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Journal of Mathematical Sciences and Informatics
Journal Homepage: https://journal.umt.edu.my/index.php/jmsi
eISSN: 2948-3697
DOI: http://doi.org/10.46754/jmsi.2023.12.001

JMSI
Journal of Mathematical Sciences and Informatics

A COMPARISON OF PREDICTIVE MODELLING TECHNIQUES FOR REDUCING PRICE VOLATILITY IN THE MALAYSIA SECTOR

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ARTICLE INFO

Article History:
Received
27 MARCH 2023
Accepted
2 DECEMBER 2023
Available online
25 JANUARY 2024

Section Editor:
Muhamad Safiih Lola

Keywords:
Forecasting;
Fisheries prices;
ARIMA;
MLFFN;
Hybrid ARIMA-MLFFN

ABSTRACT

Fisheries stand as a vital contributor to the Malaysian economy, constituting 12% of the gross domestic product. However, the pricing dynamics of fisheries have always been a concern for Malaysian citizens. Fishermen grapple with challenges in planning and decision-making, facing low prices that contrast with the elevated costs of fishing. At the same time, retailers benefit from higher fisheries prices, resulting in an upward trend in prices over time with susceptibility to fluctuations. This study aims to forecast the monthly price behaviour of many main varieties of fish consumed in Malaysia, employing the ARIMA, MLFFN and hybrid ARIMA-MLFFN methods. The dataset spans seven in-sample years (January 2010 to December 2018) and two out-sample years (January 2019 to December 2020), encompassing three fish varieties (longtail tuna, torpedo scad, and shortfin scad) across ex-vessel, wholesale, and retail prices. Forecasts were made for the prices of fisheries for the next 12 months. The findings show that all of three models are comparable, delivering highly accurate forecasts with a 96% MAPE of out-sample forecasts below 10%.

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INTRODUCTION

Price monitoring plays an important role in a country's overall macroeconomic efficiency [1]. This makes quantitative forecasting an invaluable tool for policymakers since it allows for the modelling, analysis, and prediction of various occurrences. However, achieving accurate quantitative forecasting is challenging due to the uncertainties that forecasters face [13].

Malaysia's economic growth is significantly influenced by the fisheries industry, as the country now operates as an exporter to other nations. The industry's significance makes it imperative for fishermen to model fisheries prices to assess market performance and predict future levels [6]. Fishermen have expressed dissatisfaction over the low prices of fisheries, despite customers paying high retail rates [3]. Additionally, fishermen are confronted with escalating fishing costs, such as gasoline, which they cannot pass on to customers. As a result, significant price differentials exist between retail and ex-vessel pricing in the market. Given the dynamic nature of fisheries prices, forecasting emerges as a viable solution to anticipate future price changes.

The fisheries sector is vital to the country's economy, as it is one of the world's fastest-expanding food production markets, and this growth is expected to continue [16]. As [11] suggests, the development of the fisheries sector can establish a good platform for the economy. This study investigates whether the economic value of fisheries remains significant at lower levels.

The effectiveness of a country's fisheries management relies on the pricing or sales of fisheries, determining its profitability. Numerous research studies on fisheries prices have been conducted globally. Early examples of research on fisheries prices include the ex-vessel fish price database and global seafood [11;14]. The first significant discussions and analyses on fisheries prices emerged during the 2010s, focusing on ex-vessel fish prices [15]. This study emphasises the initial development area, as ex-vessel catches greatly inflated prices intended for non-direct human consumption. The observed price differences between commodities were shown to have an impact on strongly aggregated price and landed value patterns over time.

In various fields, such as climate studies, agriculture, business, tourism, and fishing, time series forecasting has been employed to predict the future [12]. Numerous strategies, from the simple ordinary least squares method to autoregressive integrated moving average (ARIMA) models, have been employed in economics to explain and predict price performance. Time series forecasting proves to be a practical approach for anticipating aquaculture commodity prices. However, limited research publications have explored the use of time series models to predict fisheries prices. Therefore, the ARIMA and artificial neural network (ANN) methods are also employed as statistical techniques for time series forecasting.

