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FORECASTING THE DEMAND OF BIRTH CONTROL PILLS USING ARIMA-GARCH

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ABSTRACT

The demand of birth control pill at National Population and Family Planning Agency in Ogan Komering Ilir district, South Sumatra, Indonesia is significantly high, and it varies from one sub-district to another. Consequently, supplying birth control pill becomes more complicated. To help this situation, an accurate forecasting on the demand of birth control pill is required. This paper proposes the combination of Autoregressive Integrated Moving Average (ARIMA) and Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) to obtain the best model for forecasting. The data set used is within the period of January 2017 and December 2019. Three experimental scenarios were proposed to achieve the best result: 1) 80% training data and 20% test data; 2) 75 training data and 25% test data; and 3) 66% training data and 34% test data. The best model obtained is characterized with ARIMA (1,1,2) and GARCH (2,1).

Keywords: *Forecasting, ARIMA-GARCH, birth control pill, supply, demand.*

1. INTRODUCTION

The world population growth is increasing every year, especially in emerging countries like Indonesia. Based on census conducted by Indonesian Central Bureau of Statistics (2020), it was reported that there were 270.20 million populations in Indonesia with the Z generation who are between 8 and 23 years old constituted to 27.94 percent and millennial generation who are between 24 and 39 years old constituted to 25.87 percent.

The rapid population growth in Indonesia becomes the main concern of the government since the high population without the increase of life, health, and education quality leads to a development drawback. Therefore, the government through its National Population and Family Planning Agency controls the population growth by campaigning family planning program. This campaign can be realized by implementing the functions of the agency, such as controlling the population rate, organizing family planning program, educating the citizens, coaching several trainings, and providing sufficient facilities and information (National Population and Family Planning Agency, 2021).

Although the agency provides the services to any citizens starting from adolescence, the priority is given to fertile aged couple which is between 15 and 49 years old for the wife and the couple is categorized as mature enough in reproduction (National Population and Family Planning Agency, 2013).

Having continues development and education during the Family Planning Program, the awareness of the fertile aged couple increases. It also occurs in Ogan Komering Ilir district, South Sumatra, Indonesia. Currently, there are 3,737 fertile aged couples and 2,898 active users of birth control pills users. In detail, the use of contraceptive types consists of 216 people (7.45%) using Intra Uterine Device, 83 people (2.86%) using a surgical operation on women, 15 people (0.51%) using a surgical operation on male, 421 people (14.5%) using implants, 1,123 people

(38.75%) using pills, 1,026 people (35.4%) using injections, and 14 people (0.048%) using condoms.

The use of contraceptive with pill is the most preferred birth control method amongst active users of family planning program in Ogan Komering Ilir district. This trend is also in accordance with the study conducted by Kawulur et al. (2015) in different districts, although it has no analytical studies. The main reason of this trend is because of the perception amongst the society that pills is the most effective contraception in preventing pregnancy. In addition, the birth control pill is considered superior in term of reversibility. Reversibility means that the process can be terminated anytime without any long fertility restoration effect. Moreover, it has no significant impact on intercourse.

The high demand of the birth control pill in Ogan Komering Ilir district affects the stock. Moreover, the birth control pills must be taken every day on a regular basis. To overcome this problem, the agency requires an application that provides an accurate number of birth control pills. The most appropriate method to provide an accurate number is through forecasting. Forecasting is a method to predict the state of the future through the data obtained from the past (Montgomery et al., 2008). The proposed approach of forecasting is to combine Autoregressive Integrated Moving Average (ARIMA) and Generalized Auto Regressive Conditional Heteroscedasticity (GARCH). ARIMA-GARCH model is chosen because it can handle any types of data, even though several types of data require the stationery process. In addition, this method can be useful for the short-term forecasting.

2. LITERATURE REVIEW

The combination between ARIMA and GARCH methods has been proposed in previous works with various domains. Perhaps the first one was by Crawford & Fratantoni (2003), where three techniques were compared: ARIMA, GARCH and regime-switching. The case study of home price changes was quite difficult to predict, hence, the price changes are integrated so that the analysis could be performed. There were two different results in this work. First, regime-switching model outperformed others for in-sample dataset. Second, ARIMA model outperformed for out-simple dataset. However, there is no further investigation to integrate ARIMA and GARCH in this work.

