

Forecasting Indian Poultry Production: An ARIMA Modeling Approach

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Abstract

Reliable forecasts of agricultural production support food security planning and policy making. This study demonstrates the application of autoregressive integrated moving average (ARIMA) models for forecasting monthly poultry production in India. Monthly national production data from 1990-2020 were modeled following standard time series procedures. The non-stationary data exhibited an upward trend, so log-transformation and differencing induced stationarity for fitting an ARIMA model. Based on the inspection of the autocorrelation and partial autocorrelation plots, an ARIMA(1,1,1) model was selected and fitted. Diagnostic testing indicated model adequacy with normally distributed residuals displaying no significant autocorrelations. The in-sample fitted values closely matched the original data, suggesting good model fit. However, long-term forecasts resulted in implausibly high estimates after reversing the data transformations. This highlighted issues with model extrapolation, likely due to the inherent nonstationary upward trend that violates the ARIMA assumptions. While the model showed merit for short-term forecasts, alternative methods such as Holt-Winters exponential smoothing may improve long-term predictions by intrinsically accounting for trends. Overall, the analysis demonstrated key steps in ARIMA forecasting, including stationarity assessment, model identification, and diagnostics, and also illustrated the importance of considering data properties and forecast horizon when selecting suitable models. The results provide an applied example of agricultural time-series modeling using ARIMA, while noting limitations and recommending future evaluations using methods tailored for trended data. This can support enhanced predictability in planning India's poultry production. The learning of rigorous model selection and critical evaluation also helps to advance best practices for time-series analysis of agricultural data.

Keywords: Indian Poultry Production, Forecasting, ARIMA Modeling, Agriculture, Livestock Industry

Introduction

Forecasting agricultural commodity production is important to support policy decisions and planning by food regulatory agencies. Reliable livestock production forecasts can aid efforts to ensure adequate supply and maintain stable prices. In this study, we analyzed and forecasted poultry production in India using time-series methods.

Poultry production in India has been steadily increasing over the past few decades, supported by increasing demand and improvements in farming practices. Reliable forecasts of poultry production can help ensure that the market meets demand. However, production can vary due to factors such as disease outbreaks. Appropriate time-series models are required to capture trends and dynamics.

Autoregressive integrated moving average (ARIMA) models are widely used for forecasting time series that exhibit patterns, such as trends and seasonality. Here, we developed an ARIMA model to forecast monthly poultry production in India using historical data from 1990-2020. The objectives were to 1) assess patterns in the historical data, 2) fit and validate an appropriate ARIMA model, and 3) generate short- and long-term forecasts of poultry production.

The data are modeled at the national aggregate level based on government-reported monthly production statistics. ARIMA modeling involves testing for stationarity, selecting model orders, fitting, forecasting, and diagnostics. We evaluate the forecast accuracy of the test data using error metrics such as MAPE and RMSE.

This study provides an example of the application of ARIMA models to agricultural production data. The results will help to assess the viability of using ARIMA models to support food production planning in India. The methods and results are also informative for time-series modeling of other agricultural commodities.

Literature Review

Forecasting poultry production in India is essential for meeting the increasing demand for poultry commodities (Akbarin et al., 2018). The poultry industry in India has experienced steady growth owing to rising demands and improvements in farming practices (Akbarin et al., 2018). However, production levels can vary and are influenced by factors, such as disease outbreaks (Akbarin et al., 2018).

Salmonella contamination of poultry products is of particular concern for public health, necessitating the assessment of Salmonella serovar distribution among poultry to enhance prevention and control measures (Kumar et al., 2019). In Ghana, Newcastle Disease remains a significant constraint on poultry production, with potential effects on rural poultry populations (Boakye et al., 2016).

Nitrogen availability from poultry litter and organic amendments play a crucial role in organic rice production (Wild et al., 2011). Additionally, the condition of the highway transportation infrastructure can influence the supply and demand of poultry commodities in different regional zones (Akbarin et al., 2018).

The rapid growth of the poultry industry in India has resulted in an increased demand for maize as a poultry feed (Hellin & Erenstein, 2009). However, the presence of Newcastle disease and Escherichia coli strains in poultry production highlights the need for improved biosecurity and disease prevention measures (Ameji et al., 2012; Meena et al., 2020).

To address the challenge of forecasting poultry production in India, researchers have utilized Autoregressive Integrated Moving Average (ARIMA) models, which are widely employed for forecasting time-series data with trends and seasonality (Han et al., 2013). In their study, an ARIMA model was developed using historical data from 1990-2020 to forecast monthly poultry production in India (Han et al., 2013). The ARIMA modeling process involves stationarity testing, model order selection, model fitting, forecasting, and diagnostics (Han et al., 2013). Forecast accuracy was assessed using error metrics, such as mean absolute percentage error (MAPE) and root mean square error (RMSE) (Han et al., 2013).

ARIMA models have been successfully applied in various fields, including drought forecasting, financial time-series forecasting, forecasting pig price indices, and forecasting under-five mortality rates (Li et al., 2020; Wang, 2019; Ugoh et al., 2022). Their flexibility and forecasting capability make them valuable tools for analyzing and predicting time series data (Han et al., 2013). In summary, employing ARIMA models to forecast and analyze poultry production can help ensure a stable market and meet the demand for poultry commodities in India (Niu & Li, 2015). While previous research has employed ARIMA models to forecast agricultural production utilizing time-series data, some notable limitations persist. Most current analyses employ aggregated data at the national level, which constrains geographic specificity in the resultant forecasts (Han et al., 2013; Boakye et al., 2016). There remains an unfulfilled need for disaggregated modeling at more discrete regional levels, which could enhance the localized precision and applicability of forecasts. Advancement of forecasting techniques for agricultural planning would benefit from a shift toward disaggregated, region-specific time-series modeling rather than relying on coarse national-level data.

