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Forecasting of Tourist Arrivals Using Subset, Multiplicative or Additive Seasonal ARIMA Model

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Abstract Most of Seasonal Autoregressive Integrated Moving Average (SARIMA) models that used for forecasting seasonal time series are multiplicative SARIMA models. These models assume that there is a significant parameter as a result of multiplication between non-seasonal and seasonal parameters without testing by certain statistical test. Moreover, most popular statistical software such as MINITAB and SPSS only has facility to fit multiplicative models. The aim of this research is to propose a new procedure for indentifying the most appropriate order of SARIMA model whether it involves subset, multiplicative or additive order. In particular, the study examined whether a multiplicative parameter existed in the SARIMA model. Data about the number of tourist arrivals to Bali, Indonesia, were used as a case study. The model identification step to determine the order of ARIMA model was done by using MINITAB program, and the model estimation step used SAS program to test whether the model consisted of subset, multiplicative or additive order. Modeling of the data yielded an additive SARIMA model is the best model for forecasting the number of tourist arrivals to Bali. The comparison evaluation showed that additive SARIMA model yielded more accurate forecasted values at out-sample datasets than multiplicative SARIMA model. This study is valuable contribution to the Box-Jenkins procedure particularly at the model identification and estimation steps in SARIMA models. Further work involving multiple seasonal ARIMA models, such as short term load data forecasting in certain countries, may provide further insights regarding the subset, multiplicative or additive orders.

Keywords SARIMA; subset; multiplicative; additive; tourist arrivals

2010 Mathematics Subject Classification 62M10; 62P20.

1 Introduction

ARIMA is the method first introduced by Box-Jenkins [1] and until now become the most popular models for forecasting univariate time series data. This model has been originated from the autoregressive model (AR), the moving average model (MA) and the combination of the AR and MA, the ARMA models. In the case where seasonal components are included in this model, then the model is called as the SARIMA model. Box-Jenkins procedure that contains three main stages to build an ARIMA model, that is model identification, model estimation and model checking, is usually used for determining the best ARIMA model for certain time series data.

The generalized form of SARIMA model can be written as (see Wei [2], Box et al. [3], Cryer and Chan [4],)

$$\varphi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D\,Z_t = \theta_q(B)\Theta_Q(B^S)\,a_t \tag{1}$$

where

$$
\begin{aligned}
\phi_p(B) &= 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \\
\Phi_p(B^S) &= 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \\
\theta_q(B) &= 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \\
\Theta_Q(B^S) &= 1 - \Theta_1 B - \Theta_2 B^{2S} - \cdots - \Theta_Q B^{QS}
\end{aligned}
$$

where B denotes the backward shift operator; d and D denote the non-seasonal, and seasonal order of differences, respectively; and usually abbreviated as SARIMA $(p, d, q)(P, D, Q)^S$. When there is no seasonal effect, a SARIMA model reduces to pure ARIMA (p, d, q), and when the time series dataset is stationary a pure ARIMA reduces to ARMA(p, q).

To date, SARIMA models have been used in various fields of forecasting. For example, Tankersley et al. [5] applied this model to forecast groundwater fluctuations; Postma et al. [6] for projecting utilization of hospital in-patient days; Scortti et al. [7] for forecasting canine rabies in Argentina, Bolivia and Paraguay; Tseng et al. [8] for forecasting the production value of the mechanical industry in Taiwan; Papamichail and Georgiou [9] for reservoir sizing; Hu et al. [10] for prediction of Ross River virus disease in Brisbane; Mishra and Desai [11], Modarres [12], also Abebe and Foerch [13] for drought forecasting; Ediger et al. [14], also Ediger and Akar [15] for forecasting production of fossil fuel sources in Turkey; Briet et al. [16] for short term malaria prediction in Sri Lanka; Chen et al. [17] for forecasting inbound air travel arrivals to Taiwan; Abraham et al. [18] for short-term forecasting of emergency inpatient flow; Schulze and Prinz [19] for forecasting container transshipment in Germany. More recently, Pozza et al. [20] applied SARIMA to analysis of PM2.5 and PM10-2.5 mass concentration in the city of Sao Carlos, Brazil, and Durdu [21] used for forecasting of boron in Western Turkey.

