Comparing the Performance of Seasonal ARIMAX Model and Nonparametric Regression Model in Predicting Claim Reserve of Education Insurance

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Abstract. One of the biggest problems in the continuity of one's education is the education fee which is often unaffordable. Therefore, the existence of education insurance is a solution to this problem. Along with increasing public interest in education insurance, insurance companies need to adjust the claim reserves with the number of claims paid to maintain the company’s capital. Claim reserves are funds that must be provided by insurance companies to fulfill obligations to policy holders in the future. Losses and inaccuracies in the payment of insurance claims will result in the policy holder and the insurance company itself. Therefore, it is necessary to do a prediction of insurance company's monthly reserve claims. In education insurance, the claim reserve data has seasonal characteristics and the number of educational insurance claims tends to increase at the turn of the school year. These fluctuating patterns are supposed to fit the application of the SARIMA model and the nonparametric regression model with the Fourier series estimator in forecasting. Fourier series is a function that has flexibility in approaching fluctuating, seasonal, and recurring data patterns. The results showed that the prediction accuracy of the SARIMAX model was higher than the nonparametric regression model with MAPE of 15% and 4% respectively.

1. Introduction

Education is one of the components forming the human development index (HDI). The higher the level of education per capita in a country, the higher the HDI of that country. A high level of education is believed to be able to help a person achieve his goals and improve his standard of living. However, the cost of education for children is increasingly high because of inflation. This is one of the serious problems in the continuity of most people's education. Therefore, for the sake of planned education, the existence of education insurance is a solution to these problems.

Education insurance in Indonesia is included in the life insurance category. Education insurance is defined as life insurance whose services focus on education. This type of insurance provides a return value in cash as a consequence of premium payments at the time agreed upon by the insured and the insurer [1]. The development of insurance in Indonesia is very rapid. This can be seen from the number of companies that provide education insurance services. Of the total 50 life insurance companies in Indonesia, 17 companies serve education insurance and 3 of them are under the auspices of State-Owned Enterprises (BUMN).

Along with increasing public interest in education insurance, insurance companies need to adjust the reserve claims associated to the number of claims paid. This is very important to maintain the continuity of the insurance company. Claim reserves are funds that must be provided by insurance companies to fulfill obligations to policy holders in the future. These claim reserves consist of reported but not settled reserves and claims that have already occurred but have not been reported (incurred but not reported claims) [2].
Losses and inaccuracies in the payment of insurance claims will result in the policy holder and the insurance company itself. Therefore, it is necessary to do a prediction or forecasting large reserves of monthly insurance company claims. Previous research on estimating claims reserves deterministically was done by Reference [3] with the Chain Ladder method. Then research on calculating stochastic claims is carried out by Reference [4] for the Bayesian Generalized Linear Model, Reference [5] for the Lognormal Mixed Model method, and Reference [6] for the Hierarchical Generalized Linear Model (HGLM). These studies are based on the Triangle Run-off scheme which takes into account aspects such as the number of claims that occur. In this study, claim reserve data is considered as a single data that has autocorrelation without considering its forming factors. Therefore, the focus in this study is to produce accurate prediction models based on historical data.

In education insurance, data on the amount of claim reserves has seasonal characteristics. In other words, claim reserves will be high in certain periods and tend to be low in a certain period (periodic). If examined further, the number of educational insurance claims tends to increase at the turn of the school year. In addition, there is a tendency for the pattern to decrease and increase significantly when the new school year starts. Based on the fluctuating pattern, two approaches will be used in this study. This approach is a parametric model in the form of Seasonal Autoregressive Integrated Moving Average (SARIMA) and non-parametric models with Fourier series estimators for time series data. At the end, the performance of these two models in predicting claim reserve will be compared.

This paper is organized as follows. The first section presents the background of study. Then, the following section provides some literature reviews including the seasonal ARIMAX and nonparametric models. The material and method of the models are presented in the third section. The fourth section is the section in which the results is elaborated with some discussions. Finally, the fifth section concludes this study.

