

BLUE WATERS

SUSTAINED PETASCALE IN ACTION:
ENABLING TRANSFORMATIVE RESEARCH

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Editors

Barbara Jewett
Catherine Watkins

Creative Director

Steve Duensing

Graphic Designer

Megan Janeski

Project Director

William Kramer

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MULTIPHASE TURBULENT FLOW MODELING OF GAS INJECTION INTO MOLTEN METAL TO MINIMIZE SURFACE DEFECTS IN CONTINUOUS-CAST STEEL

Allocation: Illinois/75 Knh
PI: Brian G. Thomas¹
Co-PIs: Seong-Mook Cho², Surya Pratap Vanka¹, Seid Koric^{1,3}, Ahmed Taha³, Hyunjin Yang¹, Matthew Zappulla²

¹University of Illinois at Urbana-Champaign
²Colorado School of Mines
³National Center for Supercomputing Applications

EXECUTIVE SUMMARY

This project aims to develop comprehensive, sophisticated, and computationally intensive models to simulate transient multiphysics phenomena. In addition, we aim to understand defect formation mechanisms in continuous steel casting and to find practical ways to improve the process, which could greatly impact the steel industry. We have developed a new hybrid multiphase flow model to calculate argon gas behavior and bubble size distribution during the continuous casting process. In addition, we have simulated argon bubble transport and capture into the steel shell using Large-Eddy Simulations (LES) coupled with a Discrete Phase Model (DPM) for particle transport and capture. Furthermore, we have investigated the effect of moving magnetic fields on transient steel–argon flow patterns, surface velocity and level, and argon bubble distribution in the mold using LES simulations coupled with DPM and the magnetic induction magnetohydrodynamics (MHD) model. These simulations have been validated with lab-scale models and plant measurements and applied to reveal deeper insights into defect formation, enabling the investigation of optimal process conditions.

RESEARCH CHALLENGE

Continuous casting is used to manufacture more than 96% of steel worldwide [1]. Many defects in final steel products are related to complex multiphysics phenomena during continuous casting, including turbulent multiphase flow, particle transport and capture, magnetohydrodynamics, heat transfer, solidification, and thermal–mechanical behavior, as shown in Fig. 1a and 1b. This process is extremely difficult to study with lab-scale models and plant experiments owing to the hostile environment of the molten steel and the many process variables, including the thermal properties of steel and slag, process geometries, and process conditions. Thus, this work applies transient multiphase flow simulations on Blue Waters to quantify argon gas behavior, bubble size distribution, and bubble transport and capture, which influence bubble defect formation. We then studied the effect of moving magnetic fields on the flow pattern in order to investigate ways to reduce defects related to entrapped bubbles and inclusions.

METHODS & CODES

We developed a new hybrid multiphase flow model [2,3] that couples the Eulerian–Eulerian two-fluid model approach together with DPM and applied it to simulate bubble transport and behaviors, including gas pocket formation, breakup, coalescence, and size distribution evolution in the nozzle and mold. In addition, we used LES coupled with DPM and MHD models to simulate transient molten steel–argon bubble flow with and without an Electromagnetic Level Stabilizer (EMLS) moving field. We conducted these simulations using the commercial CFD program, ANSYS Fluent High-Performance Computing (HPC) on Blue Waters XE nodes. To calculate bubble transport and capture into solidifying steel shells in the mold, we implemented the LES–DPM–MHD model coupled with the advanced force balance (on each bubble at the solidification front) capture criterion model [4,5] into Blue Waters XK nodes with the multi-GPU based in-house code CUFLOW [6].

RESULTS & IMPACT

We simulated the complex gas behavior including gas pocket formation, shearing off of the gas pocket into bubbles, volumetric expansion, breakup, coalescence and evolution of the bubble size distribution in the steel continuous caster using the hybrid multiphase flow model, which has been validated by comparison

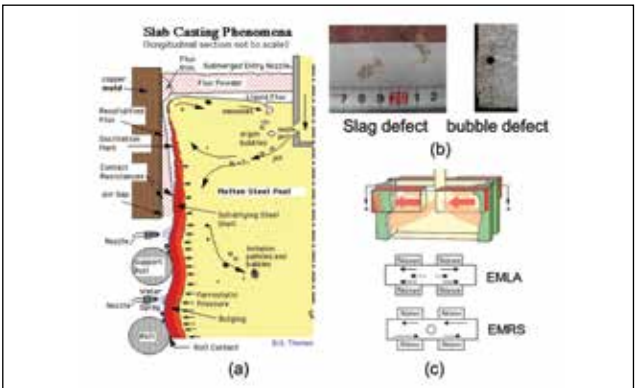


Figure 1: (a) Schematic of multiphase flow phenomena in continuous casting (CC) mold, (b) defects in CC, and (c) electromagnetic level accelerating (EMLA) and rotating stirring (EMRS) systems.

