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OPTIMIZATION OF PROCESS PARAMETERS IN COLD CHAMBER PRESSURE DIE CASTING USING DOE

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Abstract - In the present paper, optimization of process parameters of an aluminium pressure die casting operation is discussed. The quality problem encountered during the manufacturing of a die casted component was porosity and the potential factors causing it are identified through cause-effect analysis. An analysis of variance (ANOVA) is conducted to find the factors with significant effects on porosity. The pressure of the plunger used in the die casting machine and temperature of the liquid aluminium are identified as significant factors after the analysis. Then a back propagation Artificial Neural Network (ANN) is modelled and trained with these process parameters and porosity in order to predict or control the output by optimizing input process parameters.

Key Words—pressure die casting, ANOVA, ANN, Optimization, Regression Analysis.

1.INTRODUCTION

At present, optimization of manufacturing process is one of vital functions to improve the product performance as well as to achieve several other objectives. This area of optimization has received increasing attention over last few decades in many manufacturing organizations. The conventional methods of optimization fail to address this problem in the absence of well-established mathematical relationships among the input and output parameters of the process. An effective manufacturing require models that can predict in real time the effect of various process parameters of a production process. Pressure Die casting is a process in the metal casting industry. Die casting is a versatile process for producing engineered metal parts by forcing molten metal under high pressure into reusable steel moulds. Pressure die casting is an important production process. In pressure die casting the first setting of process parameters is established through guess work. Experts use their previous experience and knowledge to develop a solution for a new application. Due to rapid expansion in the pressure die casting process to produce better quality products in a short period of time, there is ever increasing demand to replace the time consuming and expert reliant traditional trial and error methods of establishing process parameters. The process has its origins in type casting machines developed in 1822. The process showed its production potential as early as the mid 1800s when it had reached a high level of automation and mechanical efficiency. An optimization process parameter problem is routinely performed in the manufacturing industry, particularly in setting final optimal process parameters. Final optimal process parameter setting recognized as one of the most important steps in manufacturing process for improving the quality of perfect products. In this system the previously, engineers used trail and error processes which depend on the engineers experience and intuition to determine initial process parameter settings. Subsequently numerous engineers applied Taguchi parameter design method to determine the optimal process parameter settings. However the trail and error process is costly and time consuming, thus it is not suitable for complex manufacturing processes (Lam, Zhai, Tai, & Fok, 2004). Hus (2004b) argued that when using a trail and error process it is impossible to verify the actual optimal process parameter setting. Moreover, Taguchi parameter design method can only find the best specified process parameter level combination which includes the discrete setting values of process parameters.

In recent time an efficient method to achieve this objective is the application of soft computing tools like FL, NN, and GA. The more complex 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 necessary to select the process parameters which affect the output most. For this reason Design of Experiment (ANOVA) can be used to identify and select those process parameters. An alternative means of applying artificial neural networks has been proposed to improve conventional Taguchi parameter design and is capable of effectively treating continuous parameter values.

II. PROBLEM IDENTIFICATION AND ANOVA

The experimental data is collected from an ISO certified manufacturing unit established in 1978 dealing with aluminium ammunition components for defence applications. Before machining the components to desired specification, they are die casted using cold-chamber machines. The aluminium alloy used with a typical composition as follows:
Copper: 3 to 3.5%, 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 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 quality assessment of die casted products the defect in the form of porosity was identified as the major issue. The density of the castings being directly related to its porosity is considered for convenience of measurement. A cause and effect analysis is conducted initially to identify the casting process parameters that may be causing the die casting porosity. The identified main process parameters can be listed in four categories as

(a) Plunger velocity
(b) Molten metal temperature
(c) Metal filling time and
(d) Hydraulic pressure
The range of the holding furnace temperature was selected at 610 -730C, the plunger velocity in the first stage was selected at 0.02-0.60 m/s and in the second stage 1.2-3.8 m/s. Further, the range of hydraulic pressure was chosen to be12-28 MPa and the filling time was varied between 40 to130 ms (millisecond). These ranges were selected based on the constraints imposed by the process set-up for the die casting. The nonlinear behaviour of the parameters of a die casting process can only be determined if multi-levels are used and hence each parameter is taken at two levels as given in Table 1.

