

Machine Learning for Predicting Chemical System Behavior of $\text{CaO-MgO-SiO}_2\text{-Al}_2\text{O}_3$ steel making slags Case Study

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1 INTRODUCTION

In today's steel industry, the drive for efficiency and sustainability has spurred the adoption of innovative technologies, notably **Artificial Intelligence (AI)**, which promises to revolutionize complex processes. By harnessing AI trained on data from productive sectors, including **thermodynamic calculations** from FactSage 8.1 software, this study aims to comprehend the liquid fraction zones of the **$\text{CaO-MgO-SiO}_2\text{-Al}_2\text{O}_3$** slag system, crucial for steel quality. Additionally, it focuses on predicting MgO percentages in the solid phases, vital for refining steel and ladle longevity, the proposed AI model ensures precise resource allocation, fostering **economic benefits and sustainable practices by minimizing process waste**. This research evaluates the performance of the AI model in **predicting MgO percentages in the solid phases of slag**, as well as **forecasting the percentages of the liquid fraction**, thereby offering insights into enhancing steelmaking efficiency.

2 METHODS

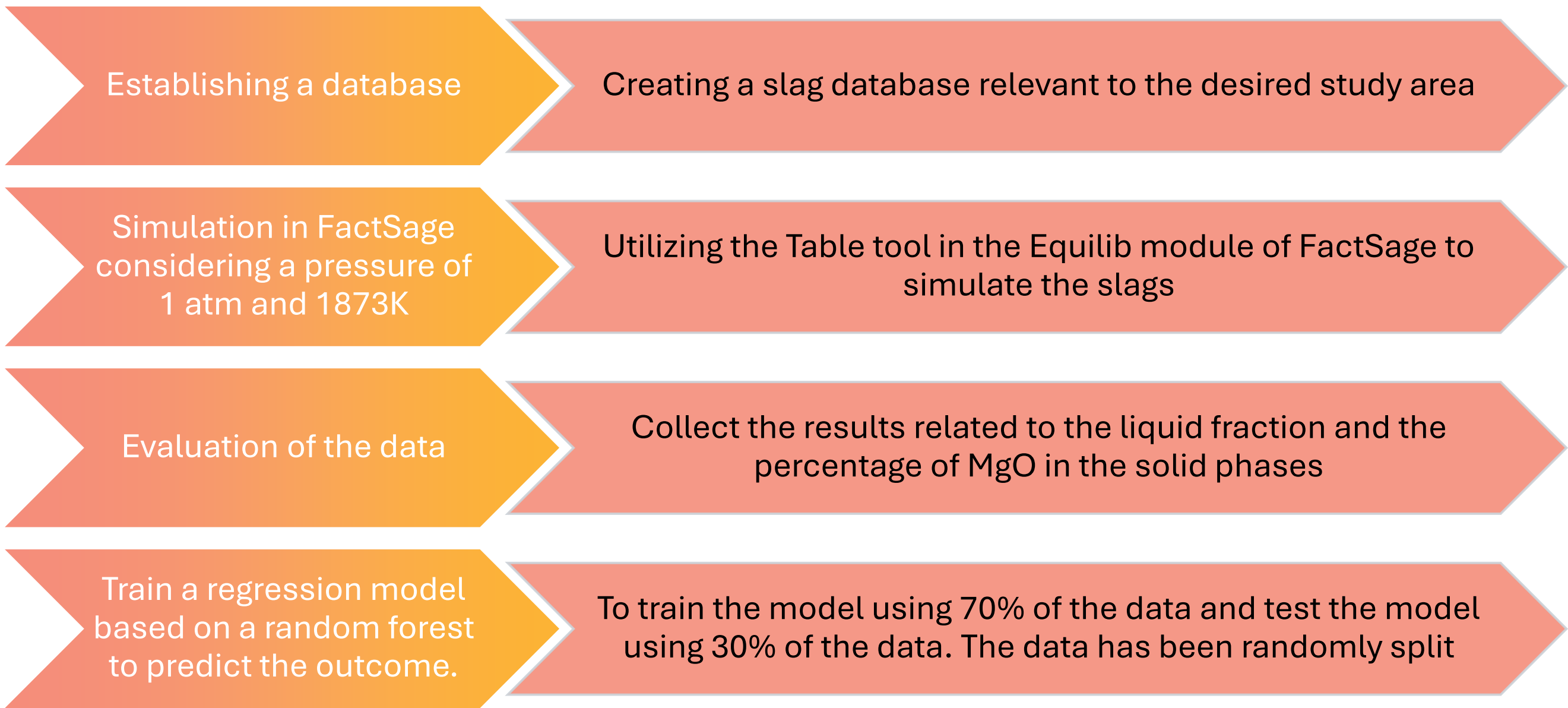


Figure 1 – Simplified Flowchart of the Methodology for Data Generation and AI Model Training

