# Weather Prediction for Strawberry Cultivation Using Double Exponential Smoothing and Golden Section Optimization Methods

**Article** *in* ILKOM Jurnal Ilmiah · December 2024

DOI: 10.33096/ilkom.v16i3.2290.305-317



Assoc. Prof. Ir. Muhammad Faisal Ph.D
Muhammadiyah University of Makassar



Hamdan Gani
Politeknik ATI Makassar

ILKOM Scientific Journal Vol. 16, No. 3, December 2024, pp. 305-317
Accredited 2nd by RISTEKBRIN No. 200/M/KPT/2020;E-ISSN 2548-7779 | P-ISSN 2087-1716

**Research Article** **Open Access (CC–BY-SA)**

# Weather Prediction for Strawberry Cultivation Using Double Exponential Smoothing and Golden Section Optimization Methods

**Herlinah [a,1]; Billy Eden William Asrul [a,2,*]; Hafsah. HS [a,3*]; Muhammad Faisal [b,4]; Swa Lee Lee [b,5]; Hamdan Gani [c,6]; Zhipeng Feng [d,7];**

[a] *Universitas Handayani Makassar, Jl. Adyaksa Baru No.1, Makassar and 90231, Indonesia*
[b] *Asia E University, Wisma Subang Jaya, No 106, Selangor and 47500, Malaysia*
[c] *Politeknik ATI Makassar, Makassar, Indonesia*
[d] *Hangzhou Normal University, Hangzhou, Zhejiang, China*
[1] *linaherlinah@handayani.ac.id;* [2] *billy@handayani.ac.id;* [3] *hafsah.hsulaeman@gmail.com;* [4] *C70105210004@aeu.edu.my;*
[5] *swa.lee@aeu.edu.my;* [6] *hamdangani@atim.ac.id;* [7] *20200058@hznu.edu.cn*
* *Corresponding author*

**Article history:** Received July 09, 2024; Revised December 03, 2024; Accepted December 18, 2024; Available online December 24, 2024

**Abstract**

Strawberry is one of the fruit commodities that has a high demand so that it is widely cultivated by most people in Bantaeng Regency to meet with the market needs. The high intensity of weather changes is the main challenge in the strawberry production, which is influenced by climate dynamics and the start season time changes. Climate change does not only affect the amount of rainfall, but also causes a shift in the rainy season and dry season start. As a result, in the cultivation of plants such as strawberries, there are often difficulties in adjusting or slow anticipation in the extreme changes of rainfall. This research began with the data collection stage through field observations, interviews, and literature studies. The design tool used a systematically organized UML, which included a use case diagram, then an activity diagram, as well as an elaboration into sequence diagrams, and class diagrams. The system was developed by implementing the PHP programming language on the interface design as well as MySQL as a database processing. The algorithm used to predict the air temperature feature, wind speed feature, and rainfall feature was Double Exponential Smoothing, followed by the optimization of the Golden Section method to select the right smoothing value. Referring to the results of this study, the system can provide planting time recommendations based on prediction of rainfall, air temperature, and wind speed parameters through a web-based platform. Based on the calculation of the accuracy value of the prediction results using the Mean Absolute Percentage Error (MAPE), the obtained forecast error value was of 5.89% for wind speed, 0.63% for air temperature, and 0.69% for rainfall. The Golden Section Optimization in Double Exponential Smoothing provided the best smoothing for prediction.

**Keywords:** Double Exponential Smoothing; Golden Section Optimization; Predictions; Strawberry; Weather.

## Introduction

Strawberries are fruits of high economic value with unique characteristics, including small size, sweetness, freshness, and visual appeal. This fruit is not only consumed directly but can be processed into several types of food products such as jams, juices, ice mixtures, and dessert supplements. Strawberry cultivation is the main livelihood for farmers living in highland areas with low temperatures. In Bantaeng Regency, strawberries are one of the main food commodities that play an important role in meeting local market demand while supporting the tourism sector. Based on data from the Central Statistics Agency of Bantaeng Regency, strawberry production has experienced significant fluctuations and downward trends. In 2015 was 700 kg, in 2016 was 200 kg, in 2017 was 600 kg, and in 2018 was 300 kg. This decrease in production was influenced by the high intensity of rainfall, causing inhibition of flower growth and strawberry clumps, as well as causing physical damage and decay of fruits. In addition, the quality of strawberries declined, such as the less sweet taste and small size, also has a negative impact on farmers' profits.

The strawberry planting pattern is ideally applied to normal rainfall, but the success of the harvest is highly dependent on climatic conditions [1], [2]. In the process of strawberry cultivation, it is important to take rainfall into account, due to the high intensity of rainfall so it is not recommended for planting activities, given its impact on the growth process of strawberry plants. Changes in erratic rainfall intensity pose a significant potential risk to sectors that are highly dependent on climatic or weather conditions. [3].

The need to know the climatic conditions during the next planting time encourages the importance of predicting rainfall, which is influenced by air temperature and wind speed [4]. High rainfall is one of the main challenges in

http://dx.doi.org/10.33096/ilkom.v16i3.2290.305-317

strawberry production systems, which are affected by climate dynamics and start season time changes. Climate change not only impacts changes in rainfall intensity, but also causes significant changes at the beginning of the rainy season or at the beginning of the dry season, which in turn affects strawberry growth patterns and yields. [1], [5]. The characteristics of fluctuating rainfall have a significant impact on the lives of living things, especially plants. [6]. This statement shows that rainfall intensity has characteristics that can change very significantly and randomly, therefore, in strawberry plant cultivation, it is often difficult to adjust or anticipate sudden and extreme changes in rainfall. Based on these observations, a rainfall prediction mechanism is needed that can provide information about the optimal planting time for the next planting season period [7].

Currently, the use of information technology greatly supports the success of the agricultural sector. By using the human prediction system, it is easier to manage agricultural products, reduce the risk of agricultural product failure, and is very helpful in making decisions to increase agricultural production in the next planting time [7]. One of the problems encountered in the agricultural sector is the weather problem that greatly affects the plant growth process [8]–[10]. In this case, weather problems can be solved by predicting the weather using an algorithm that can create a trend model of weather conditions. Weather considerations are greatly influenced by rainfall, wind speed and air temperature [11]–[13]. These variables can be used as a feature in the prediction process so that they can produce decisions for farmers in determining the right planting time in order to optimize their agricultural production [14]–[16].

Predicting weather conditions for agricultural purposes is a critical approach to optimizing crop production and ensuring food security [16]–[18]. Several studies show the importance of accurate weather forecasts to improve agricultural practices [9], [13], [19]. Weather factors such as temperature, humidity, light intensity, and soil moisture, among others, serve to determine the increase and decrease in crop production [17], [18], [20]. Therefore, the implementation of a smart irrigation system based on these factors can significantly increase crop production rates while reducing costs.

