Modal Analysis of Porosity Defects in High Pressure Die Casting with a Neural Network

KarunaKumar.G, K.Ramteja

Abstract- High Pressure Die Casting (HPDC) is a complex process that results in casting defects if configured improperly. However, finding out the optimal configuration is a non -trivial task as eliminating one of the casting defects (for example, porosity) can result in occurrence of other casting defects. The industry generally tries to eliminate the defects by trial and error which is an expensive and error -prone process. This paper aims to improve current modelling and understanding of defects formation in HPDC machines. We have conducted conventional die casting tests with a neural network model of HPDC machine and compared the obtained results with the current understanding of formation of porosity. While most of our findings correspond well to established knowledge in the field, some of our findings are in conflict with the previous studies of die casting.

Index Terms- Artificial Neural Network, High Pressure Die Casting, Porosity.

I. INTRODUCTION

High Pressure Die Casting Machine (HPDC)is complex industrial system. Inaty pical diecasting machine (Fig.1) the molten metalis poured intheshotsleevethroughaladle. After the disclosed, amovementofa plunger (piston)forcesthe metalthroughthedieresultingin that the moveablepartcoincideswiththefixedpart. Somediecastingmachinesallowforthisplungermovement to be completed in fourstages[9], however, typically it is doneintwostagesonly.Theplungerstartsinitially with alow velocity,then thevelocityincreasesduringthepiston’smotionat achange over positionandthevelocityis decreasesat the end when nearly all the liquidmetalisinjected into the die. Themetal is the ninjectedthroughgateandrunnersystematahighvelocityand pressure.

The die isthen opened and thesolidifiedpartis extractedoutbyaroboticarm.The dieislubricated with typically aliquid lubricant althoughthere are some powde rlubricants available as well. The role of a lubricant is to ease the extra ction of castingandtoavoidsolderingofthemetalwiththediesurface.

The extracted casting is thencooleddown with wate randis place dona conveyer belt for afurther treatment, orotherwisestoredon arackforlater quality controltests.The diecasting processisacomplex process consisting of over one hundred andfifty processparameters.Thecomplexity ofthe process results in many problems like blistering,andporosity.However,theporosityisbyfarthe mosthighlyoccurring defectinautomobileengine castings[1].

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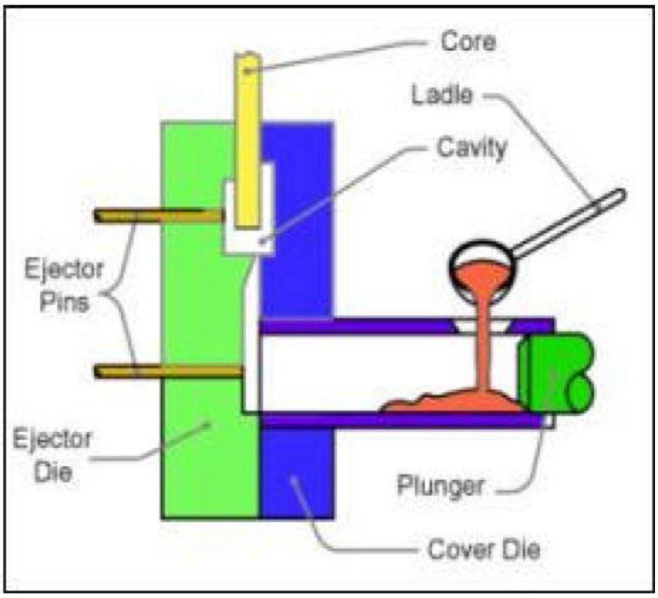

Figure 1: A diagram of a die casting machine.

II. POROSITY

Porosity is the formation of voids insidethecastingseither through theentrapment of gasor improperpressureconfigurationin HPDCmachines.Porosityis oneofthe most difficultdefects to eliminate in die casting. The industry sometimes has to settle to move porosity to a different locationinacastingratherthantoremove itcompletely.Itisinthebestinterestofindustry andtheconsumerofdiecasting (for example, car manufacturers)thatporosityiseliminatedcompletelyfrom the castings,butthisisnotalways possible to do with thecurrent level ofprocess understanding. In addition,attempts to eliminateporosity defects can affect other process settings and result in other casting defects.

The porosity can be dived into three major types, which are:

1. gas porosity;
2. shrinkage porosity, and;
3. flowporosity.