The ARIMA model allows a time series to be described by its previous data, or lagged values, as well as its stochastic error components [7]. While there has been extensive research in forecasting the performance of prices in the financial sector using time series analysis, only a small number of studies have applied these methods to predict fisheries prices. For instance, [5] evaluated the forecasting of the monthly retail price of Indian mackerel using a comparison of time series techniques, which are the Box-Jenkins and Holt's linear trend methods. Another study conducted a price analysis of various main types of Sri Lankan fisheries using the seasonal ARIMA, or SARIMA, model, considering the argument that fisheries prices have risen over time and fluctuate in costs [9]. Meanwhile, in a study conducted by [8], an investigation into web-scraped prediction data for selected fish and vegetables from the Department of Statistics revealed that longer time series provide better predictions since ARIMA relies on the number of periods in modelling.

In addition to the ARIMA model, ANN has been applied in many areas, such as forecasting aeroplane passengers [18], electricity supply [20], modelling lockdown strictness for the COVID-19 pandemic [19; 21; 22] and tourism forecasting [23]. The combination of two models, a hybrid, is considered promising to enhance forecasting performance. An example is the SARIMA backpropagation hybrid model, which combines SARIMA and the backpropagation neural network models, which was evaluated for the forecast of two seasonal time series data on the total production values for Taiwan's machinery industry. The results showed that the hybrid model performed better than the SARIMA model [24].

In 2003, Zhang applied a hybrid model that combined the ARIMA and ANN models to forecast three data series. He also found that the hybrid model outperformed both single models [25]. Hence, the objectives of this study are to select the best-performing model for fisheries price from three types of forecasting methods: ARIMA, multi-layer feedforward neural network (MLFFN) and hybrid ARIMA-MLFFN.

DATA AND METHODOLOGY

This paper uses secondary data from the Department of Fisheries, specifically focusing on selected fisheries prices from January 2010 until December 2020. The study focuses on the most favoured types of large pelagic, which are *Thuntus tongol* (longtail tuna) and *Megalaspis cordyla* (torpedo scad), along with small pelagic fish widely preferred by Malaysians, *Decapterus maruadsi* (shortfin scad). The research centres on three forecasting methods — ARIMA, MLFFN and hybrid ARIMA-MLFFN — evaluating their performance accuracy using four metrics: Mean absolute percentage error (MAPE), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE).

Autoregressive Integrated Moving Average

The ARIMA model is a stationary series involving differencing, denoted as an "integrated" (I) series. It is also known as the ARIMA (p,d,q) model. This model also involves a constant term in the equation. The stationary lag series are called "autoregressive" (AR) terms, while the forecast errors lag are called "moving average' (MA) terms. The ARIMA (p,d,q) model can be written as:

Theorem 2.1. $y_t = \delta + \O y_{t-1} + ... + \O_p y_{t-p} + a_t - \theta a_{t-1} + ... + \theta_q a_{t-q}$

where

y_t : time series origin

δ : constant

$\O_p$: autoregressive parameter

θ_q : moving average parameter

a_t : error term at time

To forecast using this model, three steps are involved in selecting the best model among all potential models [17]. Once these three steps are completed, the model can be applied to predict future values of the time series. Figure 1 illustrates the steps in the Box-Jenkins forecasting method.

