American Journal of Economics and Business Innovation (AJEBI)

ISSN: 2831-5588 (ONLINE), 2832-4862 (PRINT)

VOLUME 5 ISSUE 2 (2026)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of Economics and Business Innovation (AJEBI)
Volume 5 Issue 2, Year 2026
ISSN: 2831-5588 (Online), 2832-4862 (Print)
DOI: https://doi.org/10.54536/ajebi.v5i2.8250
https://journals.e-palli.com/home/index.php/ajebi

Global Chicken Price Forecasting Using Neural Network and Hybrid Approach

Anuj Dhakal [1*], Lila B. Karki [1], Dharma R. Katuwal [1], Yeong N. Chi [1]

Article Information

Received: May 12, 2026

Accepted: July 21, 2026

Published: August 20, 2026

Keywords

Chicken Price, Hybrid Model, Linear Forecasting, Non-Linear Forecasting

ABSTRACT

Chicken is one of the fastest-growing and most widely consumed animal protein sources globally, making price stability important for producers, consumers, processors, retailers, and policymakers. However, feeding costs, disease outbreaks, seasonal demand, supply-chain disruptions, and market uncertainty contribute to nonlinear and volatile price movements. Although several previous poultry price studies have used traditional linear models such as ARIMA and SARIMA, there is limited evidence on the comparative performance of time-series, machine-learning, and hybrid forecasting models for global monthly chicken meat prices. Therefore, this study aimed to forecast global chicken prices by identifying the most accurate model using comparative forecast evaluation metrics. Monthly chicken price data, expressed in USD/kg, were obtained from the World Bank Commodity Price Data "Pink Sheet" for January 1960 to February 2026. The study fitted Auto-ARIMA, ETS, NNAR, Theta, STL+ETS, TBATS, equal-weight averaging, cross-validation error-weighted averaging, and 14 hybrid models. Forecast performance was evaluated using ME, RMSE, MAE, MPE, and MAPE. Results showed substantial historical price variation, ranging from USD 0.30/kg to USD 2.72/kg, with a mean of USD 1.16/kg. Among the 22 fitted models, NNAR performed best, producing the lowest RMSE, MAE, and MAPE values of 0.0189, 0.0122, and 1.014%, respectively. Among hybrid models, NNAR × STL was the most accurate, indicating the value of combining nonlinear learning with seasonal decomposition. The 30-month NNAR forecast suggested relatively stable prices with moderate fluctuations through August 2028. These findings support the use of nonlinear forecasting tools for poultry market planning, feed management, risk reduction, trade monitoring, and food affordability policy.

INTRODUCTION

Chicken is one of the most demanding and fastest-growing animal protein sources globally driven by its shorter production cycle, high feed conversion ratio, greater cultural acceptability, relatively low price per unit of protein intake (Kleyn *et al.*, 2021; Karlik *et al.*, 2018; Macelline *et al.*, 2021; Damaziak *et al.*, 2019). In 2020, 40% of the global meat production was contributed by poultry meat (FAO, 2023). The U.S. is the largest producer of poultry meat, followed by China and Brazil (FAO, n.d.). Global poultry production surged from 9 million tons in 1961 to 133 million tons in 2020 (FAO, n.d.). In developing countries, approximately 80% of rural farmers are engaged in raising poultry (FAO, n.d.). One of the main drivers of this high production is strong global demand, Chicken is a low fat, highly digestible protein, and rich in polyunsaturated fatty acids, Vitamins B1 and B6, and minerals such as iron, zinc, and copper (Marangoni *et al.*, 2015; Stangierski & Lesnierowski, 2015). Because of these nutritional benefits, chicken contributes substantially to food security. Chicken has higher affordability, accessibility, and acceptability than beef and pork meat (Damaziak *et al.*, 2019; Barbut & Leishman, 2022). Economically, broilers reach marketable weight and size more quickly than cattle, pigs, and small ruminants such as goats and sheeps, making poultry production more attractive to growers (Siegel, 2014; Ramukhithi *et al.*, 2023; Adaszyńska-Skwirzyńska *et al.*, 2025). From an environmental perspective, chicken production is considered environmentally friendly because it contributes to lower greenhouse gas emissions than cattle and other ruminants. Being non-ruminant and monogastric, Chickens do not produce enteric methane (de Vries & de Boer, 2010; Dunkley & Dunkley, 2013).

As chicken is a widely consumed source of animal protein, having a significant role in livelihood, food security, and nutrition, the chicken meat price is a concern across the whole production system for farmers, processors, marketers, consumers, and policymakers (Birhanu *et al.*, 2023; Suganda *et al.*, 2024). Chicken price forecasting is essential for producers in deciding the number of birds to raise, days to keep in the cage, the time of selling, and feed and ration management (You & Hsieh, 2018; Solano-Blanco *et al.*, 2023; Pesti, 2023). From the consumer's perspective, a significant increase in chicken prices may reduce consumption; therefore, addressing affordability is important for policymakers and marketers (Lusk & Tonsor, 2016; Birhanu *et al.*, 2023). Price is important for market regulators, in trade decisions and in introducing possible market interventions (FAO, 2011; Pieters & Swinnen, 2016; Brander *et al.*, 2023). Forecasting chicken prices is also beneficial for supermarkets and restaurants in planning inventory and purchasing decisions, helping to reduce food waste and stock outs (Arunraj *et al.*; 2016;

[1] Department of Agriculture, Food, and Resource Sciences,University of Maryland Eastern Shore, Princess Anne, Maryland, 21853 United States
[*] Corresponding author's e-mail: adhakal@umes.edu

Kabadurmus *et al.*, 2023).

Most of the forecasting is found to be focused on crops such as corn, cotton, wheat, and vegetables (Khadka *et al.*, 2025; Sanwa *et al.*, 2025). A few studies on poultry prices have been estimated, but are location-specific and heavily reliant on traditional models such as ARIMA or SARIMA models, which are based on linear time-series data (Wisodewo *et al.*, 2022; Sabroso *et al.*, 2023; Kontopoulou *et al.*, 2023). However, several factors, such as feed price uncertainties, seasonality, and disease outbreaks, cause fluctuations in the price of chicken. Thus, several machine learning approaches should be considered for forecasting, which captures non-linear and complex data as well (Pandit *et al.*, 2024; Sun *et al.*, 2023). Integration of traditional and machine learning approaches builds hybrid models that improve forecasting accuracy compared to single models approaches (Khashei & Bijari, 2011; Zhang, 2003; Sun *et al.*, 2023).

