Forecasting Farmer Exchange Rate in Bali Province Using Seasonal Autoregressive Integrated Moving Average (SARIMA) Method

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Abstract. Farmer’s exchange rate (FER) is a proxy indicator to value the farmer’s purchasing rate and shows the term of trade between agricultural products and services sold and the goods purchased by farmers in producing and consuming households. FER obtained by comparing the Farmer Received Price Index with the Farmer Paid Price Index both expressed as percentages. The purpose of this study is to predict the FER of Bali Province from May 2019 to December 2019 and to count the level of purchasing power of the farmers. The monthly data of FER from January 2010 to April 2019 were used to build a seasonal ARIMA (SARIMA). Four models i.e. SARIMA(0,1,3), SARIMA(3,1,0), SARIMA(4,1,0), and SARIMA(1,1,1) with seasonal factor (0,1,1)¹² were tested. Referring AIC value for SARIMA(0,1,3) as much as 326.94 is the lowest then we infer this model is the best SARIMA model to predict the FER of Bali Province. Our research concludes the farmer’s income increases more than their expenditures.

1. Introduction
As an agricultural country, efforts to improve the welfare of farmers in Indonesia are one of several priority programs. The Indonesian Central Statistics Bureau (BPS Indonesia) has developed several indicators related to the welfare of farming communities who live in rural areas, three of which are (a) income per capita of farming families, (b) poverty levels, and (c) food security levels. Apart from the various efforts that have been made by the Indonesian government, poverty is still a serious problem in most regions of Indonesia, especially in rural areas. BPS Indonesia records a decline in the amount of poverty in rural areas by 3.69 percent per year (a decrease from 19.93 million in 2010 to 17.14 million in 2014) while in urban areas for this period, the poverty rate also lowered by 2.25 percent per year, decreasing from 11.10 million to 10.13 million [1]. Observing most of the villagers are farmers, one effort to alleviate the poverty level in rural communities is to increase ‘the recognition’ for the agricultural products of rural communities [2].

One indicator to assess the success of a farm family welfare improvement program is the Farmer Exchange Rate (FER). FER is an indicator to value the purchasing power of farm families by examining the selling price of agricultural products against the prices of goods and services needed by farm households [3, 4]. Although FER is not a perfect indicator for the farmer’s welfare, FER is suitable to use since it measures the ratio between farmer’s income
from selling the agricultural products and the price paid for the consumption of goods and services. According to BPS Indonesia [1], the formula for FER is:

\[
FER = \frac{IT}{IB} \times 100\%
\]  

In Eq. (1) IT and IB represent the price index received by farmers as a result of a price survey at the producer level and the price index paid by farmers, respectively.

This paper aims to model and to predict the FER from farmers in rural areas of Bali using historical data from January 2008 to April 2019. Refers to [3][6], agricultural products follow seasonality so we use SARIMA in modeling FER’s data as well to forecast FER for the period May to December 2019.

2. Data and Method

2.1. Data

The univariate FER’s data for this study are available from BPS Bali [5], from January 2008 to April 2019. By applying R software, we build SARIMA models follow by choosing the best model to predict the FERs from May to December 2019.

2.2. Method

The univariate time series SARIMA model is a family of ARIMA model. When Box and Jenkins [9] introduced ARIMA as a method to model time series data, this method immediately gained wide attention from experts and used it extensively on various issues such as economics, environment, engineering, and others. It is common to use the ARIMA model to understand data patterns and to forecast based on available historical data [6].

So far, there are several techniques available to predict the time-series data such as the autoregressive (AR), the moving average (MA), the ARMA, and the ARIMA model [7]. Besides, an ARIMA model can take one of three forms namely additive, multiplicative, or subset ARIMA [13]. The random variable \( \{X_t\}, t = \pm 1, \pm 2, \cdots \) is said a univariate time-series data if \( t \) represents time typically be discrete and its value is an integer. To apply time series methods in modeling as well as forecasting the future, these methods involve several steps i.e model identification, unscrambling and estimation of the traditional components such as a trend, seasonal component, cyclical component, and the irregular movement [10][12].

The time series is said to be seasonal of order \( d \) if there exists a tendency for the series to exhibit a periodic behavior every time interval \( (d) \). When the seasonal component is observed on the ARIMA model, the model is commonly referred to as seasonal ARIMA (SARIMA). A multiplicative \( (p, d, q)(P, D, Q)^s \) SARIMA model can be formulated as follows ([12]):

\[
\Phi_p(B^s) \phi(B) \nabla^d \nabla_s^D x_t = \delta + \Theta_q(B^s) \theta(B) w_t
\]

where \( x_t \) and \( w_t \) represent the realization of \( X_t \) at time \( t \) and white noise error, respectively. In Eq. (2) the polynomials \( \phi(B) \) and \( \theta(B) \) represent the AR and MA components of the model with with orders \( p \) and \( q \), respectively and the ordinary and seasonal difference in the model are represented by \( \nabla^d \) and \( \nabla_s^D \) as follows:

\[
\begin{align*}
\phi(B) &= 1 - \phi_1B - \cdots - \phi_pB^p \\
\theta(B) &= 1 + \theta_1B + \cdots + \theta_qB^q \\
\nabla^d &= (1 - B)^d \\
\nabla_s^D &= (1 - B^s)^D
\end{align*}
\]
To model as well to forecast the FER of Bali for the period May to December 2019, we follow these steps:

(i) Checking the stationarity of the data. Seasonal differencing is necessary to remove the seasonal trend. If there is a secular trend then nonseasonal differencing will be necessary. To avoid the model becomes too complex, the order of differencing, \( d \) and/or \( D \), should add up to at most 2 [11];

(ii) Identifying the appropriate model(s) by observing autocorrelation function (ACF) and/or partial autocorrelation function (PACF);

(iii) Selecting the best model by evaluating the Akaike Information Criterion (AIC) value. Model with the smallest AIC will be chosen;

(iv) Applying the best model to forecast the FER of Bali for period May to December 2019.

