Airport Visibility Prediction System to Improve Aviation Safety

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Abstract. Security and safety are the most important things in the world of transportation, especially in aviation or air transportation. Safety and security matters are affected by factors such as visibility, wind direction, wind speed, temperature, dew point and barometric pressure. The most important of these factors is visibility. In world aviation, visibility is stated if the distance is more than 5 km. If the visibility is less than 5 km, the flight will be delayed until the visibility is declared safe. Therefore, in this study a system was built to ensure visibility for flight safety and security. The data in this study were taken from the Aviation Meteorology Center of the Meteorology, Climatology and Geophysics Agency, from Juanda International Airport of Surabaya. The visibility system built has an accuracy value of 93.22% or an RMSE value of 0.06776. In this system, the most appropriate number of parameters is determined, namely: the best learning rate is 0.001, the hidden layer unit is 24, and the number of iterations is 10,000 iterations.

Keywords: Backpropagation · Visibility · predicting · system

1 Introduction

Visibility is an important thing in operating aircraft, by the Regulation of the Minister of Transportation Number KM 18 of 2010 states that no one is allowed to operate an aircraft with VFR provisions when the visibility or distance from the clouds is less than the provisions as described in the table regarding the air space. Has been determined [1]. Applicable and used viewing distances from routine and local special reports reported in METAR and SPECI observations at field visibility [2].

In a previous study, it was stated that the Deep Learning Convolutional Neural Network (CNN) method is better than the Multilayer Perceptron (MLP) based on the average value of the root mean squared error, in the case of predicting the visibility of land transportation. CNN achieved the best average results for the three-hour and nine-hour gaps, while MLP performed better for the six-hour gap [3]. The Auto-regressive Integrated Moving Average (ARIMA) model to predict better visibility for the value of the parameter variance p, d, q uses a grid technique, with the lowest MSE value of 0.00029 and the coefficient of variation value of 0.00315. The more the number of data predictions

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in the ARIMA model, the higher the MSE value [4]. Tree-Based Statistical Methods are the best method for predicting Low-Visibility Procedure Status and horizontal visibility compared to OLR (ordered logistic regression), with computational costs comparable to linear regression methods, and 30 min longer resolution [5, 6].

Factors that affect flight safety and security are visibility, wind direction, wind speed, temperature, dew point, and air pressure. One of the most important things in aviation is Visibility. In world aviation, visibility is stated if it is more than 5 km. If the visibility is less than 5 km, the flight will be delayed until the visibility is declared safe. Therefore, in this study, a system was built to predict visibility to improve flight safety and security [2, 7].

2 Method

2.1 METAR

In the world of aviation, weather reports are very important so that flight crews can prepare everything needed to get a safe and comfortable flight for passengers and crew. Metar stands for Meteorological Aerodrome Report or Airport Weather Report. A meter is a code or format that tells you the weather. Metar format has been standardized by ICAO (International Civil Aviation Organization) the highest authority in the United Nations in charge of Aviation, so this code is made to be easier to understand around the world. METAR is also useful in the morning for Ground Officers or officers on the ground in preparing the Flight Plan Route, namely the Airplane Route that will be traversed by the Aircraft after taking off to the Destination Airport. In Indonesia, institutions that specifically handle and provide aviation weather information are the Aviation Meteorology Center, Meteorology, Climatology, and Geophysics Agency (BMKG). Getting this comfort requires effort and hard work as well as high accuracy from all parties so that the flight can run smoothly to its destination without any obstacles and obstacles in the air such as bad weather, turbulence, and so on. Metar BMKG Flight data itself is subject to change. Metar data is updated every 30 min.

2.2 Linear Data Normalization (Min-Max)

With the use of the BPTT algorithm's activation function, input data normalization seeks to modify the value of the data range. Therefore, the input data value from 0 to 1 or from −1 to 1 is the input range that satisfies the requirements. Consequently, the output will fall between 0 and 1. The output must then undergo another denormalization step to yield its true value. [8] [9].

