# **Smithfield Food Inc.,**

# **Spend and Pricing Forecast**

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## **ABSTRACT**

This study focuses on enhancing predictive pricing and spending for private companies, with a specific emphasis on resin and paper. Through a comparative analysis of statistical (ARIMA and VMD-ARIMA) and machine learning models (GRU and LSTM), our objective is to optimize spending forecasts for Fast-Moving Consumer Goods (FMCG) packages involving resin and paper materials over the next 12-18 months.

This research introduces a new insight on spending forecast by integrating artificial commodities forecast to market price predictions of packaging products. It delves into the seasonality of artificial commodities and explores the relationship between commodities and their derivative products. The study's significance lies in providing empirical based spend and pricing recommendations, offering valuable insights for informed decision-making in purchasing, negotiation, and budgeting. This research aims to guide companies in adapting to the complexities of modern business environments and enhancing resilience.

Keywords: Predictive modeling, Commodity Pricing, Spending Forecast, Seasonality, ARIMA, LSTM, GRU.

## **INTRODUCTION**

This project is driven by the objective of improving the predictive pricing capabilities of private companies. It focuses on harnessing seasonality insights from historical commodity pricing trends to optimize spending forecasts for the next 12-18 months.

In this paper, we are focusing on particularly the price of risen and paper given that Fast-Moving Consumer Goods (FMCG) companies often incur substantial costs in packaging, composed of resin and paper, the project aims to accurately predict the commodity prices of these materials. By doing so, it seeks to forecast package prices in the coming 12-18 months, thereby facilitating spending projections for the company.

The importance of this initiative is underscored by the dynamic nature of the market, where fluctuations in commodity prices and supply chain costs can significantly impact on a company's bottom line. By proactively understanding and responding to these trends, a company can optimize its purchasing and negotiation strategies. The proposed analytical approach involves developing models that provide empirical based spend and pricing recommendations, enabling the company to make informed decisions about buying, negotiating agreements, and budgeting. Moreover, providing the company with the insights necessary to make informed decisions on pricing and potential hedging strategies further solidifies the company's resilience in the face of market uncertainties.

Although understand the significant of predicting commodity pricing accurately, the ongoing model optimization has indicated the difficulty of this mission, evident by *Special Focus: Forecasting Industrial Commodity Prices* published by Word Bank in April 2023 “...A widely used forecast approach, futures prices, has been shown to yield unbiased forecasts (without systematic over- or under-prediction) but inefficient forecasts (with large forecast errors in either direction). Multivariate time series models have outperformed other model-based approaches. Increasingly, machine learning techniques are being shown to yield better forecasts than traditional benchmark models, such as no-change forecasts or forecasts based on univariate time series models. However, their performance against other model-based forecast approaches has only begun to be explored.”

The current predictions focus on the commodity market for agriculture, energy and other natural resources (Qadan et al, [2019](https://www.sciencedirect.com/science/article/abs/pii/S0301420719300133?via%3Dihub)), seldom have touch upon commodity market for artificial materials. This paper is going to explore different models and validate accuracy of commodity pricing forecasting through historical data for the artificial commodity, i.e., resin and paper, and explore its seasonality.

Models for commodity pricing prediction are group into three major categories: traditional statistical approach, artificial intelligence-based methods, and hybrid methods (Vancsura et al, [2023](https://www.mdpi.com/2227-9091/11/2/27)). For this paper, we will select models from each group and compare the accuracy of the prediction. The goal is to provide an optimized model for predicting commodity market for artificial materials.

In the subsequent sections of this paper, we will delve into a comprehensive literature review, presenting various criteria and methods used for predicting time-series data. Following that, the methodology for this research will be expounded upon, detailing how historical pricing trends and input spending data of packages will be utilized to develop models. Subsequent sections will present these models, outline their testing, and finally, assess their performance. The paper will conclude with a discussion of the implications of this study, future research directions, and concluding remarks. Through this journey, we aim to contribute valuable insights that empower companies to navigate the complexities of modern business environments effectively.

## **LITERATURE REVIEW**

Hybrid method is not introduced late as a method of predicting commodities price, Xiong et al. published paper of predicting the Chinese agriculture commodities combing STL and ELM methods in 2017[[1]](#footnote-1), with promising prediction result that SAMPE and MASE on lower than ELM, SARIMA-KF, TDNN, SVR, SARIMA. However, the current papers are focusing on standalone machine learning or statistical approach.

Moreover, it has been proven over and over in multiple papers that machine learning approaches outperform statistical prediction regarding the agriculture commodities price. Zhao (2020) specifically mentions this conclusion[[2]](#footnote-2), where the study focuses on whether the machine learning model can be applied to the prediction of commodities price, comparing ARIMA and ARMA with wavelet analysis method to smooth the data and then build a model to process the hierarchical information after signal decomposition. The result is positive.