Although many previous papers have concentrated on model estimation, model identification is actually the most crucial stage in building ARIMA models, because false model identification will cause the wrong stage of model estimation and increase the cost of re-identification. In particular of SARIMA models, most of previous papers usually used directly the multiplicative model without testing whether the multiplicative parameter was significant. It means that the multiplicative SARIMA models assume that there is a significant parameter as a result of multiplicative between non-seasonal and seasonal parameters. Moreover, most popular statistical software such as MINITAB and SPSS only has facility to fit a multiplicative model. The purpose of this research is to propose a new procedure for indentifying and then testing the most appropriate order of SARIMA model whether it involves subset, multiplicative or additive order. In particular, the study will examine whether a multiplicative parameter existed in the SARIMA models. Additionally, the present study updates the Box-Jenkins procedure particularly for seasonal model.

The paper is organized as follows: a brief theoretical review about the autocorrelation (ACF) and partial autocorrelation (PACF) functions of subset, multiplicative, and additive SARIMA models, data description and the modeling method, results based on the model, evaluations of the forecast accuracy, and conclusion.

2 SARIMA Model

Three forms of SARIMA models were selected to validate whether a multiplicative parameter was significant. The theoretical explanation about ACF and PACF for these three models was focused on non-seasonal and seasonal moving average orders, i.e.

$$\mathrm{ARIMA}(0,0,[1,12,13]), \mathrm{ARIMA}(0,0,1)(0,0,1)^{12}, \text{ and } \mathrm{ARIMA}(0,0,[1,12]),$$

for subset, multiplicative, and additive model, respectively.

2.1 Subset SARIMA Model

The generalized form of ARIMA (0,0,[1,12,13]) model, then known as subset SARIMA, can be written as

$$Z_t - \mu = a_t - \theta_1 a_{t-1} - \theta_{12} a_{t-12} - \theta_{13} a_{t-13} \tag{2}$$

where θ_1, θ_{12} and θ_{13} denotes the parameters of MA orders. By using mathematical statistics, it could be shown that the ACF of this model is as follows:

$$\rho_k = \begin{cases} \dfrac{-\theta_1 + \theta_{12}\theta_{13}}{(1+\theta_1^2+\theta_{12}^2+\theta_{13}^2)} & , k=1 \\[2ex] \dfrac{\theta_1\theta_{12}}{(1+\theta_1^2+\theta_{12}^2+\theta_{13}^2)} & , k=11 \\[2ex] \dfrac{-\theta_{12} + \theta_1\theta_{13}}{(1+\theta_1^2+\theta_{12}^2+\theta_{13}^2)} & , k=12 \\[2ex] \dfrac{-\theta_{13}}{(1+\theta_1^2+\theta_{12}^2+\theta_{13}^2)} & , k=13 \\[2ex] 0 & , \text{others}. \end{cases} \tag{3}$$

2.2 Multiplicative SARIMA Model

The generalized form of ARIMA(0,0,1)(0,0,1)^{12} model, known as multiplicative SARIMA, can be written as

$$Z_t - \mu = a_t - \theta_1 a_{t-1} - \theta_{12} a_{t-12} + \theta_1\theta_{12} a_{t-13} \tag{4}$$

where θ_1 and θ_{12} denotes the parameters of non-seasonal and seasonal MA order, respectively. This model is the same with subset SARIMA model in Eq. (2) when $\theta_{13} = -\theta_1\theta_{12}$. Thus, it could be concluded that multiplicative model is part of subset model. Hence, it could be shown that the ACF of this model is as follows:

$$\rho_k = \begin{cases} \dfrac{-\theta_1}{(1+\theta_1^2)} & , k=1 \\[2ex] \dfrac{\theta_1\theta_{12}}{(1+\theta_1^2)(1+\theta_{12}^2)} & , k=11,13 \\[2ex] \dfrac{-\theta_{12}}{(1+\theta_{12}^2)} & , k=12 \\[2ex] 0 & , \text{others}\,. \end{cases} \tag{5}$$

Eq. (5) shows that the ACF values at lag 11 and 13 are equal.