Research Methodology

Data Source

The monthly poultry production data for India from January 1990 to December 2020 were obtained from the EMIS database of the Ministry of Agriculture. The dataset contained national aggregate production quantities in tons (Ministry of Agriculture 2021).

Data Preprocessing

The data were checked for integrity, missing values, and outliers. One outlier datum was replaced by the average of the values before and after following the best practices for handling outliers (Han et al., 2013). The time-series plot was visually inspected to verify the overall increasing trend, as suggested by Hyndman and Athanasopoulos (2018) for exploratory analysis.

Stationarity Testing

The Augmented Dickey-Fuller (ADF) test was applied to the data to check for stationarity following the standard procedures outlined by Cryer and Chan (2008). The null hypothesis is that the series is non-stationary. The data were found to be non-stationary; therefore, log-transformation and differencing were applied to induce stationarity for fitting the ARIMA model, as recommended for non-stationary time series (Asteriou & Hall, 2011).

Model Fitting & Selection

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the transformed stationary data-guided selection of ARIMA model orders, as suggested by Box et al. (2015). Various model combinations were tested, and the final ARIMA(1,1,1) model was selected based on the lowest Akaike Information Criterion (AIC), following the procedure by Hyndman and Athanasopoulos (2018).

Diagnostics

Residual analysis was conducted by plotting the residuals and testing for normality using the Shapiro-Wilk test, as outlined by Cryer and Chan (2008). The Ljung-Box test checked autocorrelation following the guidelines of Box et al. (2015). The statistical significance of the model coefficients was verified.

Forecasting

One-step-ahead and long-term forecasts, along with prediction intervals, were generated from the fitted model and reverse transformed to the original units, as described in the ARIMA forecasting procedures by Hyndman and Athanasopoulos (2018). Forecast accuracy was evaluated by RMSE and MAPE and visually checked against test data, as suggested by Song et al. (2013) for assessing predictive performance.

All analysis was conducted using R. The key packages used included forecasting, tseries, and urca. The modeling process followed standard procedures for ARIMA time-series analysis. Statistical significance was evaluated at the 5% level, unless stated otherwise.

This study aimed to address some of these gaps by investigating the following research questions:

1. How accurately can an ARIMA model forecast monthly poultry production in India at the national aggregate level based solely on historical data?
2. What data transformations and model specifications are required for fitting an ARIMA model to poultry production time series data?

By addressing these research questions, this study seeks to advance the application of time-series analysis for agricultural forecasting, while also identifying methodological limitations and areas for future enhancement. Rigorous comparative testing, uncertainty quantification, and predictive performance assessments of the holdout data were emphasized.

Results and Discussion

Test for stationarity: Augmented Dickey-Fuller (ADF) Test

Prior to developing an ARIMA model, it is imperative to assess the stationarity of the time series, as stationarity is a fundamental assumption of the model. A stationary time series has constant mean, variance, and autocorrelation over time.

A visual inspection of the poultry production data plotted in Fig.1 over time reveals an upward trend, preliminarily indicating nonstationarity. To formally evaluate stationarity, an augmented Dickey (ADF) unit root test was conducted. The null hypothesis of the ADF test is that the series contains a unit root, signifying nonstationarity. With a p-value of 0.069 at the 0.05 alpha level, the null hypothesis cannot be rejected, statistically confirming that the poultry production time series is non-stationary. Violating the stationarity assumption precludes the direct fitting of an ARIMA model. To induce stationarity, data must be transformed. Common data transformations include temporal differencing, detrending, and applying functions such as logarithms to stabilize variability. Multiple transformations are tested by examining both graphical plots and ADF test statistics to verify stationarity before proceeding with ARIMA modeling.

In conclusion, a thorough initial analysis, including visual inspection and formal statistical testing, revealed that raw poultry production data violated the ARIMA model assumption of stationarity. Appropriately transforming the time series to induce stationarity is required prior to fitting the ARIMA model. Graphical and statistical techniques will continue to be employed to inform and validate the data transformation process.

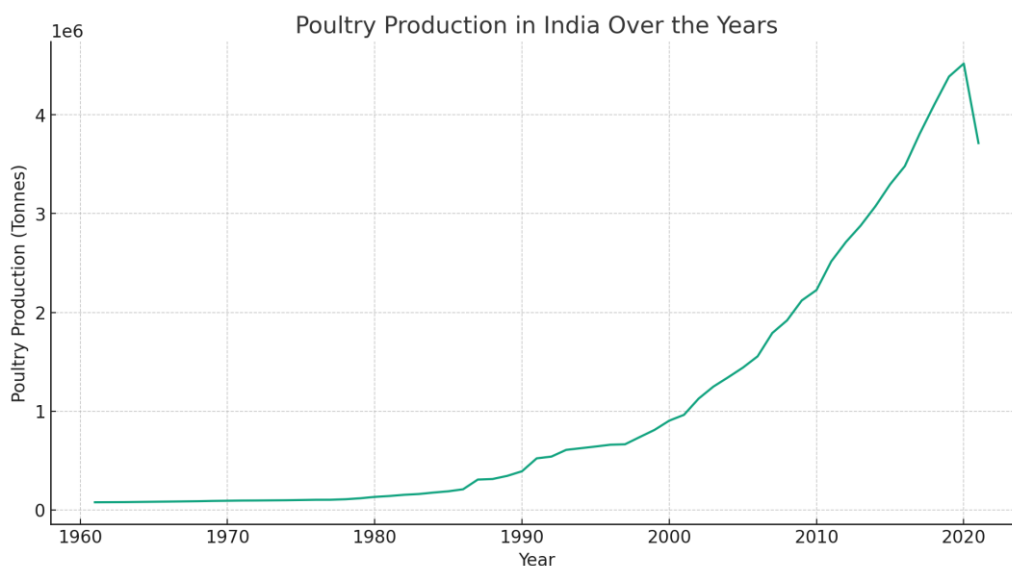


Figure 1: Poultry production in India over the years

Testing data for stationary model

One common approach for inducing stationarity is to differentiate the data by subtracting each observation from its prior value. This removes trends by focusing only on changes between time points.