This study focuses on forecasting chicken prices by comparing traditional time-series, machine-learning, and hybrid forecasting models and determining the most accurate model using evaluation metrics.

LITERATURE REVIEW

Chicken meat markets and the need for price forecasting

The global chicken market is a complex system driven by several forces of demand and supply, governed by production efficiency, consumer preferences, disease management, and other trade policies. In terms of chicken production, the USA ranks first, followed by Brazil and China (Uzundumlu & Dilli, 2023). In terms of exports, Brazil was the leading exporter, exporting around 4.34 million tons of chicken to more than 150 countries (Barros *et al.*, 2021). The price fluctuation is affected by feed costs- particularly, maize and soybeans (Uçak, Yelgen and Arı, 2023). In China, epidemics such as avian influenza and African swine fever substantially worsened not only the price volatility but also impacted different parts of the production system, such as live chicken prices and broiler chicken prices, with less impact on broiler feed prices (Xie *et al.*, 2024). Due to the COVID-19 pandemic, in Bangladesh, the price of poultry dropped sharply during the first three months (February-April 2020), which later increased by about 40%, and chicken eggs rose by 30%. However, this pandemic has resulted in some enterprises shutting down early because of the rise in feed costs, insufficient workforce, and reduced demand (Amin *et al.*, 2023).

Traditional time-series models for chicken price forecasting

To forecast beef, chicken, mutton, and overall production of meat, ARIMA has been broadly used (Nouman & Khan, 2014; Mgaya, 2019; Ozdemir *et al.*, 2025). This model has been used to estimate poultry egg price forecasting as well (Abdulhamid, Aliu, and Musa, 2026). Trend, seasonality, and structural changes were identified after plotting the historical data on chicken prices. To determine the stationarity, the Augmented Dickey Fuller (ADF) is used (Worden *et al.*, 2018). If the series is not stationary, differencing is applied, and selection of ARIMA (p.d.q) or SARIMA (p.d.q) (P,D,Q)s is done using AIC, BIC, ACF, or PACF (Hossain *et al.*, 2019; McCabe *et al.*, 1995; Zhang & Meng, 2023). Evaluation metrics like ME, MAE, RMSE, MAE, MPE, and MAPE were used to evaluate the forecast (Saigal & Mehrotra, 2012; Chicco *et al.*, 2021). Similarly, the ETS model was used in forecasting mutton and chicken prices (Klaharn *et al.*, 2024; Abdallah & Gouda, 2025). It is useful when the prices show a smooth trend or seasonal movement (Hyndman *et al.*, 2002). However, if there is a non-linear shock, ETS may not perform better (Hyndman *et al.*, 2008). Theta, STLM, and TBATS are less common in the chicken price forecasting model. STL model is used when the dataset contains strong trend and seasonal components while TBATS are used when data have multiple seasonal patterns like weekly, monthly, or annual cycles (Cleveland *et al.*, 1990; Liu *et al.*, 2025; Zhang *et al.*, 2025).

The series is decomposed into long-term and short-term components through Theta, while STLM decomposes into trend, seasonal, and remainder using ST (Theodosiou, 2011; Yang *et al.*, 2025). However, TBATS uses Box-Cox transformation, ARMA errors, trend, and trigonometric seasonal components (Elseidi, 2023; Chudo & Terdik, 2025)

Machine-learning approaches

Machine learning approaches like Neural Network Autoregression model (NNAR) have been used in the poultry industry to forecast future chicken prices based on past chicken prices (Klaharn *et al.*, 2024). NNAR is based on autoregression and an artificial neural network (Daniyar *et al.*, 2023). As this model considers nonlinear price trends, a neural network is widely used in agricultural forecasting, as agricultural prices contain nonlinear patterns and complex market behavior (Kmytiuk *et al.*, 2024). Historical chicken price data is used as an input to feed-forward neural network in the NNAR model (Sanwa *et al.*, 2025). However, this is more complex to interpret than traditional series like ARIMA as internal neural network weights are less interpretable. It is useful in chicken price forecasting as factors such as feed cost, production cycles, seasonal demand, disease outbreak, and consumer preferences have nonlinear price patterns (Zamani *et al.*, 2024; Lawrence *et al.*, 2008; Lee *et al.*, 2017).

Hybrid forecasting models

Several hybrid models, such as SARIMA-ANN, ARIMA-NNAR, ARIMA-TBATS, etc., are applied in agricultural price forecasting. Hybrid models combine forecasting from two or more models. This is beneficial because some models, such as ARIMA, capture linear structure while models like NNAR capture nonlinear structure. Similarly, models such as ETS capture trend/seasonality, STLM captures decomposed seasonal components, while TBATS captures complex seasonality. When these models are combined and forecasting is done, it gives meaningful predictions. Thus, hybrid models improve the robustness of the forecast.

MATERIALS AND METHODS

Data Source

The data presents a historical monthly price series of chicken meat, expressed in USD per kilogram, extracted from World Bank Commodity Price Data "Pink Sheet" for the period of January 1960- February 2026 to forecast the future prices, globally.

Traditional time-series models for chicken price forecasting

To forecast beef, chicken, mutton, and overall production of meat, the ARIMA model has been widely used (Nouman & Khan, 2014; Mgaya, 2019; Ozdemir *et al.*, 2025). It has also been applied to poultry egg price forecasting (Abdulhamid *et al.*, 2026). Trend, seasonality, and structural changes are identified through analysis of historical data on chicken prices. To determine stationarity, the Augmented Dickey-Fuller (ADF) is used (Worden *et al.*, 2018). If the series is not stationary, differencing is applied, and selection of ARIMA (p.d.q) or SARIMA (p.d.q) (P,D,Q)s is carried out using AIC, BIC, ACF, or PACF (Hossain *et al.*, 2019; McCabe *et al.*, 1995; Zhang & Meng, 2023). Evaluation metrics like ME, MAE, RMSE, MAE, MPE, and MAPE were used to evaluate the forecast (Saigal & Mehrotra, 2012; Chicco *et al.*, 2021). Similarly, the ETS model is used in forecasting mutton and chicken prices (Klaharn *et al.*, 2024; Abdallah & Gouda, 2025). It is useful when the prices show smooth trends or seasonal movements (Hyndman *et al.*, 2002). However, if there is a non-linear shock, ETS may not perform well (Hyndman *et al.*, 2008). Theta, STLM, and TBATS are less common in the chicken price forecasting model. STL model is used when the dataset contains strong trend and seasonal components while TBATS are used when data have multiple seasonal patterns like weekly, monthly, or annual cycles (Cleveland *et al.*, 1990; Liu *et al.*, 2025; Zhang *et al.*, 2025).

