# Development of Small Data-Based Mathematical Models for Industrial AI Applications

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Abstract— This study explores the potential of applying industrial AI using small data-based mathematical models in data-constrained environments. Mathematical models for predicting slurry viscosity, particle size distribution, and color were developed based on actual process data. The proposed models achieved high prediction accuracy with limited data, supporting effective process monitoring and data-driven decision-making. These findings suggest that small data-oriented mathematical modeling is a viable approach for the practical deployment of industrial AI.

Keywords— Industrial AI, Mathematical Modeling, Small Data Modeling, Prediction, Data-Driven Manufacturing

#### I. INTRODUCTION

Industrial AI plays a key role in improving efficiency and quality in manufacturing by leveraging large-scale data and algorithms. However, complex industrial advanced environments and high data acquisition costs often restrict access to sufficient high-quality data, limiting the application of big data-based AI [1]. Under such conditions, methods that utilize small data containing essential information are necessary. Mathematical models, based on physical laws and requiring relatively few data points for parameter estimation, provide reliable predictions even with limited data [2]. This study applies regression and predictive modeling techniques suited for small data to analyze and forecast key industrial process variables. By demonstrating the development and application of small data-based mathematical models in slurry viscosity, particle size distribution, and color prediction for ceramic and textile dyeing processes, this work aims to support the broader practical use of industrial AI.

### II. CONCEPTUAL FRAMEWORK OF INDUSTRIAL AI

Industrial AI integrates diverse data sources such as quality metrics, equipment status, supply chain information, and customer feedback to address complex challenges in industrial environments. Within the Industry 4.0 paradigm, AI serves a central role in smart manufacturing by enabling autonomous diagnostics, predictive maintenance, and quality control. Explainable AI technologies further enhance the transparency and reliability of AI-driven systems [3].

Industrial AI supports a wide range of tasks including process optimization, defect reduction, demand prediction, and new product development. The system evolves through a feedback structure that enables continuous learning and iterative improvement based on accumulated data [4].

Figure 1 presents a conceptual framework encompassing major data inputs, key functions, application domains, and performance feedback cycles. This framework illustrates how industrial AI contributes to the advancement of manufacturing through real-time data collection, analysis, and prediction-based decision support.

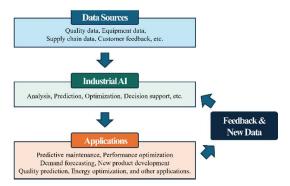


Fig. 1. Conceptual framework of Industrial AI with data sources, core functions, and application areas.

### III. CASE STUDIES OF MATHEMATICAL MODELING

This chapter presents mathematical predictive modeling cases utilizing real-world data collected under limited small data conditions, focusing on quality improvement and process stability in ceramic manufacturing and textile dyeing.

### A. Slurry Viscosity Prediction in Ceramic Manufacturing Processes

Accurate prediction of time-varying slurry viscosity is essential for stabilizing the spray drying stage in ceramic powder manufacturing. In this study, slurry viscosity was measured at regular intervals over a 24-hour period following the ball milling process, under controlled process conditions. Sixteen regression models were evaluated, and thirteen of them achieved a coefficient of determination (R²) of 1.000, demonstrating excellent predictive accuracy even with limited data [5]. Figure 2 illustrates the comparison between the measured viscosity values and the model predictions. The close agreement between the two confirms the reliability of the modeling approach in capturing viscosity variation. A user interface was also developed to enable field operators to input values and monitor prediction curves in real time, facilitating responsive control and contributing to process stability.

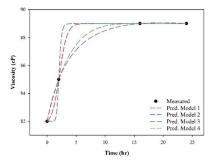


Fig. 2. Example of mathematical modeling for industrial AI: Predictive modeling of slurry viscosity in ceramic processes.

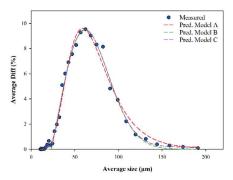


Fig. 3. Example of mathematical modeling for industrial AI: Predictive modeling of particle size distribution in ceramic processes.

# B. Particle Size Distribution Prediction in Ceramic Manufacturing Processes

To predict particle size distribution, which directly affects product quality in ceramic spray drying, samples within the same lot were repeatedly measured and averaged to obtain reliable data. Based on this, time-series predictive models for various particle size indicators (D10 to D99, minimum, maximum, and mean values) were developed [5]. Figure 3 presents a comparison between three mathematical models and measured data, confirming that the models effectively replicate the actual measurements. The developed predictive system enables real-time monitoring of particle size distribution, thereby enhancing accuracy and efficiency in onsite quality control.

### C. Color Prediction in Textile Dyeing Processes

In textile dyeing processes, accurate prediction of color characteristics according to dye concentration is essential for minimizing reproducibility issues and quality variation.

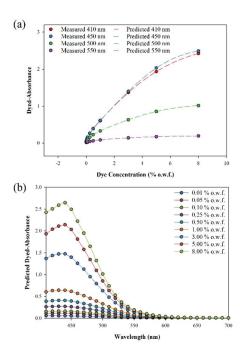


Fig. 4. Example of mathematical modeling for industrial AI: Predictive modeling of color properties based on dye concentration in textile dyeing processes.

This study developed mathematical models for absorbance based on reflectance data from actual processes, converting reflectance to absorbance for single dyes [6]. Among these models, yellow dye was selected as a representative case, with results shown in Figure 4. (a) compares measured and predicted absorbance at four wavelengths, verifying model accuracy, while (b) visualizes predicted spectra under varying concentrations within the 410–700 nm range, highlighting concentration-dependent spectral trends. The single-dye model was further applied to mixed dyes, achieving high prediction accuracy and consistent color reproducibility compared with measured values. This approach supports systematic quality control in dyeing by reducing variability and operator dependence.

### IV. CONCLUSION

This study aimed to develop small data-based mathematical models for practical industrial AI applications in data-limited environments. Focusing on slurry viscosity and particle size distribution in ceramic manufacturing processes and color prediction in textile dyeing, the feasibility of applying field-acquired data models was examined.

The proposed models achieved high predictive accuracy despite limited data and were implemented with user interfaces for real-time monitoring and data-driven decision support. These findings suggest that mathematical modeling can enhance process quality and operational efficiency, especially where big data-based AI is challenging to apply. Future work will expand the models to various processes and industries, pursuing improved prediction accuracy and broader applicability through integration with industrial AI. This approach is expected to support smart manufacturing and AI transformation (AX).

## ACKNOWLEDGMENT

This work was supported by Korea Evaluation Institute of Industrial Technology(KEIT) grant funded by the Korea government(MOTIE)(RS-2023-00259964, Development of Auto Re-learning Common Service Platform Technology for Ceramic Industry DX based on Cloud).

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