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Demand forecasting of Steel industries' finished product using ARIMA Model: Bangladesh Perspective

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Abstract

The study on demand forecasting is pertinent in countries like Bangladesh where the industry specifically heavy industries are dying for accurate demand forecast. Autoregressive Integrated Moving Average (ARIMA) model has been used to detect patterns, trends and seasonal influences in order to generate accurate short-term forecasts. Data has been collected monthly, ranging from July to June of each corresponding year. Data processing involved zero-value occurrences, time-series decomposition and performed tests of stationarity. SARIMA with Exogenous Model, ARIMA Model for VIX Index on overridden series have been developed and, forecast performance was evaluated. Moreover, prediction range by specifying confidence interval levels has been prepared. It is found a strong monthly seasonal effect of production, with peaks in the first quarter and minimum values in July-August compatible with ideal rain conditions. The start of a slight upward trend in overall production indicated slow sector expansion. The SARIMA model selected had an average forecast accuracy of MAPE=34.84% and RMSE=16,349 MT. The ambiguity reinforces the nuanced set of variables which determine if heavy industries like Steel re-rolling mills in Bangladesh are allowed to produce.

Keywords
ARIMA Model, Heavy Industries, Bangladesh, Time Series Analysis, Production Forecast

1. Introduction

Mechanized industry is an indispensable part of the economic development of Bangladesh; this sector providing job for a maximum number of people and manufacturing productivity. Accurate demand forecasting is essential to enable proper distribution and production planning which in turn helps the policymakers a great deal for making strategic decisions as Bangladesh has been on progress path into becoming a middle-income country. In heavy industries-proper such as steel, cement and large-scale manufacturing, Bangladesh witnessed a considerable advance in the later years. But agriculture has its own obstacles-like seasonal production, infrastructure constraints, and financial instability. There lies the importance of developing a state-of-the-art forecasting technique that is custom-made to the industrial context in Bangladesh.

The forecasting of demand is a pivotal activity to drive strategic planning and operational efficiency in Heavy Industries like steel Steel re-rolling mills across the globe. Heavy industry is a capital-intense and therefore mainly cost-oriented business, accurate demand forecasting plays a critical role in effective supply chain management. (S Chopra 2007). Hossain et al (context of developing countries) Heavy industry-specific challenges in Bangladesh such as infrastructure constraints, the seasonality of production due to electricity outage limitations, and economic variations (Hossain 2017). This has implications for the necessity of stronger forecasting tools for emerging economies. The process of predicting the demand in the pharma vertical would have many dimensions, which can only be drawn considering a detailed study on data market dynamics, regulation, and emerging Tech. Using the demand forecasting model, it is possible to reduce the costs of purchasing and storage of medicines. (Praphan Yawara, 2023). Optimizing inventory management in manufacturing is not a static process; it involves data analysis, technology adoption, process refinement, and partnerships with suppliers, vendors, and others. Demand forecasting enables manufacturers to have better control over their inventory, lower costs, and improve overall operational efficiency. (Pardis Roozkhosh 2023). Better prediction of heavy rainfall is the key for effective disaster management, flood control, agriculture and many more. This is a mix of tech, data science and weather forecasting. (Yutong Chen 1, 2023). Forecast studies are attempting to take a broader view of hotel forecasting without only considering one or two variables and without primarily relying on every data source available.

Utilizing historical data, sophisticated technology, and market intelligence, hotels can use different methods to optimize their cost & pricing with a view of spending the resources wisely while providing a great experience for their guests. (Nataliia Stebliuk 2022). It describes how effectively ARIMA executes forecasting and production planning in the Metal fittings industry, especially in Y-strainer production units, as they are vice versa in a well-organized supply chain management system. It encompasses demand forecasting, production planning, inventory management, capacity planning, and distribution control to fulfill customer requirements while keeping costs and disruption at the lowest level. When done well, these solutions for forecasting and production planning can enhance operational efficiency, cut down costs, and, most importantly, improve customer satisfaction as well (Natalia Velony Putri 2022). Correct forecasting in the residential space can further streamline energy infrastructure, lower consumers' energy bills, and pave the way to a sustainable energy future. (Nikos Sakkas 2021). The Autoregressive Integrated Moving Average (ARIMA) type of model was posed by Box and Jenkins in 1970 and has been commonly used all over different industries for modeling Time Series data. The ARIMA model can be substantially valuable for governments, businesses, and policymakers where trends, seasonality, and fluctuations in GDP data thrive on.