Other results of machine learning approach outperformed statistical approach includes Chen et al. (2021)[[3]](#footnote-3) where they study and design an automated agriculture commodity price prediction system with novel machine learning techniques. They propose a web-based automated system to predict agriculture commodity price. In the two series experiments, five popular machine learning algorithms, ARIMA, SVR, Prophet, XGBoost and LSTM have been compared with large historical datasets and the most optimal algorithm, LSTM model with an average of 0.304 mean-square error has been selected as the prediction engine of the proposed system; Ameur et al (2023)[[4]](#footnote-4) where they focuses on the empirical evidence of deep learning algorithms in forecasting commodity prices, using the Bloomberg Commodity Index and its component indices. The Long Short-Term Memory (LSTM) method proved effective in forecasting commodity prices, with the Bloomberg Livestock and Industrial Metals Subindices demonstrating superiority prediction than not only ARIMA but also other machine learning methods as GRU, RNN, and CNN with validation of MAPE, RMSE, and determination coefficient (R2).

However, it is not saying the statistical approach is of no use in the prediction of commodity prices. The literature[[5]](#footnote-5) also shows the decomposition method combining with machine learning or statistical methods can enhance their accuracy. The study deploys decomposition techniques (EMD, VMD) combined with BPNN and ARIMA models, focusing on corn, crude oil, and gold. Findings indicate that combined models outperform individual ones in forecasting. VMD-ARIMA excels for corn, EMD-ARIMA for crude oil, and BPNN for gold while comparing among ARIMA, BPNN and them combining with decomposition techniques. The study underscores the significance of a combined modeling approach for effective decision-making amid volatile commodity markets, encouraging future research to explore decomposition methods for improved predictability.

Table 1 Literature Review Summary

|  |  |  |  |
| --- | --- | --- | --- |
| Study | Methodology Used | | |
| Statistic | Machine Learning | Hybrid |
| Xiong et al, 2017 | - | - | STL-ELM |
| Zhao, 2020 | ARIMA | ARMA with Wavelet analysis | - |
| Chen et al, 2021 | - | LSTM | - |
| Antwi et al, 2022 | ARIMA, EMD/VMD-ARIMA | BPNN, EMD/VMD-BPNN | - |
| Ameur et al, 2023 | ARIMA | LSTM, GRU, RNN, CNN | - |

The present study places significant emphasis on seasonality and time-series data analysis in the context of commodity pricing predictions, particularly for natural resources like agricultural products. These predictions are influenced by factors such as weather conditions, leading to pronounced seasonality in pricing trends. Commonly employed models include the auto-regression family, LSTM, or their combinations. And decomposition technique is also suggested to capture the complexity of commodities pricing prediction.

According to recent research by Chen et al. (2021) and Ameur et al. (2023), commodity price prediction for natural resources using LSTM exhibits the highest accuracy, with an average R-square of 0.98. This outperforms other machine learning methods, which in turn surpass traditional statistical approaches in time-series data analysis (ARIMA).

Notably, there is a dearth of sufficient comparisons regarding prediction accuracy between hybrid and machine learning methods in the current literature, nor is their performance regarding LSTM with decomposition methods comparing to statistical methods. Moreover, the studies focus on and predict the commodities market of natural resource, there is no sufficient evidence showing the forecast of artificial materials commodity pricing will perform with same conclusions.

**DATA**

In collaboration with an international food processing company, we were provided with data on their spending reports and the market spend values for their commodities. This is comprised of three datasets. First is the Spend Report data which contains the day level total spend for each packaging material for 4 years, from 2020 to 2023. The main end goal of the project is to forecast this total spend for the next 12 months. Next dataset is called Master CDI Resin Trends data which contains month level spend for every resin and oil category used to create packaging for 12 years, from 2012 to 2023. The forecasted values of resin and oil spend will be used as input for total spend forecast for packaging material. The final dataset is called the Paper Market Intel data which contains month level total spend for every paper material used to create packaging from Oct 2017 to Jan 2024. It also contains forecasted spend for paper materials from Feb 2024 to Dec 2024. The forecasted spend of paper will be used as input for total spend forecast for packaging material. Detailed description of these datasets is given below.

Table 1: Spend Report

|  |  |  |
| --- | --- | --- |
| Variable | Type | Description |
| PURCHASING DOC. | ID | Purchase Number |
| VENDOR | Categorical | Vendor Number |
| SUPPLIER | Categorical | Supplier Name |
| MATL GR # | Categorical | Material Group Number |
| MATERIAL GROUP | Categorical | Material Group Name |
| MATERIAL # | Categorical | Material Number |
| PACKAGING GROUP | Categorical | Packaging Group Name |
| PLANT # | Categorical | Plant Number |
| PLANT | Categorical | Plant Name |
| SAP DESCRIPTION | Categorical | Names of the raw materials used |
| DATE | Date | Purchase Date |
| YEAR | Date | Purchase Year |
| MONTH # | Date | Purchase Month Number |
| MONTH | Date | Purchase Month Name |
| QUARTER | Date | Purchase Quarter |
| ORDER QTY | Numeric | Order Quantity |
| UOM | Categorical | Unit of Measure |
| NET ORDER VALUE | Numeric | Net Order Value |
| $/UOM | Numeric | Spend per Unit of Measure |
| CRCY | Categorical | Currency Type |

