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COVID-19 Case Growth Prediction Using a Hybrid Fuzzy Time Series Forecasting Model and a Machine Learning Approach

UKY YUDATAMA[1], SOLIKHIN[2], DWI EKASARI HARMADJI[3], AGUS PURWANTO[4]
[1]Department of Informatics Universitas Muhammadiyah Magelang Magelang, Indonesia
[2]Department of Informatics Engineering STMIK Himsya Semarang, Indonesia
[3]Department of Accounting Universitas Wisnuwardhana Malang, Indonesia

Corresponding author: Solikhin (Solikhin@stmik-himsya.ac.id).

ABSTRACT The COVID-19 pandemic has evolved into a global health crisis, with Indonesia particularly affected due to its high death rates compared to the rest of Asia. A significant number of unacknowledged, undocumented, or unaddressed cases further exacerbate the situation in Indonesia. Challenges arise from the growing patient population and a scarcity of resources, medical experts, and facilities. This study analyzes the daily development of COVID-19 cases in Indonesia, aiming to estimate the number of confirmed cases, recoveries, and fatalities. Introducing a novel hybrid forecasting model, we utilize the Holt-Winter triple exponential smoothing statistical method and the fuzzy time series rate of change algorithm. We apply the Triple Exponential Smoothing Holt Winter statistical model to predict future periods to the fuzzy time series. Based on the testing results, our proposed hybrid forecasting model demonstrates a very high level of predictive capacity. The acquired data are highly accurate, with a 0.15 percent confirmation rate, 0.15 percent recovery rate, and a 0.20 percent mortality rate, along with an average absolute error of less than 10% for each COVID-19 case. The findings indicate that early awareness by the COVID-19 Task Force of the status of cases is highly advantageous. This awareness can aid in formulating appropriate policies for future planning, organization, and accelerated treatment of COVID-19 in Indonesia. Consequently, successful efforts can be made to slow the emergence and spread of COVID-19 in the country.

KEYWORDS component; COVID 19; Forecasting; Fuzzy Time Series; Rate of Change; Triple Exponential Smoothing

I. INTRODUCTION

THE new coronavirus, COVID-19, has spread globally, prompting the World Health Organization (WHO) to classify it as a pandemic. Many countries witnessed a surge in COVID-19 infections from January to December of this year.

The virus was first reported to have started spreading in Wuhan, China, around mid-December 2019 [1]. On March 2, 2020, COVID-19 was identified in two cases in Indonesia [2]. By March 31, 2020, the country had confirmed 1,528 cases, with 81 recoveries and 136 deaths [3]. Subsequently, COVID-19 spread rapidly, reaching practically every part of Indonesia within a few months. Consequently, the number of people infected with COVID-19 increased, along with the number of fatalities.

The new coronavirus exhibited significant changes in its growth pattern, posing a threat due to the absence of a vaccine in Indonesia and worldwide. Consequently, COVID-19 mobility peaked in Indonesia, contributing to a death rate of 3.33%, surpassing the global average of 2.47% [4]. This trend was observed not only in Indonesia but also in Asia, North America, and Europe.

COVID-19 has become a global health problem, with Indonesia standing out as one of the countries in Asia with the highest death rate. The issue is further compounded by the number of undetected, unreported, and unaddressed cases in the country. Indonesia faces challenges in dealing with an increasing number of patients, coupled with a shortage of facilities, equipment, and medical workers.

To prepare for an increase in COVID-19 cases and deaths, estimating the number of illnesses and deaths is crucial for planning future actions and medical infrastructure.

We are particularly interested in making predictions in this study based on the issues raised above. How can we make predictions about the progression of COVID-19 cases (confirmed, recovered, and died) in Indonesia, given the formulation of the problem?

Making forecasts about the future is crucial for today's planning and strategy. This can be accomplished by accurately and realistically examining information that has surfaced from the past to the present. Time series analysis is another term for this. This makes it possible for management and administration to make informed choices.

For time series analysis, several forecasting model techniques have recently been proposed in the literature and have grown in popularity. For the fuzzy time series forecasting model, there are no assumptions that must be made.

On the other hand, because of the uncertainty they contain, the majority of time series observed in real life should be investigated using models that are pertinent to fuzzy set theory. In systems based on fuzzy set theory, uncertainty is modeled using membership values. Membership values are derived from a model's input using membership functions. Techniques based on fuzzy set theory use membership values derived from the raw data to model the uncertainty present in the data rather than to use the raw data itself. Fuzzy logic-based methods have a significant advantage over other methods, such as neural networks, because they can model uncertainty using membership values. Due to the nature of these methodologies, fuzzy logic-based approaches may perform better than other soft computing methods like artificial neural networks when dealing with uncertainty.

Your passage provides a thorough overview of the fuzzy time series technique and its application to various domains, including COVID-19 prediction. Here are a few suggestions for further clarity and coherence:

In a significant body of research, Song and Chissom [5] introduced the fuzzy time series (FTS) technique, grounded in Zadeh's [6] fuzzy set theory. Existing literature primarily focuses on solving time-invariant fuzzy time series, as categorized by Song and Chissom [7, 8] into time-variant and time-invariant groups.

Jiang [9] demonstrated the potential to forecast future tourist arrivals in China using FTS and sophisticated optimization algorithms. Similarly, stock index forecast precision can be enhanced with a novel weighted fuzzy trend time series method [10]. Additional studies emphasized the influence of effective interval length on fuzzy set generation [11, 12] and its impact on constructing fuzzy relationships [13-16].

The year-to-year percentage change is proposed as a key consideration in fuzzy time series by Stevenson and Porter [17] and Solikhin et al. [18]. Jilani [19] proposed a strategy based on partitioning past enrollment data using frequency densities, employing a time-variant, kth-order technique that outperforms current methods in enrollment prediction. Garg [20] developed a novel computational FTS model for predicting the number of outpatient visits.

Building upon these findings, we recommend a novel forecasting strategy that utilizes information from multiple angles. Employing FTS, we estimate and forecast the number of COVID-19 cases in Indonesia, integrating the Triple Exponential Smoothing (TES-Holt) statistical technique and the Rate of Change (RoC) algorithm. In this approach, Holt's TES is utilized to forecast the upcoming era using FTS as the universe collection. This ideal solution combines Holt's TES modeling with FTS modeling.