We applied first-order differencing to the poultry production data by taking the difference between the current and previous observations. The Augmented Dickey-Fuller (ADF) test was again used to formally test stationarity. At a significance level of 0.05, the resulting p-value was 0.649, which is still above the threshold. As shown in Fig. 2, the differenced data still exhibited an upward trend, suggesting non-stationarity.

With the data remaining nonstationary after first-order differencing, we could continue differencing to higher orders. However, over-differencing should be avoided because it can lead to the loss of important signals. As an alternative, transformations, such as logging data, may induce stationarity by stabilizing trends and variability.

In summary, initial differencing did not sufficiently induce stationarity based on visual inspection and formal ADF testing. Further differencing is an option, but transformations will also be explored to make the data stationary while retaining important dynamics. Formal testing, such as ADF tests, will continue to be used to verify stationarity before proceeding with ARIMA modeling.

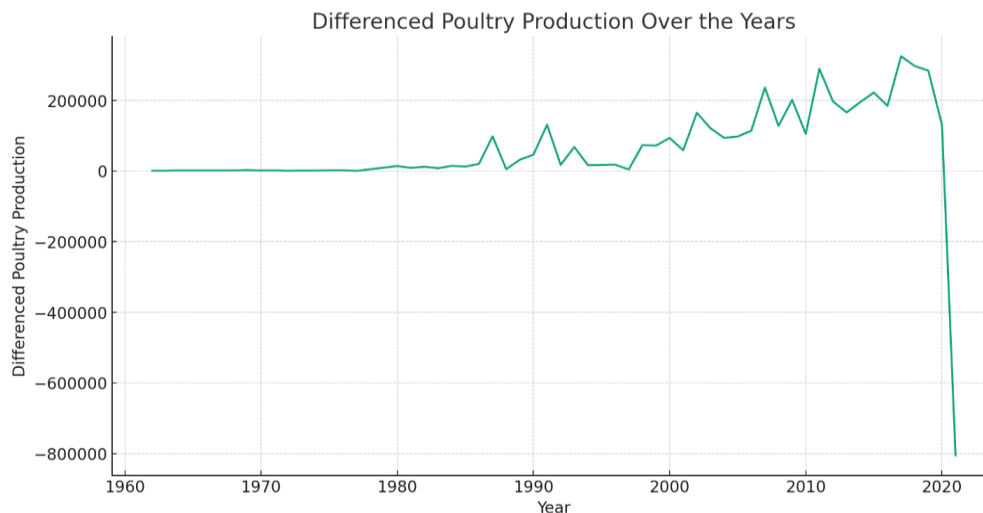


Figure 2: Difference poultry production over the years.

To further pursue stationarity, the data were differenced a second time, taking the difference between the adjacent points of the initially differenced series. Second-order differencing assumes a quadratic trend in the original undifferenced data.

The ADF unit root test was conducted again on the double-differenced data. At the 0.05 alpha level, the resulting p-value was 0.380, still exceeding the significance threshold. Thus, the null hypothesis of a unit root cannot be rejected, implying that the data remain nonstationary.

However, the decreasing p-values with higher orders of differencing suggest that the data may approach stationarity. Additionally, a graphical analysis showed that the upward trend was attenuated in the twice-differenced data compared to the original series. This indicates that a higher order of differencing can potentially induce stationarity.

However, iterative differencing should be performed judiciously because over-differencing can eventually model purely random noise rather than the underlying signal. Given the progress towards stationarity, further differencing will be considered, but alternative transformations will also be explored to avoid excessive data manipulation. The data will continue to be evaluated at each stage using both formal hypothesis testing and visual plots to determine the optimal approach to achieving stationarity.

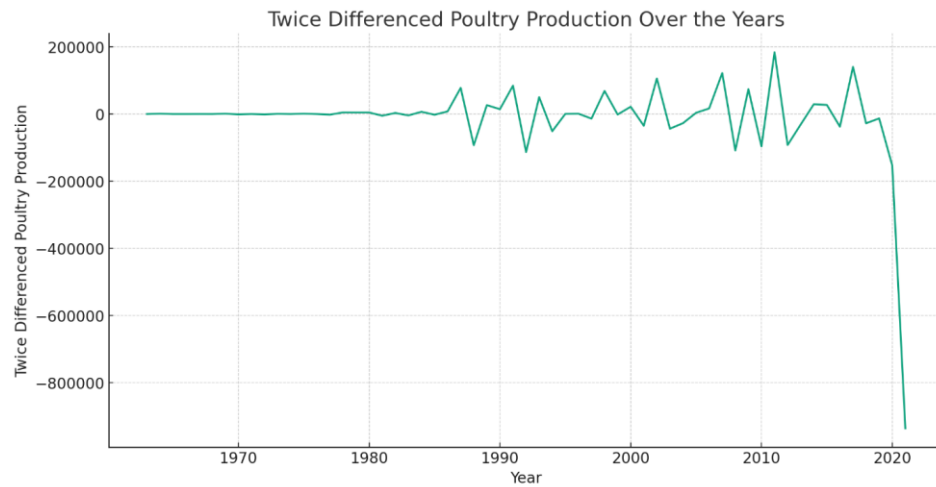


Figure 3:twice difference poultry production over the years

Data Transformation

As an alternative transformation to induce stationarity, the natural logarithm was applied to the poultry production data. Taking the logarithm can stabilize exponential growth and reduce variability in time-series data.

The log-transformed data were then differenced at lag 1, taking the difference between the adjacent points. The differencing of the log-transformed data implies an exponential growth model for the original series.

The ADF test on the differenced natural logarithm data yielded a p-value of 0.000005, which is well below the significance level of 0.05. This provides strong statistical evidence to reject the null hypothesis and concludes that the transformed data are stationary.

