IOSR Journal of Engineering (IOSRJEN) **www.iosrjen.org**
ISSN (e): 2250-3021, ISSN (p): 2278-8719
Vol. 14, Issue 9, September 2024, ||Series -1|| PP 24-27

Forecasting of Production Using Artificial Intelligence

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Received 03 September 2024; Accepted 16 September 2024

Abstract: Effective production forecasting is essential for optimizing operations and aligning production with market demand. This study investigates the application of artificial intelligence, specifically artificial neural networks (ANN), to enhance production forecasting accuracy. The research focuses on the El-Waha factory, analyzing data from 2022 to 2023. By employing ANN, the study achieved a mean absolute percentage error (MAPE) of 0.67% and an index of agreement (d) of 1.00, reflecting highly accurate forecasting performance. These results underscore the potential of artificial intelligence in improving production planning and decision-making processes, demonstrating that ANN can significantly enhance forecasting precision and operational efficiency.

Keywords: Production Forecasting, Production Management, Artificial Intelligence, Artificial Neural Networks (ANN), Mean Absolute Percentage Error, index agreement.

I. INTRODUCTION

Accurate production forecasting is crucial for companies to meet scheduled production targets and plan for various operational components, including staffing, facilities, machinery, and raw materials. Effective forecasting enables companies to anticipate market demand, adjust production schedules accordingly, and minimize reliance on chance [1]. Every manufacturing facility aims to optimize its operations to produce, sell, and profit from its products. To achieve this, companies must forecast production needs accurately, taking into account future market conditions. The accuracy of forecasts is vital as it impacts production planning. Genuine forecast errors should be minimal compared to residuals, and assessing forecast accuracy involves testing the model's performance with fresh, unseen data [2]. Erratic product demand introduces variability in the supply chain, making accurate forecasting a critical element of effective supply chain management. The ability to predict product demand reliably is essential for maintaining a competitive edge and ensuring efficient supply chain operations [3]. Previous studies have explored various forecasting models: **Mishra et al.** utilized the Autoregressive Integrated Moving Average (ARIMA) model to forecast food grain production in India. They incorporated production factors into the ARIMA model to enhance prediction accuracy, finding that forecasts were closer to observed values when these factors were included. Their study predicted Uttar Pradesh would lead in food grain production, generating 49,455 thousand tons from 19,982 thousand hectares with a productivity of 2,718 kg/ha in 2020 [4]. **Sahu et al.** compared the performance of Simple ARIMA and ARIMAX models, incorporating crop inputs in ARIMAX. The ARIMAX model demonstrated superior accuracy compared to Simple ARIMA. Their study also forecasted rice production trends, predicting West Bengal as the top producer and Punjab as a leading state in rice output for 2022, highlighting the importance of accurate forecasting for policy impact and food security [5]. **Nouf and Hartha** evaluated the effectiveness of three machine learning (ML) techniques for predicting food output: autoregressive (AR), ARIMA, and Long Short-Term Memory (LSTM) networks. Their findings indicated that while different algorithms perform better on various datasets, LSTM models showed greater adaptability and potential for improvement [6]. **Abhiram Dash et al.** compared ARIMA models with spline regression for forecasting rabi food grain production in Odisha. Their study, which analyzed data from 1970–71 to 2019–20, determined that logarithmic spline models were most suitable for forecasting future production, predicting an increase in output in the coming years [7].

This work aims to predict future production needs to align with market demand, optimize maintenance schedules, and enhance stock management. By improving forecasting accuracy, companies can better manage their production processes, ultimately boosting revenue, profit, and customer satisfaction.

II. METHODOLOGY

Data collection

Data on food production were gathered from the El-Waha factory. Table 1 presents the production quantities for the years 2022 and 2023.

Table 1. Production Quantities

Month	Quantity / 2023	Quantity / 2022
1	36353	56648
2	41626	6406
3	38161	54558
4	4984	18210
5	75468	84163
6	21432	43230
7	35305	30711
8	26332	16953
9	35478	5937
10	49479	7728
11	28109	17814
12	33012	26178

Implementation of ANN for Forecasting Production Quantities

A feedforward neural network was created with two hidden layers, each consisting of 10 nodes. The Levenberg-Marquardt (trainlm) training algorithm was selected for its effectiveness in prediction tasks. The data was divided into training, validation, and test sets in a ratio of 70%, 15%, and 15%, respectively. This division ensures that the model is trained on a substantial dataset and evaluated on a separate, unseen dataset to assess its performance. Table 2 displays the actual and forecasted production quantities along with the absolute percentage error (APE).