Our suggested discretization algorithm [20], incorporating an event-distribution strategy and a fresh interval-splitting method, enhances the forecast by favoring historical evidence. By processing earlier time series RoC data separately, inaccurate predictions are reduced, and seasonal tendencies are identified. The novel frequency-based partitions outperform traditional models in mathematics with various data frequencies.

This study suggests that incorporating all the aforementioned parameters improves the approximation. The Mean Absolute Percentage Error (MAPE) of our suggested model is considerably lower than the strategy proposed by Garg [20] in a study using the same patient data.

Given the evolving COVID-19 situation in Indonesia, we propose a hybrid forecasting model that combines the Triple Exponential Smoothing Holt Winter (TES-HW) statistical technique with the rate of change approach of fuzzy time series (FTS). To our knowledge, no studies have explored our proposed hybrid model for COVID-19 prediction, distinguishing it from earlier hybrid prediction models.

The objectives of this study include, among other things, (a) COVID-19 case analysis and forecasting in Indonesia (confirmed, recovered, and death); and (b) the implementation of a novel hybrid forecasting model for predicting the development of COVID-19 cases in Indonesia.

Despite its simplicity, the newly proposed hybrid model has demonstrated higher accuracy and a lower error rate, as indicated by performance test findings. In this study, our primary objective is to explore how our innovative hybrid forecasting model can be effectively utilized to anticipate the future development of COVID-19 cases in Indonesia over the next few years. We aim to assess the accuracy and percentage of mistakes associated with this new hybrid forecasting model.

The anticipated results of this research carry the potential to make a significant contribution, particularly in advancing a novel combination of prediction model concepts that are more effective and accurate. We envision that these findings can be instrumental for government entities, specifically the Task Force for the Acceleration of COVID-19 Case Handling. The utilization of our model may aid in early determination and strategic planning for the development of COVID-19 cases, providing valuable insights for effective decision-making and proactive measures.

II. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

Many mathematical models have been recently developed to aid in COVID-19 prediction. Machine learning algorithms employed by Satrio et al. [21] analyze time series data to predict illnesses induced by the coronavirus. Researchers in Indonesia use ARIMA and PROPHET models, along with other methods, to anticipate disease patterns in the country. Wahyuni et al. [22] utilized several linear regression models to project the future of COVID-19 in Indonesia.

Forecasting the COVID-19 pandemic in South Sulawesi, Indonesia, is possible using the Richards model proposed by Zuhairoh and Rosadi [23]. Sreeramula and Rahardjo [24] generated real-time estimates of COVID-19 from the perspective of Indonesian health policy.

Gunawan et al. [25] employed the Susceptible Infected Recovered Deceased (SIRD) model to calculate the impact of social distancing on COVID-19 in Jakarta. Wirawan and Januraga [26] developed the SEIR (Susceptible, Exposed, Infected, Recovered) model of COVID-19 to predict the spread and assess healthcare services in Bali, Indonesia.

Using this model, the way diseases spread now is compared to how they would spread in different situations. Djalante et al. [27] suggested a review and analysis of the current response to COVID-19 to offer thorough reporting and analysis of the quick response to COVID-19.

Anam et al. [28] state that other researchers used a backpropagation neural network and the Fletcher-Reeves method to figure out the effect the COVID-19 outbreak in Indonesia had on the number of COVID-19 patients in Malang.

Rasjid et al. [29] utilized long-short-term memory (LSTM) neural networks and time series smoothing to compare how well they predicted death and infection in COVID-19 patients in Indonesia.

Rendana and Idris [30] developed an algorithm to figure out how common COVID-19 and the new variant B.1.1.7 are by using ARIMA and Spearman correlation analysis. They looked at meteorological data to see if the unique variety B.1.1.7 was prevalent in three Indonesian provinces: West Java, South Sumatra, and East Kalimantan.

Swaraj et al. [31] made and tested a stacking-based ARIMA model for predicting COVID-19 cases in India. Alzahrani et al. In [32], it is mentioned that the ARIMA prediction model has been used to predict how the COVID-19 pandemic will spread in Saudi Arabia as part of ongoing public health efforts.

Arun Kumar et al. [33] used the ARIMA and SARIMA models to figure out how the number of confirmed, recovered, and dead COVID-19 cases had changed over time for the top 16 countries.

COVID-19 deaths in the US were projected using a probabilistic model presented by Taylor and Taylor [34]. Utilizing a nationwide infrastructure for real-time patient-level data, Simpson et al. [35] mined and predicted COVID-19 hospitalizations and fatalities in Scotland.

A new hybrid fuzzy time series model by Kumar and Kumar [36], making use of modified fuzzy C-means clustering, can forecast the number of COVID-19 cases and fatalities in India in the future. Algorithms for clustering COVID-19 data were developed by Afzal et al. [37].

Iloanusi and Ross [38] estimated COVID-19 case-to-death rates using meteorological data. Pincheira-Brown and Bentancor [39] proposed estimating COVID-19 infection cases using a semi-infinite general growth model. Atchadé and Sokadjo [40] reviewed and cross-validated the COVID-19 forecasting univariate model.

Using a deep learning model, Masum et al. [41] developed a continuous prognostic strategy for the COVID-19 outbreak in Bangladesh, which was then validated. Ayoobi et al. [42] also anticipated the number of new cases and the new death rate for COVID-19 over time using a deep learning-based method.

Talkhi et al. [43] established a method for modeling and estimating the number of confirmed illnesses and deaths brought on by COVID-19 in Iran by contrasting time series forecasting approaches.

III. METHODOLOGY

Figure 1 illustrates the various stages of this research, encompassing data collection, data preparation, application of the prediction model, and accuracy testing.

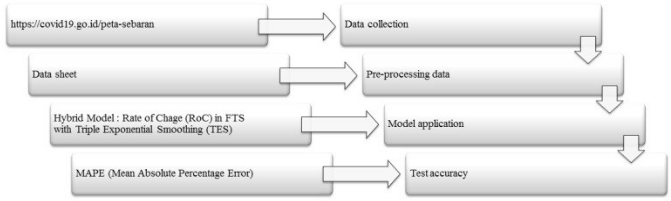

Figure 1. Research Stage.

