A Study on Analysis of Sales Forecasting of Manufacturing Industry

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ABSTRACT
This research explores the strategic implementation of predictive analytics to enhance sales forecasting, inventory management, and production planning. Historical sales data were analyzed using methods like exponential smoothing and ARIMA, with ARIMA (1,1,0) emerging as the most effective model. The analysis revealed seasonal demand fluctuations, peaking in May and dropping in December. Predictive analytics significantly boosts operational efficiency but faces challenges such as data inconsistencies and market volatility. Recommendations include improving data collection, integrating external variables, and staff training. These steps support better decision-making and adaptability. The study offers a model for other mid-sized manufacturers..

KEYWORDS: Predictive analytics, sales forecasting, inventory management, production planning, ARIMA, exponential smoothing, quantitative research, seasonal demand, digital transformation, manufacturing industry.

1. INTRODUCTION
In today's fast-evolving manufacturing landscape, data has become a key strategic asset, enabling firms to compete through insight-driven decisions rather than just cost or speed. Predictive analytics stands at the center of this shift, offering powerful tools for forecasting demand, optimizing operations, and reducing inefficiencies. For mid-sized manufacturers with a strong legacy, adopting predictive analytics presents an opportunity to enhance agility and align with emerging Industry 4.0 practices. While traditional decision-making has served well, it now risks overlooking hidden patterns and inefficiencies. The study highlights challenges such as data infrastructure, cultural resistance, and skill gaps but proposes a phased, realistic approach tailored to organizational strengths. Predictive analytics can foster integrated decision-making, employee empowerment, and strategic growth. Ultimately, this transformation supports the evolution into a resilient, future-ready enterprise.

2. NEED OF THE STUDY
This study addresses the need for predictive analysis in a small-scale soap and detergent manufacturing business to strengthen its competitiveness in a fast-changing market. By analyzing sales data and consumer trends, it aims to improve demand forecasting, production efficiency, and inventory management. For local businesses, these insights are vital for sustainable growth and resilience. Predictive analytics also supports resource optimization and environmental responsibility. Ultimately, it empowers the company to make proactive, data-driven decisions while staying rooted in community values.

3. OBJECTIVES OF THE STUDY

- To enhance the accuracy of sales forecasts by applying predictive analytics techniques to historical sales data and market trends.
- To predict future sales trends using advanced statistical methods learning models based on historical data.
- To reduce forecasting errors by improving model accuracy through continuous analysis and refinement of forecasting techniques.
- To refine sales forecasts by incorporating factors like seasonality, historical trends.

4. SCOPE OF THE STUDY

The study on predictive analysis is all about harnessing data to help a business make smarter, forward-looking decisions. Picture this: using past sales, customer trends, or even weather patterns to predict what's coming next whether it's how much product to stock, when to ramp up production, or what customers might want. The scope covers digging into the organization's data, picking the right tools like machine learning, and focusing on practical areas like streamlining the supply chain or boosting sales through targeted marketing. It's not just techy number-crunching; it's about working closely with the team to solve real problems, keeping things ethical, and building models that grow with the business. If we know more about the sector like whether it's agriculture or retail we can zoom in even tighter to make it super relevant.

5. LIMITATIONS OF THE STUDY

- Sudden changes in market conditions, consumer behaviours, or external factors can reduce the accuracy of sales forecasts.
- Sales data may be incomplete, inconsistent, or affected by anomalies like promotions or seasonal events, which can distort model accuracy.
- For new products or markets, there may be insufficient historical data to build reliable predictive models.
- Predictive models may be overly sensitive to minor data fluctuations, leading to misleading forecasts if not properly validated and tested.

6. REVIEW OF LITERATURE

Anurag A.S. and M. Johnpaul (2025) emphasize predictive analytics as key to automating supply chain management post-pandemic. AI-driven techniques like regression and decision trees improve forecasting and decision-making. These tools enhance visibility and efficiency over traditional supply chains. The chapter stresses the need to adopt such technologies for market competitiveness.