Data normalization using formula (1):

$$y = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where y is the normalized value; x_i is the (i^{th}) data; x_{min} is data with a minimum value; and x_{max} is data with a maximum value. While denormalization of data using formula (2):

$$x_i = y(x_{max} - x_{min}) + x_{min} \tag{2}$$

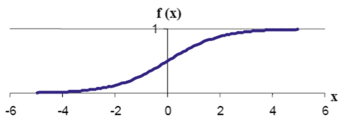

Fig. 1. Sigmoid Activation Function

2.3 The Sigmoid Activation Function

The level of activation, or the internal state of a neuron in the network, is determined by the activation function [10]. The result of this activation is typically relayed to another cell as a signal. Please take note that although a signal can be sent simultaneously to numerous other neurons, a neuron can only send one signal at a time. The majority of units in a neural network use an activation function to translate an input value into an output value.

Functions that take the shape of a S curve are referred to be sigmoid functions. A logistic function is one illustration. Due to the straightforward relationship between the function's value at a given point and its derivative value, the sigmoid function provides advantages for training neural networks using the backpropagation technique. This reduces the computing burden during learning. The sigmoid function's equation is as follows:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

In particular, this function is employed as an activation function for neural networks whose output value falls within the range of 0 and 1.

2.4 Backpropagation Algorithm

In the area of pattern recognition, backpropagation is one of the most used artificial neural network training algorithms. With several layers and a unidirectional signal flow from input to output, multi-layer feed-forward neural networks—which typically use this algorithm—are built of numerous layers. The three stages of the backpropagation training algorithm are as follows:

The following steps are taken to achieve the output value: a. input the value of the training data; b. backpropagation of the error value; and c. weight connection adjustment to reduce error value [11, 12].

The following stages are used to train artificial neural networks using the backpropagation algorithm:

a. Create a random value between -0.5 and 0.5 to use as the weights' initial value.
b. Calculate the learning rate (α).
c. When utilizing the threshold value as a stop condition, specify the error tolerance value, the threshold value, or the maximum set of epochs (when using the number of epochs as a stop condition).
d. As long as the stop condition has not been satisfied, carry out the subsequent actions (value FALSE)

1) Perform the following for each pair of training patterns.

   a) Feedforward

a. Each input unit X_i (from the 1st unit to the nth unit in the input layer, i = 1,…, n) perform the following for each pair of training patterns.;
b. For every element in the hidden layer Y_j (from the 1st unit to the pth unit; j = 1,… p) applying the activation function to the sum of the input signals weights yields the hidden layer output signal X_i. . The bipolar sigmoid activation function is utilized in this investigation. (4);

$$Y_j = f\left(V_{0j} + \sum\nolimits_{i=1}^{n} X_i V_{ij}\right) \tag{4}$$

and distributed to all overlay units.

Every element in the output layer Z_k (from the 1st unit to the mth unit, i = 1,…, n; k = 1,…, m) as the activation function in calculations (5) of the z_j- the input signals for this layer's weighted sum:

$$Z_k = f\left(W_{0k} + \sum\nolimits_{j=1}^{p} Y_j W_{jk}\right) \tag{5}$$

next distributed to all overlay units.

a) *Backpropagation*

(1) Each output unit Z_k (from 1st unit to m th unit $j = 1, \ldots, p; k = 1, \ldots, m$) receives the target pattern t_k and then computes the output layer error information (δ_k) (6). The weight and bias correction (ΔW_{jk} and ΔW_{0k}) between the hidden layer and the output layer are calculated using δ_k which is passed to the layer beneath it. According to (7) and (8):

$$\delta_k = (T_k - Z_k) f'\left(W_{0k} + \sum\nolimits_{j=1}^{p} Y_j W_{jk}\right) \tag{6}$$

