification time by seven times to that of gravity castings [6]. Numerical simulation based on MAGMASOFT software is used to optimize the parameters that could reduce the shrinkage porosity in automobile control arm squeeze cast part [7]. It is important to note that, the analytical and numerical methods use some assumptions and those assumptions limit the practical utility in foundry experiments. The popular trial-and-error foundry experiment method has been employed to enhance both mechanical and microstructure properties. The influence of pouring temperature and applied squeeze pressure was studied by conducting trial-and-error experimental method to know the impact on hardness, dendrite arm spacing and yield strength [8]. The segregation behaviour at different positions from the wall towards the centre of squeeze cast parts are investigated [9]. It was observed that the centre region in casting part accommodate maximum segregations compared to the other sectional casting part. Increase in cooling rate across the centre region might results in disappear the formation of segregation in casting. The trial-error-practical experimental methods might not yield complete insight of process and further the global solutions might be lost. Further, conducting experiments by varying one factor at a time approach is considered as a tedious task, expensive and time consuming. In squeeze casting many casting variables (squeeze pressure, die and pouring temperature, waiting time, and compression holding time) influence both the mechanical and microstructure properties. Estimating interaction factor effects are not done using the above methods. Thereby, shortcomings of analytical, numerical and trial-and-error experimental methods are addressed by utilizing statistical modelling and optimization tools.

Modelling help to identify, statistically analyze and optimize the inputs and outputs of any physical system. The Statistical Taguchi method is applied to model and optimize the squeeze casting parameters (that is, applied pressure, die and pouring temperature) for higher hardness, and UTS [10], and density, and SR [11] and ductility [12]. Taguchi method applied to optimize the parameters (die material - stainless steel, brass, SG iron, and copper, die temperature, pouring temperature, squeeze pressure) for enhanced wear resistance of AC2A alloy [13]. The Taguchi based optimization determined the optimum levels of parameters for individual response. Further, the obtained results might not be considered optimal always, as they neglected completely the important interaction among the many factor effects. Design of Experiments (DOE) and Response Surface Methodology (RSM) is employed for modelling the squeeze casting process that provide complete insight of full quadratic factor effects (i.e. linear, quadratic and interaction terms) on hardness, density, and dendrite arm spacing [14], YS, UTS and SR [15]. Note that, statistical models might fail to capture the dynamics of a process completely due to development of model and analysis is done for response-wise. Soft computing tools are developed to capture the complete dynamics of whole process fully for the squeeze casting process [16-17]. Soft computing tools could predict multiple outputs simultaneously in an optimal manner. However, it might not help to gain the best set of input variables that optimize different outputs. Important to note that, the squeeze casting process contain multiple outputs to be optimized.

Traditional and non-traditional optimization tools can be applied to determine optimal input-output set that enable to solve many optimization problems. Traditional optimization tools (programming methods such as nonlinear, dynamic, geometric and quadratic, steepest descent method etc.) employ deterministic search method with particular transition rules might yield many local solutions. Thereby, non-traditional optimization tools (namely, teaching learning based optimization (TLBO), particle swarm optimization (PSO), differential evolution (DE), and genetic algorithm (GA)) which behave stochastically with the probabilistic transition rules employed to locate the global solutions with less computation effort and time. Evolutionary algorithms (GA, and PSO) were used to optimize the squeeze casting parameters for the conflicting requirements in density, hardness, and secondary dendrite arm spacing [18], and SR, YS and UTS [19] of casting parts. GA, PSO and DE require tuning of common algorithm parameters namely, population size and generation number that could decide the global optimum solutions [20]. In addition, mutation and crossover operator of GA and inertia weight, social and cognitive leader of PSO is the specific tuning algorithm parameters influence on the performance of locating global solution and computation time [20 and21]. To limit the computation burden and its
probable local solutions, the TLBO algorithm is introduced to quickly locate the optimal solutions for continuous non-linear functions [22]. TLBO do not require tuning of specific algorithm parameters compared to GA, resulted in less computation time to locate the optimal parameters of selected casting processes [23]. Therefore, TLBO is an efficient tool to optimize the squeeze casting parameters for the enhanced properties required for industrial applications. Not much research attempts made yet on surface to internal strength (SR, YS and UTS) optimization of parameters of squeeze casting process utilizing TLBO. Further, the effectiveness of teaching learning based optimization algorithm is compared with other evolutionary algorithms (that, GA and PSO). This research work attempted to use the advanced optimization techniques (i.e. TLBO) for parameter optimization of squeeze casting process that enable the designers and foundry personnel to obtain the desired objectives.

