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Monthly Inflow Forecasting of Three Multi-Purpose Reservoirs

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Abstract— **The need for inflow discharge forecasts is the first step in the process of integrating water management. To overcome this problem, a discharge forecasting analysis system is needed. This paper adopts a seasonal autoregressive integrated moving average forecasting analysis model, SARIMA. This method was chosen and then applied to the inflow discharge data of the Wonorejo Reservoir to obtain the best model. Determination of the best model through forecasting performance measures using the minimum Mean Square Error (MSE). The best model has an MSE of 11.79 on discharge data for 18 years from 2003 to 2020. The best forecast model is then evaluated on the Bendo Reservoir and Sampean Reservoir. The difference between this paper and others is that one model is used for three different multi-purpose reservoirs and obtains feasible results for each reservoir. Therefore, the authors conclude that the forecasting results of the SARIMA $(1,0,0)(0,1,1)^{12}$ model can be applied to Wonorejo Reservoir, Bendo Reservoir, and Sampean Reservoir in East Java Province, Indonesia. The best model from the analysis process is that in the Wonorejo Reservoir, the inflow prediction is satisfactory for the next five years, the Sampean Reservoir for the next four years, and the Bendo Reservoir is the best forecast for the next three years. The results of this forecasting model can be used to analyze the optimization of multi-purpose reservoir management and reduce the risk of reservoir water shortages. Further research can be carried out to achieve extreme values in inflow discharge forecasting.**

Keywords— **Discharge forecasting; multi-purpose reservoir; SARIMA; inflow reservoir forecasting.**

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I. INTRODUCTION

Estimating discharge inflow and variability is important in analyzing water management planning, irrigation, hydropower, and river ecosystems [1]–[5]. The increasing population growth and the accompanying increases in water demand, especially for domestic, industry, and irrigation, have attracted significant interest from researchers to improve the estimation method of river discharge in the context of operational water management [6]–[8]. Researchers are currently enriching methods for forecasting discharges because of their considerable importance in water resource management [9]–[12].

The models used include the rainfall-discharge model and the discharge-discharge model (both in the form of a conceptual model), as well as a black-box model or a stochastic model [6], [13]–[15]. The stochastic model itself is preferred by hydrologists who work by adopting conditions of temporal data uncertainty. Models in the field of hydrology are very influential with time series data such as precipitation and discharge river flow [16]–[18]. The autocorrelation function in the model can describe the hydrological cycle based on the hydro-climatological variables as its constituents [19].

Various researchers have widely used the Seasonal Autoregressive Integrated Moving Average forecasting analysis model (SARIMA) to model different hydrological variables. Box and Jenkins first popularized SARIMA in 1976 as an extended model of ARIMA with non-stationary time series classes [20]. This is done to improve ARIMA's performance in the time series model. For example, Mirzavand et al. [21] applied SARIMA for forecasting groundwater levels in semi-arid environments, which were then compared with the Auto-Regressive (AR) method. The results obtained by the SARIMA model are better than the AR model.

The SARIMA model was also fit when used by Martinez-Acosta et al. [22] to obtain synthetic monthly rainfall in the Sinú River, Colombia. Moloy et al. [23] conducted an analysis of monthly rain forecasting in Bangladesh using the SARIMA model. The results obtained by the SARIMA model can be used for forecasting rain for the next 120 months. Meanwhile, Tadesse et al. [24] also used the SARIMA method to forecast the monthly discharge of the Waterval River, South Africa. Both obtained satisfactory results with the SARIMA Model. Rahayu et al. [25] used ARIMA (Autoregressive Integrated Moving Average) to analyze discharge predictions for the Amprong River in Indonesia.