This forecasting model uses historical GDP trends and gives predictions to help in budgeting, monetary policy choices, and economic planning. (K. M. Salah Uddin, 2021). Venkatachary et al., in the heavy industry sector (2021): Implemented ARIMA models for predicting steel demand in India, resulting to an impressive outcome of reaching a level of about 200 million tonnes by 2030-31. The ability of the model to show the cyclical nature of demand in the steel industry is highlighted by their particular study (Venkatachary M, 2021). Considering the seasonality of most industries, many researchers have applied Seasonal ARIMA (SARIMA) models. For example, Contreras et al. Yi, (2003) applied the SARIMA methodology to forecast electricity prices and obtained better performance than nonseasonal models (Contreras, 2003). Using the farm level data in Bangladesh, Rahman and Hasan (2016) forecasted crop production by applying SARIMA at an MAPE of 5.62% on average for agricultural products (N M F Rahman, 2016). Drawing attention to these potential methodological problems in the study, it is noted that severe seasonality shapes into Bangladesh's more broadly economy as much of it revolves around monsoon cycles. Emerging markets pose challenges associated with market volatility and external shocks. Adebiyi et al. (2014) researched the stock price forecasting performance of ARIMA models in volatile markets, comparing them to Artificial Neural Networks (ANNs), and reported that ARIMA has good enough short-term forecasting accuracies comparable to ANNs (Ayodele Ariyo Adebiyi, 2014). In the case of Bangladesh, M Monimul Huq et al. (2013) examined the volatility of the Dhaka Stock Exchange through ARIMA models, revealing that using economic indicators to assist in ARIMA model implementation contributed significantly to enhancing prediction capability in such volatile market conditions (M Monimul Huq, 2013).

Although there is a huge literature about ARIMA models and their application in many sectors, there is still a wide gap to apply this in the power sector, especially in predictable aspects of heavy industry like Bangladesh. In this study, we focus on a different context where the ARIMA model may not be so straightforward to apply in demand forecasting, i.e., when there are seasonal patterns, and the economic crisis is changing rapidly due to the rapid industrialization of a nation like Bangladesh. Various heavy industries' demand data has been collected across the country to develop and analysis the forecasting model. Prediction has been made subsequently for those sectors. This study utilizes data from steel re-rolling mills.

2. Methods

The term ARIMA composed with various components, such as: (i) Autoregressive (AR): a partially observed relationship between an observation and historical observation (i.e. with some lag), (ii) I (Integrated) component: used to seasonally adjust the data, specifically, distribution of raw observation by calculating differences, and it makes a time series stationary, (iii) Moving Average (MA): used to set the error of our model as a linear combination of its past values. In order to select the correct lags and orders of differencing, an ARIMA model is denoted as p, d, q, where: p: order of the AR term, d: is the different order, and q: order of the MA term. Data collection is the pivotal step in forecasting. Various heavy industrial sectors, such as: deformed bar, refinery, tiles, cement, automobile, wires have been selected for the data collection. After collecting data from the industries, processes followed in this study are illustrated as follows:

2.1 Data Pre-processing
Deal with the zeros, imputing or treating them as NAs. Use one of the following to test for stationarity: Ad Fuller-test and differencing in case not stationary.

2.2 Identification
Check the ACF and PACF plots to short-list potential p and q values.

2.3 Estimation
Multiple ARIMA models can be built using different combinations of p, d, and q. Choose a model for selection using information criteria (ex: AIC, BIC).

2.4 Diagnostic Checking
Check the residuals for suitable white noise using residual analysis to validate the projected model (i.e. Uncorrelated and normally distributed about zero)
.