2.3 Additive SARIMA Model

The generalized form of ARIMA (0,0,[1,12]) model, then known as additive SARIMA, can be written as

$$Z_t - \mu = a_t - \theta_1 a_{t-1} - \theta_{12} a_{t-12} \tag{6}$$

where θ_1 and θ_{12} denotes the parameters of non-seasonal and seasonal MA order, respectively. This model is the same with subset SARIMA model in Eq. (2) when $\theta_{13} = 0$. Thus, it could be concluded that additive model is also part of subset model. Moreover, this additive model in Eq. (6) could also be seen as subset ARIMA model with lower order than model in Eq. (2). It could be shown that the ACF of this model is as follows:

$$\rho_k = \begin{cases} \dfrac{-\theta_1}{(1+\theta_1^2+\theta_{12}^2)} & , k=1 \\[2ex] \dfrac{\theta_1\theta_{12}}{(1+\theta_1^2+\theta_{12}^2)} & , k=11 \\[2ex] \dfrac{-\theta_{12}}{(1+\theta_1^2+\theta_{12}^2)} & , k=12 \\[2ex] 0 & , \text{others}\,. \end{cases} \tag{7}$$

Eq. (7) shows that the main difference between additive and other models (subset or multiplicative) is the ACF value at lag 13 are equal zero.

2.4 R Program to Simulate the Theoretical ACF and PACF

To illustrate the difference between the theoretical ACF and PACF of subset, multiplicative and additive models, we use facility in R program. The following code is the program in R for generating the theoretical ACF and PACF of these three kinds of models.

```
# model1 for subset SARIMA
# model2 for multiplicative SARIMA: use theta2
# model3 for additive SARIMA: use theta3
```

```
theta1 = c(-0.6,rep(0,10),-0.9,0.3)
theta2 = c(-0.6,rep(0,10),-0.9,0.54)
theta3 = c(-0.6,rep(0,10),-0.9)

acf.model1 = ARMAacf(ar=0, ma=theta1, 50)
pacf.model1 = ARMAacf(ar=0, ma=theta1, 50, pacf=T)
acf.model1 = acf.model1[2:51]

win.graph()
par(mfrow=c(1,2))
plot(acf.model1, type="h", xlab="lag", ylim=c(-1,1))
abline(h=0)
plot(pacf.model1, type="h", xlab="lag", ylim=c(-1,1))
abline(h=0)
```

This program uses the same parameter of non-seasonal and seasonal orders, i.e. $\theta_1 = 0.6$ and $\theta_{12} = 0.9$. The difference only occurs for the last parameter, i.e. $\theta_{13} = -0.3$ for subset SARIMA, $\theta_{13} = -\theta_1.\theta_{12} = -0.54$ for multiplicative SARIMA, and $\theta_{13} = 0$ for additive SARIMA. The results of the theoretical ACF and PACF for these three models are shown at Figure 1 to Figure 3.