In the domain of inventory safety stocktaking (Jaipuria & Mahapatra, 2021), these two methods were combined to forecast the average demand of the homoscedasticity data. The result showed that the combination of these two techniques can predict better than the use of ARIMA only. The model was validated by using Bullwhip effect and net-stock amplification ratio.

Another work was proposed by Ghani & Rahim (2019) to produce the best model on predicting natural rubber price in Malaysia. The hybrid model of ARIMA-GRICH was introduced to predict the 20 days price in the future. This paper interestingly provided 20 models of ARIMA-GIRCH in various parameters. The best model obtained in this work was ARIMA (1,0)-GARCH (1,2). Various tests such as Akaike Information Criteria (AICC), Schwarz's Bayesian Information Criterion (SBC), and Hannan-Quinn Information Criterion (HQC); were conducted to validate the model.

A more dynamic dataset was analyzed by Ding et al. (2017) by combining ARIMA and GARCH methods. The number of train passengers was forecasted to provide a better information to travelers. The combined model of ARIMA and GARCH was argued to be the best one in providing expected value of short-term use on the train and predicted delays. Due to the nature of unpredictability of the dataset, the traditional methods of forecasting were considered as insufficient.

3. METHODOLOGY

Data mining is a process to find interesting patterns obtained through the large amount of data. The sources of data can be obtained through a database, data warehouse, website, or a system dynamic. It is also considered as a science of collecting, cleaning, processing, analyzing, and generating useful insight from data. Forecasting is a data mining technique to predict an event that will take place in the future. It can be divided into three types. The first type is a short-term forecasting. It is only used for the prediction in a short period such as days, weeks, and months in the future, such as industrial inspection (Prabuwono et al, 2019). The second one is a medium-term forecasting. It is used to predict an event for one or two years ahead, such as hate speech detection (Hana et al, 2020). The last one is long-term forecasting. It is used to predict an event for several years ahead in a long period, such as fraud detection (Alraouji & Bramantoro, 2014).
The short and medium forecasting are usually used for activities that is related to the operational management, budgeting, and deciding a new project while the long-term forecasting is generally used for a strategic planning.
ARIMA model used data that are not stationary (Adhikari & Agrawal, 2013). When the data in time series model is not stationary, the data are converted by applying the finite difference in points of data. The formula of ARIMA models the lag polynomial as follows:

$$\left(1-\sum_{i=}^{p}\varphi_i L^i\right)(1-L)^d X_t=\delta+\left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t \quad (1)$$

where p is autoregressive, d is the order of differencing, and q is the moving average. All these numbers are absolute numbers. These three parameters can be modified to create a new model. There are three possible models. The first model is autoregressive model. This model uses the form of (p,0,0) formulated as follows:

$$X_t=\mu'+\phi_1 X_{t-1}+\phi_2 X_{t-2}+\cdots+\phi_p X_{t-p}+e_t \quad (2)$$

where μ' is a constant, ϕ_p is autoregressive parameter at p, and e_t is error value at t period.
The second model is moving average. This model uses is (0,0,q) which is formulated as follows:

$$X_t=\mu'+e_t-\theta_1 e_{t-1}-\theta_2 e_{t-2}-\cdots-\theta_q e_{t-k} \quad (3)$$

where μ' is a constant, ϕ_p is autoregressive parameter at p, and $e\_(t\text{-}k)$ is error value at t-k period.
The third model is hybrid model. This model integrates the form of (0,d,0). The integration is basically a statement to difference the data. ARIMA model is divided into two types. The first type is without seasons. The equation of this model is as follows:

$$(1-B)(1-\phi_1 B)X_t=\mu'+(1-\theta_1 B)e_t \quad (4)$$

The second type is seasonal. The equation of this model is as follows:

$$(1-B)\left(1-B^{12}\right)X_t=(1-\theta_1 2)\left(1-\Theta_1 B^{12}\right)e_t \quad (5)$$

In general, time series data modeling must meet the requirement of constant variance (homoscedasticity). However, there are several data that have high volatility. This is indicated by the movement of variance that is not constant (heteroscedasticity). To overcome this problem, GARCH model is used. It can be defined as follows:

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_m \varepsilon_{t-m}^2 \qquad (6)$$

Python is one of the best tools for forecasting with ARIMA and GARCH models. It has two packages for modelling ARIMA, namely *pmdarima* and *statsmodels*. The required package for modeling GARCH with conditional variants is arch. *Pmdarima* package is utilized for obtaining ARIMA parameters, while *statsmodel* package is utilized to manually find the most optimal model. Amongst these three packages, only *pmdarima* package can automatically find the parameter *p* and *q* based on given criteria.
There are several steps to analyze time series data with the combination of ARIMA and GARCH as illustrated in Fig. 1. The first step is to perform a plot of native data to determine whether the data mean has been categorized as stationary or not. If not, it will perform the differencing at level one and above.

