International Research Journal of Advanced Engineering and Science
ISSN (Online): 2455-9024

# Modeling of the Multi-Input Transfer Function in Forecasting the Inflation Level in South Sulawesi

Thesya Atarezcha Pangruruk[1], Georgina Maria Tinungki[2], Erna Tri Herdiani[3]
[1,2,3]Department of Statistics, Faculty of Mathematics and Natural Sciences, Hasanuddin University, Makassar 90245, Indonesia
Corresponding Author's: tesyatareskaaa@gmail.com

***Abstract***— *In the midst of current economic developments, inflation is still a major concern for the government because inflation is one thing that cannot be ignored. Inflationary pressure in South Sulawesi occurred in several months throughout 2022 pushing the annual inflation trend forward until the expected inflation target was maintained in the range of 3±1%, so that there were three cities that experienced the highest inflation which caused South Sulawesi inflation to be higher than national inflation. Inflation is very important, especially for forecasting because it has a large impact on the economy of a region, so that policies can be made or designed. This study aims at developing a method for predicting the inflation rate of South Sulawesi from January 2023 to December 2024 by taking into account general inflation data in South Sulawesi from January 2014 to December 2022, using multi- input transfer function methods, which analyses four expenditure group variables. Two of the four expenditure group variables used in this study show a significant relationship to the inflation rate of South Sulawesi, namely the food, beverage and tobacco expenditure group variables and the housing, water, electricity and other fuel expenditure group variables indicated by p-the value of each parameter is smaller than α (0.05). An MAPE value of 43.62% was obtained by analysing actual data as well as the transfer function, indicating a good model to predict future periods.*

***Keywords***— *Forecasting; Inflation; Multi-input; Transfer Function Method.*

## I. INTRODUCTION

In life as a living being, many things can be predicted to make a plan, decision, or policy in the future, one of which is forecasting inflation. Amid current economic developments, inflation cannot be ignored because it has become the government's main concern, which has a major impact on economic growth and people welfare. The causes of the impact of inflation may vary from country to country, depending on the level of development, openness to international trade, domestic and international competition, and several other factors (Camargo et al., 2010).

During the observation period (2014-2022) the highest inflation in South Sulawesi occurred in 2014, which was 8.61% and the second highest in 2022 was 5.77% (BPS, 2023). The main cause of high inflation in South Sulawesi is the increase in the price index of the goods and services expenditure group, such as the increase in the price index in the 2014 food expenditure group of 3.44% making it the largest contributor to the formation of general inflation of Whereas in 2022 there will be inflationary pressures in South Sulawesi for several months with the highest inflation occurring due to price adjustments to the group of goods regulated by the government, namely fuel, thus pushing the annual inflation trend forward so that the inflation target is off track which is expected to be maintained in the range of $3\pm1\%$ (Kemenkeu, 2023). When there is high inflation, prices will continue to climb and people will not be able to buy the things they need. Inflation becomes very important especially for forecasting to make future policies.

Forecasting is a technique for estimating the future, which takes into account historical and current information to minimise errors (Eris et al., 2014). Two categories can be used for the forecasting methods: Qualitative as well as Quantitative. The method of quantitative forecasting is two: time series and regression (Aswi & Sukarna, 2006). Time series data analysis can be performed for one variable (univariate) and many variables (multivariate). The transfer function model is one of the quantitative forecasting models that may be used to forecast univariate and multivariate time series (Makridakis et al., 1983). A time series model combining a regression approach with ARIMA for an error, also known as a method combining causal and time series approaches is a transfer function model. In several application areas such as engineering, economics, and management science the transfer function model is a time series model that is commonly used (Liu & Hanssens, 1982). The output series $(Y_t)$ is predicted to be affected by at least one input series $(X_t)$, while other inputs will be merged into a group called noise series $(N_t)$ in the transfer function model.

A multi-input transfer function shall be used in this study with the input variables constituting the four South Sulawesi inflation expenditure groups (food, beverage, cigarette, and tobacco expenditure group; health expenditure group; clothing expenditure group; housing, water, electricity, gas, and fuel expenditure group other). (Nwobi-okoye et al., 2015) developed the concept of a transfer function to a multi-input-single-output (MISO) process but because there were complexity increases, the concept of performance coefficients was used to apply a fuzzy logic method. (Yohansa & Notodiputro, 2022) in order to predict Covid-19 cases with the result that the three input variables used show a significant relationship to the Covid -19 Jakarta case, a multi-input transfer function model was used. (O et al., 2018) to produce an output series which is proven to have been the inverse of a characteristic polynomial that lies in this circle, they used a multivariate transfer function through a stochastic dynamic filter. This study aims to understand a data modeling technique, especially modeling the South Sulawesi inflation rate through the application of multi-input transfer function analysis.



Thesya Atarezcha Pangruruk, Georgina Maria Tinungki, and Erna Tri Herdiani, "Modeling of the Multi-Input Transfer Function in Forecasting the Inflation Level in South Sulawesi," *International Research Journal of Advanced Engineering and Science*, Volume 8, Issue 3, pp. 29-38, 2023.

International Research Journal of Advanced Engineering and Science
ISSN (Online): 2455-9024

## II. METHODOLOGY

### 1. *Data Stationarity*

The assumption of stationarity in both the variance and the mean is to be verified when establishing a time series model. The stationary data are those which have the same mean and variation over time. A transformation shall be performed if the data of the test are stationary with respect to the variance, whereas a differentencing shall be carried out when it is not stationary with respect to the mean. Testing for stationarity of the mean can be done by looking at the autocorrelation plot with the value being said to be insignificant if 95% of the data is in the $\pm\frac{2}{\sqrt{n}}$ interval with $n$ being the number of observations, and can also use the Augmented Dickey-Fuller (ADF) test with the AR(1) model shown in the following equation (Tsay, 2005).

$$Y_t = \phi_1 Y_{t-1} + e_t \tag{1}$$

Hypothesis used:

$H_0 : \phi = 1$ (non-stationary data)

$H_1 : \phi < 1$ (stationary data)

Statistical test of Augmented Dickey-Fuller (ADF):

$$\tau = \frac{\hat{\phi} - 1}{S_{\phi}} \tag{2}$$

where:

$\tau$ : ADF test

$\phi$ : estimated value of AR parameters

$S_{\phi}$ : standard error value for the estimated value of AR parameters

Hypothesis used:

$H_0 = \tau > \tau_{(\alpha,n)}$ (time series data is not stationary in the mean)

$H_1 = \tau \le \tau_{(\alpha,n)}$ (time series data is stationary in the mean)