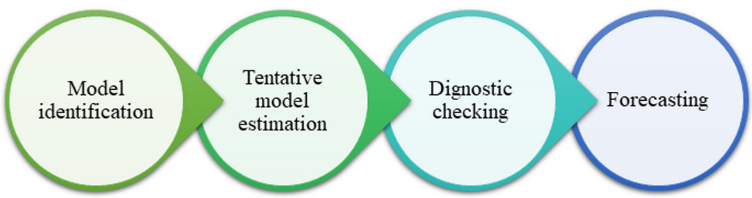

Figure 1: Steps in the Box-Jenkins forecasting method

Multi-layer Feed-forward Neural Network

To forecast fisheries prices, this study decided to employ an appropriate data transformation, specifically a feed-forward network. The go-to ANN for addressing predictive challenges in a subject matter like fisheries tends to be the multilayer perceptrons, featuring a single hidden layer feed-forward network. In this context, a feed-forward network operates without feedback from the outputs of the neurons to the network's input [10]. The data flows unidirectionally from the initial stage layers until it reaches the output node is reached, typically passing through an activation function. Feed-forward neural networks are characterised by their direct structure, where data is transmitted solely between the input and output nodes, lacking feedback from the latter. These neural networks can consist of either hidden layers or a single layer. Based on the number of layers, feed-forward neural networks are classified into two types; "single layer" and "multi-layer".

Hybrid ARIMA-MLFFN

To train an MLFFN model, the estimated and observation values from an appropriate ARIMA model are employed. The initial phase involves utilising an ARIMA model to assess time series data, as ARIMA is not adept at handling nonlinear data structures effectively. The model is constructed using the output values derived from the relevant ARIMA model, encompassing historical time series data ($y_{t-1}, y_{t-2},..., y_{t-p}$), predicted or forecast values of the ARIMA model $\hat{L}_t$, and the residuals of the ARIMA model ($\varepsilon_{t-1}, \varepsilon_{t-2},..., \varepsilon_{t-p}$).

Subsequently, in the second stage, the MLFFN model is generated, with the inputs derived from the residuals of the ARIMA model. This model uses a hyperbolic tangent as its activation function. This provides two main advantages: they are less sensitive to saturation in the later layers of a given network, and they lead to faster convergence than the standard logistic function. Finally, the output of the final hybrid model is generated.

Theorem 2.3. $y_t = \hat{L}_t + N_t$

where

$\hat{L}_t$ = linear components

N_t = non-linear components

RESULT AND DISCUSSION

ARIMA Model Analysis

The monthly plot of fisheries ex-vessel, wholesale and retail prices from 2010 to 2020 exhibits a clear trend. Furthermore, an analysis of the ex-vessel price of torpedo scad reveals that both the autocorrelation function and partial autocorrelation function quickly cut off, indicating that the time series data is stationary at the second order of differencing, I(2). Thus, based on this information, it can be concluded that the value of d in the ARIMA (p, d, q) model for this time series is d = 2. Therefore, the values of p and q parameters are 4 and 1, respectively, leading to the formation of the ARIMA (4,2,1) model. However, since this model proves to be insignificant, the autocorrelation in lag 3 and 4 is removed to achieve significance at the 0.05 level with white noise residuals. At the same time, the different wholesale and retail prices of other fish, the shortfin scad and longtail tuna, undergo a similar ARIMA process.

In this research, it is essential to calculate the error needed to enhance future predictions. Performance measurement serves as a tool to gauge the accuracy of the forecasts. This research measures performance using MAPE, MSE, MAE, and RMSE, as detailed in Tables 1 and 2. Table 1 shows the performance measurement for the in-sample data, revealing that all MAPE values for fisheries prices indicate high-accuracy forecasts. Comparatively, the forecasting for in-sample fisheries prices outperforms that of the out-sample fisheries prices, as depicted in Table 2. For instance, the ex-vessel price of shortfin scad achieves 12.87% MAPE, classifying it as a good forecast.