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 on 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 OA remain unassigned as no interaction 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

gm/cm^3	Casting 1	Casting 2	Casting 3	Casting 4	Casting 5	Casting 6	Casting 7	Casting 8
Sample 1	2	2	2.226	2.064	2.318	2.141	2.064	2
Sample 2	2.064	2.318	2	2.141	2.318	2.419	2.480	2.226
Sample 3	2	2	2	2.318	2.064	2.141	2.318	2.226
Sample 4	2.064	2.064	2	2.226	2.141	2.480	2.419	2
Sample 5	2.064	2	2.226	2.064	2	2.419	2.419	2.480
Sample 6	2.480	2.480	2.318	2.064	2.318	2	2.141	2.419
Sample 7	2.318	2.064	2	2.141	2.480	2.495	2.480	2.419
Sample 8	2.419	2.419	2.480	2.480	2.419	2.480	2	2.480

In order to construct the ANOVA summary table, the calculations for sum of squares (SS) of factors and error are as given in Table 3. The variances are found by dividing the 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 D (hydraulic pressure) are identified as having significant effects on the output (casting density).
After the identification of significant factors through ANOVA, an artificial neural network model is developed using these factors and casting density in order to predict the controllable factors to get desirable results.

III. ANN OPTIMIZATION MODEL

An ANN is a computational model made up of interconnecting artificial neurons which are the basic processing elements of the neural network. 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 but can get several experimental results of the behavior of the system.

TABLE 3.
ANOVA SUMMARY TABLE FOR DIE CASTING DENSITY

Source	*SS*	*v*	*V*	*Fdata*	*Ftable*	Significance
A	2.232	1	2.232	26.57	8.53	*Fdata> Ftable*
B	0.232	1	0.232	2.76	8.53	
C	0.50	1	0.50	5.952	8.53	
D	0.985	1	0.985	11.726	8.53	*Fdata> Ftable*
E	0.0028	1	0.0028	0.03	8.53	
e	0.168	2	0.084			
Total	4.1198	7	0.588			

F_{table} *at* 90% confidence level

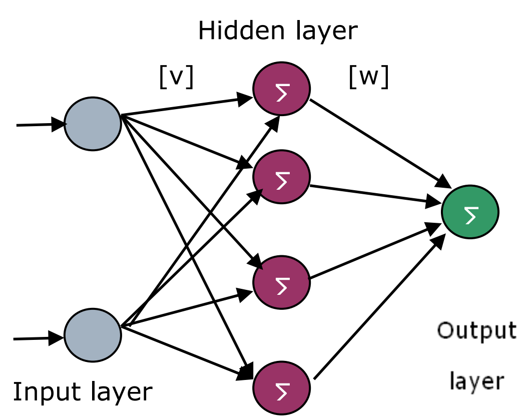

Fig.1. ANN architecture to optimize aluminum die casting density

The multi-layer feed forward neural network model for optimization or prediction is developed for the die casting density problem as in figure 1. As can be seen from the network, the two inputs are casting density and melt temperature while the output is hydraulic pressure. As the objective of the 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 and hidden-output 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 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.

IV. EXPERIMENTAL DATA COLLECTION AND TRAINING

The experimental data from the die casting unit was collected for the three parameters namely hydraulic pressure, melt temperature and casting density. The actual values of the collected data are normalized so that the values lie between 0 and 1. The main function of neural network training is to find a set of weights, which represent the mapping from the input space to the output space. It will be 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)

$$\text{Normalized value}=\frac{(x-\text{Min.value})}{(\text{Max.value}-\text{Min.value})} \qquad (1)$$

The training process for the designed 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 Mat lab® NN tool box. It is equipped with different predefined functions for pre-processing and post-processing of data to improve the rate of convergence and accuracy.All paragraphs must be indented. All paragraphs must be justified, i.e. both left-justified and right-justified.

V. IMPLEMENTATION OF OPTIMIZATION MODEL

To test and validate the model, the experimental data is divided into three sets. First, 70% of the observations 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 and to stop training before over-fitting. The last 15% will be used as a completely independent test of the NN generalization and have no effect on the training and hence provide an independent measure of network performance. The accuracy in prediction of output parameter of the NN is tested by presenting the input of testing set to the neural network. Testing sets are those 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.