3. Result and Discussion

3.1. Stationarity of the Data

This paper utilizes the FER data of Bali province from January 2008 to April 2019 to forecast. The plot of the data depicts on Fig. 1. Fig. 1 shows the FER data of Bali province has an upward (trend) pattern from year 2008 to 2012. Starting from the year 2013, the FER becomes unstable and does not show significant movement.

![Figure 1. Farmers Exchange Rate](image)

Prior to model, we examine the stationarity of the data by conducting the Augmented Dickey-Fuller (ADF) test. The ADF test the null hypothesis that the data is not stationary against the data is stationary. The result showed the ADF statistic is \(-2.245\) and the p–value of 0.474. We conclude the level of FER does not stationary and we continue to analyze the first order of differentiated series \((d = 1)\). After differencing process, the ADF test showed the series becomes stationary.

3.2. Model Identification

Knowing the series is stationary at \( d = 1 \), we continue to identify the order of AR and MA by observing the ACF and PACF plot for the differentiated data on Fig.2. Some points are identified:
For the non-seasonal pattern, the autocorrelation coefficient is significant at lag 3 and it is cuts off at lag 3. In addition, the PACF plot cuts off also at lag 3. Refers to both plot, the order of AR and MA is 3, respectively;

(ii) For the seasonal pattern, the correlation coefficient is significant at lag 12, 24 and 36 or $1s, 2s, 3s$ for $s = 12$. By noting these fact then the seasonal factor for the FER data is $(0, 1, 1)_12$ or $(1, 1, 0)_12$.

By combining the non-seasonal and seasonal pattern, we identify four candidates to model the data, namely ARIMA$(3,1,0) \times (0,1,1)_12$, ARIMA$(0,1,3) \times (0,1,1)_12$, ARIMA$(3,1,0) \times (1,1,0)_12$, and ARIMA$(0,1,3) \times (1,1,0)_12$.

3.3. Model Selection

To choose the best model, we examine the Akaike Information Criterion (AIC) value of each of the model. The best model is the model that gives the smallest AIC values. Table below lists the $\hat{\sigma}^2$, Log Likelihood, and AIC value for each models:

| Model                  | $\hat{\sigma}^2$ | Log Likelihood | AIC     |
|------------------------|-------------------|----------------|---------|
| ARIMA$(3,1,0) \times (0,1,1)_12$ | 0.6158            | -159.3         | 326.59  |
| ARIMA$(0,1,3) \times (0,1,1)_12$ | 0.6169            | -159.4         | 326.80  |
| ARIMA$(3,1,0) \times (1,1,0)_12$ | 0.9041            | -169.5         | 346.91  |
| ARIMA$(0,1,3) \times (1,1,0)_12$ | 0.8891            | -168.5         | 345.01  |
Table 1 proves the ARIMA(3,1,0)×(0,1,1)_{12} is the best model by considering it has the lowest AIC value as well the lowest variance among its competitors. The LM-Test for this model showed the $\chi^2_{12} = 4.346$ with the p-value of 0.9763, which is not significant. Refers to these figures, we decide to select ARIMA(3,1,0)×(0,1,1)_{12} as the best univariate seasonal time series model for the FER data of Bali province.

3.4. Forecasting the FER of Bali

After we select the best model for the FER data of Bali province, then we forecast the FER for eight consecutive month start from May to December 2019. Table 2 shows the forecasting values as well the forecasting errors. The forecast plot is depicted on Fig. 3.

| Period | Real Value | Predicted | Error | Percentage |
|--------|------------|-----------|-------|------------|
| 05–2019 | 103.37 | 104.00 | 0.63 | 0.61 |
| 06–2019 | 103.58 | 104.12 | 0.54 | 0.52 |
| 07–2019 | 104.89 | 104.47 | 0.42 | 0.40 |
| 08–2019 | 104.65 | 104.35 | 0.30 | 0.29 |
| 09–2019 | 104.14 | 104.67 | 0.53 | 0.51 |
| 10–2019 | 103.66 | 104.82 | 1.16 | 1.12 |
| 11–2019 | 104.35 | 104.75 | 0.40 | 0.38 |
| 12–2019 | NA | 104.28 | – | – |

Average: 0.57, 0.55

Figure 3. The Forecast Plot
4. Conclusion
This paper concluded the FER of Bali can be modeled by applying ARIMA(3,1,0) × (0,1,1)_{12} as the best univariate time series model. This model has an out-of-sample average forecasting error rate (AFER) for period May to November 2019 as much as 0.55 percent. Our model has some shortcomings, for example we did not consider the other variable(s) that might affect the FER as well our model useful only for forecasting a short time frame.

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