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FORECASTING THE NUMBER OF FOREIGN TOURISM IN BALI USING THE HYBRID HOLT-WINTERS-ARTIFICIAL NEURAL NETWORK METHOD

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ABSTRACT

Bali is one of the destinations frequently visited by tourists because it has natural beauty, especially in the tourism sector. The number of foreign tourists coming to Bali until 2019 had increased, but there was a significant decrease in 2020. Forecasting the number of tourists coming to Bali in the future is needed to provide input or recommendations to the government and business people in anticipating decisions taken in developing the tourism sector in Bali. One of the forecasting methods that can be used is the Holt-Winters method. The Holt-Winters method is a part of Exponential Smoothing, which is based on smoothing stationary, trend, and seasonal elements. However, the Holt-Winters method can only capture linear patterns, so a method is needed to capture non-linear patterns. The Artificial Neural Network method is proposed to overcome the shortcomings of the Holt-Winters Method. This research was focused on the number of foreign tourists visiting Bali using the Hybrid Holt Winters-Artificial Neural Network method. The results show that the data on foreign tourists fluctuated monthly. The best method for predicting the number of foreign tourists is the Hybrid Holt-Winters (α = 0.987, β = 0.000001, and γ = 1)-Artificial Neural Network (12-15-1) because it has the best accuracy as indicated by the MAD value of 0.036684, MSE 0.01098698 and MAPE 6.30417%.

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1. INTRODUCTION

Indonesia, with its abundance of natural resources, is a special attraction for foreign tourists. The wealth of natural resources owned by Indonesia can be an opportunity for developing the tourism sector. Tourism cannot be separated from foreign tourists [1]-[4]. Bali Island is one of the tourist places that domestic and foreign tourists often visit [1], [4]. The number of foreign tourist arrivals to Bali Province in 2015-2019 has increased yearly from 4,001,835 people in 2015 to 6,275,210 people in 2019. However, this condition has changed since the announcement of the COVID-19 outbreak as a pandemic in Indonesia in 2020 [5], [6]. The number of foreign tourists coming to Indonesia, especially in Bali, has decreased significantly, namely 1,069,473 tourists. The fall in the number of foreign tourist visits to Bali was due to the closure of access to Indonesia due to the COVID-19 pandemic and the establishment of a travel restriction policy issued by the Ministry of Law and Human Rights, which took effect on April 2, 2020, and the issuance of a travel advisory by the Ministry of Foreign Affairs to reduce the rate of spread of COVID-19 [6].

Predicting the number of foreign tourists coming to Bali in the future is needed to provide input or recommendations to the government and business people in anticipating decisions to develop the tourism sector in Bali [1], [7], [8]. One of the forecasting methods that can be used to make predictions is the *Holt-Winters* method. The *Holt-Winters* method is part of *Exponential Smoothing*, which involves three smoothing equations: stationary, *trend*, and seasonal [3], [4]. However, the *Holt-Winters* method can only capture linear patterns, so a method that can capture non-linear patterns is needed, one of which is the *Artificial Neural Network* [9]. Several researchers have done the combined (*hybrid*) model because it is proven to be able to significantly improve the accuracy of prediction when compared to using a single model [9], [10]. Therefore, a *hybrid* approach between the *Holt-Winters* method and *Artificial Neural Network* is proposed in this study. The existence of linear and non-linear components in time series data is also a complex problem in data analysis, so *hybrid* models are an effective alternative solution to improve forecasting accuracy [11].

Previous research related to this research has been conducted by Aryati et al., who applied the *Holt-Winters Exponential Smoothing* method to forecast foreign tourists coming to Indonesia [3]. Furthermore, Wiranata et al. examine the prediction of foreign tourist arrivals to Bali Province with the *Artificial Neural* Network method [5] as well as research by Seyoga et al., who compared ANN methods with *Backpropagation* algorithms, *Holt-Winters*, and Polynomial Regression to forecast dog bite cases in Bali [12]. Based on this background, this research was conducted to predict the number of foreign tourist visits to Bali with the *Hybrid Holt-Winters* method and *Artificial Neural Network* with the *Backpropagation* algorithm.

