PERFORMANCE ANALYSIS AND COMPARISON OF DEMAND FORECASTING MODELS AT AN ELECTRONICS COMPANY

Ngo Nguyen Thi Dan Quynh[1], Phan Ngo Quang Thinh[1], Pham Thi Ai Xuan[1], Nguyen Thi Diem Quynh[1], Huynh Duong Phuong Nam[1], Luong Trung Kien[1] and Duc Duy Nguyen[1*]

[1]Department of Industrial Systems Engineering, Ho Chi Minh City University of Technology
Email: duy.nguyen@hcmut.edu.vn

ARTICLE INFO

Received:
17/4/2025
Accepted:
06/7/2025
Published:
30/01/2026

Keywords:

ANN, electronics Industry, LSTM, time series forecasting

ABSTRACT

Time series forecasting encompasses both conventional statistical methods such as Moving Average, Exponentially Weighted Moving Average, and AutoRegressive Integrated Moving Average and contemporary machine learning techniques, including Artificial Neural Networks and Long Short-Term Memory. Each technique possesses inherent strengths and limitations, making the selection of an appropriate method dependent on the industry and data characteristics. This study investigates demand forecasting in the electronics sector, specifically for electronic components, to optimise resource allocation in a cost-effective and efficient manner. By evaluating the performance of various forecasting methods, comparing their effectiveness, and identifying the approach with the lowest error and highest optimisation potential, this research contributes empirical insights that support informed decision-making and promote operational efficiency.

1. INTRODUCTION

The electronics industry has been experiencing rapid growth in recent years, driven by advancements in digital technology, increasing consumer demand, and the growing complexity of supply chains. As electronic devices become more sophisticated, the demand for high-quality components and efficient manufacturing processes also rises. This creates a pressing need for accurate demand forecasting, particularly in predicting the quantity of electronic components required for testing and production preparation. Accurate demand forecasting in the supply chain is crucial for minimising costs and optimising operational efficiency, improving inventory management and ensuring that businesses allocate sufficient resources to accommodate market fluctuations. Inaccurate forecasting can lead to excess inventory, resulting in unnecessary storage costs or shortages, production disruption and negatively impacting customer satisfaction. Consequently, selecting an appropriate forecasting model is essential for enhancing operational efficiency and maintaining a competitive advantage in the electronics industry.

Modelling and accurately forecasting time-series data is challenging, and numerous statistical methods have been developed to address this issue. Traditional time-series forecasting methods such as Simple Moving Average (SMA) and Exponential Weighted Moving Average (EWMA) are widely used due to their simplicity and ease of implementation. These methods help smooth fluctuations in historical data to identify long-term trends [1], [2]. However, their effectiveness is often limited when dealing with highly volatile demand or complex relationships within the data. More advanced statistical models, such as the

AutoRegressive Integrated Moving Average (ARIMA), have been developed to overcome these limitations. ARIMA is more effective in capturing linear relationships between past and present values in a time series that being compared to traditional moving average methods [3].

With the advent of artificial intelligence (AI) and machine learning (ML), advanced models such as Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANNs) have gained increasing attention due to their ability to learn long-term dependencies and capture nonlinear patterns in time-series data. These approaches have demonstrated superior accuracy in forecasting demand for electronic components, especially in highly volatile markets. Despite these advancements, many businesses struggle to determine the most suitable forecasting approach. Some organisations use traditional models due to their interpretability and low computational requirements while others hesitate to adopt machine learning techniques due to high computational costs and the need for extensive training data. Moreover, there remains a lack of comprehensive comparative studies evaluating the effectiveness of these forecasting models in the context of electronic component demand prediction.

This study aims to analyse and compare the effectiveness of five demand forecasting models: Moving Average (MA), Exponential Weighted Moving Average (EWMA), AutoRegressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), and Artificial Neural Networks (ANNs). To conduct this analysis, several key steps were undertaken. First, historical demand data for electronic components was collected, cleaned, and preprocessed to ensure data quality. Next, the five forecasting models (SMA, EWMA, ARIMA, LSTM, ANN) were developed and trained using statistical and machine learning tools. The models were then evaluated based on key performance metrics, including Mean Absolute Deviation (MAD), Mean Squared Error (MSE), Standard Deviation of Errors (SDE), Mean Percentage Error (MPE), and Root Mean Squared Error (RMSE). Finally, the results were analysed to determine which model yields the highest forecasting accuracy for electronic component demand.

