Forecasting of wind speed using *Exponential Smoothing* and *Artificial Neural Networks* (ANN)

M F Affan*, A G Abdullah and W Surya
Department of Electrical Engineering, Universitas Pendidikan Indonesia, Jl. Dr. Setiabudhi 229, Bandung 40154, Indonesia

*fiqriaffan@student.upi.edu

**Abstract.** Wind energy is an environmentally and efficient energy source that is popular. Wind energy can be converted into electrical energy to meet the electricity needs of the community. This research presents results of Bandung's wind speed forecasting for the next 5 years which aims to determine the wind speed potential in Bandung and plan for the application of a power plant to meet the electricity needs of community, using *Exponential Smoothing* and *Artificial Neural Network* (ANN) methods, simulation process of the calculation use Zaitun time-series software. Based on simulation results forecasting value with the least error value is obtained using the *Artificial Neural Network* (ANN) method. The results of the study determined that the city of Bandung was not suitable for the establishment of a wind power because it did not meet minimum wind speed limit suitable for a wind power.

1. Introduction

Wind is a natural resource that is endless and environmentally. Wind is an indirect form of solar energy caused by uneven heating of the earth's surface [1]. Benefits of wind energy can be an alternative energy for electricity generation, besides that the benefits can be felt by living things as a source of oxygen. Wind has the potential to significantly reduce fuel costs. Wind energy is one of the most popular renewable energy sources and can reduce fuel emissions [2]. Basic problems that arise in increasing use of wind energy are discussed problems related to turbulent wind characteristics [3].

Accuracy of prediction results is a major factor in wind speed forecasting. There are two different multi-step prediction strategies, namely direct strategies and recursive strategies used to forecast wind speed, nonlinear regressive neural network was also developed to increase the accuracy of wind speed forecasting results [4].

The Numeric Wind Prediction (NWP) method can increase the complexity of the wind speed forecast model. However, this model requires a large amount of historical data, and requires different monthly data [5]. Interval analysis method and uncertainty analysis of wind speed estimates. Has advantage of being able to reduce value of uncertainty when combined. This forecasting method is used for wind power plants in Western Australia [6].

Hybrid wind speed forecasting method to overcome the loss of wind energy production, besides that this method has good ability for wind speed forecasting [7].
2. Data analysis
To Analyze wind speed data in research carried out several techniques, first technique is using Exponential Smoothing method then, compare with Artificial Neural Network (ANN) method using Zaitun Time Series software This method uses one of the tools from Microsoft Excel, usually called the conventional method. From the data that has been obtained from BMKG in Bandung, first analyze the input data, namely wind speed in units (m / sec). After that, use Data Analysis located in the Microsoft Excel 2013 menu. Then, select the Exponential Smoothing menu accompanied by wind speed data from 2000 - 2015, and forecasting results will be obtained with different damping factors. "Damping Factor" is the distinguishing coefficient between trials 1 to 9, value starts from (0.1 - 0.9). Goal is to find out what the smallest error value of forecasting.

2.1. Analysis methods using Artificial Neural Network (ANN)
Artificial Neural Network (ANN) is a software that aims to estimate or forecast certain data or values. This method uses Zaitun time-series, in the Zaitun time-series there is a program called Neural Network. Starting from data that has been obtained from BMKG in the city of Bandung. The variables are: Wind speed (m / s), Air Pressure (millibars), Air Temperature (C). Simulation stages using Zaitun time-series software:

- Enter the value of the input variable such as: Wind speed (m / s), Air Pressure (millibars), Air Temperature (C).

![Figure 1. Display menu in Zaitun time-series software.](image1)

- Then, select "Analysis" and select “Neural Network” method which will then display as in Figure 2.

![Figure 2. Display menu Analysis Neural Network.](image2)

In Figure 2, select the wind speed variable to be forecasted. Then, select "OK".

- Then, it will display as shown in Figure 3.
Determine Neural Network that will be created. In this software also can determine neural network architecture (model) parameters, activation functions, and learning algorithm parameters. During the running process, we can set stopping conditions or can use early stopping cross-validation. This research uses different parameter values just the same input layer, which is as many as 8 inputs. The activation function used is "Bipolar Sigmoid" and uses stopping condition with a Mean Square Error of 0.1.