Besides, Dastorani et al. [26] predicted monthly rainfall by comparing several methods, including Autoregressive Integrated Moving Average (ARIMA), Moving Average (MA), and Autoregressive Moving Average (ARMA). In northern Pakistan, Adnan et al. [27] compared the SARIMA and Autoregressive (AR) methods in predicting Astore River inflow and concluded that the SARIMA method is better than AR. The SARIMA method was also used to analyze fluvial flow from the Magdalena River to Cartagena Bay, Caribbean Colombia [28]. Nwokike et al. [29] predicted the frequency of monthly rainfall in Umuahia using SARIMA and Seasonal Artificial Neural Network (SANN) and found that SARIMA is a better method than SANN. Recently Azad et al. [30] proved that SARIMA–ANN hybrid model is an alternative that should be taken into account for its accuracy in predicting the reservoir water level. Overall, it can be concluded that SARIMA has better performance, especially in forecasting discharge and rainfall.

With the results of previous researchers, this article aims to forecast discharge inflow using SARIMA model. The difference with other studies is to build a model that is capable of being used for three different multi-purpose reservoirs and obtains feasible results for each reservoir with an interval of monthly and annual periods. Several aspects have been developed: the SARIMA model with seasonal time series, parameters, and the resulting error effects for each research object. The simulation results are crucial for managing the reservoir water distribution for the present and the next few years. Thus, the risk of water shortage in multi-purpose reservoirs can be minimized and improved by the estimation method for reservoir water management [31], [32].