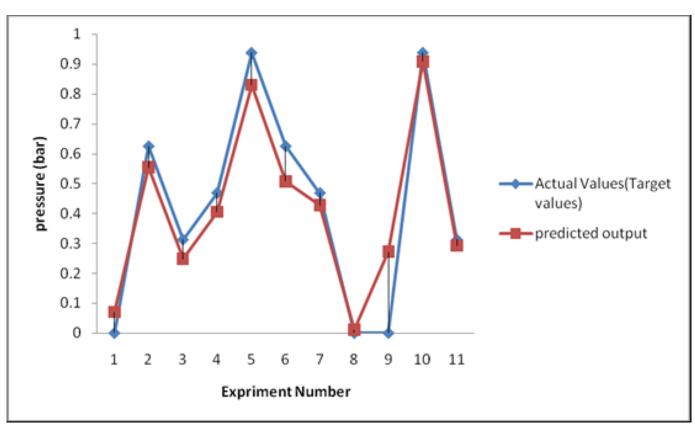

Fig 2. Comparison of predicted and actual output pressure

VI. VALIDATION USING REGRESSION ANALYSIS

Regression analysis is the statistical tool for the establishment of relationships among variables. To investigate this, experimental data as 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®

$$Z=0.369+0.047x+0.002y \qquad (2)$$

Where, z = hydraulic pressure, x = melt temperature and y = casting density

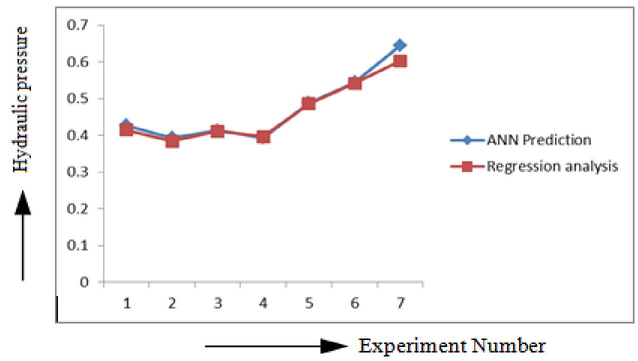

Fig. 3 Comparison between ANN and regression analysis outputs.

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

VII. CONCLUSION

The present work discussed an ANN based prediction/optimization model for a pressure die casting process of aluminium. Firstly, statistical ANOVA method was used to identify the significant controlling factors out of five 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 from 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. It has been observed that the calculated values are very close to predicted values. Similar to the present approach, multiple outputs can be considered during ANN modelling to include mechanical properties of the casting for optimization.

REFERENCES

1. Vijan, P., and Arunachalum, V.P., "Optimization of squeeze casting process parameters using Taguchi method", The International Journal of Advanced Manufacturing Technology, vol.33, 2006, pp1122-1127.
2. Syrcos, G. P., "Die casting process optimization using Taguchi methods", Journal of Materials Processing Technology, vol.135, (2003), pp 68-74.
3. Samanta, B., "Surface roughness prediction in machining using soft computing", International Journal of Computer Integrated Manufacturing, vol.22, (2009), pp 257-266.
4. Seong J. K., and Kim, K. S., "Optimization of manufacturing parameters for a brake lining using Taguchi method", Journal of Materials Processing Technology, vol.136, (2003), pp 202-208.
5. Rao, G. K. M., and Rao, M. S., and Rao, D. H., "Development of Hybrid Model and Optimization of Metal Removal Rate in Electric Discharge Machining using Artificial Neural Networks and Genetic Algorithm", ARPN Journal of Engineering and Applied Sciences, vol.3, (2008), pp20-30.
6. Prasad, K .D.V.Y., "Prediction of die casting process parameters by using an artificial neural network model for zinc alloys", Journal of Materials Processing Technology, vol.89, (2010), pp 583-590.
7. Dalquist, S., and Gutowski, T., "Life Cycle Analysis of Conventional Manufacturing Techniques: Die Casting," LMP-MIT-TGG-Dec-2004, pp 1-7.
8. Zagloel, T. Y., and Al-Aina, F., "Gram Optimization using Taguchi Method of Parameter Design and Neural Network Process Model in Packaging Industry," 2nd Asia Pacific Conference on Manufacturing System 4-5 November 2009, Yogyakarta, Indonesia," pp 9-15.
9. Mahapatra, S. S., and Patnaik, A., "Optimization of wire electrical discharge machining (WEDM) process parameters using Taguchi method," International Journal of Advanced Manufacturing Technology, vol.53, (2006), pp 1-15.
10. Tachiang, K., Liu, N, M., & Chou, C, C., "Machining parameters optimization on the die casting process of magnesium alloy using the grey-based fuzzy algorithm", International Journal of Advanced Manufacturing Technology, vol.38, (2008),pp 229-237.