- Then, select the "Start" button to begin the learning process. The process starts until the condition stops being fulfilled or has reached the maximum specified iteration.
- The training process can stop at any time if, clicking the “Stop” button while the learning process is still running.
- After the running process is complete, select the "View Result" button to display the training results. As in Figure 4.

Figure 3. Display menu Neural Network Analysis.

Figure 4. Display of the Neural Network Result.
In Figure 4, select the forecasted result for 5 years, and choose the chart that appears only in the graphs Actual and Predicted, Actual and Forecasted, Actual vs. Predicted. Because, you want to compare charts of actual and predictive values and graphs of actual and forecasting values.

3. Result and discussion

3.1. Estimated calculation of wind speed data using the Exponential Smoothing method

Exponential Smoothing is one of the conventional methods in the field of forecasting (estimation / forecasting) using tools from Microsoft Excel. Exponential Smoothing works by using input from the wind speed itself so that it can predict wind speed in the following year, but in this method using error as one of the indicators of forecasting accuracy itself. Greater the error value, the value of forecasting itself is still not accurate. Conversely, if the error value is small then the forecasting value itself is accurate. In analyzing wind speed data, one of them uses conventional methods using Exponential Smoothing.

3.1.1. Exponential Smoothing training process. Based on forecasting experiments using the Expansion Smoothing method. Enter the value "Input Range", "Damping Factor", and "Output Range". In the value of "Input Range" uses the value of Bandung city wind speed from 2000 to 2015. For "Damping Factor" conducted an experiment from 0.1 - 0.9 in order to see how much error value was obtained. "Output Range" value itself is the result of wind speed forecasting obtained from Input Range. After conducted a trial and error 9 times as much as the Dumping Factor value 0.1 - 0.9 in order to find out which Damping Factor is more efficient. Meanwhile, the error value is obtained from the formula: (dumping factor value - wind speed value) / wind speed value. Then, get the results as in Figure 5.

![Figure 5. Graph of wind speed forecasting data using Exponential Smoothing.](image)

After getting the forecasting results as shown in Figure 5, the average error value of 9 trials is obtained:
Table 1. Result error average value.

| Damping Factor | Error Average |
|----------------|---------------|
| 0.1            | 13.98 %       |
| 0.2            | 14.89 %       |
| 0.3            | 14.90 %       |
| 0.4            | 15.89 %       |
| 0.5            | 15.30 %       |
| 0.6            | 16.68 %       |
| 0.7            | 18.08 %       |
| 0.8            | 19.02 %       |
| 0.9            | 17.97 %       |

Based on Table 1, average error results from trial 1 to trial 9 were obtained with different Damping Factors. It can be concluded that the most optimal average value is in experiment 1 with Damping Factor 0.1. This method can be one way to get optimal forecasting value. By looking at the error value for each experiment. Because, error value can be a reference to assess whether value is optimal or not. Greater error value, greater forecasting value error rate, smaller the error value, smaller error value of forecasting value.

3.1.2. Analysis of Exponential Smoothing results. Table 2 is the forecasting result obtained from the Damping Factor value of 0.1 in Experiment 1:

Table 2. Forecasting results using Exponential Smoothing.

| Year | 2016 | 2017 | 2018 | 2019 | 2020 |
|------|------|------|------|------|------|
|      | 3.16 | 3.08 | 3.45 | 3.15 | 5.09 |

It can be seen that from Table 2 the increase in the value of Bandung wind speed forecasting results is not so significant. Because, the wind speed in general is not so big the increase value if there are no natural factors that influence it, such as tornadoes, tornadoes and others.

Figure 6. Forecasting results with real data wind speed.

In Figure 6, it can be concluded that forecasting wind speed is not very accurate, this is because at the time of simulation there is a high error value. Exponential Smoothing itself is an algorithm that has a fair amount of trial and error. Evidence that the error is still too high can be seen in Table 1. The error value itself was obtained during training on forecasting data, the author here tries to train up to 9x by
entering different Damping Factor values. The forecasting results themselves are not very accurate because each method and algorithm has its own weaknesses.