One of the prediction methods used to determine the trend in the strawberry planting time includes the Double Exponential Smoothing [20]–[22]. Forecasting techniques from past data are very appropriately implemented in the case of time prediction [23]–[25]. Previous studies have been conducted to predict the weather. However, rainfall, wind speed and air temperature were researched independently. They were carefully researched to find out the good weather for the planting time in agriculture [2], [7], [13]. The Exponential Smoothing was employed to predict vegetable harvest. The prediction accuracy level was 82.9%. The best α value in this study was 0.5 from the calculation results of Mean Absolute Percentage Error (MAPE), the next research predicted the results of product sales with an accuracy level of 94.01%. In the study, the production data of goods in the previous year was used as training data for the smoothing process [25]–[27], where the prediction process was highly dependent on determining the value of Alpha (α) [22], [24], [26], [28], [29]. There were also studies that predict rainfall from the agricultural sector by paying attention to time series data which was taken into consideration in the schedule of the agricultural planting time.

The novelty of this research lies in the use of the Golden Section to optimize smoothing parameters in the Double Exponential Smoothing algorithm. This approach overcomes a weakness found in previous studies, where prediction accuracy was highly dependent on the selection of smoothing scores. By using the Golden Section, the current study improves the optimization of smoothing parameters by considering time series data related to rainfall, air temperature, and wind speed to determine the planting time of strawberries every year. Unlike previous research, this study focuses on determining the strawberry planting period based on the results of climate forecasting which includes prediction of wind speed data, air temperature data, and rainfall data, by utilizing a combination of Double Exponential Smoothing algorithms and optimization of smoothing parameters through the Golden Section method. [30]–[33].

This approach has not been widely applied in previous studies, especially in the context of weather prediction for agriculture. The selection of the right smoothing parameters is crucial in improving prediction accuracy, considering that the smoothing value directly affects the forecast results. By combining the Golden Section method, this study not only improves the accuracy of predictions, but also provides a more systematic and efficient solution in determining optimal parameters based on historical data. In addition, the method used emphasizes the processing of time series data which includes three important variables for strawberry farming, namely rainfall, air temperature, and wind speed. This approach allows for more comprehensive and relevant climate forecasting to determine the ideal planting time. The combination of the Double Exponential Smoothing algorithm with optimization using the Golden Section also strengthens the contribution of this research in providing a prediction model that is superior to conventional methods.

Thus, this research offers innovative approaches that can support agricultural adaptation to climate change more effectively.

This research was carried out using rainfall, wind speed and air temperature variables which were used simultaneously in predicting the best weather for planting trends. The data used from 5 different years (2016, 2017, 2018, 2019 and 2020), the 2020 data was used as data to evaluate the prediction results from the previous 4 years. The data was obtained from the Center for Meteorology, Climatology, and Geophysics. The focus of this study was on optimizing smoothing parameters so that the looping process can be minimized but does not reduce the best accuracy results of the prediction process.

This study compared the prediction accuracy performance of the Double Exponential Smoothing type. The Smoothing Parameters with Hold Exponential Smoothing, Brown Double Exponential Smoothing and Hold Winters Exponential Smoothing methods were used as methods to be compared. Then, the best prediction results were optimized with the Golden Section Optimization method. This was conducted to get the best and optimal prediction of rainfall, wind speed and air temperature. So that it can produce a model performance evaluation to support agricultural planting patterns for Strawberry planting.

## Method

### *A. Research Mechanism*

In this study, several stages were carried out to predict the weather by paying attention to rainfall intensity, air temperature, and wind speed data obtained from the Region IV Meteorology, Climatology, and Geophysics Center. The data obtained was from 2016 to 2020 from January to December in every year.

In **Figure 1**, the first stage was started with the collection of datasets for the prediction process, where rainfall, air temperature, and wind speed data were used as parameters for data training. The second stage was followed by data normalization to prepare the data cleaning process so that the training process can be carried out. The third stage was a comparison for each Exponential Smoothing model. The prediction data was then calculated as an RMSE value. The fourth stage was to optimize the best model from the comparison of prediction accuracy results to get the optimal model.

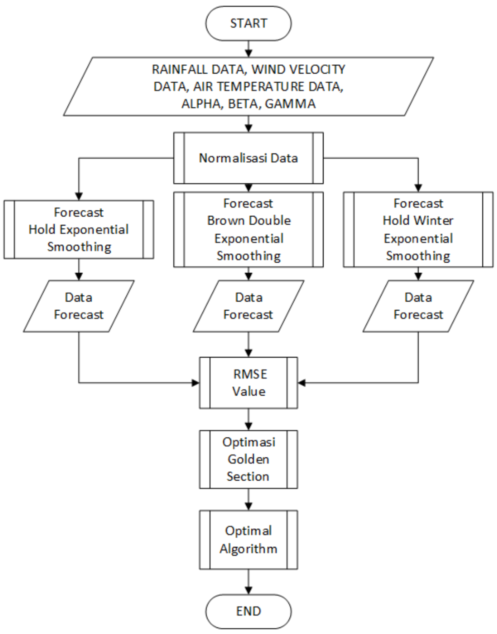


**Figure 1.** Double Exponential Smoothing Optimization Flow Diagram

### *B. Double Exponenetial Smoothing*

At the method stage of Exponential Smoothing, the smoothing value was obtained before the actual data, if the existing data contained a trend component. This was to obtain a single smoothing value. It was necessary to add multiple smoothing for trend adjustment. Double Exponential Smoothing algorithm applied to handle linear trends was a two-parameter approach with the Smoothing Holt method. In Hold Method, the trend was not carried out by direct smoothing but by double smoothing. The smoothing process value trend was applied by utilizing parameters that were different from the parameters used for the actual data or original data of the smoothing process. Double

Exponential Smoothing method applied if there was a trend in the data set. [21], [25], [27], [34].

The Double Exponential Smoothing formula can be shown as follows:

$$S'_t = \alpha Xt + (1-\alpha)S'_{T-1} \tag{1}$$

$$S"_t = \alpha S'_t + (1-\alpha)S"_{T-1} \tag{2}$$

$$A_t = 2S'_t - S"_t \tag{3}$$

$$b_t = \frac{\alpha}{(1-\alpha)} S'_t - S"_t \tag{4}$$

$$F_{t+m} = A_t + b_t \tag{5}$$

where:

$S'_t$ = Value with smoothing 1 at time $t$
$S"_t$ = Value with smoothing 2 at time $t$
$X_t$ = Actual data over time
$A_t$ = Interception on the data at time $t$
$b_t$ = trend value on the data at time $t$
$\alpha$ = Smoothing constant
$F_{(t+m)}$ = Forecast value for the time $t+1$
$m$ = Future time
$\alpha$ = Smoothing coefficient ( $0 < \alpha < 1$ )

### *C. Golden Section Optimization*

Optimization is a term that is often used to reduce or increase a function ($f(x)$) which is referred to as an objective function. Golden Section method is one of the ways or methods of numerical optimization that can be applied to functions that have the property of unimodal. The golden section optimization function is used in DES to find the best parameters that produce the most accurate forecast [35]–[37].

