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Novel Bayesian Inference Based Approach to Identify Critical Parameters Affecting Mechanical Properties of Investment Castings

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In addition to shape fidelity and internal soundness, mechanical properties have also become critical acceptance criteria for investment cast parts. These properties, including ultimate tensile strength, yield strength and percentage elongation, are driven by the chemical composition of cast alloy as well as process parameters related to wax making (time taken for injection, press room temperature and humidity) and other steps in investment casting: shell making, dewaxing, and melting. It is however, difficult to identify the most critical parameters and their specific values resulting in the mechanical properties. This is achieved in the present work by employing Bayesian inference to compute posterior probability values for each input parameter. This is demonstrated on real-life data collected from an industrial foundry. Controlling the identified parameters within the specific range of values resulted in improved mechanical properties. Unlike computer simulation, artificial neural networks and statistical methods explored by earlier researchers, the proposed approach is easy to implement in industry for controlling and optimizing the parameters to achieve the desired range of mechanical properties.

Keywords: *Bayesian Inference, Investment Casting, Mechanical Properties, Process Parameters.*

1. Introduction

Investment castings used in critical applications like aerospace and biomedical need to be free of internal defects as well as possess the desired mechanical properties like ultimate tensile strength, yield strength, and percentage elongation to provide the required functionality and service life. The casting quality and mechanical properties are greatly affected by the flow, solidification and microstructure of cast metal in the ceramic shell. These phenomena in turn depend on the chemical composition of the alloy and various process parameters. There is a need to identify the most critical parameters and their range of values to enable controlling and optimizing these parameters, thereby minimizing quality problems and achieving the desired mechanical properties. This is however, a challenging task since there are a large number of parameters involved in investment casting process. Moreover, it should be possible to implement the proposed approach in industrial foundries.

In the past, several researchers have explored different techniques for predicting the effect of alloy composition and selected process parameters on mechanical properties, though mainly for sand and die casting processes. These include computer modeling and simulation of metal flow and solidification [1-3]; statistical methods (mainly multiple regression analysis) [4-5]; and artificial neural networks [6-8]. There is very little work to identify critical parameters and their specific range of values to achieve the desired range of mechanical properties.

A relatively new approach called Bayesian inference can be explored for the above purpose. It relies on the Bayes' rule that estimates the probability of occurrence (prediction) based on the evidences (observations). The basic methodology is presented next, followed by testing in an industrial foundry.

2. Methodology

The basic methodology is shown in figure 1. Input data related to process parameters (wax making, shell making, melting and pouring) and alloy composition is collected, and stored in Microsoft Excel spreadsheet. This data is processed using Bayesian inference to identify critical parameters and their specific range of values affecting mechanical properties. This involves computation of posterior probabilities (programmed in Excel), briefly explained next.

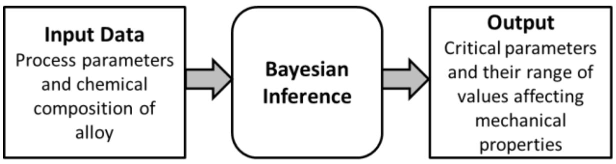

Fig. 1 Basic methodology

The total range of each input parameter as well as mechanical property is divided into four ranges (i = 1 to 4), and the observed value of each input is placed in one of the four ranges. The input parameter addend (P_{IP}) and mechanical property addend (P_{MP}) are calculated. The values of posterior probability for the upper range of mechanical properties (R_{MP4}) are computed for all input parameters from an input data. This in turn requires computing the values of *local probability* (*LP*), *prior odd* (O_{prior}), *joint probability* (*JP*), *conditional probability* (*CP*), *likelihood ratio* (*LR*), and *posterior odd* (O_{post}) based on input data. The relevant equations are given in table 1.

Table 1 Computation of posterior probabilities [9]

Parameters	Equation
LP_{IPRi}	N_{IPRi}/N_{IP}
$O_{prior(IPRi)}$	$LP_{IPRi}/(1- LP_{IPRi})$
$JP_{MPRi/ IPRi}$	$N_{IPRi/MPRi}/N_{MPRi}$
$CP_{IPRi/MPRi}$	$P_{MPRi}* JP_{MPRi/ IPRi}/ LP_{IPRi}$
$LR_{MPRi/ IPRi}$	$CP_{IPRi/MPRi}/(1- CP_{IPRi/MPRi})$
$O_{post(MPRi/(IPRi)}$	$O_{prior(IPRi)} * LR_{MPRi/ RIPi}$
PR_{IPRi}	$O_{post(MPRi/(IPRi)}/(1+ O_{post(MPRi/(IPRi)})$

The values of posterior probabilities are used to identify the critical parameters affecting mechanical properties. An input parameters and its specific range of values are considered to be critical if its value of posterior probabilities is high.

3. Testing

The input data of more than 450 heats related to process parameters and chemical composition of alloy was collected from an industrial foundry. The part is a steel valve body used in automobiles (figure 2). The foundry measured the mechanical properties (ultimate tensile strength, yield strength and percentage elongation) for each batch, by casting sample bars along with the castings in each batch, and testing each sample bar on an universal testing machine as per ASTM A370 (figure 2). The total data set comprised 30 input parameters and three output parameters.

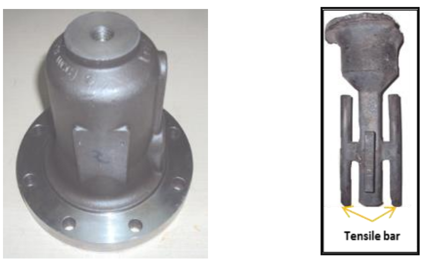

Fig. 2 Industrial casting & tensile bar

The input data was entered into the system in the form of Microsoft Excel sheet. This data was analyzed using Bayesian inference as described earlier, to compute posterior probabilities. Posterior probability of metal preparation time (one of the input parameters) for the desired ultimate tensile strength (for 4^{th} range) is shown in table 2.

Table 2 Posterior probability of metal preparation time

Parameters	Values
LP_{IPR1}	0.96
$O_{prior(IPR1)}$	29.80
$JP_{MPR4/ IPR1}$	1
$CP_{IPR1/MPR4}$	0.11
$LR_{MPR4/ IPR1}$	0.12
$O_{post(MPR4/(IPR1)}$	3.58
PR_{IPR1}	0.78

The optimal range of other critical parameters (posterior probability more than 0.5) were similarly identified: viscosity of primary slurry (19 to 24 sec); pH of primary slurry (9.0 to 9.1); metal preparation time (100 to 139 minutes); Molybdenum (0.002 to 0.010 %). Using these values, 10 heats were melted, from which 22 castings were poured and tested. The mechanical properties were found to be in the desired range for 15 castings.

To summarize, usefulness of Bayesian inference methodology has been successfully demonstrated for determining the optimal range of process parameters and alloy composition, to improve quality assurance of industrial investment castings. The relative ease of implementing and using the proposed methodology make it valuable for practical application.

References

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