Table 1: A summary of the performance measurement of in-sample fisheries prices

Price	Fish	MAPE			MAE			MSE			RMSE		
		ARIMA	ANN	Hybrid	ARIMA	ANN	Hybrid	ARIMA	ANN	Hybrid	ARIMA	ANN	Hybrid
Ex-vessel	Torpedo	3.29885	2.088	4.3137	0.143645	0.0767	0.1949	0.037943	0.0101	0.0771	0.19479	0.100499	0.277669
	Shortfin	5.433892	3.8477	8.122	0.22612	0.1254	0.3608	0.105385	0.0346	0.3608	0.324631	0.186011	0.600666
	Tuna	3.520602	2.7863	5.6173	0.185616	0.1256	0.3206	0.064673	0.0478	0.1749	0.254309	0.218632	0.41821
Wholesale	Torpedo	2.520519	2.3316	4.1477	0.137167	0.1033	0.0962	0.032138	0.0217	0.2376	0.17927	0.147309	0.487442
	Shortfin	4.134813	2.924	3.4908	0.229281	0.1146	0.187	0.107504	0.0238	0.073	0.327877	0.154272	0.270185
	Tuna	3.23236	2.8336	4.9046	0.221601	0.1689	0.3687	0.08745	0.0409	0.2293	0.29572	0.202237	0.478853
Retail	Torpedo	1.640952	1.3857	2.8589	0.126751	0.0262	0.2245	0.032578	0.1112	0.0987	0.180495	0.333467	0.314166
	Shortfin	3.586176	4.5276	4.5323	0.269899	0.1877	0.3545	0.141313	0.0797	0.2279	0.375916	0.282312	0.477389
	Tuna	3.026435	2.4894	4.1592	0.272455	0.2054	0.3998	0.116959	0.0844	0.3018	0.341993	0.290517	0.549363

Table 2: Summary of performance measurement of out-sample fisheries price

Price	Fish	MAPE			MAE			MSE			RMSE		
		ARIMA	ANN	Hybrid	ARIMA	ANN	Hybrid	ARIMA	ANN	Hybrid	ARIMA	ANN	Hybrid
Ex-vessel	Torpedo	9.085296	2.1497	2.0406	0.498344	0.1274	3.0243	0.299403	0.0314	0.0364	0.547177	0.1772	0.190788
	Shortfin	12.87014	4.7748	5.6915	0.739988	1.4099	0.4415	0.59586	3.3292	0.2622	0.77192	1.82461	0.512055
	Tuna	6.59951	5.037	7.0632	0.440012	0.573	0.5918	0.322693	0.0259	0.4423	0.568061	0.160935	0.665056
Wholesale	Torpedo	11.47188	2.7682	3.8011	0.793044	0.1518	0.2485	0.849521	0.0273	0.411	0.921695	0.165227	0.641093
	Shortfin	5.831542	2.1779	5.8438	0.466609	0.4409	0.4676	0.310723	0.2695	0.3299	0.557425	0.519134	0.574369
	Tuna	5.254215	3.1391	5.1716	0.445729	0.559	0.4798	0.281131	0.2624	0.3542	0.530218	0.51225	0.595147
Retail	Torpedo	8.962359	2.0103	2.6548	0.881541	0.0673	0.764	0.903779	0.1998	0.1267	0.950673	0.44699	0.355949
	Shortfin	5.183822	4.8175	5.4966	0.557676	0.295	0.4131	0.523444	0.1149	0.2877	0.723494	0.338969	0.536377
	Tuna	3.519788	3.3846	3.5551	0.418904	0.2466	0.4251	0.26624	0.111	0.2852	0.515984	0.333167	0.534041

MLFFN Model Analysis

In this study, each time series has one output node, and the selection of nodes is guided by the MAPE measurement. Figure 2 illustrates an example of an ANN, specifically the Levenberg-Marquardt algorithm applied to the wholesale price of torpedo scad. This implementation, conducted in MATLAB, seeks to establish relationships between each input and output. The process involves evaluating hidden neurons 10 times, with each simulation test for hidden neurons being executed 30 times to identify the best model. This model was developed by using a variety of distinct input variables. Tables 1 and 2 show the result of the best MLFFN model with the corresponding MAPE values.

