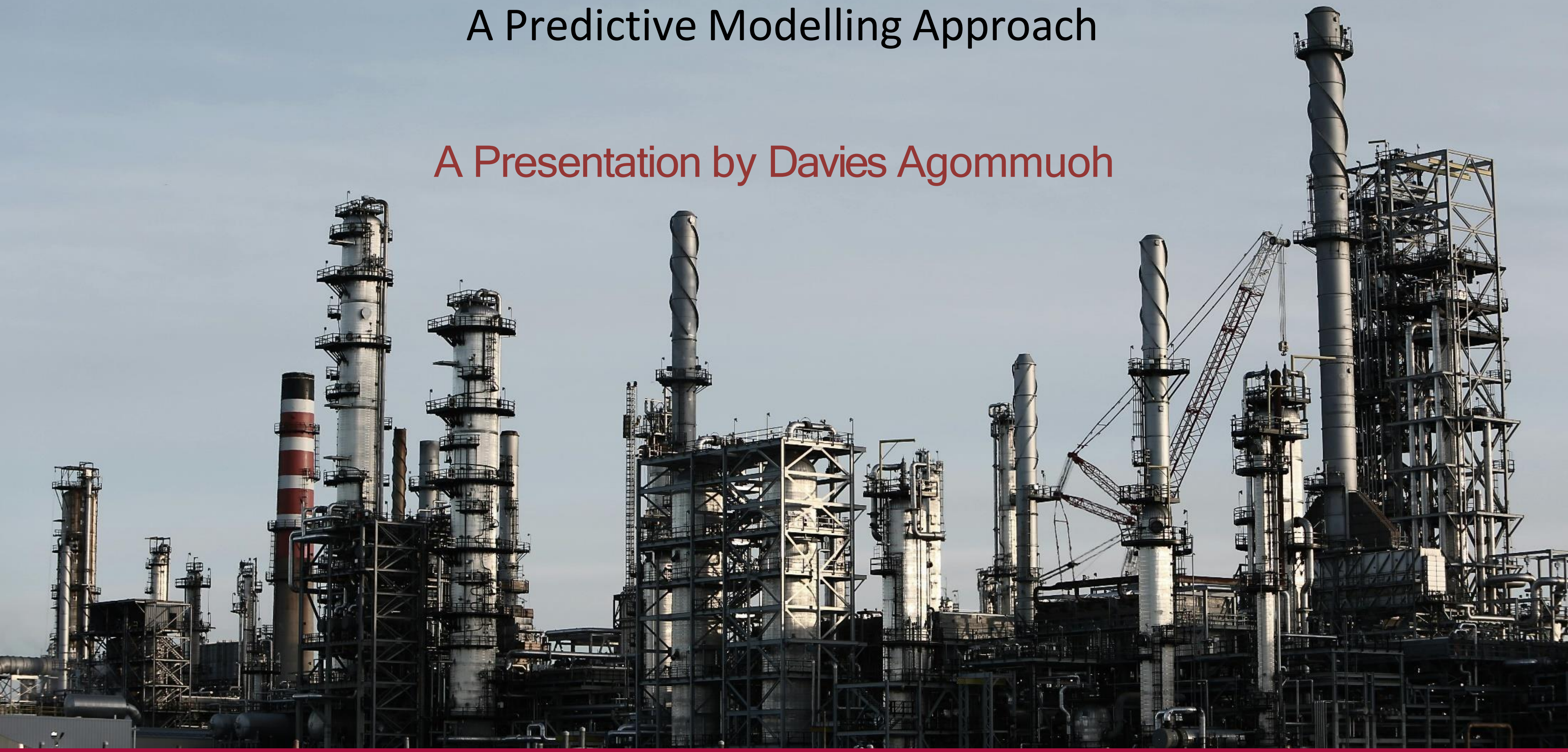
Optimizing Steam Usage in Chemical Cellulose Production

A Predictive Modelling Approach

A Presentation by Davies Agommuoh



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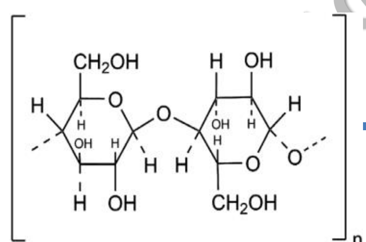
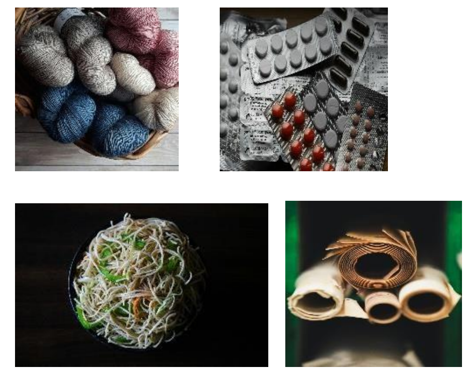
Introduction

Cellulose, particularly in the form of dissolving pulp, serves as a key raw material in various industrial processes, including those in the textile, tobacco, food, and pharmaceutical sectors, among others.

