Advances in Automobile Engineering

Manjunath Patel et al., Adv Automob Eng 2015, 4:1
http://dx.doi.org/10.4172/2167-7670.1000111

Review Article Open Access

Modelling in Squeeze Casting Process-Present State and Future Perspectives

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Abstract

The growing demand in today's competitive manufacturing environment has encouraged the researchers to develop and apply modelling tools. The development and application of modelling tools help the casting industries to considerably increase productivity and casting quality. Till date there is no universal standard available to model and optimize any of the manufacturing processes. However the present work discusses the advantages and limitations of some conventional and non-conventional modelling tools applied for various casting processes. In addition the research effort made by various authors till date in modelling and optimization of the squeeze casting process has been reported. Furthermore the necessary steps for prediction and optimization are high lightened by identifying the trends in the literature. Ultimately this research paper explores the scope for future research in online control of the process by automatically adjusting the squeeze cast process parameters through reverse prediction by utilizing the soft computing tools namely, Neural Network, Genetic Algorithms, Fuzzy-logic Controllers and their different combinations. The present work also proposed a detailed methodology, starting from the selection of process variables till the best process variable combinations for extreme values of the outputs responsible for better product quality using experimental, prediction and optimization methodology.

Keywords: Forward and reverse modelling and optimization; Soft computing; Squeeze casting process; Statistical tools

Abbreviations: ABC: Ant Bee Colony; ANFIS: Adaptive Network Fuzzy Interface System; BHN: Brinell Hardness number; BBD: Box Behnken Design; BPNN: Back Propagation Neural Network; CCD: Central Composite Design; DM: Die Material; DOE: Design Of Experiments; DP: Pressure Duration; DT: Die Temperature; FDM: Finite Difference Method; FEM: Finite Element Method; FFD: Full Factorial Design; FL: Fuzzy Logic; FVM: Finite volume Method; FV: Filling Velocity; GA: Genetic Algorithm; GA-FL: Genetic Algorithm Fuzzy Logic; GA-NN: Genetic Algorithm Neural Network; HTC: Heat Transfer Coefficient; HV: Vickers Hardness; MM: Morphological Matrix; NN: Neural Network; PSO: Particle Swarm Optimization; PT: Pouring Temperature; SA: Simulated Algorithm; SP: Squeeze Pressure; SR: Surface Roughness; TD: Time Delay; TLBO: Teacher Learning Base Algorithm; UTS: Ultimate Tensile Strength; YS: Yield strength

Introduction

In today's competitive world industries are searching for light weight materials possess high strength to weight ratio with less defective processing methods. This drawn much attention towards the research to search for alternative processing method to limit the weakness of one technology with the strength of the other. Casting process considered being one among the most economical route to manufacture the automobile and aerospace components. The most common problem with the conventional casting method is the probable occurrence of defects like shrinkage and the porosity. To overcome these limitations, researchers tried to integrate the immense features of economy and design flexibility of conventional casting process (pressure die casting and gravity) and strength and integrity of forging process. This integrated casting method is termed as squeeze casting which works based on the concept of pressurized solidification. The investigations were carried out in castings with simple geometries by using either gap measurement method or heat conduction methods on heat transfer coefficients (HTC). However, it was observed that interfacial [1-15], processing methods [16-19], casting geometry and size [20,21], physical and chemical conditions [22], mold and casting material properties [23], process variables [24-28] and so on directly affect the HTC. The combined effect of these factors influences the HTC, thereby making it difficult to separate and study the main effects of the factors. It is to be noted that the HTC greatly influences the mechanical and micro-structure properties. Although past few decades researchers\investigators tried to improve the mechanical and micro-structure properties, but it is under intensive study since the existence of the probable squeeze casting defects such as oxide inclusion, porosity, extrusion segregations, centre line segregations, sticking, cold laps, extrusion debonding, blistering, under fill, shrinkages, hot tearing and case deboning [29,30]. The major parameters that affect the quality of the squeeze cast components such as squeeze pressure, pressure duration, time delay in pressurizing the metal, pouring temperature, die temperature, inoculants, filling velocity, lubrication type, film thickness and its adherence, melt quality and quantity etc. It is understood that proper control of these parameters may eliminate the possible squeeze casting defects. There is no universal standards available to control the above said process variables to achieve the desired squeeze cast components. Hence in the present work discusses the steps followed by various researchers till date to optimize the squeeze casting process are discussed, the scope for future directions in squeeze casting process for achieving the desired results are to identified through the trends in available literature and their main differences with squeeze casting process.