3.2. Estimated calculation of wind speed data using the Artificial Neural Network (ANN) method

Artificial Neural Network (ANN) is an abstract simulation of the nervous system in the human brain containing a group of neurons interconnected with each other [8]. Neural networks are parallel distributed processors, made of simple units, and have the ability to store knowledge obtained experimentally and ready to use for various purposes [9]. One of the computational methods in the field of forecasting (estimation / forecasting) using the Zaitun Time-Series software. Artificial Neural Network works with the learning and training process using iterations, input layers, hidden layer inputs, and outputs. Data from each input variable includes: Wind Speed (m / s), Air Pressure (millibars), Air Temperature (C). This ANN learning process uses the Trial and Error system, where in this system data cannot be obtained if only one training is carried out. However, the data can be obtained if as much training has been carried out until the results are optimal.

3.2.1. ANN training process. In this ANN training the inputs used are 3 variables: Wind Speed (m / sec), Air Temperature (C), and Air Pressure (Millibars). The following are data on wind speed, air temperature, and air pressure.

| Years | Wind Speed (m/sec) | Air Temperature (C) | Air Pressure (mb) |
|-------|--------------------|---------------------|------------------|
| 2000  | 3,08               | 28,05               | 925,55           |
| 2001  | 3,5                | 27,03               | 928,45           |
| 2002  | 3,12               | 28,55               | 926,33           |
| 2003  | 5,31               | 28,77               | 1010,55          |
| 2004  | 4,3                | 28,49               | 1010,55          |
| 2005  | 4,3                | 23,4                | 922,22           |
| 2006  | 4,8                | 23,44               | 921,4            |
| 2007  | 3,1                | 23,5                | 922,1            |
| 2008  | 1,2                | 23,2                | 922,5            |
| 2009  | 1,8                | 23,4                | 922,9            |
| 2010  | 2,2                | 23,2                | 921,8            |
| 2011  | 3                  | 23,4                | 922,1            |
| 2012  | 3,2                | 23,4                | 923              |
| 2013  | 3                  | 23,5                | 923,1            |
| 2014  | 3,3                | 23,4                | 923,73           |
| 2015  | 2,14               | 23,5                | 924,1            |

In this analysis, the input of training values randomly aims to be able to see the results of forecasting with the smallest error value.

- Training 1:

| Input layer | 8   |
|-------------|-----|
| Hidden Layer | 12  |
| Output Layer | 1   |
| Learning Rate | 0,005 |
| Momentum    | 0,05 |
| Error       | 0,125507 |
### Table 5. Forecasting result of training 1.

| Years | Forecasting Result |
|-------|--------------------|
| 2016  | 1,6797             |
| 2017  | 1,8521             |
| 2018  | 1,8938             |
| 2019  | 2,5844             |
| 2020  | 2,6402             |

- **Training 2:**

### Table 6. Training value 2.

| Input layer | 8 |
|-------------|---|
| Hidden Layer| 20|
| Output Layer| 1 |
| Learning Rate| 0,004|
| Momentum    | 0,04|
| Error       | 0,135976|

### Table 7. Forecasting result of training 2.

| Years | Forecasting Result |
|-------|--------------------|
| 2016  | 1,0598             |
| 2017  | 1,1330             |
| 2018  | 1,3475             |
| 2019  | 1,5023             |
| 2020  | 1,8806             |

- **Training 3:**

### Table 8. Training value 3.

| Input layer | 8 |
|-------------|---|
| Hidden Layer| 15|
| Output Layer| 1 |
| Learning Rate| 0,006|
| Momentum    | 0,06|
| Error       | 0,119820|