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Forecasting models

Auto. Arima Model

An autoregressive Integrated Moving Average (ARIMA) model, developed by Box and Jenkins (1970), is a linear time-series model that forecasts data at regular time intervals. It is useful when the series can be made stationary through differencing. It consists of autoregressive (AR), integration (I), and moving average (MA). The AR and MA terms are based on the strength of temporal correlation, while the I term involves differencing a nonstationary series into a stationary series (Zhang, 2018). ARIMA is mainly used for univariate time series forecasting suitable for predicting agricultural production, prices, trades, and several other forecasting applications (Mehrmolaei & Keyvanpour, 2016; Gaddi *et al.*, 2025).

The general model of ARIMA is written as

Where:

$$ARIMA(p,d,q) \ldots\ldots\ldots (1)$$

- p = Autoregressive order
- d= Number of differences needed for stationarity
- q= Moving average order (Zhang, 2018; Shumway and Stoffer, 2017).

In terms of econometrics, it can be written following Hyndman and Khandakar, 2008 as:

where:

$$\phi(B)(1-B)^d y_t = c + \theta(B)\ \varepsilon t \ldots\ldots\ldots\ldots (2)$$

- B is the backshift operator
- ϕ(B)represents sAR terms
- θ(B)represents MA terms, and
- ε_t is white-noise error.

Error, Trend, Seasonal Exponential Smoothing (ETS) model

The major application of this model lies when the series has error, trend, and/or seasonality (De Livera, 2010; Crevits & Croux, 2016). This is widely used in the agricultural sector for demand and price forecasting as well as for estimating seasonal crop-market data.

The general model of ETS can be written as:

where:

$$ETS(E,T,S)\ldots\ldots\ldots (3)$$

- E= error type: (additive or multiplicative)
- T= trend type: (none, additive, damped, multiplicative)
- S= seasonal type: (none, additive, multiplicative)

A simple additive ETS model can be written as:

$$y_t = l_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t \ldots\ldots\ldots (4)$$

Where:

- l_tis level
- b_tis a trend, and
- s_tis seasonality

(Hyndman *et al.*, 2002; Hyndman *et al.*, 2008)

Neural Network Autoregression (NNAR) model

This is widely used for non-linear and complex time series forecasting (Almarashi *et al.*, 2024; Maleki *et al.*, 2024).

The general NNAR model is written as:

$$NNAR(p,k)\ldots\ldots\ldots\ldots\ldots (5)$$

or for seasonal data:

$$NNAR(p, P, k)_m \ldots\ldots\ldots\ldots (6)$$

where:

- p= number of non-seasonal lag inputs
- P= number of seasonal lag inputs
- k= number of hidden nodes
- m= seasonal frequency

An econometric NNAR model is:

$$y_t = f(y_{t-1}, y_{t-2}, \ldots, y_{t-p}) + \varepsilon_t \ldots\ldots\ldots\ldots (7)$$

where f(·)is a nonlinear function by the neural network (Sanwa, *et al.*, 2025).

Theta model

The Theta model is used for a series with a trend and for univariate forecasting. The original time series is decomposed into different "theta lines," which are forecasted separately and then combined (Assimakopoulos & Nikolopoulos, 2000). Higher and lower theta values indicate short-term valuation and smoother long-term behavior, respectively (Nikolopoulos & Thomakos, 2019).

The general model of Theta Model is written as:

$$\nabla^2 Z_t(\theta) = \theta \nabla^2 Y_t \ldots\ldots\ldots (8)$$

Where,

Y_tis the original series and

Z_t (θ)is the transformed theta line (Fiorucci, 2016).

Seasonal Trend Decomposition using Loess and Forecasting Model (STLM)

This model is mainly useful for data with strong seasonal patterns. This model decomposes the series into trend, seasonal, and remainder components using STL and conducts forecasting for the seasonally adjusted data (Liu & Zhang, 2024; Sohrabbeig & Musilek, 2023).

The general STLM model is:

$$y_t = T_t + S_t + R_t \ldots\ldots\ldots (9)$$

where:

- T_t= trend component
- S_t= seasonal component
- R_t= remainder component

The seasonally adjusted component is then forecast using models such as ARIMA or ETS:

$$SA_t = y_t - S_t \ldots\ldots\ldots\ldots (10)$$

Forecasts are obtained by forecasting SA_tand then adding back the seasonal component (Cleveland *et al.*, 1990).

Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend, and Seasonal components (TBATS model)

This model is used for complex seasonal time series, mainly used for high-frequency data having multiple seasonality (Yu *et al.*, 2021).

A simplified structure of the TBATS model is:

$$y_t^{(\omega)} = l_{t-1} + \phi b_{t-1} + \sum s_{t-m}^{(i)} + d_t \ldots\ldots\ldots\ldots (11)$$

where:

- y_t^((ω))= Box-Cox transformed series
- l_t= level
- b_t= trend
- s_t= seasonal component
- d_t= ARMA error component
- ϕ= damping parameter (Zhao and Zhang, 2022).

Hybrid forecasting models

Several hybrid models, such as SARIMA-ANN, ARIMA-NNAR, ARIMA-TBATS, etc., are applied in agricultural price forecasting. Hybrid models combine forecasting from two or more models. This is beneficial because some models, such as ARIMA, capture linear structure while models like NNAR capture nonlinear structure. Similarly, models such as ETS capture trend/seasonality, STLM captures decomposed seasonal components, while TBATS captures complex seasonality. When these models are combined and forecasting is done, it gives meaningful predictions. Thus, hybrid models improve the robustness of the forecast.

A general hybrid model combines forecasts from multiple models:

$$\hat{y}_{t+h}^{Hybrid} = w_1 \hat{y}_{t+h}^{(1)} + w_2 \hat{y}_{t+h}^{(2)} + \cdots + w_k \hat{y}_{t+h}^{(k)} \ldots\ldots\ldots\ldots (12)$$

where:

- "y" ̂_"t+h" ^(("i"))= forecast from model i
- "w" _"i" = weight assigned to model i
- "∑" "w" _"i" "=1"

The most common examples are L

- ARIMA + ETS
- ARIMA + NNAR
- ETS + Theta
- ARIMA + ETS + NNAR + TBATS
- Equal weight hybrid
- CV weight hybrid (Bates & Granger, 1969; Timmermann, 2006)

Model evaluation metrics

Model evaluation metrics are used to compare predicted values with the actual values that help to determine the most accurate model.

Mean Error (ME):

$$\mathrm{ME} = \frac{1}{n} \sum e_t \ldots\ldots (13)$$

It measures the average bias and reflects that if the value is near to zero, the estimated forecasts are less biased (Hyndman and Koehler, 2006).