This study contributes to understanding demand forecasting in electronics manufacturing by integrating traditional time-series models with advanced machine-learning techniques. It provides a comprehensive comparative analysis of traditional statistical models and modern machine learning approaches and an empirical evaluation of forecasting performance using real-world data. The findings of this study can assist businesses in improving their forecasting strategies, optimising inventory management, and enhancing production planning.

2. LITERATURE REVIEW

2.1. Literature review

Time series forecasting, or forecasting in general, has played a crucial role in evaluating how the future demand for a single product will fluctuate in short-term and long-term periods. The Simple Moving Average (SMA) is a basic model frequently used in short-term forecasting for a time series; despite being simple, this model shows high effectiveness in dealing with time series and forecasting a short-term period. SMA model was used the to predict several COVID-19 cases in Pakistan for 3 months [4]. However, using a simple model like SMA may lead to inaccurate predictions when dealing with unstable data. A study was conducted comparing EWMA models as a basis for a self-starting forecasting approach to address this [5].

The ARIMA model is one of the most widely applied models for short-term forecasting across various data types. It has been used to forecast air pollution levels in Pakistan, as demonstrated in [5]. AIC and BIC are rarely used in forecasting as they are not great statistical models. However, it can be used effectively with small datasets, AIC was utilised as a metric to evaluate and determine an optimised ARIMA model [6]. The simplicity of ARIMA makes it highly accessible for different time series applications, and its ability to integrate with other models further enhances its suitability for hybrid forecasting approaches.

Machine learning methods can be ideal for short-term time series forecasting due to their high adaptability to complex and nonlinear patterns. These methods have more significant potential than ARIMA in dealing with those time series with external factors. The comparison of different models to find the most suitable one was conducted in [6]. To evaluate and identify the best model for short-term forecasting in the oil and gas industry. Moreover, the forecasting capabilities of machine learning techniques-such as ANN and LSTM have been extensively explored in the literature, and neural networks have been applied to build forecasting models. A hybrid model was proposed that integrates ARIMA and ANN for forecasting specific time series [8]. Similarly, ANN and ARIMA had been applied models for short-term demand forecasting in the electricity sector [9]. To overcome the memory limitations of ANN, the LSTM model has been utilised in [10], for example,applied LSTM for forecasting semiconductor material production.

Table 1. Research Gap

Author	Method	Sector	Evaluation metrics
[4]	MA	Covid-19	MSE, MAPE
[5]	EWMA		RMSE
[6]	ARIMA	Environment	RMSE, MAE, MAPE
[7]	LSTM, ARIMA, Prophet	Oil production	MAE, RMSE, R-squared
[8]	ARIMA & ANN		MAE, MSE
[9]	ARIMA & ANN	Energy	MAPE
[10]	ARIMA & LSTM	Semiconductor	MAE, MAPE, RMSE
This study	LSTM, SMA, ARIMA, ANN	Electronics Industry	RMSE

Evaluation method: The Root Mean Square Error (RMSE) is employed as the primary evaluation metric, as it quantifies prediction errors in the same units as the original dataset, making interpretation and comparison easier. RMSE is chosen to evaluate how different methods are affected by the outliers, enables the identification of the most appropriate model for the given dataset.

2.2. Theoretical framework

SMA (Simple Moving Average Forecasting)

This time series forecasting method is based on the moving average of past data. It is used to smooth fluctuations and identify overall trends, aiding in forecasting future values. Simple Moving Average (SMA) computes the average of the most recent N data points.

SMA(k): The simple moving average of the order k, denoted as SMA(k), is the mean of the last k observations.

$$Y_{t+1} = \frac{X_t + X_{t-1} + ... + X_{t-k+1}}{k} = \frac{\sum_{i=1}^{k} X_{t-k+1}}{k} \quad (1)$$

where Y_{t+1}: forecasted demand for the period $t+1$; X_t : actual demand in past periods t; k: number of periods in the moving average.