DES has two parameters that need to be optimized $\alpha$ (for levels) and $\beta$ (for trends). The gold ratio optimization function helps to find $\alpha$ and $\beta$ values that optimize prediction accuracy. The gold ratio optimization process revolves through several possible parameter values and measures performance by using criteria such as Mean Squared Error (MSE) and Mean Absolute Percent Error (MAPE). The gold ratio optimization function helps to achieve optimal parameters for DES through a repetitive and systematic search approach, thereby improving the accuracy of time series estimates. Double exponential smoothing forecasting can be used to make the selection of alpha and beta values more effective in the early stages of forecasting, so that optimal alpha and beta values for forecasting can be obtained. This method applies the principle of reducing the limit range $(x)$ where the optimal objective function (maximum or minimum) can be generated iteratively. To find the new symmetry points $X_1$ and $X_2$ we need the value of $r$ (golden ratio) [33], [38], [39].

Function $x2$ is the minimum function value compared to the function value $X_1$ ($F(x_2) < F(x_1)$). The interval $[a = x_1]$ is omitted because the minimum value is not at that interval. $[a = x_1;\ b = b]$ creates a new interval with the length $h' = h - rh.x_1 = x_2;\ x_2 = a + rh'$. This process continues until $|x_2 - x_1|$. For iteration $\leq \varepsilon, x_2 - x_1 = 2rh - h\, 5(a)$ and the same distance from the equation after determining the first point is $x_1 - a = h' - rh'\, 5(b)$.

## Result and Discussion

The data used in forecasting were rainfall data, air temperature data and wind speed data from 2016 to 2019 where the data in 2020 was used as forecasting testing data to test the accuracy of forecast calculation results with the application of the Double Exponential Smoothing method. The forecasting process was carried out for the next year, the forecast calculation used alpha values of 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9. The following **Table 1** is the data of rainfall, air temperature, and wind speed from 2016 to 2020 to predict data for 2021

**Table 1.** Rainfall Data, Air Temperature Data, and Wind Speed Data

| Rainfall Data | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Year Data*** | ***January*** | ***Februar*** | ***Mar*** | ***Apr*** | ***May*** | ***Jun*** | ***Jul*** | ***Aug*** | ***Sep*** | ***Oct*** | ***Nov*** | ***Des*** |
| 2016 | 308 | 166 | 369 | 306 | 139 | 247 | 238 | 20 | 179 | 136 | 357 | 273 |
| 2017 | 154 | 337 | 212 | 150 | 321 | 468 | 228 | 228 | 150 | 149 | 304 | 457 |
| 2018 | 497 | 312 | 178 | 0 | 346 | 0 | 399 | 30 | 0 | 0 | 340 | 0 |
| 2019 | 541 | 238 | 315 | 141 | 82 | 244 | 5 | 4 | 0 | 0 | 121 | 0 |

| Rainfall Data | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2020 | 323 | 134 | 245 | 236 | 313 | 307 | 242 | 59 | 118 | 135 | 73 | 185 |
| **Air Temperature Data** | | | | | | | | | | | | |
| ***Year Data*** | ***Jan*** | ***Feb*** | ***Mar*** | ***Apr*** | ***May*** | ***Jun*** | ***Jul*** | ***Aug*** | ***Sep*** | ***Oct*** | ***Nov*** | ***Des*** |
| 2016 | 19 | 19.3 | 19 | 18.8 | 19.6 | 18.9 | 18.4 | 18.8 | 19 | 19.3 | 19.4 | 19.5 |
| 2017 | 19.4 | 18 | 18.9 | 18.8 | 19.1 | 18.6 | 18 | 18.6 | 21.2 | 21.3 | 21.1 | 21.4 |
| 2018 | 20.5 | 20.4 | 21 | 21.1 | 20.9 | 20 | 19.9 | 19.5 | 21.7 | 21.4 | 21 | 21 |
| 2019 | 20.8 | 20.7 | 20.8 | 21.2 | 21.1 | 20 | 19.8 | 19.8 | 20.9 | 22.7 | 22.1 | 21.1 |
| 2020 | 21.2 | 21.5 | 21 | 20.7 | 21.2 | 20.6 | 19.9 | 20.7 | 21.2 | 21.6 | 22 | 21.5 |
| **Wind Speed Data** | | | | | | | | | | | | |
| ***Year Data*** | ***Jan*** | ***Feb*** | ***Mar*** | ***Apr*** | ***May*** | ***Jun*** | ***Jul*** | ***Aug*** | ***Sep*** | ***Oct*** | ***Nov*** | ***Des*** |
| 2016 | 3.3 | 3.3 | 2.9 | 2.8 | 3 | 1.9 | 1.8 | 1.9 | 2 | 1.9 | 3.1 | 3.2 |
| 2017 | 6.5 | 8.6 | 3.5 | 3.7 | 4.3 | 3.4 | 5.1 | 5.8 | 4.9 | 4.7 | 3.7 | 5.3 |
| 2018 | 6.1 | 6.1 | 4.5 | 3.9 | 2.8 | 2.4 | 2.3 | 4.5 | 6 | 4.8 | 3.7 | 4.4 |
| 2019 | 5.8 | 3 | 3.9 | 3.9 | 4.3 | 4.6 | 4.5 | 4.6 | 4.8 | 3.1 | 2.4 | 1.3 |
| 2020 | 4.5 | 4.3 | 3.1 | 3.1 | 2.9 | 5 | 5.5 | 4.8 | 6 | 4.5 | 3.2 | 3.5 |

### *A. Rainfall Calculation*

To find the value of the first smoothing in the following month in 2017 to 2019, the same process was carried out with the first smoothing in January 2017 to January 2019. The S't value or smoothing first every month was from 2016 to 2019. The calculation process was carried out in January with *an alpha* value of 0.5, the same process was carried out out until December.