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Received December 11, 2014; **Accepted** January 07, 2015; **Published** January 16, 2015

Citation: Manjunath Patel GC, Krishna P, Parappagoudar MB (2015) Modelling in Squeeze Casting Process-Present State and Future Perspectives. Adv Automob Eng 4: 111. doi:10.4172/2167-7670.1000111

Modelling Approaches

Modelling refers to the method of identifying, establishing and analyzing the input-output relationships of the physical system. Generally the modelling tools are classified into two types namely

1. Conventional modelling tools (Finite element method, Response surface methodology, Design of experiments etc.,)

2. Unconventional modelling tools (Soft computing tools like particle swarm optimization, genetic algorithm, neural networks, fuzzy logic and their different combinations)

In recent years the modelling tools are used in various manufacturing systems to statistically analyze the inputs and outputs and establish the input-output relationships. Further to meet the stringent requirements of the industries modelling tools are used in two ways.

Forward modeling

Forward modelling aims to predict the response for the known set of input parameters.

Reverse modelling: Reverse modelling aims at determining the appropriate set of the inputs for the desired output. Furthermore reverse modelling helps in online control of the process by adjusting the input parameters responsible for the desired output.

In recent years, lot of research work carried out to improve the mechanical and micro-structure properties. However most of the research happened during those periods aimed for enhancing the properties though mathematical modelling approach, classical engineering experimental approach, numerical and analytical studies, statistical experimental approaches, soft and hybrid computing approaches.

Mathematical modelling approach

Finite elemental analysis method (FEM) [31-35], finite volume method (FVM) [36], finite difference methods (FDM) [37], and enthalpy method are the mathematical tools which were employed to simulate squeeze casting processes. On observing from the literatures, all the models which are capable of making effective simulations were noted. However, in terms of computational complexity and programming use of finite based on element and difference methods for complex geometries gave better results in compensation with time consumption. Using continuity and momentum equations [38], the major shrinkage problem in castings and the pressure drops in the mushy zone were calculated. The physics involved in the processes namely, radiation, conduction, convection, pressure transfer, feeding flow, phase and mass transfers, solidification and successive stages and stress/strain behaviour were considered by these models. It is quite difficult to implement mathematical formulation in numerical simulations [39], assumptions made during solidification stage, computational complexity, time consuming. Furthermore, simulation results are highly reliant on how best the software code could capture the information of physics of the process, material characteristics and boundary conditions namely heat transfer coefficients between metal-mould interfaces [40]. For numerical simulations, design of experiments (DOE) was recently used by some authors, because the replication of experiments was not required, there were no uncontrollable parameters affecting the responses, and the significant factors influencing responses and optimization were quickly identified.

Casting simulation software approach

Simulation software often used in most of the foundries applications for decision making, where human process knowledge is not sufficient or the process calibration takes higher time than the manufacturing process can afford [41], to find the solution to bring the process to an optimal condition with less possible defects. To address the problems related to mold filling, solidification stages, filling velocity and temperature profile estimations, any casting, Procast and magma soft were utilized by the authors [42-44] to simulate the squeeze casting process. The initialization of accurate boundary conditions was the most difficult part in casting simulation software packages. Assumptions were made in boundary conditions that temperature of air around the mould was ambient and also suitable for the heat transfer coefficients [45]. Simulation software's often used for new products, where large number of products needs to be manufactured under repetitive order. However, simulation software often considered to be inefficient due to high capital initial investment, lots of assumptions to be made in regards with material transport phenomenon and boundary conditions and practical castings are difficult to achieve the desired results in actual shop floor, not suitable for continuous simulation for cyclic analysis while searching for optimal process conditions, high computational costs and need for experts advice to interpret the obtained results. These reasons made lots of researchers to search for alternate method to optimize the process. In recent years, some authors [46,47] used procast simulation software to predict temperature difference and the solidification time of the squeeze cast components. Since optimizing the process requires huge number of input-output data and is considered to be impractical either through experimental or simulation software alone. So authors adopted statistical design of experiment (DOE) to limit the simulation trial runs and to find the optimal squeeze casting condition.