EWMA (Exponentially Weighted Moving Average)

Exponentially Weighted Moving Average (EWMA) is a time series analysis method used for trend identification and forecasting, which assigns exponentially decreasing weights to past observations, giving more importance to recent data. The weighting coefficient governs the smoothing process. α, and the formula is expressed as:

$$Y_{t+1} = \alpha X_t + (1-\alpha) X_{t-1} \quad (2)$$

where α is the smoothing factor; X_t is the current data value.

ARIMA (AutoRegressive Integrated Moving Average)

ARIMA (Auto Regressive Integrated Moving Average) is a widely used model in time series analysis for forecasting future values based on historical data.

$$Y_t = \theta_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_\rho Y_{t-\rho}$$
$$\varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - ... - \theta_q \varepsilon_{t-q} \quad (3)$$

where: Y_t: the differenced series of order d; ϕ_ρ: the autoregressive (AR) coefficients; θ_q: the moving average (MA) coefficients; ε_t: white noise.

There are several methods to determine the parameters p and q. One approach proposed by Akaike (1974) is to select the best model from a group of models using the AIC (Akaike's Information Criterion) index:

$$AIC = -2\ln(L) + 2(p+q+k+1) \quad (4)$$

For the ARIMA model, the corrected AIC formula (AICc) is presented as follows:

$$AIC_c = AIC + \frac{2(p+q+k+1)(p+q+k+1)}{n-p-q-k-2} \quad (5)$$

where L: likelihood probability of the data series occurring; p: degree of the autoregressive component, AR(p); q: degree of the moving average component, MA(q); $k=1$ if $c \neq 0$, and $k=0$ if $c=0$ (with c being a constant in the model); n: number of data points. In this research, ARIMA will be determined automatically by using Minitab.

ANN (Artificial Neural Network)

An Artificial Neural Network (ANN) is a computational model inspired by the human brain's neural system, simulating how biological neurons (nerve cells) process information. ANN is a crucial component of Machine Learning (ML) and Deep Learning (DL), widely used in predictive analytics and pattern recognition. ANNs are designed to handle complex problems that traditional computational methods struggle with by structuring information into layers. These layers process input data, apply transformations, and execute machine learning tasks to achieve optimal results.

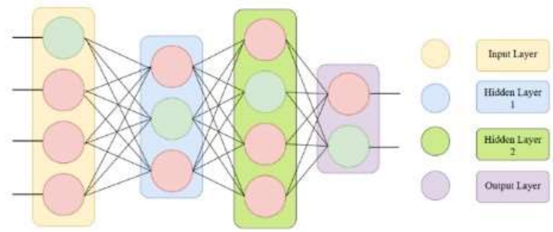

Figure 1. An ANN network

LSTM (Long Short-Term Memory)

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN), one of the most widely used machine learning techniques. The key feature of LSTM lies in its forget gate, which allows the model to discard irrelevant data, improving the accuracy of predictions compared to using the entire dataset indiscriminately.

The equation of LSTM will be presented below:

$$f_t = \sigma(W_{fh} h_{t-1} + W_{fx} x_t + b_f) \quad (6)$$

$$i_t = \sigma(W_{ih} h_{t-1} + W_{ix} x_t + b_i) \quad (7)$$

$$\tilde{c}_t = \tanh(W_{\tilde{c}h} h_{t-1} + W_{\tilde{c}x} x_t + b_{\tilde{c}}) \quad (8)$$

$$c_t = c_{t-1} + i_t \cdot \tilde{c}_t \quad (9)$$

$$o_t = \sigma(W_{oh} h_{t-1} + W_{ox} x_t + b_o) \quad (10)$$

$$h_t = o_t \cdot \tanh(c_t) \quad (11)$$

where i_t: input/update gate's activation vector; x_t: input vector to the LSTM unit; h_{t-1}: hidden state from the previous timestamp. h_t: hidden state vector, also known as the output vector of the LSTM unit; c_{t-1}: cell state vector from previous timestamp (long-term memory); c_t: cell state vector at the current timestamp; $\tilde{c}_t$: cell input activation vector; o_t: output gate's activation vector; b: Bias; W: weights; f_t: forget the gate's activation vector