Seyed Hamed Godasiaei (2025) investigates the predictive modeling of microplastic adsorption in aquatic environments using advanced machine learning techniques. Findings highlight the importance of the n-octanol/water distribution coefficient in predicting organic pollutant fate and emphasize the RNN model's accuracy (0.967) in forecasting microplastic behavior, contributing to efforts in combating microplastic pollution.

Y., Bensaali, F., and Amira, A. (2023) present a systematic review of Big Data Predictive Analytics (BDPA) from 2014 to 2023. The study focuses on how big data techniques are used to forecast future events by analyzing historical patterns. A total of 109 articles were reviewed using a Systematic Literature

Review (SLR) approach. The authors propose a taxonomy with seven major application categories based on the reviewed content.

Harshdeep Chhikara, Sumit Chhikara, and Lovelesh Gupta (2025) examine how AI and machine learning are revolutionizing financial decision-making, analytics, and risk management. The chapter highlights enhanced efficiency and innovation, particularly in emerging economies. It also addresses ethical concerns, emphasizing data privacy and the importance of Explainable AI for transparency and trust.

7. RESEARCH METHODOLOGY

Research is a systematic and detailed exploration of a specific topic or field. It involves collecting, organizing, presenting, and analyzing relevant information. It is considered a scientific form of investigation. Defined by the dictionary, research is a careful inquiry aimed at discovering new facts.

RESEARCH DESIGN

Research design refers to the detailed plan outlining methods and procedures for gathering information to address problems. It defines what data to collect, from where, and how. The structure of data collection and analysis depends on the research type, which can vary widely.

TYPE OF RESEARCH

This study employs a quantitative time series forecasting approach to predict future sales based on historical sales data

DATA COLLECTION METHOD

The study utilizes Secondary data source to forecast future sales.

SECONDARY DATA: Historical sales records were extracted from the company's sales database, covering the period This includes time-stamped records of sales volume, revenue, and product categories. The secondary data serves as the quantitative foundation for forecasting using time series models.

DATA ANALYSIS TOOL

- Exponential Smoothing
- Auto Regressive integrated Moving Average**.**

I EXPONENTIAL SMOOTHING

Exponential smoothing is a time series forecasting method for univariate data that's used to make short-term forecasts

MONTHS	SALES	FORECAST
2022		
January	245000	245000
February	73500	245000
March	196000	210700
April	294000	2207760
May	269500	225008
June	269500	233906.4
July	220500	241025.1
August	196000	239620.1
September	269500	228736.08

October	196000	236888.86
November	318500	228711.09
December	245000	246668.87
2023		
January	196000	246335.1
February	220500	236268.08
March	171500	233114.46
April	294000	220791.57
May	220500	235433.26
June	269500	232446.6
July	196000	239857.28
August	220500	231085.83
September	269500	228968.66
October	220500	237074.93
November	196000	233759.94
December	147000	226207.95
2024		
January	220500	210366.36
February	171500	212393.09
March	220500	204214.47
April	196000	207471.58
May	392000	205177.26
June	343000	242541.81
July	269500	262633.45
August	196000	264006.76
September	171500	250405.41
October	245000	234624.33
November	196000	236999.4
December	196000	228559.57

II ARIMA (Auto Regressive Integrated Moving Average)

ARIMA, standing for Autoregressive Integrated Moving Average, is a widely used statistical method for time series forecasting.

Model Description			
			Model Type
Model ID	sales	Model_1	ARIMA (0,0,1)

Model Statistics							
Model	Number of Predictors	Model Fit statistics		Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Normalized BIC	Statistics	DF	Sig.	
sales-Model_1	0	.022	22.152	12.200	17	.788	0

Parameter Estimates for Sales Model

ARIMA Model Parameters								
					Estimate	SE	T	Sig.
sales-Model_1	Sales	No Transformation	Constant		2.287E5	1.111E4	20.584	.000
			MA	Lag 1	-.144	.170	-.847	.403