2. RESEARCH METHODS

2.1 Data Source

The research data was on the number of foreign tourists visiting Bali by the entrance. The data was obtained from the official publication of the Bali Provincial Statistics Agency. The observation data were collected monthly from January 2009 to April 2022, totaling 160 [6].

2.2 Research Steps

The research steps taken were as follows:

1. Perform descriptive analysis of the data of the number of foreign tourists visiting Bali;
2. Conduct data standardization;
3. Perform modeling and forecasting using *Holt-Winters* with the following steps:
   a. Determine the values of the *level* smoothing parameter (α), *trend* (β), and seasonal component (γ);
   b. Perform forecasting;
   c. Calculate the forecasting accuracy of the *Holt-Winters* method;
   d. Calculate the error/disagreement *of the* data.
4. Model and forecast using *Hybrid Holt Winters-Artificial Neural Network* with the following steps:
   a. Input the lagged data from the *Holt-Winters* model;
   b. Divide the data into *training* and *testing* data. The data composition used in this research is 70:30, 80:20, and 85:15;
   c. Define *inputs* and targets;
   d. Establish network architecture;
   The network architecture consists of determining the number of neuron units in the hidden layer, determining the activation function, determining the network parameters, namely the maximum iteration (*epoch*), *learning rate*, and momentum;

   e. Train the *Artificial Neural Network* with the *backpropagation* algorithm on the *training* data;
   f. Test the network using *testing* data.
5. Perform data unstandardization;
6. Find the forecasting accuracy of the best model.

2.3 Data Standardization

The technique of changing the scale to make the range of values 'standard' based on the initial data's standard deviation and average values is known as data standardization. Data standardization in this study was carried out before further testing because there was some data with a value of 0 in several months in 2021. Data standardization can be calculated with the following equation:

$$X' = \frac{X-\mu}{\sigma} \tag{1}$$

X is the actual data, μ is the mean, and σ is the standard deviation of the actual data [5], [12].

2.4 *Holt-Winters* Method

The Holt-Winters method applies a prediction equation (F_t) and three smoothing components, which include equations for *level* (L_t), *trend* (b_t), and seasonal components (S_t) with smoothing parameters of α, β, and γ [3], [9], [13]. The *Holt-Winters* method was divided into two parts based on the type of seasonality: multiplicative and additive. If the seasonal component is constant, the additive approach can be used. Meanwhile, the multiplicative method was used when the seasonal element was proportional to the *trend* level. *The Holt-Winters* equation with multiplicative seasonal elements was formulated in the following equation [3]:

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} - b_{t-1}) \tag{2}$$
$$b_t = \beta(L_t - L_{t-1})(1-\beta)b_{t-1} \tag{3}$$
$$S_t = \gamma \frac{Y_t}{L_t}(1-\gamma)S_{t-1} \tag{4}$$
$$F_{t+m} = (L_t - b_{tm})S_{t-s+m} \tag{5}$$

Description:

L_t	= Element *level* at time *t;*
b_t	= *Trend* element at time *t;*
S_t	= Seasonal element at time *t;*
F_{t+m}	= Forecasting at time *t* + *m;*
α, β, γ	= Smoothing parameter whose value is in the interval 0 to 1;
m	= number of prediction periods ahead;
s	= Seasonal length;
Y_t	= Observation data at time *t*.

The values of *level*, *trend*, and seasonal components can be initiated with the following equation:

$$L_s = \frac{1}{s} + (Y_1 + Y_2 + \cdots + Y_s) \tag{6}$$
$$b_s = \frac{1}{s} \times (\frac{Y_{s+1}-Y_1}{s} + \frac{Y_{s+2}-Y_2}{s} + \cdots + \frac{Y_{s+ss}-Y_s}{s} \tag{7}$$
$$S_p = \frac{S_p}{L_s}, \, with\, p = 1,2,3, \ldots, s \tag{8}$$

The calculation of the seasonal additive type *Holt-Winters* method was done with the following equation:

$$L_t = \alpha(Y_t - S_{t-s})(L_{t-1} - b_{t-1}) \tag{9}$$
$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{10}$$
$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-1} \tag{11}$$
$$F_{t+m} = L_t - b_{tm} + S_{t-s+m} \tag{12}$$