2. Literature Review

2.1 The Definition of Claim and Claim Reserve

Claims are collateral for the risk or damage that held by the insurance company to insurance customer in accordance with the policy agreement [7]. Incurred claims consist of reported claims and unreported claims. Claim reserves are funds that must be provided by insurance companies to cover obligations to policyholders in the future. As with claims, claim reserves consist of claims reserves in the settlement process (reported claims) and reserve claims that have occurred but have not been reported (unreported claims) [8].

2.2 Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is a combination of Autoregressive (AR) and Moving Average (MA) models and differencing processes \((d)\) order for non-seasonal data and \(D\) order for seasonal data) to time series data [9][10]. Based on seasonality, ARIMA model can be divided into seasonal and non-seasonal ARIMA. There will be an additional term for seasonal ARIMA model, which is the order for seasonality.

In general, non-seasonal ARIMA model can be written as ARIMA \((p,d,q)\) mathematically as follow [9],

\[
\phi_p(B)(1-B)^dY_t = \theta_q(B)a_t,
\]

where,

\((p,d,q)\) = AR order \((p)\), differencing order \((d)\), and MA order \((q)\)

\(\phi_p(B)\) = the coefficients of non-seasonal AR model with order \(p\)

\(\phi_p(B) = (1-\phi_1B-\phi_2B^2-...-\phi_pB^p)\)

\(\theta_q(B)\) = the coefficients of non-seasonal AR model with order \(q\)

\(\theta_q(B) = (1-\theta_1B-\theta_2B^2-...-\theta_qB^q)\)

\(a_t\) = residual at \(t\).
If \( d = 0 \), then \( \theta_0 \) is a mean of the process whereas \( d \geq 1 \) means that \( \theta_0 \) is the coefficient of deterministic trend.

For multiplicative Seasonal ARIMA Model, it can be written as ARIMA \((P,D,Q)\). The Box-Jenkins multiplicative model for seasonal ARIMA is presented below \([9]\),

\[
\Phi_s(B^S)\phi_s(B)(1-B)^d(1-B^S)^d Y_t = \theta_s(B)\theta_s(B^S)a_t \tag{2}
\]

where,

\[
\begin{align*}
(p,d,q) &= \text{AR order (p), differencing order (d), dan MA order (q)} \\
(P,D,Q) &= \text{AR order (P), differencing order (D), dan MA order (Q), seasonal order (S) for seasonal data} \\
\phi_s(B) &= \text{coefficient of non-seasonal AR with order } p, \text{ where } \phi_s(B) = (1 - \phi_s B - \phi_s B^2 - \ldots - \phi_s B^s) \\
\theta_s(B) &= \text{coefficient of non-seasonal MA with order } q, \text{ where } \theta_s(B) = (1 - \theta_s B - \theta_s B^2 - \ldots - \theta_s B^q) \\
\Phi_s(B^S) &= \text{coefficient of seasonal AR (S) with order } P, \text{ where } \Phi_s(B^S) = (1 - \Phi_s B^S - \Phi_s B^{2S} - \ldots - \Phi_s B^{PS}) \\
\theta_s(B^S) &= \text{coefficient of seasonal MA (S) with order } Q, \text{ where } \theta_s(B^S) = (1 - \theta_s B^S - \theta_s B^{2S} - \ldots - \theta_s B^{QS}) \\
a_t &= \text{residual at } t.
\end{align*}
\]

2.3 Autoregressive Integrated Moving Average with Exogenous Variable (ARIMAX)

ARIMAX is an ARIMA model with the addition of particular variables \([11]\). In this study, the variable of interest is the dummy variables for Indonesia presidential election in 2018. The model in the seasonal ARIMA equation can be rewritten as follows \([12]\),

\[
Y_t = \frac{\theta_s(B)\theta_s(B^S)a_t}{\Phi_s(B^S)\phi_s(B)(1-B)^d(1-B^S)^d} \tag{3}
\]

The first model is known as ARIMAX model with stochastic trend. In this model, there will be non-seasonal or seasonal differencing order. The model is written below,

\[
Y_t = \beta S_{t,j} + \ldots + \beta S_{p,j} + \delta V_t + \ldots + \delta V_{r,j} + \frac{\theta_s(B)\theta_s(B^S)}{\Phi_s(B^S)\phi_s(B)(1-B^S)^d(1-B^S)^d}a_t \tag{4}
\]

Another model is ARIMAX model with deterministic trend in which it does not involve differencing order. It can be presented as

\[
Y_t = \gamma t + \beta S_{t,j} + \ldots + \beta S_{p,j} + \delta V_t + \ldots + \delta V_{r,j} + \frac{\theta_s(B)\theta_s(B^S)}{\Phi_s(B^S)\phi_s(B^S)}a_t \tag{5}
\]

where \( S_{t,j} - S_{p,j} \) is the seasonal effects, \( V_t - V_{r,j} \) is the dummy variable for calendar variation, and \( \gamma \) is the coefficient for trend.