**First Smoothing Value ($S'$)**

$$S'2016 = 308$$
$$S'2017 = 0.5\,(154) + (1 - 0.5)\,(308) = 231$$
$$S'2018 = 0.5\,(497) + (1 - 0.5)\,(231) = 364$$
$$S'2019 = 0.5\,(541) + (1 - 0.5)\,(364) = 452.5$$

**Second Smoothing Value ($S$")**

$$S"2016 = 308$$
$$S"2017 = 0.5\,(231) + (1 - 0.5)\,(308) = 269.5$$
$$S"2018 = 0.5\,(364) + (1 - 0.5)\,(269.5) = 316.75$$
$$S"2019 = 0.5\,(452.5) + (1 - 0.5)\,(316.75) = 384{,}625$$

After determining the value of $S"_t$, it was followed by the stage of determining the value of $A_t$ or constant. For the solution step, which was multiplied by the amount of Single Exponential ($S'_t$) precipitation minus the result of the double exponenential $S'_t$ summation, the solution was as follows:

**Constant Value ($A_t$)**

$$A2016 = 308$$
$$A2017 = 2(231) - 269.5 = 192.5$$
$$A2018 = 2(364) - 316.75 = 411.25$$
$$A2019 = 2(452.5) - 384{,}625 = 520{,}375$$

**Slope Value ($b_t$)**

The next step was to find the Slope ($b_t$) value by determining the value of $\alpha/((1-\alpha))$ then multiplied it by the sum of the single exponential smoothing ($S'_t$) value minus the sum of the Double exponential ($S"_t$).

$$b2016 = \frac{0{,}5}{(1-0{,}5)}(308 - 308) = 0$$
$$b2017 = \frac{0{,}5}{(1-0{,}5)}(231 - 269.5) = -38.5$$
$$b2018 = \frac{0{,}5}{(1-0{,}5)}(364 - 316.75) = 47.25$$

$$b2019 = \frac{0,5}{(1-0,5)}(452.5 - 384.625) = 67.875$$

**Forecast Value ($F_t$)**

Table 2 explains that to determine the forecast value or Ft+m was done by adding the αt and bt values that have been obtained. Here's how to solve it:

$$F2016 = At + bt = 308 + 0 = 308$$
$$F2017 = At + bt = 192.5 + (-38.5) = 154$$
$$F2018 = At + bt = 411.25 + 47.25 = 458.5$$
$$F2019 = At + bt = 520{,}375 + 67{,}875 = 588{,}255$$
$$F2020 = At + bt = 520{,}375 + 67{,}875\,(2) = 656{,}125$$

**Table 2**. Rainfall forecast data

| Moon | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| January | 308 | 154 | 458.5 | 588.25 | 656.125 |
| February | 166 | 337 | 354.95 | 274.5 | 281.8125 |
| March | 369 | 212 | 138.75 | 267.25 | 263.5625 |
| April | 306 | 150 | -39 | 64.5 | 33 |
| May | 139 | 321 | 391.5 | 133.75 | 108.125 |
| June | 247 | 468 | 55.25 | 182.25 | 167.6875 |
| July | 238 | 228 | 396.5 | 45.25 | -12.375 |
| August | 20 | 228 | 82 | 6.5 | -10.5 |
| September | 179 | 150 | -7.25 | -44.95 | -87.6875 |
| October | 136 | 149 | 3.25 | -34 | -68.8125 |
| November | 357 | 304 | 326.75 | 116.75 | 61.0625 |
| December | 273 | 457 | 46 | -68.25 | -148 |

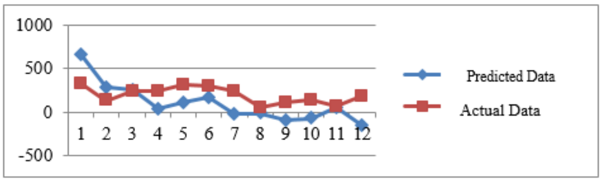


**Figure 2**. Comparison of actual rainfall data with forecast data

In Figure 2, it is a comparison of the prediction results and the actual data. It can be seen that in March in the 3rd data, there was a similarity between the actual value and the predicted value with rainfall of 263 millimeters (mm). And the similarity of values in month 11 (November) was 61.06 millimeters (mm). After the prediction stage, the first smoothing value, the second smoothing, constant value, slope value, and forecast value for February to December were carried out in the same process as in January.

### *B. Air Temperature Calculation*

The calculation process carried out for the air temperature was January with *an alpha* of 0.4

**First smoothing value ($S'$)**

$$S'2016 = 19$$
$$S'2017 = 0.4\,(19.4) + (1-0.4)\,(19) = 19.16$$
$$S'2018 = 0.4\,(20.5) + (1-0.4)\,(19.16) = 19.696$$
$$S'2019 = 0.4\,(20.8) + (1-0.4)\,(19.696) = 20.1376$$

**Second smoothing value ($S''$)**

$$S''2016 = 19$$
$$S''2017 = (0.4)(19.16) + (1-0.4)\,(19) = 19.064$$
$$S''2018 = (0.4)(19.696) + (1-0.4)\,(19.064) = 19.3168$$
$$S''2019 = (0.4)(20.1376) + (1-0.4)\,(19.3168) = 19.64512$$

**Constant value ($A_t$)**

$$A2016 = 19$$
$$A2017 = 2\,(19.16) - 19{,}064 = 19{,}256$$

$A2018 = 2\,(19{,}696) - 19.3168 = 20.0752$
$A2019 = 2\,(20.1376) - 19.64512 = 20.63008$

**Slope Value ($b_t$)**

$$b2016 = \frac{0{,}4}{(1-0{,}4)}(19 - 19) = 0$$
$$b2017 = \frac{0{,}4}{(1-0{,}4)}(19.16 - 19.064) = 0.064$$
$$b2018 = \frac{0{,}4}{(1-0{,}4)}(19.696 - 19.3168) = 0.2528$$
$$b2019 = \frac{0{,}4}{(1-0{,}4)}(20.1376 - 19.64512) = 0.32832$$

**Forecast Value ($F_t$)**

$F2016 = 19 + 0 = 19$
$F2017 = 19{,}256 + 0{,}064 = 19.32$
$F2018 = 20.0752 + 0.2528 = 20{,}328$
$F2019 = 20.63008 + 0.32832 = 20.9584$
$F2020 = 20.63008 + 0.32832\,(2) = 21.28672$

**Table 3** shows the dataset for air temperature forecasting every month from 2016 to 2020

**Table 3.** Results of Air Temperature Forecasting

| Moon | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| January | 19 | 19.32 | 20.328 | 20.9584 | 21.28672 |
| February | 19.3 | 18.26 | 19.764 | 20.6472 | 20.93136 |
| March | 19 | 18.92 | 20.568 | 21.0704 | 21.42432 |
| April | 18.8 | 18.8 | 20.64 | 21.456 | 21.9136 |
| May | 19.6 | 19.2 | 20.48 | 21.168 | 21.4592 |
| June | 18.9 | 18.66 | 19.684 | 20.1032 | 20.32016 |
| July | 18.4 | 18.08 | 19.472 | 19.9616 | 20.24128 |
| August | 18.8 | 18.64 | 19.296 | 19.8048 | 19.99104 |
| September | 19 | 20.76 | 21.864 | 21.5952 | 21.94336 |
| October | 19.3 | 20.9 | 21.62 | 22.884 | 23.4568 |
| November | 19.4 | 20.76 | 21.224 | 22.2352 | 22.68576 |
| December | 19.5 | 21.02 | 21.308 | 21.4424 | 21.70992 |

**Table 3** shows a dataset for air temperature forecasting every month from 2016 to 2020. A comparison of the prediction results and the actual data can be seen in **Figure 3**, which shows the similarity of prediction values in January, June, and July.