3. PROBLEM STATEMENT

The enterprise encounters significant challenges due to the absence of a robust demand forecasting methods for electronic component quantities in the future. The quantity assessment process mainly relies on customer orders. However, the demand fluctuates monthly, has resulted in instances of overproduction, which in turn compromises component quality and overall supply chain efficiency. Previously, as a newly established company with a limited customer base, the make-to-order (MTO) production model was adopted. However, sudden fluctuations in customer demand - especially right before product shipment - have led to frequent mismatches between production output and actual market demand. Therefore, this study aims to develop a more effective demand forecasting method to optimise production and minimise the risks of surplus or shortage of components by analysing the effectiveness of the forecasting methods and comparing them; based on the analysis, identifying the model that best fits the company's dataset. The data has been provided by the company – historical demand of electronics device (pcs). The Root Mean Squared Error (RMSE) is employed as the primary performance metric to measure the performance of the methods.

4. METHODOLOGY

4.1. Method

As illustrated in Figure , the research process comprises several essential stages. First, topic selection involves identifying the problem to be discussed and conducting research accordingly. Next, the literature review examines previous studies related to the research topic, with a comparison table created to highlight connections between prior research and the current study. The problem statement provides a detailed description of the research problem and the specific case study used in the analysis. Following this, the determination of research objectives establishes the goals of the study, guiding further research, data collection, analysis, and conclusions. The theoretical framework discusses the theoretical foundations of the forecasting methods employed in the study. Data processing involves cleaning, organising, and preparing the dataset for analysis. In model development, appropriate forecasting models are applied and fine-tuned to optimise models for structured data processing. The results section presents the outcomes of the forecasting model, including error metrics and performance evaluations. The discussion provides a comparative analysis of forecasting errors and key insights from model evaluation. Finally, future works outlines potential directions for extending the research based on the study's findings while identifying its limitations within the chosen field.

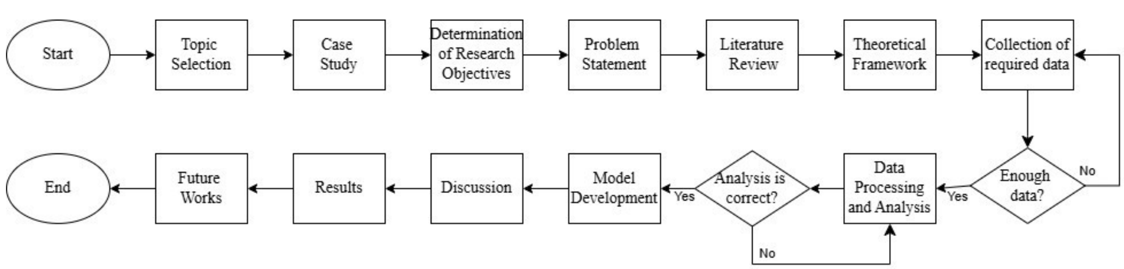

Figure 2. Research Methodology

4.2. Data processing

The company initially collected monthly data on production quantities, but there are certain irregularities, including outliers and missing values. Specifically, two outlier observations were identified , one in January 2023 (the early recovery phase after the US-China trade tensions) [11] and another in August 2023 (preparing for the end-of-year shopping season) [12]. There is one missing value in January 2020 (due to company closure during the COVID-19 outbreak) [13]. To ensure the dataset's suitability for further analysis, the data processing was performed using the Interquartile Range (IQR) method, and missing cells were filled with the mean value of an entire column.

Outlier values are detected by comparing them with the lower limit (Q1−1.5×IQR) and upper limit (Q3+1.5×IQR) [14]. These extreme values are subsequently replaced with the upper limit to minimise the impact on the analysis. Meanwhile, missing data is handled by filling it with the mean value to maintain continuity and prevent distortion of the overall distribution. After processing, the data shows fluctuations and evident changes from month to month. The selected models - SMA, EWMA, ARIMA, LSTM, and ANN - are used to forecast. These models aim to forecast production quantities under make-to-order (MTO) production strategy, in which goods are only manufactured after receiving specific customer orders rather than being produced for stockpiling. This approach is particularly suitable for businesses facing high product customization demands, unpredictable order volumes, or high inventory holding costs.