The website of the Task Force for the Acceleration of COVID-19 Processing in Indonesia accepts data submissions in the xlsx format, utilizing digital data documents downloaded from official publications. This study specifically focuses on the evolution of three COVID-19 case stages: confirmation, recovery, and death. Data was collected between November 1, 2020, and October 31, 2021.

The data in xlsx format undergoes processing to eliminate missing values. Subsequently, adjustments are made to the data sheet column structure as needed, the data is converted to numeric type, and a stationarity test is conducted to ensure data stability without any noticeable increase or decrease.

To implement the proposed hybrid forecasting model, a machine-learning approach is employed. The prediction procedure of this model is detailed in multiple steps, as illustrated in Figure 2.

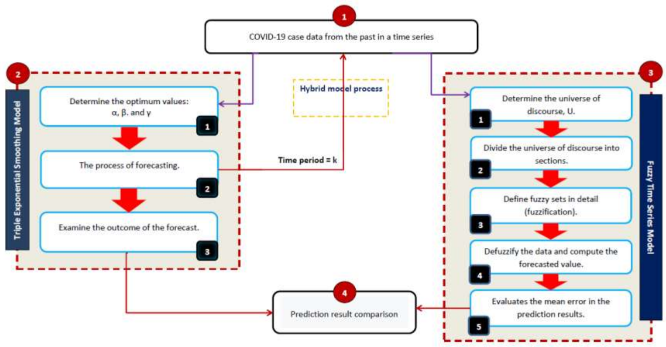

Figure 2. A Novel Hybrid Model for Predicting COVID-19 Case Development

A. DEFINING COVID-19 CASE DATA

The COVID-19 case data is represented as a time series using the formula X = ($x1$, $x2$, $x3$, ..., xn), where numbers track the daily rise of COVID-19 cases in Indonesia from November 1, 2020, to October 31, 2021. Secondary data was compiled from official sources processed and published by the government's Task Force for the Acceleration of COVID-19 Handling, accessible via the official website at https://covid19.go.id/peta-sebaran. We assert the validity and reliability of this secondary data for the purposes of our study.

In this research, time series data for confirmed cases (X) includes {2696, 2618, 2973, 3356, 4065, 3778, 4262, 3880, 2853, 3779, ..., 523}. Recovered cases (X) are represented by {4141, 3624, 3931, 3785, 3860, 3563, 3712, 3881, 3968, 3475, ..., 497}. Similarly, death cases (X) are documented as {74, 101, 102, 113, 89, 94, 98, 74, 75, 72, ..., 17}. This information is visually presented in Figure 3.

B. TRIPLE EXPONENTIAL SMOOTHING MODEL

Step 1: Determine the optimal values for the parameters α, β, and γ.

The Holt-Winter Triple Exponential Smoothing (TES) technique, suitable for data with trend and seasonal patterns, requires the careful determination of parameters α, β, and γ for accurate predictions. As misjudging these parameters can lead to imprecise forecasts, a trial procedure is imperative to obtain optimal values. Despite the examination of 729 potential combinations within the 0 to 1 range, the sequential testing process becomes less efficient and time-consuming. To streamline this, users can employ a solver to determine the most favorable values for α, β, and γ, typically based on historical data.

Step 2: The process of forecasting.

The estimation procedure makes use of the statistical technique known as Triple Exponential Smoothing, as specified in equation 1, ..., 11.

$$Lt = \alpha \left({}^{Yt}/_{S(t-m)} \right) + (1-\alpha)\big(L(t-1) + T(t-1)\big), \quad (1)$$

$$Tt = \beta\big(Lt - L(t-1)\big) + (1-\beta)\, T(t-1), \quad (2)$$

$$St = \gamma \left({}^{Yt}/_{Lt} \right) + (1-\gamma) S(t-m), \quad (3)$$

$$F(t+k) = (Lt + k * Tt) * S(t-m+k). \quad (4)$$

Here, L represents an estimate of the level (influenced by parameter α), T is an estimate of the trend (influenced by parameter β), and S is an estimation of seasonality (influenced by parameter γ). The value of the measurement or observation at time point t is denoted by Yt, F represents the forecasted value for the upcoming period, and the variable k represents the number of steps ahead in time forecasting.

For the specific case when M (the number of periods in a season) equals 4 (quarterly):

$$S1 = Y1/average\ (Y1, Y2, Y3, Y4); \quad (5)$$

$$S2 = Y2/average\ (Y1, Y2, Y3, Y4); \quad (6)$$

$$S3 = Y3/average\ (Y1, Y2, Y3, Y4); \quad (7)$$

$$S4 = Y4/average\ (Y1, Y2, Y3, Y4); \quad (8)$$

$$L5 = Y5\ /\ S1; \quad (9)$$

$$T5 = Y5/S1;\ Y4/S4. \quad (10)$$

Use equation 11 for seasonal value:

$$S5 = \gamma\ (Y5\ /\ L5)\ + (1-\gamma)\ S\ (5-4). \quad (11)$$

Here, S1 represents the seasonal value for the first time point, S2 for the second time point, S3 for the third time point, S4 for the fourth time point, and S5 for the fifth time point.

Similarly, Y1, Y2, Y3, Y4, and Y5 represent the measurement or observation values at the first, second, third, fourth, and fifth time points, respectively.