2.5 Forecasting Procedure
After choosing the best combination of p, d, and q, model has been applied for short-term forecasting, i.e., for next 12 months. Accuracy of the result has been checked using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) forecasting error model. The outcome has been compared with the actual values and model performance has been evaluated.

2.6 Seasonality and Zero Values Handling
We will now be looking at some analytical methods that just take the original data and reference the patterns that are found in it. Let's see what type of Seasonal ARIMA (SARIMA) model could be eligible to fit the annual seasonality. Secondly, we will treat the zeroes in the data (especially those that appeared in July and August) using several possible approaches. The variations include the most popular and simple solution by treating them as missing data fields and filling in the gaps with interpolation techniques, incorporating dummy variables to control for these seasonal closures, or applying a mixed-effect model able to correct for zero inflation present in the data. Based on these characteristics of the data, we deal with this oddity in the dataset through these strategies to build a reliable and robust forecasting model that can accurately reflect Bangladesh's heavy industry production behavior.

3. Data Collection
This study used the data set of monthly demand of finished products in industries. A total of 39 time points are included and it captures observations from January,2021 to March,2024. The production values are in MT and varies between 0 to 64,595MT with production zero in July 2021, July 2022, Aug 2023 and Sep 2023. March 2023 has reported maximum production of 64,595 MT. There may be seasonal trends indicated in the data, as production lows typically occur around July and highs near Q1 on a yearly basis.

4. Results and Discussion
4.1 Numerical Results
The preprocessing of data started with an inspection for the time series data covering a total of January 2021 to March 2024 (39 months) and ranging from 0 MT to 64595 MT with zero values found in July 2021, July 2022, August 2023 and September 2023. Results of the time series decomposition analysis revealing trends, seasonality, and residuals. The overall trend indicated a slight growth of production by years, and the seasonality indicated distinct annual peaks with low seasons monthly in July-August. The chart of residuals depicted strict volatility, suggesting the possibility of initial order ARIMA behavior. After this, stationarity with Augmented Dickey-Fuller test has been checked which gave a stat -4.2432 and p-value = 0.0006. Since the p-value was lower than 0.05, it is assumed that the series is stationary (though due to its clear trend, we will still take differences into consideration for model selection). The ACF and PACF analysis pointed towards potential AR terms of 1 or 2 and down toward MA terms of 1 or 2. Various

ARIMA and SARIMA models were fitted as part of the model selection process, with the former producing an AIC of 854.99 for best fitting ARIMA (1,1,1) model while the latter had overall better performance with reduced AIC at 592.18 for best fitting SARIMA (1,1,1)(1,1,12). The better fit allowed to capture yearly seasonality more accurately using any larger order seasonal multiple than that can be exploited here resulting in a local minima solution in favor of ARMA (p,q). For the SARIMA (1,1,1) (1,1,12) model, the residual analysis indicates mean -1983.73 with a standard deviation of 18604.44. The Ljung-Box test gave a statistic of 5.108 (p-value = 0.9542, so exceeds 0.05) meaning residuals are not (significantly) autocorrelated. Following these results, 12 months forecast has been made with the SARIMA (1,1,1) (1,1,1,12) model. Table 1 listed the results.

Table 1. Forecasted production for 12 months

Month	Forecasted Production (MT)	95% Confidence Interval
April 2024	39,375	(0 – 79,743)
May 2024	48,970	(4,724 – 93,216)
June 2024	41,114	(0 – 87,449)
July 2024	20,297	(0 - 68,395)
August 2024	19,706	(0 – 69,462)
September 2024	19,384	(0 – 70,737)
October 2024	40320	(0 – 93,222)
November 2024	46,494	(0 – 100,907)
December 2024	48,013	(0 – 103,889)
January 2025	50,958	(0 – 108,248)
February 2025	58,681	(11.72 – 117,351)
March 2025	58,282	(0 – 118,300)

The model was run over the last 12 months actuals with a MAPE (Mean Absolute Percentage Error) of ~34.84% and RMSE of 16349.45 MT indicating that while patterns/seasonality are well captured by the model, forecast uncertainty is also high – something to be rather concerned about as an early warning. lower confidence interval (CI) values should not fall below zero since production values cannot be negative. Due to this reason, negative lower CI values with 0 has been replaced to reflect the practical reality of production being non-negative.