In HPDC, the first two types of porosity are mostly encountered.The gas porosity (Fig. 2) is the porosity in casting due to the presence of gas. This type can arise from:

1. Gas produced during process;
2. entrapped air,and;
3. melt composition

The shrinkage porosity (Fig. 3) is due to shrinking of metal, so that the metal loses volume and hence more metal is required to fill the gaps (voids) produced. In high pressure die casting, it is hoped that this problem can be minimized with the application of pressure to fill the voids when metal is in the solidification state.

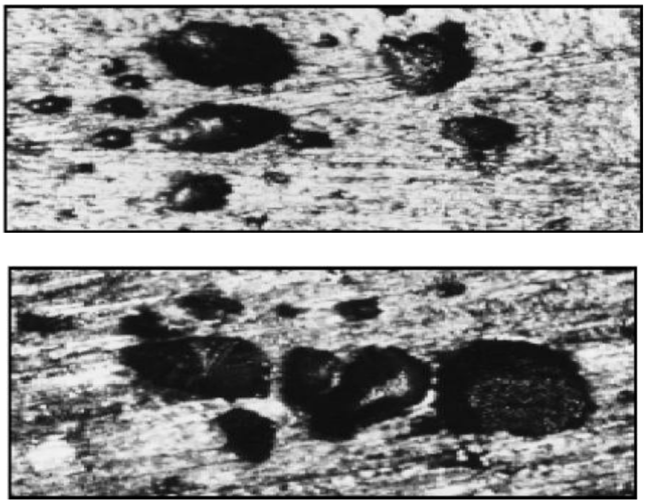

Figure 2: Gas porosity with medium (top figure)and large sized pores (bottom figure).

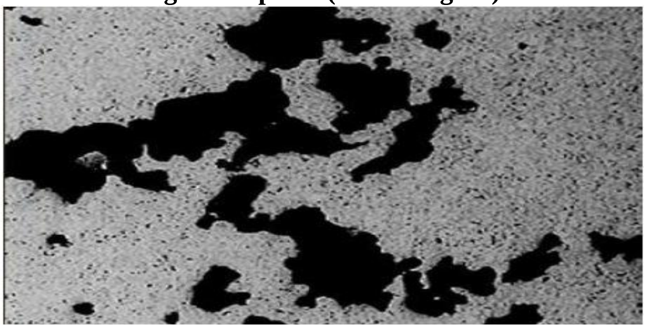

Figure 3: Interconnected shrinkage porosity.

Formation of porosity in die castingsisa combination ofprocessparameters,meltcomposition, and solidification properties under high pressure.

We will discuss process related porosity formation mechanisms in detail which covers solidification and gas related (entrapped) formation. Melt related porosity formation is not discussed in detail primarily because hydrogen entrapment in HPDC is not a big problem. Hydrogen can be considered seriously if the scrap is re-melted which we assume is not the case.

The specific reason for porosity formation is undesirable states of shot sleeve, cavity, vent and gates, runners, solidification pressure, lubricant quantity and steam formation from water during the process.

Shot sleeve related parameters are perhaps the most sensitive one when it comes to entrapped air porosity. The parameters like acceleration, stage velocities, diameter, or even deceleration are all shot related parameters determining the formation of metal wave patterns which can be a crucial factor in deciding whether air becomes entrapped.

As soon as the metal is ladled, the goal is to begin injection as soon as possible but still at the right time in the case of a cold chamber die casting machine. It should begin soon because the metal starts to solidify in the shot sleeve and if metal with solid particles is injected into the die, the high velocities can cause die wear and may contribute to die erosion and to a deteriorated quality of the castings. It is not recommended to inject metal immediately because it can destroy the wave pattern and can entrap air in different forms. Henceshot command delay is the first process parameter to be selected carefully. Another process parameter to be optimized is the firststage velocity. If it is too low or too high, it can contribute to wrong wave formation. It is further explained with the help of a Fig. 4.

The wave forms if slow shot velocity (1st stage velocity) is too slow in the Fig. 4. The wave gets on top of the air and the air is injected into the cavity.

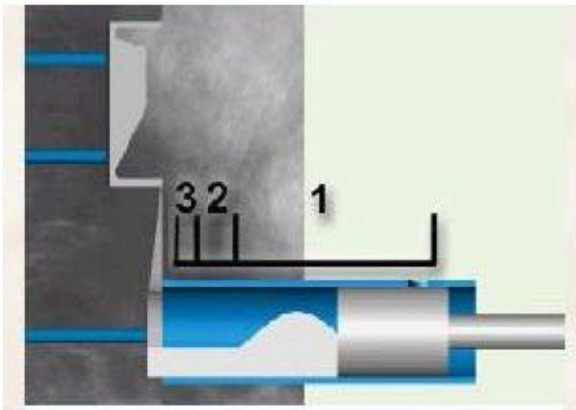

Figure 4: Entrappedairbelowthemetalwave.