As for checking the stationarity of the variance, it can be seen by using a plot if the variance fluctuations are not too large. In testing the stationarity, you can use the Box-Cox transformation shown in the following equation (Box et al., 2016).

$$W = Y_t^{(\lambda)} = \begin{cases} \frac{Y_t^{\lambda} - 1}{\lambda}, & \lambda \neq 0 \\ \ln \quad Y_t, & \lambda = 0 \end{cases} \tag{3}$$

where:

$Y_t^{(\lambda)}$ : transformation data

$Y_t$ : observation at t-th time

$\lambda$ : transformation parameters

### 2. *Autoregressive Integrated Moving Average (ARIMA)*

George Box and Gwilym Jenskin invented an Autoregressive Integrated Moving Average model of ARIMA so that it's also known as the "boxJenskin" model. The ARIMA method only uses one variable as the basis for forecasting, so this model which becomes the independent variable is the dependent variable (lag) and the residual value of the previous period. The ARIMA development model consists of Autoregressive (AR) with order p and Moving Average (MA) with order q. Integrated to the ARIMA model with d orientation is carried out if the time series data is not stationary in the mean which can be seen from each Time Series, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF) plot. General model of time series ARIMA (p, d, q) can be written as follow (Wei, 2006).

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B) a_t \tag{4}$$

where:

$\phi_p(B) : 1 - \phi_1 B - \phi_1 B^2 - \ldots - \phi_p B^p$ is a stationary parameter AR

$\theta_q(B) : 1 - \theta_1 B - \theta_1 B^2 - \ldots - \theta_q B^q$ is an invertible parameter MA

$a_t$ is a residual value which is white noise with $a_t \sim (0, \sigma_\alpha^2)$

In the analysis of time series data, there is also an ARIMA model with a seasonal pattern of period S with differencing D, denoted as ARIMA $(P, D, Q)^S$. The ARIMA model $(p,d,q)(P,D,Q)^S$, in general can be written as follows (Wei, 2006).

$$\phi_p(B)\Phi_p(1-B)^d(1-B^s)^D Y_t = \theta_q(B)\Theta_Q(B^S)a_t \tag{5}$$

where:

$\Phi_p(B^S) : 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \ldots - \Phi_p B^{ps}$

$\Theta_Q(B^s) : 1 - \Theta_1 B^S - \Theta_2 B^{2S} - \ldots - \Theta_Q B^{QS}$

$(1-B)^d$ : non-seasonal differencing of the order d

$(1-B^S)^D$ : the seasonal differencing of period S to order D

$a_t$ : residual value which is white noise with $a_t \sim WN(0, \sigma_\alpha^2)$

### 3. *Transfer function*

The transfer function model is a multiple series of forecasts that combine certain characteristics of the univariate ARIMA model with some features of regression analysis (Makridakis et al., 1983). In the transfer function, there is an input series $(X_t)$, an output series $(Y_t)$, and all other effects called disturbances $(N_t)$. To obtain future predictions, the transfer function method can be used. The model of the transfer function shall be as follows (Wei, 2006).

$$Y_t = v_0 X_t + v_1 X_{t-1} + v_2 X_{t-2} + \ldots + N_t \tag{6}$$

or

$$Y_t = v(B) X_t + N_t \tag{7}$$

with:



Thesya Atarezcha Pangruruk, Georgina Maria Tinungki, and Erna Tri Herdiani, "Modeling of the Multi-Input Transfer Function in Forecasting the Inflation Level in South Sulawesi," *International Research Journal of Advanced Engineering and Science*, Volume 8, Issue 3, pp. 29-38, 2023.

$Y_t$ : stationary output series
$X_t$ : stationary input series
$N_t$ : error variable (noise series) that follows a particular ARMA model
$v(B)$ : $v_0 + v_1 B + v_2 B^2 + \ldots$ transfer function model coefficients or impulse response weights.

Impulse response weights can be expressed as follows:

$$v(B) = \frac{\omega_s(B)B^b}{\delta_r(B)} \tag{8}$$

A multi-input transfer function model is a transfer function model that has two or more input variables. The form of the multi-input transfer function model can be written as follows (Wei, 2006).

$$y_t = \sum_{j=1}^{k} \frac{\omega_j(B)}{\delta_j(B)} B^{b_j} x_{jt} + \frac{\theta(B)}{\phi(B)} a_t \tag{9}$$

where:

$\omega_j(B)$ : $\omega_0 - \omega_1 B - \omega_2 B^2 - \ldots - \omega_s B^s$,
$\delta_j(B)$ : $1 - \delta_0 - \delta_1 B - \delta_2 B^2 - \ldots - \delta_r B^r$,
$\theta(B)$ : $1 - \theta_1 B - \ldots - \theta_q B^q$,
$\phi(B)$ : $1 - \phi_1 B - \ldots - \phi_p B^p$,
$j$ : number of input series
$y_t$ : transformed and differentiated $Y_t$ values
$x_t$ : transformed and differentiated $X_t$ values
$a_t$ : random disturbance value
$r, s, p, q,$ and $b$ constant

*A. Identification of transfer function model*

- Prewhitening input series and output series

Prewhitening is a series of transformations aimed at simplifying the input series and reducing all known patterns to ensure that only white noise remains. Before the prewhitening process, an ARIMA model for $x_t$ is built as follows:

$$\phi_x(B)x_t = \theta_x(B)\alpha_t \tag{10}$$

Then the prewhitening input series $(\alpha_t)$ is:

$$\alpha_t = \frac{\phi_x(B)}{\theta_x(B)} x_t \tag{11}$$

with:

$\alpha_t$ : whitening input series
$\phi_x(B)$ : operator Autoregresive
$\theta_x(B)$ : operator Moving Average
$x_t$ : stationary input series

The output series prewhitening process for $y_t$ follows the $x_t$ prewhitening process for the input series with the following equation:

$$\beta_t = \frac{\phi_x(B)}{\theta_x(B)} y_t \tag{12}$$

with:

$\beta_t$ : whitening output series
$\phi_x(B)$ : operator *Autoregresive*
$\theta_x(B)$ : operator *Moving Average*
$y_t$ : stationary output series

- Calculation of cross-correlation function for the input series and output series

Then calculate a cross-correlation between these two series following the prewhitening process in both input and output series. The crosscorrelation function measures the extent to which the relationship between the two variables is whitened. The degree of relationship between $X$ at time $t$ and value of $Y$ at time $t+k$ is determined by the cross-correlation between $X$ and $Y$. The correlation function between $\alpha_t$ and $\beta_t$ at the k-th lag is:

$$r_{\alpha\beta}(k) = \frac{C_{\alpha\beta}(k)}{S_\alpha S_\beta(k)}, \quad k = 0, \pm 1, \pm 2, \ldots \tag{13}$$

with:

$r_{\alpha_t\beta_t}(k)$ : cross-correlation between $\alpha_t$ and $\beta_t$ on the k-th lag
$C_{\alpha\beta}(k)$ : covariance between $\alpha_t$ and $\beta_t$ at the k-th lag
$S_\alpha$ : standard deviation of the series $\alpha_t$
$S_\beta$ : standard deviation of the series $\beta_t$

- Determination of (b, r, s) for the transfer function model that relates the input and output series

The constant b, r, s is determined by the structure of cross-correlation functions or impulse weights between $\alpha_t$ and $\beta_t$. After determining b, r, s, the parameters of the temporary transfer function are then estimated as follows:

$$\hat{v}(B) = \frac{\hat{\omega}(B)}{\hat{\delta}(B)} \tag{14}$$

- Initial estimation of the noise series $(n_t)$

The directly measured impulse response weights make it possible to calculate an initial estimate of the noise series $(n_t)$ of the transfer function model with:

$$\hat{n}_t = y_t - \hat{y}_t \tag{15}$$

$$\hat{n}_t = y_t - \frac{\omega(B)}{\hat{\delta}(B)} x_{t-b} \tag{16}$$

- Assignment $(p_n, q_n)$ to the ARIMA model $(p_n, 0, q_n)$ of the noise series $(n_t)$

Then the value $(n_t)$ will be modeled using the ARIMA approach to obtain the order of $p_n$ and $q_n$. The noise series model $(n_t)$ can be expressed as follows:

$$\phi_n(B)n_t = \theta_n(B)a_t \quad (17)$$

where:

$\phi(B)$ : $p$ order autoregressive polynomial of $n_t$

$\theta(B)$ : $q$ order moving average polynomial of $n_t$

$a_t$ : residuals from the $n_t$ series

The next step is to find the value of $a_t$ series using an equation (16) as soon as you have $n_t$ series, so that the $a_t$ series values are obtained as follows:

$$y_t = v(B)x_{t-b} + n_t \quad (18)$$

$$y_t = \frac{\omega(B)}{\delta(B)} x_{t-b} + \frac{\theta(B)}{\phi(B)} a_t \quad (19)$$

*B. Estimation of parameter model*

The Maximum Likelihood approach, which reduces the conditional least squares function by including the $\omega, \delta, \phi,$ and $\theta$ parameters, was used at this stage for the parameter estimation of the transfer function model. After identifying equation (19), then estimate the parameter $\delta = (\delta_1, \ldots, \delta_r)'$, $\omega = (\omega_0, \omega_1, \ldots, \omega_s)'$, $\theta = (\theta_1, \ldots, \theta_q)'$, $\phi = (\phi_1, \ldots, \phi_p)'$, and $\sigma_a^2$. Then equation (19) can be written as follows:

$$\delta_r(B)\phi(B)y_t = \phi(B)\omega_s(B)x_{t-b} + \delta_r(B)\theta(B)a_t \quad (20)$$

or

$$c(B)y_t = d(B)x_{t-b} + e(B)a_t \quad (21)$$

with

$$c(B) = \delta(B)\phi(B) = (1 - \delta_1 B - \ldots - \delta_r B^r)(1 - \phi_1 B - \ldots - \phi_p B^p)$$
$$= (1 - c_1 B - c_2 B^2 - \ldots - c_{p+r} B^{p+r}),$$

$$d(B) = \phi(B)\omega(B) = (1 - \phi_1 B - \ldots - \phi_p B^p)(\omega_0 - \omega_1 B - \ldots - \omega_s B^s)$$
$$= (d_0 - d_1 B - d_2 B^2 - \ldots - d_{p+s} B^{p+s}),$$

and

$$e(B) = \delta(B)\theta(B) = (1 - \delta_1 B - \ldots - \delta_r B^r)(1 - \theta_1 B - \ldots - \theta_q B^q)$$
$$= (1 - e_1 B - e_2 B^2 - \ldots - c_{r+q} B^{r+q}),$$

then,

$$a_t = y_t - c_1 y_{t-1} - \ldots - c_{p+r} y_{t-p-r} - d_0 x_{t-b} + d_1 x_{t-b-1} + \ldots + d_{p+s} x_{t-b-p-s} + e_{r+q} a_{t-r-q} \quad (22)$$

where $c_i, d_j,$ and $e_k$ are functions of $\delta_i, \omega_j, \phi_k,$ and $\theta_l$. Assuming that $a_t$ follows the distribution of $N(0, \sigma_a^2)$, the conditional likelihood function is as follows:

$$L(\delta, \omega, \phi, \theta, \sigma_a^2 \mid b, x, y, x_0, y_0, a_0) = (2\pi\sigma_a^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma_a^2}\sum_{t=1}^{n} a_t^2\right], \quad (23)$$

for $t = 1, 2, \ldots, n$ by reducing the conditional sum of squares function in order to estimate values for these parameters using a maximum likelihood estimation, i.e.:

$$S_0(b, \delta, \omega, \phi, \theta) = \sum_{t=1}^{n} a_t^2 (b, \delta, \omega, \phi, \theta \mid x_0, y_0, a_0) \quad (24)$$

*C. Diagnostic models*

At this stage, goodness of fit testing needs to be done to find out if the model is feasible if there is no significant correlation between the residuals of the transfer function model and the input series after the prewhitening process and there is no significant correlation between the residuals of the transfer function model. In this test, the residual $\hat{a}_t$ is tested by:

- Calculation of autocorrelation for residual values (b, r, s) connecting the input and output series

This calculation will be carried out using the Ljung-Box test with the following statistics (Wei, 2006):

$$Q = n(n+2)\sum_{k=1}^{k} (n-k)^{-1} \hat{\rho}_k^2 \quad (25)$$

with:

$k$ : lots of data

$n$ : the number of lags tested

$\rho_k$ : presumed residual autocorrelation of period k

with the rejection criteria $H_0$ if $Q_{hit} > \chi^2_{(\alpha,df)}$ table, with degrees of freedom $K$ minus the number of model parameters or $p - value < \alpha$.

