ENHANCED KNOWLEDGE IN SCIENCES AND TECHNOLOGY
e-ISSN: 2773-6385

EKST

Vol. 4 No. 1 (2024) 153-161
https://publisher.uthm.edu.my/periodicals/index.php/ekst

# Predicting Trend of Producer Price Index in Malaysian Manufacturing Sector: A Comparative Analysis of Time Series Models

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DOI: https://doi.org/10.30880/ekst.2024.04.01.018

**Article Info**

Received: 27 December 2023
Accepted: 3 June 2024
Available online: 27 July 2024

**Keywords**

Time series, Forecasting, ARIMA, Artificial Neural Network (ANN), Producer Price Index (PPI)

**Abstract**

This study aims to explore the importance of the Producer Price Index (PPI) in the Malaysian manufacturing sector and develop improved forecasting models for the PPI. The PPI is a crucial economic indicator that measures the average change in prices received by domestic producers for their goods and services. This study employs the Box-Jenkins model and Artificial Neural Network (ANN) as forecasting models for the Malaysian manufacturing sector's PPI data. Evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are utilized to compare forecast performances. The results show that the ANN model (MAE: 0.4337, MAPE: 0.4080) has the lower value of MAE and MAPE compared to the ARIMA model (MAE: 0.5154, MAPE: 0.4830). These findings suggest that the ANN model demonstrates a higher accuracy in forecasting, establishing its superior forecasting performance over the ARIMA model. In conclusion, the results provide critical insights for policymakers, businesses, and investors to adeptly manage risks, formulate effective policies, and make well-informed decisions within the manufacturing sector.

## 1. Introduction

The Producer Price Index (PPI) serves as a critical economic indicator, measuring the average change in prices received by domestic producers for their goods and services over time. In the context of Malaysia's manufacturing sector, which has been a pivotal driver of the country's economic and industrial growth, understanding the dynamics of the PPI becomes crucial [1]. The Malaysian manufacturing sector encompasses diverse industries, including electronics, chemicals, machinery, textiles, and automobiles, significantly contributing to employment, exports, and value-added activities. The PPI, consisting of input, output, and overall price indices, plays a pivotal role in tracking economic trends and providing valuable information for future inflation scenarios [2].

The research background underscores the importance of the PPI in Malaysia's manufacturing sector, emphasizing its role as an analytical tool to monitor price movements, inflationary pressures, and overall economic health. As Malaysia aims for sustainable economic development, the PPI becomes instrumental in offering insights into cost structures, business performance, and policy formulation. The Autoregressive Integrated Moving Average (ARIMA) model, a forecasting tool is introduced as methods to analyse time series data and forecast future opportunities based on past performance [3][4].

Neural networks, categorized into Biological Neural Networks (BNN) and Artificial Neural Networks (ANN) [5]. BNN, observed in biological systems, relies on intricate electrical signals transmitted through interconnected neurons. In contrast, ANN is a computational model designed to emulate the parallel processing nature of the human brain. Used widely for tasks like estimating energy consumption in buildings, ANN excels in handling complex relationships among variables [6]. Load forecasting methods encompass regression-based models, time series approaches, Support Vector Machines, and hybrids, with ANN chosen here for its ability to approximate non-linear functions in electrical load profiles [7]. Despite its effectiveness, ANN operates as a black-box model, lacking interpretability and struggling with unknowns or uncertainties [8]. It operates by minimizing errors between target and output through adjustable weights, resembling a learning process and falling under the umbrella of artificial intelligence.

The problem statement articulates the challenges associated with forecasting the PPI accurately. Despite advancements in statistical models and forecasting techniques, predicting future trends in the PPI remains complex due to multifaceted factors such as input cost fluctuations, demand and supply dynamics, global economic conditions, and policy interventions. The inherent volatility and nonlinear patterns of the PPI pose challenges to traditional forecasting methods [9]. The need for improved forecasting methods is highlighted to enhance accuracy, reliability, and effectiveness in managing risks, formulating monetary policies, and developing business strategies. Other previous studies were done in using forecasting method with the statistics technique in worldwide according to various fields of studies [10, 11, 12, 13].

