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FORECASTING COVID-19 IN INDONESIA WITH VARIOUS TIME SERIES MODELS

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Abstract: In this study, Covid-19 modeling in Indonesia is carried out using a time series model. The time series model used is the time series model for discrete data. These models consist of Feedforward Neural Network (FFNN), Error, Trend, and Seasonal (ETS), Singular Spectrum Analysis (SSA), Fuzzy Time Series (FTS), Generalized Autoregression Moving Average (GARMA), and Bayesian Time Series. Based on the results of forecast accuracy calculation using MAPE (Mean Absolute Percentage Error) as model evaluation for confirmed data, the most accurate case models is the bayesian model of 0.04%, while all recovered cases yield MAPE 0.05%, except for FTS = 0.06%. For data for death cases SSA and Bayesian Models, the best with MAPE is 0.07%.

1. INTRODUCTION

Since the outbreak of the case of the spread of the Coronavirus known as Covid-19 in China, to be precise the city of Wuhan. Now more than 200 countries have contracted this virus, including Indonesia. WHO has stated that the status of this pandemic has spread throughout the world and has claimed many victims. The results showed that the incubation period for Covid-19 was around 10-14 days, ensuring there was no virus in these patients (Linton *et al.*, 2020). At the moment the whole country is fighting against this virus so it doesn't spread and kill its citizens.

In Indonesia, since it was announced by the government on March 2, 2020, the first case of Covid-19 has yet to show any signs of decreasing cases Covid-19 cases. Until the 50th day, Covid-19 has spread in thirty-four (34) provinces in Indonesia, 7135 patients have been infected, 842 patients recovered and 616 died due to Covid-19.

The government's efforts to tackle covid-19 include bringing in PPE (Personal Protective Equipment) equipment, Rapid tests, and various medical equipment from China and Korea. In addition, the government has implemented a system of Physical Distancing, Large-Scale Social Restrictions (PSBB), and Work From Home (WFH) so that the Covid-19 virus does not spread widely.

Researchers are trying to predict when the peak and end of the Covid-19 Pandemic in Indonesia will be. ITB researchers using Richard's Curve predict that the peak number of daily Covid-19 cases will be at the end of March 2020 and end in mid-April 2020 with the largest daily cases at 600. UI researchers developed the SIRU (Susceptible, Infected, Reported, and Unreported) Model, According to UI researchers the peak of the pandemic occurred on April 16 with 546 new positive cases and the accumulation reached 17,000, the end of the pandemic will take place between the end of May and the beginning of June. Meanwhile, researchers from UGM, using the PPDM (Probabilistic Data-Driven Model) Model, stated that the maximum cases of Covid-19 were 6,174 cases and would end around the end of May 2020.

Fauziyyah (2020) conducted an analysis of the Covid-19 Pandemic Sentiment on streaming with Text Mining Python. Herlawati (2020) analyzed the pattern of the spread of Covid-19 using the Support Vector Regression model. Nuraini *et al.* (2020) conducted endemic-based simulation of Covid-19 modeling in Indonesia at the beginning of the emergence of Covid-19 in Indonesia using the Richards Curve. Parhusip (2020) tracing the spread of Covid-19 in the world and Indonesia with the SVM, Bayesian, and Gaussian Regression models. Darmawan *et al.* (2021a) conducted Autocorrelation Analysis of Covid-19 based on Hijri Calendar and the same year, Darmawan *et al.* (2021b) analyzed Covid-19 daily forecasting during Ramadhan in Countries with high muslim population. Utami *et al.* (2022) uses Local Polynomial Kernel Nonparametric, Regression to modeling Covid-19 daily cases in Semarang, Indonesia.

Other research studies on Covid-19, including in the field of religion (Arifin, 2020), examine a new phenomenon in pesantren by online reading. Hutahaen *et al.* (2020) conducted a survey of 100 congregants about worship at church, 25 out of 100 people expect live streaming services during the pandemic.