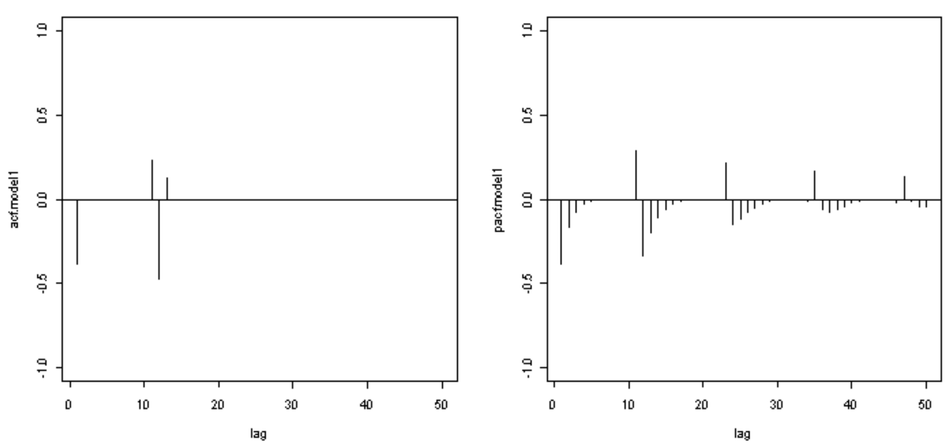

Figure 1: Theoretical ACF and PACF of Subset SARIMA

3 Data

In this paper, a monthly datasets about the number of tourist arrivals to Bali, Indonesia, from 1989 to 1997, was used as a case study. These data were obtained from the Indonesia Central Bureau of Statistics (see www.bps.go.id). Bali is the main destination of the international tourists who visit Indonesia, and these data also have seasonal pattern. Ismail et al. [22] analyzed these tourism data using intervention analysis. The last 12 observations are reserved as the test for forecasting evaluation and comparison (out-sample dataset or testing data).

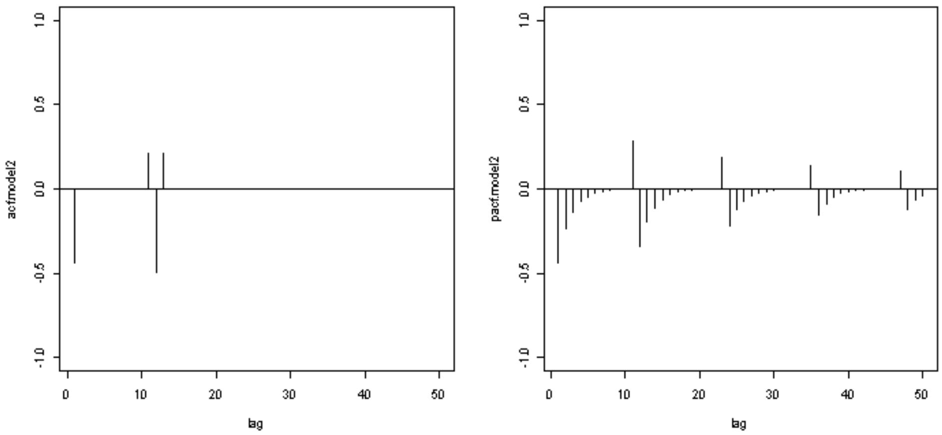

Figure 2: Theoretical ACF and PACF of Multiplicative SARIMA

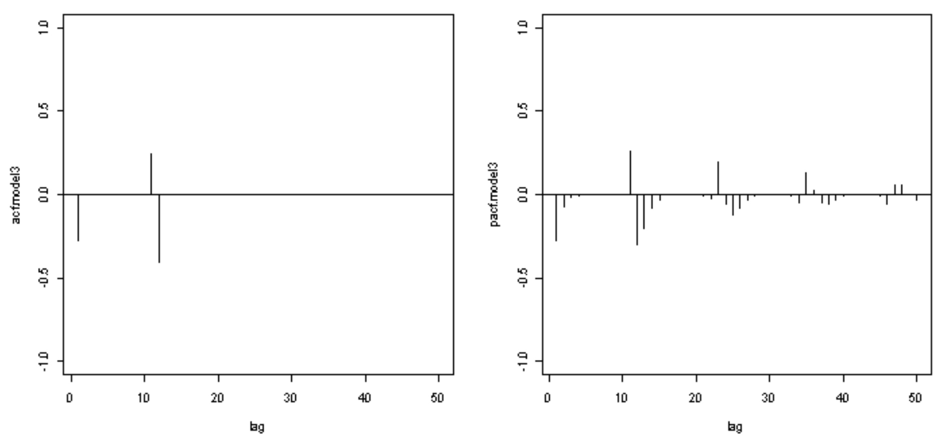

Figure 3: Theoretical ACF and PACF of Additive SARIMA

4 The Proposed Procedures of Modeling

As we know, there are three main stages in building an ARIMA model based on Box-Jenkins procedure, i.e. (1) model identification, (2) model estimation and (3) model checking. These stages of building an ARIMA model are described in Figure 4.