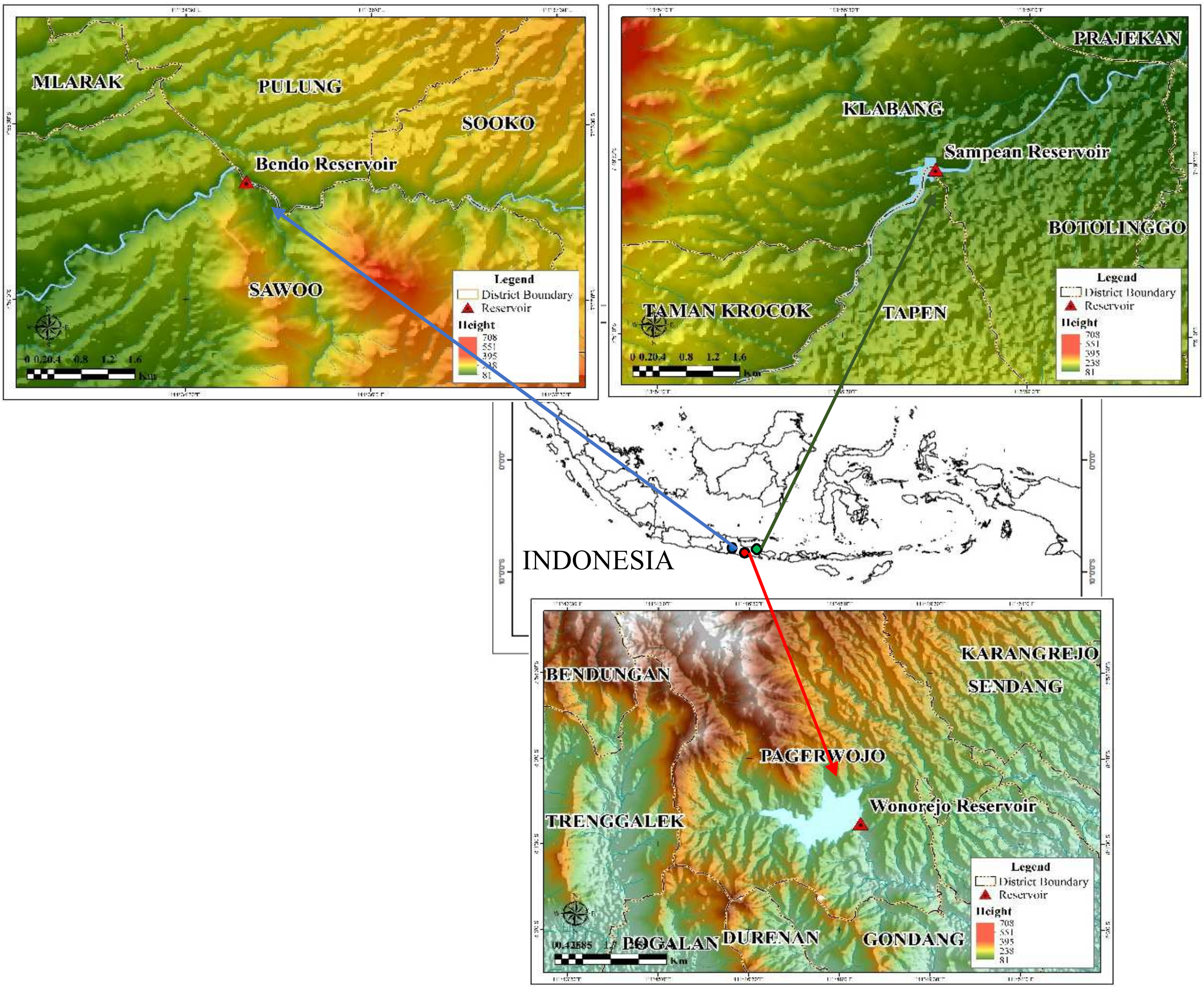

Fig. 1 Locations of the studied reservoirs (Red : Wonorejo, Green : Sampean, and Blue: Bendo Reservoir)

II. Materials and Method

The inflow simulation was carried out in three (3) reservoirs in East Java Province – Indonesia, namely Wonorejo reservoir, Bendo reservoir, and Sampean reservoir, shown in Figure 1, and their coordinates are listed in Table 1. These reservoirs were selected because they are multi-purpose reservoirs with long-term inflow and rainfall data.

TABLE I
COORDINATES OF STUDIED RESERVOIRS

No.	Name of reservoir	Latitude (S)	Longitude (E)
1	Wonorejo	8°01'06.10"	111°47'51.84"
2	Bendo	7°55'59.65"	111°34'59.39"
3	Sampean	7°49'34.20"	113°56'14.32"

The analysis in this study involves two stages, as shown in Figure 2. The first step is to perform a time series analysis of how stationarity in the mean and variance as described by Adnan et al. and previous researchers [22]–[24], [27], [29]. If an unstable variance value is obtained, a log transformation is carried out with λ = 0. Seasonal and non-seasonal were also searched for stationarity and normality. Next, the second stage is to identify the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) for seasonal and non-seasonal. ACF and PACF are tools to measure the correlation that exists in each data series, both with the previous value and the next value, as well as the correlation between variables and lag. Correlation values in ACF and PACF are then used to determine the initial values for non-seasonal p, seasonal q, and P Q parameters. From this initial determination, trial and error were then carried out on the possible parameter values to obtain the best model with the smallest error indication on MSE [25].

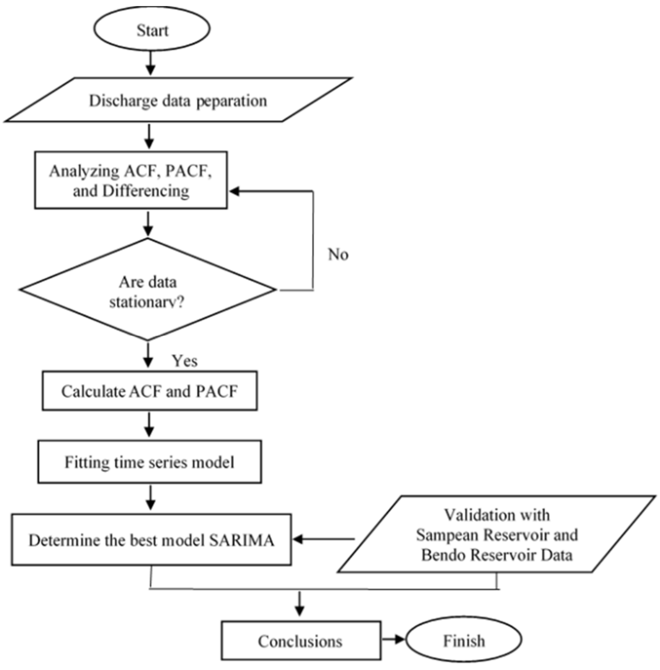

Fig. 2 Flow chart of forecasting inflow reservoir using SARIMA

The following is the formulation of SARIMA [33]:

$$a_p(B)A_p(B^s)(1-B)^d(1-B^s)^D Y_t = \theta_o + e_q(B)E_Q(B^s)r_t \quad (1)$$

where, polynomials characteristics originating from the order p and q in the autoregressive section and moving averages in the non-seasonal component are indicated by $a_p(B)$ and $e_q(B)$. Meanwhile, P and Q for autoregressive parts in seasonal components are represented by $A_p(B^s)$ and $E_Q(B^s)$. $(1-B)$, respectively and $(1-B^s)$ are regular and seasonal differencing operators. The value of d serves as the number of times the series is differentiated to eliminate trend effects and D for seasonal effects in the series. Y_t is the observation value with time t, while 0 is a fixed value. The variable represents the random error in this model r_t.

Meanwhile, the statistical error is calculated using MSE as given in equation (2):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(f_i - O_i)^2 \quad (2)$$

where, n is number of samples, f is the forecasted inflow data from SARIMA model, and O is Observed inflow.

III. Results and Discussion

The first analysis was to identify the inflow plot in the Wonorejo Reservoir. This is done before determining the best model for inflow prediction with the SARIMA model. Figure 3 shows a historical plot of monthly inflow at Wonorejo Reservoir from January 2003 to December 2020. The inflow shows a remarkable seasonal pattern, but the annual mean does not differ significantly. The periodic peak of the rainy season occurs around January, while in the dry season, the lowest value is in August for each year. Based on the figure, it can be stated that the plot of the data series has a constant rhythm except for the seasonal part.

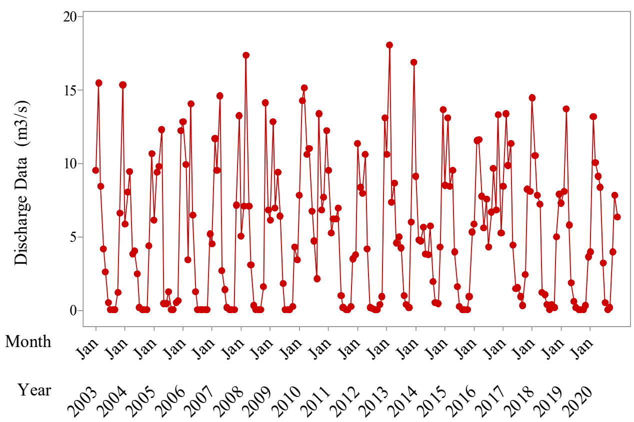

Fig. 3 Time series plot of inflow data of Wonorejo Reservoir

Figure 3 shows a significant spike observed over an interval every 12-months intervals (delay 12, 24, 36,..). The 12th PACF plot lag reinforced this seasonal pattern. This significant change can be interpreted that the analyzed monthly inflow is not stationary. The analysis for the SARIMA method begins with identifying whether the data is stationary or seasonal. In Figure 4, stationarity is identified through the Box-Cox transformation plot for stationarity to variance. It then examines ACF as well as PACF to determine whether it is stationary at the mean or not. The variance stationarity test suggests that the data was nonstationary on the variance (λ ≠ 1). Then, the first transformation was carried out, and the data became stationary in variance marked (λ = 1) as shown in Figure 5.

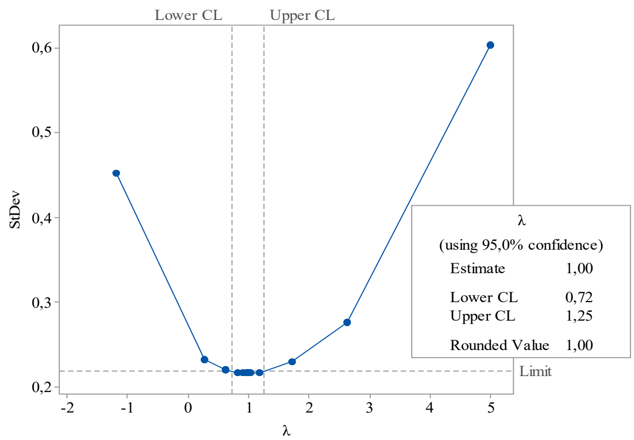

Fig. 4 Box-Cox Transformation showing non stationary to variance for Inflow data of Wonorejo Reservoir