The air in cavity can be entrapped due to the problems in runners or ventilation. The vents should be big enough to let the air escape and be located nearthe last spot to solidify. The runner should not have sharp corners in general. If the vents are working properly the air entrapped can escape to a sufficient extent.

One of the main purposes of application of high pressure in die casting is to minimize shrinkage. In HPDC, no extra metal is generally provided to reduce shrinkage porosity which is a result of volumetric contraction.

Many die casters still find shrinkage related porosity despite of applying enough pressure. Research in the area suggested that the pressure applied can be different than the actual pressure developed inside cavity. It happens because of insufficient biscuit size or too big a size and unexpected solidification. Our neural networkmodel has learned that the pressure which develops in the cavity is a decisive factor as shown in our results section later.

The extreme temperature and presence of water atdie surface can produce porosity due to steam.Water can accumulate on die from sprayer andleaking water cooling lines.

If the biscuit is too small it can solidify first or evenmetal in shot sleeve can solidify which can take thepressure off from cavity. If the biscuit size is wrongthen the pressure applied at the tip of plungercannot reach the desired intensification pressuremeant to remove porosity.

The process is needed to be modelled and beunderstood well to reduce defect appearances in thecastings. Thus the aim of this work is to enhance your understanding of porosity formation in die castings.

III. METHODOLOGY

Computational intelligence techniques that include artificial neural networks, genetic algorithms, simulated annealing and fuzzy logic have shown a promise in many areas including industrialengineering where the use of neural networks [6, 7,13], genetic algorithms [7] and fuzzy logic [3] isquite prominent.

The capability of Artificial Neural Networks (ANNs) to learn complex relationships well has made thema popular methodology for understanding the behaviour of complex systems like robot guidance [10], job shop scheduling [7]and die casting [6, 8, 13]. Computationally, ANNs in their most common form of a multilayer perceptron(MLP) are distributed parallel processing systems capable of a fault tolerance and efficient learning and are robust to noise and disturbances. They are connectionist structures composed of nodes called neurons and arcs connecting the neurons with weights associated with the arcs. Weights are adaptable and they are the main learning parameters of the network. The network learns typically by using a back- propagation learning algorithm [11] which updates the weights. The network has generally three types of layers called input, output and hidden layers. The information is presented in a pre-processed or raw format into the input layer of the network and the predictions are obtained at the output layer of the network. Mathematically, a MLP can be seen as either:

$$y_j = \Phi\left(\sum_{\substack{i=1\\ j=1}}^{\substack{i=n\\ j=m}} x_i w_{ij}\right)$$

Where,

Φisa sigmoidfunctionlike

$$f(x) = \frac{1}{1+\exp(-x)}$$

$y_j$is the j[th]neuron in the currentlayer,

$x_i$is the feed-in from the previous layer, and

$w_{ij}$are the weights connecting the two layers,or it can also be represented in the matrix form as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ \cdot \\ y_n \end{bmatrix} = \Phi \begin{bmatrix} w_{11} & w_{12} & \cdot & \cdot & \cdot & w_{1m} \\ \cdot & \cdot & \cdot & \cdot & \cdot & w_{2m} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ w_{m1} & \cdot & \cdot & \cdot & \cdot & w_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{bmatrix}$$

The MLP adjust the weight matrix during thelearning and is able to generalize for the data that ithasn't seen during the learning. Please note thatsigmoid function Φ is applied to each individualelement of the matrix after multiplication. An MLP were selected for this work as the aim of the current research is an understanding and modelling of the casting defects in terms of machine parameters.

IV. EXPERIMENTAL SETUP

We have used MLP to model location and quantityof porosity in a high pressure die casting. The data used to train the network consisted of process parameters related to porosity and location and quantity measures of porosity in the castings. The process parameters included 1st stage velocity, 2[nd]stage velocity, change-over position, intensification of tip pressure, cavity pressure, squeeze tippressure, squeeze cavity pressure and biscuit thickness. The quality measures were X-Ray quality grades at four different locations used to represent porosity defects. The network was train edusing back-propagation algorithm [11]. The output of the network was the quality measures at four different locations named A, C, E and F. These quality measures are X-Ray grades ranging from one to four with one representing minimum level of porosity at the designated location and four as the worse. An occurrence of porosity level of four on any of the four locations of die casting results in a product being rejected. For accuracy and knowledge extraction reasons we have treated the porosity as a function approximation problem. The MLP that we have used to model die casting machine behaviourand to predict porosity defects is shown in Fig.5.