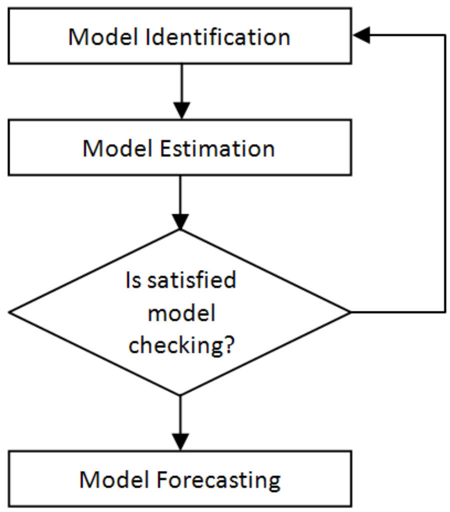

Figure 4: The Stages of Building ARIMA Models

Most of previous researches usually used directly a multiplicative SARIMA model when the ACF and PACF indicated that the data contained both non-seasonal and seasonal orders. In this research, we proposed a more precise model identification step particularly at the lags as implication of multiplicative orders. As an example, for monthly data that indicated consisting MA orders both in non-seasonal (ACF at lag 1) and seasonal (ACF at lag 12), we must check first whether ACF at lag 13 is equal to zero (indicate additive model) or not (indicate multiplicative if tend to equal with ACF at lag 11, or subset model if difference from ACF at lag 11), as illustrated previously at Figure1-3.

Then, we validate the significance of multiplicative parameter at the model estimation step. In this step, we suggest to use SAS program that contains facility to fit subset, multiplicative and additive SARIMA models. In particular, the new stages that we propose in model estimation steps are as follows:

1. Fit the subset SARIMA model first and test whether the multiplicative parameter is significant.

2. a. If the multiplicative parameter is significant, then continue to test whether this coefficient is the same with the multiplication between non-seasonal and seasonal coefficients. If YES, it means that the appropriate model is multiplicative SARIMA. If NOT, it means that the subset SARIMA is the appropriate model for the time series data.

b. If the multiplicative parameter is insignificant, it means that the appropriate model is additive SARIMA.

5 Results

The following are the results at the three main stages in building an ARIMA model based on Box-Jenkins procedure, i.e. (1) model identification, (2) model estimation and (3) model checking.

5.1 Model Identification

The time series plot of the dataset is shown in Figure 5. The plot shows that the data have seasonal and trend patterns with increasingly variation of variance. It means that the data not yet satisfy the stationary condition, both in mean and variance. MINITAB program is used in this identification step.