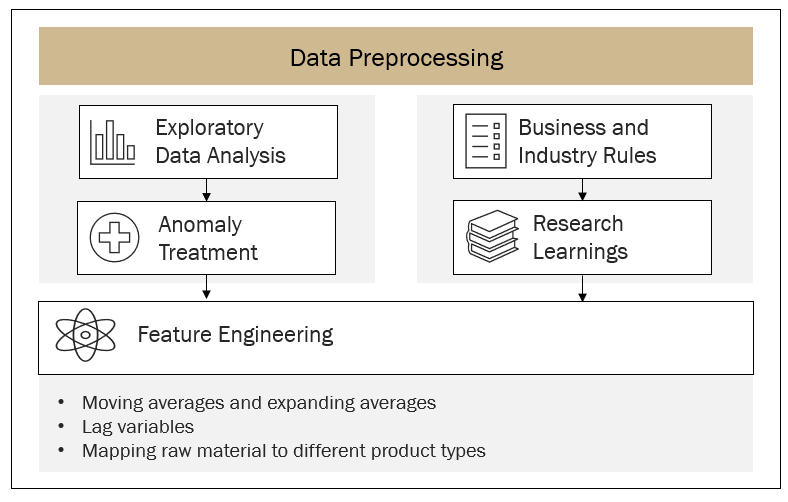
Table 2: Master CDI Resin Trends

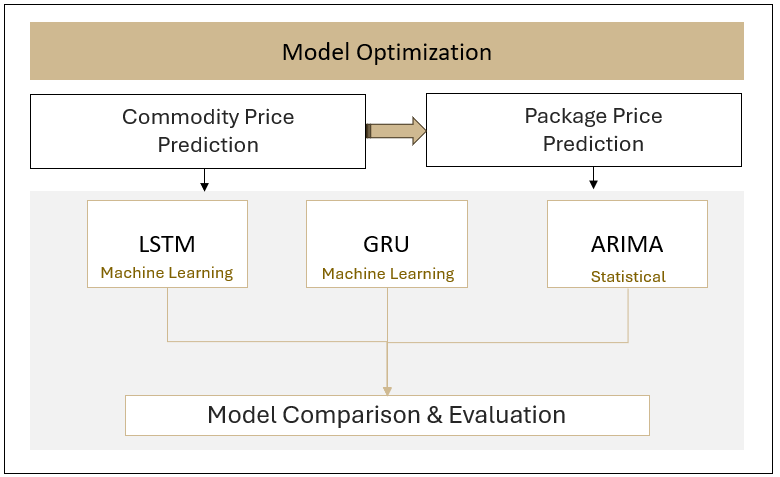
|  |  |  |
| --- | --- | --- |
| Variable | Type | Description |
| Month | Date | Month and Year |
| Column1 | - | - |
| HDPE MED QUAL - BACK PAGE YES Jan 2023 $0.20 NMA | Numeric | Spend for Resin HDPE MED QUAL |
| Chg | Numeric | Difference in Spend with previous month for Resin HDPE MED QUAL |
| HDPE HMW FILM | Numeric | Spend for Resin HDPE HMW FILM |
| Chg2 | Numeric | Difference in Spend with previous month for Resin HDPE HMW FILM |
| HDPE HIC MLDG | Numeric | Spend for Resin HDPE HIC MLDG |
| Chg3 | Numeric | Difference in Spend with previous month for Resin HDPE HIC MLDG |
| LDPE - BACK PAGE YES Jan 2023 $0.25 NMA | Numeric | Spend for Resin LDPE |
| Chg4 | Numeric | Difference in Spend with previous month for Resin LDPE |
| LLDPE BUTENE - BACK PAGE YES Jan 2023 $0.24 NMA | Numeric | Spend for Resin LLDPE BUTENE |
| Chg5 | Numeric | Difference in Spend with previous month for Resin LLDPE BUTENE |
| LLDPE HEXENE - BACK PAGE YES Jan 2023 $0.23 NMA | Numeric | Spend for Resin LLDPE HEXENE |
| Chg6 | Numeric | Difference in Spend with previous month for Resin LLDPE HEXENE |
| Nylon 6 | Numeric | Spend for Resin Nylon 6 |
| Chg10 | Numeric | Difference in Spend with previous month for Resin Nylon 6 |
| Nylon 66 | Numeric | Spend for Resin Nylon 66 |
| Chg11 | Numeric | Difference in Spend with previous month for Resin Nylon 66 |
| PET RESIN | Numeric | Spend for Resin PET RESIN |
| Chg12 | Numeric | Difference in Spend with previous month for Resin PET RESIN |
| POLYPROPYLENE - BACK PAGE YES | Numeric | Spend for Resin POLYPROPYLENE |
| Chg7 | Numeric | Difference in Spend with previous month for Resin POLYPROPYLENE |
| POLYSTYRENE GPPS | Numeric | Spend for Resin POLYSTYRENE GPPS |
| Chg8 | Numeric | Difference in Spend with previous month for Resin POLYSTYRENE GPPS |
| PS HIPS | Numeric | Spend for Resin PS HIPS |
| Chg83 | Numeric | Difference in Spend with previous month for Resin PS HIPS |
| PVC (GP) | Numeric | Spend for Resin PVC (GP) |
| Chg9 | Numeric | Difference in Spend with previous month for Resin PVC (GP) |
| Ethylene Glycol (EG) | Numeric | Spend for Resin Ethylene Glycol (EG) |
| Chg113 | Numeric | Difference in Spend with previous month for Resin Ethylene Glycol (EG) |
| Unsaturated Polyester | Numeric | Spend for Resin Unsaturated Polyester |
| Chg115 | Numeric | Difference in Spend with previous month for Resin Unsaturated Polyester |
| PPI Commodities | Numeric | Spend for Resin PPI Commodities |
| Chg13 | Numeric | Difference in Spend with previous month for Resin PPI Commodities |
| Nylon (CMAI) | Numeric | Spend for Resin Nylon (CMAI) |
| Chg14 | Numeric | Difference in Spend with previous month for Resin Nylon (CMAI) |
| Crude Oil | Numeric | Spend for Crude Oil |
| Chg16 | Numeric | Difference in Spend with previous month for Crude Oil |
| Crude Oil 2 | Numeric | Spend for Crude Oil 2 |
| Chg15 | Numeric | Difference in Spend with previous month for Crude Oil 2 |