11. Dobrzanski, L. A., Domagala, J., and Silva, J. F., “Application of Taguchi method in the optimization of filament winding of thermoplastic composites,” Archives of Materials Science and Engineering, vol.28, (2007), pp 130-140.
12. Lindeke, R R., and Liou, Y. H. A., “Methods for Optimization in the Manufacturing system –the Taguchi method an Engineering Approach to its Implementation,” Journal of Mechanical Working Technology, vol.20, (1989), pp 205-216.
13. Chan, K. Y., Kwong, C..K., and Fogarty, T. C., “Modelling manufacturing process using a genetic programming based fuzzy regression with detection of outliers,” Information Science, vol.180.,(2010), pp 506-518.
14. Chiang K. T., Liu, N. M., and Tsai, T. C., “Modeling and analysis of the effects of processing parameters on the performance characteristics in the high pressure die casting process of Al–SI alloys”, International Journal of Advanced Manufacturing Technology, vol.41, (2009), pp 1076-1984.
15. Surace, R. A. C. D. F., Ludovico, A. D., and Boghetich, G., “Application of Taguchi method for the multi-objective optimization of aluminium foam manufacturing parameters”, International Journal of Material Forming , vol.3, (2010), pp 1-5.
16. Jiang W., Fan, Z., Liao, D., Dong, X., and Zhao, Z., “A new shell casting process based on expendable pattern with vacuum and low-pressure casting for aluminium and magnesium alloys,” The International Journal of Advanced Manufacturing Technology, vol.51,(2010), pp25-34.
17. Yen, C., Lin, J. C., and Li, W., “The selection of optimal cooling parameters for the multi-cavity die”, International Journal of Advanced Manufacturing Technology, vol.26, (2005), pp 228-235.
18. Karunakar, D. B., and Datta, G. L., “Prevention of defects in castings using back propagation neural networks”, The International Journal of Advanced Manufacturing Technology, vol.39, (2008), pp1111-1124.
19. Wen, J. L., Yang, Y. K., and Jeng, M. C., “Optimization of die casting conditions for wear properties of alloy AZ91D components using the Taguchi method and design of experiments analysis”, The International Journal of Advanced Manufacturing Technology, vol.41, (2009), pp430-439.
20. Akarte, M. M., Ravi, B., and Creese, R. C., “Casting process selection using AHP and Fuzzy logic”, International Seminar on Manufacturing Technology, Beyond 2000, Bangalore , Nov.1999.
21. Matti, S., Vapalahti, S., and Vainola, J., “Use of simulated porosity for avoidance of casting defects”, International GIFA congress Metal casting 94, (1994).
22. Lin, Y., “Study on Manufacturing process optimization of light guiding plate for soft computing”, Engineering Materials, vol.364, (2008), pp43-47.
23. Odyobi, O. A., and Umoru, L. E., “Application of soft computing techniques in materials engineering : A review”, African Journal of Mathematics and Computer Science Research, vol.2, (2009), pp 104-131.
24. Wen –Chin Chen, Gong-Loung Fu and Pei-Hao,(2008), “Development of the Optimized Manufacturing Process Model by "Taguchi method”, Advanced Materials Research”, vol.33, pp 1413-1418.
25. Dote, Y., and Ovaska, S. J., “Industrial Applications of Soft Computing: A Review”, Proceedings of the IEEE, vol.89,(2001), pp 1243-1265.
26. Chandrasekaran, M., Muralidhar, M., Krishna, C. M., and Dixit, U. S., “Application of soft computing techniques in machining performance prediction and optimization: a literature review”, International Journal of Advanced Manufacturing Technology, vol.46, (2010), pp 445-464.
27. Muhammed, O. S., Saleh, H. R., and Alwan, H. L., “Using of Taguchi Method to Optimize the Casting of Al–Si /Al2O3 Composites”, Engineering and Technology Journal, vol.27, (2009), pp 1143-1150.
28. Haq, A. N., Guharaja, S., and Karuppannan, K. M. “Parameter optimization of CO2 casting process by using Taguchi method”, International Journal of Advanced Manufacturing Technology, vol.3, (2009), pp 41-50.
29. Guharaja, S., Haq, A. N., and Karuppannan, K. M., “Optimization of Green sand casting process parameters by using Taguchi method”, International Journal of Advanced Manufacturing Technology, vol.30, (2006), pp 1040-1048.
30. Yang, W., Geni, M., Wang, T., and Zhuang, Z., “Development of the Optimized Manufacturing Process Model by Taguchi method”, Advanced Materials Research, vol.33, (2008), pp 1413-1418.

Sukthomya, W., and Tannock, J. D. T., "Taguchi experimental design for manufacturing process optimization using historical data and a neural network