2.5 *Artificial Neural Network* (ANN)

ANN is an algorithm miming how the human nervous system works to study a phenomenon. ANN consists of interconnected *input*, *hidden*, and *output* layer components. The connectivity of the *input*, *hidden*, and *output layers* are represented by weights whose values will always be updated until they reach the desired target. The *input* layer connects the observation data to the processing algorithm. The *hidden* layer connects the *input* layer with the *output* layer, which is the expected value **[14]**. Neural networks can provide high accuracy because they accommodate *non-linear* components in relatively complex data patterns **[11]**, **[15]**.

2.6 *Backpropagation Neural Network*

The backpropagation algorithm is also called backpropagation because in the processing of *input* data forwarded to the *output* layer if it has not met the desired target, it will be forwarded back to the *hidden* layer and forwarded to the *input* layer **[16]**. *The Backpropagation* algorithm has the advantage of adjusting to observational data and a small error rate. The *Backpropagation* algorithm is widely used on complex data because it adjusts network conditions to the data given in the learning stage **[17]**. The *backpropagation* learning algorithm is as follows **[14]**:

1. Assign weights to each network;
2. Each unit in the input layer $(x_i, i = 1,2,3, \dots, n)$ receives the input signal x and passes it on to all units in the hidden layer;
3. Each unit in the *hidden* layer $\left(z_j, j = 1,2,3, \dots, p\right)$ sums the weights of the *input* signals with the following formula:

$$z_{in_j} = v_{0j} + \sum_{i=1}^{n} x_i v_{ij} \tag{14}$$

   and apply the activation function to calculate the signal at the following output layer:

$$z_j = f(z\_in_j) \tag{15}$$

4. Each output unit $(y_k, k = 1,2,3, \dots, m)$ sums the weights of the incoming signals with the following equation:

$$y\_in_k = w_{0k} + \sum_{j=1}^{j} z_j w_{jk} \tag{16}$$

   and apply the activation function to calculate the output signal as follows:

$$y_k = f(y\_in_k) \tag{17}$$

5. Each output unit $(y_k, k = 1,2,3, \dots, m)$ receives a pattern that matches the *input* training pattern and calculates the *error* value with the following equation:

$$\delta_k = (t_k - y_k) f'(y\_in_k) \tag{18}$$

6. Calculate the weight correction with the following equation:

$$\Delta w_{jk} = \alpha \delta_k z_j \tag{19}$$

7. Calculating bias correction to update w_{jk} with the following equation:

$$\Delta w_{0k} = \alpha \delta_k \tag{20}$$

   and send δ_k to the unit at its below *layer*.
8. Each unit in the hidden layer $\left(Z_j, j = 1,2,3, \dots, p\right)$ sums the *input* deltas and multiplies by the derivative of the activation function to calculate the *error* with the following equation:

$$\delta_j = \delta\_in_j f'\left(z\_in_j\right) \tag{21}$$

9. Calculate the *input* layer weight correction with the following equation:

$$\Delta w_{ij} = \alpha\delta_j x_i \quad (22)$$

10. Each output unit $(y_k, k = 1,2,3, \dots, m)$ updates the weights and bias $(j = 0, \dots, p)$ with the following equation:

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \quad (23)$$

11. Each hidden unit $(z, j = 1,2,3, \dots, p)$ updates the weights and bias $(i = 0, \dots, n)$:

$$w_{ij}(new) = w_{ij}(old) + \Delta w_{ij} \quad (24)$$

12. Stop the process if it meets the desired parameters.

2.7 *Hybrid Holt Winters-Artificial Neural Network*

The hybrid Holt-Winters Artificial Neural Network method is performed by applying the *Holt-Winters method* to predict the observation data. The *Artificial Neural Network method* is applied to forecast the residuals generated from the *Holt-Winters* method **[18]**. The *following equation can describe the hybrid Holt-Winters Artificial Neural Network* method:

$$y_t = L_t + N_t \quad (25)$$

Observation data y_t will be modeled *by* its linear component with *the Holt-Winters* method represented *by* L_t. Its non-linear component is modeled by *Artificial Neural Network* (N_t) **[19]**.