For context, this relates to inherent seasonal patterns that we covered in the previous section on seasonal patterns our analysis found a strong annual seasonal pattern was present. Peak production occurs in the first quarter of each year (January-March), and there is a dip in output around July-August. There could be various explanations for this pattern, as the spikes in Q1 might actually represent an uptick in demand due to the start of the fiscal year or perhaps optimal weather. The July/August fall will probably be during the Bangladesh monsoon, which causes disruption to output and transport. Such seasonal trends indicate the need for a strategic buffer in inventory to make up for production certainty. Trend showed production is slightly up from 2021 to 2024 Increased local market demand, structural advantage of increasing production capacity and emerging export markets may be a potentially good sign for the Heavy Industries sector in Bangladesh. Still, the cautiousness of this trend indicates that there are huge barriers to faster growth. Figure 1 depicts the forecasted demand for steel re-rolling mill.

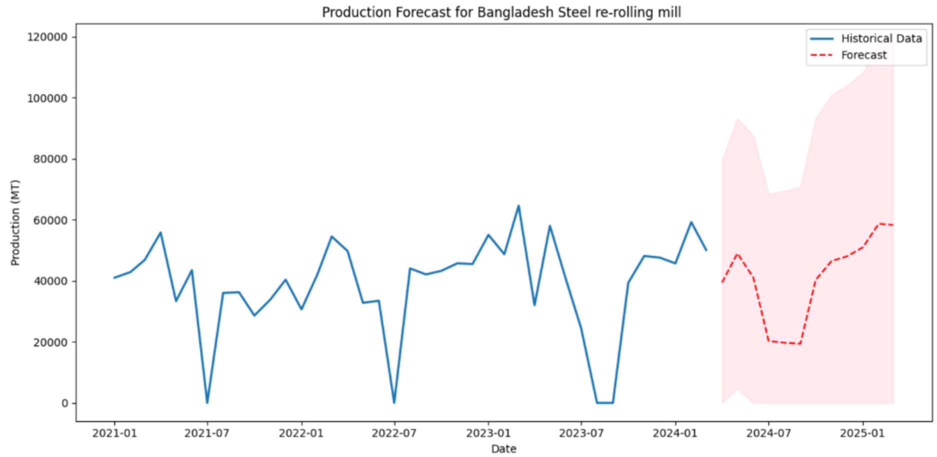


Figure **1**. Production Forecast for Bangladesh Steel Re-rolling Mill

In terms of model performance, the SARIMA (1,1,1) (1,1,1,12) outperformed ARIMA with a 1.44 AIC gain to this lower value of 592.18 and initial metrics of 34.84% MAPE and an RMSE in MT of 16349.45**.** These performances suggest that seasonal-ness are the most important features to consider when doing demand forecasting in such a domain. With a 34.84% MAPE (mean absolute percentage error), this signifies a middle level of final precision and thus is appropriate for general planning applications, while the RMSE (root mean squared error) of 16349.45 metric tons highlights the high volatility in new production data.

Now looking forward to 12 months, it can be seen a continuation of this seasonal pattern, the next peak is expected in Q1-2025 and another bottom in July-2025. The model assumes that seasonal valuable boards will persist permanently for production plans and resource allocations. The July 2024 forecast has it dropping to the historical average trend value of 20297.55 MT. The large confidence intervals (0 – 68395 MT for July 2024) underscored the high level of forecast uncertainty that comes with out-of-sample predictions.
Figure 2(a,b, and c) show the residuals of the forecasted value.