The research objectives are outlined with a focus on applying forecast models, comparing forecasting methods' performance using metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), and ultimately forecasting the PPI in the Malaysian manufacturing sector using the best model. The scope of the study delves into a dataset spanning over 13 years, obtained from the Department of Statistics Malaysia (DOSM) website. The data is divided into training and testing sets, with two forecasting methods Box-Jenkins model and Neural Network model employed for analysis. The significance of the study is emphasized, highlighting how the PPI provides insights into price dynamics, aids in assessing firm profitability and competitiveness, informs policymakers in formulating effective policies, and contributes to economic forecasting and modelling exercises.

Lastly, this research seeks to shed light on the pivotal role of the PPI in Malaysia's manufacturing sector and the challenges associated with forecasting it accurately. By employing advanced forecasting models and methodologies, the study aims to contribute to the enhancement of economic decision-making, risk mitigation, and overall economic stability in Malaysia.

## 2. Methodology

This study utilizes the Malaysian manufacturing sector's Producer Price Index (PPI) data. The data set is monthly data range from January 2010 to December 2021, sourced from the Department of Statistics Malaysia [14]. Forecasting involves a hybrid approach, combining autoregressive integrated moving average (ARIMA) time series models and machine learning techniques, such as artificial neural networks (ANN). Evaluation metrics include mean absolute error and root mean squared error. The forecasting process, executed in Microsoft Excel, Minitab, and MATLAB, aims to provide accurate PPI predictions, aiding policymakers, businesses, and investors in decision-making.

### 2.1 Box-Jenkin (ARIMA)

Box-Jenkins Model is a mathematical model that is used to forecast the time series with specific fulfilment. Box-Jenkins Model is also known as Autoregressive Integrated Moving Average (ARIMA) as it consists of autoregressive, moving average and differencing models. Box-Jenkins Model requires some procedures before running the model. The procedures of Box-Jenkins included identifying, selecting, and assessing conditional mean models [15]. The guiding equation 1 of the expanded equation of Non-Seasonal ARIMA Model can be describe as [16]:

$$yT' = c + \emptyset 1\, y'T - 1 + \ldots + \emptyset\, p\, y'T - p + \theta 1\, T - 1 + \cdots + \theta\, q\, T - q + T \qquad (1)$$

where, $y_T{}'$ is Differenced series value, $y_T{}'_{-p}$ is Lagged value of $y_T$, $T_{-q}$ is Lagged errors, $\emptyset$ is Autoregressive parameter, and $\theta$ is Moving average parameter.

In the Box-Jenkins modelling process, begins with a simple look at a time series plot to spot trends, seasonality, and peculiar patterns. The focus then shifts to ensuring the stability of mean and variance over time, aligning with Box-Jenkins assumptions. To solve variance issues, transformations like logarithms are applied, and if the mean isn't stable, differencing subtracts consecutive observations to smooth out trends. Autocorrelation and partial autocorrelation functions come into play next, helping identify potential ARIMA models [17]. Based on insights from these functions and practical knowledge, potential ARIMA models are tentatively chosen. The identification of ARIMA models as shown in Table 1.

**Table 1** *Identification of ARIMA model*

| ACF | PACF | Model |
|---|---|---|
| Decay to zero with exponential pattern | Cuts off after lag $p$ | AR($p$) |
| Cuts off after lag $q$ | Decay to zero with exponential pattern | MA($q$) |
| Decay to zero with exponential pattern | Decay to zero with exponential pattern | ARIMA ($p, q$) |
| Cuts off after lag $q$ | Cuts off after lag p | AR($p$) or MA($q$) |

Moving on, estimating parameter values is crucial. Statistical software is used to find coefficients for the selected ARIMA model based on available time series data. Diagnostic checks follow to ensure residuals (differences between actual and predicted values) meet model assumptions, like randomness. If issues arise, adjustments or alternative approaches are considered. Finally, with a validated model in hand, forecasting for future time periods is done, utilizing the established ARIMA model's capabilities. The process, while involving some technical steps, essentially boils down to understanding the data, adjusting as needed, and leveraging statistical tools for reliable forecasts.