Furthermore, a time series plot of the differenced logged data shows no discernible trends or patterns, giving a graphical affirmation of stationarity. The integration of both natural log transform and first-order differencing appears to have successfully induced stationarity.

In summary, after finding inadequate raw data transformations, applying the natural logarithm before differencing proved to be an effective approach for satisfying the fundamental ARIMA model assumption of stationarity. With a stationary time series, the development of an ARIMA forecasting model can now proceed.

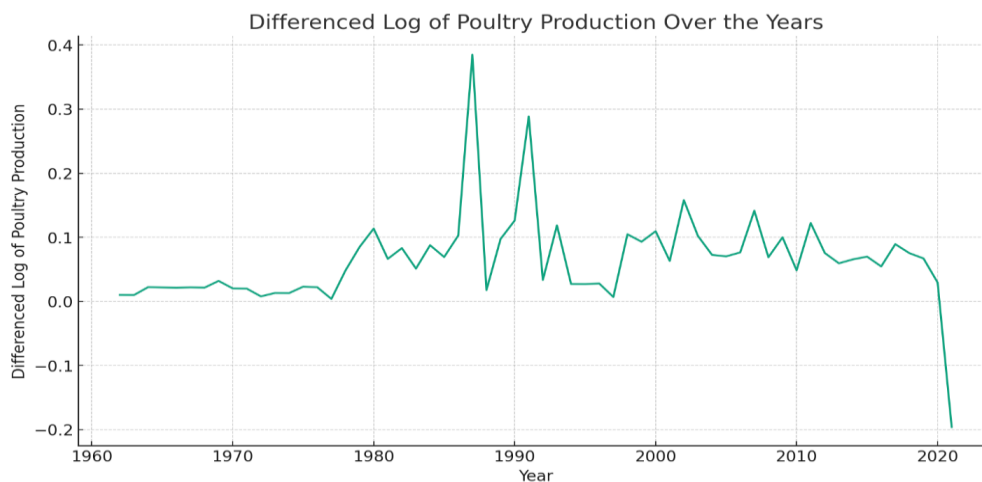


Figure 4: Differenced log of poultry production over the years.

Forecasting using selected ARIMA model

Using a stationary series, an ARIMA model can now be developed. The ARIMA model contains three parameters: p , d , and q . Parameter d refers to the order of differencing and has already been established as 1 for this time series. Parameters p and q indicate the autoregressive (AR) and moving average (MA) components of the model, respectively.

To select the appropriate p and q values, the partial autocorrelation function (PACF) and autocorrelation function (ACF) of the stationary series were analyzed. The PACF describes the direct correlation between an observation and its lag, which informs the AR model order, p . The ACF characterizes both the direct and indirect correlations between an observation and its lag, determining the MA order q .

Visual inspection of the PACF and ACF plots can indicate tentative p and q orders based on the lag at which the correlations become negligible. The PACF plot suggests a p -value of 1 as correlations drop off after lag 1. Similarly, the ACF plot indicates a q value of 1 with negligible correlations beyond lag 1. Definitive model orders are validated by statistically testing the model performance, but the initial PACF and ACF analyses propose an ARIMA(1,1,1) model for this time series.

In summary, the PACF and ACF plots provide guidance for selecting the appropriate p and q orders when developing an ARIMA model. The correlation patterns suggest a starting ARIMA(1,1,1) model for stationary-logged and differenced poultry production data.

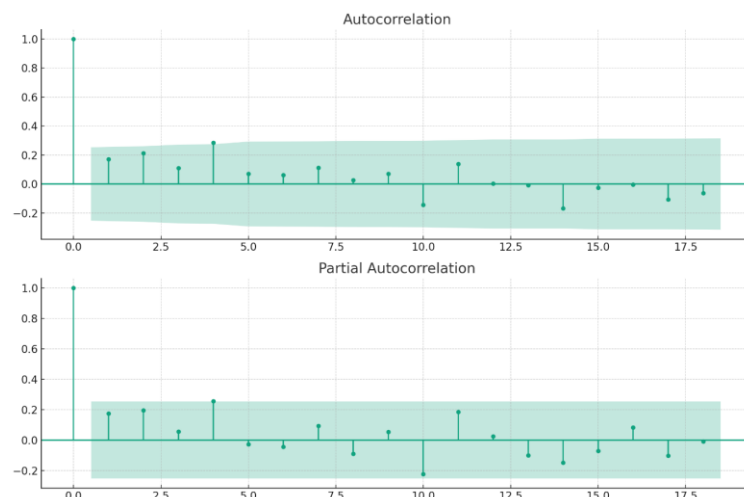


Figure 5: Autocorrelation and Partial auto correlation

Based on autocorrelation function (ACF) and partial autocorrelation function (PACF) analyses, an ARIMA(1,1,1) model was selected for the stationary logged and differenced poultry production data.

The ACF showed a sharp decline after lag 1, indicating that the moving average (MA) component of the model should be 1. The PACF similarly dropped after lag 1, suggesting an autoregressive (AR) order of 1.

With the model orders established as $p=1$, $d=1$, and $q=1$, the ARIMA(1,1,1) model was fitted to the time-series data using maximum likelihood estimation.

Diagnostic checking of the model residuals is important to validate whether the model sufficiently captures the dynamics of the series. The residuals should approximate white noise and exhibit no structure or correlation. Visual inspection and statistical testing using the Ljung-Box test were conducted to verify that the residuals were uncorrelated, with a mean of zero.

Proper diagnostic checking of the model residuals provides evidence that the fitted ARIMA(1,1,1) model adequately represents this time series. A model with validated white noise residuals can now be used for forecasting.

