Application of Artificial Neural Network for Optimization of Cold Chamber Aluminium Die Casting

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Abstract-- In the present paper an optimization of process parameters of a cold chamber aluminium die casting operation is discussed. The quality problem encountered during the manufacturing of a die casted component was porosity and the various potential factors causing it are identified through a thorough cause-effect analysis. The Ishikawa diagram (cause and effect diagram) was constructed to identify the casting process parameters that may affect the porosity. An analysis of variance (ANOVA) is further conducted to find the factors having significant effects on porosity. The pressure of the plunger used in the die casting machine and the temperature of the liquid aluminium are identified as significant factors after the ANOVA test. Then a back propagation ANN is modelled and trained with the above two process parameters and porosity in order to predict or control the output by optimizing the input process parameters.

Keywords: Cold Chamber Die Casting, Porosity, Ishikawa Diagram, ANOVA, ANN

1. INTRODUCTION

Optimization of manufacturing process has always been considered as one of the important tasks to improve the quality of the product and to achieve several other objectives. This area of research has received immense attention over last few decades in a number of manufacturing organizations. The conventional methods of optimization fail to address this problem quality concern in the absence of well-established mathematical relationships among the input and output parameters of the process. The present work deals with optimization of cold chamber die casting process of the aluminium alloy LM6.

An efficient method for optimization is the application of soft computing tools like fuzzy logic, artificial neural network and genetic algorithm as reported in several works[1-2-3].The more complex, nonlinear and complicated the process parameters relationships are, the better the suitability of implementing soft computing tools. However before applying soft computing tools for the optimization of the input process parameters it is very much necessary to select the process parameters which affect the output most. For this reason ANOVA and Taguchi method can be used to identify and select the affecting process parameters and also to find the optimum levels of selected parameters. Some of the applications of Taguchi method and design of experiments related to die casting problems can be found in references [4-5-6-7-8] & [9].The present work follows a combined approach of selecting the significant factors for the quality problem i.e. porosity in die casted components and then back propagation ANN modelling to optimize the process parameters .

The paper has been divided into four sections. The first section contains introduction to the background of the problem and related literature in the area of soft computing applications in the field of metal casting and ANOVA based optimizations. The second section deals with the aim of the work, relevant details on the case study and identification of the significant factors through ANOVA. In section 3, the development and training of ANN with collected data from the case problem is discussed along with the analysis and optimization of the problem. Finally the concluding remarks and the scope of future work are given in section 4.

II. PROBLEM IDENTIFICATION AND ANOVA

The experimental data for the current work is collected from an ISO certified manufacturing unit established in 1978 which deals with aluminium ammunition components for defence applications. Before machining the components to the desired specification, they are die casted using cold-chamber die casting machines. The aluminium alloy LM6 used for die casting has a typical composition as follows: Copper: 0.1%, Silicon: 0.7%, Magnesium: 0.10%, Iron: 0.6%, Manganese: 0.5%, Nickel: 0.1%, Zinc: 0.1%, Lead: 0.1%, Aluminium: Rest The die casting machine used in the industry is fully equipped with appropriate instrumentation and a data acquisition, control system and monitoring system for the analysis and investigation of the inter-relationships of different die casting parameters.

During the quality assessment of die casted products the defect in the form of porosity was identified as the major issue for deteriorated quality. The density of the castings being directly related to its porosity is considered & studied for the convenience of measurement. A cause and effect analysis is further conducted initially to identify the casting process

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parameters that may be causing the die casting porosity. The main process parameters which are identified can be listed in four categories as

(a) Hydraulic pressure
(b) Metal filling time
(c) Molten metal temperature and
(d) Plunger velocity

The range of the melting furnace temperature was selected at 610 -730^{0}C, the plunger velocity in the first stage was selected at 0.02-0.60 m/s and in the second stage it was selected at 1.2-3.8 m/s. Further, the range of hydraulic pressure was chosen to be12-28 Mpa while the filling time was varied between 40 to130 ms (millisecond). These ranges were selected based on the various constraints imposed by the process set-up for the die casting. The nonlinear behavior of the parameters of a die casting process can only be determined if multi-levels of process parameters are used and hence each parameter is taken at two levels as given in Table 1 below.