2.8 The Goodness of the Forecasting Model

1. *Mean Absolute Deviation* (MAD)

MAD is the absolute price of the difference between the actual data and its predicted value divided by the number of observations. The following equation obtains the MAD value **[12]**:

$$MAD = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \quad (26)$$

2. *Mean* Squared *Error* (MSE)

MSE is the sum of the squares of the difference between the actual data and the predicted value divided by the number of observations. The following equation obtains the MSE value **[5]**:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2 \quad (27)$$

3. *Mean Absolute Percentage Error* (MAPE)

MAPE describes the average percentage deviation from the prediction results. The MAPE value is obtained by the following equation **[20]**, **[21]**:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100\% \quad (28)$$

Description:

n = number of observations.
Y_t = observation of the *t-th* period.
$\hat{Y}_t$ = Predicted Value at *t-th* period.

3. RESULTS AND DISCUSSION

Descriptive analysis was conducted to determine the general data description of the number of foreign tourists visiting Bali. An overview of the data on the number of tourists coming to Bali is presented in Table 1 and Figure 1.

Table 1 . Descriptive analysis of the number of foreign tourists coming to Bali

N	*Mean*	*Minimum*	*Maximum*	Standard deviation
160	286872	0	624366	167465.6

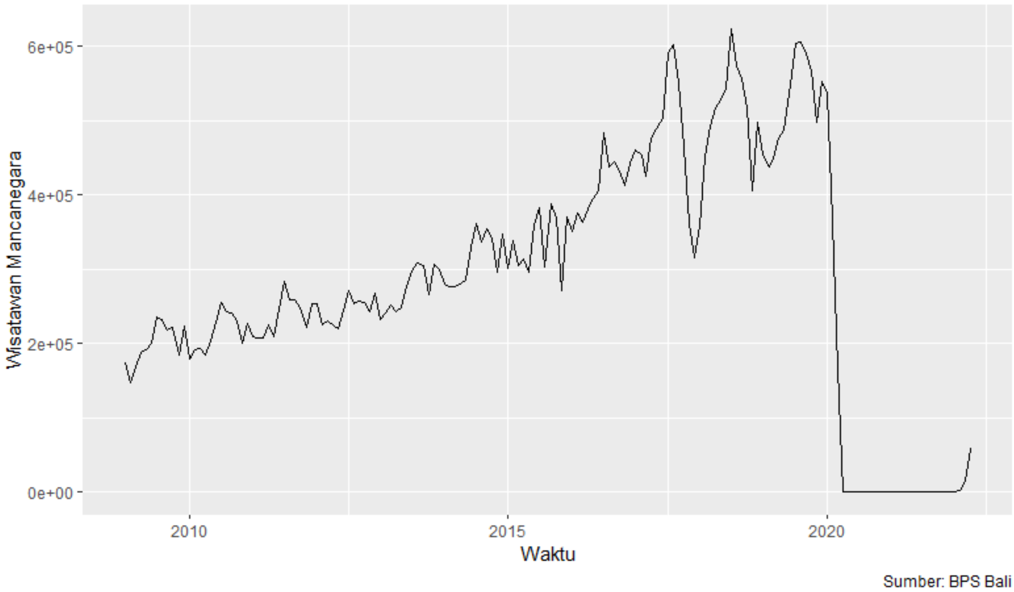

Figure 1. The plot of the number of foreign tourists visiting Bali from January 2009-April 2022.

Based on Figure 1 and Table 1, it can be seen that every month the number of tourists coming to Bali fluctuates and tends to increase from 2009 to 2019. However, in 2020, there began a decline in the number of foreign tourists due to the closure of access from outside the country. From January 2009 to April 2022, the number of foreign tourists coming to Bali reached the highest number in July 2018; namely, 624336 tourists, and the lowest number in July, August, September, and December 2021 was 0 tourists.