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum | e_t | \ldots\ldots\ldots (14)$$

MAE expresses in the original unit of data and measures the average absolute forecast error. The lower value of MAE reflects better accuracy (Hyndman & Koehler, 2006; Hyndman & Athanasopoulos, 2021)

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum e_t^2} \ldots\ldots\ldots (15)$$

This metric is useful when large forecasting errors are undesirable, with lower RMSE value reflecting higher predictive accuracy (Hyndman & Koehler, 2006)

Mean Percentage Error (MPE):

MPE can be expressed as:

$$MPE = \frac{100}{n}\sum_{t=1}^{n}\left(\frac{e_t}{y_t}\right) \ldots\ldots\ldots (16)$$

A positive MPE suggests that the model tends to under-forecast, negative MPE indicates over-forecast, and MPE close to zero means low average percentage bias (Hyndman & Koehler, 2006; Hyndman & Athanasopoulos, 2021)

Mean Absolute Percentage Error (MAPE):

MAPE can be expressed as:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n} \left| \frac{e_t}{y_t} \right| \ldots\ldots\ldots (17)$$

The lower MAPE indicates better forecast accuracy. For example: If MAPE= 3%, it means that the forecast has errors by about 3% on average. MAPE is not reliable when the actual values are close to zero (Hyndman & Koehler, 2006; Hyndman & Athanasopoulos, 2021).

RESULTS AND DISCUSSIONS

Table 1 represents the descriptive statistics of global monthly chicken prices. The mean monthly chicken price was $1.16 per kg., with a standard deviation of 0.60, and the median price was $1.13. The prices varied widely, ranging from the minimum price of $0.30 to the maximum of $2.72, showing considerable variation within the chicken prices over the series.

Table 1: Descriptive Statistics

Variable	Minimum	Maximum	Mean	Median	SD	25th Percentile	75th Percentile
Chicken price	0.2974	2.7227	1.1627	1.1334	0.6050	0.6156	1.6367

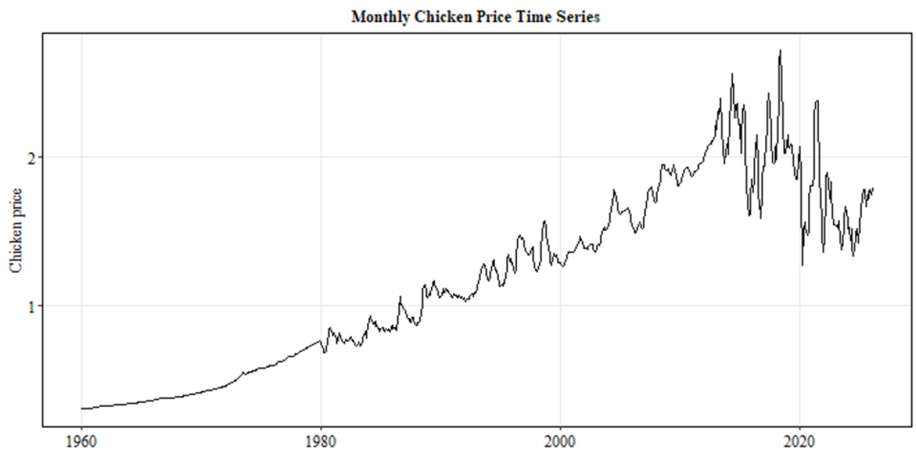

Figure 1: Time series plot of monthly chicken prices (1960-2026)

Figure 1 shows an overall increase in monthly chicken prices over time, reaching peak with pronounced fluctuations, followed by a similar downward trend. As the series is not linear or constant, having noticeable dynamics in prices, multiple forecasting approaches are considered when estimating the forecasted value. To analyze and interpret the pattern of series, the data is employed to decompose into trend, seasonal, and irregular/random components.

Time-series decomposition and seasonal adjustment

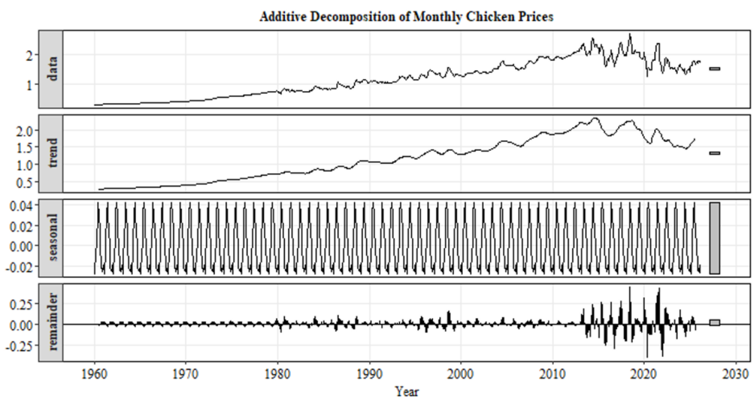

Figure 2: Decomposition of an additive time series (1960-2026)

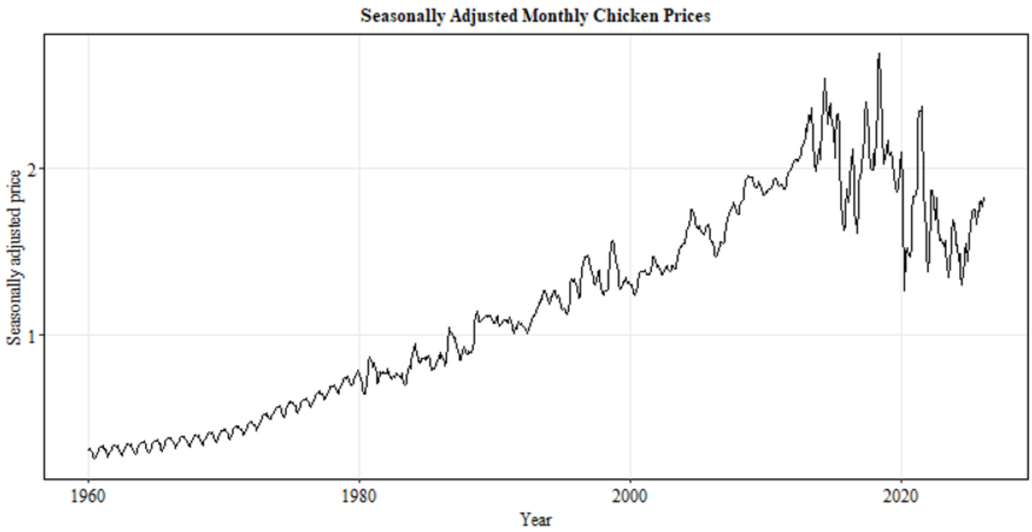

Figure 3: Seasonally adjusted monthly chicken prices (1960-2026)

The decomposition of additive time series was done to categorize the series into trend, seasonality, and remainder/noise components. This is done when the size of seasonal fluctuations seems constant over time series. The figure shows that in addition to random variation, the series is affected by a structured time-based pattern. Specifically, the long-run price trend is shown by the trend component, while the within-year seasonal movements is reflected by the seasonal component. The other component, i.e., remainder, captures the irregular fluctuations or movements of the series that are not attributed to either of the components.