III. VALIDATION MODEL

To validate the performance of the ANN, the mean absolute percentage error (MAPE) was used to analyze the actual and forecasted production quantities, which was determined based on Equation (1). **MAPE= (Σ|$A−P$|/Ani=1) / n *100%** (1)

where:

A: The actual value for production quantity.

P: The forecasting value for production quantity.

n: Number of Experimental.

The MAPE value was 0.67%, indicating that the model has good forecasting accuracy. Additionally, Fig. 1 presents a comparison between the actual and forecasted production quantities. It shows that the ANN forecasting model effectively reflects the actual production values.

Table 2. Actual and Forecasted Production Quantities and Absolute Percentage Error (APE)

Month	Quantity of Production		Error	APE
	Actual	Forecasted		
1	56648	56648.02	0.02	0
2	6406	6406.99	0.99	0.02

3	54558	54557.03	0.97	0
4	18210	18210.04	0.04	0
5	84163	84163.01	0.01	0
6	43230	43230.09	0.09	0
7	30711	30706.57	4.43	0.01
8	16953	16978.32	25.32	0.15
9	5937	5827.4	109.6	1.85
10	7728	8092.34	364.34	4.71
11	17814	17057.09	756.91	4.25
12	26178	27040.74	862.74	3.3
13	36353	35857.49	495.51	1.36
14	41626	41754.29	128.29	0.31
15	38161	38145.99	15.01	0.04
16	4984	4984.84	0.84	0.02
17	75468	75467.86	0.14	0
18	21432	21432.11	0.11	0
19	35305	35304.94	0.06	0
20	26332	26332	0	0
21	35478	35478	0	0
22	49479	49479	0	0
23	28109	28109	0	0
24	33012	33012	0	0

The Index of Agreement (d) was also calculated to assess the model's efficiency using Equation (2).

$$\mathbf{d = 1 - \Sigma(A-P)^2 / \Sigma(IP-\bar{A}I)^2 + (IA-\bar{A}I)^2} \qquad (2)$$

Where:

A: Actual value for production quantity.

Ā: Average actual value for production quantity.

P: Predict a value for production quantity.

The Index of Agreement (d) value is 1.00, indicating a perfect match between the model's predictions and the observed data.

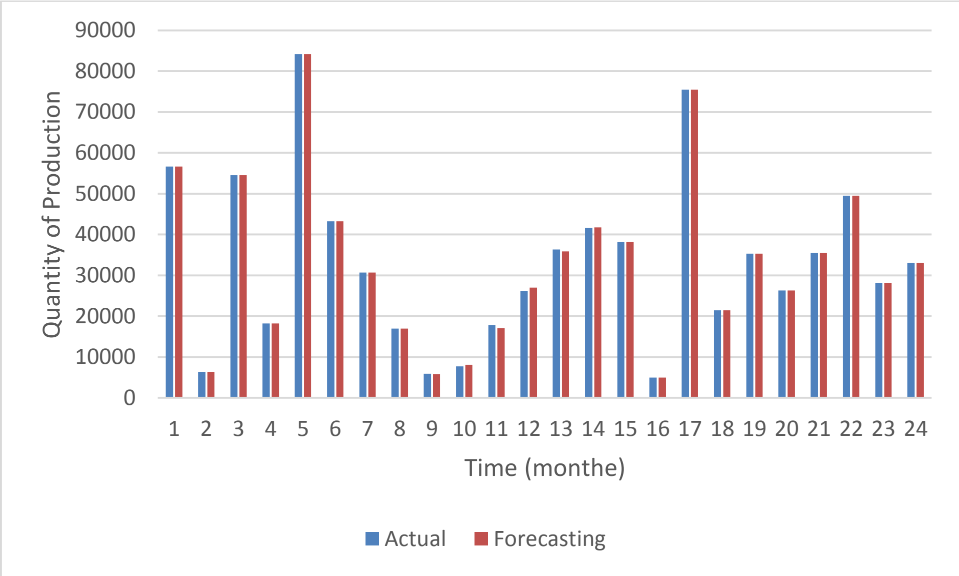

Figure 1. The actual and forecasting of production quantity

VI. CONCLUSION

Production forecasting, also known as demand forecasting, is a critical aspect of production sequence management. Its integration with other business functions makes it one of the most crucial planning processes for future business operations. In this context, the ANN method was tested and evaluated for forecasting production quantities using historical data from the El-Waha factory's food production. The accuracy of the developed model was assessed by calculating the mean absolute percentage error (MAPE) and the Index of Agreement (d). The values obtained were 0.67% for MAPE and 1.00 for the index, indicating that the model is reliable, accurate, and effective for forecasting production quantities. These results provide dependable guidance with a specified error rate for informed decision-making.

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