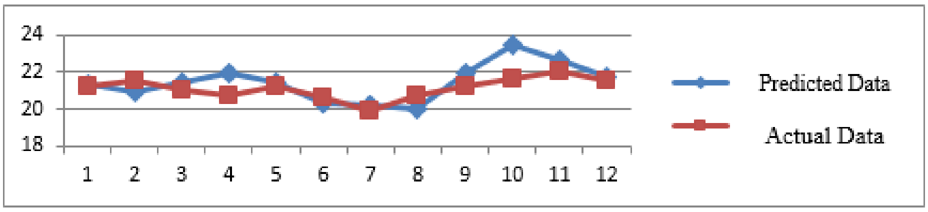


**Figure 3**. Comparison of actual temperature data with forecast data

## C. Wind Speed Calculation

The calculation process carried out for the air temperature was January with an alpha value of 0.3

**First Smoothing Value ($S'$)**

$S'2016 = 3.3$
$S'2017 = 0{,}3(6{,}5) + (1-0.3)(3.3) = 4{,}26$
$S'2018 = 0{,}3(6{,}1) + (1-0.3)(4{,}26) = 4{,}812$
$S'2019 = 0.3(5{,}8) + (1-0.3)(4{,}812) = 5.1084$

**Second Smoothing Value ($S''$)**

$S''2016 = 3.3$

$S"2017 = 0.3(4{,}26) + (1-0.3)(3.3) = 3.588$
$S"2018 = 0.3(4{,}812) + (1-0.3)(3.588) = 3.9552$
$S"2019 = 0.3(5.1084) + (1-0.3)(3.9552) = 4.30116$

**Constant Value ($A_t$)**

$A2016 = 2\,(3.3) - 3.3 = 3.3$
$A2017 = 2\,(4.26) - 3.588 = 4.932$
$A2018 = 2\,(4{,}812) - 3.9552 = 5.6688$
$A2019 = 2\,(5.1084) - 4.30116 = 5.91564$

**Slope Value ($b_t$)**

$$b2016 = \frac{0{,}3}{(1-0{,}3)}(3.3 - 3.3) = 0$$
$$b2017 = \frac{0{,}3}{(1-0{,}3)}(4.26 - 3.588) = 0.288$$
$$b2018 = \frac{0{,}3}{(1-0{,}3)}(4.8152 - 3.9552) = 0.3672$$
$$b2019 = \frac{0{,}3}{(1-0{,}3)}(5.1084 - 4.30116) = 0.34596$$

**Forecast Value (Ft)**

$F2016 = 3.3 + 0 = 3.3$
$F2017 = 4{,}932 + 0{,}288 = 5{,}22$
$F2018 = 5.6688 + 0.3672 = 6.036$
$F2019 = 5.91564 + 0.34596 = 6.2616$
$F2020 = 5.91564 + 0.34596\,(2) = 6.60756$

**Table 4.** Wind Speed Forecast Results

| Moon | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| January | 3.3 | 5.22 | 6.036 | 6.26 | 6.60 |
| February | 3.3 | 6.48 | 6.729 | 4.93 | 5.04 |
| March | 2.9 | 3.26 | 4.058 | 4.12 | 4.28 |
| April | 2.8 | 3.34 | 3.757 | 3.97 | 4.11 |
| May | 3.0 | 3.78 | 3.309 | 3.93 | 4.05 |
| June | 1.9 | 2.8 | 2.695 | 3.93 | 4.20 |
| July | 1.8 | 3.78 | 3.189 | 4.13 | 4.42 |
| August | 1.9 | 4.24 | 4.947 | 5.03 | 5.39 |
| September | 2.0 | 3.74 | 5.357 | 5.48 | 5.90 |
| October | 1.9 | 3.58 | 4.564 | 4.04 | 4.27 |
| November | 3.1 | 3.46 | 3.658 | 2.97 | 2.94 |
| December | 3.2 | 4.46 | 4.613 | 2.80 | 2.69 |

In **Table 4**, the wind speed forecast data was shown every month from 2016 to 2020. A comparison of the prediction results and actual data can be seen in **Figure 4**, which explained that there was a similarity in the predicted value of wind speed in September with a value of 5.9 knots.

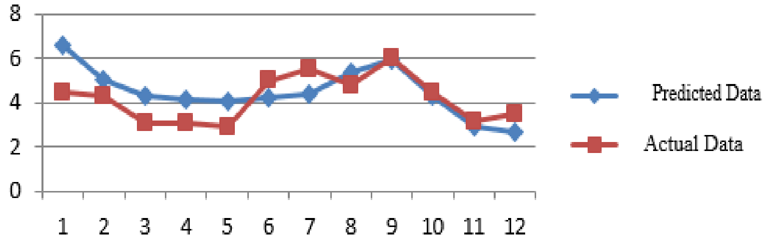


**Figure 4.** Comparison of actual wind speed data with forecast data

### *D. Performance Evaluation Results*

**Table 5.** Comparison of Accuracy of Mean Absolute Percentage Error Method

| Prediction Results | MAPE | | |
|---|---|---|---|
| | *Hold Exponential Smoothing* | *Brown Double Exponential Smoothing* | *Hold Winters Exponential Smoothing* |
| 1 | 0,201 | 0,211 | 0,212 |
| 2 | 0,042 | 0,051 | 0,055 |
| 3 | 0,159 | 0,163 | 0,165 |
| 4 | 0,212 | 0,235 | 0,383 |
| 5 | 0,560 | 0,597 | 0,581 |
| 6 | 0,803 | 0,812 | 0,817 |
| 7 | 0,713 | 0,733 | 0,793 |
| 8 | 0,086 | 0,988 | 0,186 |
| 9 | 0,580 | 0,597 | 0,581 |
| 10 | 0,753 | 0,812 | 0,763 |
| 11 | 0,673 | 0,733 | 0,893 |
| 12 | 0,,886 | 0,988 | 0,889 |

In **Table 5**, the results of the comparison of the calculation of the data analysis method with the Mean Absolute Percentage Error were presented. The smallest MAPE value result for 12 prediction result data was obtained by using *the* Hold Exponential Smoothing method, where the entire data had the smallest value from the comparison between Brown Double Exponential Smoothing and Hold Winters Exponential Smoothing. From table 5, it shows that the Smallest Value was found in the 2nd data with a value of 0.042, meaning that the best planting period was in February. In the final stage, predictions for all data from January to December from 2016 to 2020 was made. Therefore, a comparison of the accuracy results of the hold, brown, and hold winters smoothing methods was carried out for the exponential smoothing method.