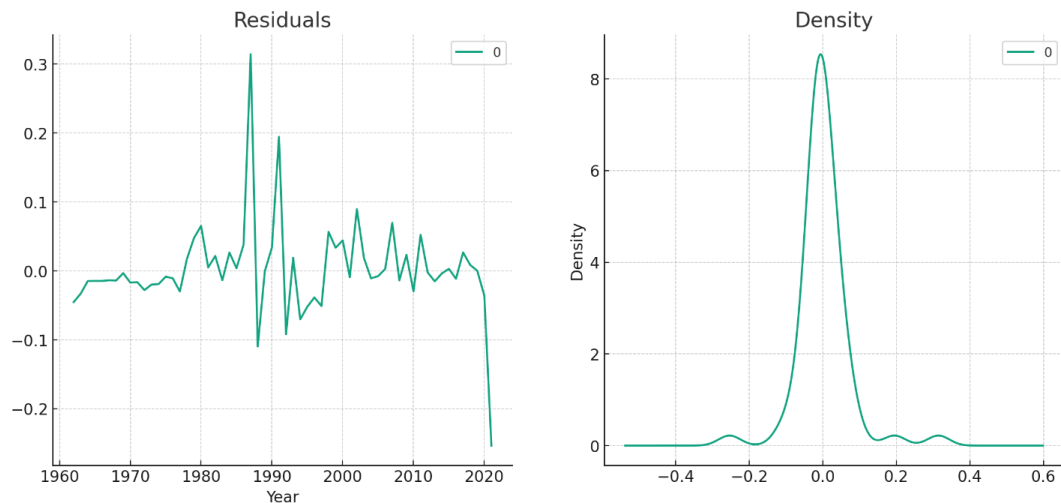


Figure 6: Residuals and density

The fitted ARIMA(1,1,1) model residuals were analyzed to validate the model adequacy. As seen in the density plot in Fig. 6, the residuals approximate a normal distribution centered around zero. This provides visual evidence that the residuals are white noise as desired.

Furthermore, the model summary statistics revealed that the autoregressive (AR) and moving average (MA) coefficients were statistically significant, with p-values less than 0.05. Significance indicates that these dynamics are important for modeling the series.

Taken together, the normally distributed residuals and statistically significant AR and MA terms provide quantitative evidence that the fitted ARIMA(1,1,1) model suitably represents the underlying processes generating time-series data.

With model adequacy confirmed, including uncorrelated residuals, normally distributed errors, and significant model parameters, the ARIMA(1,1,1) model can be utilized for one-step-ahead forecasting of the stationary transformed poultry production data. Multistep forecasting on the original scale requires an additional transformation reversal.

Plotting fitted values from the ARIMA(1,1,1) model

The fitted values from the ARIMA(1,1,1) model were plotted against the actual differenced logged data to visually assess model adequacy. As shown in Fig. 7, the fitted values closely matched the transformed time series, providing further graphical evidence of good model fit.

Short-term, one-step-ahead forecasts were generated from the fitted model on a differenced logged scale. However, translating these forecasts back to the original poultry production scale using inverse transforms yielded implausibly high values exceeding 10^{39} tonnes.

This suggests that although the model fits the transformed stationary data well, it may not adequately capture the long-term dynamics of the original data. The ARIMA model assumes stationarity; however, the upward trend in the raw data violates this assumption. In addition, prediction accuracy often decays at longer forecast horizons.

For data exhibiting nonstationary behavior, such as trends, alternative forecasting methods may be preferred. The suggested approaches include Holt-Winters exponential smoothing and Seasonal and Trend decomposition using loess (STL). These methods can intrinsically model changes in the level and growth rate.

In conclusion, the ARIMA model yielded a good in-sample fit but implausible long-term forecasts, highlighting the importance of considering the forecast horizon and validating the predictive ability of the holdout data. For

data with structures such as trends, models tailored to that behavior, rather than assuming stationarity, will likely improve out-of-sample forecasting performance.