Seasonal adjustment was done following the decomposition to eliminate seasonal patterns that help explain the fundamental trend in chicken prices (Figure 3). This seasonally adjusted plot explains the nonseasonal variation in the series, which enables the evaluation of the persistence of chicken prices, once the seasonal effects are removed. With this basic structure of a series, the statistical properties of the series need to be assessed through stationarity and autocorrelation diagnostics.

Preliminary diagnostics: Stationarity, ACF, and PACF

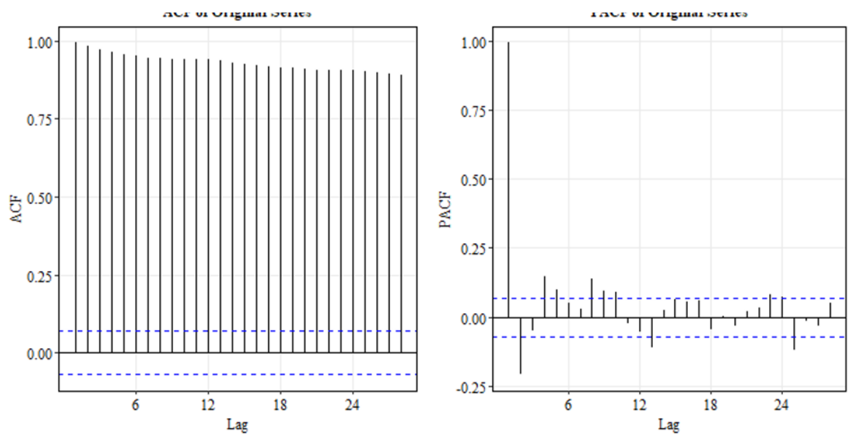

Figure 4: ACF and PACF of the original series

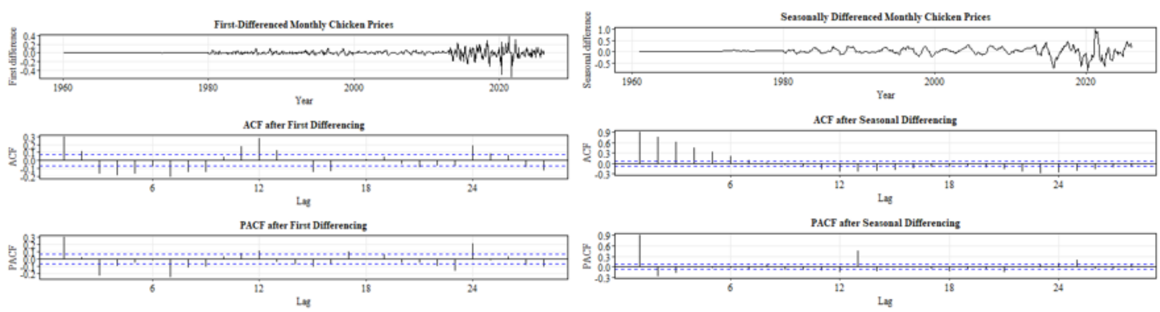

Figure 5: ACF and PACF after First differencing and Seasonal differencing

To assess the stationarity of the monthly chicken price series, the Augmented Dickey- Fuller (ADF) test was done for the original series, first differencing, and seasonally differenced series. For the original series, Dickey-Fuller statistics were found to be -2.28, with a p-value of 0.46. As the p-value is greater than 0.05 (significance level), it indicates the failure to reject the null hypothesis of a unit root. It indicates that the original monthly chicken price series was non-stationary and requires transformation.

Following the differencing, the Dickey-Fuller statistic given by the ADF test was -12.71, having a p-value of 0.01, signifying that the series after differencing was stationary. Likewise, the Dickey-Fuller statistic for seasonally differenced series was -8.53, with a p-value of 0.01, indicating that the seasonally transformed series was stationary. Thus, the non-stationary behavior of the original monthly chicken price series was eliminated through differencing.

Fitted models and estimated model structures

Table 2: Selected Fitted Time-Series Models for Monthly Chicken Prices

Model class	**Selected model**	**Model fit statistics/ information**
ARIMA	ARIMA (3, 1, 0) (1, 0, 1) [12]	ar1 = 0.2583, ar2 = 0.0852, ar3 = −0.1721, sar1 = 0.8493, sma1 = −0.6873; σ^2 = 0.002847; log likelihood = 1200.26; AIC = −2388.51; AICc = −2388.40; BIC = −2360.46
ETS	ETS (M, N, N)	alpha = 0.9999; sigma = 0.0342; AIC = −83.51; AICc = −83.48; BIC = −69.48
NNAR	NNAR (25, 1, 13) [12]	Average of 30 networks; 25-13-1 architecture; 352 weights; σ^2 = 0.0003572
THETA	Theta model	Implemented through Theta forecasting procedure; evaluated as a standalone benchmark model
STL + ETS	STL + ETS (M, N, N)	STL decomposition combined with the ETS (M, N, N) model on seasonally adjusted data
TBATS	TBATS	Fitted as a standalone candidate model for potentially complex temporal structure

Note. ARIMA = autoregressive integrated moving average; ETS = exponential smoothing state space; NNAR = neural network autoregression; STL = seasonal-trend decomposition using Loess; TBATS = trigonometric, Box-Cox transformation, ARMA errors, trend, and seasonal components; AIC = Akaike information criterion; AICc = corrected Akaike information criterion; BIC = Bayesian information criterion.

Auto- ARIMA, ETS, NNAR, Theta, STL+ETS, and TBATS were fitted to the monthly chicken price series. These six models were fitted to identify and quantify the structural pattern of time series data.

The selected ARIMA model was ARIMA (3,1,0) (1,01) [12]. It means that under the non-seasonal component, the model uses three non-seasonal autoregressive (AR) terms, differencing was performed once to achieve stationarity, and there was no non-seasonal moving average (MA) term. Under the seasonal component, the model uses one seasonal AR term with no seasonal differencing and one seasonal MA term. The seasonality repeats every 12 periods, as the data were in monthly terms.