Unlike the make-to-stock (MTS) model, which focuses on producing in advance based on demand forecasts, MTO enables companies to reduce waste, avoid excess inventory, and align production more closely with actual market needs. However, MTO also places greater importance on the accuracy of short-term forecasting, as any mismatch between production readiness and customer orders can lead to delays, inefficiencies, or missed opportunities. In this context, accurate forecasts for the upcoming three months to one quarter are crucial for ensuring timely labor allocation, procurement planning, and capacity adjustment. By applying models such as SMA, EWMA, ARIMA, LSTM and ANN, the company can proactively prepare for future orders while maintaining operational flexibility and cost-effectiveness. Ultimately, the MTO strategy, supported by robust forecasting, allows the company to be more responsive and competitive in a dynamic market environment.

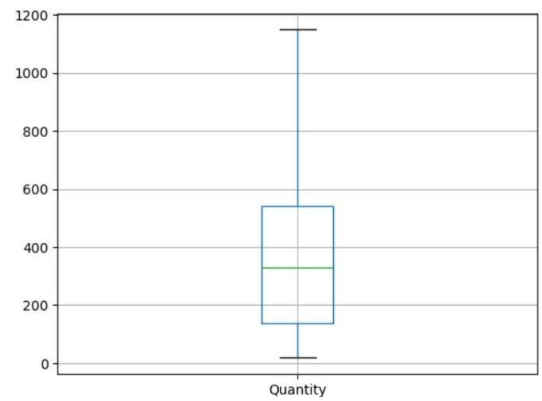

Figure 3. Boxplot after Data Processing

SMA: used to smooth the data and forecast short-term trends, assisting in workforce estimation.

EWMA: chosen to reflect recent fluctuations, helping with accurate labour planning quickly.

ARIMA: For short-term forecasting, coordinate the workforce for the upcoming quarters.

ANN: used to detect complex patterns and optimise forecasts for periods of strong fluctuations.

LSTM: forecasts abnormal demand, optimises labour allocation, and reduces risk.