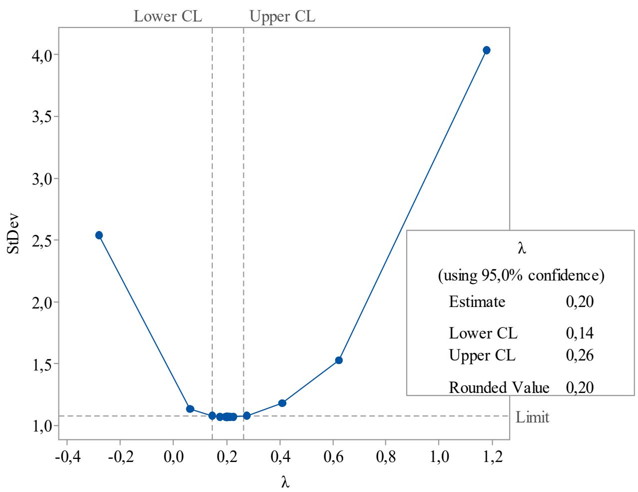

Fig. 5 Box-Cox Transformation showing stationary to variance for Inflow data of Wonorejo Reservoir after the 1st transformation

The SARIMA model was identified by plotting the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), as shown in Figure 6. The ACF plot depicted in Figure 6 dies down sinusoidally, while the PACF in Figure 7 plot dies down exponentially. In addition, significant positive changes occurred in the 1st, 2nd, and 3rd lags. The ACF plot begins to be disrupted after the 4th lag on the non-seasonal component. The significant negative spike in ACF occurred at the 12th delay and decomposed after experiencing the 23rd delay in the seasonal component. Therefore, non-seasonal Moving Average values (MA) are at 1-3, and one Seasonal Moving Average (SMA) value is recommended in the identification of the next model. Likewise, significant changes in PACF occurred in lag 1 for non-seasonal conditions and lag 12 and 24 for seasonal conditions in Figure 7. Thus, the SARIMA (p, d, q) (P, D, Q)^S model is used in this study. Based on these conditions, there are more than fifteen SARIMA models identified and selected based on the five lowest error ratings