## 2.2 Artificial Neural Network

The neural network described consists of three layers: the Input Layer, the Hidden Layer, and the Output Layer (see Fig. 1) [18]. A simple neural network with three input neurons is visualized in Fig. 1. The guiding equation 2 of a neuron can be described as [19]:

$$Y = f\left(\sum_{X=1}^{n}(wixi)\right) \tag{2}$$

where, $Y$ is output, $f$ shows the activation function to introduce non-linearity, $w$ shows the weight on each connection to the neuron, $x$ shows the input of the neuron.

In the Input Layer, represented by nodes X1, X2, and X3, the network takes in the features of the input data, such as pixel intensities in the case of handwritten digit classification. The Hidden Layer, with a single node labelled (1WX), performs calculations by taking the weighted sum of inputs from the previous layer and applying an activation function to produce an output. The Output Layer, represented by node Y, provides the final prediction or output of the network, typically ranging between 0 and 9 in tasks like digit classification.

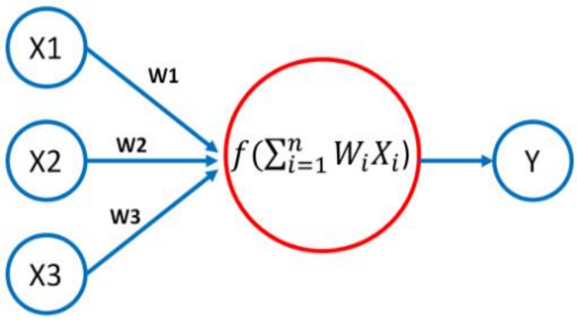



**Fig. 1** *Simple Neural Network*

The connections between nodes are depicted by arrows, each associated with a weight determining the strength of input influence. During training, these weights are adjusted iteratively using algorithms like gradient descent to minimize the error between predicted and actual values [20]. The network's operation involves multiplying input values by corresponding weights, summing the weighted inputs, passing the sum through an activation function for introducing non-linearity, and finally sending the output to the Output Layer. This basic neural network, despite its simplicity with just one hidden layer and one neuron, demonstrates fundamental principles of neural network functioning. Through training and weight adjustments, it can learn intricate relationships in data, making it applicable for tasks like classification, regression, and pattern recognition [21].

**Table 2** *Data preparation for ANN model*

| INPUT | | | | | | OUTPUT |
|---|---|---|---|---|---|---|
| $M_1$ | $M_2$ | $M_3$ | → | $M_{11}$ | $M_{12}$ | $M_{13}$ |
| $M_2$ | $M_3$ | $M_4$ | → | $M_{12}$ | $M_{13}$ | $M_{14}$ |
| $M_3$ | $M_4$ | $M_5$ | → | $M_{13}$ | $M_{14}$ | $M_{15}$ |
| ↓ | ↓ | ↓ | → | ↓ | ↓ | ↓ |
| $M_{130}$ | $M_{131}$ | $M_{132}$ | → | $M_{140}$ | $M_{141}$ | $M_{142}$ |
| $M_{131}$ | $M_{132}$ | $M_{133}$ | → | $M_{141}$ | $M_{142}$ | $M_{143}$ |
| $M_{132}$ | $M_{133}$ | $M_{134}$ | → | $M_{142}$ | $M_{143}$ | $M_{144}$ |

Table 2 shows the dataset that consisting of 144 entries, is prepared with columns $M_1$ to $M_{13}$. The data is structured to form a matrix of 132 rows and 12 columns, representing monthly data. The output spans from $M_{13}$ to $M_{144}$. The dataset is fed into an ANN application, specifically a Non-linear Autoregressive with external input (NARX) neural network. The input (xt) and output (yt) are employed, with the former having 12 columns and the latter having a single column. The network includes hidden layers with weights, biases, and a sigmoid function. The output layer uses the linear activation function to predict yt.

Data is loaded into the MATLAB neural net time series app, specifying 'loadin' for input and 'loadout' for target (real output). The time series format is set to 'Matrix row,' dividing the 132 rows into 70% training, 15% validation, and 15% testing. Default settings include 10 hidden neurons and 2 delays. A calculation based on Heaton's suggestion sets the hidden neurons to 100.

The 'Levenberg Marquardt' training algorithm is chosen, and training commences. The Mean Squared Error (MSE) and R-squared values are displayed post-training. Performance metrics, error histograms, regressions, and time series responses are visualized. The process includes examining error autocorrelation and input-error cross-correlation.