Wood



Dissolving Pulp



Textile, drugs, food, paper

This presentation focuses on the production of dissolving pulp from wood as the primary raw material at a real-world pulp mill.

Brief Process Description

1. Hardwood timber, primarily Eucalyptus and Acacia, is processed into wood chips in the woodyard.

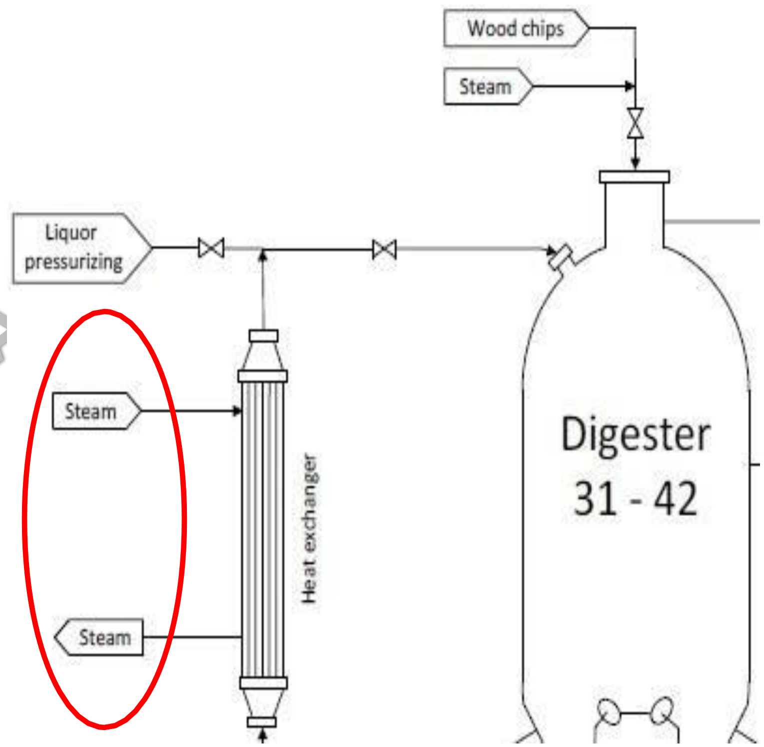
2. Wood chips are loaded into batch digesters with magnesium bisulphite liquor, where steam aids in the cooking process. The goal is to remove lignin and liberate chemical cellulose from the wood resulting in pulp

3. Steam is used to pack wood chips into the digesters by expanding the chips, removing trapped air, and ensuring efficient loading. This steam, at 165°C and 550 kPa, aids in optimal liquor absorption during the cooking process. The steam supply rate is 17-20 tonnes per hour.

4. The pulp is bleached to remove residual lignin and adjust cellulose molecular weight. The bleached pulp is dried and processed, while magnesium recovery reclaims magnesium oxide and SO2 for reuse.