- Calculation of cross-correlation between residual values (b, r, s) and input series that has been prewhitening

This calculation is used to check the noise series $(a_t)$ and the input series $(x_t)$ are independent of each other. Using equation (25), the appropriate formula for this test is as follows:

$$Q = n(n+2)\sum_{k=0}^{k} (n-k)^{-1} \rho_{xy}^2(k) \quad (26)$$

The number of degrees of freedom for $Q$ is independent of the number of parameters estimated in the noise model.

*D. Using transfer function models for forecasting*

The transfer function model can be used to forecast by entering the transfer function parameter values and the input and output series values from the previous steps once the previous steps have been completed. Forecasting is calculated using the following equation:

$$y_t = \sum_{j=1}^{m} v_j(B) x_{jt} + n_t \quad (27)$$

or

$$y_t = \sum_{j=1}^{m} \frac{\omega_j(B)}{\delta_j(B)} B^{bj} x_{jt} + \frac{\theta(B)}{\phi(B)} a_t \quad (28)$$

where $v_j(B)$ is the transfer function for the j-th input series $x_{jt}$ and $a_t$ is assumed to be independent for each input series $x_{it}$ and $x_{jt}$ are uncorrelated for $i \neq j$.

## III. Result and Discussion

TABLE 1. Descriptive Statistics of Research Variables (percent)

| Variable | Minimum | Maximum | Mean | Std. Dev |
|---|---|---|---|---|
| General inflation of South Sulawesi ($Y$) | −0.86 | 2.75 | 0.33 | 0.50 |
| Food, beverage, cigarette and tobacco group ($X_1$) | −1.28 | 2.80 | 0.36 | 0.62 |
| Health group ($X_2$) | −0.23 | 2.84 | 0.28 | 0.38 |
| Clothing group ($X_3$) | −0.77 | 3.10 | 0.28 | 0.54 |
| Housing, water, electricity, gas and other fuel groups ($X_4$) | −0.11 | 1.49 | 0.26 | 0.33 |

The descriptive results of the research variables above show that the average inflation in South Sulawesi in the 2014-2022 period was $0.33\%$ with a minimum value of $-0.86\%$. This was due to a fall in the price of goods and services included in the food expenditure category for September 2018 as well as transport, communication and financial services. In addition, a rise in prices of goods and services covered by the food production category contributed to an overall maximum rate of $2.75\%$ which took place in December 2014. The average inflation for the food, drink, cigarette and tobacco group is $0.36\%$ with a minimum value of $-1.28\%$ occurring in October 2022 and a maximum value of $2.80\%$ occurring in April 2022. Inflation for the health group has an average of $0.28\%$ with a minimum value of $-0.23\%$ occurring in November 2021 and a maximum value of 2.84% occurring in April 2020. The average inflation for the clothing category is 0.28% with a minimum value of $-0.77\%$ occurred in November 2017 and a maximum value of 3.1% occurred in July 2015. Meanwhile the housing, water, electricity, gas and other fuels group had an average of 0.33% with the minimum value was $-0.11\%$ which occurred in February 2016 and the maximum value was 1.49% which occurred in December 2014.

*1. Identify the arima model (stationary data)*

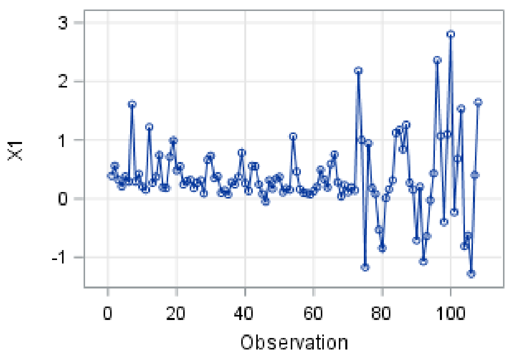


Fig. 1. plot time series data for the food, drink, cigarette and tobacco group ($X_1$)

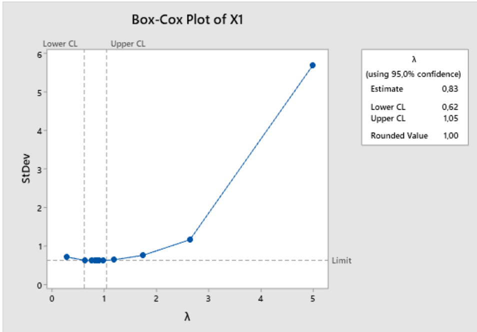


Fig. 2. box-cox plot of inflation data for the food, beverage, cigarette and tobacco group ($X_1$)

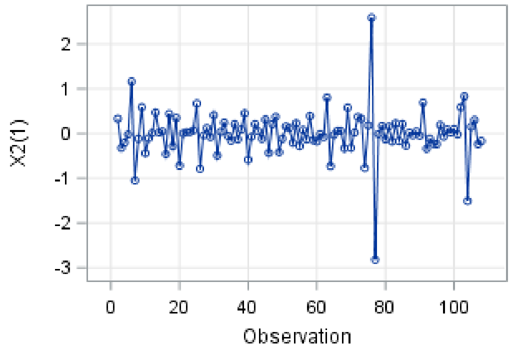


Fig. 3. plot time series data for the health group ($X_2$) after differencing

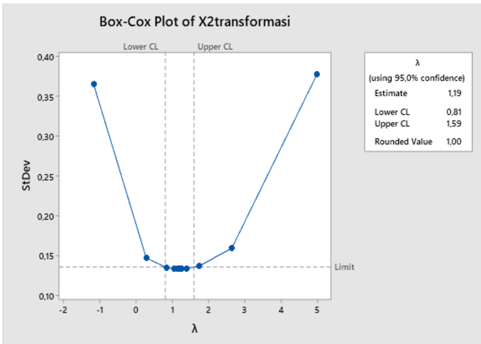


Fig. 4. box-cox plot of health group data ($X_2$) after transformation

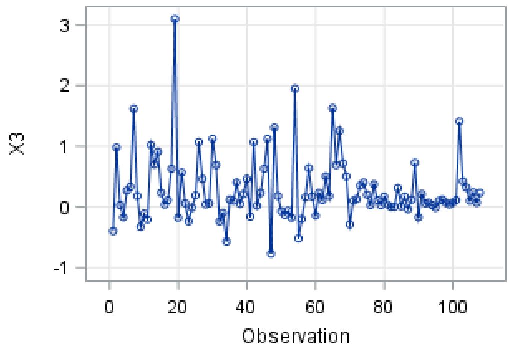


Fig. 5. plot time series data for the clothing group ($X_3$)