In summary, the ANN structure, data preparation, and training process were detailed, emphasizing the application of NARX neural networks for time series forecasting. The methodology encompassed input-output alignment, data loading, division into training-validation-testing sets, and the selection of appropriate parameters for effective training and prediction.

## 3. Results and Discussions

PPI has consistently been a hot issue for many researchers as a crucial macroeconomic indicator. Investors and economists have long used research on the Producer's Price Index (PPI) to predict the future course of monetary policy. Understanding the factors that influence the PPI in the manufacturing sector is crucial for accurate forecasting. Several studies have examined the determinants of producer prices index. A study investigates the impact of exchange rate fluctuations, oil prices, and labour costs on the PPI in Malaysia. They find that exchange rate changes and oil prices significantly affect the PPI, highlighting the importance of considering these factors in forecasting models [22]. PPI in Malaysian Manufacturing Sector has been used in this study. Time series plot of PPI in Malaysian Manufacturing Sector as shown in Fig. 2.

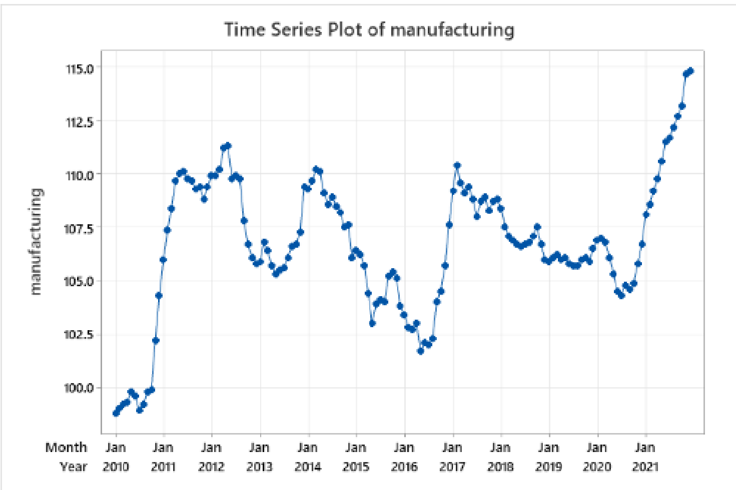



**Fig. 2** *Time series plot for Producer Price Index in Malaysian Manufacturing Sector*

Based on Fig. 2 it shows that the PPI in Malaysian Manufacturing Sector data did not show any clear trend or seasonality.

## 3.1 Box-Jenkin (ARIMA)

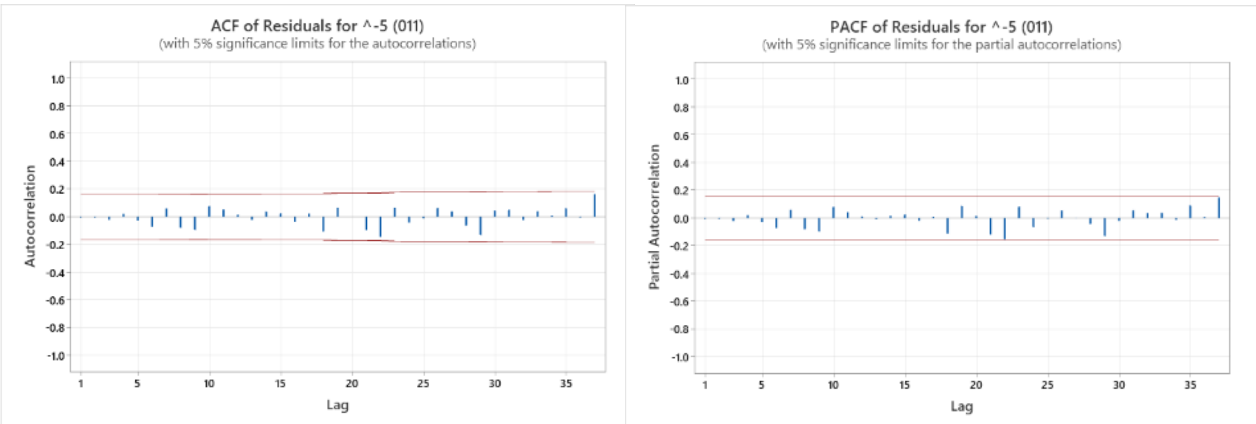
In predicting the Producer Price Index (PPI) for the Malaysian manufacturing sector using the Box-Jenkins method, several crucial steps were undertaken. Initially, the data's variance stability was assessed through a Box-Cox plot in Minitab software. The rounded value of λ indicated instability, requiring a Box-Cox transformation by raising the PPI values to the power of five. The transformed data's Box-Cox plot then confirmed stability, with λ values within control limits.