From the above research studies, especially researchers who involve statistical aspects, the models that are commonly used are for continuous data. Covid-19 data, as we know, is discrete data. In this study, the authors tried to model the time series data from Covid-19 in Indonesia using various time series models based on discrete data. The time series model used is a time series model for this discrete data, namely, Feed Forward Neural Network (FFNN) (Suhartono,2007), Error, Trend and Seasonal (ETS), Singular Spectrum Analysis (SSA), Fuzzy Time Series, Generalized Autoregression Moving Average (GARMA) and Bayesian Time Series. By using this model, it is expected to provide accurate forecasting results.

2. TIME SERIES MODEL

2.1. Feed Forward Neural Network (FFNN)

In statistical modeling, FFNN can be viewed as a flexible class of non-linear functions. In general, this model works by accepting a vector of input x and then calculating a response or output by processing (propagating) x through the process of interrelated elements (Fig.1).

$$\hat{y}(k) = f^0 \left[\sum_{j=1}^{q} \left[w_j^0 f_j^h \left(\sum_{i=1}^{p} w_{ji}^h x_{i(k)} + b_j^h \right) + b^0 \right] \right] \tag{1}$$

where $x_{i(k)}$ is input variable as much as p, $(j = 1,2,\ldots p), \hat{y}_{(k)}$ is the estimated value of the output variable, K Input-target data pair index $(x_{i(k)}, y_{(k)}), k = 1,2,\ldots.,n$; w_{ji}^h is the weight of the i-th input to the j-th neuron in the hidden layer, $(j = 1,2,\ldots q), b_j^h$ is bias to the j-th neuron in the hidden layer, $(j = 1,2,\ldots,q), f_j^h$ is the activation function in the j-th neuron in the hidden layer, w_j^o is the weight of the j-th neuron in the hidden layer leading to the neuron in the output layer, b^o bias in neurons in the output layer, f^o the activation function of neurons in the output layer.

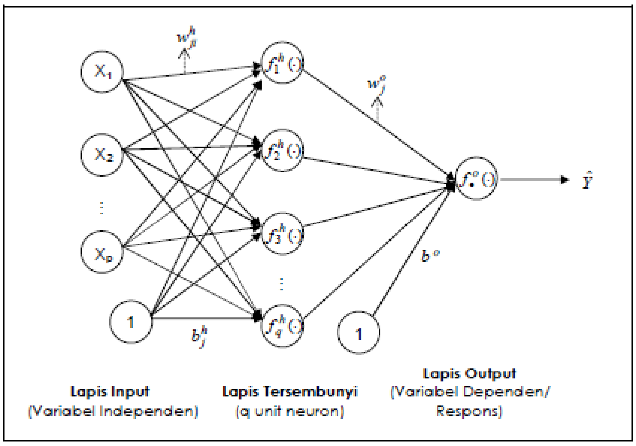

Figure 1: FFNN architecture with one hidden layer, p input units, q neuron units (Source: Ph.D. Thesis of Suhartono)

2.2. Exponential Smoothing Model with State Space Approach

This model was developed by (Hyndman, 2008), which is a development of the exponential smoothing model commonly known as ETS (Error Trend and Seasonal). In this model, the trend and seasonal components are described in more detail. The trend is divided into 5 categories; N (None), A (Additive), Ad (Additive Damped), M (Multiplicative), and Md (Multiplicative Damped) while the seasonal components are divided into N (None), A (Additive) and M (Multiplicative).

The exponential model with the state space approach as a whole is divided into 30 models. The general model involves a state vector and its state space equation has the following equations:

$$\begin{aligned} y_t &= \omega(x_{t-1}) + r(x_{t-1})\varepsilon_t \\ x_t &= f(x_{t-1}) + g(x_{t-1})\varepsilon_t \end{aligned} \tag{2}$$

where $\{\varepsilon_t\}$ is *Gaussian White noise* with variance $\sigma^2$and $\mu_t = \omega(x_{t-1})$.

To write an equation, definition, theorems, picture, table, etc., authors should follow the following format.

2.3. Singular Spectrum Analysis (SSA)

SSA is a flexible time series model because it is included in the nonparametric class (Golyandina and Korobeynikov, 2014). The SSA modeling procedure consists of Embedding, Singular Value Decomposition, Grouping, Diagonal Averaging, and forecasting (Golyandina *et al.*, 2013).