Table 2. Calculation for RoC

X	Date	Confirmed		Recovered		Death	
		Time Series Data	RoC	Time Series Data	RoC	Time Series Data	RoC
X1	11/01/2020	2696	-	4141	-	74	-
X2	11/02/2020	2618	-2.89	3624	-12.48	101	36.49
X3	11/03/2020	2973	13.56	3931	8.47	102	0.99
X4	11/04/2020	3356	12.88	3785	-3.71	113	10.78
X5	11/05/2020	4065	21.13	3860	1.98	89	-21.24
X6	11/06/2020	3778	-7.06	3563	-7.69	94	5.62
X7	11/07/2020	4262	12.81	3712	4.18	98	4.26
X8	11/08/2020	3880	-8.96	3881	4.55	74	-24.49
X9	11/09/2020	2853	-26.47	3968	2.24	75	1.35
...	...	...	...	...	...	...	...
X365	10/31/2021	523	-15.65	497	-28.8	17	-37.04

C. HYBRID MODEL PROCESS

The forecasting process employs a hybrid model. In this combination model for forecasting the t+k period, the statistical method Triple Exponential Smoothing is utilized to generate forecasting data. This generated data then serves as actual data in the prediction process, using a rate of change algorithm approach in the FTS method for forecasting the t+k period, as given in Equation 4.

Step 3: Examine the outcome of the forecast.

The MAPE model is employed to evaluate the effectiveness of various prediction models, including seasonal forecasting models, in this experiment. A smaller MAPE value indicates a more accurate forecasting model [44]. In this study, we utilize the MAPE approach, as outlined in equations 12 and 13.

$$PE_i = \left| \frac{X_i - F_i}{X_i} \right| \times 100\%, \quad (12)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} |PE_i|. \quad (13)$$

The significance of MAPE in prediction lies in its ability to address issues related to interpreting accuracy measures relative to the size of the anticipated value [44], as illustrated in Table 1.

Table 1. MAPE is significance prediction

MAPE	Signification
<10%	excellent predictive ability
10–20%	good predictive ability
20–50%	predictive ability sufficient
>50%	poor predictability

D. FUZZY TIME SERIES WITH RoC MODEL

Step 1: Create a definition for the universe of discourse, abbreviated as U.

In the observation of our algorithm, we define the Rate of Change (RoC) from time t to time t+1 as the set of speech features to be utilized. The RoC of time series data is calculated by applying equation 14, incorporating discretization techniques.

$$RoC_{(t+1)} = \frac{(X_{(t+1)} - X_{(t)})}{X_{(t)}} \times 100, \tag{14}$$

where X(t+1) denotes the value at index time t+1, and X(t) represents the actual value at index time t. RoC stands for the Rate of Change in value between time t and time t+1. The calculated RoC results are presented in Table 2 and graphically illustrated in Figures 5a, 5b, and 5c.

This stage is crucial for precisely assessing the accuracy and inaccuracy of the proposed new hybrid forecasting model's performance. A comprehensive list of references should be placed at the end of the paper, arranged in the order of presentation in the text, with square brackets around the citation numbers.

In alignment with the RoC, the lowest level (LL) and highest level (HL) are determined. The uncertainty (U) can be calculated using equation 15.

$$U = [LL - D_1,\ HL + D_2], \tag{15}$$

where D1 and D2 are integers used to elucidate the universe of discourse, denoted by the symbol U.

For confirmed cases, determined from the RoC data, LL = -44.85 and HL = 103.39, with D1 as -2.15 and D2 as 2.61. Recovered cases yielded LL = -57.11 and HL = 85.93, with D1 = 0.89 and D2 = 0.07. Death cases were determined to have LL = 65.81 and HL = 369.23, with D1 as -2.19 and D2 as 3.77.

Thus, the U definition for confirmed cases is {-47.00, 106.00}, for recovered cases is {-58.00, 86.00}, and for death cases is {-68.00, 373.00}, as seen in Table 5.

Using equation 16, we count the number of class intervals [45] that have occurred thus far.

$$M = 1 + 3{,}3 * \log(n). \tag{16}$$

Here, M represents the total number of intervals, and n is the total amount of RoC data. Given that there are 365 RoC data points for each case (confirmed, recovered, and dead) due to the same factor, the number of intervals can be observed in Table 5.

M=1+3.3*log (365)
M=9.46 ≈ 9

Equation 17 is then employed to determine the length of the distance between two points.

$$L = HL - LL/M, \tag{17}$$

The interval length for confirmed cases is calculated as L = (106.00 – (-47.00)/9 = 17. For recovered cases, the interval length is L = (86.00 – (-58.00)/9 = 16. In death cases, the interval length is L = (373.00 – (-68))/9 = 49. The results of the interval lengths are presented in Table 5.

Thus, the technique yields the same interval length for each case, resulting in the following intervals:

For confirmed cases: u1 = {-47.00, -30.00}, u2 = {-30.00, -13.00}, u3 = {-13.00, 4.00}, u4 = {4.00, 21.00}, u5 = {21.00, 38.00}, u6 = {38.00, 55.00}, u7 = {55.00, 72.00}, u8 = {72.00, 89.00}, and u9 = {89.00, 106.00}.

For recovered cases: u1 = {-58.00, -42.00}, u2 = {-42.00, -26.00}, u3 = {-26.00, -10.00}, u4 = {-10.00, 6.00}, u5 = {6.00, 22.00}, u6 = {22.00, 38.00}, u7 = {38.00, 54.00}, u8 = {54.00, 70.00}, and u9 = {70.00, 86.00}.

For cases of death: u1 = {-68.00, -19.00}, u2 = {-19.00, 30.00}, u3 = {30.00, 79.00}, u4 = {79.00, 128.00}, u5 = {128.00, 177.00}, u6 = {177.00, 226.00}, u7 = {226.00, 275.00}, u8 = {275.00, 324.00}, and u9 = {324.00, 373.00}. The outcomes are presented in Table 6.

Step 2: Depending on the frequency, the intervals in the created universal set U can be separated into various different intervals, as follows:

Determine the frequency by calculating the appropriate RoC at each interval. Based on the frequency of occurrence, divide the interval into several smaller intervals. If the frequency value falls within the range of 0 and 1, the interval is either kept constant or is not subdivided into smaller intervals, depending on the value of the frequency. Specifically, we adopt and modify the proposals of Stevenson and Porter [17], Solikhin et al. [18], Jilani et al. [19], and Garg et al. [20].

The same technique should be applied for the subsequent division of the period.

Step 3: Define fuzzy sets in detail (fuzzification).

A fuzzy set, defined by the divided interval (sub-interval) and RoC fuzzification, is utilized to construct each xi fuzzy set. For instance, the fuzzy set xi embodies the change in linguistic value of RoC over time.

