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A systematic approach to model and optimize wear behaviour of castings produced by squeeze casting process

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ABSTRACT

The present work is an attempt to produce squeeze cast component with excellent wear resistance property. The material wear rate in squeeze casting depends on appropriate selection of pressure duration, squeeze pressure, die temperature and pouring temperature. Experiments are conducted and data is collected as per central composite and box-behnken design approaches. The input-output relationship developed by utilizing central composite design is found to be statistically adequate and yielded better prediction accuracy. Recurrent and back propagation neural networks are trained by using data generated from best response model. The huge training data in batch mode helps to capture fully the dynamics of squeeze casting process. The recurrent neural network outperformed both, the back propagation neural network and central composite design. Genetic algorithm, desirability function approach, and particle swarm optimization are used to determine best set of squeeze casting conditions that locate the extreme values and will result in minimum wear rate. Particle swarm optimization and genetic algorithm outperformed desirability function approach, as the former carried out search in many directions at multi dimensional space, simultaneously. The results of non-linear regression, neural network based models, the performance of different optimization techniques are compared and some concluding remarks are made.

1. Introduction

Casting is a complex manufacturing process with a large number of variables and techniques. Minimum porosity, heat-treatable, weldable, high productivity, superior mechanical properties, better surface finish, refined microstructure, and good castability of ferrous and non-ferrous special alloys are major advantages of squeeze casting over conventional casting processes [1]. Squeeze casting finds major applications in automobile industries due to the integral features of casting and forging process [1,2]. The major class of research work reported during past two decades is on improving mechanical and microstructure properties using one factor at-a-time [3–5] and analytical methods [6–8]. The critical observations revealed that, controlling the squeeze casting variables (like, applied pressure, dwell time, mould temperature, mould materials, pouring temperature and so on) are mandate for quality castings. However, the above methods were limited only to develop input-output relationships and estimate the individual and interaction factor effects. Taguchi method was implemented successfully to analyze the influence of squeeze casting variables on some properties (namely, density, surface roughness, hardness, yield strength, ultimate tensile strength and wear resistance) with a limited number of experiments [9–14]. Mould materials (that is, copper, stainless steel, brass, hot die steel, spheroid graphite iron and cast iron) on the above said properties were found insignificant [10,11]. However, their work was limited to derive response equation that could include all linear and interaction terms.

Design of experiments (DOE) with response surface methodology (RSM) is a powerful tool used to plan experiments collect input-output data, analyse collected data, and develop input-output relationships. Central composite design (CCD) and box-behnken design (BBD) were successfully applied to model the squeeze casting process [15]. The performances of central composite design was found better for the responses, namely, surface roughness, yield strength and Box-behnken design for ultimate tensile strength response [16,17].

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Nomenclature

A	Pressure duration (uncoded form)
ANN	Artificial neural network
B	Squeeze pressure (uncoded form)
BBD	Box-behnken design
BPNN	Back propagation neural network
C	Pouring temperature (uncoded form)
CCD	Central composite design
D	Die temperature (uncoded form)
DFA	Desirability function approach
GA	Genetic algorithm
PSO	Particle swarm optimization
RNN	Recurrent neural network
RSM	Response surface methodology
R_a	Average surface roughness
WR	Wear rate
WR_{CCD}	Model (central composite design) predicted wear rate
WR_{BBD}	Model (box-behnken design) predicted wear rate
X_1	Pressure duration (coded form)
X_2	Squeeze pressure (coded form)
X_3	Pouring temperature (coded form)
X_4	Die temperature (coded form)
Δw	Difference in weight of the sample before and after wear test
P	Density
T	Time
b_0, b_i, b_{ii} *and* b_{ij}	Coefficients of regression equation
E	Statistical error term

The mechanical parts/objects during services may contact with one another and continuously start losing the material surface due to relative motion as a result of friction. Thus, the mechanical parts (namely, shafts, gears, springs etc.) limit to use in service immediately after the castings being made due to poor wear resistance. The squeeze casting variables influence on Al-Si alloys wear behaviour was studied [18,19]. They had limited their work to develop mathematical input-output relationship that could predict the wear rate for the known set of squeeze casting variables. Attempt was made by authors [14] to establish wear rate prediction equation for the squeeze casting variables. However, the input-output relationships developed earlier had not considered few linear and interaction terms and model accuracy was not included. It is important to note that, the response equations, developed by utilizing experimental data will help foundry-men to predict the squeeze casting wear behaviour for the known set of process variables, without conducting the actual experiments.