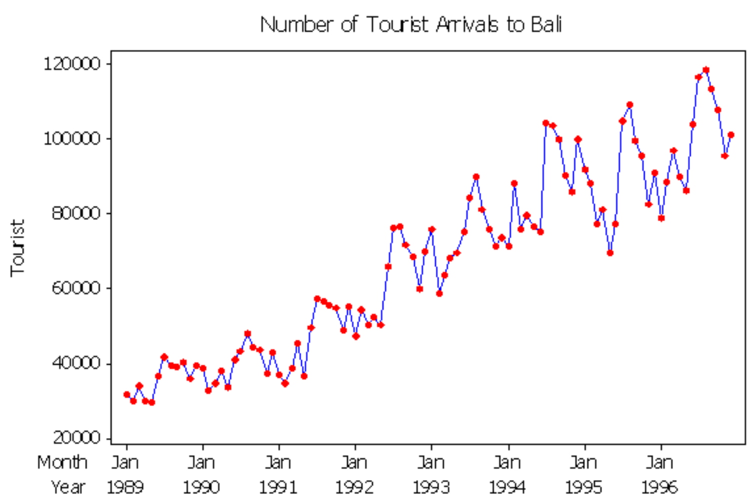

Figure 5: Monthly Data About the Number of Tourist Arrivals to Bali, Indonesia

By using logarithm transformation and difference both non-seasonal (d=1) and seasonal (D=1, S=12), then the data become stationary series, and the ACF and PACF are shown in Figure 6-7. Based on the graphs at Fig. 6, it could be seen that even though the estimated values are not significant, the ACF at lag 11 and 13 tend to have difference values, i.e. ACF at lag 13 looks larger than at lag 11. It indicates that no strong evidence to identify multiplicative model. Furthermore, the graphs at Figure 7 show that the estimated value of ACF at lag 11 is significant, whereas at lag 13 is not significant. Again, it indicates that no strong evidence to identify multiplicative model as illustrated on the theoretical ACF and PACF at the previous section.

In general, ACF and PACF for these two series suggest that both of non-seasonal and seasonal MA orders exist in the tentative SARIMA model. Then, the important question is whether the models are subset, multiplicative or additive ones.

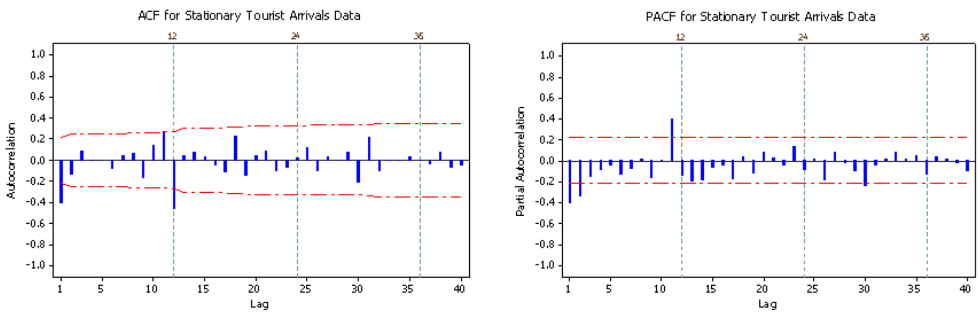

Figure 6: ACF and PACF for Stationary Tourist Arrivals Data

5.2 Model Estimation

Based on the proposed stages at model estimation step, the subset ARIMA is fitted first to know whether the parameter of multiplicative effect is significant. SAS is used in this step, and the following code is an example of the program for estimating subset, multiplicative and additive SARIMA models.

```
proc arima data=tourist;
   identify var=zt(1,12) nlag=24;
   run;

   /*** for subset SARIMA model ***/
   estimate q=(1,12,13) noconstant method=ml;
   run;

   /*** for multiplicative SARIMA model ***/
   estimate q=(1)(12) noconstant method=ml;
   run;

   /*** for additive SARIMA model ***/
   estimate q=(1,12) noconstant method=ml;
   run;
```

The results of subset ARIMA are shown at Table 1.

The estimation output at Table 2 shows that the estimated parameter θ_{13} is insignificant or statistically not difference with zero. It means that there is no evidence to use multiplicative SARIMA model for this case. So, the model estimation continues to fit the additive model and the results are shown at Table 2.

Table 3: Summary output for multiplicative SARIMA models at the tourist arrivals data

Maximum Likelihood Estimation

Table 1: Summary Output for Subset SARIMA Models at the Tourist Arrivals Data

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr >|t|	Lag
MA1,1	0.50689	0.13644	3.72	0.0002	1
MA1,2	0.53150	0.14967	3.55	0.0004	12
MA1,3	−0.03838	0.12347	−0.31	0.7559	13

Variance Estimate	0.007997
Std Error Estimate	0.089425
AIC	−155.542
SBC	−148.285
Number of Residuals	83

Table 2: Summary Output for Additive SARIMA Models at the Tourist Arrivals Data

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr >|t|	Lag
MA1,1	0.42838	0.13194	3.25	0.0012	1
MA1,2	0.57162	0.14258	4.01	<.0001	12

Variance Estimate	0.007997
Std Error Estimate	0.089968
AIC	−154.616
SBC	−149.779
Number of Residuals	83

Table 3: Summary Output for Multiplicative SARIMA Models at the Tourist Arrivals Data