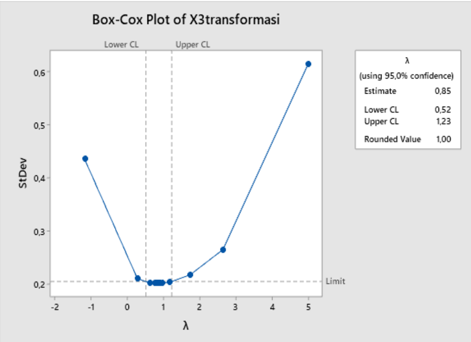


Fig. 6. box-cox plot of clothing group data ($X_3$) after transformation

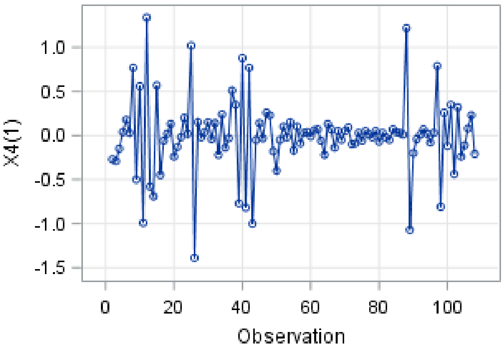


Fig. 7. plot time series data for the housing, water, electricity, gas and other fuel group ($X_4$) after differencing

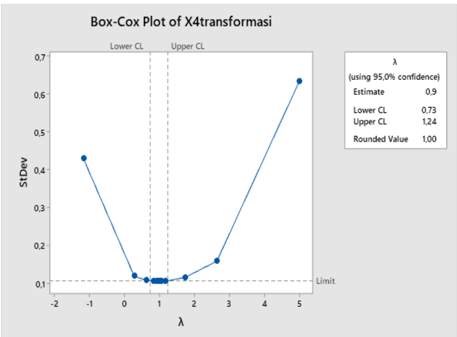


Fig. 8. box-cox plots of housing, water, electricity, gas and other fuel group data ($X_4$) after transformation

In order to determine if data meet the static assumption or do not, statistical similarity must be established. A Boxcox plot may be used to check stationarity of data in a variance, as well as the mean and time series plots for checking stationarity. Fig. 1 and Fig. 5 have been stationary without differencing, while for Fig. 3 and Fig. 7 are stationary after the differencing process has been carried out once. After the data is stationary, the next stage can be carried out. The figure above shows plots that are stationary in variance and stationary in the mean for all input series variables.

*2. Identify Autoregressive Integrated Moving Average model process*

We can determine the ARIMA model for each input series using the ACF and PACF plots as follows:

*A. Data for the food, beverage, cigarette and tobacco groups*

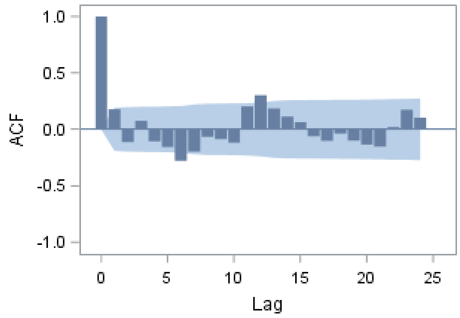


Fig. 9. Plot ACF data for the food, drink, cigarette and tobacco group ($X_1$)

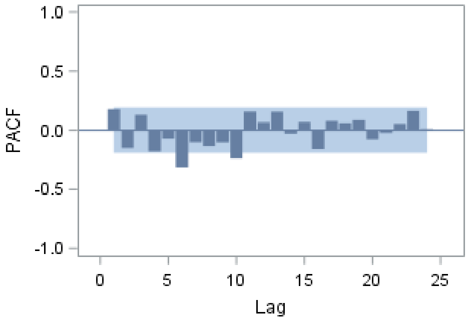


Fig. 10. Plot PACF data for the food, drink, cigarette and tobacco group ($X_1$)

The results are shown in Fig. 9 and Fig. 10, the ACF plot shows a cut off pattern after lag 6 and lag 12 and the PACF plot dies down. Based on the stationary lags of the ACF and PACF plots, the temporary ARIMA model formed for the inflation input series for the food, beverage, cigarette and tobacco group is ARIMA (0,0,[6,12]).

$$X_{1t} = 0.37594 + (1 - 0.28227B^6 - 0.39297B^{12})a_t$$

*B. Data for the health group*

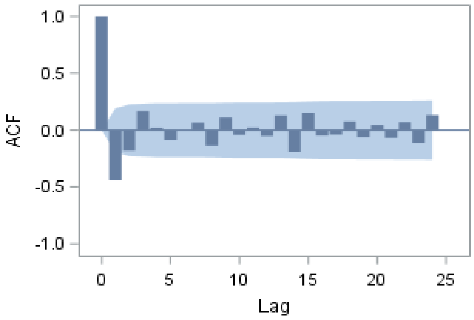


Fig. 11. Plot ACF data for the health group ($X_2$) after differencing

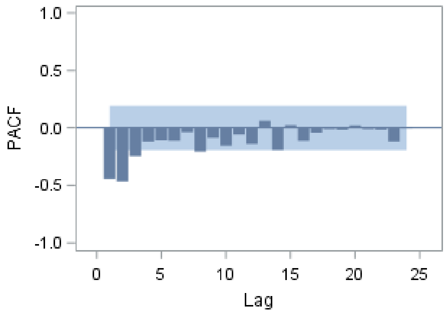


Fig. 12. Plot PACF data for the health group ($X_2$) after differencing

After differencing once, the results of the ACF and PACF plots for the inflation input series for the health group are shown in Fig. 11 and Fig. 12. The ACF plot shows a cut-off pattern after lag-1 and the PACF plot shows a dies down pattern. From the resulting lag, a temporary ARIMA model is obtained from the input series for the health group, namely ARIMA (0,1,1).

$$(1-B)^1 X_{2t} = \quad -0.0019 + (1-\theta_1 B^1) a_t$$

*C. Data for the clothing group*

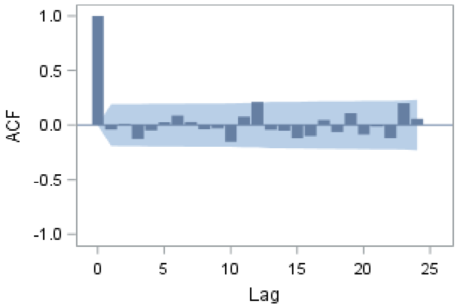


Fig. 13. Plot ACF data for the clothing group ($X_3$)

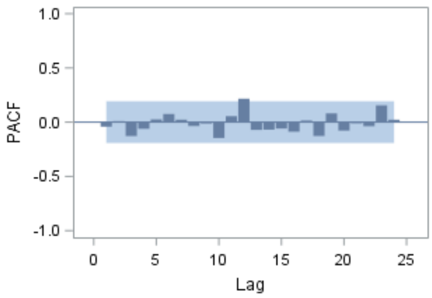


Fig. 14. Plot PACF data for the clothing group ($X_3$)

Based on Fig. 13 and Fig. 14, the ACF plot shows a cut-off pattern after lag 12 and the PACF plot also shows a cut-off pattern after lag 12. From the ACF and PACF plots obtained, the temporary models formed are ARIMA (12,0,12), ARIMA (12 ,0,0), and ARIMA (0,0,12). ARIMA models that meet the assumptions of parameter significance and white noise are ARIMA (12,0,0) and ARIMA (0,0,12) models. Because there is more than one ARIMA model, the best model will be selected based on the smallest AIC value.