Table 3: Paper Market Intel

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | | Type | Description |
| Month | | Date | Month Start Date |
| High Performance Linerboard, 35-36 lb, Open Market, US East [1] | LOW SIDE | Numeric | Low Side Market Value for High Performance Linerboard |
| HIGH SIDE | Numeric | High Side Market Value for High Performance Linerboard |
| Recycled Linerboard, 30-/31-lb, US East, US East [2] | LOW SIDE | Numeric | Low Side Market Value for Recycled Linerboard |
| HIGH SIDE | Numeric | High Side Market Value for Recycled Linerboard |
| Recycled Linerboard, 30-/31-lb, US West, US West [2] | LOW SIDE | Numeric | Low Side Market Value for Recycled Linerboard |
| HIGH SIDE | Numeric | High Side Market Value for Recycled Linerboard |
| Semichemical Corrugating Medium, 26lb, Open Market, US East, Open Market, US East [3] | LOW SIDE | Numeric | Low Side Market Value for Semichemical Corrugating Medium |
| HIGH SIDE | Numeric | High Side Market Value for Semichemical Corrugating Medium |
| Unbleached kraft linerboard, 42-lb, FAS US for export to Central/South America, United States [4] | LOW SIDE | Numeric | Low Side Market Value for Unbleached kraft linerboard |
| HIGH SIDE | Numeric | High Side Market Value for Unbleached kraft linerboard |
| Unbleached Kraft liner, 42 lb, Open Market, US East [5] | LOW SIDE | Numeric | Low Side Market Value for Unbleached Kraft liner |
| HIGH SIDE | Numeric | High Side Market Value for Unbleached Kraft liner |
| White Top Linerboard, 42lb, Open Market, US East, Open Market, US East [6] | LOW SIDE | Numeric | Low Side Market Value for White Top Linerboard |
| HIGH SIDE | Numeric | High Side Market Value for White Top Linerboard |

## **METHODOLOGY** [15 points]





For context, the spending is based on the package material price, and package price is based on the commodity price. Therefore, to achieve our goal of spending forecast, we must train the model to predict commodity prices and package price based on the historical prices. The end goal is to use the predicted commodity price to correctly forecast the unit price of different product packages. Therefore, we will require two different pricing prediction models for commodity prediction and packaging material predictions.

We begin by doing due data preprocessing for example, one hot encoding for categorical variables, and feature engineering variables such as time, lag etc. We will go over these in more detail in the “data” section of this paper.

Before building our model, we need to split the dataset into training, test, and validation sets. Since both datasets are time series in nature, we take that into consideration and make sure our split is not random but instead based on recency. Since we are going to predict future dates, we want to test our model on the most recent dates to get a measure of accuracy. Therefore, instead of randomly assigning datapoints to test or train, we will use recency as a factor for an 80/20 split for training and testing on our data.

We will train the first model on paper and resin data to predict commodity pricing using ARIMA, LSTM, Transformer, GRU, and combining with decomposition methods. Given that we have monthly pricing from 2012 to 2023, we only have 143 data points. We will try to use recency as the splitting criteria in creating our folds for cross-validation. We will use RMSE and MAPE as our evaluation criteria for our models. RMSE is utilized because it gives us accurate answer of the actual distance of the predicted data with the actual data. MAPE is utilized because it gives percentage accuracy, which can be used to compare across varied materials.

For the second model based on packaging material pricing, we will first train the package price prediction based on the historical commodity price along with the one-hot encoded and weighted portion of its composed commodity category e.g., LLDPE. Given that we have data for 2019 to 2023, we will use 42 months of data for training and use the last 18 months of data for validation and testing. This would make it an 80/20 split for training and testing. Given the time series nature, we will use ARIMA, VMD-ARIMA, LSTM, Transformer, GRU, and combining with decomposition methods to make predictions trying to achieve highest level of accuracy. Since we are predicting prices of packaging materials and our data has low standard deviation with no significant proportion of outliers, it is more appropriate to capture the spread of errors across all prediction with the RMSE and MAPE instead of other using other loss functions.