3.1 Data Standardization

The data on the number of foreign tourists visiting Bali was standardized first before other modeling using the Equation (1). The calculation of standardization for the first data is January 2009 as follows:

$$X' = \frac{174541 - 286872}{167465{,}6}$$

$$X' = -0{,}67077$$

The standardization calculation process was carried out similarly until the last observation in April 2022.

3.2 *Holt-Winters* Method

The smoothing parameter values for *level* (α), *trend* (β), and seasonality (γ) are sought by *trial* and *error* to maximize forecasting accuracy. The results of the *Holt-Winters* method of estimating the smoothing parameter values on the data of the number of foreign tourists visiting Bali are presented in Table 2.

Table 2. Values of the modulator parameters for *level* (α), *trend* (β), and seasonality (γ)

α	β	γ	MSE

0.1	0.1	0.1	4.614869
0.1	0.1	1	6.335249
1	0	0	0.7410499
1	0.0001	0.0001	0.7410939
0.987	0.0001	0.0001	0.7442204
0.987	0.001	1	0.7302701
0.987	0.0001	1	0.7299058
0.987	0.00001	1	0.7298682
0.987	**0.000001**	**1**	**0.7298645**
0.9876	0.0001	1	0.7302666
0.988	0.000001	1	0.7304731
0.998	0.000001	1	0.738818
0.99	0.1	1	0.7562277
0.99	0.0001	1	0.7318452
0.5	0.000001	1	1.702242

Based on Table 2, the value of the *level* parameter (α) of 0.987, *trend* (β) of 0.000001, and seasonal (γ) of 1 is the best parameter in the *Holt-Winters* method because it produces the smallest MSE value of 0.7298645. Furthermore, with the parameters of the *Holt-Winters* model obtained, the prediction of the number of foreign tourists coming to Bali in the next 12 months is presented in Figure 2.

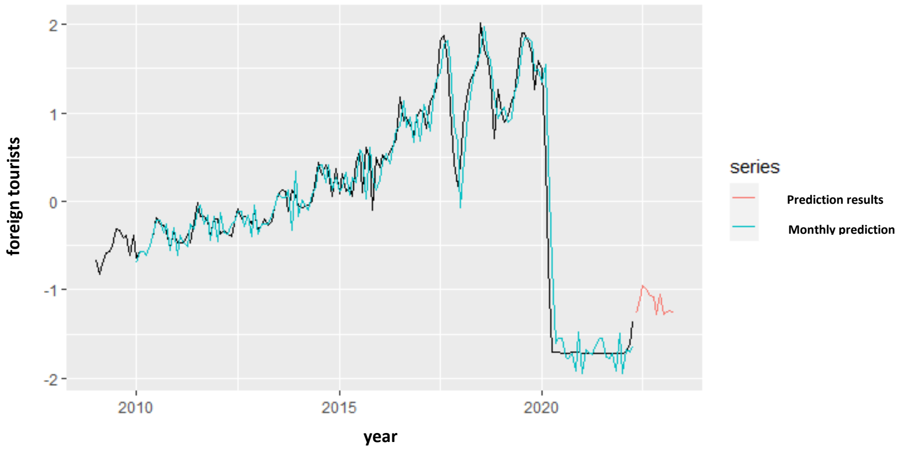

Figure 2. The plot of prediction results of data on the number of foreign tourists coming to Bali with the *Holt-Winters* method

After obtaining the predicted data value on the number of foreign tourists coming to Bali with the *Holt-Winters* method (α = 0.987; β = 0.000001 and γ = 1), the next process was to calculate the leftover data by subtracting the actual data from the predicted data. The residual value obtained was processed by the *Artificial Neural Network* (ANN) method using the *backpropagation* algorithm to find the best architecture for forecasting the number of foreign tourists coming to Bali in the next period. The value of the leftover data with the *Holt-Winters* method (α = 0.987; β = 0.000001 and γ = 1) is presented in Table 3.