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr >|t|	Lag
MA1,1	0.66100	0.07733	8.55	<.0001	1
MA2,1	0.89211	0.25828	3.45	0.0006	12

Variance Estimate	0.006033
Std Error Estimate	0.077672
AIC	−169.157
SBC	−164.319
Number of Residuals	83

5.3 Model Checking and Forecasting

By using Ljung-Box test, all models at Table 1-2 satisfy assumption that the residuals are white noise. Then, the process continues to calculate the forecasting values based on the subset or additive and multiplicative models for performance comparison and evaluation. Moreover, the evaluation focuses on the comparison between additive and multiplicative model. The output of multiplicative SARIMA model for tourist arrivals data is shown at Table 3. From Table 1-3, three estimated SARIMA model could be written as:

(a) Subset SARIMA model

$$Z_t^* = a_t - 0.50689a_{t-1} - 0.53150a_{t-12} + 0.03838a_{t-13} \tag{8}$$

(b) Additive SARIMA model

$$Z_t^* = a_t - 0.42838a_{t-1} - 0.57162a_{t-12} \tag{9}$$

(c) Multiplicative SARIMA model

$$Z_t^* = a_t - 0.66100a_{t-1} - 0.892110a_{t-12} + (0.66100 \times 0.89211)a_{t-13} \tag{10}$$

where $Z_t^* = \ln(Z_t) - \ln(Z_{t-1}) - \ln(Z_{t-12}) + \ln(Z_{t+13})$ and Z_t is the actual data, i.e. the monthly number of tourist arrivals to Bali.

The summary of the comparison results between additive and multiplicative model for are shown at Table 4.

6 Discussion

The model identification step for SARIMA models showed that there were different of ACF and PACF between subset, multiplicative and additive models, particularly at lag order as

Table 4: The Results of Performance Comparison Between Models at In-sample and Out-sample Datasets

SARIMA Model	In-sample		MSE
	MSE	AIC	at out-sample
Multiplicative	0.006033	−169.157	0.011225
Additive	0.008094	−154.616	0.008422

a multiplication between non-seasonal and seasonal orders. Theoretical results illustrated that evaluation ACF and PACF in this lag of multiplication order is the most important stage of model identification step for seasonal model.

The results of performance evaluation show that multiplicative model yields better forecast at in-sample dataset, or less MSE and AIC, than additive SARIMA model even though the estimated parameter of multiplicative effect was not significant. However, the evaluation at out-sample dataset shows that additive model produces more accurate forecasted values than multiplicative SARIMA model. Thus, this empirical evidence shows that more careful identification is needed to determine the order of SARIMA model and not directly choose multiplicative model.

7 Conclusion

This paper has discussed about three kinds of seasonal ARIMA models, namely subset, multiplicative and additive SARIMA models, including the theoretical of ACF and PACF, how to simulate these values by using R program, and how to test by using SAS program at model estimation of Box-Jenkins procedure. Most of the previous researches just used directly a multiplicative SARIMA model without identifying intensely ACF or PACF at lag as multiplication order and testing whether the multiplicative parameter was significant.

In general, these empirical results show that the determination of orders in SARIMA model must consider about subset, multiplicative or additive orders. Moreover, the understanding pattern of theoretical ACF and PACF for these three kinds of model orders are very important to determine an appropriate tentative model for certain seasonal time series data. In addition, the results also illustrated that the multiplicative SARIMA model yielded less accurate forecasted values than additive model for forecasting tourist arrivals data.

Hence, the proposed stages in model estimation step to test the significance of the multiplicative parameter should be used concurrently with model identification of ACF and PACF for seasonal time series data. It means that we must revise the Box-Jenkins procedure for seasonal ARIMA model, i.e. to not directly use multiplicative SARIMA model particularly at model identification and estimation steps. It also suggests the forecasters to use the statistical program that has facility for testing the multiplicative parameter model, such as SAS program. Moreover, further research involving multiple seasonal ARIMA models, such as short term load data forecasting in certain countries that recently become one of the central topics in forecasting, may provide further insights regarding the subset, multiplicative or additive orders.

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