In the Embedding stage, the Covid-19 univariate data is converted into a $K \times L$ sized matrix with L = T-K + 1, L is known as the Length Window (2 <L <T / 2). The matrix formed is commonly known as the Trajectory Matrix or Trajectory Matrix. While the Singular Value Decomposition stage determines the Triple Eigenvalue of the matrix, where X is the Path Matrix. Furthermore, the triple Eigen formed were grouped by.

The third step is Diagonal Averaging. In this step, the multivariate data is returned to univariate with the equations:

$$y_k = \begin{cases} \frac{1}{k}\sum_{m=1}^{k} y^*_{m,k-m+1} & for 1 \le k < L^* \\ \frac{1}{L^*}\sum_{m=1}^{L^*} y^*_{m,k-m+1} & for L^* \le k \le K^* \\ \frac{1}{T-k+1}\sum_{m=k-K^*+1}^{T-K^*+1} y^*_{m,k-m+1} & for\ K^* < k \le T \end{cases} \tag{3}$$

The next step is to forecast using the Linear Recurrent Formula (LRF) in the following steps:

1. Result data in step *Diagonal Averaging* $Y_{T+M} = (y_1, y_2, \ldots, y_{T+M})$ stated as follows:

$$y_i = \begin{cases} \tilde{x}_i & for\ i = 1, \ldots, T, \\ \sum_{j=1}^{L-1} a_j y_{i-j} & for\ i = T+1, \ldots, T+M \end{cases} \tag{4}$$

2. Series $y_{T+1}, \ldots, y_{T+M}$build M *recurrent forecast* with coefficients $\{a_j, j = 1, \ldots, L-1\}$.

2.4. Fuzzy Time Series

The Fuzzy Time series model was first developed by Song & Chissom (1993), now this model is further developed by (Chen, 1996) and (Singh, 2008) until the R package about the Fuzzy Time Series appears. Fuzzy logic works by mapping the degree of membership of a value which is then used to determine the results to be generated based on predetermined specifications.

Procedures of the *forecast* by *Fuzzy Time Series Chen*:

1. Find the set U from the time series data.
   $U = [U_{min}, U_{max}]$
   with U_{min} is the smallest data and U_{max} is the highest data.
2. Determine the width of the interval with the frequency distribution.
3. A fuzzy set is formed by looking at the number of different frequencies, then the first most frequencies are divided into h equal intervals.

4. Define the fuzzy set A_i and perform fuzzification on the actual observed data, for example, A_1, A_2, …, A_p.
5. Define the set A_1, A_2, …, A_p fuzzy for U.

$$A_1 = 1u_1 + 0.5u_2 + 0u_3 + \ldots + 0u_p$$
$$A_2 = 0.5u_1 + 1u_2 + 0.5u_3 + \ldots + 0u_p$$
.
.
$$A_p = 0u_1 + 0u_2 + 0u_3 + \ldots . + 0.5u_{p-1} + 1u_p$$

6. Creating tables of Fuzzy Logical Relationship (FLR) based on actual data. FLR can be denoted by $A_i \rightarrow A_j$, where A_i is called the current state and Aj is called the next state.
7. Determine the weight of the FLR relation to be Fuzzy Logical Relationship Group (FLRG) by including all relationships (all relationships) and assigning weights based on the same sequence and iteration.
8. Transfer the FLRG weight into the form of a standardized weighting matrix.
9. Determine the predictive value defuzzification with the following equation

$$F_i = w_{i1} \times m_1 + w_{i1} \times m_2 + \ldots . + w_{ip} \times m_p \tag{5}$$

where F_i is *forecast*, m_i is the middle value, and w^* is the standardized weight matrix