**Table 6.** Comparison of Accuracy of Mean Absolute Deviation method

| Prediction Results | MAD | | |
|---|---|---|---|
| | *Hold Exponential Smoothing* | *Brown Double Exponential Smoothing* | *Hold Winters Exponential Smoothing* |
| 1 | 0,119 | 0,125 | 0,134 |
| 2 | 0,032 | 0,041 | 0,046 |
| 3 | 0,123 | 0,135 | 0,140 |
| 4 | 0,208 | 0,215 | 0,211 |
| 5 | 0,549 | 0,560 | 0,555 |
| 6 | 0,797 | 0,798 | 0,799 |
| 7 | 0,705 | 0,708 | 0,711 |
| 8 | 0,075 | 0,080 | 0,079 |
| 9 | 0,552 | 0,564 | 0,577 |
| 10 | 0,740 | 0,810 | 0,750 |
| 11 | 0,573 | 0,733 | 0,882 |
| 12 | 0,,881 | 0,990 | 0,890 |

In **Table 6**, the results of the comparison of the calculation of the data analysis method with the Mean Absolute Deviation Error are presented. The results of the smallest MAD value for the 12 prediction result data were also obtained using the Hold Exponential Smoothing Method, where the entire data had the smallest value from the comparison between Brown Double Exponential Smoothing and Hold Winters Exponential Smoothing. From Table 6, it is seen that the smallest value is in the 2nd data, with a value of 0.032 meaning that the best planting period was in February.

**Table 7.** Comparison of Mean Square Error Accuracy

| Prediction Results | MSE | | |
|---|---|---|---|
| | *Hold Exponential Smoothing* | *Brown Double Exponential Smoothing* | *Hold Winters Exponential Smoothing* |
| 1 | 0,117 | 0,121 | 0,126 |
| 2 | 0,029 | 0,030 | 0,033 |

| **Prediction Results** | **MSE** | | |
|---|---|---|---|
| | ***Hold Exponential Smoothing*** | ***Brown Double Exponential Smoothing*** | ***Hold Winters Exponential Smoothing*** |
| 3 | 0,121 | 0,130 | 0,130 |
| 4 | 0,119 | 0,211 | 0,210 |
| 5 | 0,471 | 0,480 | 0,463 |
| 6 | 0,694 | 0,701 | 0,725 |
| 7 | 0,685 | 0,708 | 0,711 |
| 8 | 0,050 | 0,055 | 0,065 |
| 9 | 0,542 | 0,555 | 0,548 |
| 10 | 0,680 | 0,797 | 0,799 |
| 11 | 0,480 | 0,514 | 0,516 |
| 12 | 0,,738 | 0,743 | 0,752 |

In **Table 7**, it presents the process of testing the comparison of the calculation of the data analysis method with the Mean Square Error. The result of the smallest MSE value for the 12 prediction result data was also obtained by using the Hold Exponential Smoothing method, where the entire data had the smallest value from the comparison between Brown Double Exponential Smoothing and Hold Winters Exponential Smoothing. From Table 7, it was still obtained that the smallest value was in the 2nd data, with a value of 0.029. This means that the best planting time in February. This indicated that the conclusion of the three evaluation stages obtained that the best planting time prediction was in 2020 was in February.

**Table 8.** Prediction Optimization Results with *the Golden Section* in 2020

| **Prediction Results** | **Actual Data** | | | **Hold Exponential Smoothing** | | | **Hold Exponential Smoothing + Optimization Golden Section** | | |
|---|---|---|---|---|---|---|---|---|---|
| | ***Rainfall*** | ***Wind Speed*** | ***Temperatures*** | ***Rainfall*** | ***Wind Speed*** | ***Temperatures*** | ***Rainfall*** | ***Wind Speed*** | ***Temperatures*** |
| 1 | 323 | 4,5 | 21,2 | 310 | 4,3 | 20,2 | 322 | 4,5 | 21,1 |
| 2 | 134 | 4,3 | 21,5 | 133 | 4,1 | 20,2 | 134 | 4,3 | 21,5 |
| 3 | 245 | 3,1 | 21 | 242 | 3,2 | 19 | 245 | 3,1 | 20,9 |
| 4 | 236 | 3,1 | 20,7 | 237 | 3,1 | 19,8 | 235 | 3,0 | 20,6 |
| 5 | 313 | 2,9 | 21,2 | 309 | 2,9 | 19,8 | 312 | 2,9 | 21,1 |
| 6 | 307 | 5 | 20,6 | 308 | 4,5 | 20,1 | 307 | 5 | 20,5 |
| 7 | 242 | 5,5 | 19,9 | 246 | 5,0 | 20,1 | 241 | 5,3 | 19,9 |
| 8 | 59 | 4,8 | 20,7 | 55 | 4,2 | 18,9 | 58 | 4,7 | 20,7 |
| 9 | 118 | 6 | 21,2 | 116 | 5,7 | 19,5 | 117 | 6 | 21,2 |
| 10 | 135 | 4,5 | 21,6 | 136 | 4,1 | 21 | 135 | 4,6 | 21,5 |
| 11 | 73 | 3,2 | 22 | 70 | 2,9 | 23 | 72 | 3,1 | 22,9 |
| 12 | 185 | 3,5 | 21,5 | 187 | 3,3 | 22 | 184 | 3,4 | 21,6 |

In **Table 8**, the actual data from rainfall, wind speed and air temperature were compared with the prediction results of Hold Exponential Smoothing (HES), which was also compared with the prediction results from Golden Section Optimization *(GSO)*, it can be seen that the hold exponential smoothing that has been optimized for its smoothing value obtained prediction results that were close to the actual data every month.