Classical engineering experimental approach

The classical engineering experimental studies deals with varying one parameter at once and maintaining the rest of the mid-values within their corresponding levels. The experiments performed by various researchers using classical engineering approach to study the effects of squeeze pressure, casting temperature, die temperatures, time delay, inoculants and pressure duration on solidification time, density, secondary dendrite arm spacing, grain size, hardness, tensile and impact strengths of different aluminium based alloys [48-60]. The following advantages and limitations have been identified from the above discussed literatures,

Advantages:

1) Classical engineering approach helps in knowing the behaviour of the process parameters from one level to the other for the response measured

2) It helps in identifying the range of the process parameters showing significant contribution, thus helps in determining the optimal process parameter range to fulfill the preliminary requirements for studying the complete insight information of the process through statistical design of experiments.

Limitations:

1) In most literatures the authors attempted the conventional engineering approach to perform the experiments and analysis wherein, increase in process variable number and levels, increases the need of real experiments to be conducted.

2) In squeeze casting process there is large number of interconnected process variables and the results obtained from the said approach may

not reveal the combined influence of the input parameters on the measured outputs.

3) It is to be noted that the classical engineering experimental approach can only suggest the optimal process parameter levels and are completely different from those of global optimal process parameter setting.

4) The practical guidelines suggested by the authors to optimize the process may not help the foundry men unless the input-output relationships are expressed in mathematical form.

5) The use of conventional engineering approach uses varying one parameter at once after keeping the rest parameters at its mid-values. However it is important to mention that several process variables need to be simultaneously varied to know the complete insight information of individual and the combined (interaction) effect of the factors on the response of interest under investigation.

Statistical Design of Experiments (DOE)

Statistical DOE, proved to be the cost effective modelling tool compared to the conventional engineering approach from the past few decades. The major advantages of statistical design of experiments are reduces number of experiments, several process variables can be simultaneously studied, estimate the percent contribution of each individual and the combined (interaction) effect parameters on the response (output) under investigation, graphically represents the behaviour of the process parameter on the response when the variable shifts from one level to the other and establishes the input-output relationship allows the user to know the quantitative change in the output values corresponding to the input variables from one set of values to another sets, thus helps to provides complete insight information of the process. There has been lot of research work carried out by various researchers to tackle the problems related to squeeze casting using statistical taguchi method. It is to be note that the taguchi method employed to optimize the squeeze cast process variables to maximize or minimize the response for different materials under investigation (Table 1).

It is noted that the following key observations made from the above literatures of using statistical taguchi method to optimize the squeeze casting process are,

1) The taguchi method suggests the best process parameter levels (local optimum) and is completely different from those of optimum process parameter setting (Global minimum).

2) The use of taguchi method cannot reveal the information of behaviour of the response with respect to the input variables varied from one set of values to the other. This information is of paramount importance for a foundry-man to control the process accurately and this can be identified with the help of response surface plots obtained using response surface methodology of design of experiments.

3) The developed models to optimize the squeeze casting process are not used to check the prediction precision for a few experimental cases. It is of paramount importance for any foundry men in selection of the most influencing process parameter setting without performing the real experiments.

4) A separate model for each output expressed as a function of squeeze cast process parameters was observed.

5) The recommended design matrix of taguchi method limits to test all important factor combinations under experimental investigations.