2.5. GARMA (Generalized Autoregressive Moving Average)

The GARMA model is an extension of the ARIMA model (Zeger and Qaqish, 1988) and (Benjamin, 2003), in contrast to the ARIMA model the GARMA model can be used for Count data such as the case that occurred in Covid-19. This model expands the univariate Gaussian ARMA demonstrate to an adaptable observation-driven show for non-Gaussian time arrangement permitting to demonstrate continuous and discrete time series data (Albarracin *et al.*, 2019). GARMA (p, q) was first defined as having a response which is an Exponential family as follows

$$f(yt|D_t) = exp\left\{\frac{y_t\theta_t - b(\theta_t)}{\frac{\phi}{A_t}} + c\left(y_t, \frac{\phi}{A_t}\right)\right\} \tag{6}$$

where θ_t and $\phi$are canonic parameter and scale parameter and A_t is a prior weight that is known. $\mu_t = E(Y_t|D_t) = b'(\theta_t)$is a predictor of $\eta_t$with *link function g*. Here, $D_t = \{x_t, \ldots, x_1, y_{t-1}, \ldots, y_1, \mu_{t-1}, \ldots, \mu_1\}$ is the *set of previous information*. The GARMA model transforms into

$$g(\mu_t) = \eta_t = x_t^T\beta + \sum_{k=1}^{p}\phi_k\left(g(y_{t-k}) - x_{t-k}^T\beta\right) + \sum_{k=1}^{q}\theta_k\left(g(y_{t-k}) - \eta_{t-k}\right)$$

where β, θ, and ϕ are parameters of GARMA Which are estimated by the *Maximum Likelihood method*.

2.6. Bayesian Time Series

The Bayesian Time-series mathematical model (Taylor *et al.*, 2011), has a basic model

$$y_{t,j} = Z_t^T\alpha_t + \beta^T x_{t,j} + \varepsilon_{t,j} \tag{7}$$

This model is a regression model. This model allows using non-Gaussian error families in the formula there are four choices of Gaussian, Logit, Poisson, and Student. This model can involve the variable predictor or not, if it does not involve the predictor variable then this model becomes an ordinary state space time series model. This model cannot be used for missing value data for predictors but allows missing value for the response variable.

3. DATA OF COVID-19

Covid-19 data is discrete data (Count data) consisting of data on patients with Covid-19 (Confirmed Cases), recovered patients (Recovered Cases), and patients who died from covid-19 (Deaths Cases). The government continues to announce the three data, while the overall data can be seen on the official website of Covid-19 in Indonesia.

4. COVID-19 DATA ANALYSIS

In this section, covid-19 data is analyzed using R software by involving several packages to run time series models. The analysis is carried out per day (daily forecast) starting from March 2020 to May 2021.

The R package used in this analysis are:

1. *Rssa*. This package is used to run the Singular Spectrum Analysis (RSSA) Model.
2. *AnalyzeTS*. This package is used to run *Fuzzy Time Series* Model.
3. *Tswge*. This package is used to run GARMA (*Generalized Autoregressive Moving Average*) Model.
4. *Bsts*. This package is used to run the *Model of Bayesian Time Series*
5. *Forecast*. This package is used to run the Exponential Smoothing Model with the State-space (ETS) approach and the Feed Forward Neural Network (FFNN) Model.

Evaluation of the forecasting results used Mean Absolute Percentage Error (MAPE) with the following equation

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{F_i - X_i}{X_i}\right| \times 100\% \tag{8}$$

4.1. Analysis of Confirmed Cases

The Confirmed Cases Forecast was carried out for 12 days starting from day 430 to day 441 for the six models, the MAPE results can be seen in table 1.

Table 1. Forecast accuracy for COVID-19 confirmed cases data from Day 430 to Day 441

Day	FFNN	ETS	SSA	FTS	GARMA	Bayes_TS
D-430	0.01	0.02	0.01	0.10	0.04	0.06
D-431	0.03	0.01	0.00	0.02	0.09	0.02
D-432	0.09	0.05	0.06	0.01	0.06	0.04
D-433	0.08	0.04	0.06	0.07	0.04	0.01
D-434	0.07	0.07	0.14	0.13	0.12	0.13
D-435	0.01	0.03	0.04	0.11	0.03	0.05
D-436	0.01	0.00	0.02	0.07	0.13	0.01
D-437	0.02	0.04	0.05	0.05	0.01	0.03
D-438	0.10	0.12	0.12	0.04	0.08	0.07
D-439	0.11	0.12	0.11	0.02	0.09	0.04
D-440	0.03	0.08	0.11	0.05	0.04	0.02
D-441	0.04	0.00	0.03	0.08	0.02	0.04
MAPE	0.05	0.05	0.06	0.06	0.06	0.04