3 RESULTS | DISCUSSION

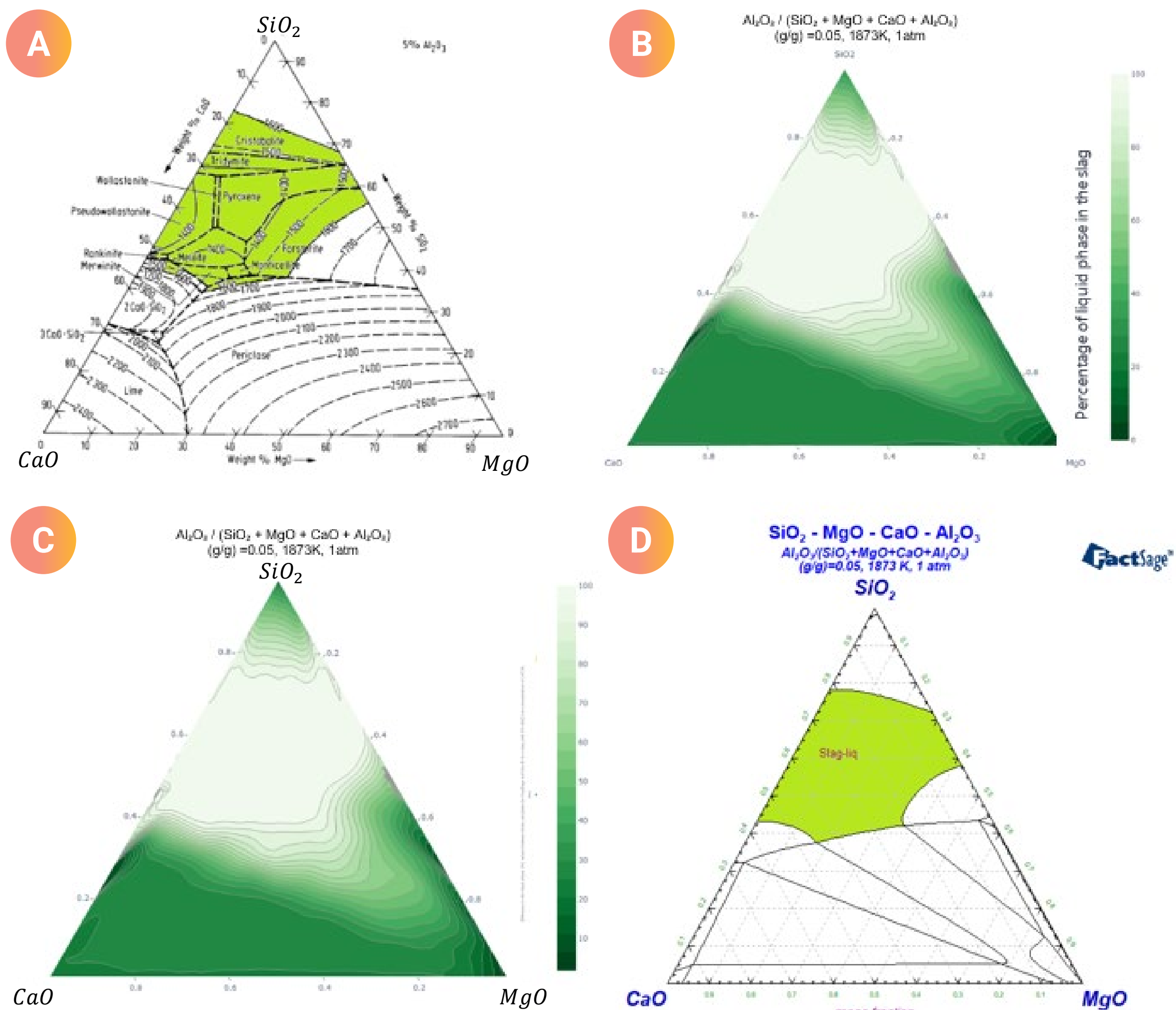


Figure 2: (A) Liquidus surface: 100% Liquid in green (Osborn et al., 1954); (B) Liquidus surface calculated by FactSage; (C) Liquidus surface calculated by AI; (D) Liquidus surface calculated and built using the Phase Diagram mode in FactSage. The diagrams are made in the $\text{CaO-MgO-SiO}_2\text{-Al}_2\text{O}_3$ system with 5% Al_2O_3 by mass with temperature at 1873K and pressure at 1 ATM.

TABLE 1 – Variation of oxides in the database used for AI training. The variation steps for each oxide are set at 1. Temperature at 1873K and pressure at 1 ATM.