2.4 Nonparametric Regression with Fourier Series Estimator

Nonparametric regression approach is used to determine data patterns that cannot be estimated by parametric curve models. This is because this model will produce large errors and variances. Fluctuating patterns of educational insurance claims are felt to be in accordance with Fourier series applications in forecasting. Fourier series is a function that must be resolved in the form of fluctuating data, taken, and repeated \([13]\). The process of repeating data patterns occurs at the value of the dependent variable for different independent variables \([14]\).

Given paired data, parametric regression for observations that correspond to the paired data are:

\[
y_t = g(t_i) + \epsilon_i; \quad \epsilon_i \sim IIDN(0, \sigma^2) \tag{6}
\]
where \( y_i \) is a response variable, \( t_i \) is a predictor variable for nonparametric regression. The function \( g(t_i) \) is unknown and estimated by functions in nonparametric regression and \( \varepsilon_i \) is a random error which is assumed to be identical, independent, and normally distributed with mean 0 and variance \( \sigma^2 \) [15].

The advantage of nonparametric regression is that it has high flexibility. The flexibility in question is that the pattern of data scattered in scatter plots can determine the shape of the regression curve based on estimators in nonparametric regression. One of the estimators used in nonparametric regression is Fourier series [16][17].

This study provides an alternative approach to predict claim reserve data in monthly time series which has a combination of trend and seasonal patterns using nonparametric regression with Fourier series estimators. The approach is appropriate because in nonparametric regression, Fourier series is added with linear functions. It can mathematically accommodate trend and seasonal data patterns in accordance with education insurance claims reserve data.

3. Material and Method

3.1. Data Sources and Research Variables

This study is a quantitative research that focuses on data analysis. The data used is time series data for 12 years (144 months) starting from January 2006 to December 2017. The data are secondary data from one of the state-owned education insurance that has a main branch office in Surabaya. The dependent variable in this study is the amount of claim reserves in billion rupiah, while the independent variable used is the monthly period.

In this study, data is divided into training data and testing data. Training data is used in the estimation process of the model while testing data is used to determine the accuracy of the prediction of the amount of claim reserves. Data from January 2006 to December 2015 is considered as training data and data from January 2016 to December 2017 as testing data.

3.2. Steps of Analysis

The steps of analysis in this study are as follows. Firstly, the descriptive statistics analysis is conducted in order to see the characteristic of the returns. This step is followed by the univariate and multivariate modelling using ARIMAX and VARX. ARIMAX modelling involves the following steps: (1) Identifying data patterns through the results of a time series plot, (2) Determining the type of trend, namely deterministic trend, (3) Eliminating the effects of calendar variations of response with deterministic trend fitting equation so that we will get an error, (4) ARIMA modelling of the error if the error does not meet the assumption of white noise that involves identifying the model order by looking at ACF and PACF plots to obtain a significant lag, parameter estimation of ARIMA model with Conditional Least Square estimation, examining the assumption of residuals. If not met, then go back to identification step. If the assumptions are met then we merge ARIMA model with the model equations in step (3). Then, we calculate the goodness criteria of the model obtained by using RMSE. Final model will be used to forecast the data.