Table 1 reveals the MAPE value for twelve-step-ahead prediction performances (day 430 to day 441) for proposed models. The Bayes Model shows the smallest Average MAPE value which is 0.04% then the FFNN and ETS models are 0.05% and the largest is The SSA, GARMA, and FTS models are 0.06%. Meanwhile, if seen from the number of forecasting results that are fit (MAPE = 0%), then the ETS Model is at most 2 pieces (days), namely day 436 and day 441. These findings successfully delight the short term forecasting of COVID-19 confirmed cases up to 12 days ahead. However, it can be seen that overall MAPE is still around 0-6% indicating very close to the real data. For this reason, we still suggest the same probability of all proposed models to predict better for short horizon for Indonesia COVID-19 case. Therefore, bayes model performs the best among others.

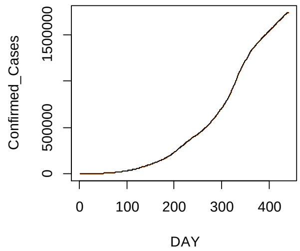

Figure 2.a. Plot of *Confirmed Forecast* Until D- 441

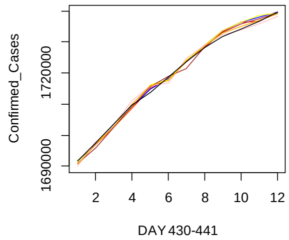

Figure 2.b. Plot of *Confirmed Forecast* from D- 430 to D-441

Plots are differentiated based on the forecast color of the FFNN Model in red, ETS is blue, SSA is yellow, FTS is pink, GARMA is brown, Bayes_TS is orange, and black is the actual data. In general, the model follows the actual data. Figure 2.a.

The values that are under forecast or over forecast that are large enough (above 100) will produce lines that are far from the black line (actual data), from the line in Figure 2.b, it appears that all models have some under forecast or over the forecast.

4.2. Analysis of Recovered Cases

Table 2. Forecast Accuracy for COVID-19 Recovered Cases Data from Day 430 to 441

Day	FFNN	ETS	SSA	FTS	GARMA	Bayes_TS
D-430	0.03	0.07	0.01	0.07	0.07	0.05
D-431	0.00	0.03	0.04	0.07	0.00	0.02
D-432	0.04	0.05	0.05	0.09	0.03	0.01
D-433	0.02	0.01	0.00	0.07	0.05	0.03
D-434	0.08	0.06	0.10	0.04	0.06	0.09
D-435	0.06	0.08	0.12	0.20	0.10	0.09
D-436	0.01	0.01	0.00	0.13	0.13	0.02
D-437	0.06	0.05	0.05	0.01	0.10	0.07
D-438	0.10	0.07	0.06	0.05	0.03	0.07
D-439	0.07	0.08	0.07	0.05	0.01	0.05
D-440	0.03	0.03	0.09	0.09	0.03	0.01
D-441	0.05	0.05	0.00	0.02	0.01	0.03
MAPE	0.05	0.05	0.05	0.07	0.05	0.05

Based on Table 2 above shows the MAPE value for 12 days (day 430 to day 441), the five models namely FFNN, ETS, SSA, GARMA, and Bayes produce the same MAPE value of 5% while the FTS model is 0.07%. Meanwhile, if seen from the number of forecasting results that are fit (MAPE = 0%), the SSA Model is at most 3 pieces (days), namely the 433-rd day, 436-rd day, and 441-st day.

