Prediction of Meteorological Parameter Time Series Data for the Forest Fire Early Warning System

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Abstract. A forest fire early warning system must be developed to reduce the impact of greater community losses. One effort to develop an early warning system is to use a forest fire hazard index as a potential assessment guide. The main factor which is a parameter in the fire hazard index calculation method is the meteorological parameter. In general, to know today's fire hazard index is calculated from today's weather conditions, but the need for an early warning system is to know the future fire hazard index. Based on a series of meteorological conditions data held for thirty-six months, using the backpropagation algorithm, it is estimated that the meteorological conditions will be several months to come. Several meteorological parameters have their respective roles, the unknown contribution of which is calculated. In this study, each parameter will be measured by predicting time series data and compared with the results of calculations. The method of calculating the forest fire index used is the McArthur Forest Fire Danger Index with the meteorological parameter elements are temperature, relative humidity, wind speed, and drought factor. Each parameter was trained in artificial neural networks and tested its predictions to produce accuracy for data series temperatures of 91.67%, the relative humidity of 83.33%, and wind speed of 50%.

1. Introduction

Forest fires hit several regions in Indonesia in 2019 covering the provinces of Jambi, Riau, and most of Kalimantan. The extreme dry season this year has resulted in combustible forest fuel. Drought increased in August to September resulting in the number of forest fires increasing [1]. With the slightest trigger of dry forest, floor conditions will easily become a fire. Smoke pollution resulting from combustion makes Indonesia a producer of carbon dioxide which is detrimental to human health [2]. In addition to health impacts, smoke that crosses national borders also impacts economically, ecological disturbance, and loss of habitat for flora and fauna [3].

Forest fires are always associated with drought. Drought is caused by meteorological parameters such as temperature, humidity, rainfall, or precipitation [4]. Some calculation methods use dew, number of days from the last rain, and wind speed to determine the value of a forest fire hazard index. The assessment of fire potential is measured based on a ranking system based on meteorological information which is then classified in a fire hazard index [5]. Based on the value of the hazard index can then be predicted the level of risk that might occur so as to take preventive action [6].

The calculation of the fire hazard index based on meteorological parameters approaches values that correspond to reality is based on the previous day's weather [7]. Calculation of the same day or the maximum the next day is ideal because the weather has not changed significantly. But an early warning
system requires a prediction of a hazard index that will occur in the next few days or several months in the future. By knowing the state of meteorology in the next few months, a simulated index calculation can be calculated more accurately.

Previous research on the prediction of forest fires was carried out using two weather parameters namely relative humidity and rainfall [8]. Based on these two parameters, fire prediction is only based on the drought factor, where the lower the rainfall, the lower the humidity on the ground on the forest floor. Low soil moisture causes the forest fuel on it to burn easily.

2. Methodology

2.1. McArthur Forest Fire Danger Index (MFFDI)

The potential for forest fires must be measured using certain calculations in order to obtain certainty in value. In general, the calculation of the likelihood of a forest fire is measured using an index value. In the world, many models of forest fire hazard index calculation have been developed, one of which is the McArthur Forest Fire Danger Index (MFFDI). MFFDI is the most trusted fire hazard index calculation model in Australia because it uses weather variables and fuel information [9]. The approach to calculating the fire hazard index according to McArthur, which is defined in the McArthur Mark 5 Forest Fire Danger Meter, is written in Equation 1 [10]

\[
FFDI = 2 \exp(-0.45 + 0.987 \ln DF + 0.03387 T - 0.0345 H + 0.0234 U),
\]

where DF=Drought Factor, T=Temperature, H=Humidity, U=Wind Speed.