TABLE 2. Criteria for Selecting the Best Model

| **ARIMA Models** | **AIC** |
|---|---|
| ARIMA (12,0,0) | 173.034 |
| ARIMA (0,0,12) | 173.487 |

Table 2 shows that the ARIMA model (12,0,0) is the best model with an AIC value of 173.034. Based on the best model, the temporary model formed from ARIMA (12,0,0) is:

$$X_{3t} = \quad 0.2829 + (1 - 0.22297B^{12} - 0.22297B^{13}) a_t$$

*D. Data for the housing, water, electricity, gas and other fuel group*

Based on Figure, the ACF and PACF plots for the housing, water, electricity, gas and other fuel groups show the ACF plot cut off after lag 1, while the PACF plot shows a dies down pattern. Then the temporary model formed from the plot results is ARIMA (0,1,1).

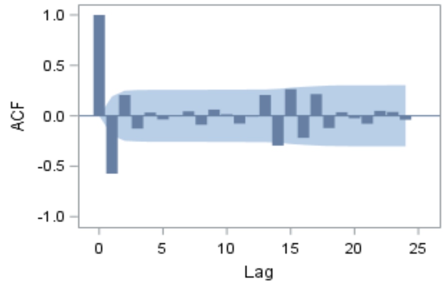


Fig. 15. Plot ACF data for the the housing, water, electricity, gas and other fuel group ($X_4$) after differencing

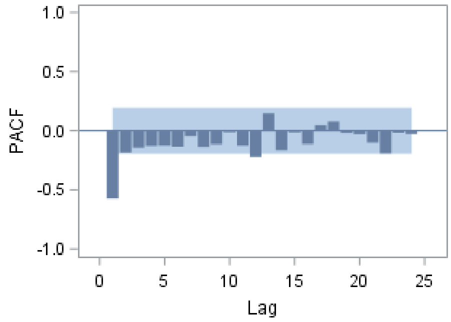


Fig. 16. Plot PACF data for the the housing, water, electricity, gas and other fuel group ($X_4$) after differencing

$$(1-B)^1 X_{4t} = \quad -0.004 + (1 - 0.84893B) a_t$$

3. Prewhitening input series and output series

After all variables meet the assumptions of a significance parameter test that is smaller than $\alpha$ (0,05) and white noise testing with a p-value greater than $\alpha$ (0,05), the next step is to carry out the prewhitening process for the input series and the output series. The prewhitening results from the input series Food, beverage, cigarette and tobacco group ($X_1$), Health group ($X_2$), Clothing group ($X_3$), Housing, water, electricity, gas and other fuel groups ($X_4$) obtained the following model:

$\alpha_{1t} = X_{1t} - 0.37594 + 0.28227\alpha_{1t-6} - 0.39297\alpha_{1t-12}$
$\alpha_{2t} = X_{2t} + 0.0019 - X_{2t-1} + \alpha_{2t-1}$
$\alpha_{3t} = X_{3t} - 0.2829 - 0.22297(X_{3t-12} + X_{3t-13})$
$\alpha_{4t} = X_{4t} + 0.004 - X_{4t-1} + 0.84893\alpha_{4t-1}$

After prewhitening process for the input series, the pre-whitening process will also be carried out for the output series. Prewhitening of the general inflation output series in South Sulawesi ($Y$) follows prewhitening of the input series that has been done for each variable.

$\beta_{1t} = Y_{1t} - 0.37594 + 0.28227\beta_{1t-6} - 0.39297\beta_{1t-12}$
$\beta_{2t} = Y_{2t} + 0.0019 - Y_{2t-1} + \beta_{2t-1}$
$\beta_{3t} = Y_{3t} - 0.2829 - 0.22297(Y_{3t-12} + Y_{3t-13})$
$\beta_{4t} = Y_{4t} + 0.004 - Y_{4t-1} + 0.84893\beta_{4t-1}$

4. Determination of (b,r,s) for the Transfer Function Model that Relates the Input and Output Series

Formation of the initial transfer function model can be done by using a Cross-Correlation Function (CCF) plot on the input series and output series that have undergone a prewhitening process by determining the order (b,r,s) of the Cross-Correlation Function (CCF) plot. Cross-Correlation Function (CCF) plots between each input series and output series are presented in Fig. 17, Fig. 18, Fig. 19, and Fig. 20 as follows.

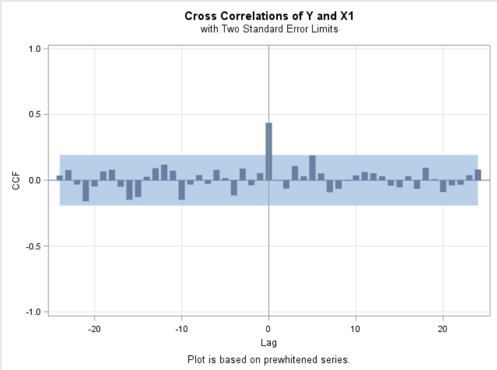


Fig. 17. Cross-Correlation Function plot between general inflation South Sulawesi($Y$) and food, beverage, cigarette and tobacco group ($X_1$)

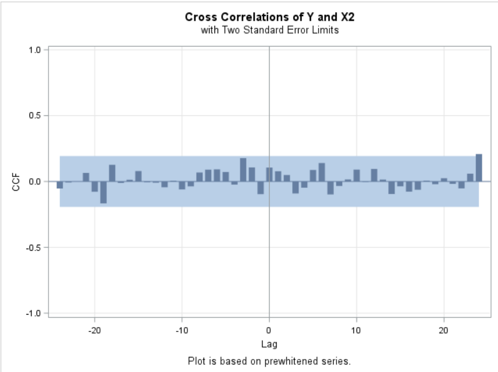


Fig. 18. Cross-Correlation Function plot between general inflation South Sulawesi($Y$) and food, beverage, cigarette and tobacco group ($X_2$)

