Chapter 10

Squeeze Casting Parameter Optimization Using Swarm Intelligence and Evolutionary Algorithms

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ABSTRACT

This chapter is focused to locate the optimum squeeze casting conditions using evolutionary swarm intelligence and teaching learning-based algorithms. The evolutionary and swarm intelligent algorithms are used to determine the best set of process variables for the conflicting requirements in multiple objective functions. Four cases are considered with different sets of weight fractions to the objective function based on user requirements. Fitness values are determined for all different cases to evaluate the performance of evolutionary and swarm intelligent methods. Teaching learning-based optimization and multiple-objective particle swarm optimization based on crowing distance have yielded similar results. Experiments have been conducted to test the results obtained. The performance of swarm intelligence is found to be comparable with that of evolutionary genetic algorithm in locating the optimal set of process variables. However, TLBO outperformed GA, PSO, and MOPSO-CD with regard to computation time.

INTRODUCTION

The hybrid squeeze casting process was developed by combining the distinct features such as strength, integrity, economic and design flexibility of conventional casting (gravity and die casting) and forging processes (Rajgopal, 1981). The benefits of the squeeze casting process over conventional casting and forging process are near net-shape castability, simpler tooling construction, high productivity, refined structure, improved surface finish, heat-treatability, minimum porosity and segregations, ability to cast ferrous, non-ferrous and wrought alloys (Rajgopal, 1981; Ghomashchi & Vikhrov, 2000). These benefits have helped the squeeze cast parts to find their applications in automobile parts, namely piston, cylinder, clutch housing, brake drum, engine block, connecting rod, wheels, suspension arm, hubbed flanges, barrel heads, truck hubs, and so on (Rajgopal, 1981; Ghomashchi and Vikhrov, 2000; Krishna, 2001).

The diversified applications of squeeze casting process had attracted the researchers' attention toward squeeze casting process across the globe during the 1990s and 2000s. A wide range of research has been reported using analytical, numerical and classical engineering experimental approaches. Yang (2007) determined solidification time using one dimensional analytical model such as Gracias virtual and steady state heat flow models. It should be noted that casting density and mechanical properties improve with low solidification time. Chattopadhyay (2007) carried out the solidification simulation using a numerical approach by solving Navier-Stokes equation coupled with energy equation. The solidification time was found to be inversely proportional to the interfacial heat transfer coefficient. Krishna (2001) had reported that the heat transfer coefficient in metal castings to be dependent mainly on geometry, size, casting shape, mold materials, physical, chemical and interfacial conditions and major interactions among them. You, Wang, Cheng and Jiang (2017) conducted a numerical simulation based on the finite element method using Procast software. They tried to improve the injection mechanism of the squeeze casting process by optimizing the control parameters. Li, Yang and Xing (2017) used Magma software to locate the shrinkage cavity and related defect in the squeeze cast part. The results showed that the shrinkage cavity and its defects were eliminated after adjusting the squeeze cast parameters (casting temperature, filling velocity, and squeeze pressure). However, the cast simulation software uses many assumptions and is difficult to match withthe actual casting practice. Jacob and Michael (2012) had made several assumptions while estimating the heat transfer coefficient during squeeze casting of aluminum alloys. Aweda and Adeyemi (2009) studied the effect of casting temperature and squeeze pressure on heat transfer coefficients using numerical and classical engineering experimental approaches. It is important to note that the experiments were conducted for a fixed pressure duration. Fan et al. (2010) investigated the effect of squeeze pressure variations on density, secondary dendrite arm spacing and mechanical properties without varying pressure duration and temperature influencing parameters during their experiments. They found a steady increase in the properties up to 120 MPa squeeze pressure,thereafter they remained constant. Maleki, Niroumand and Shafyei (2006; 2009) examined the influence of squeeze pressure, die and pouring temperature on density, mechanical, micro and macrostructure properties using the classical approach of varying one factor at a time Wang et al. (2016) and Jahagiri et al. (2017) studied the effect of applied pressure and pouring temperature on the mechanical and microstructure properties of aluminum and magnesium squeeze cast parts using the classical engineering experimental approach. However, the effects of die temperature and applied duration of squeeze pressure were not considered in their research work. Hong, Lee and Shen (2000) analyzed squeeze pressure, waiting time, inoculants, degassing, pouring and die temperature effects on formation of macro-segregation using classical engineering experimental approach. Rajagopal and Altergott (1985) identified many direct squeeze

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