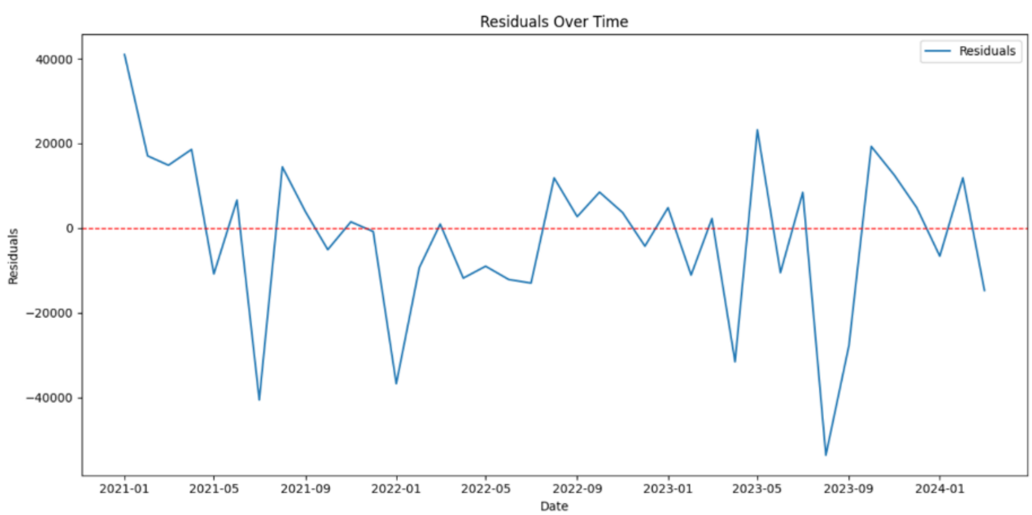


Figure 2 a. Residual plots (a) Residuals Over Time

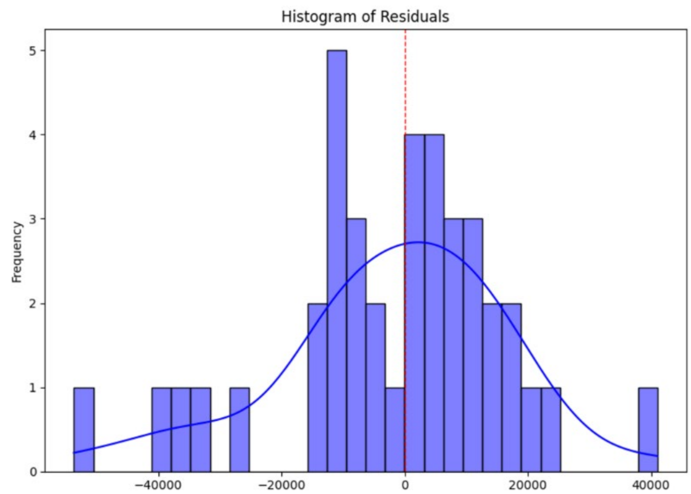


Figure 2 b. Residual Plot (b)Histogram of Residuals

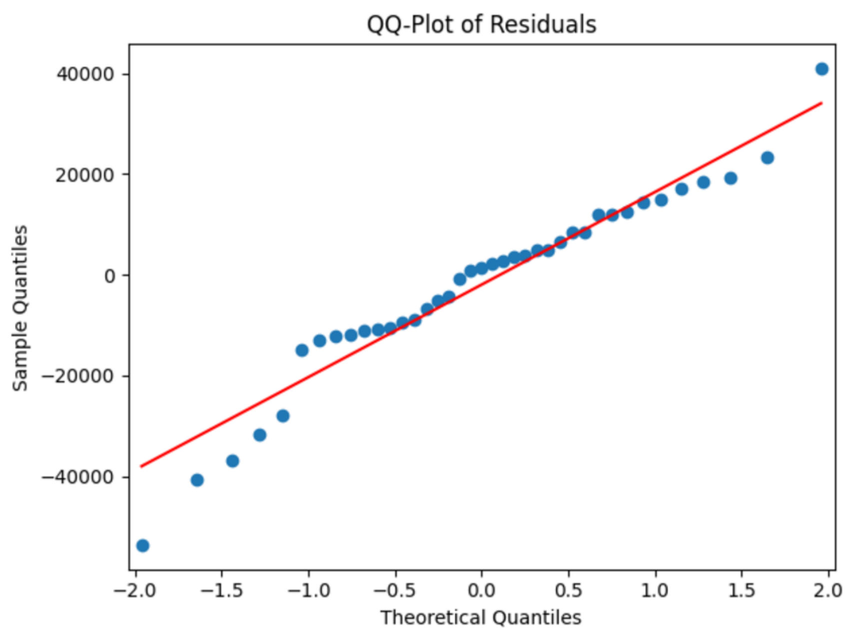
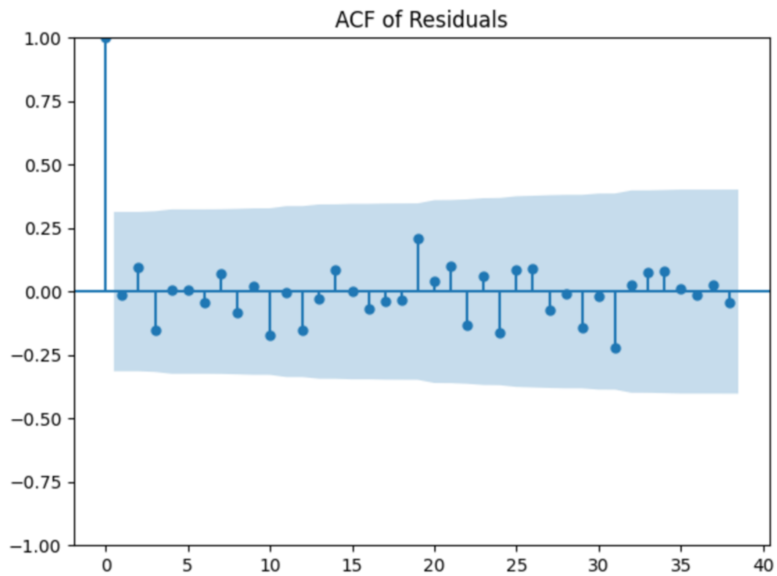


Figure 2 c.Residual Plot (c)QQ plots on residuals



(d)

Figure 2 d. Residual plots (a) Residuals Over Time, (b) Histogram of Residuals, (c) QQ plots on residuals, and (d) ACF of residuals

The implications for industry are several based on these findings. The interplay between the seasonality in demand, supply, and operational characteristics means that preparation is critical, this can include aggressive maintenance during downtime windows, inventory stocking ahead of prompt months, and changes to workforce scheduling. While growth planning appears strong, the relatively low pace indicates areas for strategic investment and policy instruments aimed at speeding up sector development. That is why far-sighted risk management – flex production, multi-sources, agile inventory systems powered by smart technology that can instantly read demand signals enter the equation with wide confidence bands. Although data-driven decision-making performs well, there remains room for better forecasts with advanced techniques and models, resulting in a higher number of data points. Last, aspects like economic environment/dynamics of the policy/location market/forces/shock/cats in the area can be introduced that were not well captured statistically, so you supplemented a forecast or models going into considerations for doing something beyond just models. The industry leaders and policymakers will need to weigh these factors.

6. Conclusion

In this study, a SARIMA model was introduced to predict the demand for finished product in heavy industries of Bangladesh like steel re-rolling mill. Analytics showed seasonality by year; Q1 peaks and July-August production dips were prominent. This is likely the monsoon season and shows how the weather impacts factory production in Bangladesh. While there were signs of some movement generally up in production, this was more suggestive of a mild growth scenario for the heavy industries category. This very modest trend is a harbinger for further growth and more broadening opportunities. SARIMA (1,1,1) (1,1,1,12) Mean Absolute Percentage Error (MAPE): 34.84 % and Root Mean Squared Error (RMSE) of 16,349 MT Model Performance: Moderate forecasting accuracy The preliminary model SARIMA (1,1,1) (1,1,1,12) production is a challenging combination of capturing significant patterns in the data while also identifying the substantial variability in productions. The fact that the best we can do is to extend those error bars into the future reflects the wide confidence intervals in our six-month forecast, especially for those later months. Such undetermined nature mirrors the intricate and lively role of the elements that determine output within its heavy industry sectors in Bangladesh.

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