Table 1. Process Parameters with their values at two levels

Parameter designation	Process parameters	Level 1	Level 2
A	Molten metal temperature (ºC)	610	730
B	Plunger velocity first stage (m/s)	0.02	0.6
C	Plunger velocity second stage (m/s)	1.2	3.8
D	Hydraulic pressure (Mpa)	12	28
E	Metal filling time (ms)	40	130

In order to identify the significant factors affecting the density of casting, an experimental design is conducted using an orthogonal array (OA). It is a fractional factorial matrix which assures a balanced comparison of levels of any factor or interaction of factors [10]. Represented as a matrix of numbers arranged in rows and columns where each row represents the level of the factors in each run, and each column represents a specific factor that can be changed from each run. An orthogonal array, L8 (27), is selected for the present problem having five factors at two levels each. The last two columns of the Orthogonal Array remain unassigned as no interaction of factors is considered during the significance testing. Factor A is assigned to column 1, factor B assigned to column 2 and so on till factor E to column 5 of the L8 OA. The eight experimental trials are carried out as per the level settings for the factors in the OA and the observations are tabulated as in Table 2. Further, under each trial, eight sample castings are produced and their densities are as given in the Table 2.

Table 2. Densities in gm/cm3 of eight die casting samples under each trial of L8 OA

Trial	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1	2.0	2.0	2.226	2.064	2.318	2.141	2.064	2.0
2	2.064	2.318	2.0	2.141	2.318	2.419	2.480	2.226
3	2.0	2.0	2.0	2.318	2.064	2.141	2.318	2.226
4	2.064	2.064	2.0	2.226	2.141	2.480	2.419	2.0
5	2.064	2.0	2.226	2.064	2.0	2.419	2.419	2.480
6	2.480	2.480	2.318	2.064	2.318	2.0	2.141	2.419
7	2.318	2.064	2.0	2.141	2.480	2.495	2.480	2.419
8	2.419	2.419	2.480	2.480	2.419	2.480	2.0	2.480

Now, In order to construct the ANOVA summary table, the calculations for sum of squares (SS) of factors and error is carried out and are as given in Table 3. The variances are found by dividing the sum of squares (SS) with their corresponding degree of freedom (ν). The F_{data} for all the factors are obtained by using the variance of error. The value of F_{table} is read from statistical table and the significance is tested by comparing both F values. From this analysis, factors A (molten metal temperature) and factor D (hydraulic pressure) are identified as the factors having significant effects on the output (casting density).

After the identification of significant parameters through ANOVA, an artificial neural network model is developed using these parameters and casting density in order to predict the controllable factors to get desirable results.

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Table 3. ANOVA summary table for die casting density

Source	***SS***	***v***	***V***	F_{data}	F_{table}	**Significance**
A	2.232	1	2.232	26.57	8.53	$F_{data} > F_{table}$
B	0.232	1	0.232	2.76	8.53	
C	0.500	1	0.500	5.952	8.53	
D	0.985	1	0.985	11.72	8.53	$F_{data} > F_{table}$
E	0.002	1	0.002	0.03	8.53	
e	0.168	2	0.084			
Total	**4.119**	**7**	**0.588**			

F_{table} at 90% confidence level

III. ANN OPTIMIZATION MODEL

Artificial Neural Network (ANN) refers to the computing systems whose fundamental concept is taken from analogy of the human biological neural networks. Many day to day tasks involving intelligence or pattern recognition are extremely difficult& complex to automate, but appear to be performed very easily by animals. The neural network of an animal is part of its nervous system, containing a network of specialized cells called neurons (nerve cells). An ANN is basically a computational model made up of interconnecting artificial neurons which are the basic processing elements of the neural network. In a biological system, learning involves adjustments to the synaptic connections between neurons. It is an information processing paradigm inspired by biological nervous systems and they learn from their experience or by data training. Learning or training involves adjustments to the synaptic weights between neurons. Neural nets are suitable when one cannot formulate an algorithmic solution to a problem due to complexity & non linearity but can get several experimental results of the behavior of the system.