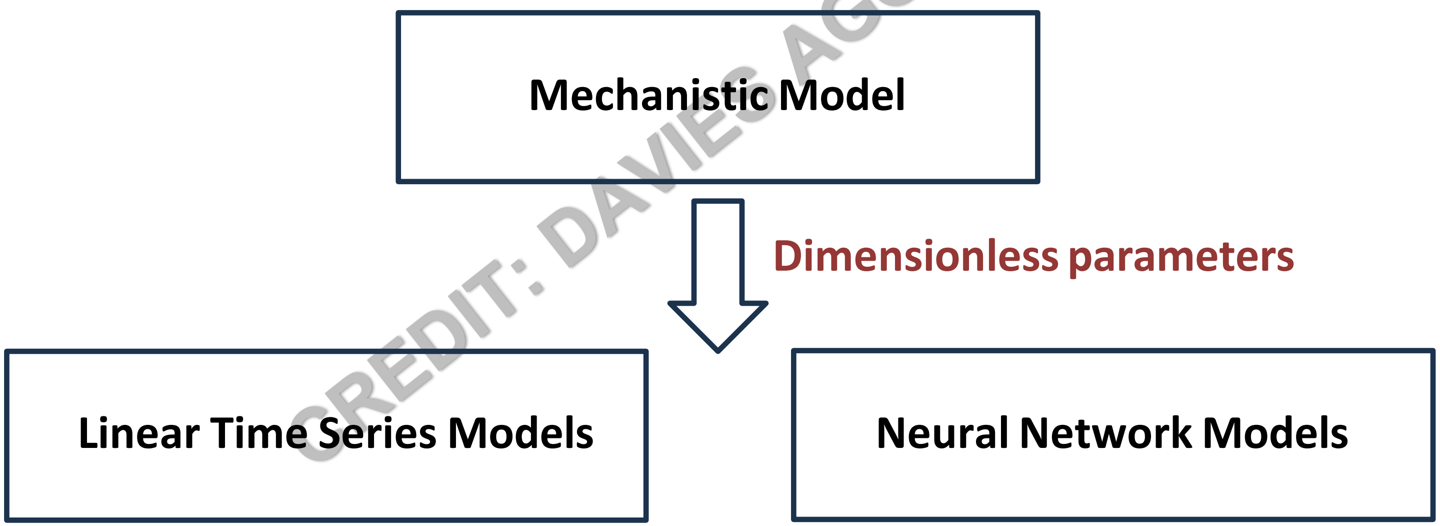
Problem Statement

The pulp mill faces challenges in efficiently managing steam use in batch digesters for dissolving pulp production. Due to the process's complexity, predicting steam needs is difficult, leading to excess steam production and wasteful venting. Accurate steam predictions would allow for precise allocation, reducing waste, improving scheduling, and avoiding utility overload. Accurately forecasting steam demand for the next digester batch is hindered by a lack of sufficient plant data



Proposed Solution