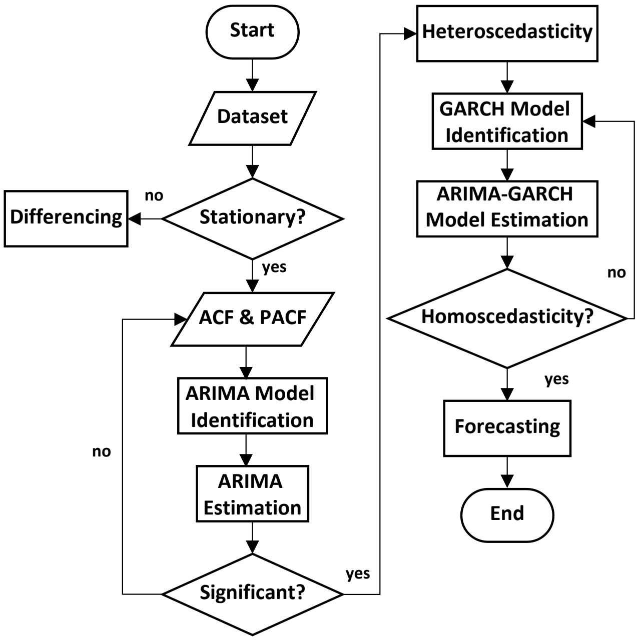

Figure 1. ARIMA-GARCH Flowchart

The second step is to look at the plot of Auto Correlation Function (ACF) and Partial Autocorrelation Function (PACF). Both plots are used to compare the fittest model to perform the time series forecasting. The third step is to perform a model estimation. Once the model parameter is obtained, it tests the significance of the coefficients. If the coefficient generated in the model is not significant, the model cannot be used for forecasting.
The fourth step is to carry out a heteroscedasticity test to determine whether the data are heteroscedastic or not. This step is important to determine the GARCH model, perform the autocorrelation test on the ARIMA model estimation results, and determine the ARIMA-GARCH model. The fifth step is to test residual assumption by using the significant ARIMA-GARCH models. The sixth step is to

select the best model. The best model should meet the parsimony principle stating that simplicity is the best. It means that the fewer the parameter has, the more precise the model is. The best model also needs to meet the predefined assumption, or at least close to it. Moreover, it is important to persist on the model that has the highest level of accuracy. In other word, it has the smallest error. The last step is to utilize the best model to predict the future.

4. RESULTS AND DISCUSSION

The data used in this study are from January 2017 to December 2019. In machine learning, the dataset is normally divided into two. The first one is training dataset, which is used in the forecasting. The second one is testing dataset, which is used as a comparison to the forecasting result. Datasets are used in three experiments with different proportions: 80% training data with 20% testing data, 75% training data with 25% testing data, and 66% of training data with 34% testing data.
To understand the data, the dataset is converted into a visualization as illustrated in Fig. 2. With the data visualization, it can be understandably examined that the birth control pill demand fluctuates within two years. It is also interesting to note that it decreases dramatically from the beginning to midterm of 2019. However, there is no further logical explanation from the agency regarding to these phenomena. Hence, it paves the way the research to scientifically explain them.