As seen in **Figure 5**, the prediction results on the 2nd and 3rd data showed the smallest difference from the actual data. The $2^{nd}$ data of the prediction results had the same values of the rainfall, wind speed and air temperature features, while the $3^{rd}$ data of the prediction results had the same values of the rainfall and wind speed features. The Golden Section Optimization in the case of rainfall prediction minimized the selection of smoothing range values so that the prediction process of trend values used as training data can be selected accurately. From the results of the evaluation and optimization methods, the planting time was obtained in the second data and the third data. This means that the best planting time was between February in the second data and March in 2020 as seen in the third data.

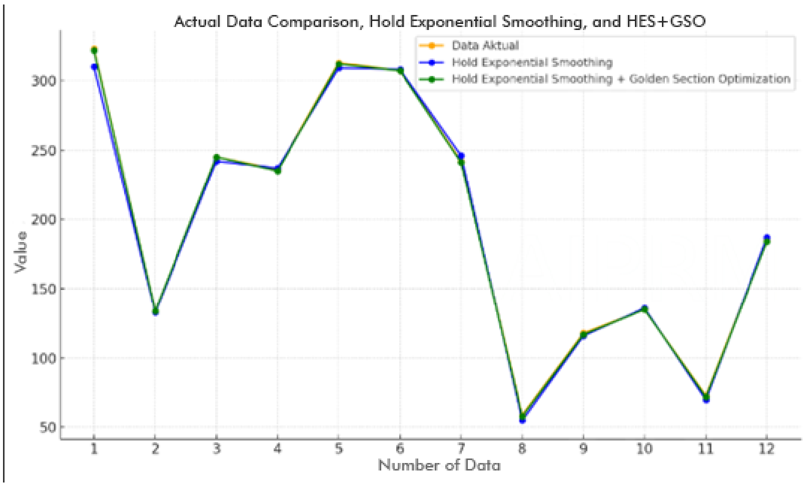


**Figure 5.** Comparison of actual data with HES and HES+GSO forecast results

## Conclusion

Based on the test results, the system was able to predict the weather and the best planting time by using the Double Exponential Smoothing method and the Holt Smoothing method which was optimized with the Golden Section method. The system was made according to the design and can successfully predict the best strawberry planting time. The results of this test show that the functionality was made as expected, as well as the measurement of forecast error values in air temperature data, wind speed data, and rainfall data in the calculation of Mean Absolute Percentage Error (MAPE) with 0.5 Alpha value of rainfall, 0.4 Alpha value of air temperature and 0.3 Alpha value of wind speed. These were interpreted as the best parameter for the data. This explained that the smallest Mean Absolute Percentage Error (MAPE) value was 0.042, the smallest Mean Absolute Deviation (MAD) value was 0.032 and the smallest Mean Square Error *(MSE)* value was 0.029. These mean that the best smoothing method can be obtained using Hold Exponential Smoothing. After optimization with the Golden Section method, the actual value and the prediction value in February and March were the same, as shown in the second data and the third data of the prediction results.

A suggestion for further research is to find the optimum value of the smoothing coefficient ($\alpha$) value with *a* Non-Linear Programming optimization algorithm combined with a Deep Learning algorithm to be able to process not only monthly rainfall data, but also predict daily or hourly rainfall data.

## References


[1] A. UM, "Deep Learning: A Climate Smart Agriculture Tool for Groundnut Farmers," *J. Energy Environ. Sci.*, vol. 2, no. 1, pp. 1–13, 2024, doi: 10.23880/jeesc-16000111.

[2] R. Parvez and N. H. K. Chowdhury, "Weather and Crop Management Impact on Crop Yield Variability," *Agric. Food Sci. Res.*, vol. 7, no. 1, pp. 7–15, 2020, doi: 10.20448/journal.512.2020.71.7.15.

[3] Sanyam, "Predicting the Seed Cotton Yield With Value Added Medium Range Weather Forecast Data Using CROPGRO-Cotton Model at Bhathinda, Punjab," *J. Agrometeorol.*, vol. 26, no. 1, pp. 99–102, 2024, doi: 10.54386/h.v26i1.2244.

[4] A. M. S. Kheir, "Developing Automated Machine Learning Approach for Fast and Robust Crop Yield Prediction Using a Fusion of Remote Sensing, Soil, and Weather Dataset," *Environ. Res. Commun.*, vol. 6, no. 4, p. 41005, 2024, doi: 10.1088/2515-7620/ad2d02.

[5] A. Ullah, S. E. Saqib, and H. Kächele, "Determinants of Farmers' Awareness and Adoption of Extension Recommended Wheat Varieties in the Rainfed Areas of Pakistan," *Sustainability*, vol. 14, no. 6, p. 3194, 2022, doi: 10.3390/su14063194.

[6] U. Acharya, A. L. M. Daigh, and P. G. Oduor, "Factors Affecting the Use of Weather Station Data in Predicting Surface Soil Moisture for Agricultural Applications," *Can. J. Soil Sci.*, vol. 102, no. 2, pp. 419–431, 2022, doi: 10.1139/cjss-2021-0034.

[7] I. Oshodi, "Machine Learning-Based Algorithms for Weather Forecasting," *Int. J. Artif. Intell. Mach. Learn.*, vol. 2, no. 2, pp. 12–20, 2022, doi: 10.51483/ijaiml.2.2.2022.12-20.

[8] J. Shook, "Crop yield prediction integrating genotype and weather variables using deep learning," *PLoS One*, vol. 16, no. 6, 2021, doi: 10.1371/journal.pone.0252402.

[9] X. Huang, "Aerosol as a critical factor causing forecast biases of air temperature in global numerical weather prediction models," *Sci. Bull.*, vol. 66, no. 18, pp. 1917–1924, 2021, doi: 10.1016/j.scib.2021.05.009.

[10] J. Han, "Joint Air Quality and Weather Predictions Based on Multi-Adversarial Spatiotemporal Networks," *35th AAAI Conference on Artificial Intelligence, AAAI 2021*, vol. 5. Pp. 4081–4089, 2021.

[11] G. Zhang, "Solar forecasting with hourly updated numerical weather prediction," *Renew. Sustain. Energy Rev.*, vol. 154, 2022, doi: 10.1016/j.rser.2021.111768.

[12] W. Xu, "Wind speed forecast based on post-processing of numerical weather predictions using a gradient boosting decision tree algorithm," *Atmosphere (Basel).*, vol. 11, no. 7, 2020, doi: 10.3390/atmos11070738.

[13] R. Meenal, "Weather prediction using random forest machine learning model," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 22, no. 2, pp. 1208–1215, 2021, doi: 10.11591/ijeecs.v22.i2.pp1208-1215.

[14] B. Kosovic, "A comprehensive wind power forecasting system integrating artificial intelligence and numerical weather prediction," *Energies*, vol. 16, no. 3, 2020, doi: 10.3390/en13061372.