Given these challenges, a hybrid approach combining mechanistic models, statistical time series models, and artificial neural networks (ANNs) is proposed. This research will compare mechanistic models, ARIMA/ARIMAX, and neural networks (LSTM, GRU, CNN) to effectively model steam demand.



Proposed Solution

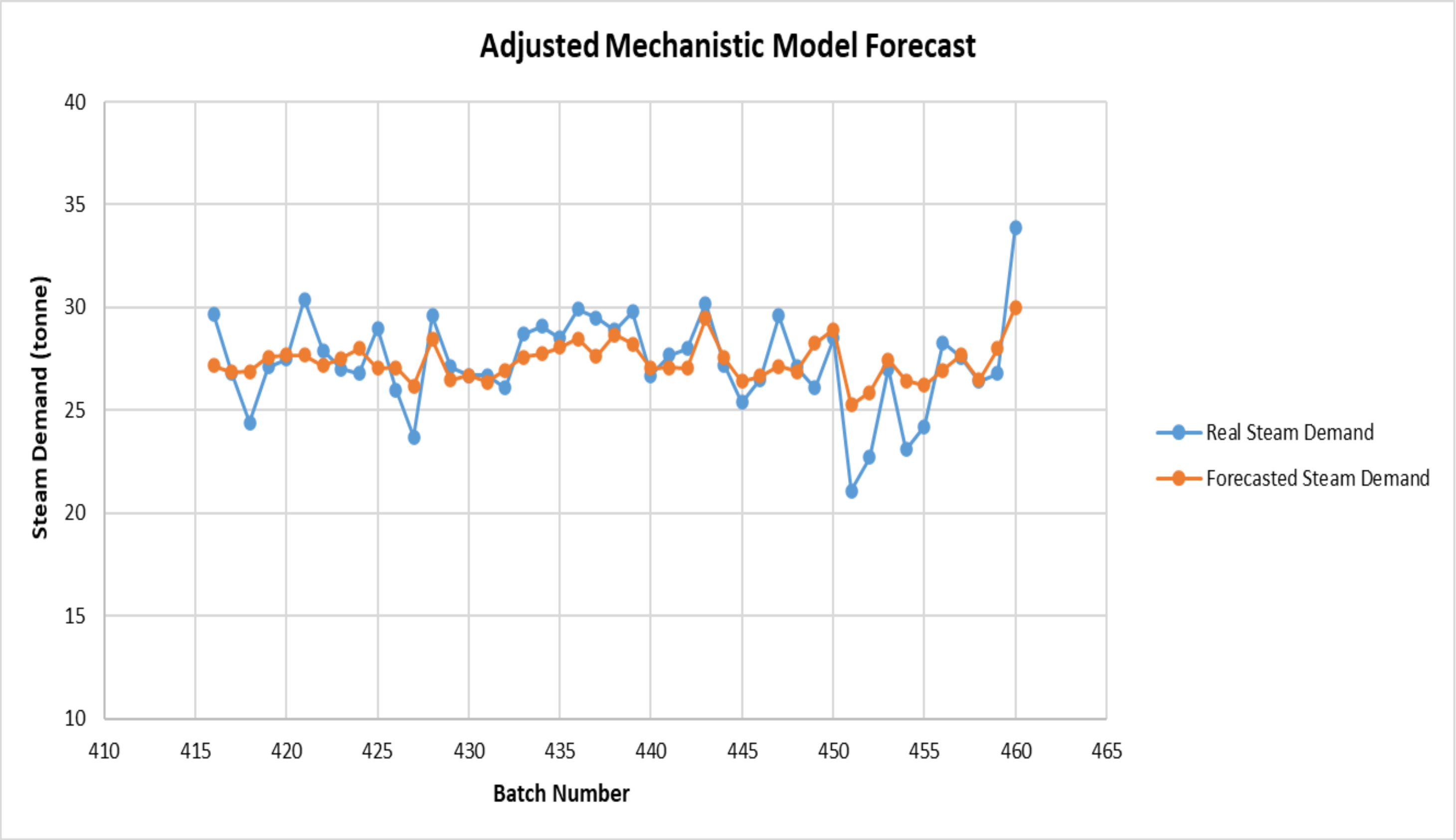
Mechanistic Model: This model is grounded in the energy balance equation for a batch reactor, simplified into three dimensionless parameters. These parameters act as predictors for steam demand as sufficient plant data is unavailable and are also used as exogenous variables in both the linear time series and neural network models.