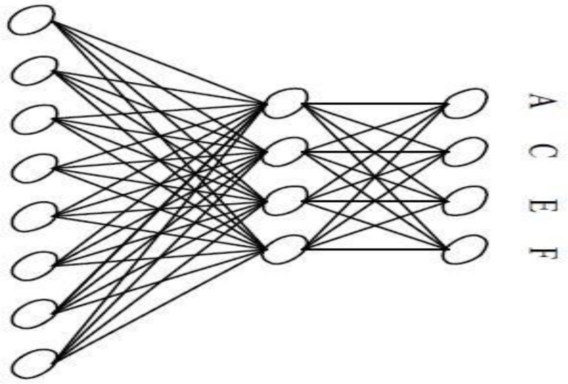

Figure 5: The neural network model used in this work to predict porosity at different physical locations in a 95mm AY2 Die Casting.

V. RESULTS

Aftermodellingofdiecastingprocesswithan MLPtoasufficientdegreeofaccuracy,weconductedconventionaldiecastingtestsby varyingoneofthe processparametersand keepingtheotherconstant. Thiswasdone withasimulatedprocessratherthan on actualdie casting machineas forthe experimentation on a die casting machine could resultaconsiderablewasteofresources intermsof metal, manpower and energyand incurs asignificant cost. Fig.6 shows a relationshipbetweenthequantitymeasures of porosityand the logarithmofslowstage velocity.Theslowvelocity-porositycurve showthattheobtainedresultsarein agreementto what has been obtained by[4], modeledmathematicallyin[5]andas suggestedby [12].The neuralnetworkmodel ofporosity show thattheporositydecreases sharplywithincreasein1st stagevelocity(slowspeedvelocity)andthen thecurve's sharpness decreases as thevelocityapproaches Garber'scriticalvelocity. It couldbe noticedthat thenetworkisgeneralizingwellhereandisable tomodelthe correctporositybehaviour.

Itisnoticeable foralltheresultsthatthelevelofporosity is constant on aminimumlevel forlocation C and F at the casting.

The data was collected from a machine which was producingcastings with the requirement to move porosity awayfromlocationsA,C,EandF. Itseemsthattheoperationwassuccessfultokeep porosityaway fromlocationsC andF.

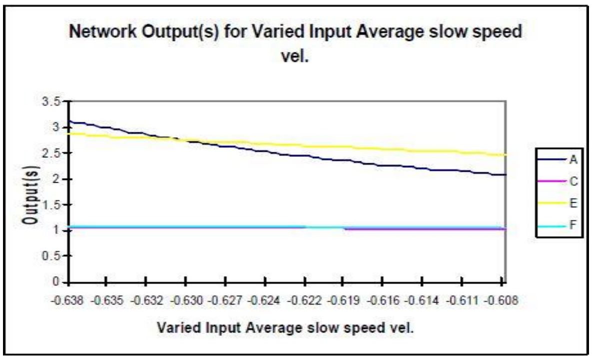

Figure 6: Relationship between the level of porosity and the logarithm of slow stage velocity (also known as 1st stage velocity).

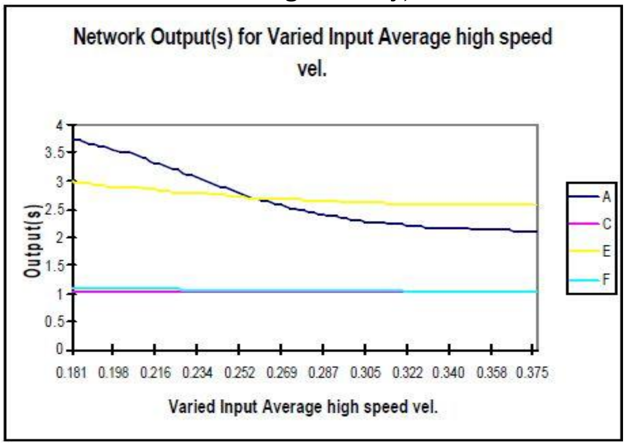

Figure 7: Relationship between the level of porosity and the logarithm of high stage velocity (also known as 2nd stage velocity).

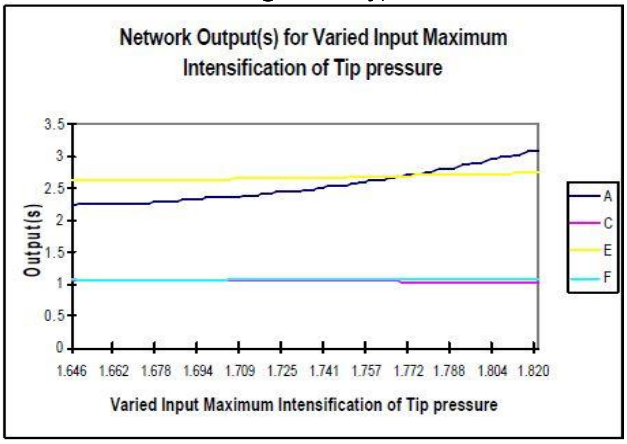

Figure 8: Relationship between the level of porosity and the logarithm of intensification of tip pressure.