The drought factor is the value of the potential ease of burning forest fuels and has become an important component in the calculation model of the forest fire hazard index. As a multiplicative factor, the drought factor is treated specifically compared to other parameters so Noble et al. write Equation 1 into Equation 2 [11].

\[
FFDI = 2DF^{0.987} \exp(-0.45 + 0.03387 T - 0.0345 H + 0.0234 U),
\]

To simplify the calculation model and focus on the prediction of meteorological parameters, in this study the drought factor is given a value of 10. Equation 1 or Equation 2 is a manual calculation model to measure the magnitude of the potential for a forest fire. In this study, the results of manual calculations are used as basic data to be compared with the results of predictive data using the Backpropagation algorithm. The assessment of the forest fire hazard index is categorized in 5 situations, which are presented in Table 1.

| Fire Danger Rating | McArthur FFDI Range |
|--------------------|---------------------|
| Low                | 0 – 5               |
| Moderate           | 5 – 12              |
| High               | 12 – 24             |
| Very high          | 24 – 50             |
| Extreme            | 50+                 |

2.2. Backpropagation Algorithm

In general, artificial neural network architecture using a backpropagation algorithm can be described as consisting of three layers, namely the input layer, the hidden layer, and the output layer. Each layer consists of neuron cells. Backpropagation calculates the error contribution of each neuron, adjusting the weight of the neuron by determining the gradient using the function [13]. The cell in the next layer receives the accumulated weighted sum of each cell in the input layer multiplied by the weight of each connection. The strength of artificial neural networks is that each neuron in a layer is connected and is weighted with a neuron in the next layer [14].
Each computational iteration, backpropagation performs two stages, namely the advanced calculation stage to get the error tolerance threshold value, and performs a weight correction at the backward calculation stage. Both of these stages are done repeatedly so as to get the mean squared error value as specified.

Research related to the use of artificial neural networks to predict meteorological parameters carried out in Tokyo which shows that rainfall volumes can be predicted accurately, even can predict unexpected local heavy rainfall [15].

2.3. Location
The location of this research was conducted in the Bukit Soeharto Community Forest, one of the tropical rain forests. Located at attitude 0.6710286 and longitude 116.773446.10 in the area of East Kalimantan Province. This region was chosen to be the location of the study because it has a history of forest fires in the 2014-2016 time period so that it can facilitate the comparison between predictions and actual facts.

The drought that hit the Bukit Soeharto Forest in 2005 is the worst drought recorded in recent years resulting in the number of fires increasing [16]. In 2014, 2016, and 2019 the Bukit Soeharto forest also experienced fires. Repeated fires indicate that the forest fire early warning system is not yet working well.

2.4. Formating Data
The data series used in this study are monthly data from meteorological parameters including maximum temperature, rainfall, and wind speed. The data are presented in time series totaling 36 months, divided into 24 months for training and 12 months for testing.

Each component of meteorological parameters (temperature, relative humidity, and wind speed) is trained on artificial neural networks arranged with the composition of the data series. The training data is 24 months and the time series is determined for 12 months, 12 data patterns will be obtained for each training. In this study, neurons in the input layer were determined by 12 cells containing months 1st to 12th months to recognize the target of the 13th month as cells in the output layer. The next pattern is the 2nd to the 13th months as cells in the input layer to recognize the 14th month as cells in the output layer, and so on. Table 2 shows the backpropagation component design.

| Parameters                   | Value                 |
|------------------------------|-----------------------|
| Input neuron                 | 12                    |
| Hidden neuron                | 20                    |
| Output neuron                | 1                     |
| Learning rate                | 0.1                   |
| Mean Squared Error           | 0.001                 |
| Activation function          | Sigmoid, pureline     |

The difference in data units used by each parameter is different, so the data needs to be normalized using the sigmoid binner function. This function converts all data values into a range of values between 0 to 1 although basically no data actually reaches an absolute value of 0 or 1. This normalization uses Equation 3.

\[
X' = \frac{0.8 \times (X - b)}{(a - b)} + 0.1,
\]

where \(X'\) = normalized data, \(X\) = original data, \(a\) = maximum, \(b\) = minimum.
3. Result
Using the network architecture as presented in Table 2, the network recognizes the pattern of all parameters well. Table 3 shows that each parameter converges under 1000 iterations. This shows that the introduced data series can easily be recognized by the network. In this study, training and testing of data using the Matlab R2016 software tool. The command is written in the form of m.file syntax using the Neural Network Toolbox function. Each parameter is trained one by one, then tested with new data.