	% Al_2O_3	% CaO	% FeO	% MgO	% MnO	% SiO_2
Maximum	50	87	2	30	1	50
Minimum	0	20	2	0	1	10

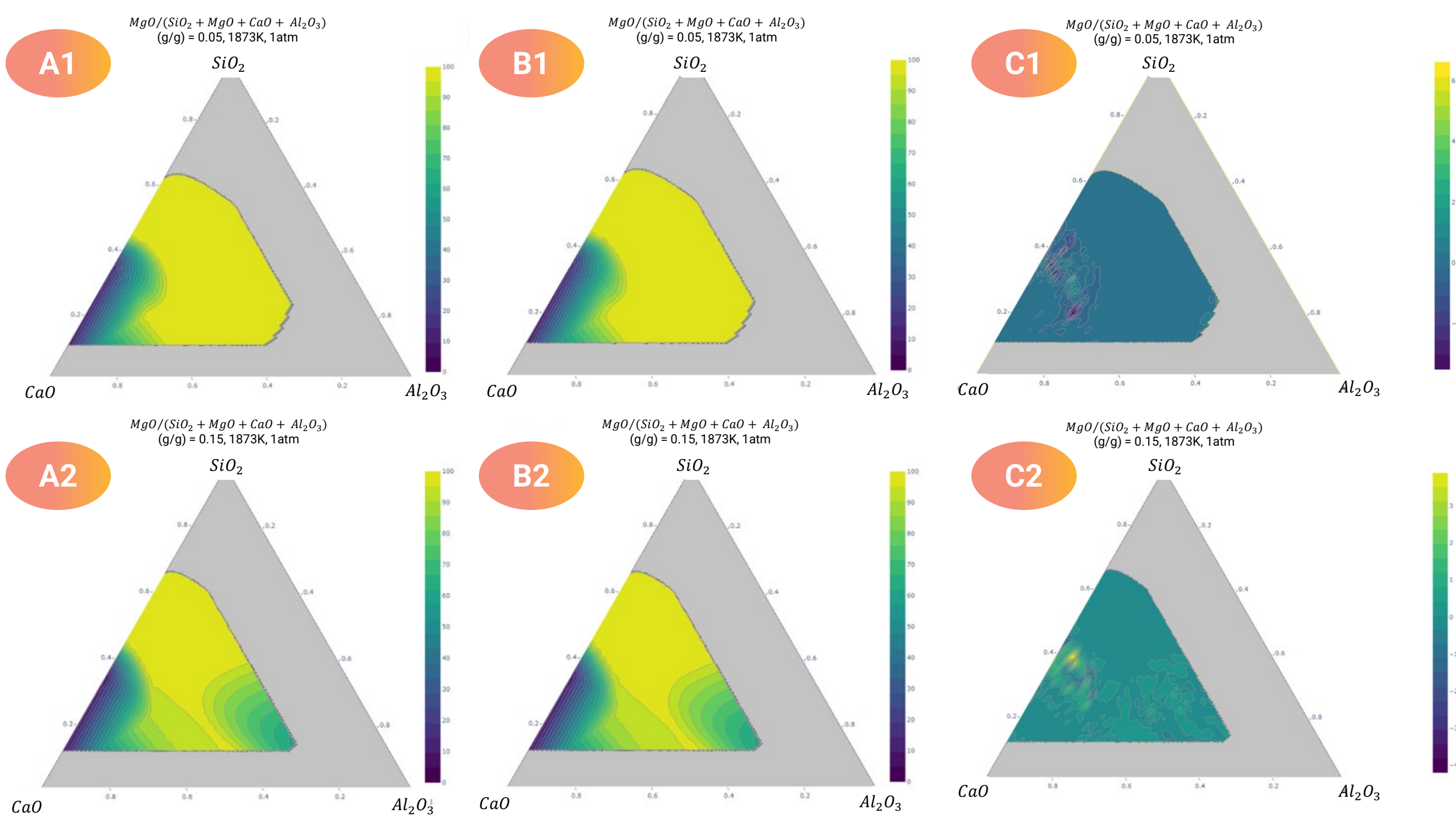


Figure 3: In the diagrams, (A) represents the percentage of liquid fraction of the slag calculated by FactSage at 1873K. (B) represents the percentage of liquid fraction of the slag calculated by the AI model. (C) represents the difference between the responses from FactSage and the AI Model. The numbers 1 and 2 appearing after the letters represent 5% and 15% of MgO in the slag, respectively.