5. CONCLUSION

5.1. Result

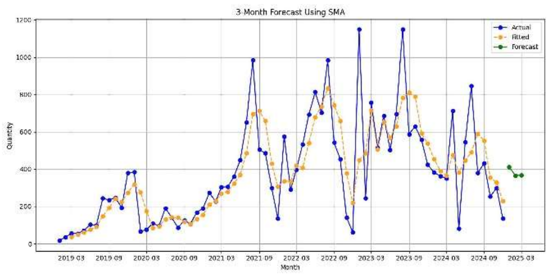

Figure 4. Result using the SMA method

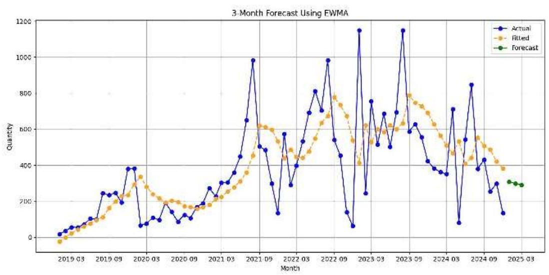

Figure 5. Result using the EWMA method

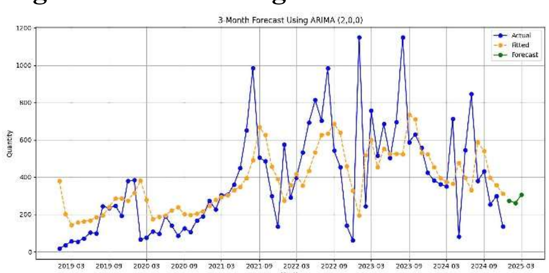

Figure 6. Result using the ARIMA method

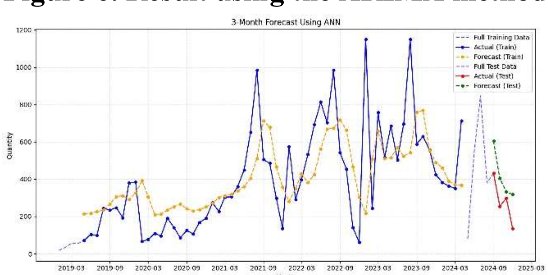

Figure 7. Result using the ANN method

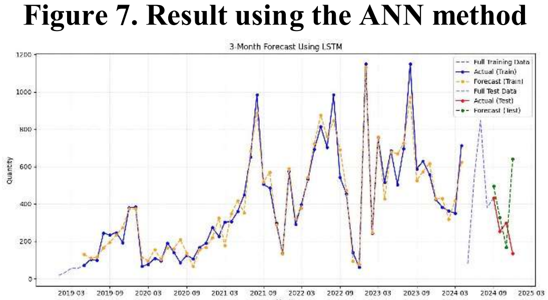

Figure 8. Result using the LSTM method

The three traditional models, including SMA, EWMA, and ARIMA, all capture the overall trend of the data effectively. SMA and EWMA offer the advantages of smoothing and ease of implementation. However, their ability to track sharp fluctuations remains limited, especially when the data exhibits significant peaks and troughs. Both ANN and LSTM models demonstrate good fitting performance on the training data and are capable of capturing complex fluctuations in the time series. Compared to ANN, LSTM achieves better alignment with actual data in both the test and forecast periods, thanks to its ability to retain long-term dependencies and learn deeper sequential patterns. LSTM clearly outperforms in forecasting during highly volatile periods.

5.2. Discussion

Table 2. Hyperparameters and RMSE of forecasting from models

Methods	Parameters	RMSE
SMA	n = 3	237.896
EWMA	α = 0.2679, n = 3	229.357
ARIMA	p = 2, d = 0, q = 0	223.499
ANN	In_nodes = 4, Hid_nodes = 3 Out_nodes = 1, Epoch = 500, Batch_size = 500	156.536
LSTM	In_nodes = 4 Hid_nodes = 7 Out_nodes = 1, Epoch = 500, Batch_size = 500	151.391

Table 3. Comparison of Error Values

Error Method	MAD	MSE	SDE	MPE
SMA	179.183	56594.346	237.847	32.640
EWMA	173.913	52604.802	228.397	43.674
ARIMA	384.204	49951.923	225.166	62.112
ANN	146.329	24503.429	55.598	67.359
LSTM	**136.915**	**22919.109**	**64.601**	**68.391**

Based on the table above, the LSTM method has the smallest RMSE error and other error values. Therefore, the LSTM method is chosen as the optimal method. The demand forecast for the next 3 months in 2025 using the LSTM method can be seen in Table 4.

Table 4. Demands for the next 3 months in 2025

Period	Jan	Feb	Mar
Demand (pcs)	329	169	642

5.3. Future works

In recent years, the electronics industry has experienced significant growth, leading to an increasing demand and greater complexity in forecasting, particularly in estimating the number of electronic components required for testing. Accurate forecasting optimises not only optimises production processes and inventory management but also ensures that workforce resources are adequately allocated to meet market demands, ultimately enhancing profitability and customer satisfaction.

Forecasting in the electronics industry is a critical factor that directly impacts production costs and service levels, as demand forecasting requires high accuracy. Current forecasting models have addressed some errors, with "the Artificial Neural Network (ANN) method evaluated and compared in this study. This method is proved to be the most effective technique. However, its accuracy is not yet optimal. Since each forecasting method has strengths and limitations, a hybrid forecasting strategy that integrates multiple methodologies could be a viable solution for future advancements.

In the case study conducted at an electronics company, the research team utilised data from the initial phase of a newly established manufacturing plant. Due to the limited availability of historical data, forecasting errors were significant. It will take several more years to refine the dataset to fully leverage the advantages of different forecasting methodologies, thereby improving accuracy and reducing errors. This study can be further expanded and developed by employing a hybrid forecasting approach - combining multiple methods as proposed by the research team. This will also enable periodic model improvements, investments in data infrastructure across different companies, and the integration of real-world feedback.

Furthermore, these forecasting models can be incorporated into Enterprise Resource Planning (ERP) systems. This integration would facilitate seamless production planning, workforce management, and timely decision-making, ultimately enhancing operational efficiency.

Acknowledgments

We acknowledge Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for supporting this study.

References

[1] Gardner ES. Exponential smoothing: The state of the art. J Forecast. 1985;4(1):1-28.

[2] Lotysh V, Gumeniuk L, Humeniuk P. Comparison of the effectiveness of time series analysis methods: sma, wma, ema, ewma, and kalman filter for data analysis. Inform Autom Pomiary W Gospod Ochr Śr. 2023; 13(3):71-4.