$$\Delta W_{jk} = \alpha.\delta_k.Y_j \tag{7}$$

$$\Delta W_{0k} = \alpha.\delta_k \tag{8}$$

(1) The layer error information is calculated by for each unit in the hidden layer (from the first unit to the pth unit i = 1,…, n; j = 1,…, p; k = 1,…., m) (9) (δ_j) Hidden. The weight and bias correction between the input layer and the hidden layer are then determined using δ_j (ΔV_{ij} and ΔV_{0j} respectively). It can be seen in (10) (11):

$$\delta_j = \left(\sum\nolimits_{k=1}^{m} \delta_k W_{jk}\right) f'\left(V_{0j} + \sum\nolimits_{i=1}^{p} X_i V_{ij}\right) \tag{9}$$

$$\Delta V_{ij} = \alpha.\delta_j.X_i \tag{10}$$

$$\Delta V_{0j} = \alpha.\delta_j \tag{11}$$

a) *Updates to Weights and Bias*

(1) The bias and weights are corrected for each unit of the y_k output (from the first unit to the m-unit), the bias and weight (j = 0,…, p; k = 1,…., m) so that the new bias and weights are (12):

$$W_{jk}(new) = W_{jk}(old) + \Delta W_{jk} \tag{12}$$

The bias and weights i = 0,..., n j = 1,..., p) in the hidden layer are similarly updated using the formula shown in (13) from the first unit to the p-unit:

$$V_{ij}(new) = V_{ij}(old) + \Delta V_{ij} \tag{13}$$

Use the following formula (14) to get the MSE (Mean Squared Error):

$$MSE = (T_k - Z_k)^2 \tag{14}$$

Z_k output value and T_k output target's squared differences.

1) Test for the stop condition: The stop condition is TRUE if either the number of epochs has not exceeded the maximum epoch or the MSE value is greater than or equal to the error tolerance value.

Use the feedforward method with the final weights during the matching and recognition process.

3 Results and Discussion

3.1 Flowchart

Figure 1 is a system process flow that begins with data input, to produce predicted results. The data input process is the user's process of entering historical data which will be processed by the system. The input variable of Backpropagation is the process of entering variables that will be used in the training process using the Backpropagation method. The training process begins with the normalization process, then the training process is carried out using the Backpropagation method. The end of the training process is the final weight and the value of RMSE (Root Mean Square Error). The final weight will be used for the prediction process with the calculation process using the feedforward Backpropagation step. The final result of this system is the prediction result (Fig. 2).

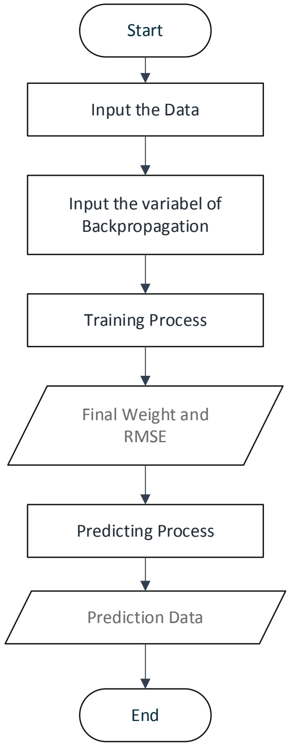

Fig. 2. System Flowchart

3.2 Network Architecture

The backpropagation network architecture is shown in Fig. 3. It is possible to change the quantity of input layers, hidden layers, and output layers.

3.3 Data

Training data and test data are taken from the official website of the Center for Aviation Meteorology, Meteorology, Climatology and Geophysics Agency which is accessed on the http://aviation.bmkg.go.id/web/ page.