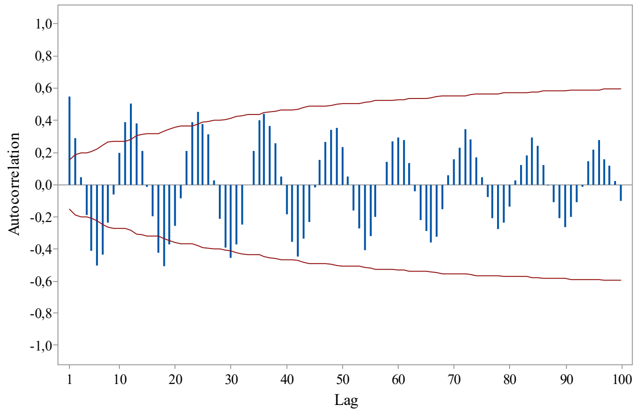

Fig. 6 Plot of ACF for Wonorejo Reservoir inflow

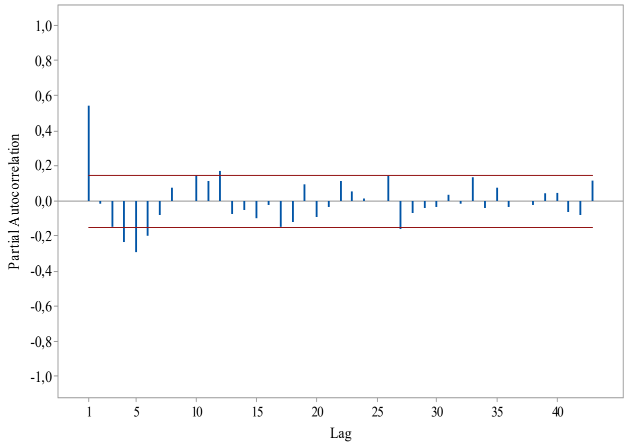

Fig. 7 Plot of PACF for Wonorejo Reservoir inflow

TABLE II
ERROR VALUE MSE IN SAMPLE FOR SARIMA MODELS

SARIMA Models (p,d,q)(P,D,Q)S	**MSE**
$(1,1,1)(1,1,1)^{12}$	11.21
$(2,1,1)(2,1,1)^{12}$	17.93
$(2,1,1)(2,2,1)^{12}$	20.60
$(1,0,0)(2,2,1)^{12}$	16.15
$(1,0,0)(0,1,1)^{12}$	10.41

The best model is a model that meets the parameter significance requirements, has white noise residuals, and has the smallest model error value. This study uses Mean Square Error (MSE) with values based on the desired forecast length, namely one year (12 months), two years (24 months), and up to six years (72 months). The list of MSE values in the sample data for each model is presented in Table 2. The analysis shows that the model (1,0,0) $(0,1,1)^{12}$ has the smallest MSE error value, significant parameters, and white residue.

TABLE III
TEST RECAPITULATION ON SARIMA MODELING RESULTS

Model	**MSE**					
	12 Monts	**24 Monts**	**36 Monts.**	**48 Monts**	**60 Monts**	**72 Monts**
SARIMA (1,0,0) $(0,1,1)^{12}$	20.71	15.50	13.61	12.79	11.79	18.35

The best model is verified based on the MSE between the forecasted and observed inflow. The out-of-sample MSE value for each model is shown in Table 3. Thus, the best model for the Wonorejo Reservoir is $(1,0,0)(0,1,1)^{12}$. The forecasted inflows generated from the best SARIMA model are plotted on a time series graph, as shown in Figure 8. The plot illustrates an agreement in patterns between the historical data and the predicted data generated from the best SARIMA model.

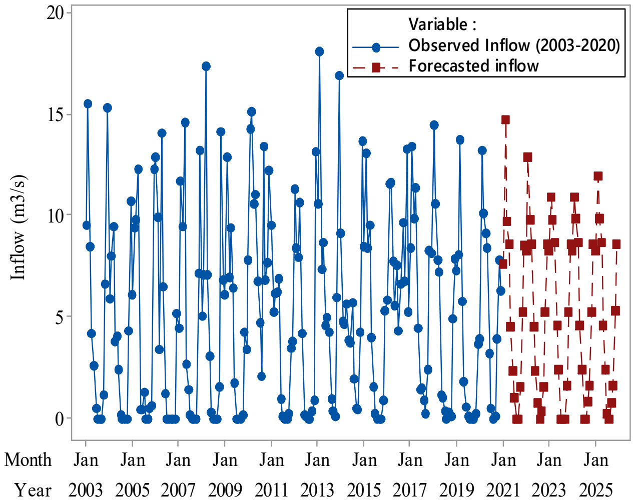

Fig. 8 Time series plot of observed inflow (2003 – 2020) and forecasted inflow of Wonorejo Reservoir

The time series of historical, validated and forecasted monthly inflows to the Wonorejo Reservoir are shown in figure 8. The forecast inflow was determined by a model builder using the $(1,0,0)(0,1,1)^{12}$. The temporal pattern for the validated and historical inflow are in good agreement. It is also obvious that the model was not able to satisfactorily capture the high discharge value. However, high discharge is more relevant for flood control, while normal and low discharge conditions are more important for the optimization of water distribution. Thus, this model is acceptable for predicting the inflow to the Wonorejo reservoir. The type of SARIMA model and its capability to forecast inflow are in line with the findings by Adnan et al. and Tadesse et al. [24], [27]. It is interesting to note that there is a decreasing trend in the predicting error from the first year to the 5th year. But the error increased again significantly in the 6th year.