To determine the expected value of the RoC in equation 18, we find the middle point of the interval using the triangle membership function proposed by Jilani et al. [19].

$$FRoC = \begin{cases} \dfrac{1 + 0.5}{\dfrac{1}{a_1} + \dfrac{0.5}{a_2}} & ,if\ j = 1, \\[2ex] \dfrac{0.5 + 1 + 0.5}{\dfrac{0.5}{a_{j-1}} + \dfrac{1}{a_j} + \dfrac{0.5}{a_{j+1}}} & ,if\ 2 \le j \le n-2, \\[2ex] \dfrac{0.5 + 1}{\dfrac{0.5}{a_{n-1}} + \dfrac{1}{a_n}} & ,if\ j = n. \end{cases} \tag{18}$$

Step 4: Defuzzify the data and estimate its value.

Forecasting data $F_{(t)}$ is calculated based on the results of RoC forecasting (F_{RoC}). The $F_{(t)}$ value is determined using equation 19.

$$F_{(t)} = (F_{RoC}/100 * x_{(t-1)}) + x_{(t-1)} \tag{19}$$

In this case, $x_{(t-1)}$ represents the real data up to the time of t-1.

Step 5: Calculate the mean error associated with the predictions, as given in equation 12 and 13.

E. PREDICTION RESULT COMPARISON

A comparison is made at this step based on the examination of the forecast outcomes of each model.

IV. RESULTS

A. TIME SERIES DATA OF COVID-19 CASES

The investigation utilized data on the progression of COVID-19 cases spanning from November 2020 to October 2021. To visually comprehend the pattern of the data under study, it is initially presented graphically in Figure 3. Our findings are derived from daily data on COVID-19 case progression in Indonesia, specifically focusing on confirmed, recovered, and death cases [46]. By concentrating on these observations, we can forecast the subsequent time.

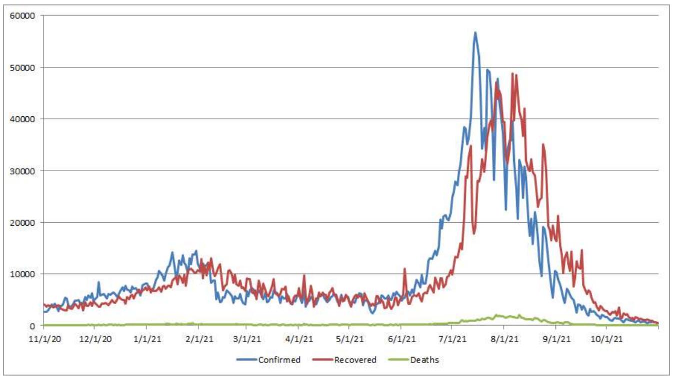

Figure 3. A graph depicting the progression of COVID-19 cases in Indonesia.

For forecasting the next time period, we employ an FTS model with a RoC algorithm that is integrated TES-HW model.

B. TRIPLE EXPONENTIAL SMOOTHING MODEL OUTCOME

This discovery leads to the identification of the optimal alpha, beta, and gamma parameters. According to Holt [47], three variables govern the relative smoothing of recently made observations: Gamma (γ) controls the smoothing for calculating the frequency of seasonal elements, Beta (β) regulates the smoothing for calculating the frequency of trend elements, and Alpha (α) controls the smoothing for calculating the frequency of level or base components.

Wheelwright et al. [48] note that the values of α, β, and γ, ranging between 0 and 1, are chosen either randomly or by minimizing the error value of the estimate. The triple exponential smoothing method utilizes three smoothing constants. Alpha (α) determines the relative smoothing of the observations, Beta (β) controls the smoothing for measuring the emergence of trend components, and Gamma (γ) regulates the smoothing for inferring the occurrence of seasonal components.

In this study, the values of alpha, beta, and gamma were determined through trial and error to minimize the forecasting error value on testing data. Various combinations of alpha, beta, and gamma values employed in this investigation are presented in Table 3. As depicted in Table 3, the Triple Exponential Smoothing model with the optimal parameters (α), (β), and (γ) emerges as the most reliable indicator of COVID-19 disease progression in Indonesia, encompassing confirmed cases, recovered cases, and deaths.

Table 3. Optimal, Alpha, Beta, and Gamma Value Results MAPE's Significance Prediction

Case	Aplha (α)	Beta (β)	Gamma (γ)
Confirmed	0.91	0.03	0.58
Recovered	0.84	0.01	0.14
Death	0.51	0.08	0.13

Figures 4a, 4b and 4c illustrate the outcomes of projecting the progression of COVID-19 instances using the triple exponential smoothing model. These figures depict the prediction results based on the optimal parameters alpha, beta, and gamma from Table 3. Specifically, Figures 4a, 4b, and 4c show how the forecasted results for all COVID-19 cases align with the actual data. In this study, the traditional TES-HW method is used to predict the time period t+1 using the optimal parameters alpha, beta, and gamma, as shown in Table 3. If you apply equations 1, 2, and 3, then for the period of October 31, 2021, confirmed cases, the estimated level value (Lt) is 566.97, the estimated trend (Tt) is -174.77, while the estimated seasonal value (St) is 0.92.

For the recovered cases, the estimated level value (Lt) is 513.39, the estimated trend (Tt) is -90.42, and the estimated seasonal value (St) is 0.99. In the cases of death, the estimated value of the level (Lt) is 19.19, the estimated trend (Tt) is -3.16, and the estimated value of the seasonality (St) is 1.01. Therefore, using equation 4, the projected value for November 1, 2021, is: Confirmed cases: $F_{(\text{Nov 1, 2021})} = (566.97 + 1 * -174.77) * 0.92 = 361$; Recovered cases: $F_{(\text{Nov 1, 2021})} = (513.39 + -90.42) * 0.99 = 441$; Death cases: $F_{(\text{Nov 1, 2021})} = (19.19 + -3.16) * 1.01 = 17$.

With the FTS method and the RoC algorithm, these results are used to make forecasting data that will be used as real data in forecasting.