Table 1 is METAR data. YYGGiiZ is a column for displaying data when data is retrieved. 010100Z is the data entry time, namely the 01st of the month of filling, which is June 1st. 0100 indicates the charging time, which is 01.00 UTC. DddffKT is a column to display wind direction and speed data. 230 indicates 2300 cardinal directions, namely from the west. 03 is the wind speed which is 03 knots. TT/DP is a column for displaying temperature data, temperature, and dew point. 26/25, namely the temperature of 260 C and the dew point of 250 C. QPPPP is a column for displaying air pressure. Q1010 indicates that the air pressure is 1010 hPa. Vis is a column to display visibility. 9999 means the visibility is 10.00 km. Because the system can only enter a maximum of 4 digits, so the highest number is 9999. Q

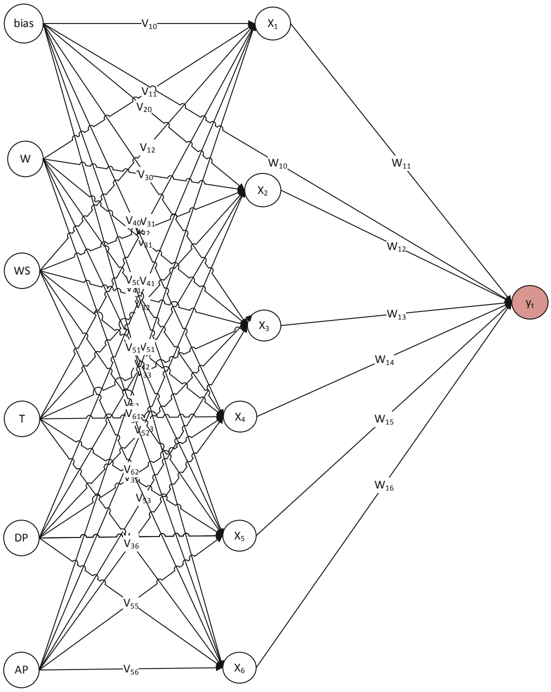

Fig. 3. Backpropagation Network Architecture

Table 1. The Metar Data

YYGGiiZ	dddffKT	Vis	TT/DP	QPPPP
010100Z	23003KT	9999	26/25	Q1010

The METAR data is converted into data as shown in Table 2. Table 2 is the input data. Input data is data that is entered into the system.

From the data in Table 2 then in the normalization process so that the data in Table 3 is ready to enter the training process.

The variable T−1 is the Visibility value at time t−1 in kilometers (km). Variable W is the value of the degree of wind direction at time t. Variable WS is the value of wind speed in knots at time t. The TP variable is the temperature value in degrees Celsius at time t. The DP variable is the dew point speed value in degrees Celsius at time t. Variable AP is the value of air pressure in hPa units at time t. And Variable T is the Visibility value at time t in kilometers (km).

Table 2. Input Data

No	Time (UTC)	Visibility (km)	Wind (degree)	Wind Speed (knot)	Temperature (Celcius)	Dew Point (Celcius)	Air Pressure (hPa)
1	1.00	10	230	3	26	25	1010
2	1.30	10	190	2	27	26	1010
…	…	…	…	…	…	…	…

Table 3. The Normalized data

No	UTC	T-1	W	WS	TP	DP	AP	T
1	1.00	1	0,5278	0,1	0,8276	0,1	0,75	1
2	1.30	1	0	0,1	0,8276	0,6667	0,75	1
…	…	…	…	…	…	…	…	…

3.4 Proses Training

The input layer, hidden layer, learning rate, error aim, and output layer are the variables or factors utilized in system testing. As required, these parameters can be altered. The data that comes from the normalization phase is what is processed throughout the training process. The number of input layer units is 6 units, according to the number of variables, namely T−1, W, WS, TP, DP, and AP. The number of units of the output layer is 1 unit, which is the target value. Meanwhile, the Learning rate, the number of Hidden Layer units, the Error Goal value, and the number of iterations are determined based on system testing, to get the most appropriate variable value.