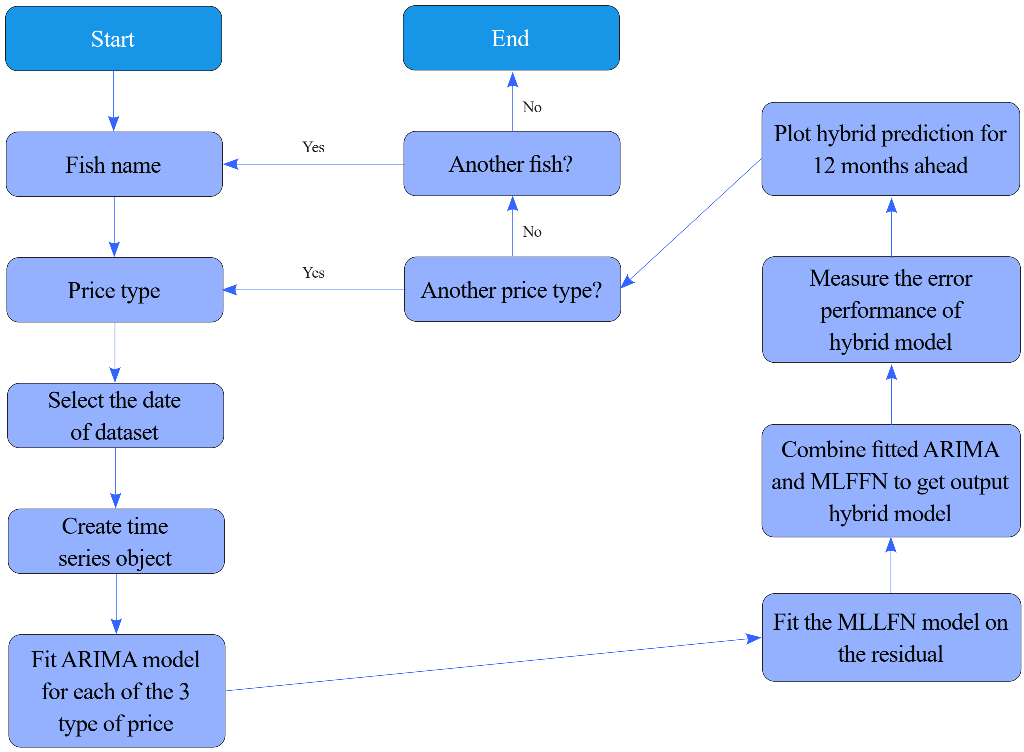

Figure 2: The algorithm of the hybrid ARIMA-MLFFN model for fisheries price prediction

Hybrid ARIMA-MLFFN Model Analysis

The optimal hybrid ARIMA-MLFF model for the ex-vessel price of shortfin scad is designed to capture both the nonlinear component and the error terms from the linear part. Hence, the optimal hybrid model has six input nodes, six hidden nodes, and one output node. The structure of the hybrid model is illustrated in Figure 3, showcasing the intricate design of this model.

A hybrid model comprises both linear and nonlinear components, and in this context, it can be expressed as follows:

$$\hat{Z}_t = \hat{L}_t + \hat{N}_t$$

$$y_t - 0.25y_{t-1} - 1.129y_{t-2} + 2.0.39y_{t-3} - 3.8919y_{t-4} - 1.9008y_{t-5} - 0.4269y_{t-6} = (1 - 1.00929\beta^1)a_t$$

$$+w_0 + w_1h_{1,t} + w_2h_{2,t} + w_3h_{3,t} + w_4h_{4,t} + w_5h_{5,t} + w_6h_{6,t}$$

where $h_{j,t} = [1 + \exp[-(v_{j0} + v_{j1}e_{t-1} + v_{j2}e_{t-2} + v_{j3}e_{t-3} + v_{j4}e_{t-4} + v_{j5}e_{t-5} + v_{j6}e_{t-6})]]^{-1}$