Linear and non-linear regression models

The authors [61] used two level full-factorial design of experiment (FFD) to investigate the effects of applied pressure, percentage of modifier and die temperature on percent elongation and tensile strengths of the squeeze cast components. The use of two-level FFD, considered as linear regression model helps to reduce the number of experiments and provides complete insight information of main (linear) and interaction (combined) effects of process variables on outputs under investigation. Nevertheless, the major drawback of the two-level full factorial design is the non-linear effect (if any) in the output function cannot be recognized. To identify the curvature effect the independent variables should have at least three levels. It is important to note that the numbers of experiment need to be conducted through full factorial design increases with number of levels (ref Eq. [1]).

$$\text{Number of experiments}=(\text{Levels})^{\text{Factors}} \quad (1)$$

It is to be note that the curvature effect can be obtained through the use of non-linear regression models namely box-behnken design

Ref.	Material	Process variables	Response	Remarks
[61]	LM24	S_P, D_T and D_P	BHN and UTS	Optimizing P_T and die lubricant can significantly improve the casting quality
[62]	LM24	S_P, D_T and D_P	BHN and UTS	GA successfully searched the process parameters that can yield maximum possible UTS and BHN of cast components
[63]	AC2A	S_P, D_T, P_T, D_P and D_M	BHN and UTS	S_P, D_T and D_P are observed as the most significant parameters contributing towards the responses
[64]	AZ80	S_P, D_T and D_P	HV, % elongation and UTS	The heuristic MM approach has been utilized to find the optimized process parameters for highest possible properties.
[65]	2017A	S_P, D_T and P_T,	HV and UTS	S_P and P_T showed significant contribution towards HV and UTS of cast components
[66]	AC2A	S_P, D_T, P_T, D_P and D_M	YS	GA finds the best optimum process parameter setting using the response equation derived through taguchi method
[67]	LM6	S_P, D_T and D_M	SR	Higher surface finish can be achieved with varying P_T, D_T and S_P
[68]	LM6	S_P, D_T and D_M	SR	S_P and D_T are the critically parameters responsible for enhanced squeeze casting surface finish
[69]	AlSi9Cu3	P_T, S_P, F_V and D_T	% elongation, HBS and UTS	S_P, F_V, D_T and P_T are listed in ascending order based on significant importance towards the responses
[70]	AC2A	S_P, D_T, P_T, D_P and D_M	Wear resistance	GA shown slight improvement in the wear resistance property as compared to taguchi and XL solver methods
[71]	LM20	S_P, D_T and P_T	Density and SR	The application of grey relational analysis finds the single optimal casting condition for both the responses.

Table 1: Statistical taguchi method applications in squeeze casting process.

(BBD) and central composite design (CCD) of experiments. Not much work has been reported yet with the use of non linear regression models for the applications in squeeze casting process. However linear and non-linear regression models are successfully implemented to develop the input-output relationship of various casting processes namely cement bonded moulding [62,63], green sand moulding [64,65], resin bonded sand mould system [66], sodium silicate-bonded moulding system [67], die casting [68-70] and evaporative casting process [71]. The following key observations drawn from the linear and non-linear regression models such as,

1) Majority of the authors studied the input-output relationships of the process using main effect and the surface plots. This study helps for a foundry man to accurately control the process.

2) The authors tested for the prediction accuracy of the developed linear and non-linear regression models for few random test cases. Comparison of the developed model performance can help the foundry men for selection of the optimum process parameter setting without conduction of experiments.

3) In statistical design of experiments, only one response can be determined at a time as a function of input parameters. It is to be note that generally in any casting process different outputs are measured for the same input casting (parameter) conditions. Hence an integrated system development is mandatory to estimate all the outputs simultaneously because the probabilities of inter-dependency among the outputs were more.

4) Reverse modelling through response equation derived through statistical tools might be difficult to perform because the models are developed independently, interdependency among the output responses might be lost and the transformation matrix might not be invertible always [72].