The average high speed velocity, also known as second stage velocity (Fig. 7) has a purpose to meet the resistance offered by gate and runner system and to inject the metal immediately as it reaches the end of shot sleeve. The critical high speed velocity is found to bewith in the range of sensitivity analysis and it can be calculated as follows from the graph.

Critical 2nd stage shot velocity is *ALog*(0.375) = 2.371 m/s, where *ALog*(.) is the Antilog to the base10.

This observation is interesting in the sense that it shows clearly the ability of the neural network to model die casting process well along with the next observation .

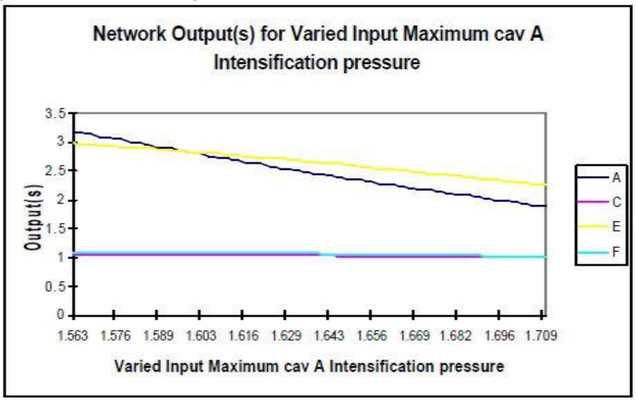

Figure 9: Relationship between the level of porosity and the logarithm of maximum cavity "A" pressure. Note that the machine used to collect data was a multi cavity machine. Similar results were obtained for the other die cavity.

The Fig. 8 should be seen in tandem with the Fig. 9 - the maximum cavity. "A" pressure in Fig. 9 is low in magnitude comparing to the intensification of tip pressure in Fig. 8. In fact, part of the tip pressure is transferred to the cavity. Please note the die under consideration is a multi-cavity die, hence we are referring it as "Cavity A". The neural network isable to learn that it is this factor which has the realeffect on porosity and show a decreasing trend in porosity level as the pressure inside cavity increases.

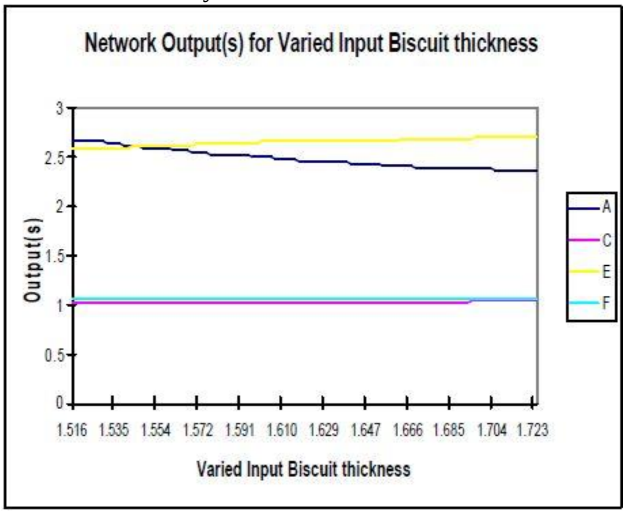

Figure 10: Relationship between the level of porosity and the logarithm of a biscuit size.

The results shown in Fig. 10 are interesting in the sense that they are conflicting to that available in the literature [2]. We can see a slight increase in porosity at the location E (in conflict to the literature) and a decrease in porosity at the location A (in accordance to the literature). It may have to do something with the thermal state of the die. It can also be interpreted as a different critical biscuit size requirement to reduce porosity at different locations. This finding is significant and requires further investigation.

VI. CONCLUSIONS

Inthis paperan attempt was made toimprovecurrent modellingand understandingofporosity defects inHPDC machines.We have conducted conventional diecastingtestswithaneuralnetwork modelof HPDC machine and comparedthe obtained results with thecurrentunderstanding of the porosity defects. Whilemostof our findings correspondwelltoestablishedknowledge inthefield,someofourfindingarein conflictwiththe previous studies of die castingand assuchare significantandrequire furtherinvestigation.

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