## **MODEL(s)**

***Modeling Techniques for Resin Price Prediction***

**1. Long Short-Term Memory (LSTM)**

*Description*: Long Short-Term Memory networks, a type of recurrent neural network, are well-suited for sequence prediction problems due to their ability to capture long-term dependencies in data sequences. In our project, LSTMs were applied to forecast resin prices by learning from sequences of past prices and other relevant features.

*Pros*: Capable of learning long-range dependencies; robust against the vanishing gradient problem common in standard recurrent networks.

*Cons*: Computationally intensive; prone to overfitting on smaller datasets.

Tuning Parameters: We experimented with various configurations including learning rate, number of layers, and neurons per layer.

*Relevance*: LSTMs were chosen due to their proven effectiveness in similar time series forecasting tasks, as indicated in the literature.

**2. Gated Recurrent Unit (GRU)**

*Description*: GRUs are a variation of LSTMs designed to be more efficient and simpler. They use a gating mechanism to regulate the flow of information, which simplifies the training process without significant performance compromise.

*Pros*: Requires less computational resources than LSTMs; simpler architecture leads to faster training times.

*Cons*: May underperform compared to LSTMs on more complex datasets.

*Tuning Parameters*: Like LSTMs, we tuned the learning rate, layers, and neurons.

*Relevance*: Selected for their efficiency, GRUs were considered a viable alternative to LSTMs for our resin price prediction when computational resources were limited.

**3. Transformer**

*Description*: Transformers utilize self-attention mechanisms to weigh the significance of different parts of the input data. For our project, this model was adapted to handle time series data by treating time steps as sequential inputs in the self-attention calculation.

*Pros*: Highly parallelizable, which speeds up training; excels in capturing relationships in data irrespective of distance between points in the sequence.

*Cons*: Can be memory intensive due to the self-attention mechanism.

Tuning Parameters: Adjustments were made in the number of attention heads, depth of the model, and learning rate.

*Relevance*: Chosen for their state-of-the-art performance in sequence modeling tasks across various domains.

**4. Autoregressive Integrated Moving Average (ARIMA)**

*Description*: ARIMA models are a staple in time series forecasting, designed to model time-dependent structures in the data. We used ARIMA to benchmark against more complex machine learning models.

*Pros*: Well-understood; does not require large datasets.

Cons: Assumes linearity and stationarity in the time series data.

*Tuning Parameters*: Parameters p, d, and q were iteratively selected.

*Relevance*: ARIMA served as a baseline model to assess the incremental benefit of more sophisticated techniques.

**5. Variational Mode Decomposition ARIMA (VMD-ARIMA)**

*Description*: This method combines variational mode decomposition with ARIMA to handle non-linear and non-stationary time series data more effectively.

*Pros*: Enhances ARIMA’s ability to model more complex data patterns.

*Cons*: More complex to configure and interpret.

*Tuning Parameters*: In addition to ARIMA’s p, d, q parameters, we tuned the number of modes in VMD.

*Relevance*: Aimed to improve the predictive accuracy over standard ARIMA by decomposing the series into modes that can be individually modeled.

***Model Selection and Hyperparameter Optimization***

**Model Selection Criteria**

The selection of appropriate forecasting models was predicated on a combination of theoretical suitability, evidence from extant literature, and specific data characteristics inherent to our project. The inclusion of LSTM, GRU, Transformer, ARIMA, and VMD-ARIMA models was guided by their established efficacy in handling time series data with distinct features such as non-linearity, non-stationarity, and varying intervals of data collection. Prior research (provide citations here) has demonstrated the robust performance of LSTM and GRU in capturing long-term dependencies, whereas Transformer models have shown superior capability in managing large datasets with complex patterns. ARIMA models, being a benchmark in time series analysis, were selected for their simplicity and effectiveness in smaller, more stable datasets. VMD-ARIMA was considered due to its enhanced capability to address non-stationarity by decomposing the time series into adaptively determined intrinsic modes before ARIMA modeling.

**Hyperparameter Optimization**

Hyperparameter tuning was conducted to optimize each model's performance. A comprehensive grid search was implemented for LSTM, GRU, and Transformer models, where key parameters such as the number of layers, number of neurons per layer, and learning rate were varied systematically. For ARIMA and VMD-ARIMA, the parameters p, d, and q were determined through iterative testing.

The optimization process involved evaluating model performance using rolling window cross-validation, which is particularly suited for time series data. This method ensures that each fold is used both for training and validation, simulating a more realistic forecast scenario. The performance metrics employed included the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE), which provided a balanced view of model accuracy and error magnitude.

**Model Optimization and Final Selection**

The models' performance was rigorously compared using the collected metrics, with results tabulated for clarity. This comparison not only highlighted the absolute performance of each model configuration but also facilitated an understanding of the impact of various hyperparameters on forecasting accuracy.

The final model selection was based not solely on forecasting accuracy but also considered computational efficiency and ease of implementation. The LSTM model, for instance, demonstrated the best performance across several metrics but required significant computational resources. A trade-off analysis was thus essential to balance accuracy with practical deployment considerations.