Modelling using soft computing approach

The limitations of conventional modelling tools such as only one response can be determined at a time and the practical requirement is to obtain the input variable combinations that will produce the desired output through reverse prediction might be difficult using statistical tools. These problems can be effectively tackled through soft computing tools like GA, NN, FL, PSO and their different combinations. NN considered being excellent modelling tool to map the complex non-linear relationships among the input and output. It is to be note that neural networks learns with learning examples and need to be trained with huge input-output data base [73]. In recent years neural networks has been applied for the squeeze casting process to forecast the solidification time, temperature difference and secondary dendrite arm spacing [74] of the squeeze cast components. To avoid the rule of thumb, expert advice, try-error method used in shop floor practice, neural networks has been successfully implemented to predict filling time, solidification time and casting defects ,surface defects [75,76], solidification time [77,78], filling time and porosity , injection time [79,80], of pressure die casting process. To predict interfacial heat transfer coefficients at metal-mould interface [81], compressive strength, secondary dendrite arm spacing [82], mechanical properties [83], permeability [84] of different casting processes the soft computing based neural networks were used. To accurately control the quality of the moulding sands [85] and to predict the presence/absence of the casting defects [86] such as hot crack, misrun, scab blow hole and air lock in the sand mould system, NN is used. It is to be note from the above literatures authors successfully implemented to predict the outputs (responses) from the known set of inputs (process parameters) via forward modelling.

Although neural networks are capable of making effective predictions but it have some limitations such as probability of getting trap with local optimum solution is high and requires huge input-output data base for training. However prediction accuracy of the neural network majorly relies on quality and the quantity of the training data. Collection of huge data base through real experiments is impractical for the researchers\investigators. It is to be note that some authors used linear (FFD) and non-linear regression (CCD and BBD) models to perform the experiments and establish the process input-output relationship. The statistical adequacy of the developed models is tested using co-efficient of co-relation (R^2) and with few practical castings of few randomly generated test cases. The input-output data has been artificially generated using regression equation derived through real experiments, by selecting the process variables within their corresponding parameter range corresponding to the model which gives higher R^2 value.

Modelling using neural-network based approaches

The most practical requirement in industry is to predict the combination of process variables capable to produce the desired output through reverse prediction [83]. Till date, No much work reported yet to carry out the reverse mapping for the squeeze casting process. However some authors utilized successfully the better learning capabilities of neural networks and population based search method of genetic algorithms to tackle the problems related to green sand moulding system, cement bonded moulding system [87], sodium silicate-bonded, carbon dioxide gas hardened moulding sand system [88] and pressure die casting [89]. It is important to note that in their work the thousand sets of input-output data have been generated artificially though the response equation obtained via statistical models. Batch learning mode adopted for both neural network trained with error back propagation (BPNN) and genetic algorithms (GA-NN). In a typical neural network system the synaptic weights are generated initially at random, performs forward computation through the use of transfer functions (linear, sigmoid), predicts the network outputs, compares the network output with the target values to determine the error and those are updated to minimize the error in prediction. BPNN uses steepest descent approach (problem with getting trap at local minima region is more) and in GA-NN, GA (GA search the optimal solution in wide space and the probability of getting trapped with local solution is less) performs the task to minimize the error. However it is also important to mention that both models are capable of making effective prediction for forward and reverse prediction of the randomly generated test cases.