In the trial process, the learning rate is compared to 0.1; 0.01; and 0.001; with the number of hidden layers compared, namely 24 and 48; with the number of iterations 1000, 5000, and 10,000. Table 4 is the result of the training process in the form of the RMSE value and the level of system accuracy.

The best learning rate is 0.001 with 24 hidden layer units and 10000 iterations, according to the test results presented above.

Figure 4 is a graphic image of the change in the RMSE value.

Table 4. Comparison of RMSE Values in the Training Process

Learning Rate	Hidden Layer	Iterate	RMSE	Akurasi %
0,1	24	1000	0,52459	47,54
0,01	24	1000	0,07823	92,18
0,001	24	1000	0,06941	93,06
0,1	48	1000	0,52456	47,54
0,01	48	1000	0,08756	91,24
0,001	48	1000	0,06917	93,08
0,1	24	5000	0,52457	47,54
0,01	24	5000	0,07579	92,42
0,001	24	5000	0,06826	93,17
0,1	48	5000	0,52459	47,54
0,01	48	5000	0,07646	92,35
0,001	48	5000	0,06906	93,09
0,1	24	10000	0,52459	47,54
0,01	24	10000	0,07353	92,65
0,001	**24**	**10000**	**0,06776**	**93,22**
0,1	48	10000	0,52459	47,54
0,01	48	10000	0,07636	92,36
0,001	48	10000	0,06805	93,20

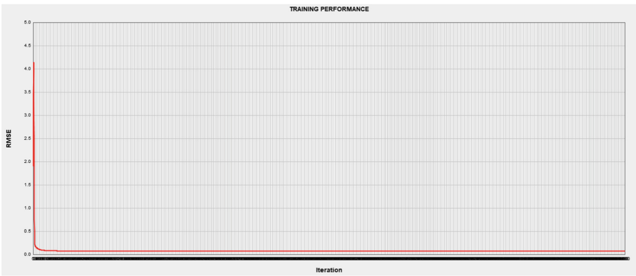

Fig. 4. RMSE graph

Figure 5 is a graphic of the output value, which is compared with the target, and the predicted results.

Table 5 is a comparison table of target and output values in the form of normalized results, and in the form of actual values that have been denormalized.

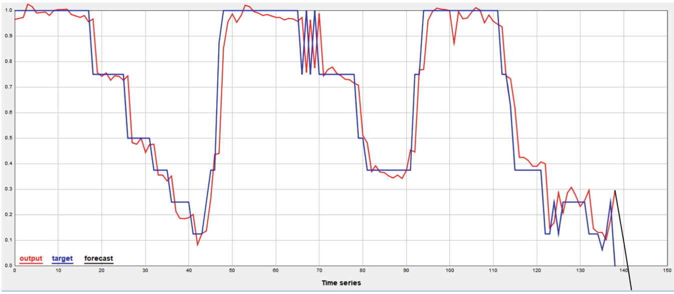

Fig. 5. Comparison graph of output values, targets, and predicted results.

Table 5. Comparison of Output and Target Values

No	Target (Normalization)	Output (Normalization)	Difference (Normalization)	Target (Real)	Output (Real)	Difference (Real)
1	1	0,964964459	0,035035541	10	9,71971567	0,2802843
2	1	0,967702422	0,032297578	10	9,741619373	0,2583806
…	…	…	…	…	…	…

4 Conclusion

This visibility prediction system was built to improve flight safety and security. The input layer in this system consists of Visibility, wind direction, wind speed, temperature, dew point, and air pressure values. The value of the input layer is taken from the official website of the Center for Aviation Meteorology, Meteorology, Climatology, and Geophysics which is accessed on the http://aviation.bmkg.go.id/web/ page.

The results of the accuracy value of the visibility prediction system built using the Backpropagation method, which is a value of 93.22% or an RMSE value of 0.06776. With the most appropriate parameters set, namely: the best learning rate is 0.001, the number of hidden layer units is 24, and the number of iterations is 10000 iterations.

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