Enhancing Rheocasting Process Control with AI-based Systems

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***Abstract*— Semisolid casting has emerged as an attractive alternative to conventional casting methods due to its potential to yield superior mechanical properties, reduce environmental pollution, and decrease production costs. However, optimizing process parameters and controlling the casting process remains challenging. Process control largely relies on human expertise, which is associated with significant time and cost expenditures. In response, this study presents a third-circle research project to investigate the correlation between the casting process and the solidification process. The study proposes leveraging AI technology to digitize the entire process control, thereby increasing the reliability and stability of cast products' quality. The research will focus on understanding the key factors influencing the casting process and developing an AI-based decision support system to aid in process parameter selection and optimization. The outcomes of this study are expected to contribute to the development of more reliable and efficient semisolid casting processes.**

I. INTRODUCTION

Manufacturing industries are facing the challenge of meeting the requirement of carbon neutrality, and casting is also no exception. Saving energy usage and limiting the pollution emission forced foundries to use a more sustainable casting process which can also maintain the cast product quality. Semisolid casting is one of those new innovative casting methods, which was initially discovered by Fleming and his Ph.D. student Spencer in the 1970s [1]. The unique casting process trimmed the cast product microstructure from a tree shape (dendritic) to a globular shape (shown in Figure 1), and it helps semisolid casting to offer better product quality, a wider range of material choices, and a longer die life. Meanwhile, it requires less energy and less emission and waste in the production process [2], [3], [4]. The semisolid casting process has two branches based on the cast route difference: (1) thixo-casting involves pre-preparing the cast stock, which is remelted to a semisolid state (containing over 50 % solid fraction) before forming the final shape. In contrast, (2) rheo-casting involves transforming liquid into a semi-solid state (containing both liquid and solid) as a middle-stage preparation before proceeding with the final forming process. Due to its cost and complexity, rheo-casting is more widely used in most applications, with RheoMetal^{TM} being a prominent example.

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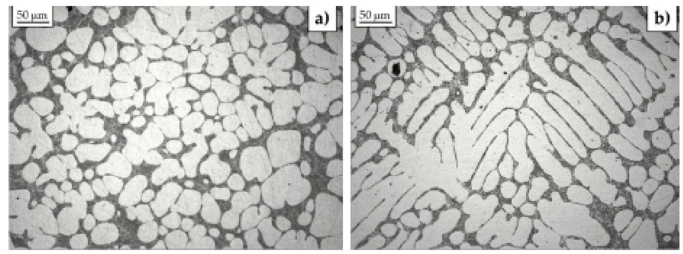

Fig. 1. The difference of A356 casting microstructure for a) the semi-solid casting; b) the traditional casting [5]

A. RheoMetal^{TM} process

The casting process of RheoMetal ^{TM} is shown in Figure 2. RheoMetal ^{TM} process, by introducing an external Entropy Exchange Material (EEM), can transform liquid metal into a semisolid slurry consisting of globular-shaped solid particles, and the next homogenization process ensures that the particles are evenly distributed throughout the melt, resulting in improved properties, and more consistent quality for the final cast product [6], [7], [8], [9].

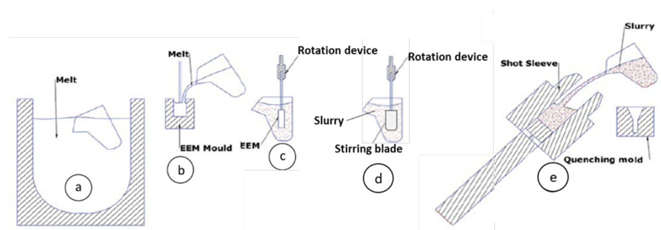

Fig. 2. RheoMetal ^{TM} slurry-making process: a) EEM preparation;b) EEM casting process; c) slurry making; d) slurry homogenization; e) final formation process [6]

II. THE CHALLENGE FOR THE SEMISOLID CASTING

Despite offering numerous benefits, semisolid casting still presents challenges in the industry application. The semisolid slurry process alters the rheology of the cast melt from close to the Newtonian fluid to non-Newtonian fluid. Those generated solid particles bring uncertainty and complexity to the production process control [5].

Jarfors et al. [10] identified that current applied rheology models were insufficient for the process prediction in semisolid casting due to the lack of consideration for the interaction between generated particle and process parameter. They suggested the Herschel-Bulkley fluid model as a more suitable alternative. However, further validation for the rheology model is still necessary for understanding the solidification route in the semisolid casting process and controlling the slurry-making process, and ultimately improving production quality.

Equation 1 [11] shows the Herschel-Bulkley fluid equation, where k is the consistency index, n is the power law exponent, $\dot{\gamma}$ [1/s] represents the shear rate, and τ_c [Pa] is the fluid yield stress, μ [Pa*s] is viscosity.

$$\mu = k(\dot{\gamma})^{n-1} + \frac{\tau_c}{\dot{\gamma}} \tag{1}$$

Semisolid casting process control highly relies on the human expert experience for the casting process parameters setting, which is also often limited to certain alloys. Understanding the process parameters is time-consuming, costly, and difficult. Furthermore, it can bring material waste and carbon dioxide emissions from errors made by humans in casting experiments. As a result, the industrial application for semisolid casting is hindered, and the potential benefits are also limited. Artificial intelligence (AI) has the potential for helping to address this issue by gaining knowledge of the casting process based on limited experimental data for various alloys and providing support for controlling the casting process of different alloys. Many researchers [12], [13], [14] have tried to use AI for defect prediction and casting parameter prediction and control in High-Pressure Die Casting (HPDC) process. They have demonstrated that AI is an efficient tool for helping to control defects in the casting product by guiding input parameter settings during the casting production process. However, for semisolid casting, it is still a lack of sufficient studies related to AI applications for improving the semisolid casting process. Utilizing AI to assist operators in enhancing efficiency and quality would be highly beneficial for the semisolid casting process.

III. Purpose of Ph.D. project

This project's main goal is to develop an AI system that improves the process control of semi-solid casting, ultimately leading to a more efficient and reliable production process.

For achieving this goal, the whole study will be divided into two steps: 1) Understanding the relationship between solidification and process parameters. In this phase, we will investigate the correlation between casting slurry preparation process parameters and solidification in semi-solid casting. This step is crucial for establishing the foundational physical theory upon which the AI system will be developed. Casting experimental settings and the result data will serve as inputs for the AI system. At the end of this stage, the AI system will acquire the knowledge of the correlation between solidification and process parameters to identify and generate the most appropriate process parameters based on alloy composition and application requirements while assisting operators in monitoring the entire production process. 2) Casting product quality control: In this phase, we will study the physical principles governing the cast product forming process and the final product quality in semi-solid casting. The cast product images and the quality test result will be fed into the AI system, allowing it to predict the quality of the cast products by analyzing the product images. This approach will enable real-time, non-destructive evaluation of cast products, facilitating rapid quality control and minimizing material wastage. By integrating the insights derived from both stages, the AI system will contribute to a more efficient, reliable, and sustainable semi-solid casting process.

The preliminary results achieved in the project indicate that the model built on the ensemble algorithm has a high potential to replace physical measurements [15], which is called thermal analyze, currently employed for collecting critical alloy data in the casting process.

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