Similarly, the other selected exponential smoothing model is ETS(M, N, N). M means a multiplicative error structure, while N, N indicates that the model has no trend component and no seasonal component. Such a simple exponential smoothing model with multiplicative errors is appropriate for such a series that does not exhibit a systematic seasonal pattern and whose level changes over time.

To capture nonlinear trends in the series, a neural network autoregression (NNAR) model is generally accepted, which uses past lagged observations. The model selected NNAR (25,1,13) [12], indicating the model with 25 non-seasonal lags, 1 seasonal lag, and 13 hidden nodes, averaged over 30 networks, having a seasonality of 12 periods. NNAR model showed the smallest residual variance compared to ARIMA and ETS.

Comparative forecasting performance of individual and hybrid models

Table 3: Forecast Accuracy of Individual Models for Monthly Chicken Prices

Model	**ME**	**RMSE**	**MAE**	**MPE**	**MAPE**
EQUAL	0.000878	0.045219	0.023073	0.063506	1.602095
CV.ERRORS	0.000901	0.046570	0.023592	0.064924	1.632182
AUTO.ARIMA	0.000844	0.053158	0.025302	0.068887	1.717363
ETS	0.001884	0.059843	0.029313	0.165703	1.972675
NNAR	0.000057	0.018900	0.012225	−0.021187	1.013955

THETA	0.001951	0.058532	0.032619	0.149202	2.390710
STL + ETS	0.001950	0.046779	0.022928	0.189208	1.609041
TBATS	−0.000793	0.054130	0.026244	−0.053995	1.779021

Note. The best-performing model is bolded. Lower RMSE, MAE, and MAPE indicate better predictive performance. ME = mean error; RMSE = root mean square error; MAE = mean absolute error; MPE = mean percentage error; MAPE = mean absolute percentage error.

Table 3 compares six individual models, 2 all- modeling averaging approaches, and 14 hybrid models to determine the best model that accurately predicts the monthly chicken price. Of all the fitted individual models, NNAR was found to be the best. The second best model was STL+ETS, with RMSE= 0.047 and MAPE= 1.609, followed by Auto ARIMA, performing moderately with RMSE=0.053 and MAPE= 1.71. However, ETS, THETA, and TBATS did not perform better than NNAR, as they showed larger errors.

For model averaging, EQUAL and CV. ERRORS approaches were adopted. The EQUAL approach is performed by identically allocating weight to all component models, while the CV. ERRORS uses cross-validation error metrics that assign a lower validation error and better performance.

The RMSE and MAPE for EQUAL were 0.045 and 1.602, respectively, while those for CV. ERRORS recorded 0.047 and 1.632, respectively. Compared to CV. ERRORs, EQUAL performed better, although neither outweighed NNAR.

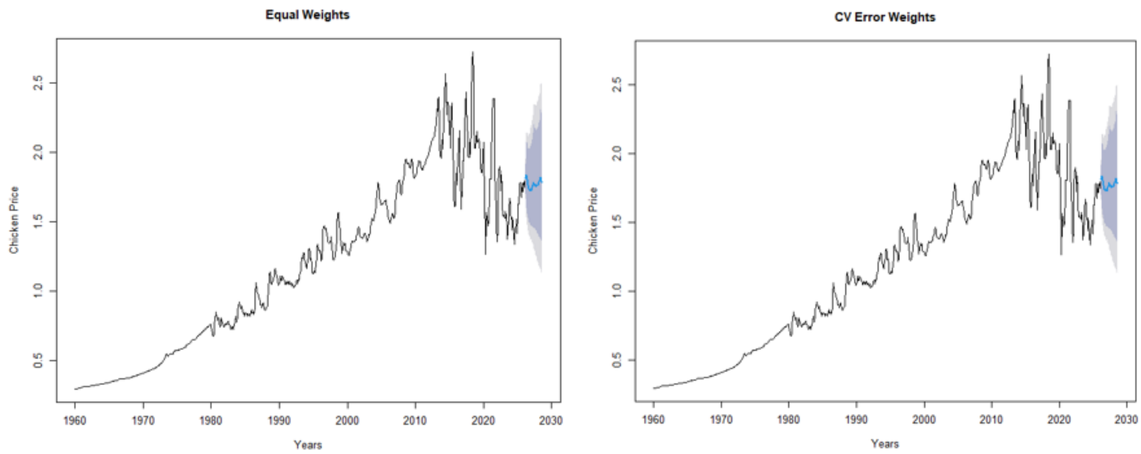

Figure 6: Equal Weight and CV Error Weights (1960-2028)

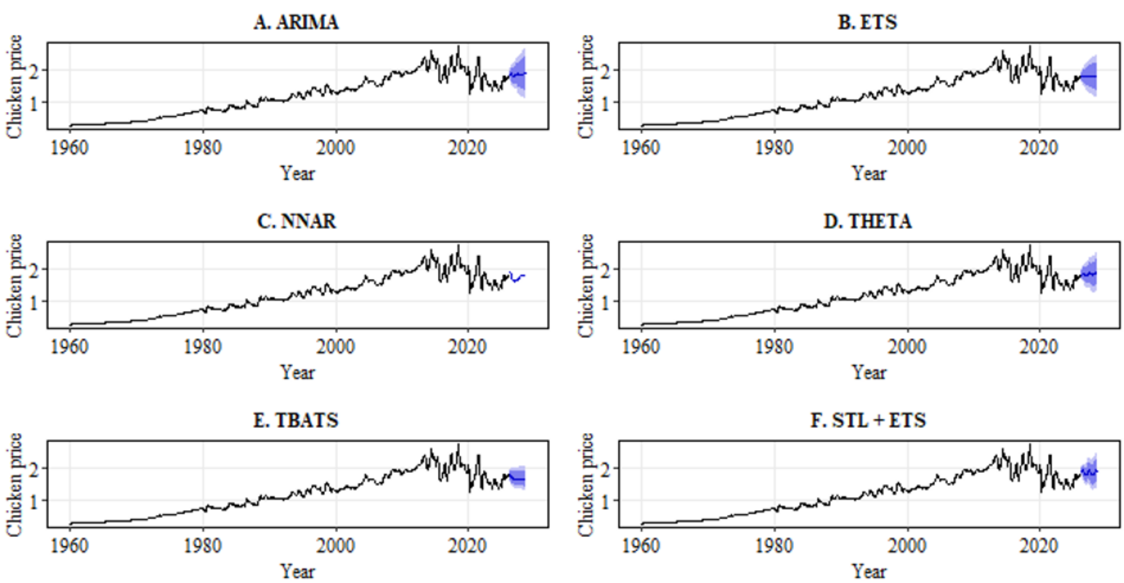

Figure 7: Performance of the individual forecasting model (1960-2028)