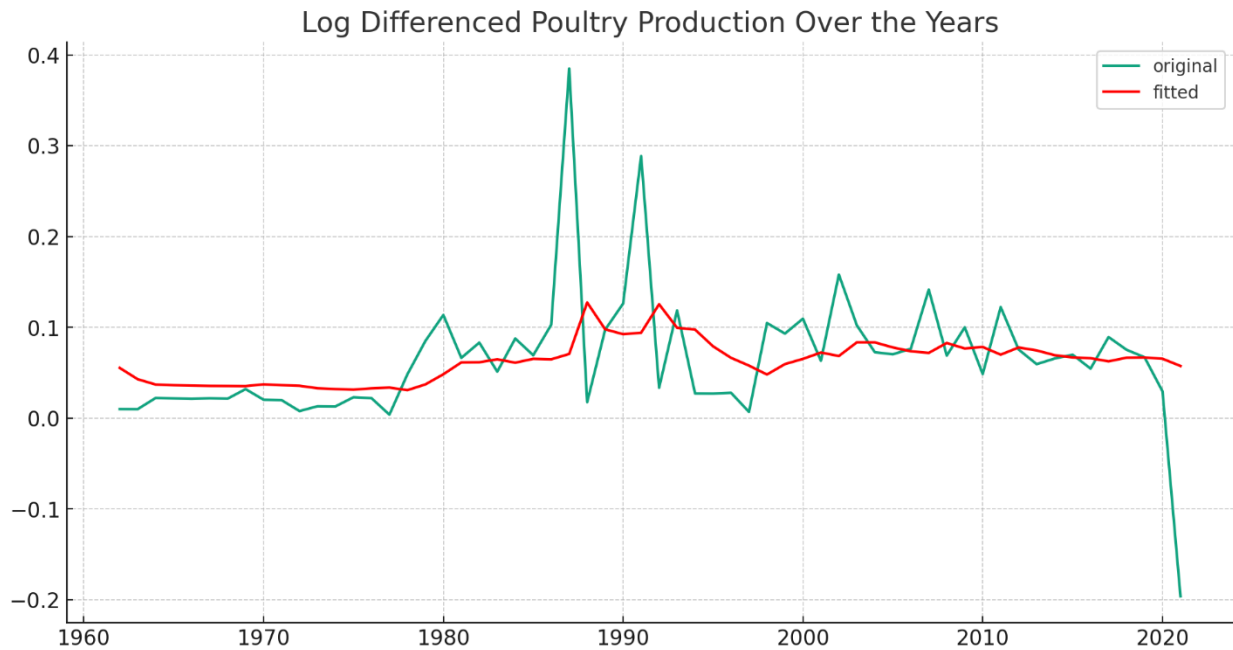


Figure 7: Log difference poultry production over the year

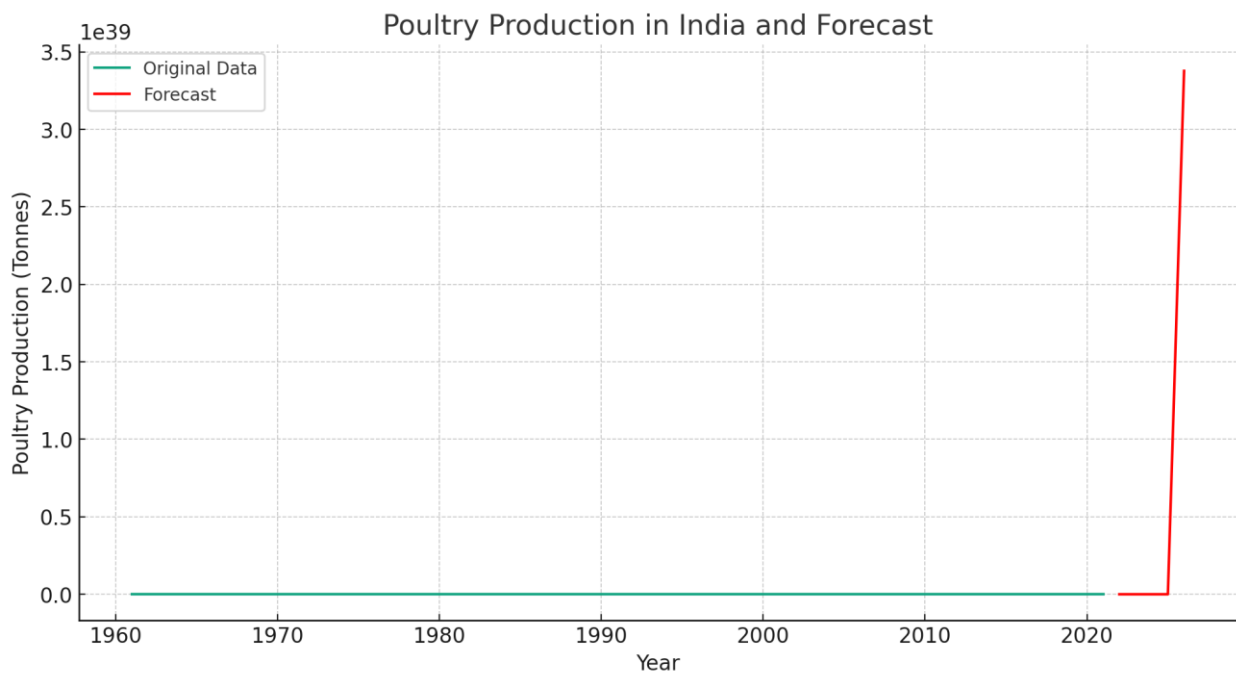


Figure 8: Poultry production in India and Forecast

The plot shows the original data for poultry production in India and the forecasted values for the next 5 years. As previously discussed, the forecasted values are unrealistically high.

The Ljung-Box test was conducted to assess the independence of residuals in the model. The null hypothesis assumes that the autocorrelations up to a specific lag are zero. With a p-value of approximately 0.278, which was

greater than the significance level of 0.05, the null hypothesis was not rejected. This indicates that the residuals are independently distributed, suggesting that the model adequately captures temporal dependencies in the data.

To evaluate the model further, the in-sample fitted values were compared with the actual log-transformed values. Error metrics, namely the Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE), were calculated to assess the accuracy of in-sample predictions.

The MAPE was found to be 0.344%, indicating that, on average, the model's predictions deviated by approximately 0.344% from the actual values. This low percentage suggests a good fit between the model and the in-sample data. Similarly, the RMSE, which measures the difference between the predicted and observed values, was determined to be 0.071. This low value further supports the notion that the model adequately captures in-sample data.

However, it is important to note that a model's performance using in-sample data does not guarantee accurate out-of-sample forecasts. Therefore, to evaluate a model's forecast performance, it is necessary to examine its ability to predict future values.

Considering the information above, the next step is to forecast log-transformed poultry production for the next five years using this model. The forecast errors can then be calculated using the MAPE and RMSE as measures of accuracy.