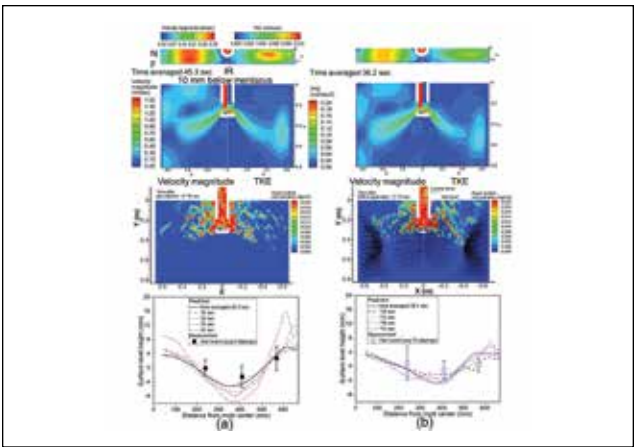


Figure 2: Multiphase flow patterns, argon bubble distribution, and surface level variations in continuous casting (CC) mold (a) without and (b) with EMLS (Electromagnetic Level Stabilizer).

with several lab-scale experiments [7]. The model was able to simulate realistic argon bubble distributions in the molten steel pool in the continuous caster, which enabled more accurate prediction of bubble defects, including their size and location in the steel product.

Argon bubble transport and capture into the steel shell in the mold during continuous slab casting with and without double-ruler Electromagnetic Braking (EMBr) were simulated using LES–DPM–MHD models with particle capture. The models showed good agreement with measurements of size distribution and location of captured bubbles in the steel slabs. The models also revealed the effect of bubble size on residence time of the bubbles in the mold, with and without double-ruler EMBr, which is an important factor influencing bubble defect formation that is being quantified in this work [4,5].

Furthermore, we quantified transient flow patterns, surface velocity and level, and argon bubble distribution in the mold, with and without an EMLS moving magnetic field, using the LES–DPM–MHD model as shown in Fig. 2. The LES models showed good agreement with measurements of surface velocity, surface level profiles, and their fluctuations from nail dipping tests conducted in the commercial caster. The EMLS reduced up-and-down wobbling of the steel jet and made the jet deflect slightly downward due to the strong electromagnetic forces induced near the narrow face. Thus, the jet flow had a longer path toward the mold top surface, resulting in lower and more stable surface velocity and level, which can reduce slag-entrapment defects (Fig. 1b). In addition, the strong Lorentz forces near the narrow faces braked the jet and transported the argon bubbles farther away from the steel shell, which decreased the chance of bubble-capture defects.

The validated transient multiphase flow models on Blue Waters can be applied in parametric studies to find optimum process conditions to reduce defects. This could enable significant savings in the cost of steel production and improve product quality.

WHY BLUE WATERS

Development of accurate multiphysics models of steel continuous casting for a more detailed understanding of defect formation mechanisms and improvement of the process requires great computational resources to be accurate. Specifically, to capture the complex and interrelated phenomena on a micrometer scale, the large domain size (over 1 m³) and long timescale of some of the macroscale flow phenomena (up to a minute) require many computational cells (~100 million) and many timesteps, owing to the very small timestep size (smaller than ~10⁻⁴ seconds). In the current work, we achieved an over 3,000 times faster calculation with ANSYS FLUENT HPC on Blue Waters XE nodes, compared to an ordinary workstation PC. Furthermore, the multi-GPU in-house CUFLOW codes accomplished a good parallel scalability on Blue Waters XK nodes, showing only 48 hours of wall-clock time for 30 seconds of fully developed LES–MHD flow in a 14-million-cell domain. Thus, the parallel supercomputing environment on Blue Waters is greatly contributing to accurately quantifying the complicated multiphysics phenomena with high resolution in order to improve understanding of defect formation in this complex commercial process.

PUBLICATIONS & DATA SETS

Jin, K., S.P. Vanka, and B.G. Thomas, Large Eddy Simulations of Electromagnetic Braking Effects on Argon Bubble Transport and Capture in a Steel Continuous Casting Mold. *Metallurgical and Materials Transaction B*, 49B (2018), pp. 1360–1377.

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