Table 3. The value of the leftover data with the *Holt-Winters* method

Year	January	February	March	...	November	December
2009	NA	NA	NA	...	NA	NA
2010	0.053847	0.000037349	3.32E-05	...	0.031216	-0.05973
2011	0.151957	-0.08487723	-0.00072	...	0.054116	-0.03079
...	...	...	...	...	...	...
2020	0.146039	-1.081659	-1.1934	...	0.202186	-0.2303
2021	0.234614	-0.03762351	-0.001	...	0.199818	-0.22532
2022	0.229488	-0.02635831	0.0782			

3.3 *Hybrid Holt Winters-Artificial Neural Network* Method

The initial stage in applying the *Hybrid Holt Winters-Artificial Neural Network* method was by dividing the *Holt-Winters* method data into 2 parts, namely *training data* and *testing* data. This research applied 3 compositions of data division, namely 70% *training data*-30% *testing data*, 80% *training data*-20% *testing data*, and 85% *training*-15% testing data. It was intended to see the consistency of ANN architecture accuracy in forecasting.

The next step was to define the network input and target. The input data used amounted to 12, the residual of the first month to the 12th month in the first year. Meanwhile, the target data amounted to one, namely the 13th month data or the first month in the second year. The use of 12 input data was because it was monthly data, and with 12 months, it was expected to represent the diversity of annual data. The input and target data for building the ANN network are presented in **Table 4**.

Table 4 . ANN network *input* and target data

Observation	*Input*					Target
	X1	X2	...	X11	X12	
1	0.053847	0.000037349	...	0.031216	-0.0597257	0.151957
2	3.73E-05	3.32453E-05	...	-0.05973	0.1519573	-0.08488
3	3.32E-05	-0.000533342	...	0.151957	-0.0848772	-0.00072
4	-0.00053	-0.002393326	...	-0.08488	-0.0007183	0.145578
...	...	...	...	...	...	...
134	-0.03762	-0.001003329	...	-0.22532	0.2294883	-0.02636
135	-0.001	0.02662427	...	0.229488	-0.0263583	0.0782
136	0.026624	-0.09866211	...	-0.02636	0.0781999	0.288298

The formation of ANN network architecture based on the *Backpropagation* algorithm was carried out by setting the target *error* parameter 0.001; the maximum number of iterations is 1000 with a *learning rate of 0.*1 and a *momentum constant of* 0.95. The architecture formed was selected by paying attention to the smallest MSE, MAD, and MAPE values in the architecture testing process. Based on three experiments on the composition of 70% *training* -30% *testing*, 80% *training* -20% *testing*, and 85% *training*- 15% *testing*, the best architecture is found in the hidden layer with 15 neurons. A comparison of forecasting accuracy on training and testing data is presented in **Table 5**.

Table 5. The best architecture is based on 3 composition trials of 70% *training*- 30% *testing*, 80% *training*- 20% *testing*, and 85% *training*- 15% *testing*.

Network architecture	Training Composition: Testing	*Training*			*Testing*		
		MAD	MSE	MAPE	MAD	MSE	MAPE
12-15-1	70% : 30%	0.0044	0.0009964	0.0075	0.4596	3.4072	61.2522
12-15-1	80% : 20%	0.0046	0.00096967	0.0078	0.5866	3.9147	33.4288
12-15-1	85% : 15%	0.0055	0.00097098	0.0532	**0.2109**	**2.9064**	**11.8**

Based on **Table 5**, the 12-15-1 architecture is the best in the 3 *training* and *testing* compositions. The three architectures were then selected by considering the smallest MSE, MAD, and MAPE values in the network *testing* process to avoid *overfitting*. Therefore, the 12-15-1 network architecture with a *training* composition of 70% *training*- 30% *testing* was determined as the best architecture with a MAD value of 0.2109, MSE value of 2.9064, and MAPE value of 11.8%. An overview of the ANN architecture based on the best *Backpropagation* algorithm with 85% *training* and 15% *testing* data composition is presented in **Figure 3**.