Modelling using fuzzy logic based approaches

In recent years the application of fuzzy logic models has been increasing rapidly due to the following reasons like easy to understand, implement, ability to handle uncertainty and imprecise data and exact mathematical formulation is not required [90]. The fuzzy logic model works based on the concepts of thinking and reasoning capabilities of our human brain and this concept has been successfully implemented to develop the input-output relationship of a system to solve complex real world problems [91]. It is to be note that there are generally two types of fuzzy modelling system namely linguistic type (Mamdani approach) and precise type (Takagi-Sugeno) fuzzy modelling system. The manually constructed mamdani based fuzzy logic approach and adaptive network based Takagi and Sugeno approach has been successfully implemented to predict the secondary dendrite arm spacing and density of the squeeze casting components [92,93]. The authors successfully established the input-output relationship using Mamdani based fuzzy system for various casting applications namely cement-bonded sand mould, resin-bonded sand mould [94] and green sand mould [95,96] system. However it is noteworthy that in approach 1, the manually constructed fuzzy system was used by the authors, wherein the knowledge of human expertise decides the rule and data base of the fuzzy logic controller. Furthermore, since the developed, manually-constructed rule-base relies majorly on the knowledge of human expertise about the process, it is not considered to be optimal always. Therefore, the rule and data base were optimized in the second approach. Additionally, by using the evolutional genetic algorithm in the approach 3, the authors also tried to automatically evolve the rule and the data base. Nevertheless, the procedure adopted to get the training data is the same as that adopted for the genetic neural system. For a few test cases, the performance of all the fuzzy logic based approaches has been compared midst themselves and with that of the neural network based approaches. The results shown both neural network approaches and the fuzzy logic approaches are capable of making forward and reverse predictions effectively.

Optimization

FFD, CCD, BBD and taguchi method are the traditional optimization methods and the solutions obtained from these methods are not the global solutions. The global optimization method is the one deal with identifying the best combination of the process variables for extreme values of the response. Genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), teaching-learning based (TLBO) algorithm and so on are considered to be the unconventional optimization tools used to determine the best parameter setting for the desired performance in any manufacturing processes. Generally these algorithms can be effectively used to find the best process parameter setting for the single and the multi-response depending on interest of the researcher/investigator. Noteworthy that, traditional methods are essential which provides the response equations derived through well planned statistical experiments. The response equations can be used as an objective functions to find the best process parameter setting, which are usually the global highest/lowest depending on the optimization problem. Noted that few limited work reported to optimize the squeeze casting process via GA. It is important to note that they used response equation derived through taguchi method for optimization and authors neglected some of the important main and interactions effects in the derived response equation. It is to be note that the response equation must have the main, square and interaction parameter effects to gain the complete insight of the process. More recently evolutionary algorithms (GA and PSO) are used for multi-response optimization of the green sand mould system. The optimized parameter setting suggested by the PSO and GA are compared with the experimental cases and the results shown PSO outperforms GA in terms of for extreme values prediction of all the responses and computational efficiency [97].