[3] Khashei M, Bijari M. A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. Appl Soft Comput. 2011; 11(2):2664-75.

[4] Chaudhry RM, Hanif A, Chaudhary M, Minhas S, Mirza K, Asif T, et al. Coronavirus Disease 2019 (COVID-19): Forecast of an Emerging Urgency in Pakistan. Cureus [Internet]. 2020; Available from: https://www.cureus.com/articles/32115-coronavirus-disease-2019-covid-19-forecast-of-an-emerging-urgency-in-pakistan [cited 2025 Feb 3]

[5] Yu J, Kim SB, Bai J, Han SW. Comparative Study on Exponentially Weighted Moving Average Approaches for

the Self-Starting Forecasting. Appl Sci. 2020; 10(20):7351.

[6] Kumar U, Jain VK. ARIMA forecasting of ambient air pollutants (O_3, NO, NO_2 and CO). Stoch Environ Res Risk Assess. 2010; 24(5):751-60.

[7] Ning Y, Kazemi H, Tahmasebi P. A comparative machine learning study for time series oil production forecasting: ARIMA, LSTM, and Prophet. Comput Geosci. 2022; 164:105126.

[8] Khashei M, Bijari M. An artificial neural network (p,d,q) model for timeseries forecasting. Expert Syst Appl. 2010; 37(1):479-89.

[9] Tarmanini C, Sarma N, Gezegin C, Ozgonenel O. Short term load forecasting based on ARIMA and ANN approaches. Energy Rep. 2023; 9:550-7.

[10] Wang CC, Chien CH, Trappey AJC. On the Application of ARIMA and LSTM to Predict Order Demand Based on Short Lead Time and On-Time Delivery Requirements. Processes. 2021; 9(7):1157.

[11] Nilsson L, Nolte S. The economic impact of the US-China trade dispute. Int Econ Econ Policy. 2023; 20(4):709-28.

[12] Advertising R. Pre-Holiday 2023 Shopping Trends and Insights [Internet]. Rakuten Advertising Blog. 2023. Available from: https://blog.rakutenadvertising.com/insights/pre-holiday-shopping-trends-2023/ [cited 2025 Feb 21]

[13] Naseer S, Khalid S, Parveen S, Abbass K, Song H, Achim MV. COVID-19 outbreak: Impact on global economy. Front Public Health [Internet]. Available from: https://www.frontiersin.org/journals/public-health/articles/10.3389/fpubh.2022.1009393/full. 2023 [cited 2025 Feb 25];10.

[14] Swami R, Dave M, Ranga V. IQR-based approach for DDoS detection and mitigation in SDN. Def Technol. 2023; 25:76-87

PHÂN TÍCH HIỆU QUẢ VÀ SO SÁNH CÁC MÔ HÌNH DỰ BÁO NHU CẦU TẠI MỘT CÔNG TY ĐIỆN TỬ

TÓM TẮT

Dự báo chuỗi thời gian bao gồm cả các phương pháp thống kê truyền thống như Trung bình dịch chuyển, Trung bình dịch chuyển có trọng số theo hàm mũ và Mô hình Tự hồi quy tích hợp Trung bình dịch chuyển, cũng như các kỹ thuật học máy hiện đại như Mạng nơ-ron nhân tạo và Bộ nhớ dài - ngắn hạn (LSTM). Mỗi kỹ thuật đều có những ưu điểm và hạn chế riêng, khiến việc lựa chọn phương pháp phù hợp phụ thuộc vào ngành nghề và đặc điểm dữ liệu. Nghiên cứu này tập trung vào dự báo nhu cầu trong lĩnh vực điện tử, cụ thể là các linh kiện điện tử, nhằm tối ưu hóa việc phân bổ nguồn lực một cách hiệu quả và tiết kiệm chi phí. Bằng cách đánh giá hiệu suất của nhiều phương pháp dự báo, so sánh hiệu quả của chúng, và xác định cách tiếp cận có sai số thấp nhất cùng tiềm năng tối ưu hóa cao nhất, nghiên cứu này đóng góp những bằng chứng thực nghiệm hỗ trợ ra quyết định sáng suốt và thúc đẩy hiệu quả vận hành.

Từ khóa: *ANN, công nghiệp điện tử, dự báo chuỗi thời gian, LSTM*