Furthermore, sensitivity analysis on key hyperparameters such as learning rate and number of layers confirmed the robustness of the selected model configurations. This analysis provided insights into the dependency of model performance on hyperparameter values, indicating potential areas for further optimization.

***Conclusion***

The methodological rigor applied in the selection and optimization of models for this project ensured that the final forecasting model was not only theoretically sound but also empirically robust. The multi-faceted approach, encompassing theoretical rationale, empirical performance, and practical feasibility, underpins the reliability and validity of the forecasting results, which are crucial for strategic decision-making in resin price management.

This section of your paper will effectively communicate the careful thought and scientific rigor that went into model selection and optimization, providing a solid foundation for the credibility of your research findings.

## **RESULTS**

For model comparison, RMSE and MAPE were used for a balanced approach, leveraging RMSE for assessing overall prediction accuracy while incorporating MAPE to gauge percentage errors, providing a comprehensive view of model performance across different metrics. This decision reflects a meticulous strategy aimed at capturing both the magnitude and relative accuracy of predictions, ensuring a thorough evaluation of the model's effectiveness.

As per the requirement, two separate models had to be built; to predict commodity prices and to predict packaging material prices for the following months. Multiple approaches were taken to make predictions on these datasets as discussed below.

**Commodity Price Prediction**

The best performing models were LSTM and GRU with similar performances in terms of RMSE and MAPE. Both approaches perform better than ARIMA and VMD-ARIMA. However, the improvement between ARIMA and VMD-ARIMA is clear.

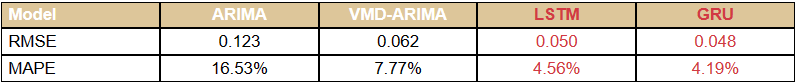


Figure: Model comparison in terms of RMSE and MAPE to find best algorithm

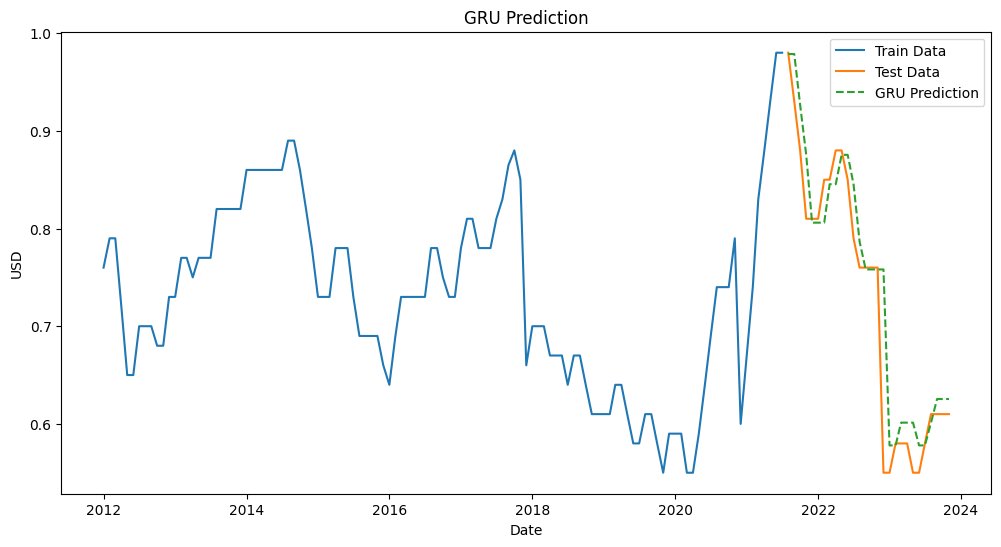


Figure: Visualization of predictions made by GRU in comparison to Testing Datasets

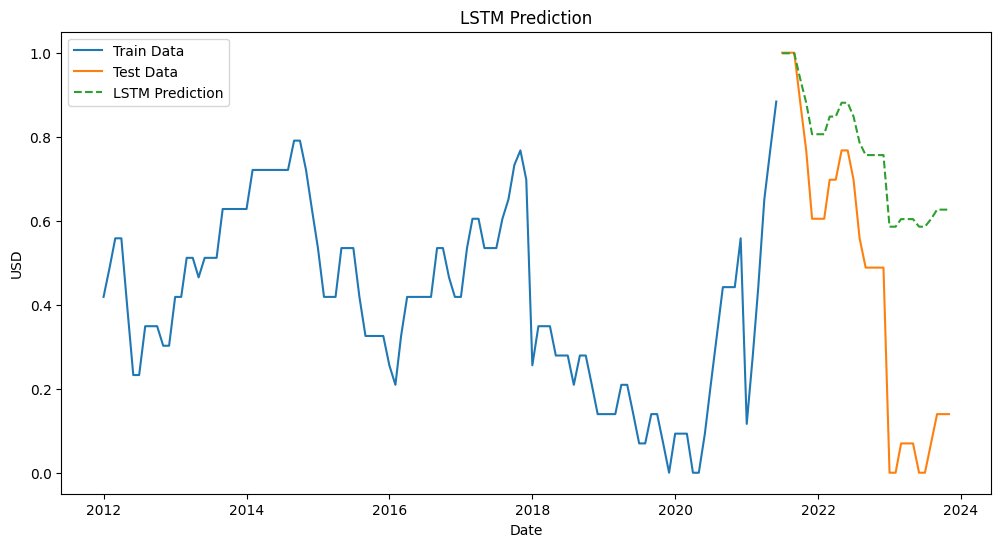


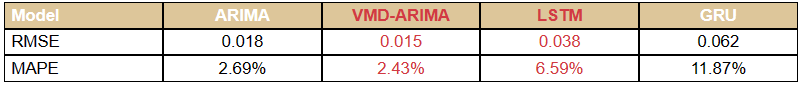
Figure: Visualization of predictions made by LSTM in comparison to Testing Datasets