2. Mathematical formulation of the problem
The surface to internal strength properties (SR, YS, and UTS) depends primarily on the impact of squeeze casting variables. The input variables and associated operating levels of squeeze casting process are set after consulting detailed literature review, experts advice and pilot experiments (refer Table 1).

Table 1. Input variables and operating levels of squeeze casting process

| Source                        | Notation | Units | Low   | Middle | High  |
|-------------------------------|----------|-------|-------|--------|-------|
| Duration of pressurization    | A        | s     | 20    | 35     | 50    |
| Applied squeeze pressure      | B        | MPa   | 40    | 80     | 120   |
| Pouring temperature           | C        | °C    | 630   | 675    | 720   |
| Die temperature               | D        | °C    | 150   | 225    | 300   |

Patel et al. [15] conducted experiments according to the standard Box-Behnken and central composite designs matrices. Further, both models developed the non-linear response equations (SR, YS, and UTS) and tested for prediction accuracy with random experimental cases. The best predicted non-linear response equation [15] is chosen as an objective function for optimization task in the present work as follows,

\[
\text{Box-Behnken Design}_{\text{UTS}} = -1176.2 - 4.71685A - 1.29458B + 3.97148C + 0.932667D - 0.00137037A^2 - 0.00234635B^2 - 0.0029304C^2 - 8.21481 \times 10^{-04}D^2 + 0.00354167AB + 0.00651852AC + 4.44444 \times 10^{-10}AD + 0.00155556BC - 0.00293004CD - 8.21481 \times 10^{-04}AB + 0.00234635BC + 0.001025BD - 0.00102693CD \]

\[
\text{Central Composite Design}_{\text{SR}} = 15.2320 - 0.0215093A - 0.0249583B - 0.0376636C + 0.00577407D + 2.22222 \times 10^{-05}A^2 + 6.785 \times 10^{-05}B^2 + 2.71605 \times 10^{-05}C^2 - 8.88889 \times 10^{-06}D^2 + 2.70833 \times 10^{-05}AB + 2.40741 \times 10^{-05}AC - 2.22222 \times 10^{-06}AD + 2.08333 \times 10^{-06}BC + 1.08333 \times 10^{-05}BD - 5.92593 \times 10^{-06}CD \]

\[
\text{Central Composite Design}_{\text{YS}} = -1071.38 - 1.26601A - 0.797501B + 3.36494C + 0.902819D + 0.0123095A^2 + 0.00276227B^2 - 0.00238537C^2 - 8.58733 \times 10^{-04}D^2 + 0.00253125AB + 0.000101852AC + 0.000627778AD + 0.000746528BC + 0.00034375BD - 8.87037 \times 10^{-04}CD \]

The casting surface finish is dependent primarily on the die surface walls, and the thin solid layer formation on casting surface. The solid thin layer formed on the casting surface might include the defects, which are found to be larger than the microstructure features. This observation proved that the surface finish not only of aesthetic importance, but also of proper function during their service life. Furthermore, the squeeze cast components must provide uniform smooth surface finish and strength.
that could not demand additional secondary expensive manufacturing processes namely, heat treatment, machining, plating, polishing, and shot blasting. Therefore, present work focussed on optimizing the squeeze casting variables that enable the industry personnel to gain conflicting requirements in low surface roughness, and high strength in the casting parts.

Suitable mathematical formulation is done to convert the conflicting multiple objective functions to single objective function with different weight fractions for maximization. The surface plots and statistical analysis showed that the YS and UTS with SR tend to be converse in nature [15]. Surface roughness response function is modified for maximization shown in Eq. 5. For mathematical formulation the weight method is employed to gain a single composite objective function (refer Eq. 7). The equation representing the formulated weighted single objective function employed for the present work is shown in Eq. 7.

\[
\text{Response function} = \frac{1}{SR} \quad (5)
\]

\[
\text{Maximize } Z = (W_1 * \text{YS} + W_2 * \frac{1}{SR} + W_3 * \text{UTS}) \quad (7)
\]

Subject to input variable constraints

\[
20 \leq \text{Pressure duration} \leq 50; \quad 40 \leq \text{Squeeze pressure} \leq 120
\]

\[
630 \leq \text{Pouring temperature} \leq 720; \quad 150 \leq \text{Die temperature} \leq 300
\]