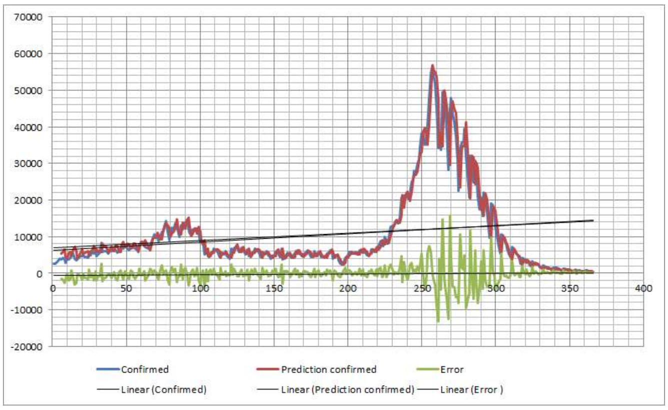

Figure 4a. Graph of forecasting results using TES-HW: confirmed cases

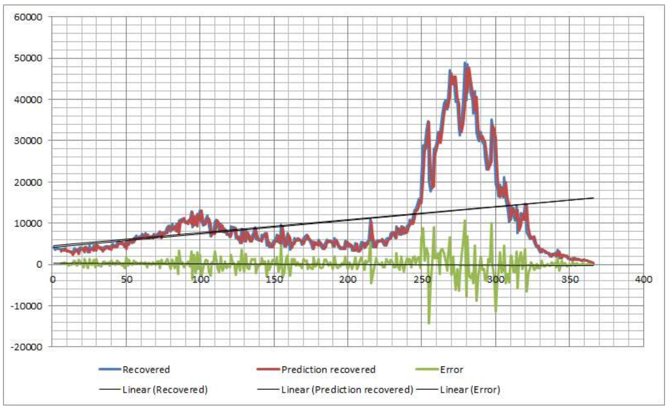

Figure 4b. Graph of forecasting results using TES-HW: case recovered

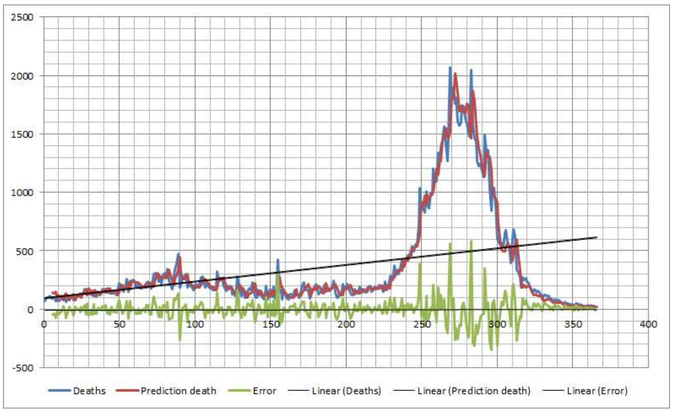

Figure 4c. Graph of forecasting results using TES-HW: death cases

Indices of prediction accuracy are utilized to compare forecasting methods, aiming to identify the method with the smallest forecasting error. The results of the MAPE approach for evaluating prediction performance are presented in Table 4, indicating an accuracy of 0.17% for confirmed cases, 0.16% for recovered cases, and 0.22% for death cases.

Table 4. MAPE Results on TES-HW Model

Confirmed	Recovered	Death
0.17%	0.16%	0.22%

C. FUZZY TIME SERIES WITH ROC MODEL OUTCOMES

Commencing with the data rate of change (RoC) described by equation 14 and visualized in Figures 5a, 5b, and 5c, we can discretize time-series events and define the universe of speech based on the RoC.

The discretization step in fuzzy time series theory serves to reduce the complexity of the discourse universe. This step is instrumental in preparing the discourse universe for numerical assessment by interconnecting instances from various historical periods.

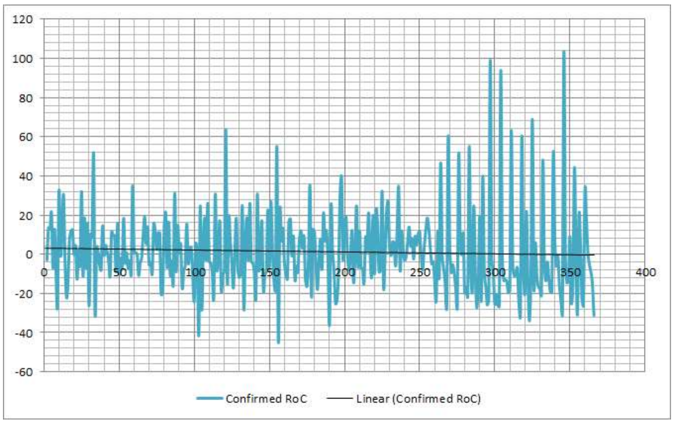

Figure 5a. Graph of the result of calculating the rate of change: confirmed cases