**Package Price Prediction**

When predicting package material prices, there were multiple ways to split the data. To predict these packaging material prices, two different segregation criteria were used, and their results are as follows.

*Material Group Level*

Considering the data was trained with monthly average, with less data point both ML approach is not robust. As the fluctuation in package price is small, VMD-ARIMA performed best to successfully capture the trend and seasonality.

Figure: Model comparison in terms of RMSE and MAPE

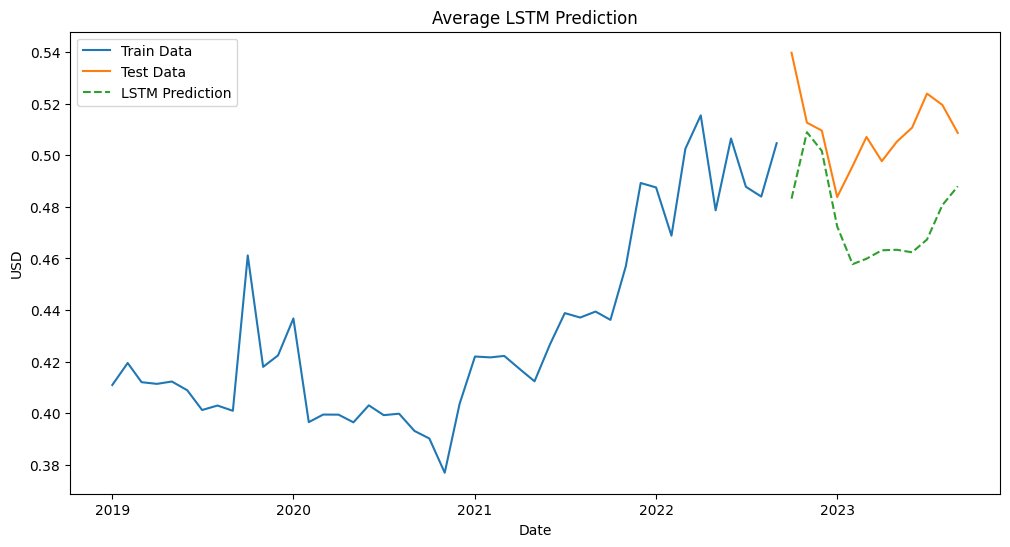


Figure: Visualization of predictions made by LSTM in comparison to Testing Datasets

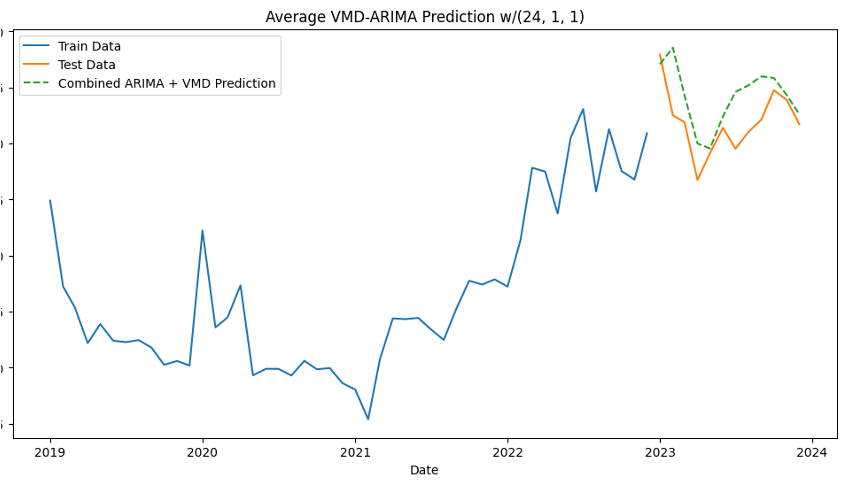


Figure: Visualization of predictions made by VMD-ARIMA in comparison to Testing Datasets

*Material Level*

Given the irregular monthly data points, an LSTM time series approach for package material forecasting at material level is unsuitable, leading to the consideration of a non-sequential predictive model as an alternative.