The next step involved constructing Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to assess the data's stationarity. The ACF plot revealed non-stationarity, notably at lag 1, and 5 lags beyond the confidence interval, prompting differencing to ensure stationarity. After differencing, the ACF and PACF plots confirmed stationarity, showcasing a random pattern. Because of differencing is done once, therefore d=1 needs to be considered during the selection of the Arima model. These plots guided the identification of a suitable Autoregressive Integrated Moving Average (ARIMA) model, with cutoffs observed at lag three. The *p*-values of the final estimate parameters and the Ljung-Box statistics value were then considered in model selection, aiming for statistical significance.

**Table 3** *Comparison between ARIMA model*

| ARIMA model | Type | *p*-value (Final estimate of parameter | P-value (Modified Box-Pierce (Ljung-Box) Chi-Square) | | | | MS |
|---|---|---|---|---|---|---|---|
| | | | 12 | 24 | 36 | 48 | |
| ARIMA (1,1,1) | AR 1<br>MA 1 | 0.000<br>0.053 | 0.026 | 0.059 | 0.121 | 0.096 | 1.97582E+17 |
| ARIMA (1,1,0) | AR 1 | 0.000 | 0.045 | 0.072 | 0.149 | 0.113 | 1.91210E+17 |
| ARIMA (0,1,1) | MA 1 | **0.000** | **0.071** | **0.158** | **0.308** | **0.224** | **1.89499E+17** |

Based on Table 3, it presents the final estimates of parameter, the model (1,1,0) and (0,0,1) with the *p*-value less than 5% significance level which is 0.000. Hence, it can be summarized that the coefficient is statistically significant, and the model should be kept. Besides, the model (1,1,0) has a *p*-value of Ljung-Box statistics almost 0.05, which is at lag 12 (0.045). Hence, it can be ensured that coefficient is may not statistically significant. Next, for the value of MS, model ARIMA (0.1.1) (1.89499E+17) has smaller value compared to other two models which is model ARIMA (1,1,1) (1.97582E+17) and model ARIMA (1,1,0) (1.91210E+17). Hence, model ARIMA (0.1.1) is chosen as the best model based on how strongly the model fits the data.




(a) (b)

**Fig. 3** *ACF (a) and PACF (b) for Yt^5d1 (0,1,1)*

In addition, Fig. 3 (a) and (b) show the best-fitting model, further checks on ACF and PACF plots for ARIMA (0,1,1) confirmed stationarity. With no lags exceeding the confidence interval, it was established that the data was normal and stationary, allowing for subsequent forecasting of PPI data using the ARIMA (0,1,1) model.

Lastly, the Box-Jenkins method involved ensuring variance stability through transformation, addressing non-stationarity through differencing, and selecting the best ARIMA model based on statistical measures. The chosen model, ARIMA (0,1,1), exhibited stationarity and was deemed suitable for forecasting the PPI in the Malaysian manufacturing sector.

## 3.2 Artificial Neural Network

In employing the Artificial Neural Network (ANN) method for predicting the Producer Price Index (PPI) in the Malaysian manufacturing sector, the methodology involved key steps in MATLAB. The network, once set up, underwent training, producing valuable insights into its accuracy and fitness. Table 4 displays the number of epochs, time taken, and crucial metrics. The performance measure exhibited a notable improvement from 1.74e+03 to 3.16e-24, signifying enhanced accuracy. The decreasing gradient indicated convergence towards a minimum in the loss function.