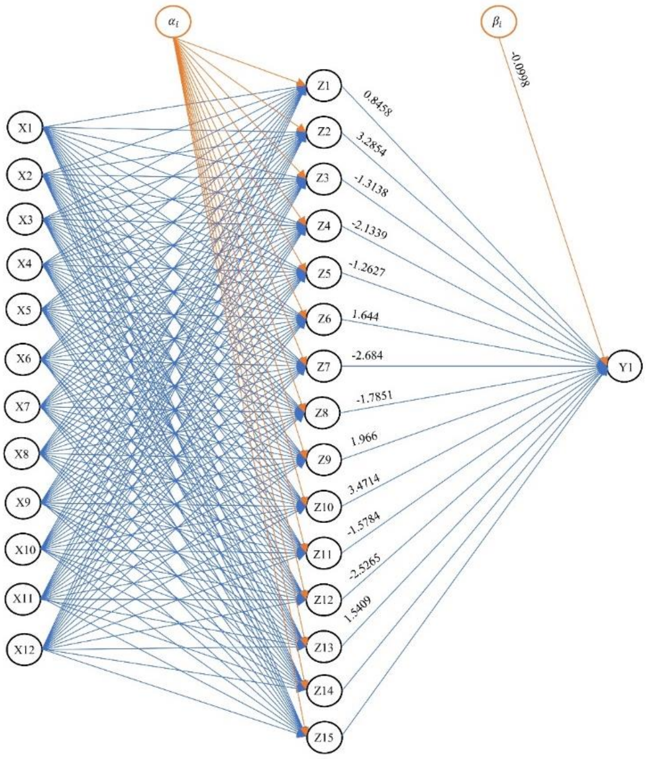

Figure 3 . ANN architecture with *Backpropagation* algorithm on *training* data composition 85% *testing data* 15%

3.4 Data Unstandardization

Data unstandardization was done to convert the output results into the actual data scale. The formula used is as follows:

$$X = X' \times \sigma + \mu$$

Calculation of data unstandardization on the first forecast results, namely data for May 2022, as follows:

$$X = -1.2710543 \times 167465.6 + 286872$$
$$X = 74014.129$$

The same process was carried out to calculate data unstandardization on the results of forecasting data on the number of foreign tourists visiting Bali.

3.5 Comparison of Forecasting Results

After obtaining forecasting results on data that has been standardized with the *Holt-Winters* (α = 0.987; β = 0.000001 and γ = 1) and *Hybrid Holt-Winters* (α = 0.987; β = 0.000001 and γ = 1)-Artificial *Neural Network* (12-15-1) methods, then a comparison was made to see the best method for equalizing data on the number of foreign tourists visiting Bali based on the forecasting accuracy value presented in **Table 6**.

Table 6. Comparison of Perolt-Winters forecasting accuracy

Methods	MAD	MSE	MAPE
Holt Winters (α = 0.987; β = 0.000001 and γ = 1)	0.157682	0.7298645	57.4322
Hybrid Holt-Winters (α = 0.987; β = 0.000001 and γ = 1)-Artificial *Neural Network* (12-15-1)	0.036684	0.01098698	6.30417

Figure 4 . Plot of predicted value data on *the Holt-Winters* method, *Hybrid Holt Winters-Artificial Neural Network* method, and actual data on the number of foreign tourists visiting Bali

Based on **Table 6** above, it can be seen that the forecasting accuracy value of the *Holt-Winters Hybrid* method (α = 0.987; β = 0.000001 and γ = 1)-Artificial *Neural Network* (12-15-1) is better than the *Holt-Winters* method (α = 0.987; β = 0.000001 and γ = 1) to forecast the number of foreign tourists coming to Bali because it has a low prediction error value; namely the MAD value of 0.036684; MSE value of 0.01098698 and MAPE value of 6.30417%. A comparison graph of the forecasting results between the *Holt-Winters* method and the *Hybrid Holt-Winters-Artificial Neural Network* method against actual data is presented in **Figure 4**.

4. CONCLUSIONS

The *hybrid Holt-Winters-Artificial Neural Network* method effectively equalizes the number of foreign tourists visiting Bali because it produces a much better forecast than the *Holt-Winters* method. Based on data analysis, the best method to equalize the number of foreign tourists visiting Bali is the *Hybrid Holt-Winters* (α = 0.987; β = 0.000001 and γ = 1)-Artificial *Neural Network* (12-15-1) method because it produces the best accuracy shown by the MAD value of 0.036684, MSE 0.01098698 and MAPE 6.30417%.

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