Proposed Methodology

Till date the authors followed to model the squeeze casting process using classical engineering experimental approach, analytical, theoretical approaches, and taguchi method. Each method has some advantages and limitations. To address the major limitations identified in the above methods (Figure 1), the detailed experimental, prediction and optimization methodologies are proposed. In manufacturing processes, two or more process variables critically influences the outputs. Identifying the process variables and their corresponding range can be effectively determined using the classical engineering experimental approach. However, classical engineering experiments estimate only the main effects of the process variables. Estimation of interaction effects via classical engineering experiments require more experiments to be conducted compared to statistical design of experiments. Therefore, the influencing process variables and corresponding levels via classical experimental approach are used to model the process using statistical design of experiments and response surface methodology. Modelling the process help the investigator to study the influence of independent variables, establish input-output relationship, identify the significant and insignificant process variables and further for prediction of the outputs for the known combination of inputs. This helps the foundry personnel to select the most influential input variables, without the requirement of prior background knowledge about the process mechanics and materials. Furthermore, these models help the manufacturing industries to predict the outputs without conduction of experiments, thus avoids material waste, energy consumption, existing expert reliant try-error-method, high cost involved in virtual casting simulation runs and need of expertise to interpret the obtained simulated results. However, statistical design of experiments fail to capture the interdependency among the outputs, thus restricts the model to use for online control of the process in the manufacturing industry. Online process control requires the models to predict multiple outputs and inputs simultaneously, thus helps to adjust automatically the process variables for the desired output. Statistical design of experiments might fail to estimate simultaneously more than one output simultaneously, because experimental data is collected and analysis are carried out based on response wise. Furthermore, the stringent requirement for the manufacturing industry is to predict the input parameters for the desired output (reverse prediction). Reverse prediction using statistical models requires the transformation matrix must be invertible always and are difficult with the interaction parameters in the regression equations. Further, statistical modelling tools fail to capture the interdependency among the outputs present, in any. Therefore, for online process control and capture output interdependencies an alternative tool need to be developed, that could estimates both inputs and outputs simultaneously. Soft computation tools namely GA, PSO, ABC, NN, FL, TLBO and corresponding diverse combinations proved as excellent tools to conduct forward and reverse predictions, particularly in manufacturing applications. The soft computing tools require huge (say 1000) input-output data for training and conducting actual experiments are infeasible for a foundry man to fulfill the requirements. Thus, the response equations derived through statistical models were used to generate artificially by selecting process variables between their corresponding ranges. The soft computing models are adaptively trained to update weights for the minimum error. The trained models are used to predict the random test cases to confirm the prediction precision of the models developed. The best model can be used for online monitoring, to automatically adjust the process variables for the desired outputs. It is noteworthy that, prediction helps the investigator to determine the outputs as well as inputs, but fail to estimate the global extreme values of the output, responsible for the best product quality (minimum defects). To determine the extreme values for the conflicting outputs (minimum is better for one response and maximum is better for other and vice versa) pose difficulties. For single output there is only one set of input variable combinations, whereas there are many combinations of optimum conditions for multiple outputs. Thus the multi-objective problems can be addressed effectively using evolutionary algorithms.