Hybrid Models

Table 4: Forecast Accuracy of Hybrid Models for Monthly Chicken Prices

Model	ME	RMSE	MAE	MPE	MAPE
Hybrid 1 (ARIMA × ETS)	0.001364	0.055075	0.026488	0.117295	1.792796
Hybrid 2 (ARIMA × NNAR)	0.000456	0.032887	0.018383	0.022311	1.331492
Hybrid 3 (ARIMA × TBATS)	0.000026	0.052844	0.025257	0.007446	1.710266
Hybrid 4 (ARIMA × STL)	0.001397	0.048520	0.023233	0.129047	1.604866
Hybrid 5 (ETS × NNAR)	0.000990	0.035733	0.019806	0.071107	1.415843
Hybrid 6 (ETS × TBATS)	0.000546	0.055881	0.027017	0.055854	1.821868
Hybrid 7 (ETS × STL)	0.001917	0.050808	0.024677	0.177456	1.698313
Hybrid 8 (NNAR × TBATS)	−0.000383	0.033300	0.018771	−0.039361	1.362323
Hybrid 9 (NNAR × STL)	0.001023	0.028956	0.016718	0.083272	1.238632
Hybrid 10 (TBATS × STL)	0.000578	0.047741	0.022911	0.067607	1.578769
Hybrid 11 (ARIMA × ETS × NNAR)	0.000945	0.040809	0.021401	0.069341	1.499258
Hybrid 12 (ARIMA × ETS × STL)	0.001559	0.050859	0.024482	0.141266	1.678775
Hybrid 13 (ARIMA × NNAR × STL)	0.000967	0.036314	0.019243	0.077451	1.373646
Hybrid 14 (ARIMA × ETS × NNAR × STL × TBATS)	0.000800	0.043454	0.022037	0.067644	1.529303

Table 4 compares the performance of different hybrid models used for forecasting monthly chicken prices using ME, RMSE, MAE, MPE, and MAPE. ARIMA was combined with ETS, NNAR, TBATS, and STL in Hybrid 1-4, respectively. From Hybrid 5-7, ETS was combined with NNAR, TBATS, and STL, while Hybrid 8 and 9 combined NNAR with TBATS and STL, and Hybrid 10 combined TBATS and STL. Hybrid 11 combined ARIMA, ETS, and NNAR, Hybrid 12 combined ARIMA, ETS, and STL, Hybrid 13 combines ARIMA, NNAR, and STL, and Hybrid 14 combines ARIMA, ETS, NNAR, STL, and TBATS.

In terms of the hybrid model, the hybrid of NNAR and STL was found to be the best because of its lowest ME (0.001023), RMSE (0.0289), MAE (0.016), and MAPE (1.239). This shows that forecasted values through this model were closest to the observed values because of the smallest average forecasting error, better accuracy percentage, and negligible systematic bias. Though the negative value of ME and MPE tends to underpredict, the strength is sufficiently small, which is unlikely to affect the estimate.

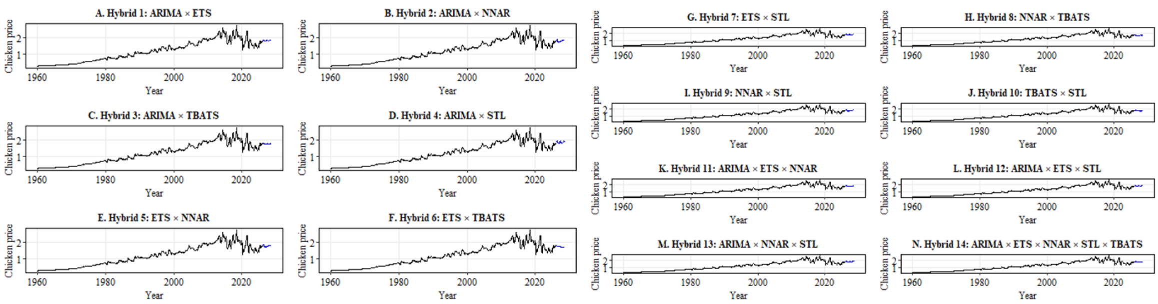

Figure 8: Performance of the hybrid forecasting models (1960-2028)

Interpretation of the best-fitting model

Table 5: Best-Fitting Forecasting Model for Monthly Chicken Prices

Criterion	Result
Best model	NNAR
ME	0.000057
RMSE	0.018900
MAE	0.012225
MPE	−0.021187
MAPE	1.013955

Of 22 models estimated, NNAR was found to be the most precise model for forecasting monthly chicken prices. The mean error (ME) of 0.000057 was extremely small and close to zero, suggesting that the forecasting was unbiased, which tends to give no overprediction and underprediction. Similarly, the mean percentage error (MPE) of -0.021187 was also almost zero, having very little tendency towards underprediction, which is negligible practically.

Likewise, the values of RMSE and MAE are 0.0189 and 0.0122, respectively, signifying low prediction errors compared to actual monthly chicken prices. Additionally, as RMSE is highly sensitive to large deviations, a lower value of RMSE further indicates that the larger forecast errors were substantially limited. The MAPE value of 1.0140, it explains that the predicted value by this model deviates from the actual monthly chicken prices by 1.01%, suggesting an accurate forecasting model.

Thus, it implies that the series contains a nonlinear temporal structure, which is modeled by the neural network autoregressive model relative to other forecasting techniques.