**Table 4** *Training Progress*

| Unit | Initial Value | Stopped Value | Target Value |
|---|---|---|---|
| Epoch | 0 | 5 | 1000 |
| Elapsed Time | - | 00:00:07 | - |
| Performance | **1.74e+03** | **3.16e-24** | 0 |
| Gradient | 3.7e+03 | 3.71e-11 | 1e+07 |
| Mu | 0.001 | 1e-08 | 1e+10 |
| Validation Check | 0 | 0 | 6 |

Fig. 4 presents the regression for training, validation, test, and overall datasets. The overlap of the fit line with the diagonal line (Y = T) suggested the model's precise matching of predicted values with the actual PPI values during training. The training graph, with a perfect correlation coefficient (R=1), indicated a flawless linear relationship between predicted and actual values. However, this perfect fit raised concerns about potential overfitting to the training data.

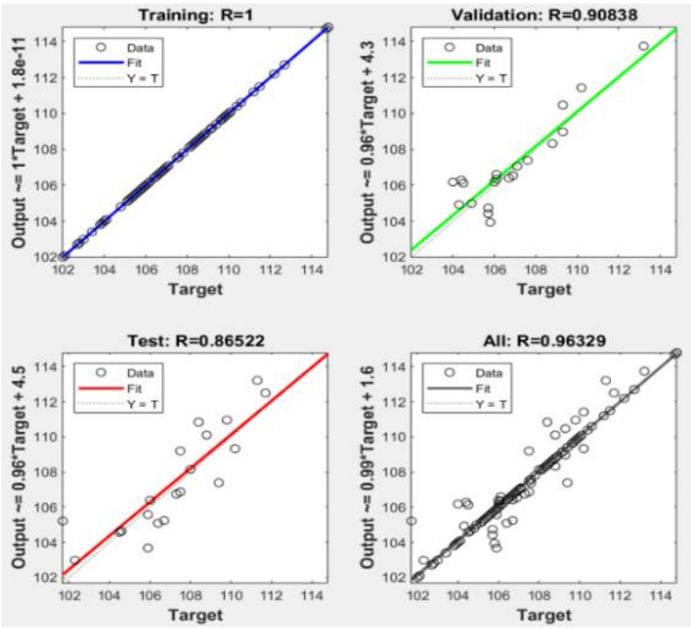



**Fig. 4** *Regression plot*

The validation graph, as shown Fig. 4 in with an R value of 0.90838, mirrored the training data's performance, indicating the model's ability to generalize to unseen data. While generally positive, a perfect fit on validation data may still raise overfitting concerns if the model is overly complex. The test graph, with an R value of 0.86522, denoted a moderately strong positive correlation, suggesting a linear relationship between predicted and actual values. Some variability or scatter in the data was expected in real-world scenarios.

For the all-data graph, the R value of 0.96329 demonstrated a strong positive correlation across the entire dataset. The model showcased good performance in predicting PPI values, capturing underlying patterns effectively. Although some minor deviations from the fit line were observed, indicating room for improvement, the overall accuracy was reasonably high.

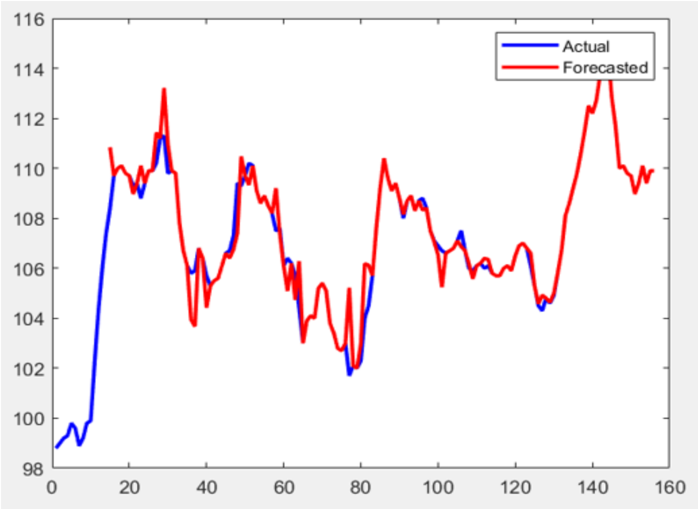



**Fig. 5** *Time series of Actual vs Forecast*

Furthermore, Fig. 5 as a time series plot compared the actual and forecasted data highlighted the model's ability to capture the general trend of PPI changes. While the forecast line closely followed the actual line, some discrepancies emerged, particularly around PPI peaks. The model tended to underestimate or overestimate values in certain periods, suggesting a need for improvement in accuracy and precision.