**Table 3. Data Training Network Convergence**

| Parameters      | Convergent iteration |
|-----------------|----------------------|
| Temperature     | 413                  |
| Relative Humidity| 299                  |
| Wind Speed      | 751                  |

In addition to practicing the three parameters, then also training the forest fire hazard index pattern for 24 months. Backpropagation also succeeded in recognizing the pattern that was observed and converged on the 566th iteration.

After the data is successfully trained and tested with the same data, it shows perfect test results where 100% of the data is recognized. Next, predict the data 12 months later without first training. The results are shown in Figure 3.

4. Discussion
Referring to Figure 3, it proves that the prediction of data series from meteorological parameters using backpropagation is of good accuracy. Temperature parameters are well-predicted patterns. Of the 12 patterns tested, only one prediction error was made in the 9th month (91.67%). In general, the results of manual calculations and backpropagation predictions show the same pattern, which is stable.
The relative humidity parameter also has a good prediction accuracy rate with 2 data errors from 12 patterns tested (83.33%). Prediction errors occur in the second and eighth data. Both data are predicted to be higher than the target set. This is in line with the trend of the development of relative humidity data which has increased from the first data to the 12th data. Shown in Figure 3, Relative humidity is depicted with a graph that continues to increase.

The third parameter tested is wind speed. In contrast to the other two parameters, wind speed has poor predictive accuracy. With an error of 6 times from 12 data (50%) shows that the wind situation is very unstable and difficult to predict based on the data series. This is not a final conclusion, it needs to be tested again with a greater amount of data to determine wind speed patterns in this region.

As a comparison of the three parameters tested, the forest fire hazard index was also tested. The results show that 10 data are predicted to be true and 2 data are false namely data 3 and data 7. Referring to the facts of the fire, it shows that the third month did indeed occur. So that even though it is incorrectly predicted, it can still be tolerated because backpropagation predicts a hazard index that is also high (0.8), compared to the results of manual calculations assessing hazard index 0.7.

The second error is a prediction on the 7th data which predicts a fire with a hazard index of 0.7, compared to the results of the manual calculation of 0.1. Based on a combination of data between temperature, relative humidity, and wind speed, it shows that the high-temperature value in the 7th month and other parameters are stable. This should be suspected as the cause of prediction error.

### Table 4. Comparison of Prediction Results

| Pattern | Temperature | Relative Humidity | Wind Speed | FFDI Prediction | Fact of Forest Fire |
|---------|-------------|-------------------|------------|----------------|---------------------|
| 1       | True        | True              | False      | True           | No                  |
| 2       | True        | False             | True       | True           | No                  |
| 3       | True        | True              | False      | False          | Yes                 |
| 4       | True        | True              | True       | True           | No                  |
| 5       | True        | True              | True       | True           | No                  |
| 6       | True        | True              | False      | True           | No                  |
| 7       | True        | True              | False      | False          | No                  |
| 8       | True        | False             | False      | True           | No                  |
| 9       | False       | True              | True       | True           | No                  |
| 10      | True        | True              | False      | True           | No                  |
| 11      | True        | True              | True       | True           | No                  |
| 12      | True        | True              | True       | True           | No                  |

Based on the summary of the prediction results presented in Table 4 shows that the meteorological parameters of temperature and relative humidity produced promising results. However, the wind speed shows an unstable prediction result. The temperature parameter is only one of 12 predicted data and relative humidity is twice wrong in predicting. Wind speed parameter is 6 times wrong in predicting, whereas, in the early warning system, wind speed is very important to be one of the factors causing fires.

Table 4 of the Forest Fire Danger Index (FFDI) Prediction column shows that in 12 months there were only two prediction errors. Both errors consist of one error that can still be tolerated and one prediction error that is far different. As a final conclusion of this study, the prediction of data series for each parameter is something that must be considered in the future, although it is very risky if one parameter is wrong in predicting it will affect the overall prediction results. However, the prediction of each parameter will make it easier to know in advance what precautions need to be taken.

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