Forecasted monthly chicken prices

Table 6: Thirty-Month Point Forecast of Monthly Chicken Prices from the Best-Fitting NNAR Model

Forecast month	Point forecast	Lower 95% CI	Upper 95% CI
Mar 2026	1.8433	1.8069	1.8811
Apr 2026	1.8713	1.8107	1.9292
May 2026	1.8670	1.7918	1.9362
Jun 2026	1.7691	1.6817	1.8469
Jul 2026	1.6833	1.5861	1.7742
Aug 2026	1.6453	1.5312	1.7487
Sep 2026	1.6541	1.5216	1.7891
Oct 2026	1.6468	1.5063	1.7848
Nov 2026	1.6652	1.5225	1.8082
Dec 2026	1.6066	1.4653	1.7597
Jan 2027	1.6098	1.4677	1.7592
Feb 2027	1.6415	1.4986	1.8052
Mar 2027	1.6437	1.4791	1.8319
Apr 2027	1.6670	1.5044	1.8768
May 2027	1.6624	1.5192	1.8868
Jun 2027	1.6656	1.5400	1.9046
Jul 2027	1.7010	1.5762	1.9796
Aug 2027	1.7087	1.5621	2.0204
Sep 2027	1.7425	1.5871	2.1000
Oct 2027	1.7553	1.5731	2.1651
Nov 2027	1.7967	1.5899	2.2143
Dec 2027	1.8199	1.5964	2.1696
Jan 2028	1.8172	1.5868	2.0906
Feb 2028	1.8124	1.5726	2.0343
Mar 2028	1.7956	1.5376	2.0277
Apr 2028	1.7919	1.5263	2.0643
May 2028	1.8111	1.5517	2.1083
Jun 2028	1.7923	1.5240	2.0811
Jul 2028	1.7691	1.5054	2.0589
Aug 2028	1.7529	1.4854	2.0585

The best-fitted NNAR model suggests that the monthly chicken prices remain comparatively stable with slight fluctuations over the prediction horizon.

In March 2026, the point forecasts begin at $1.8433, then vary slightly in the subsequent months. Forecasted prices for 2026 often fluctuate within a small range, falling from $1.8713 in April and $1.8670 in May to around $1.6066 in December. This suggests that prices will likely soften by the end of 2026, with $1.6098 in January, $1.6415 in February, and $1.6670 in April, indicating no significant structural break in the near future.

The model predicts a small recovery and some month-to-month volatility starting in mid-2027. Prices are expected to increase from 1.6656 in June 2027 to 1.8199 in December 2027, then to 1.8172 in January 2028 and 1.8124 in February 2028. Prices stay in a fairly stable range, ending at 1.7529 in August 2028, despite a minor subsequent easing. Therefore, rather than a rapid increase or a long-term collapse, the projection path shows ongoing oscillation around a moderate price level.

The results show the volatility in the global chicken price, indicating a need for time-series forecasting models. This variation may be reflected by variation in feed costs, market demand, and disease outbreaks that affect chicken markets. The selected model for ARIMA was ARIMA (3,1,0) (1,0,1) [12], which indicates that after first differencing, chicken price depends on the price in the previous three months without forecasting non-seasonal moving average errors. The yearly seasonality was captured by the model, which indicates that the price is related to previous year seasonal patterns and past seasonal shocks. The selected ETS model was ETS (M, N, N,), representing multiplicative forecast errors, with no trend after smoothing and without a seasonal component. The NNAR model selected was NNAR (25,1,13) [12], implying that the model used 25 past price values, one seasonal lag, and 13 hidden neurons to capture nonlinear patterns, with seasonality of 12 months for forecasting. It suggests that chicken prices are driven by complex nonlinear dynamics and that lagged monthly prices and recurring seasonal effects from prior years strengthen the future price predictions.

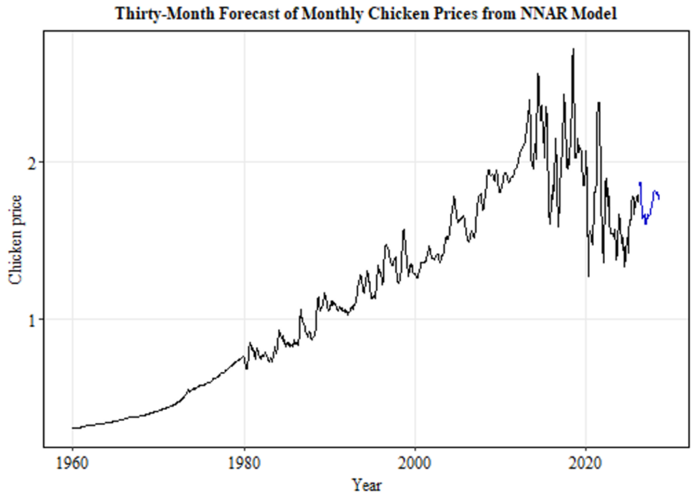

Figure 9: Thirty-Month Point Forecast of Monthly Chicken Prices from the Best-Fitting NNAR Model (1960-2028)

The NNAR was the most accurate forecasting model, suggesting that the price series contains nonlinear patterns that were captured more effectively by the neural network-based NNAR model compared to traditional linear models. Among the hybrid models, NNAR with STL performed better. This may be because NNAR captures nonlinear dynamics in price series, while STL differentiates trends and seasonal patterns, and their combination improves forecasting accuracy, relative to other hybrid models. The non-linearity of chicken prices is due to volatility, disease outbreaks, fluctuating seasonal and festival-related demand, supply chain disruptions caused by labor and market volatility, international trade policies, and consumer preferences (Kharin *et al.*, 2023; Zamani *et al.*, 2024; Meilany *et al.*, 2025; Sattar *et al.*, 2021; Unveren and Luckstead, 2020; Duangnate *et al.*, 2025). The overall forecast by the NNAR model shows a relatively stable pattern with slight fluctuation, indicating short-term market adjustments and possible seasonal variation.

Due to non-stationary behavior and high price fluctuations in chicken, for example, from \$0.30 to \$2.72, the market faces significant risk, underscoring the need for price forecasting. The findings suggest the adoption of a nonlinear forecasting approach for the prediction of chicken prices. The machine learning approach to forecasting, such as NNAR, helps farmers, market analysts, and policymakers plan production, rations, and feed management based on precise chicken price projections. The volatility of chicken prices also urges the need to closely observe feed costs, as it has direct correlation to overall chicken production costs. Thus, an effective and efficient forecasting approach should be adopted. The use of instruments such as insurance and forward contracts could be encouraged, given the substantial fluctuations in chicken prices. The forecasted results encourage investment in different stages of supply chains, such as the establishment of a processing plant, cold storage, and marketing infrastructure. The results also suggest that unexpected shocks such as fuel costs, feed price spikes, and disease outbreaks like avian influenza can affect the market price of chicken. As chicken is an important protein source for many individuals globally, the change in the price of chicken also affects household affordability and ultimately affect nutritional requirements in the long term.

CONCLUSION

Through a comparison of traditional time series, machine learning approaches, and a hybrid forecasting model, NNAR was found to be the most accurate model for forecasting, with the lowest values of ME, MAE, RMSE, and MAPE. Among the hybrid models, NNAR x STL was found to be the best, as it combined nonlinear series with a seasonal component. The 30-month forecast of chicken prices through the NNAR model reflects stability with moderate fluctuations. Overall, NNAR and its hybrid with STL were found to be the most effective models for forecasting global chicken prices.

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