In conclusion, the ANN method demonstrated success in capturing the PPI trends in the Malaysian manufacturing sector. However, considerations for potential overfitting and areas of improvement, such as addressing underestimation or overestimation in specific periods, were identified for future model refinement.

## 3.3 Forecasting Performance Evaluation

**Table 5** *Comparison of forecasting performance*

| Accuracy Measure | Forecasting Method | |
|---|---|---|
| | ARIMA Model | ANN Model |
| MAE | 0.5154 | **0.4337** |
| RMSE | **0.6794** | 1.0212 |
| MAPE | 0.4830 | **0.4080** |

Based on Table 5, the ARIMA and ANN models are compared for their prediction accuracy using measures like mean absolute error (MAE), mean square error (MSE), and mean absolute percentage error (MAPE). Lower values in these metrics indicate better accuracy. The evaluation, conducted using Microsoft Excel and MATLAB, favoured the ANN model (MAE: 0.4337, MAPE: 0.4080) over the ARIMA model (MAE: 0.5154, MAPE: 0.4830). Although the ARIMA model had a slightly lower root mean square error (RMSE) at 0.6794 compared to ANN's 1.0212, the overall conclusion leaned towards the ANN model for superior forecasting performance. These findings suggest that the ANN model is more likely to be accurate in predicting values, making it a better choice compared to the ARIMA model, as per the analysis of the employed accuracy measures.

## 4. Conclusions

The Box-Jenkins method effectively forecasted the Producer Price Index (PPI) in the Malaysian Manufacturing Sector. It tackled data challenges through preprocessing, stabilizing variance, and making mean stationary. ARIMA (0,1,1) emerged as the best-fit model, indicating a first-order autoregressive component and a first-order differencing term. This model successfully generated PPI forecasts, emphasizing the importance of data preprocessing and model selection for accurate time series forecasting.

The Artificial Neural Network (ANN) method performed well in predicting PPI across training, validation, and test data, capturing underlying patterns effectively. Despite occasional deviations, high correlation values (R) signify strong relationships between predicted and actual values. However, concerns about overfitting arise due to perfect R-values on training and validation graphs, indicating potential challenges in generalizing to unseen data.

Comparing ARIMA and ANN models, the ANN model outperformed MAE and MAPE, suggesting higher forecasting accuracy. Despite a slightly lower RMSE, the overall evaluation favours the ANN model for better forecasting reliability, especially considering key metrics like MAE and MAPE.

To make forecasting models more reliable, a few recommendations are given. It's important to check the model on new data not used during training, using techniques like regularization, or early stopping if overfitting is seen. Testing the model on unseen data is crucial for confirming its generalization abilities, and monitoring for overfitting during modelling is essential. Understanding where the model's predictions differ from real values helps in finding areas for improvement. Adding diversity to data and collecting more validation data can reduce overfitting risks. The goodness of fit for regression models should be assessed with measures like R-squared or residual analysis. If linear models don't work, exploring non-linear relationships is suggested. Adjusting parameters, adding variables, or trying different structures can enhance accuracy. Investigating and addressing autocorrelation in error series is advised, along with understanding specific input variables. Investigating periods of prediction discrepancies is crucial. Generalization checks on new data and potential refinements should be part of the evaluation process.

## Acknowledgement

The authors would thank the Faculty of Applied Sciences and Technology, Universiti Tun Hussein Onn Malaysia for its support.

## Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

## Author Contribution

*The authors confirm contribution to the paper as follows:* ***study conception and design:*** *Mohammad Rosada Tarmuji, Kamil Khalid;* ***analysis and interpretation of results:*** *Mohammad Rosada Tarmuji, Kamil Khalid;* ***draft manuscript preparation:*** *Mohammad Rosada Tarmuji, Kamil Khalid, Mohd Saifullah Rusiman. All authors reviewed the results and approved the final version of the manuscript.*

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