**Forecasting of Production Using Artificial Intelligence**

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**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.

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1. **INTRODUCTION**
2. 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].
3. 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.
4. **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). Top of Form

Bottom of Form

**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).

Top of Form

Bottom of Form

**d =1- Σ(𝐴−𝑃)2 /Σ(IP−ĀI)2 +(I𝐴−ĀI)2 ( 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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