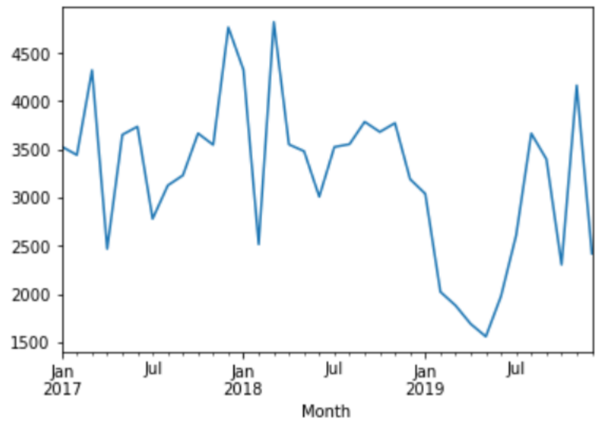

Figure 2. The Pill Demand Data Visualization

The stationary test for the demand of birth control pill is performed by validating whether the monthly demand shows a constant value or not. If the monthly average shows a constant value, the data are categorized as stationary. On the other way around, if the average value shows a non-constant value, the data are categorized as non-stationary. From the previous data visualization, it can be concluded that the birth control pill demand data are not stationer.
The characteristic of stationarity is not only concluded from data visualization within the specified period, but also from correlogram testing on ACF and PACF as shown in Fig. 3 and 4.
The ACF and PACF correlograms confirm the stationary test that the data used in the study are not stationer. This is indicated by the coefficient value on each lag of ACF and PACF which is far from zero point. In addition, the ACF and PACF coefficient values also show a fluctuating value. The coefficient value of ACF is high on lag 1. There is a decrease in lag 2, and an increase in lag 3. It remains fluctuates in the next consecutive lags. Hence, the non-stationary trend in this dataset is evident.

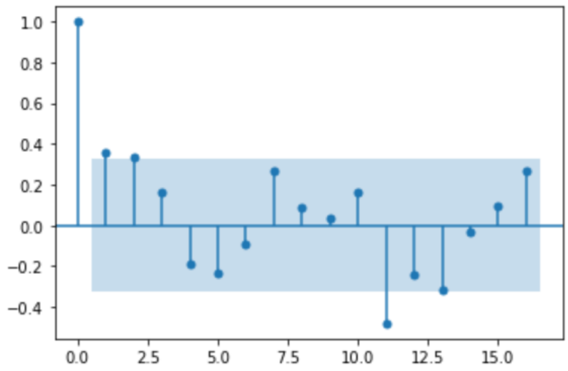

Figure 3. ACF Correlogram

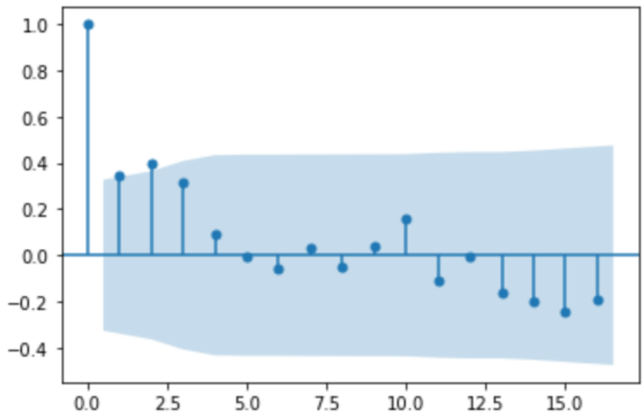

Figure 4. PACF Correlogram

The not-stationary value needs to run the differencing to be a stationer value. It is carried out by calculating a predefined difference so that the data become stationary on a particular level. Fig. 5 shows the result of the first-degree differencing.

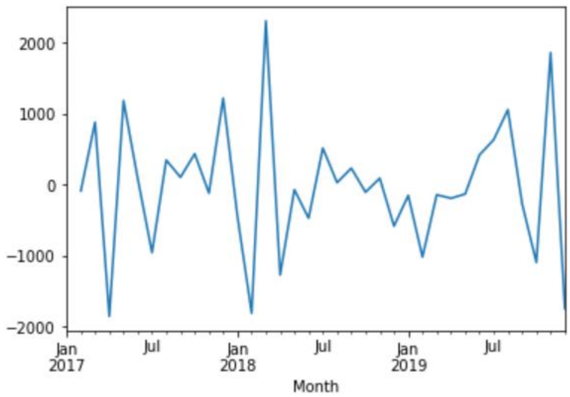

Figure 5. Differencing Result

Data differencing is not solving the problem of the exponential decrease in ACF and PACF. The exponential decline indicates that the suitable model is ARIMA (*p*, *d*, *q*). To have a more detailed ARIMA model, it requires the value of parameters *p*, and *q*. The value of parameter d is already obtained from the differencing at level 1. In other words, the data have been stationary.