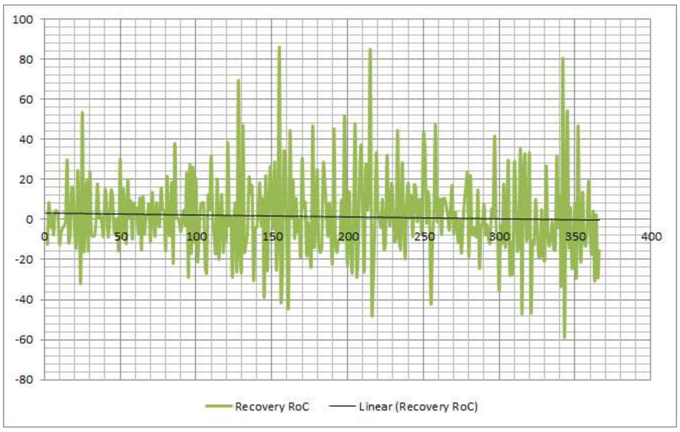

Figure 5b. Graph of the result of calculating the rate of change: case recovered

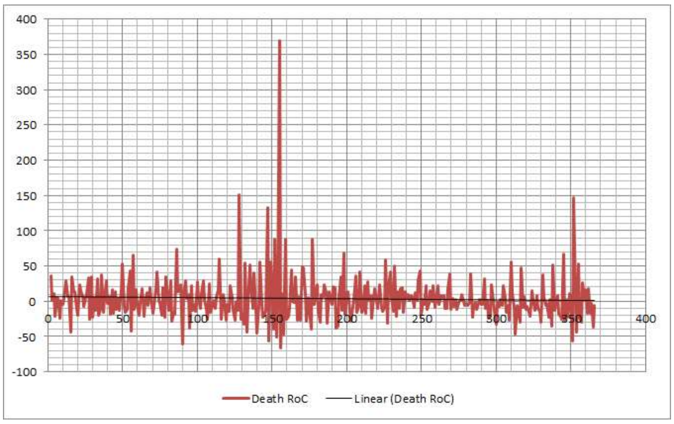

Figure 5c. Graph of the result of calculating the rate of change: death cases

Utilizing the formed RoC results, the initial step in defining the universe U discourse involves equations 15, 16, and 17. This encompasses determining the lowest level (LL) and the highest level (HL), rounding off the number, determining the number of periods, and establishing the length of each interval. Table 5 presents the results of defining the discourse universe U and the frequency of RoC usage.

Tabel 5. The Results in Definition of The Universe of Discourse (U)

U	Confirmed Case		Recovered Case		Death Case	
	Interval	Frequency	Interval	Frequency	Interval	Frequency
U1	{-47.00, -30.00}	9	{-58.00, -42.00}	6	{-68.00, -19.00}	62
U2	{-30.00, -13.00}	71	{-42.00, -26.00}	17	{-19.00, 30.00}	255
U3	{-13.00, 4.00}	150	{-26.00, -10.00}	77	{30.00, 79.00}	41
U4	{4.00, 21.00}	88	{-10.00, 6.00}	139	{79.00, 128.00}	3
U5	{21.00, 38.00}	29	{6.00, 22.00}	75	{128.00, 177.00}	3
U6	{38.00, 55.00}	10	{22.00, 38.00}	33	{177.00, 226.00}	0
U7	{55.00, 72.00}	5	{38.00, 54.00}	13	{226.00, 275.00}	0
U8	{72.00, 89.00}	0	{54.00, 70.00}	2	{275.00, 324.00}	0
U9	{89.00, 106.00}	3	{70.00, 86.00}	3	{324.00, 373.00}	1

After dividing the discourse universe U into equal intervals, such as u1, u2, u3..., un, the interval was then split into a number of sub-intervals based on their numerical frequency. Following are the steps:

calculate the frequencies within each interval using the RoC data; divide the interval into various sub-intervals based on the number of frequencies; depending on whether there are 1 or 0 RoC frequencies, the interval is either fixed or not split.

For instance, considering confirmed cases in Table 5: The interval {-47.00, -30.00} has a frequency of nine, allowing it to be divided into nine sub-intervals. The interval {-30.00, -13.00} can be divided into 71 sub-intervals, and so on.

After forming sub-intervals for each example, the subsequent step is to determine the middle value of each sub-interval and apply the triangular membership function using Equation 18. This function estimates both the predicted RoC and the anticipated progression of COVID-19 situations, categorized as confirmed, recovered, and death.

Figures 6a, 6b and 6c depict the estimated rate of change (FRoC), and calculations in equation 19, as shown in Figure 7, provide estimates for the status of COVID-19 cases, including confirmed, recovered, and death cases. The MAPE of this hybrid model, as shown in Table 6, further evaluates its performance.

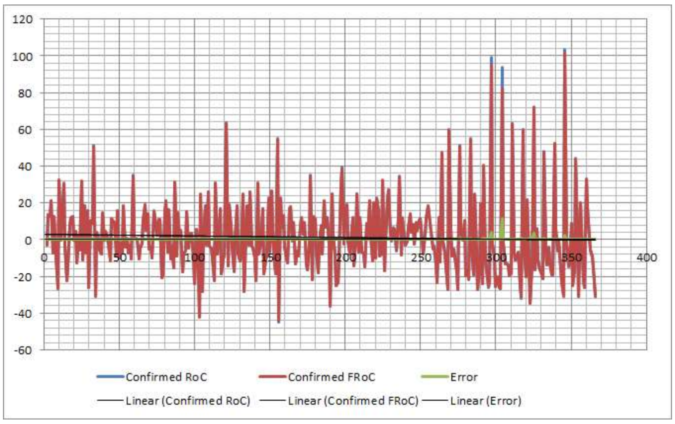

Figure 6a. Graph of the result of forecasting the rate of change (F_{RoC}): confirmed cases

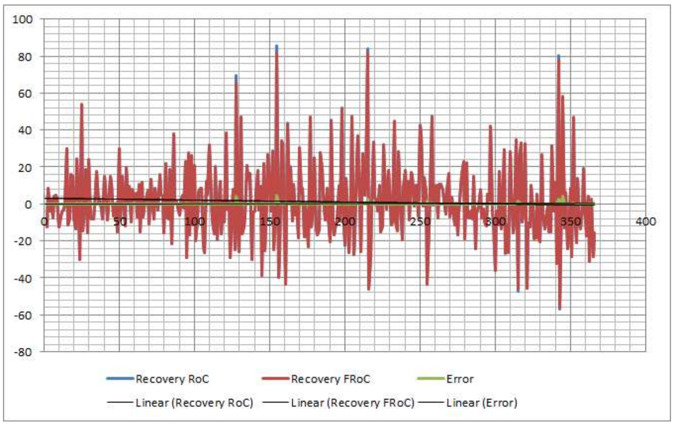

Figure 6b. Graph of the result of forecasting the rate of change (F_{RoC}): case recovered