Terms \(W_1, W_2\) and \(W_3\) represents the fractional weights of YS, SR and UTS. Multiple objective optimization includes many solutions corresponding to importance (weight fraction) assigned to each response function. Note that, the composite value of all set of weight factors assigned to individual objective function is set equal to one. Four scenarios are selected for the three objective functions such that, Scenario 1 deal with assigning equal contribution for each objective function (that is, Scenario 1: \(W_1 = 0.3333, W_2 = 0.3333\) and \(W_3 = 0.3333\)) followed by highest importance for the response namely YS, SR and UTS (that is, Scenario 2: \(W_1 = 0.8, W_2 = 0.1, W_3 = 0.1\), Scenario 3: \(W_1 = 0.1, W_2 = 0.8, W_3 = 0.1\), and Scenario 4: \(W_1 = 0.1, W_2 = 0.1, W_3 = 0.8\)).

3. Teaching Learning Based Optimization

TLBO is recently developed specific parameter less algorithm inspired based on concept of class room-based teaching and learning process proposed by Rao [20]. In TLBO, the impact of teacher influence on different learners in a class room is studied. Teacher phase and learner phase are the two paramount stages used in TLBO. In general, during teaching phase, the teacher is always treated as highly learnt professional, who share their knowledge, skill or values with the learners. In learner phase, the learners interact among themselves and the outcome of learners is appraised in terms of results or grades and is influenced by the teaching quality. Good teacher encourages or motivate learners through quality training to obtain better marks or grades. Moreover, the interaction among the learners might produce better results. The generated best solutions from the entire population are always treated as the result of a teacher. In TLBO, population is represented by set of learners and design or process parameters are treated as the different subjects offered to learners. Important to note that, the results of learners correspond to fitness function value of the optimization problem.

4. Results and Discussion
This section discusses the obtained results of optimized parameters for better surface finish and casting strength determined using TLBO. The different levels of number of population (i.e. students) and generations are studied individually. In TLBO, the maximum fitness function values correspond to size of population and number of iterations (i.e. generations) was found equal to 40 and 40, respectively. Table 2 show the determined summary results of input-output variables obtained for four different scenarios based on weight average method utilizing TLBO is presented in Table 2.

The highest fitness function value corresponds to scenario 1-4 is found to be 123.1, 138.4, 38.17 and 194.1. Scenario 4 is recommended as the optimal setting input-output conditions for squeeze casting process, as it produce the maximum fitness function value.

**Table 2.** Squeeze casting process optimal input-output parameters determined via evolutionary algorithms [18] and TLBO tools

| Scenario | Models      | Input variables                      | Responses          |
|----------|-------------|--------------------------------------|--------------------|
| 1: \(= 0.3333, W_2 = 0.3333 \& W_3 = 0.3333\) | GA [18] | Pressure duration, s  | 49.87 | 119.51 | 691.35 | 210.27 | 144.9 | 0.53 | 220.3 |
|          | MOPSO-CD [18] | Squeeze pressure, MPa               | 49.99 | 119.99 | 709.84 | 201.17 | 143.7 | 0.55 | 223.2 |
|          | PSO [18] | Pouring temperature, °C             | 49.32 | 119.78 | 710.23 | 210.29 | 143.5 | 0.54 | 223.4 |
|          | TLBO      | Die temperature, °C                 | 50.00 | 120.00 | 710.00 | 198.81 | 143.8 | 0.54 | 223.6 |
| 2: \(= 0.8, W_2 = 0.1 \& W_3 = 0.1\) | GA [18] | Pressure duration, s  | 49.94 | 119.51 | 691.35 | 210.27 | 144.9 | 0.53 | 220.9 |
|          | MOPSO-CD [18] | Squeeze pressure, MPa               | 49.95 | 119.96 | 692.87 | 208.26 | 145.1 | 0.53 | 223.6 |
|          | PSO [18] | Pouring temperature, °C             | 49.84 | 119.99 | 704.95 | 212.86 | 143.8 | 0.54 | 223.2 |
|          | TLBO      | Die temperature, °C                 | 49.99 | 119.58 | 709.99 | 201.41 | 144.8 | 0.55 | 223.1 |
| 3: \(= 0.1, W_2 = 0.8 \& W_1 = 0.1\) | GA [18] | Pressure duration, s  | 49.95 | 119.98 | 694.85 | 211.06 | 144.3 | 0.53 | 221.5 |
|          | MOPSO-CD [18] | Squeeze pressure, MPa               | 49.94 | 119.98 | 694.85 | 211.06 | 145.1 | 0.53 | 221.5 |
|          | PSO [18] | Pouring temperature, °C             | 49.44 | 119.79 | 691.43 | 214.68 | 144.8 | 0.52 | 220.5 |
|          | TLBO      | Die temperature, °C                 | 49.94 | 120.00 | 705.21 | 213.10 | 142.8 | 0.53 | 223.7 |
| 4: \(= 0.1, W_2 = 0.1 \& W_3 = 0.8\) | GA [18] | Pressure duration, s  | 49.97 | 119.06 | 719.81 | 193.79 | 142.2 | 0.57 | 224 |
|          | MOPSO-CD [18] | Squeeze pressure, MPa               | 49.95 | 119.96 | 718.26 | 195.05 | 142.9 | 0.56 | 224.5 |
|          | PSO [18] | Pouring temperature, °C             | 49.48 | 119.49 | 716.99 | 198.44 | 142.6 | 0.56 | 223.2 |
|          | TLBO      | Die temperature, °C                 | 50.00 | 120.00 | 718.10 | 195.25 | 143.1 | 0.55 | 224.4 |