The next step is to determine the value of *p* and *q* by performing the measurement on the level of accuracy of the prediction by using the value of Root Mean Square

Error (RMSE). The smaller value of RMSE represents the more accurate prediction. RMSE value is calculated by the equation as follows:

$$RMSE = \frac{\sqrt{\Sigma(X-Y)^2}}{n} \qquad (7)$$

The objective of RMSE measurement carried out in this research is to determine the model feasibility. The RMSE result of the ARIMA model is listed in Table 1. In total, there are 16 models used to predict the birth control pill demand. The 16 models consist of four models of p=1 & q=1, five models of p=2 & q=2, and seven models of p=3 & q=3. The best model is determined by the RMSE value of each model. The value with the smallest RMSE is the best model. Hence, it can be concluded that the best model is the model (1,1,0) with an RMSE value of 28.95859113.

Table 1. RMSE Result of ARIMA Model

p=1, q=1	RMSE	p=2, q=2	RMSE	p=3, q=3	RMSE
0,1,0	30.27045	2,1,0	29.99	3,1,0	30.9144
0,1,1	31.4436	2,1,1	31.56105	3,1,1	30.84477
1,1,0	28.95859	0,1,2	32.19161	3,1,2	32.07179
1,1,1	32.03904	1,1,2	33.48134	0,1,3	32.09673
		2,1,2	31.64016	1,1,3	31.55155
				2,1,3	32.33728
				3,1,3	29.46354

Once the ARIMA model is obtained, the parameter test needs to be carried out. This test is used to find out whether the parameters of the estimation result are significant or not. The parameter test is conducted in Eviews software (Agung, 2011).
The parameter test has criteria of the probability value which should be less than 5% significant level. As listed in Table 2, the significance level of the parameter test result is 0.0041. Hence, it can be concluded that ARIMA (1,1,0) model is a significant model.

Table 2. Estimation Test

Variable	Coefficient	Std.Error	t-Statistic	Prob
C	11.38108	132.986	0.085581	0.0932
AR (1)	-0.561038	0.202494	-2.77064	0.0122
SigmaQ	577292.6	176945.5	3.262545	0.0041

The heteroscedasticity test is required to determine whether the ARIMA model has a constant error or not. If the model has the variance that is not constant, the model has the problem of heteroscedasticity.
Fig. 6 shows the heteroscedasticity on ARIMA (1,1,0) using White method that results two Chi-Square values, namely 0.0014 and 0.0028. Because both values are less than 0.05, it is concluded that the data contain heteroscedasticity. Therefore, this data characteristic requires the combination of ARIMA-GARCH model.

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

F-statistic	2.62E+23	Prob. F(9,17)	0.0000
Obs*R-squared	27.00000	Prob. Chi-Square(9)	0.0014
Scaled explained SS	25.11462	Prob. Chi-Square(9)	0.0028

Figure 6. ARIMA heteroscedasticity test results

To get the significant model of GARCH, another analysis in Eviews software [11] is required. Fig. 7 presents the estimated GARCH model. The first variable is GARCH (-1), and the second variable is GARCH (-2).

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	154.6504	157.8649	0.979638	0.3273
AR(1)	-0.357420	0.115722	-3.088613	0.0020
Variance Equation				
C	166190.1	79898.44	2.080016	0.0375
RESID(-1)^2	0.538694	0.488928	1.101785	0.2706
GARCH(-1)	0.798608	0.319801	2.497205	0.0125
GARCH(-2)	-0.429248	0.173873	-2.468750	0.0136

Figure 7. The results of GARCH model

The values of probability on GARH (-2) and GARCH (-1) are 0.0136 and 0.0136. These two values form GARCH (2,1) that is significant because it is less than 0.05. At this point, it can be inferred that ARIMA (1,1,0)-GARCH (2.1) is the best model. After obtaining the ARIMA-GARCH model, it is necessary to test whether the parameters from the estimation are significant or not. This test is conducted to determine whether the ARIMA (1,1,0)-GARCH (2.1) model generates variance inconstantly or not.

Fig. 8 shows repeated heteroscedasticity test conducted in this research. The obtained Chi-Square probability value is 0.8162. Because the probability is less than 0.05, the model is considered accepted. In other words, ARIMA (1,1,0)-GACRH (2,1) is currently not heteroscedastic.