After that, we construct nonparametric regression modelling based on Fourier series estimators based on References [15] and [16]. The different thing with these previous studies in this study is that the data used is time series data. The model formation starts by determining the value of Generalized Cross Validation (GCV) based on the input value of the oscillation parameter \( (k) \) based on training data with the following formula:

\[
GCV(K) = \frac{n^{-1}y^T(1-A(k))^T(1-A(k))y}{(n^{-1}trace(1-A(k)))^2} \tag{7}
\]
Then, the optimal oscillation parameter value is determined based on minimum GCV with considering the concept of model simplicity. After that, determining the values of regression parameter estimators in vector form as follows

$$\hat{\beta} = (T[K]^T T[K])^{-1} T[K]^T y$$

(8)

After having the estimator in Equation (4), the equation that contains the Fourier series estimator for nonparametric regression in the following forms:

$$\hat{y}_t = \frac{\hat{a}_0}{2} + \hat{a}_t + \sum_{k=1}^{K} \hat{a}_k \cos k t_t$$

(9)

Then, we determine the goodness of fits such as Mean Square Error (MSE) and coefficient of determination ($R^2$). Finally, the prediction of claim reserve is obtained.

To compare the prediction accuracy of the two model, Mean Absolute Percentage Error (MAPE) is used. It is defined as

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

(10)

where $y_i$ is the actual value, $\hat{y}_i$ is the predicted value, and $n$ is the sample size.

4. Result and Discussion

In education insurance, the claim reserve follows seasonal pattern with increasing trend. Time series plots of 10-year-monthly claim reserve is given in Figure 1. The number is denoted in billion rupiah. The red dashed line shows the position of the seventh month (August).

![Figure 1. The amount of monthly claim reserve in 10 years](image)

Based on Figure 1, the plot reveals that claim reserve tends to increase in August or a month before it. This month is normally the start of new educational year in Indonesia, especially for the high school and below. Therefore, it is not surprising for us to get this kind of seasonal pattern as this month is the time for paying the tuition and other fundamental fees (for new student). Moreover, the claim reserve has an increasing trend as the school fee in Indonesia is continuously rocketed. Besides, the raising trend in claim reserve is also caused by the raise in the number of customer.
To model seasonal pattern data, a seasonal ARIMA model is normally used. This model is one of the parametric approach group which consider some assumptions that should be satisfied. In some conditions, the assumption is hard to be achieved. Therefore, we will have another model that do not need many assumptions (nonparametric approach). The model used is nonparametric regression model with Fourier series estimator. The fluctuation pattern in Figure 1 supports the use of Fourier series since the series has periodical pattern.

4.1. Modelling with Seasonal ARIMA

The fundamental requirement in ARIMA modelling is to have stationary series. The rounded value of Box-Cox transformation should be unity in order to have stationary-in-variance series. Furthermore, the Augmented Dickey-Fuller (ADF) test was conducted to examine the stationarity in mean of the claim reserve data. The results are given in Table 1.

| Dickey-Fuller | Lower CL | 0.71 |
|---------------|----------|------|
| Lag order     | 8        | 1.85 |
| P-value       | <0.01    | 1.00 |

Table 1 depicts the p-value of ADF test that is very small and the rounded value is unity. Therefore, the 10-year-claim reserve data are stationary both in mean and variance.

4.1 The ARIMAX Modelling

Although the series is stationary, there is an increasing trend in the data as shown in Figure 1. Thus, this trend will be eliminated by placing trend variable “t”, where $t = 1, 2, 3, \ldots$, and regress it with the claim reserve series (i.e. ARIMAX modelling with $t$ as the exogenous variable. Table 2 gives information of the summary of regression of $t$ on claim reserve series.

| Series       | Variable | Coefficient | P-value |
|--------------|----------|-------------|---------|
| Claim reserve| Constant | 19.066      | 0.000   |
|              | T        | 0.2083      | 0.000   |

Based on Table 2, the trend variable significantly affect claim reserve series. Then, diagnostic checking is conducted on the residual. The ACF and PACF plots of residuals are given in Figure 2.

Figure 2. The ACF and PACF of residuals
orders for SARIMA are \( \text{SARIMA}(1,0,0)(1,0,0)^{12} \) and \( \text{SARIMA}(1,0,0)(1,0,1)^{12} \). After trying to run those models, both order have significant coefficients but only \( \text{SARIMA}(1,0,0)(1,0,1)^{12} \) with zero mean satisfies the white noise assumption of SARIMA residual (see Table 3 for the model coefficient and Figures 3 and 4 for the residual diagnostic checking).