[15] S. Taheri, "Learning-based power prediction for geo-distributed Data Centers: weather parameter analysis," *J. Big Data*, vol. 7, no. 1, 2020, doi: 10.1186/s40537-020-0284-2.

[16] P. Zhao, "Extending a joint probability modelling approach for post-processing ensemble precipitation forecasts from numerical weather prediction models," *J. Hydrol.*, vol. 605, 2022, doi: 10.1016/j.jhydrol.2021.127285.

[17] T. Siddique, "A Survey of Uncertainty Quantification in Machine Learning for Space Weather Prediction," *Geosciences (Switzerland)*, vol. 12, no. 1. 2022, doi: 10.3390/geosciences12010027.

[18] M. Nasir, "Prediction of Properties of Concrete Cured Under Hot Weather Using Multivariate Regression and ANN Models," *Arabic. J. Sci. Eng.*, vol. 45, no. 5, pp. 4111–4123, 2020, doi: 10.1007/s13369-020-04403-y.

[19] B. K. Jeon, "Next-day prediction of hourly solar irradiance using local weather forecasts and LSTM trained with non-local data," *Energies*, vol. 13, no. 20, 2020, doi: 10.3390/en13205258.

[20] X. Chen, "Short-Term Load Forecasting and Associated Weather Variables Prediction Using ResNet-LSTM Based Deep Learning," *IEEE Access*, vol. 11, pp. 5393–5405, 2023, doi: 10.1109/ACCESS.2023.3236663.

[21] B. J. Zaini, "Comparison of double exponential smoothing for holt's method and artificial neural network in forecasting the Malaysian banking stock markets," *ASM Sci. J.*, vol. 13, pp. 1–5, 2020, doi: 10.32802/asmscj.2020.sm26(1.4).

[22] M. R. Hossain, "Empirical mode decomposition based double exponential smoothing method for daily stock price forecasting," *AIP Conference Proceedings*, vol. 2423. 2021, doi: 10.1063/5.0075360.

[23] E. L. Amalia, "Passenger volume forecasting information system for PT. KAI Daop 2 Bandung using double exponential smoothing method," *IOP Conference Series: Materials Science and Engineering*, vol. 732, no. 1. 2020, doi: 10.1088/1757-899X/732/1/012080.

[24] M. Talbi, "Time series forecasting cancers cases in Algeria using double exponential smoothing method," *Res. J. Biotechnol.*, vol. 19, no. 3, pp. 1–12, 2024, doi: 10.25303/1903rjbt01012.

[25] E. Hasmin, "Data Mining for Inventory Forecasting Using Double Exponential Smoothing Method," *2020 2nd International Conference on Cybernetics and Intelligent System, ICORIS 2020*. 2020, doi: 10.1109/ICORIS50180.2020.9320765.

[26] H. Maulana, "The Prediction of Export Product Prices with Holt's Double Exponential Smoothing Method," *2020 3rd International Conference on Computer and Informatics Engineering, IC2IE 2020*. Pp. 372–375, 2020, doi: 10.1109/IC2IE50715.2020.9274679.

[27] R. Mumpuni, "Design and implementation of inventory forecasting system using double exponential smoothing method," *Proceeding - 6th Information Technology International Seminar, ITIS 2020*. Pp. 119–124, 2020, doi: 10.1109/ITIS50118.2020.9321038.

[28] F. Liantoni, "Forecasting bitcoin using double exponential smoothing method based on mean absolute percentage

error," *Int. J. Informatics Vis.*, vol. 4, no. 2, pp. 91–95, 2020, doi: 10.30630/joiv.4.2.335.

[29] A. Rahmawati, "Comparing The Accuracy of Holt's and Brown's Double Exponential Smoothing Method in Forecasting The Coal Demand Of Company X," *Proceedings of the International Conference on Industrial Engineering and Operations Management*. Pp. 460–469, 2021.

[30] M. Hani'ah, "Parameter Optimization of Holt - Winters Exponential Smoothing Using Golden Section Method for Predicting Indonesian Car Sales," *Proceedings - IEIT 2021: 1st International Conference on Electrical and Information Technology*. Pp. 21–26, 2021, doi: 10.1109/IEIT53149.2021.9587379.

[31] R. Liu, "A Golden Section Method for Univariate One-Dimensional Maximum Likelihood Parameter Estimation," *Lecture Notes in Electrical Engineering*, vol. 571. Pp. 2571–2580, 2020, doi: 10.1007/978-981-13-9409-6_314.

[32] H. Yang, "Erratum: Fault location of active distribution networks based on the golden section method (Mathematical Problems in Engineering (2020) 2020 (6937319) DOI: 10.13039/501100001809)," *Mathematical Problems in Engineering*, vol. 2021. 2021, doi: 10.1155/2021/3581807.

[33] U. H. Rathod, “Predicting the Optimum Performance of a Vertical-Axis Savonius Wind Rotor With Parametric Modeling Using Artificial Neural Network and Golden Section Method,” *J. Comput. Inf. Sci. Eng.*, vol. 23, no. 2, 2023, do: 10.1115/1.4054691.

[34] P. Silitonga, "Forecasting acceptance of new students using double exponential smoothing method," *Journal of Critical Reviews*, vol. 7, no. 1. Pp. 300–305, 2020, doi: 10.31838/jcr.07.01.57.

[35] C. Zhang, "Identification Method of Voltage Sag Exposed Area Based on Golden Section," *Proceedings - 2021 6th Asia Conference on Power and Electrical Engineering, ACPEE 2021*. Pp. 1572–1577, 2021, doi: 10.1109/ACPEE51499.2021.9436825.

[36] J. F. Lin, "Application of Golden Section Search Method in the Design of a Combined Muffler," *2023 10th International Conference on Soft Computing and Machine Intelligence, ISCMI 2023*. Pp. 156–160, 2023, doi: 10.1109/ISCMI59957.2023.10458502.

[37] T. Zhou, "Sortie resolution method of radon ambiguity transform based on golden section iteration," *Proceedings of SPIE - The International Society for Optical Engineering*, vol. 12087. 2021, doi: 10.1117/12.2624694.

[38] M. Abdelouahhab, "Optimization of the Reaction Temperature During Phosphoric Acid Production Using Fibonacci Numbers and Golden Section Methods," *Chem. Africa*, 2024, doi: 10.1007/s42250-024-00971-w.

[39] Y. Liang, "Optimal Design of Pulse Repetition Frequency for SAR Imaging Using the Golden Section Method," *CISS 2021 - 2nd China International SAR Symposium*. 2021, doi: 10.23919/CISS51089.2021.9652356.