F-statistic	0.053629	Prob. F(1,280)	0.8170
Obs*R-squared	0.054001	Prob. Chi-Square(1)	0.8162

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 04/26/20 Time: 08:26
Sample (adjusted): 3 284
Included observations: 282 after adjustments

Figure 8. ARIMA-GARCH Heteroscedasticity Test Result

Once the model is not heteroscedastic, ARIMA (1,1,0)-GARCH (2.1) is experimented with three scenarios. The first scenario is conducted by forecasting the dataset comprised of 80% training data and 20% testing data as illustrated in Fig. 9, where the red line refers to the forecasting result and the blue line is the actual value. In general, the difference between the predicted and actual value is not big. Moreover, the trend of predicted and actual value is similar. After the ninth month, the predicted value visually seems to be in opposite trend compared to the actual value. However, this can be explained that the two trends are considered the same if there is one month shift between the two series.

The second scenario is conducted by forecasting the dataset that comprises of 75% train data and 25% testing data as illustrated in Fig. 10. The result has similar trend compared to the first scenario. Only the first months demonstrates a slightly different trend. Again, it is interesting to note that after the ninth month, the predicted value visually seems to be in opposite trend compared to the actual value.

The third scenario is conducted by forecasting the dataset comprised of 66% training data and 44% testing data as illustrated in Fig. 11. The result is also similar to the first two scenarios. However, the forecasted value remains higher than the actual value in a longer period compared to the first two scenarios until more than five months. In general, it can be concluded that the three scenarios show no big difference between the predicted and actual values. Similar to the first two experiments, it is interesting to note that after the ninth month, the predicted value visually seems to be in opposite trend compared to the actual value.

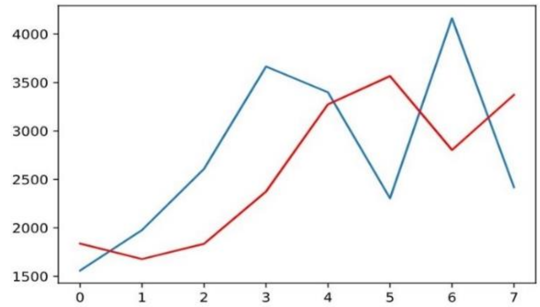

Figure 9. The First Forecasting Experiment

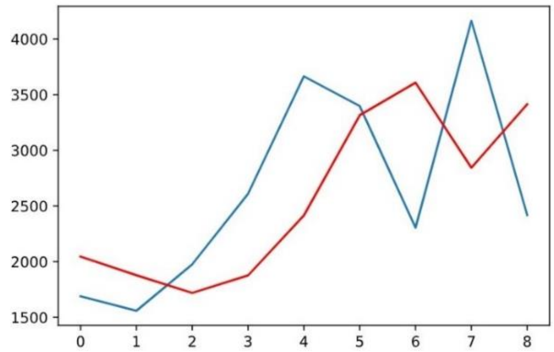

Figure 10. The second forecasting experiment

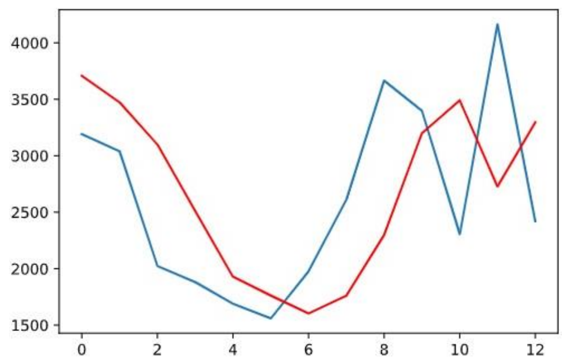

Figure 11. The third forecasting experiment

5. CONCLUSION

This paper proposes to combine ARIMA and GARCH modelling technique to predict the demand of birth control pills with a case study at National Population and Family Planning Agency in Ogan Komering Ilir district. The result shows that best model is ARIMA (1,1,0)-GARCH (2.1) which plots the forecasted data similar to the pattern of actual data. Three different scenarios are provided to support the claim. Moreover, the model is validated through various tests, such as heteroscedasticity and RMSE tests. In the future, it is suggested to combine ARIMA with other methods without any dependency on data heteroscedasticity, such as maximum likelihood. Moreover, it is interesting to predict the birth control pill demand data with correlation analysis for marriage season and demography datasets.

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