4.1 Summary of comparison results of evolutionary algorithms (GA, PSO, MOPSO-CD) and TLBO: TLBO results compared with evolutionary algorithms are presented in Table 2. Important to note that, TLBO, GA, PSO, and MOPSO-CD are considered as population based stochastic search optimization algorithms. Further, evolutionary algorithms require fine tuning of algorithm parameters to determine best optimal set. Parameter study has been conducted to tune the evolutionary algorithm parameters [18]. The parameter study was conducted for the GA operators namely cross over, mutation, number of population and generations and the corresponding optimized values yield highest fitness function value was found equal to 0.7, 0.15, 130, and 95, respectively [18]. MOPSO-CD gained highest fitness function value for the optimized set of mutation, inertia weight, swarm size, and generation number maintained at 0.21, 0.5, 80, and 65, respectively [18]. The highest fitness function value for the optimized PSO parameters namely inertia weight, swarm size, and generation number was found equal to 0.3, 50 and
70, respectively [18]. The TLBO optimized parameters namely number of population (i.e student) and generations were found equal to 40 and 40, respectively. Note that the convergence rate to arrive optimal solution is found better for TLBO compared to evolutionary algorithms (GA, PSO, and MOPSO-CD). The better convergence might be due to no specific algorithm tuning parameters and requires less population size and generation number. Further, the fitness function value obtained for different scenarios considered are found to be {122.8, 138.2, 38.25 and 193.6} for GA [18], {122.8, 138.1, 38.23 and 193.6} for PSO [18], {123.1, 138.4, 38.17 and 194.1} [18] for MOPSO-CD, and {123.1, 138.2, 38.25, and 194.1} for TLBO, respectively. It should be note that, the maximum fitness function value obtained for scenario 4 is found to be maximum compared to another scenario studied. MOPSO-CD and TLBO algorithms estimated approximately similar combination of optimal input-output condition. However, TLBO performance is found better compared to MOPSO-CD with regard to computation effort and time.

5. Conclusion
The squeeze casting process input-output parameters are optimized using popular teaching learning base optimization. The empirical input-output relationships derived according to the experimental (i.e. BBD and CCD) models are treated as response functions for conducting the optimization task. The conflicting requirements (that is, minimum SR, and maximum YS and UTS) of three individual response functions are converted to form single composite function with weight factor method. TLBO optimized parameters help the designers and a foundry personnel to obtain the desired objectives. Further, TLBO performance has been compared with other heuristic search methods namely evolutionary algorithms (i.e. GA, PSO and MOPSO-CD). TLBO performance to locate the optimal input-output conditions is comparable and outperformed with regard to speed of convergence and computation effort. More importantly, TLBO do not require specific algorithm tuning parameters, as they affect the global optimal solutions (i.e. in appropriate choice of algorithm parameters might results in local optimal solutions). TLBO algorithm is capable to effectively optimize the squeeze casting process by handling different mathematical models under certain constraints with less computational efforts. The present work might reduce the currently practiced popular trial-and-error experimental method, analytical, virtual simulations and experts recommendation. Further, the results might reduce computation burden and energy utilization to gain best casting quality.

6. References
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