ARIMA Model Fit Statistics for Sales Forecasting

Model Fit											
Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.022	.	.022	.022	.022	.022	.022	.022	.022	.022	.022
R-squared	.022	.	.022	.022	.022	.022	.022	.022	.022	.022	.022
RMSE	5.847E4	.	5.847E4	5.847E4	5.847E4	5.847E4	5.847E4	5.847E4	5.847E4	5.847E4	5.847E4
MAPE	22.161	.	22.161	22.161	22.161	22.161	22.161	22.161	22.161	22.161	22.161
MaxAPE	214.299	.	214.299	214.299	214.299	214.299	214.299	214.299	214.299	214.299	214.299
MAE	4.261E4	.	4.261E4	4.261E4	4.261E4	4.261E4	4.261E4	4.261E4	4.261E4	4.261E4	4.261E4
MaxAE	1.680E5	.	1.680E5	1.680E5	1.680E5	1.680E5	1.680E5	1.680E5	1.680E5	1.680E5	1.680E5
Normalized BIC	22.152	.	22.152	22.152	22.152	22.152	22.152	22.152	22.152	22.152	22.152

8. SUMMARY OF FINDINGS

The study looked at sales data from 2022 to 2024 and found that the ARIMA (0,0,1) model gave the most accurate forecasts. It had the lowest error rates compared to other models like ARIMA (1,0,1) and (1,1,0), making it both simple and effective. While Exponential Smoothing did a decent job at capturing overall trends, it struggled with sudden changes, such as the sales spike in May 2024. The Holt-Winters model didn't perform as well either, likely because there wasn't enough data to fully support its more complex structure. Despite their differences, all models showed a clear seasonal pattern sales tended to peak in May and drop in December. Using ARIMA (0,0,1), the study predicted that sales would likely peak again in June 2026 and hit a low in April 2025. These forecasts are especially useful for planning inventory and production. Overall, the ARIMA (0,0,1) model is recommended for long-term forecasting, especially when supported with better data and additional external factors to improve accuracy.

9. SUGGESTIONS

- Adopt ARIMA (0,0,1) as the primary sales forecasting model for its accuracy and simplicity.
- Use 2025–2026 forecasts to adjust inventory, increasing stock for May and June peaks and reducing it for December lows to cut holding costs.
- Improve forecast accuracy by incorporating external data on promotions, regional events, and competitor pricing.
- Train employees on SPSS for ARIMA (0,0,1) modeling and time series analysis to build a data-driven culture.
- Test ARIMA (0,0,1) against machine learning models long-term using richer datasets to enhance predictive power.
- Monitor forecast performance monthly, recalibrating ARIMA (0,0,1) or exploring alternative configurations if errors rise.
- Invest in automated forecasting tools or integrate SPSS with sales databases for real-time data updates.

10. CONCLUSION

The study on predictive analysis for sales forecasting showcases the power of data-driven decision-making in pump and motor manufacturing. Using historical sales data from 2022–2024, advanced techniques like Exponential Smoothing, Holt-Winters, and ARIMA models were applied to predict future trends. The ARIMA (0,0,1) model proved most effective, with the lowest RMSE (58,470) and a competitive MAD (42,610). Its simplicity and accuracy make it ideal for reliable forecasting. The findings highlight the potential of predictive analytics to optimize operations. Implementing ARIMA (0,0,1) can enhance inventory, production, and strategic planning.

BIBLIOGRAPHY

JOURNALS REFERRED

1. Anurag A. S. and M. Johnpaul (2025) Predictive Analytics: Facilitating the Process of Supply Chain Automation.
2. Seyed Hamed Godasiaei (2025) Predictive modelling of microplastic adsorption in aquatic environments using advanced machine learning models.
3. Susanti, R., & Prasetyo, E. (2023) Data Quality Problem in Predictive Analytics.
4. Luan, H., & Tsai, C.C. (2021) Systematic Review of Machine Learning Applications in Precision Education.

WEBSITES REFERRED

1. www.modernanalyst.com
2. www.iiba.org