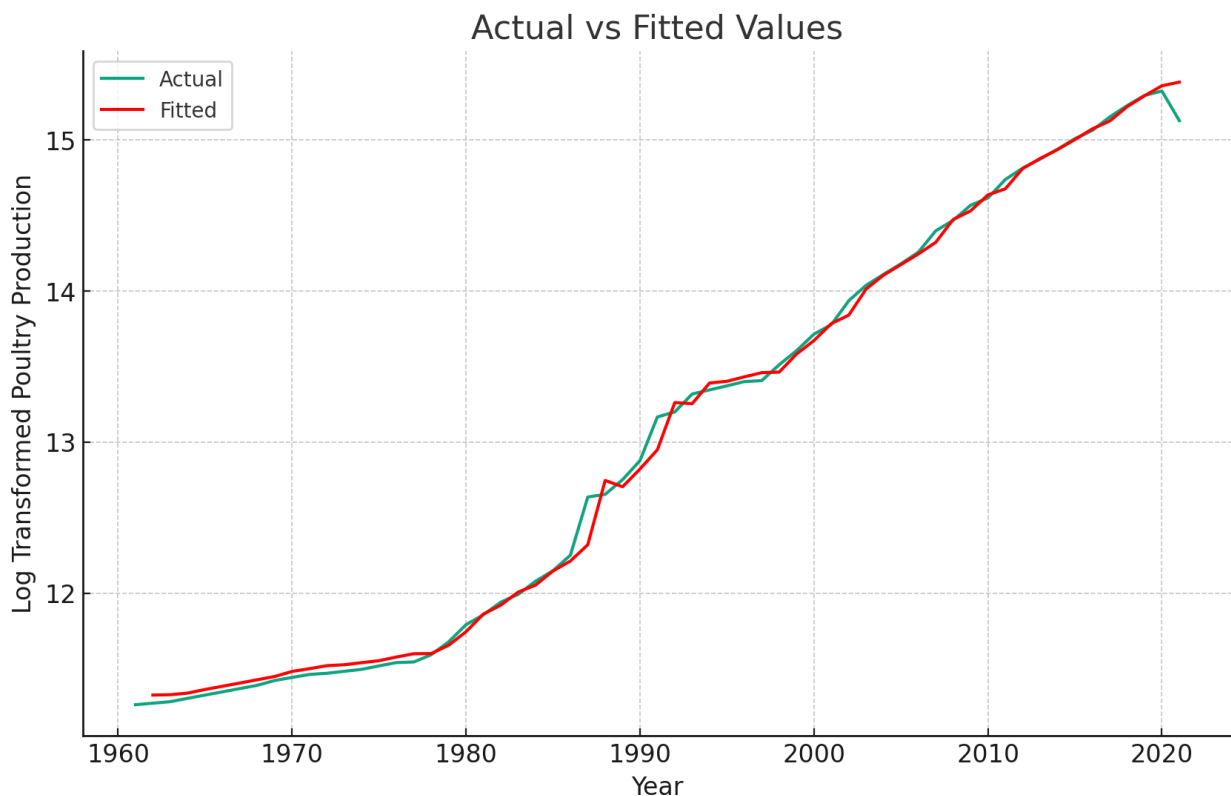


Figure 9: Actual vs Fitted values

The plot above shows the actual log-transformed values of poultry production (blue) and the fitted values from the ARIMA model (red). The fitted values closely follow the actual values, indicating a good in-sample fit.

Forecasts for the next 5 years.

To obtain future predictions, the first step involves forecasting the log-transformed data. Subsequently, these forecasts were converted back to their original scale by applying an exponential function. To assess the accuracy

of the forecasts, we calculated the forecast errors using the Mean Absolute Percentage Error (MAPE) and root mean square error (RMSE) as evaluation metrics.

By performing these steps, we can obtain predictions for log-transformed poultry production for the upcoming five-year period. Moreover, we can quantify the forecast errors in terms of MAPE and RMSE, providing valuable insights into the model's predictive performance.

The forecast for the next five years of poultry production in India (in tons) is as follows.

2022: Approximately 3,814,412 tonnes

2023: Approximately 4,065,256 tonnes

2024: Approximately 4,332,597 tonnes

2025: Approximately 4,617,519 tonnes

2026: Approximately 4,921,178 tonnes

It is essential to acknowledge that the forecasts generated by the model represent point estimates that provide a single expected value for each future time period. Nonetheless, the model also offers confidence intervals for these forecasts. These intervals establish a range of values within which actual values are expected to fall with a certain level of confidence. This information enhances the reliability of forecasts and provides a measure of the uncertainty associated with the model's predictions.