Linear Time Series Models: ARIMA and ARIMAX models were used to predict steam demand, with ARIMAX incorporating the exogenous variables from the mechanistic model.

Artificial Neural Networks: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Convolutional Neural Network (CNN) models were employed to capture complex, non-linear relationships in steam usage. These models were applied sequentially, reflecting their ability to detect intricate patterns in the data.

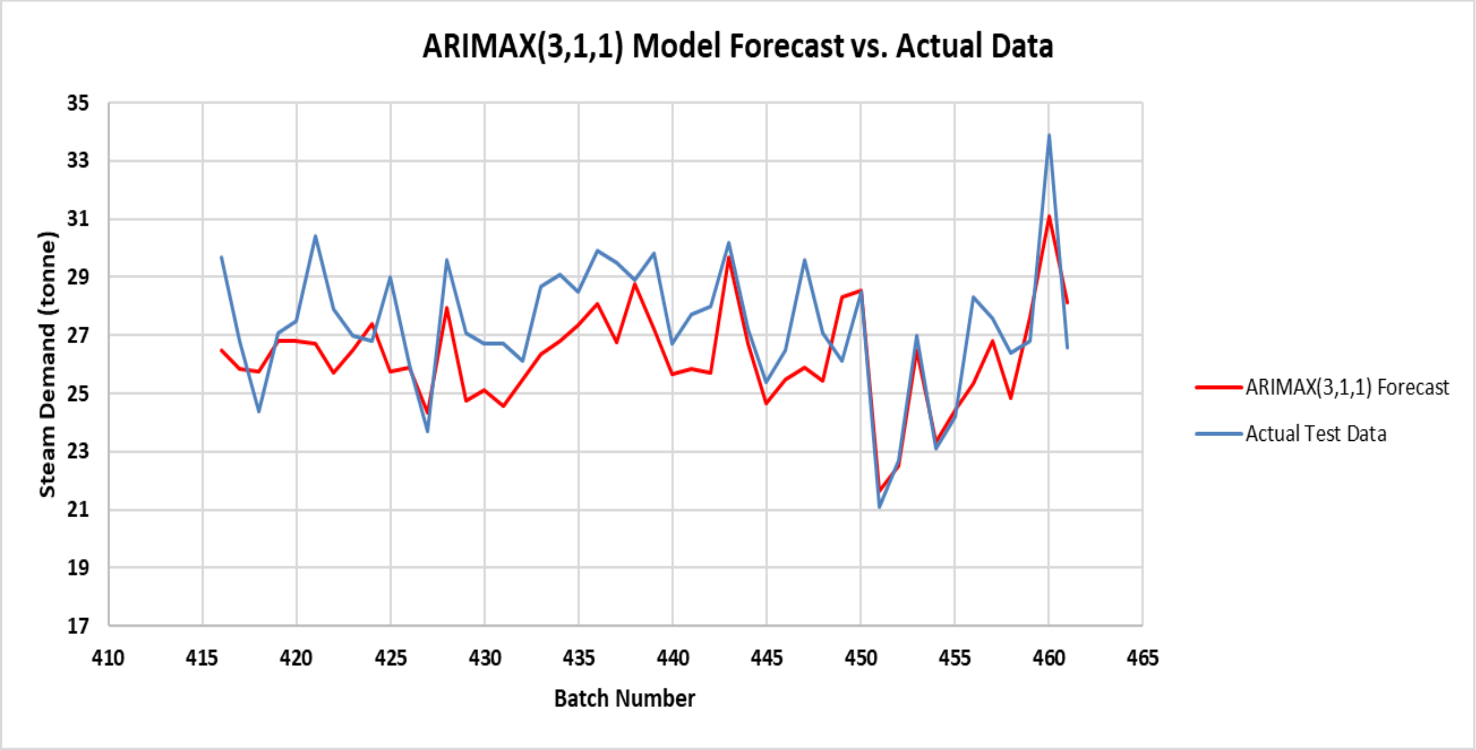
Model Evaluation: The models were compared using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics. The upcoming slides will present the forecast graphs and error metrics for each model. All models are developed in Python.