| Variable | Coefficient | Std. Error | t-Statistic | P-value |
|----------|-------------|------------|-------------|---------|
| AR(1)    | 0.5163      | 0.0797     | 6.48        | 0.000   |
| \( \text{SAR} \) (12) | 0.9963      | 0.0152     | 65.38       | 0.000   |
| \( \text{SMA} \) (12) | 0.8552      | 0.0787     | 10.87       | 0.000   |

Table 3 reveals that all of the coefficients of \( \text{SARIMA}(1,0,0)(1,0,1)^{12} \) model are significant. Moreover, there is no cut off in ACF plot in Figure 3 that means the residual is white noise. In addition, the QQ plot in Figure 4 shows that the residual follows normal distribution as the p-value of Kolmogorov-Smirnov test is quite large.

![Figure 3. The ACF of residuals of SARIMA(1,0,0)(1,0,1)^{12} model](image)

![Figure 4. The QQ plot of residual of SARIMA(1,0,0)(1,0,1)^{12}](image)

Based on Tables 2 and 3, the final ARIMAX model of claim reserve can be written mathematically as
\[ \hat{y}_t = 19.066 + 0.2083 t + 0.5163 \gamma_{t-1} + 0.9963 \gamma_{t-12} - 0.5144 \gamma_{t-13} - 0.8552 \alpha_{t-12} + \alpha_t, \]

where \( \varepsilon_t \sim N(\mu, \sigma^2) \).

This model is known as SARIMAX(1,0,0)(1,0,1)\(^2\) with trend variable as the exogenous variable. The final step is to forecast the claim reserve series using the final model. The forecast results is given in Figure 5.

Figure 5. The forecast results of SARIMAX(1,0,0)(1,0,1)\(^2\) model

Figure 5 provides information on forecasting results of claim reserve based on SARIMAX(1,0,0)(1,0,1)\(^2\) model. We plotted the forecast with the actual value for the next two year. The figures show that the model can follow the actual pattern closely with MAPE 4.025%.

4.2. Modelling with Nonparametric Regression

In this study, the number of claim reserves is predicted using nonparametric regression with the Fourier series approach. Paired data is given which contains one independent variable, and one dependent variable \( (t_i, y_i) \), \( i = 1, 2, \ldots, n \) shows the number of observations in the training data. The general form of nonparametric regression equations with Fourier series estimators which refers to References [16] and [17] for paired data are as follows:

\[
y_i = \frac{\alpha_0}{2} + \gamma t_i + \sum_{k=1}^{K} a_k \cos k t_i + \varepsilon_i; \varepsilon_i \sim \text{IIDN}(0, \sigma^2) \]

where \( \gamma, \alpha_0, \) and \( a_k \) are regression parameters whose values are estimated based on the least squares method. The oscillation parameter is denoted by \( k = 1, 2, \ldots, K \), \( \varepsilon_i \) is an identical random error, independent and normally distributed with zero mean and variance \( \sigma^2 \). In the form of vector equations, Equation (12) can be constructed into

\[
y = T[K] \beta + \varepsilon; \varepsilon \sim \text{IIDN}(0, \sigma^2 I) \]

where \( y = (y_1, y_2, \ldots, y_n)^T, \varepsilon = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n)^T, \beta = \left( \frac{\alpha_0}{2}, \gamma, a_1, \ldots, a_K \right)^T \),

and \( T[K] = \begin{pmatrix} 1 & t_1 & \cos t_1 & \cdots & \cos K t_1 \\ 1 & t_2 & \cos t_2 & \cdots & \cos K t_2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & t_n & \cos t_n & \cdots & \cos K t_n \end{pmatrix} \).
and I is an identity matrix. Based on the least squares method, the regression parameter estimator vector is obtained according to (6).

By using training data, Equation (5) is used to determine the GCV value for each $k$. In Equation (5) the numerator is MSE, and $A(K) = T[K] (T[K]^T T[K])^{-1} T[K]^T$ is the hat matrix. Figure 6 shows GCV values from $k = 1$ to $k = 120$ with $k = 118$ being the optimal $k$ which has minimum GCV value.