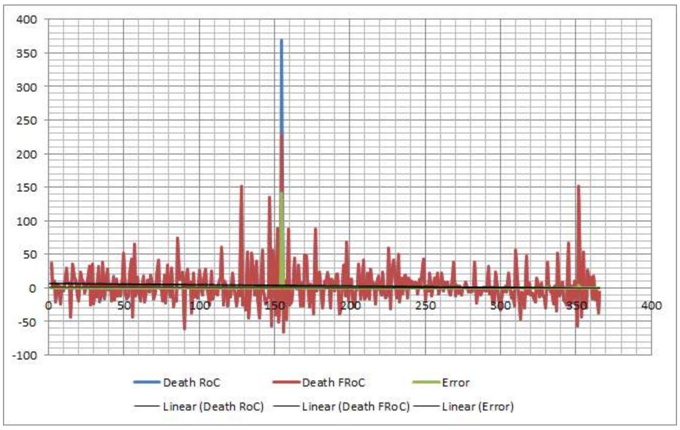

Figure 6c. Graph of the result of forecasting the rate of change (F_{RoC}): death cases

Based on what this proposed hybrid model says will happen, here are the predictions for November 1, 2021: Confirmed cases : $F_{(Nov\ 1,\ 2021)} = (-31.11/100 * 523) + 523 = 248$. Recovered cases : $F_{(Nov\ 1,\ 2021)} = (-15.51/100 * 497) + 497 = 355$. Death cases : $F_{(Nov\ 1,\ 2021)} = (-5.83/100 * 17) + 17 = 15$. Figure 7 shows the final prediction results using equation 19.

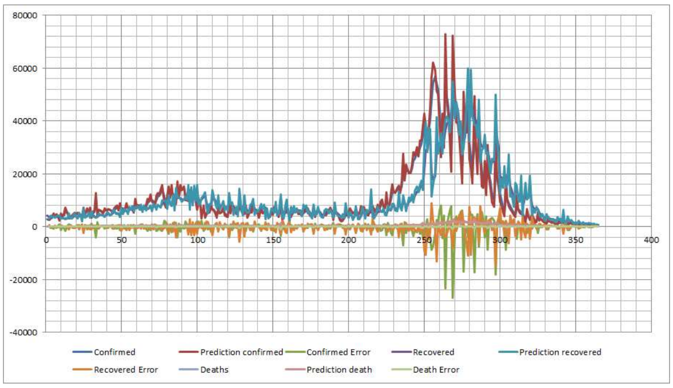

Figure 7. Graph of the result of forecasting Hybrid Model

D. COMPARISON RESULTS

As anticipated in the study, the hybrid model demonstrates superior performance compared to the triple exponential smoothing model, as illustrated in Table 6, which presents the results of comparing the predictions from both models.

Furthermore, referring to Table 1 on MAPE Significance in Prediction, it is noteworthy that both models fall into the category of very high prediction capability. The outcomes for each COVID-19 example exhibit a MAPE of less than 10%, affirming their effectiveness in handling predictions.

Table 6. The Results in Definition of The Universe of Discourse (U)

Confirmed	Recovered	Death
0.15 %	0.15 %	0.20 %

V. CONCLUSIONS

The results obtained from the experiments in the last section highlight the significant advantages of forecasting with the hybrid model developed in this study. The accuracy of the predictions can be categorized as exceptionally good, with a mean absolute percentage error of less than 10 percent for each case of COVID-19.

Our study demonstrates that the hybrid model proposed in this research is highly suitable for making predictions based on time series data. In the examination of COVID-19 cases in Indonesia, the accuracy in calculating confirmed, recovered, and dead cases was notably high. The error test yielded very small results using the absolute mean percentage error method, showing a positive rate of 0.15 percent for confirmed cases, 0.15 percent for recoveries, and 0.20 percent for deaths. Comparatively, the accuracy of this hybrid model surpasses the results obtained using the triple exponential smoothing model developed by Holt-Winter. Therefore, based on the information provided, the COVID-19 Handling Task Force can rely on the prediction results outlined above to inform their decisions regarding the planning, management, and acceleration of COVID-19 handling in Indonesia for the upcoming years.

Looking ahead, we hope that other researchers will further utilize and enhance this hybrid prediction model. The aim is not only to apply it to forecasts beyond the realm of COVID-19 issues but also to address broader and more complex situations.

VI. ACKNOWLEDGMENT

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Assoc. Prof. Dr. UKY YUDATAMA, S.Si., M. Kom, M.M. *as a permanent lecturer in the Informatics Engineering study program, Faculty of Engineering, University of Muhammadiyah Magelang, Graduated of doctoral program Computer Science, University of Indonesia with Cumlaude predicate. Active in the Association of Computer Higher Education (APTIKOM) Central Java Province as an Advisory Board, besides that he is also active as a reviewer in various reputable international journals and a reviewer for national journals indexed by Sinta. The achievements he has achieved include in 2018 being named the best reviewer in the Journal of Information Technology & Computer Science (JTIIK) Brawijaya University Malang and in 2020 also being named The Best Reviewer International Conference on Computer Science and Its Application in Agriculture (ICOSICA 2020), Bogor Agricultural Institute. The author is also active in carrying out research and scientific publications as indicated by the Scopus H-index score of 7 and for Google Schoolar's H-index of 11. Author Email: uky@ummgl.ac.id.*

SOLIKHIN *works at College of Informatics and Computer Management Himsya Semarang, Indonesia. Current position as assistant professor in the Department of Informatics Engineering. He attended AKI University for undergraduate studies and Diponegoro University for postgraduate studies. Both institutions awarded him bachelor's and master's degrees. His areas of expertise and research interests include computer science, business intelligence, decision support systems and information systems.*

Dr. DWI EKASARI HARMADJI, SE, AK, MM *works at Wisnuwardhana University, Malang, Indonesia. Current position is assistant professor in the Department of Accounting. A bachelor's degree was obtained at Padjajaran University, a master's degree was obtained at Labora College of Management, and a Doctoral degree was obtained at Brawijaya University. His areas of expertise and research interests include: financial accounting and public sector accounting.*

AGUS PURWANTO *works at College of Informatics and Computer Management Himsya Semarang, Indonesia. He holds the position of assistant professor in the Information Systems Department. He attended Surakarta University for undergraduate studies and Dian Nuswantoro University for postgraduate studies. Both institutions awarded him bachelor's and master's degrees. His areas of expertise and research interests include computer networks, computer science, business intelligence, software engineering, decision support systems, information systems, and management information systems.*