Mechanistic Model



RMSE = 2.03
MAE = 1.63

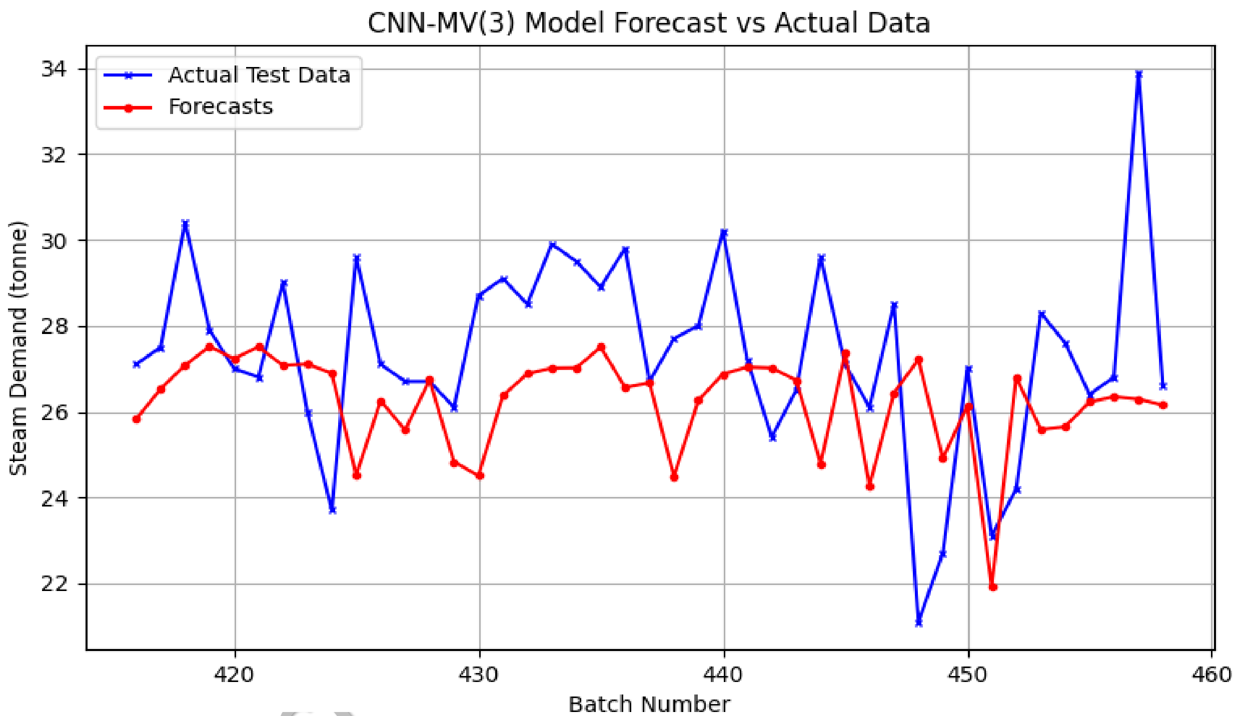
Linear Time Series Model



RMSE = 2.29

MAE = 1.93

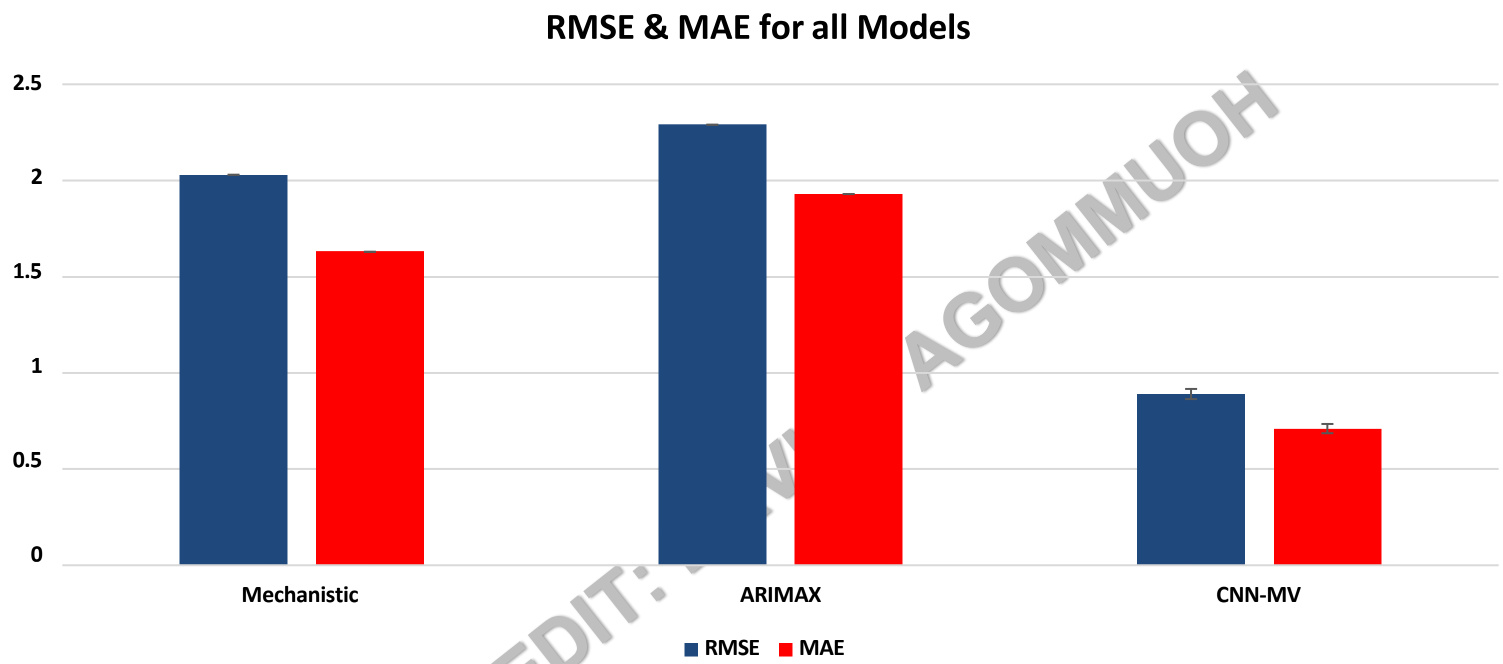
Neural Network Model



RMSE = 0.89
MAE = 0.71

For brevity, this only displays the results of the best performing neural network model, the Convolutional Neural Network (CNN)

Conclusion



The CNN model outperforms the others. While CNNs are typically used in image recognition, with proper data processing, they can be highly effective for chemical engineering applications as well.

Recommendation

Given the potential of Convolutional Neural Networks (CNNs) demonstrated in this study, I recommend further enhancing the steam demand forecasting models by exploring alternative reaction orders and incorporating advanced techniques like ARDL and Kalman filtering. To improve model precision, additional data on wood and liquor loading for each batch would be invaluable.

The success of CNN suggests a broader application of AI methods within process plants, and I would welcome the opportunity to collaborate on these initiatives in the broader manufacturing industry.