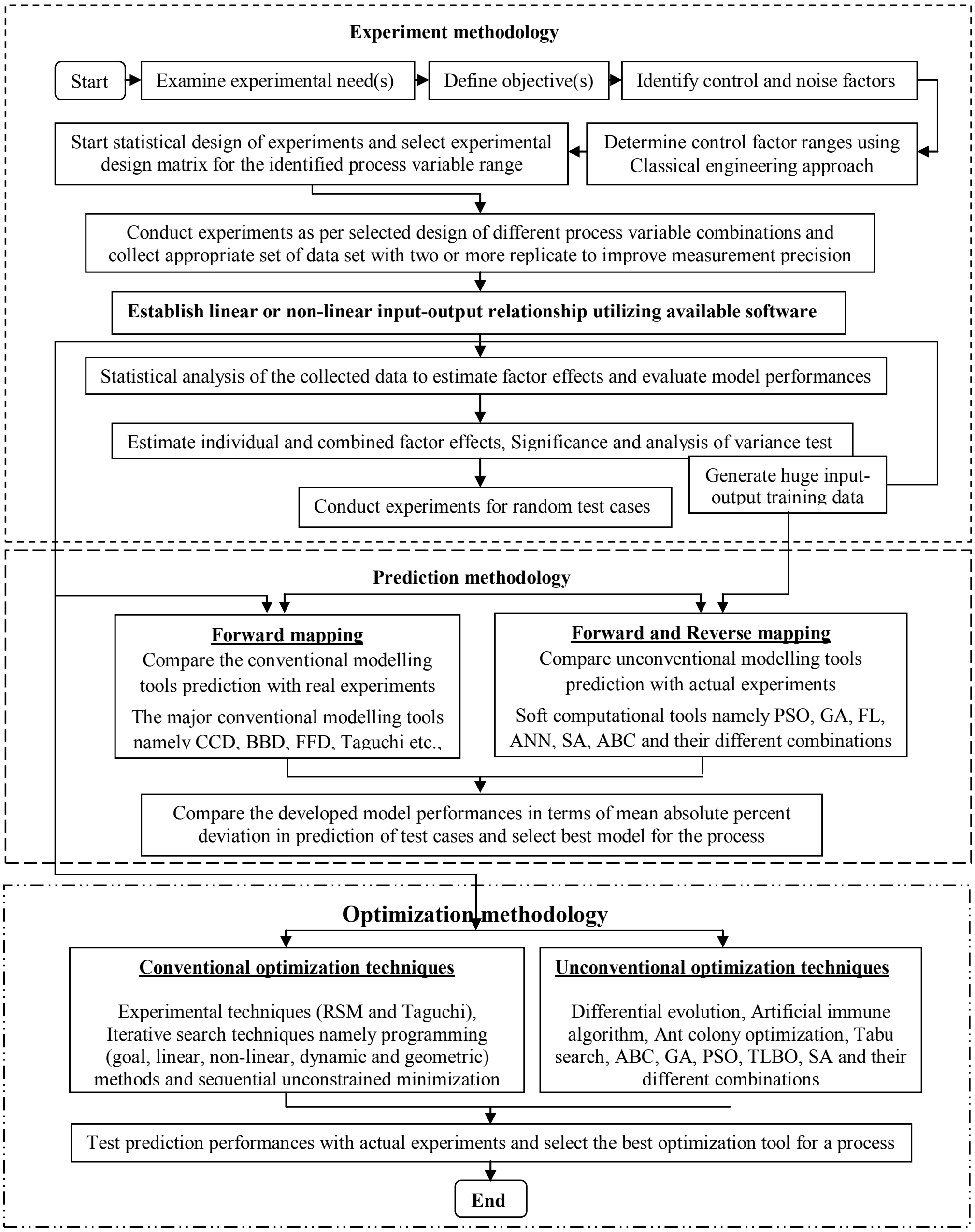

Figure 1: Proposed Methodology for Modelling, Prediction and Optimization.

Concluding Remarks

The present work describes the current state of art and the future scope for improving the squeeze cast component quality through the applications of conventional and unconventional modelling tools. The meaningful conclusions are drawn for the current work,

1) Conventional engineering approach of varying one parameter at once after maintaining the rest at the middle helps in deciding the process variable range for statistical design of experiments. However, the data from the literature survey and opinion of expert persons from the industry along with pilot experiments will help to identify all process variables and their operating range.

2) Casting simulation software is capable of making effective prediction, but it is not suitable for large simulation trials for cyclic analysis in bringing the solution to an optimal conditions. Further, simulation software lacks in considering the local conditions in formulating the problem.

3) Statistical design of experiments can be successfully implemented in foundry applications to analyze, identify the percent contribution of main (individual) and the interaction (combined) effect of process variables on the response under investigation. In other-words, it helps to understand the sensitivity of process variables. Further, the regression equations developed from the models can be used to make prediction of the response for the known set process variables.

4) The statistical modelling tools are capable of making prediction only one response at a time. In multi input-output casting system all the response are measured for the single process parameter conditions, hence development of integrated system to predict the responses simultaneously is mandatory.

5) Soft computing tools can predict multi response at a time and meets the practical requirement of the foundry men to know the recommended process parameter setting for the desired output through reverse prediction.

6) The single optimal process parameter setting for all the response can be obtained through the use of optimization algorithms such as ABC, PSO, TLBO, SA, and GA and so on.

Although much research efforts reported in the available literatures, still the process industries and researchers are not using powerful modelling tools to improve the squeeze cast components. The use of statistical tools establishes the input-output relationship and provides the complete insight of the process, but fails to meet specific industry requirements. The soft computing based approaches can be efficiently used for predicting the input variables required to achieve the desired response (reverse mapping). It is noteworthy that reverse mapping can be used in online control of the process. The incremental mode of training data in soft computing approach will up-date process variables required to obtain the desired response values. Hence, the on-line control of the process can be made by adjusting the process variables quickly. The proposed methodology help the industry personnel to select and adjust the most influential process parameter any manufacturing process to achieve the desired quality with reduced time and resource consumption.

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Citation: Manjunath Patel GC, Krishna P, Parappagoudar MB (2015) Modelling in Squeeze Casting Process-Present State and Future Perspectives. Adv Automob Eng 4: 111. doi:10.4172/2167-7670.1000111