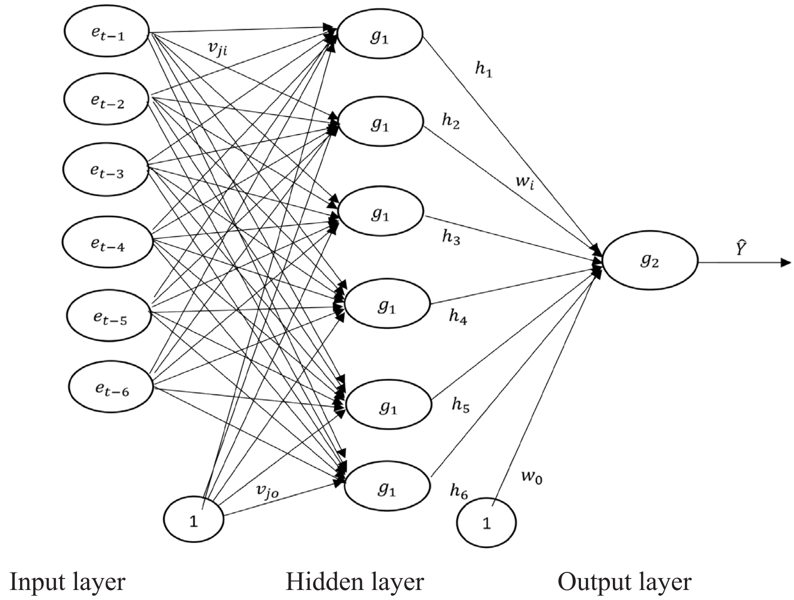

Figure 3: The hybrid ARIMA-Multilayer feed-forward neural network (MFFNN) model with six input lag variables, six hidden nodes, one output node and a sigmoid transfer function in the hidden layer, as well as a linear transfer function in the output layer

This study uses the Levenberg-Marquardt configuration with log-sigmoid and linear functions for the analysis. While [2] stated that ANN that uses the backpropagation network is superior in forecasting fisheries catch, the findings of this study align with the idea that the MLFFN analysis of ex-vessel, wholesale, and retail prices for torpedo scad, shortfin scad and longtail tuna is better in forecasting fisheries prices.

The MAPE results indicate that, for ARIMA and MLFFN, the in-sample forecasting tends to outperform the out-sample forecasting. In contrast, the majority of out-sample MAPEs for hybrid models surpass their in-sample counterparts. This aligns with the assertion by [4] that hybrid methods are superior to both ARIMA and ANN methods in predicting wheat production. The performance measurement summary in Tables 1 and 2 highlights that MLFFN and the hybrid model demonstrate high accuracy predictions, while the ARIMA model for ex-vessel and wholesale prices of shortfin scad achieves good forecasting.

Compared with a single ARIMA model, the standard errors of the MLFFN and ARIMA-MLFFN hybrid models are lower. Consequently, both the MLFFN and hybrid models performed better and provided more accurate forecasts. Fishermen or consumers are thus encouraged to consider either MLFFN or the hybrid method for forecasting fisheries prices.

CONCLUSION

This study concludes that the MLFFN and hybrid ARIMA-MLFFN approach emerged as the most effective method for anticipating the retail price of torpedo scad throughout the period of 2010-2020, as evidenced by the lowest RMSE and MAPE values. The hybrid technique was employed to predict the twelve-month fisheries prices, given the growing significance of the species focused on in this study as key indicators in the fisheries sector.

The monthly ex-vessel, wholesale, and retail prices of shortfin ccad, torpedo scad, and longtail tuna serve as valuable inputs for decision-making among fishermen, fishmongers, and planners in Peninsular Malaysia. The time series analysis of fish prices proves crucial in revealing underlying trend and seasonality patterns, providing essential insights for effective fisheries management..

Despite the inherent challenges in forecasting fisheries prices, the MLFFN and hybrid models have demonstrated their effectiveness in meeting the study's objectives. This underscores their role as reliable proxies for forecasting fisheries prices, offering valuable insights to fishermen, fishmongers, and consumers. The ability to anticipate future fisheries prices is crucial for observing the country's economic state and mitigating the impact of price fluctuations.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

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