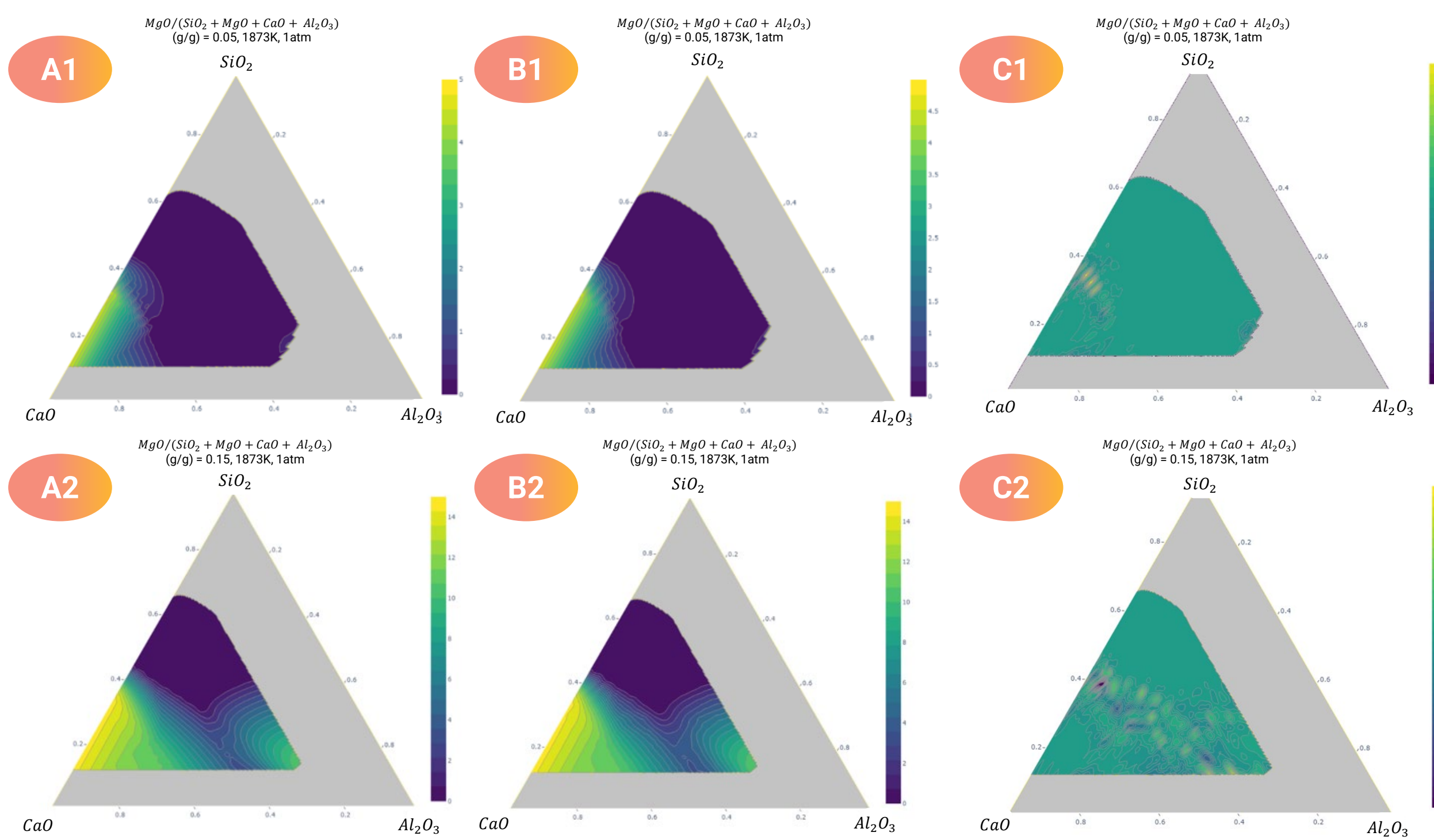


Figure 4: In the diagrams, (A) represents the percentage of MgO in solid fraction of the slag calculated by FactSage at 1873K. (B) represents the percentage of MgO in solid fraction of the slag calculated by the AI model. (C) represents the difference between the responses from FactSage and the AI Model. The numbers 1 and 2 appearing after the letters represent 5% and 15% of MgO in the slag, respectively.

4 CONCLUSION

The integration of AI technology in industrial processes significantly enhances efficiency and provides real-time responses. This study compares an AI model's predictions based on FactSage with actual outcomes, highlighting FactSage's importance for understanding slag processes. However, **AI offers advantages in refining process parameters, optimizing slag composition, and minimizing waste**. Results indicate AI's potential to accurately predict slag behavior, aligning with established theoretical frameworks. **Increasing data input improves model accuracy, suggesting potential for specialized models**. Future research could explore AI's interpretation of solid precipitate formation, enhancing its utility alongside laboratory tests and thermodynamic tools.