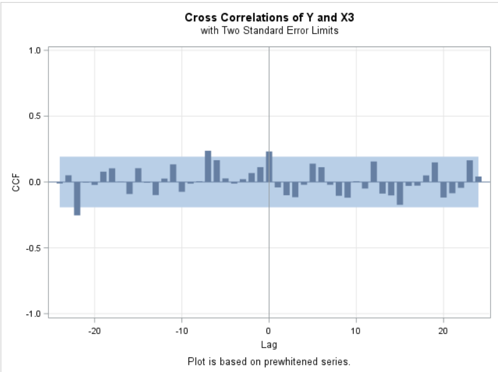


Fig. 19. Cross-Correlation Function plot between general inflation South Sulawesi($Y$) and clothing group ($X_3$)

Based on Fig. 17, the order (b,r,s) between general inflation in South Sulawesi and the food, beverage and tobacco group is (b=0, r=0, s=0). Fig. 18 shows that the order (b,r,s) between general inflation in South Sulawesi and the health group is (b=0, r=0, s=0). Fig. 19 shows that the order (b,r,s) between general inflation in South Sulawesi and the clothing group is (b=0, r=2, s=0). Fig. 20 shows that the order (b,r,s) between general inflation in South Sulawesi and the housing, water, electricity and other fuel groups is (b=0, r=0, s=0). After identifying the order (b,r,s) for each input series, the initial model of the multi-input transfer function is obtained as follows:

$$y_t = 0.39X_{1t}+0.14X_{2t}+\frac{0.07}{1-08B-0.9B^2}X_{3t}+0.66X_{4t}+n_t$$

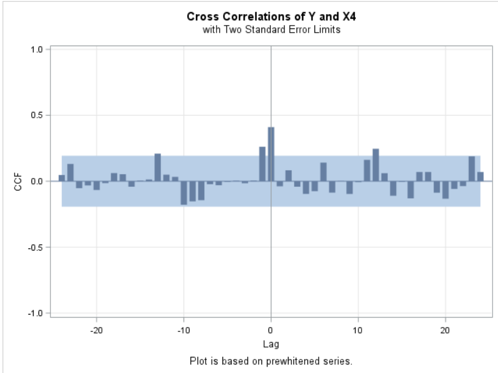


Fig. 20. Cross-Correlation Function plot between general inflation South Sulawesi($Y$) and housing, water, electricity, gas and other fuel group ($X_4$)

## 5. *Initial Estimation of the Noise Series ($n_t$)*

To calculate the value of noise series ($n_t$) in order to get an equation it is necessary to use the original model of a multiinput sequence transfer function which has been created as follows:

$$n_t = y_t - 0.39X_{1t} - 0.14X_{2t} - \frac{0.07}{1-08B-0.9B^2}X_{3t} - 0.66X_{4t}$$

In order to obtain the remainder of the white noise, it is next necessary to establish a noise series ARIMA model. A noise series model corresponding to the transfer function's assumptions is ARIMA (12,0,0). The parameter estimation results of the multi-input transfer function model are shown in the table below:

TABLE 3. Parameter Significance Test for the Final Model of the Multi-Input Transfer Function

| Model | Parameter | Estimation | Standard Error | *p-value* | Var | Decision |
|---|---|---|---|---|---|---|
| (b=0, r=0, s=0) | $\phi_{12}$ | 0.24 | 0.10 | 0.02 | $Y$ | Significant |
| | $\omega_{01}$ | 0.33 | 0.06 | <.00 | $X_1$ | Significant |
| (b=0, r=0, s=0) | $\omega_{02}$ | 0 | 0.09 | 0.93 | $X_2$ | Not significant |
| (b=0, r=2, s=0) | $\omega_{03}$ | 0.10 | 0.06 | 0.07 | $X_3$ | Not significant |
| (b=0, r=0, s=0) | $\delta_1$ | 0.44 | 0.20 | 0.02 | $X_3$ | Significant |
| | $\delta_2$ | -0.70 | 0.23 | 0.00 | $X_3$ | Significant |
| AR (12) | $\omega_{04}$ | 0.50 | 0.11 | <.00 | $X_4$ | Significant |

| Model | Parameter | Estimation | Standard Error | *p-value* | Var | Decision |
|---|---|---|---|---|---|---|
| (b=0, r=0, s=0) | $\phi_1$ | 0.28 | 0.10 | 0.00 | $Y$ | Significant |
| (b=0, r=0, s=0) | $\omega_{01}$ | 0.36 | 0.06 | <.00 | $X_1$ | Significant |
| AR (12) | $\omega_{04}$ | 0.53 | 0.11 | <.00 | $X_4$ | Significant |

The two tables shown in Table 3 show that after reducing the variable $X_2$ and $X_3$ into the model, the parameters $X_1$ and $X_4$ have met the assumption of parameter significance, namely the p-value is smaller than α (0.05). So that the noise series model formed is:

$$n_t = (1 - 0.28035B^{12})a_t$$

*6. Diagnostic Models*

The next stage is testing the feasibility of the model by testing the autocorrelation of residual values and cross-correlation between the residual values and each input series.

TABLE 4. Residual Autocorrelation Test for The Final Model of The Multi-Input Transfer Function

| Model | Lag | Chi-Square | DF | p-value | Decision |
|---|---|---|---|---|---|
| (b=0, r=0, s=0) (b=0, r=0, s=0) AR (12) | 6 | 19.09 | 5 | 0.1088 | *white noise* |
| | 12 | 23.66 | 11 | 0.1043 | |
| | 18 | 24.25 | 17 | 0.1127 | |
| | 24 | 29.09 | 23 | 0.1773 | |

Based on Table 4, the p-values of all lags are greater than α (0.05), which means that there is no autocorrelation in the residual values.