Figure: RMSE and MAPE by LSTM

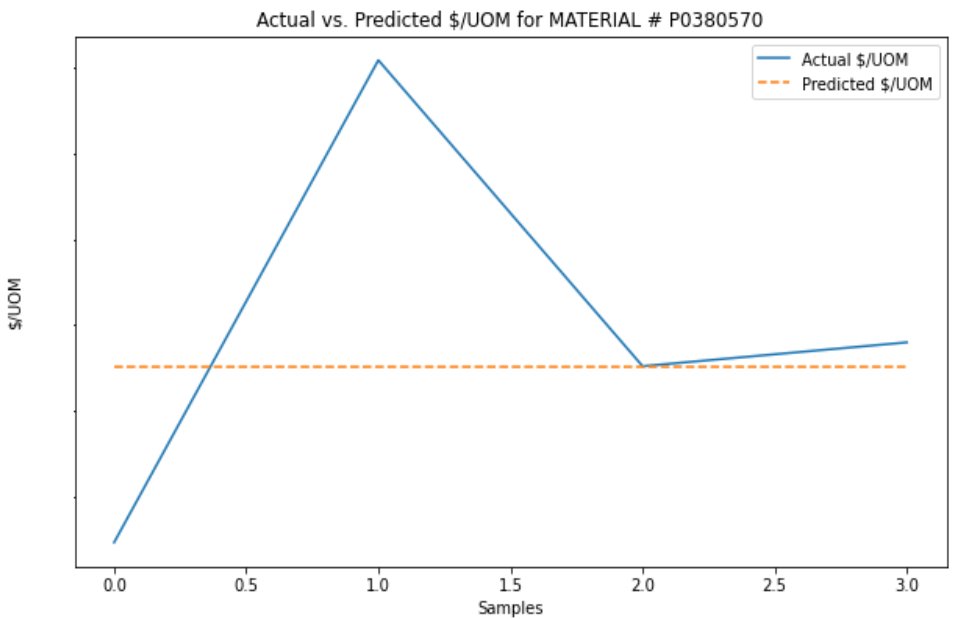


Figure: Actual vs Predicted price for a single material per unit of measure

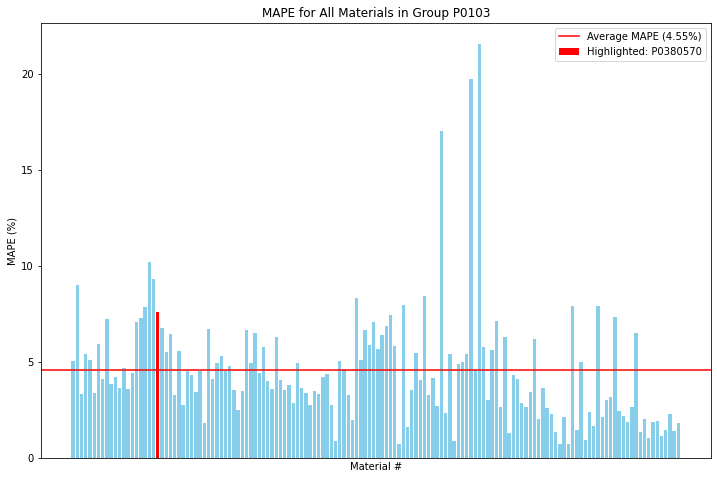
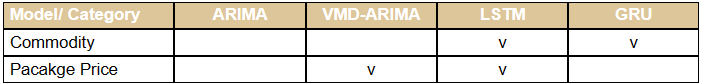
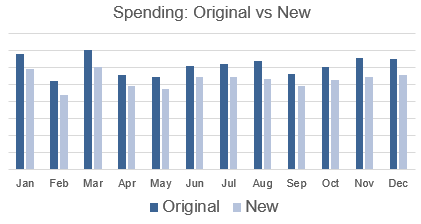


Figure: Visualization of MAPE across all materials in a single material group

It is recommended to run the commodity prediction with LSTM or GRU and package price prediction with VMD-ARIMA or LSTM. However, the performance of LSTM and GRU package price model is limited to monthly prediction due to the data characteristic. The model could be more robust by gaining daily commodity price for the training of package price prediction model.



Using the current model, following the predicted average price, the company will save 10-16% per month or 13% per year by avoiding overpriced packaging.



## **CONCLUSIONS**

With our model outputs predicting the commodity and package prices for the next 12 years, our stakeholders can leverage this information in various ways.

* Optimizing their hedging strategy and buying future commodities based on predicted prices.
* Allocate budget to maximize buying of materials at lower prices.
* Negotiate deals with their vendors leveraging the predicted market prices.

Having obtained high accuracy in our models with our limited dataset, we believe there is good potential for further improvement of our models, by trying and testing out the following ways to enhance them.

* The data for both commodities and package prices were both available at monthly level for our models. Trying out different granularity of data like weekly or daily might yield good results, due to both higher granularity of the data, increased data points, and new observed seasonality trends at these levels.
* Since our models deal with predicting market prices, there is a scope for incorporating more market related variables into the dataset which might further enhance the models. Information like market trends, inflation, vendor location etc. could provide better depth to our datasets.
* While we provided a holistic output for all commodities, materials, and material groups, for future scope, different models and approaches can be tried out for each individual commodities and materials, and hence great accuracy could be obtained at individual material levels.

Thus overall, we can say that though we had great accuracy in our models' outputs, we believe that there are many ways our prediction analysis can be taken further, and fine-tuned, to provide even better value for the stakeholders.

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