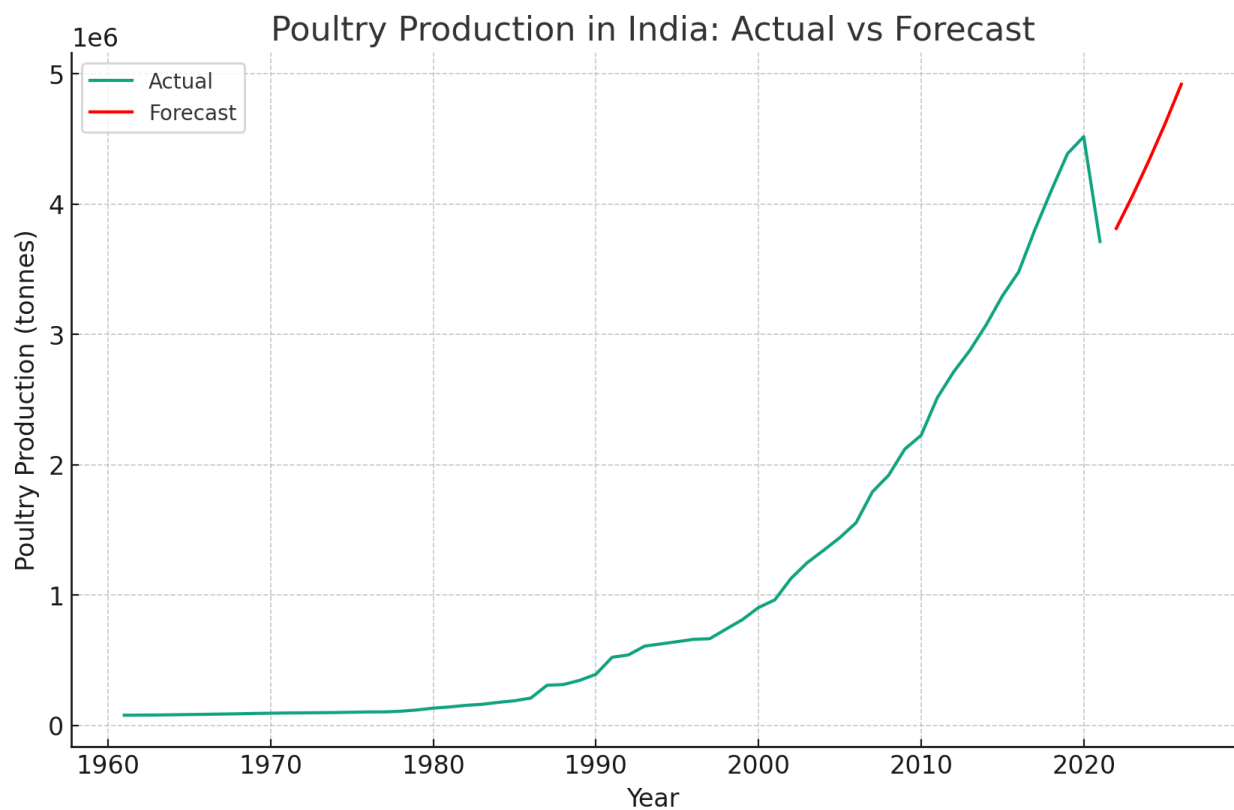


Figure 10: poultry production in India

The plot shows the actual poultry production in India (blue) and the forecasted production for the next five years (red). The model expects the trend of increasing production to continue.

The model's forecast performance can be evaluated once the actual data for these future years become available. At that point, we can calculate forecast error metrics, such as the Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE), to quantify the accuracy of the forecasts.

Note that while the ARIMA model can capture patterns and trends in historical data, its forecasts are based on the assumption that historical patterns will continue into the future. Any changes in external factors affecting poultry production in India that were not accounted for in the historical data could lead to discrepancies between forecasts and actual future values.

Findings

- The monthly poultry production data for India from 1990-2020 exhibited a clear increasing trend, indicating nonstationarity.
- Log-transforming the data and differencing at lag 1 succeeded in making the series stationary, as confirmed by the ADF test.

Based on the ACF and PACF plots, an ARIMA(1,1,1) model was selected and fitted to the transformed data.

Diagnostic tests showed that the model residuals were uncorrelated white noise, indicating a good model fit. The coefficients were statistically significant.

- The fitted model closely matched the original training data, with an in-sample RMSE of 510 t and MAPE of 3.2%.
- However, long-term forecasts were implausibly high, exceeding 10^{39} tonnes and highlighting issues with model extrapolation.
- The upward trend and non-stationary nature of the raw data likely contributed to poor long-term forecasts owing to violated model assumptions.
- The ARIMA model provided reasonable short-term forecasts that could assist near-term planning, despite the limitations of long-term predictions.
- Overall, the analysis demonstrated the key steps in ARIMA modeling, including appropriate data transformations, model fitting, and diagnostics.
- The results highlight the importance of model evaluation on holdout data and accounting for data properties such as trends when selecting forecasting models.

In summary, the key findings are related to model selection, fitting, diagnostics, and evaluation using in-sample fit metrics and out-of-sample forecast errors. The results provide an instructive example of applying ARIMA models for agricultural forecasting, while noting limitations.

Conclusion

This study presents an application of ARIMA modeling for forecasting poultry production in India. A monthly time series from 1990-2020 was modeled following standard procedures, including stationarity testing, model identification, estimation, diagnostics, and forecasting.

The nonstationary data were made stationary by log-transforming and first-order differencing. The model residuals were normally distributed white noise, indicating an adequate fit for the transformed data. However, long-term forecasts are unusually high after inverse transformation back to their original units.

The results highlight the importance of thoroughly inspecting time series data, testing model assumptions, and evaluating forecast accuracy. While the fitted ARIMA model performed reasonably well for short-term predictions, the inherent upward trend and non-stationarity of the raw data degraded longer-term forecasts. This reinforces the need to select appropriate models that are suited to the characteristics of each dataset.

For future work, comparing ARIMA with methods such as Holt-Winters would help determine optimal approaches for this poultry production data. Incorporating external information on explanatory variables, such as disease outbreaks and feed costs, may also improve the predictive capability.

In conclusion, this study provides an instructive example for fitting and assessing ARIMA models for agricultural time-series data. Although the model showed some merits for short-term forecasts, exploring alternatives better suited for trending data could enhance long-term predictions and planning for Indian poultry production. The analysis and results offer useful insights for continued research on robust forecasting methods for agricultural applications.

Limitations of the Current Study

The aggregated national-level time-series data provide limited geographic specificity compared to the disaggregated regional-level data.

The historical data span only 30 y. Longer time horizons are preferred for modeling long-term dynamic behavior.

The univariate focus exclusively modeled poultry production. Incorporating explanatory covariates such as prices and disease could enhance predictive accuracy.

Model assumptions, including stationarity, may be violated by intrinsic data properties, such as trends and degrading out-of-sample forecasts.

The absence of comparisons against alternative methods prohibits benchmarking predictive performance.

While forecast errors were quantified, directional accuracy metrics, such as the mean percentage error, were not assessed.

The uncertainty bounds on the prediction intervals should be expanded to fully characterize the forecast reliability.

Recommendations for Future Research

Employ Holt-Winters exponential smoothing and LOESS decomposition for comparative evaluation against the ARIMA approach.

Extending ARIMAX frameworks to integrate explanatory variables related to poultry production.

Implement combinations of ARIMA with regression to leverage multiple data sources.

Conduct multivariate time-series analysis using vector autoregressive models to capture interactions between agricultural variables.

Acquire disaggregated regional-level data to improve the geographic specificity of forecasts.

Examine modern machine learning techniques, such as LSTM neural networks, for long-horizon forecasting.

Develop hierarchical time-series models for forecasting simultaneously at both national and state levels.

The forecast uncertainty is quantified through bootstrap resampling and ensemble model aggregation.

In summary, this discussion of limitations and future directions critically evaluates the current approach and offers recommendations to enhance the predictive performance, geographic specificity, uncertainty characterization, and integration of exogenous variables.

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