TABLE 5. Residual Cross-Correlation Test with The Input Series of The Food, Beverage, Cigarette and Tobacco Group ($X_1$)

| Lag | Chi-Square | DF | p-value |
|---|---|---|---|
| 5 | 9.49 | 6 | 0.1479 |
| 11 | 11.14 | 12 | 0.5167 |
| 17 | 12.47 | 18 | 0.8220 |
| 23 | 14.34 | 24 | 0.9386 |

TABLE 6. Residual Cross-Correlation Test with The Input Series of The Housing, Water, Electricity, Gas and other Fuel Groups ($X_4$)

| Lag | Chi-Square | DF | p-value |
|---|---|---|---|
| 5 | 9.49 | 6 | 0.1479 |
| 11 | 11.14 | 12 | 0.5167 |
| 17 | 12.47 | 18 | 0.8220 |
| 23 | 14.34 | 24 | 0.9386 |

Based on Table 6, the p-value of all the lags in each input series shows that the correlation between the residual values and each input series is not significant at α (0.05). So it can be concluded that the multi-input transfer function model can be used in forecasting with the final model of the multi-input transfer function as follows:

$$y_t = 0.07429 + 0.36418X_{1t} + 0.53984X_{4t} + (1 - 0.28035B^{12})a_t$$

7. Forecasting

Forecasts will be based on a model of the feasible transfer function. The chart below presents results of the transfer function, as well as forecast inflation for South Sulawesi for Januari 2023 to December 2024.

Based on Fig. 20, it shows that the transfer function forecasting plot has a pattern that slightly resembles the actual data. From the calculation of the MAPE value between the actual data and the transfer function data, 43.62% is obtained. Based on the table made by Lewis (1982) it is said that the MAPE value in the range of 20% -50% is good enough to be interpreted for use in forecasting. Then the MAPE value from the South Sulawesi inflation rate transfer function model is good enough to be used in forecasting the next period. The results of forecasting the inflation rate of South Sulawesi for the next period are presented in the table below.

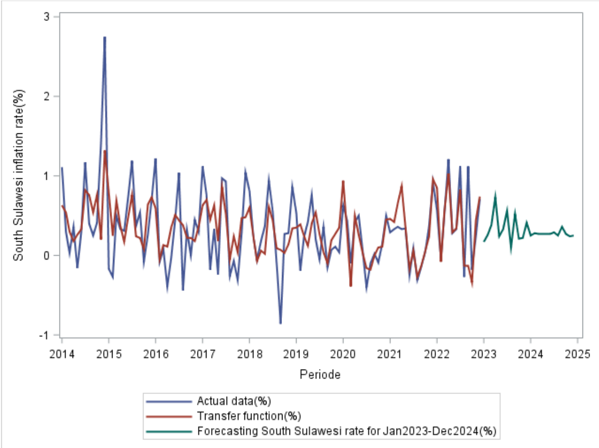


Fig. 20. Actual data, transfer function and inflation rate forecast for the coming period

TABLE 7. Forecasting The Inflation Rate of South Sulawesi in The Coming Period (Jan2023-Dec2024)

| Period | Forecasting | Period | Forecasting |
|---|---|---|---|
| Jan-23 | 0.17 | Jan-24 | 0.25 |
| Feb-23 | 0.26 | Feb-24 | 0.28 |
| Mar-23 | 0.38 | Mar-24 | 0.27 |
| Apr-23 | 0.73 | Apr-24 | 0.27 |
| May-23 | 0.24 | May-24 | 0.27 |
| Jun-23 | 0.33 | Jun-24 | 0.27 |
| Jul-23 | 0.56 | Jul-24 | 0.29 |
| Aug-23 | 0.10 | Aug-24 | 0.25 |
| Sep-23 | 0.52 | Sep-24 | 0.36 |
| Oct-23 | 0.21 | Oct-24 | 0.27 |
| Nov-23 | 0.22 | Nov-24 | 0.24 |
| Dec-23 | 0.41 | Dec-24 | 0.25 |

## IV. CONCLUSION

The data for the inflation rate in South Sulawesi from January 2014 until December 2022 are used to develop a model that is expected to show an inflation rate in South Sulawesi for the periode January 2023 to December 2024. It is considered that two out of four input variables are significant when defining a South Sulawesi inflation rate forecasting model based on the analysis of the transfer function namely, the variable group expenditure on food, beverages and tobacco($X_1$) and the variable group expenditure on housing, water, electricity and other fuels($X_2$). According to the multi-input transfer function model developed, it is possible to estimate that inflation rates in South Sulawesi will remain relatively stable over the next 24 months cross-correlation, ranging from 0.10% -0.73%.

## REFERENCES

1. Aswi, & Sukarna. (2006). *Analisis Deret Waktu Analisis: Teori dan Aplikasi*. Andira Publisher.
2. BPS. (2023). *Inflasi Tahunan Menurut 5 Kota Inflasi 2020-2022*. Badan Pusat Statistik Provinsi Sulawesi Selatan. https://sulsel.bps.go.id/indicator/3/1784/1/inflasi-tahunan-menurut-5-kota-inflasi-.html
3. Camargo, M. E., Filho, W. P., Dullius, A. I. dos S., & Malafaia, G. C. (2010). Transfer Function and Intervention Models for the Study of

Brazilian Inflationary Process. *African Journal of Business Management*, *4*(5), 578–582.

4. Eris, P. N., Nohe, D. A., & Wahyuningsih, S. (2014). Peramalan Dengan Metode Smoothing dan Verifikasi Metode Peramalan Dengan Grafik Pengendali Moving Range (MR) (Studi Kasus: Produksi Air Bersih di PDAM Tirta Kencana Samarinda) Forecasting with Smoothing and Verification Methods with Moving Range (MR) Cont. *Jurnal EKSPONENSIAL*, *5*(2), 120–129.
5. Kemenkeu, S. (2023). *Press Relase Kinerja APBN Sulawesi Selatan s.d. 31 Desember tahun 2022*. https://djpb.kemenkeu.go.id/kanwil/sulsel/id/data-publikasi/berita-terbaru/2887-press-release-kinerja-apbn-sulawesi-selatan-s-d-31-desember-tahun-2022.html
6. Liu, L. M., & Hanssens, D. M. (1982). Identification Of Multiple-Input Transfer Function Models. *Communications in Statistics - Theory and Methods*, *11*(3), 297–314.
7. Makridakis, S., Wheelwright, S. C., & McGee, V. E. (1983). *Forecasting Methods and Application* (2nd Editio). John Wiley & Sons.
8. Nwobi-okoye, C. C., Okiy, S., & Clement, A. (2015). Performance Evaluation of Multi-Input – Single- Output ( MISO ) Production Process Using Transfer Function and Fuzzy Logic : Case Study of a Brewery. *AIN SHAMS ENGINEERING JOURNAL*. https://doi.org/10.1016/j.asej.2015.07.008
9. O, N. G., H, E. E., & Amos, E. (2018). *Multivariate Transfer Function Modeling . An Application*. *5*(5).
10. Yohansa, M., & Notodiputro, K. A. (2022). *Multi-Input Transfer Function Model for Covid-19 Incidences in Jakarta*. *020022*(December).