Available online at www.sciencedirect.com
ScienceDirect
Procedia CIRP 56 (2016) 209 – 214
www.elsevier.com/locate/procedia

9th International Conference on Digital Enterprise Technology - DET 2016 – "Intelligent Manufacturing in the Knowledge Economy Era

Visual Analytics as an enabler for manufacturing process decision-making

Danielle Soban[a*], David Thornhill[a], Santosh Salunkhe[a], Alastair Long[a]

[a]*Queen's University Belfast, Ashby Building, Stranmillis Road, Belfast BT9 5AH, United Kingdom*

*. Tel.: +44(0)2890974181; fax: +44(0)2890975598. *E-mail address:* d.soban@qub.ac.uk

Abstract

The goal of an optimal manufacturing process is to maximize product performance while minimizing cost, time, and waste. A critical component of this optimization is the appropriate selection of process parameters. While central physical concepts often serve as a starting point, specific parameter selection is frequently done manually, based on operator skill, experience, and intuition. As a result, process optimization is often iterative, non-repeatable, and lacking in traceability. Further, there is no fundamental insight gained into the relationship between process parameter selection and critical process outputs. This paper explores the use of visual analytics as an enabler for manufacturing process decision making. An emerging science, visual analytics couples analytical reasoning with the substantial capability of the human brain to rapidly internalize and understand data that is presented visually. Through the use of interactive interfaces, visual analytics provides a mechanism through which the operator, engineer, and decision-maker can cooperate in real-time with both simulation, experimental, and operational data, facilitating trade studies, what-if analysis, and providing crucial insight into correlations and relationships that drive process optimization. As an exemplar, the concept of visual analytics is applied to the simulation of a notional high pressure die casting process, with the goal of gaining insight into those parameters that contribute to high scrap rates, particularly air entrapment.

Peer-review under responsibility of the scientific committee of the 5th CIRP Global Web Conference Research and Innovation for Future Production

Keywords: high pressure die casting; visual analytics; manufacturing process; decision-making

1. Introduction

High pressure die casting (HPDC) is the dominant means of producing aluminium alloy castings for the automotive industry. Traditionally, it was primarily used for casting engine components but as the requirements to reduce cost and weight have increased and sustainability demands full recyclability, HPDC is now also being used to cast complex car body components such as sub-frames, suspension components and even the structural framework for car doors. Across the industry, the complexity of castings is tending to increase with finer detail applied to minimise unnecessary material. This of course increases the difficulty for the HPDC industry to manufacture consistent castings.

1.1. The High Pressure Die Casting Process

In essence the high pressure die casting process is quite simple. Molten metal, in this case aluminium alloy, is lifted in a crucible attached to a robotic manipulator from a holding furnace and is decanted from the crucible into a shot tube through a hole in the top; at this point the metal only fills the lower half of the shot tube (Fig. 1a). A piston in the shot tube pushes the metal forward towards the die at moderate velocity (typically below ½ m/s) causing the level to rise until the tube is completely full (Fig. 1b); during this phase a vacuum is applied to the die to reduce the possibility of entrained air being trapped in the casting. This achieved, the piston velocity increases twentyfold, filling the die with metal in approximately one tenth of a second (Fig. 1c). The die being liquid cooled causes the liquid metal in contact with its surface

Peer-review under responsibility of the scientific committee of the 5th CIRP Global Web Conference Research and Innovation for Future Production
doi:10.1016/j.procir.2016.10.056

to chill and over a few seconds the casting will solidify. When the metal is completely solid, the die halves open allowing a robotic manipulator to grab the casting as ejector pins push it away from the fixed die (Fig. 1d). With this completed the die closes and the process can begin again, with the whole cycle takes less than 2 minutes for large parts.

Ideally when castings are produced they should all be perfect. Realistically, there will always be some scrap castings manufactured; perhaps one or two percent is acceptable. Unfortunately, with some complex parts this can rise to as much as 10% and even higher. Of course the scrap is recycled, although each time metal is remelted energy is consumed and a small amount of the aluminium will be lost as it oxidises to form dross. In addition the cost of running the casting machine is lost and the factory's casting capacity is reduced.