The same procedure of building the SARIMA $(1,0,0)(0,1,1)^{12}$ model and its reliability was applied to Sampean Reservoir and Bendo Reservoir, and both are multi-purpose and located in the same province. The summary of modelling results and the time series plot are presented in Table 4 and Figure 9-10.

TABLE IV
THE RESULTS OF THE SARIMA MODELLING (1,0,0) (0,1,1)12

Reservoir Data	MSE					
	12 Monts.	24 months	36 months	48 months	60 months	72 months
Sampean Reservoir	9.05	13.77	11.70	10.64	10.91	10.98
Bendo Reservoir	11.18	17.72	10.10	10.87	27.08	34.87

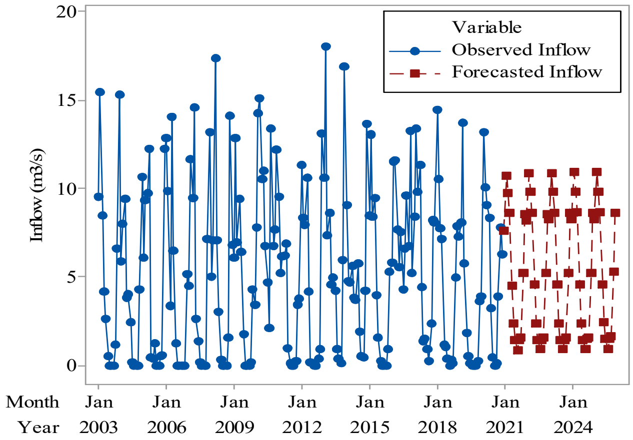

Fig. 9 Time series plot of the historical and forecasted inflow for Bendo Reservoir

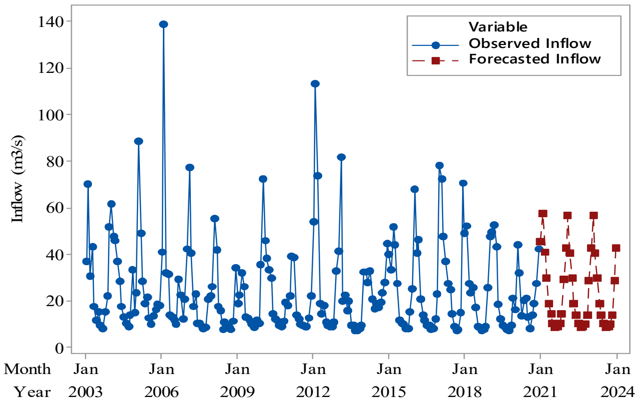

Fig. 10 Time series plot of the historical and forecasted inflow for Sampean Reservoir

The empirical results are quite satisfactory from the best SARIMA model applied to the Bendo Reservoir and Sampean Reservoir. In Table 4, the SARIMA model applied to the Sampean reservoir is suitable for forecasting for the next four years, while the Bendo Reservoir has the best forecast for the next three years. Although, the model can satisfactorily predict the normal inflow for each reservoir, and it was unable to capture the extremely high inflow.

IV. Conclusion

In order to optimize reservoir operation with regard to temporal and sectoral water distribution, current and future discharge inflow information is very important. In this study, discharge inflow at the Wonorejo Reservoir was modeled and predicted by SARIMA model with $(1,0,0)(0,1,1)^{12}$. The best model is selected not only based on the smallest residuals but also from the similarly monthly average flow rate graph with the historical inflow. The best models that have been selected and applied to the flow rate data of Bendo and Sampean Reservoirs produce good results. At Sampean Reservoir, the satisfactory predictions are for forecasting up to four years ahead, while at Bendo Reservoir, the best forecast is for the next three years. Further along these lines should explore modeling using forecasting other methods that show good results that have been done by other researchers [34], [35]. Aims to reduce errors and improve predictions at high or extreme values that cannot be predicted well in this analysis.

In addition, it is necessary to consider meteorological variables such as wind speed, humidity, and solar radiation that may affect the inflow to the reservoir.

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