Soft computing tools (that is, neural network, particle swarm optimization, genetic algorithm, fuzzy logic and their diverse combinations) capture non-linearity of manufacturing process accurately. Neural networks uses non-linear based activation function for network output computation. In recent past, neural network models were used to develop input-output relationships of squeeze casting process and successfully predicted the solidification time [20], temperature difference [21], density, secondary dendrite arm spacing [22], surface roughness, yield strength and ultimate tensile strength [23]. Neural networks were trained by using input-output training data generated by utilizing input-output relations. It is to be noted that, these input-output relations were developed with the help of experimental data and statistical tools such as DOE and RSM. The neural networks prediction performances are found to be comparable with those obtained from conventional regression analysis techniques [23–26]. Response equations with accurate predictions will reduce the cost of conducting trial experiments, material waste, and helps foundry personnel to take quick decisions. There exists a wide scope to develop neural network models for studying the behaviour of wear.

The production of good quality castings depends mainly by selection of appropriate combination of process variables. Trial and error methods need high computation time and results obtained may have many sub-optimal solutions. To combat this situation, optimization tools are used to determine the best combination of process variables responsible for optimum output values. The optimization task can be performed for both single and multiple outputs. DFA was applied successfully to determine the best process variable conditions for quality castings [27]. Desirability (d) is a quality indicator term whose value varies in the range between zero and one. The zero value corresponds to fully undesirable, whereas one signifies completely desirable or best output value. DFA is considered as a traditional optimization tool that follows deterministic search procedure. This search technique may result in many local (sub optimal) solutions. Conversely, non-traditional search tools (particle swarm optimization (PSO), genetic algorithm (GA), and so on) determine global solutions in many distinct directions and spatial locations simultaneously. GA was used to determine the best parameter set responsible for quality castings (hardness, ultimate tensile strength, surface roughness, yield strength and wear) of squeeze casting process [9,14]. Evolutionary (GA and PSO) algorithms were utilized to determine the optimal input variable combinations for green sand moulding [28], machining [29], welding [30], and tube spinning processes [31]. From the above literature, the input output relations in squeeze casting process are found to be highly non-linear and complex. Hence, a systematic study is needed to know the impact of input variables on output and establish good control over the process using, statistical modelling tools such as DOE and RSM. Further, the process mechanics and dynamics of manufactured parts along with accuracy in prediction can be effectively tackled with the help of artificial neural networks. Moreover, the efforts is also needed to determine the best set of squeeze casting variables that could results in a minimum wear rate of squeeze casting parts. Not much research efforts are made to model, simulate and optimize the squeeze casting process for wear rate. There is a significant scope to systematically study to model, simulate and optimize the squeeze casting process using statistical (DOE, RSM, and DFA) and soft computing tools (BPNN, RNN, GA, and PSO).

2. Experimental methodology, modelling and optimization

Five steps, followed to reach the defined objectives of the present work (that is, model, simulate and optimize the wear rate of cast parts in squeeze casting process) are discussed below.

Step 1: Selecting squeeze casting variables and their levels

Squeeze casting parts are usually affected by the defects such as, segregations (i.e. extrusion, and centreline), shrinkage, cold laps, oxide inclusion, hot tears, blistering, under-filling, and de-bonding (case and extrusion) [1,2,32,33]. The choice of input variables and decision on the operating levels are of paramount importance to establish control over the process and minimize the defects. Too wide operating range of variables may result in an infeasible solution on the response surface, conversely too narrow range will result in incomplete or poor information about the process [16,17]. Higher squeeze pressure will have demand on high-tonnage equipment facility and more capital investment. On the other-hand low squeeze pressure might not be sufficient to eliminate the accumulated gases between die-metal interfaces, resulting in poor interfacial heat transfer. Low duration of pressure application might not help the metal to attain the desired casting strength,