Although the casting process is in essence simple, there are hundreds of parameters that affect the process, resulting in unacceptable scrap rates that further lead to loss of revenue and a decrease in factory casting capacity. Traditionally, all of the parameters are manually adjusted to produce good castings based on the experience of the die casting engineer. Experience will have determined boundaries for many parameters to allow good castings for most of the time. However, this manual process if often untraceable, unrepeatable, and notably does not add overall insight into the effect of the parameters themselves on the outcome. This paper aims to address the early phase of a project to analyse the consequences of parametric variability in a production environment with the objective of making the manufacturing process as robust as possible and consequently reducing the level of scrap produced for complex automotive engine castings, such as a cylinder block.

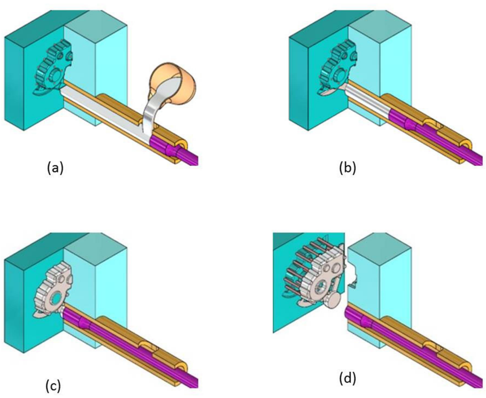

Fig. 1. Typical high pressure die casting process.

1.2. Current Die Casting Optimization

Substantial research has been done on the optimization of the high pressure die casting process. Taguchi's method has been applied by some scholars [1-3] to the die-casting process in order to establish the optimal combination of design parameters. Their study focused on investigation of effects of various die casting control parameters, including the die temperature, injection velocity, and cooling time on the defects in the castings. While other researchers used design of experiments techniques [4-7] for experimentation, the data was further analysed to optimise defects like shrinkage, gas porosity and cold shuts.

Soft computing techniques such as artificial neural networks and genetic algorithms were used by various researchers to map the complex relationship between process conditions and quality indexes [1, 8-11]. Unlike traditional hard computing, the essence of soft computing is that it is aimed at accommodating the universal inaccuracy of the real world. Thus, the principle of soft computing is to exploit the tolerance for imprecision, uncertainty, and partial truth to achieve robustness, low solution cost, and better rapport with reality[12].

In other research, computational fluid dynamics software packages such as Meltflow and ProCAST were used to simulate, verify experimental results and optimize casting design/process by using qualitative parameters [11, 13, 14]. For analysis of defects, computer aided casting simulation techniques can be efficient and accurate. The quality and yield of the casting can be efficiently improved by computer assisted casting simulation technique in shortest possible time and without carrying out the actual trials on foundry shop floor. However, optimization for casting integrity requires a quantitative casting integrity assessment technique, which allows the modelling and quantification of defects [15]. Krimpenis et al., have rightly stated that although die-casting parameters have been studied by various researchers, a unified method that can optimize all process parameters simultaneously regarding one criterion or a combination of criteria is still at its infancy [11]. Die-casting is a typical multidisciplinary system involving many disciplines such as hydrodynamics, heat transfer and elastic-plastic mechanics and their coupled relations are intricate. Moreover there are many inherent uncertainties. Yourui et al, [16] proposed a reliability-based multidisciplinary optimization (RBMDO) model and concluded that the application of RBMDO procedure is suited to optimize the multidisciplinary system like die-casting with epistemic uncertainty.

All of the above research and optimization strategies rely on finding a single, optimum setting of parameters to maximize results and minimize defects for a specific die casting circumstance. The key difference to using a visual analytics approach to explore the same data set is the inherent understanding and insight into the behavior of the process that is gained by the analyst. This insight is then translated into parameter strategies that are applicable across a wide variety of process circumstances.