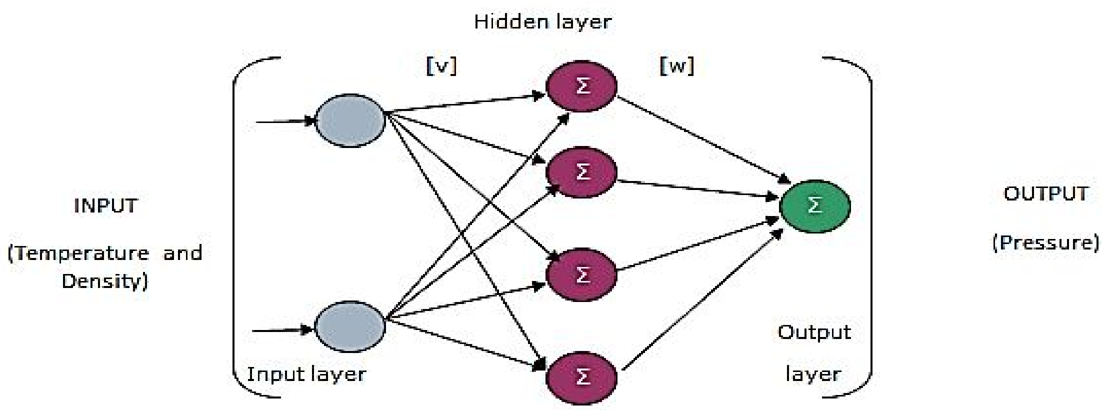

Fig. 1 ANN architecture to optimize aluminum die casting density

The multi-layer feed forward neural network model for optimization or prediction developed for the die casting density problem as in Figure 1 above. As can be clearly observed in the network, the two inputs are casting density and melt temperature while the output parameter is the hydraulic pressure. As the objective of the newly developed ANN model is to find the values of two controllable factors for a required casting density, hence the casting density is used as input to find the unknown hydraulic pressure for a given set of input parameters.
The weight vectors between input-hidden layers and hidden-output layers are presented by [v] and [w] respectively. In order to train or teach the ANN, sets of input and output data are required which can be obtained from the cold chamber die casting process as experimental data. The values of the weights, which give the minimum error, are to be selected for future prediction of outputs.

3.1 Experimental Data Collection and training

The experimental data from the die casting unit was collected for the three parameters namely hydraulic pressure, melt temperature of aluminium and the casting density. The actual values of the collected data are normalized in order that the values lie between 0 and 1. The main aim of the neural network training is to find a set of weights, which represent the

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mapping from the input space to the output space. It will be quite difficult to converge to a set of data, if the input and output parameters are not normalized. Also, normalization is required because the parameters used for training will have different units of measurement and to prevent saturation of the sigmoid function.

The collected data (x) are normalized using relation (1)

$$Normalised\ Value = \frac{(x - min.value)}{(max.value - min.value)} \quad (1)$$

The training process for the ANN network consists of two phases. First, the feed forward stage during which the input is presented to the neural network and corresponding output is calculated. This output is then compared with the desired output from the training data set and the error is calculated as the difference between the two outputs. On the basis of the error, weights are updated during the back propagation stage in order to minimize the error. The modelling, simulation and transfer functions for the ANN is implemented on a Matlab® NN tool box. It is already equipped with different predefined functions for pre-processing and post-processing of data to improve the rate of convergence and accuracy.

3.2 Implementation of optimization model

To test and validate the ANN model, the experimental data is divided into three sets. First, 70% of the observed data will be used for training the network and the weights are adjusted to minimize its error. Another 15% of the data will be used to validate that the network is generalizing efficiently and to stop training before over-fitting. The last 15% will be used as a completely independent test of the ANN generalization and have no effect on the training and hence provide an independent measure of the network performance. The accuracy in prediction of output parameter of the ANN is tested by presenting the input of testing set to the neural network. Testing sets are those new sets of input for which outputs are known but they have not been used for training the neural network.

During training, the mean squared error (MSE) is observed as 1.92430e -1, at validation test the MSE is 3.27483e -2 and at 15% testing the MSE is 1.35651e -1. Mean squared error is the average squared difference between output and target and lower values for MSE are better.