![Figure 6](image1.png)

**Figure 6.** The change of GCV value for $k = 1$ to 120

![Figure 7](image2.png)

**Figure 7.** The change of GCV value around the optimal $k$
Figure 8. The change of GCV value for $k=1$ to 10

Figure 6 shows changes in GCV values around the optimal $k$, while Figure 7 shows changes in GCV values for $k=1$ to $k=10$. Without considering the simplicity of the model, the Fourier series estimator with $k=118$ is selected. However, the selection of $k=118$ has a deficiency that is a long form of estimator and has a high computational complexity. Thus, considering the simplicity of the model is needed in selecting oscillation parameters beside the minimum GCV concept. Based on Figure 8, it can be seen that there is a large decrease in GCV value for $k=6$. The GCV value for $k=6$ is the minimum value compared to $k=1$ to 5. Hence, the Fourier series estimator in nonparametric regression with $k=6$ was chosen to predict the reserve amount of educational insurance claims. For $k=6$, the estimator is obtained as follows:

$$
\hat{y}_i = 19,0967 + 0,2077 t_i - 0,1188 \cos t_i - 0,024 \cos 2t_i - \cos 3t_i + 0,2221 \cos 4t_i + 0,2145 \cos 5t_i + 1,016 \cos 6t_i. \quad (14)
$$

The Fourier series estimator in nonparametric regression in Equation (14) has MSE of 4.4246 and $R^2$ of 78.4886%. This $R^2$ value is quite good, considering that we chose a model based on the principle of simplicity. The value of $R^2$ is determined by the following formula:

$$
R^2 = \frac{(\bar{y}-\bar{y})'(\bar{y}-\bar{y})}{(y-y)'(y-y)} \quad (15)
$$

Then, forecasting is done based on (14) using testing data. Figure 9 gives information about the results of the comparison between testing data and forecast. Although the estimator with the smallest GCV ($k=118$) is not selected, by selecting the Fourier series estimator for $k=6$ in this model, the predicted value follows the increasing pattern of the testing data but cannot fit it well. The amount of claim reserves equals a tendency to rise over a certain period. In addition, seasonal fluctuations are also predicted to continue, and will reach the highest value in a certain period of one year. The results of the prediction of the reserve amount of educational insurance claims based on the Fourier series estimator in nonparametric regression have a small MAPE value of 15.42%.
Based on the results on nonparametric regression modeling, it can be concluded that the prediction of the reserve amount of educational insurance claims using the Fourier series estimator in nonparametric regression has good results. The indicator of goodness is shown by the small MSE value with large $R^2$. In addition, in predicting the reserve amount of educational insurance claims, the Fourier series estimator in nonparametric regression has a small MAPE value. The other indicator is that the difference in the results of the prediction of the data testing is also not too far away, and mostly according to the condition that the number of educational insurance claims has an increasing trend, and will reach the highest value in a certain period of one year. This condition is expected to be anticipated by education insurance companies in Indonesia.

4.3. The Model Comparison

The parametric model outperforms the nonparametric model in prediction accuracy based on MAPE. The MAPE of SARIMAX model is almost one-third of that of nonparametric regression model. Moreover, the prediction result is plotted in Figure 10.
Figure 10. The forecast comparison among two methods

Based on the prediction results in Figure 10, the SARIMAX prediction can follow the pattern of actual data smoothly but the prediction of nonparametric model only follows the increasing trend without capturing the periodical pattern. A raising trend is expected as more people have awareness in their future education. Both models give the same information about this raising trend. However, the nonparametric model in which the selected maximum GCV value is 6, cannot explain seasonal feature in claim reserve. This does not agree with the real pattern of education insurance claim reserve in Figure 1, claim reserve of education insurance has seasonal pattern where the peak is in July or August (the beginning of new educational year in Indonesia).

The reason for this can be explained by the selection of optimal GCV value in nonparametric regression. The optimum GCV is at \( k = 118 \) but it is bothersome to have that much parameters. Another reason is because our estimator is based on Fourier series which has continuous dimension. When we apply that to time series data, which is discrete, the performance will be not as good as in the continuous case.

5. Conclusion

To conclude, both models (parametric and nonparametric) find the increasing trend and seasonal pattern in the predicted values of claim reserve. However, the parametric model follows the pattern smoother than that of nonparametric model. Furthermore, based on the predicting accuracy using MAPE, the parametric model (SARIMAX) had better performance than nonparametric model.

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