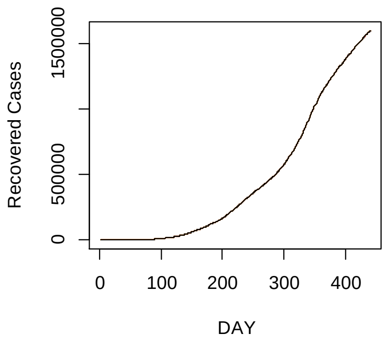

Figure 3.a plot of *Recovered Forecast* until D-441

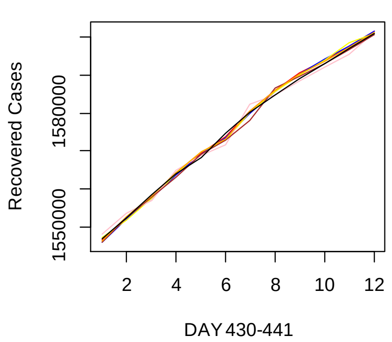

Figure 3.b plot of Recovered *Forecast* from D-430 to D-441

Plots are differentiated based on the forecast color of the FFNN Model in red, ETS is blue, SSA is yellow, FTS is pink, GARMA is brown, Bayes_TS is orange, and black is the actual data. In general, the model follows the actual data. Figure 3.a.

Large enough under forecast or over forecast values will produce lines that are far from the black line (actual data), from the line in Figure 3.b, it appears that all models have some under forecast or over the forecast.

4.3. Analysis of Deaths Cases

Table 3. MAPE Value of Six Models from Day 430 to Day 441 (*Deaths Cases*)

Day	FFNN	ETS	SSA	FTS	GARMA	Bayes_TS
D-430	0.04	0.08	0.01	0.00	0.15	0.10
D-431	0.13	0.09	0.14	0.22	0.07	0.10
D-432	0.03	0.00	0.02	0.06	0.06	0.00
D-433	0.03	0.06	0.04	0.04	0.16	0.03
D-434	0.01	0.05	0.02	0.07	0.04	0.00
D-435	0.07	0.10	0.14	0.07	0.10	0.08
D-436	0.11	0.13	0.10	0.01	0.21	0.13
D-437	0.15	0.09	0.07	0.31	0.08	0.16
D-438	0.14	0.21	0.13	0.05	0.26	0.17
D-439	0.07	0.13	0.05	0.07	0.03	0.03
D-440	0.00	0.01	0.03	0.07	0.16	0.06
D-441	0.14	0.10	0.05	0.08	0.04	0.00
MAPE	0.08	0.09	0.07	0.09	0.11	0.07

Based on Table 3 above shows the MAPE value for 12 days (day 430 to day 441), the best model is SSA and Bayes produces the same MAPE value of 0.07% while the FFNN model is 0.08%. Likewise, when viewed from the number of fit forecasting results (MAPE = 0%), then the Bayes Model is at most 3 pieces (days), namely the 432nd day, 434th day, and 441st day.

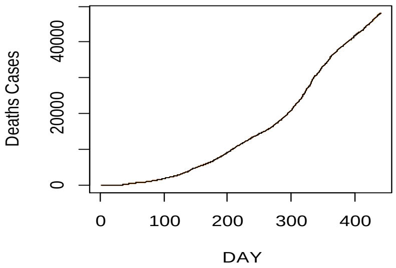

Figure 4.a. Plot of D*eaths Forecast* until D-441

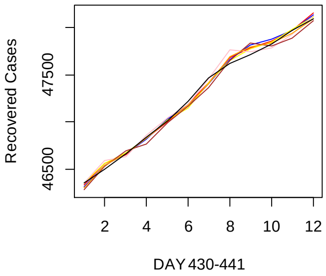

Figure 4.b. Plot of Deaths *Forecast* from D-430 to D-441

Plots are differentiated based on the forecast color of the FFNN Model in red, ETS is blue, SSA is yellow, FTS is pink, GARMA is brown, Bayes_TS is orange, and black is the actual data. In general, the model follows the actual data. Figure 4.a.

The values that are under forecast or over forecast that are large enough will produce lines that are far from the black line (actual data), from the line in Figure 4.b, it appears that all models are good enough, following the movement of the actual data.

5. CONCLUSION

The best model in the forecast for Data Confirmed cases is the Bayesian Model with a MAPE of 0.04%. For Data Recovered cases all models are quite accurate to produce MAPE 0.05% except FTS 0.07%. The two best models in the forecast for Data Deaths cases are the Bayesian Model and SSA with a MAPE value of 0.07%. In general, all the models used in this study are quite accurate in modeling covid-19 data in Indonesia.

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