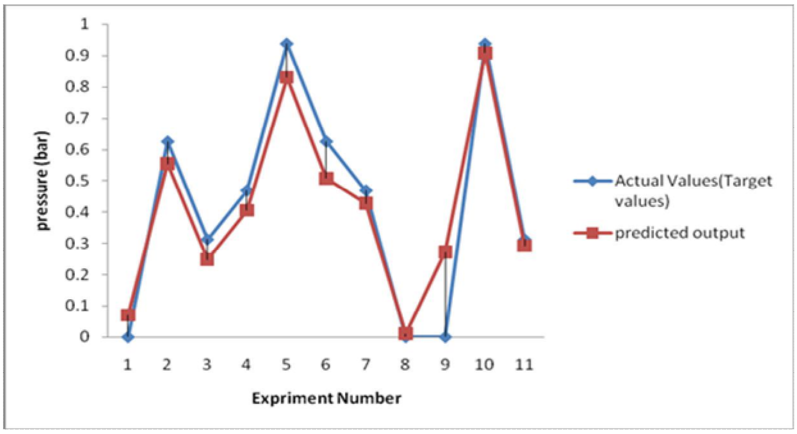

Fig. 2 Comparison of predicted and actual output pressure

3.3 Validation using regression analysis

Regression analysis is a statistical tool used for the establishment of relationships among variables. To investigate this, experimental data as already collected earlier on hydraulic pressure, casting density and melt temperature is used. The objective of regression analysis is to produce an estimate of these three parameters, based upon the information contained in the data set.

Using the collected data, regression equation (2) is obtained using MINITAB®

$$z = 0.369 + 0.047x + 0.002y \quad (2)$$

Where, z = Hydraulic Pressure, x = Melt Temperature and y = Casting Density

Now a comparison can be made between the output results obtained by the ANN model and regression analysis using the test data set as discussed earlier. The plot of seven predicted outputs from both approaches is depicted in Figure 3. As can be seen from the figure, the prediction of ANN model is very much conforming to that of regression analysis for this problem and hence can be used for inferences.

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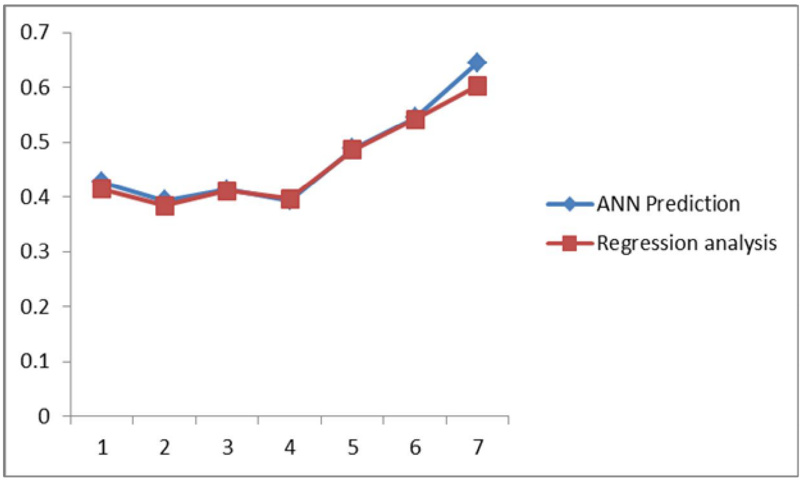

Fig. 3 Comparison between ANN and regression analysis outputs

4. CONCLUSION

The present work discussed an ANN based prediction/optimization model for a die casting process of aluminium alloy LM6. Firstly, statistical ANOVA method was used to identify the significant controlling factors out of the five parameters affecting the density of castings. Then those selected factors are used during the ANN modelling. Hundred experimental observations were collected and used for 70% training, 15% validation and 15% testing. In order to achieve a required density of casting the corresponding settings of hydraulic pressure and melt temperature can be predicted with the help of the neural network. Actual data were tested to find the error in prediction. Further, the calculated values from a regression analysis are compared with predicted ANN model. Similar to the present approach, multiple outputs can be considered during ANN modelling to include mechanical properties of the casting for optimization.

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