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Chapter XI

High-Pressure Die-Casting Process Modeling Using Neural Networks

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Abstract

This chapter presents the application of a neural network to the industrial process modeling of high-pressure die casting (HPDC). The large number of inter- and intradependent process parameters makes it difficult to obtain an accurate physical model of the HPDC process that is paramount to understanding the effects of process parameters on casting defects such as porosity. The first stage of the work was to obtain an accurate model of the die-casting process using a feed-forward multilayer perceptron (MLP) from the process condition monitoring data. The second stage of the work was to find out the effect of different process parameters on the level of porosity in castings by performing sensitivity analysis. The results obtained are in agreement with the current knowledge of the effects of different process parameters on porosity defects, demonstrating the ability of the MLP to model the die-casting process accurately.

Introduction

HPDC is a process used to produce various structural elements for the automotive industry, such as transmission cases, engine sump, rocker covers, and so on. The process begins with pouring melted aluminum in the shot sleeve cylinder through a ladle. After the die is closed, the metal is pushed inside the die cavity by moving a plunger. The plunger starts initially with a low velocity, then the velocity increases during the piston's motion, and the velocity is decreased at the end when nearly all the liquid metal is injected into the die. The metal is injected through gate and runner system at a high velocity and pressure. The die is then opened and a robotic arm extracts the solidified part. The die is lubricated to facilitate the extraction of casting and to avoid soldering of the metal with the die surface. The extracted casting with a biscuit is then cooled down with water and is placed on a conveyer belt for further treatment or otherwise stored on a rack for quality-control tests.

The HPDC process is a complex process, consisting of over 150 inter- and intradependent process parameters. For example, there is a dependency between the gate velocity, the fill time, and the die temperature (Davis, 1978). If the fill time and the gate velocity are optimized, the die temperature becomes less critical. The interaction between the fill time and the metal pressure is also well-known (Walkington, 1990). The complexity of the process results in many problems like blistering and porosity. While the complexity of HPDC makes it difficult to obtain an accurate physical model of the process, having an accurate model of the die-casting process is paramount in order to understand the effects of process parameters on casting defects such as porosity.

Porosity is a defect in which the HPDC machine produces castings with pores in them as a result of either gas entrapment or vacuum due to poor metal flow at the location of pore occurrence. Porosity is by far the most highly occurring defect in automotive engine castings, resulting in the largest percentage of scrap of engine-component castings (Andresen & Guthrie, 1989). At the same time, porosity is one of the most difficult defects to eliminate in die casting. It is in the best interest of the industry (e.g., car manufacturers) and the consumer of die castings that porosity is eliminated completely from the castings, but this is not always possible to do with the current level of process understanding. The industry generally has to settle to move porosity to different noncritical locations in a casting rather than to remove it completely. In addition, attempts to eliminate porosity defects can affect other process settings and result in other casting defects.

Understanding of how HPDC process parameters influence casting defects such as porosity can eventually lead to determining the optimal process parameters to reduce the chance of defects occurring in the castings. The variety and often conflicting nature of the states of process parameters makes it hard in practice to achieve a globally optimized process with no defects in castings. Thus, the industry is generally opting for defect reduction on the basis of intended use of the casting; for example, a casting that has to be attached to other parts using bolts should not have weakness close to the bolt hole. It is crucial that there is either low or no porosity in the area close to the hole, while defects that lie in other parts of the same casting that does not affect structural integrity of the casting can be tolerated.

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