### Table 9. Forecasting result of training 3.

| Years | Forecasting Result |
|-------|--------------------|
| 2016  | 1,2254             |
| 2017  | 1,3355             |
| 2018  | 1,5501             |
| 2019  | 2,0246             |
| 2020  | 2,3400             |
• Training 4:

| Table 10. Training value 4. |
|----------------------------|
| Input layer | 8 |
| Hidden Layer | 25 |
| Output Layer | 1 |
| Learning Rate | 0.007 |
| Momentum | 0.07 |
| Error | **0.133075** |

| Table 11. Forecasting result of training 4. |
|--------------------------------------------|
| Years | Forecasting result |
| 2016 | **1.1693** |
| 2017 | **1.2760** |
| 2018 | **1.3416** |
| 2019 | **1.8359** |
| 2020 | **2.2870** |

• Training 5:

| Table 12. Training value 5. |
|-----------------------------|
| Input layer | 8 |
| Hidden Layer | 30 |
| Output Layer | 1 |
| Learning Rate | 0.008 |
| Momentum | 0.08 |
| Error | **0.126161** |

| Table 13. Forecasting result of training 5. |
|--------------------------------------------|
| Years | Forecasting Result |
| 2016 | **1.0581** |
| 2017 | **1.1303** |
| 2018 | **1.2216** |
| 2019 | **1.4177** |
| 2020 | **1.6407** |

![Figure 7. Optimal graph of actual value and forecasted at the 3rd training.](image-url)
3.2.2. ANN analysis of forecasting results. After training using the ANN method, the author gets various error values and forecasting values. Below is the value of error and forecasting that has been trained by ANN:

**Table 14. Error value in each training.**

| Training  | Error Value | Error Percentage |
|-----------|-------------|------------------|
| Training 1| 0.125507    | 12.55%           |
| Training 2| 0.135976    | 13.59%           |
| Training 3| 0.119820    | 12%              |
| Training 4| 0.133075    | 13.30%           |
| Training 5| 0.126161    | 12.61%           |
| Average   | 0.127101    | 12.71%           |

In training ANN input data the learning process in each algorithm certainly has its own error value without the exception of the ANN algorithm. The table above shows that the error value of each forecasting result is not much different, because wind speed has a value that is not much different each year. From the error value data above can be obtained the average error value of each ANN forecasting result which is equal to 12.71% while the minimum and maximum error values are 12% for the minimum and 13.59% for the maximum.

Analysis of forecasting value from 5 training times

- **Training 1:** In training 1 the maximum value of wind speed occurs in 2020 at 2.6402 (m / sec) and the value of drinking wind speed occurs in 2016, which is 1.6797 (m / sec). The average value of forecasting wind speed in training 1 is 2.130 (m / sec).
- **Training 2:** In training 2 the maximum value of wind speed occurs in 2020 at 1.88 (m / sec) and the minimum value occurs in 2016 which is 1.60 (m / sec). The average value of wind speed forecasting on training 2 is 1.384 (m / sec).
- **Training 3:** In training 3 the maximum value of wind speed occurs in 2020 at 2.34 (m / sec) and the minimum value occurs in 2016 which is 1.22 (m / sec). The average value of forecasting wind speed in training 3 is 1.7 (m / sec).
- **Training 4:** In training 4 the maximum value of wind speed occurs in 2020 at 2.28 (m / sec) and the minimum value occurs in 2016 which is 1.16 (m / sec). The average value of forecasting wind speed in training 4 is 1.58 (m / sec).
- **Training 5:** In training 5 the maximum value of wind speed occurs in 2020 at 1.64 (m / sec) and the minimum value occurs in 2016 which is 1.05 (m / sec). The average forecasting speed of wind at training 5 is 1.29 (m / sec).
3.3. Comparison of forecasting results for Exponential Smoothing and Artificial Neural Network (ANN)

Based on Table 2, the forecasting results obtained using the Exponential Smoothing method were carried out in Experiment 1 using the Dumping Factor value of 0.1 and compared with the results found in Table 9 forecasting value using Artificial Neural Network which was carried out in the 3rd training. The author compares the results of forecasting from the two methods by comparing the error value in each result. Forecasting obtained. For the value of errors contained in the forecasting results using the Exponential Smoothing method of 13.98%. Whereas for the error value found in the Artificial Neural Network (ANN) method, it is 0.119820 if the number is converted into (%) to 12%.

Can be concluded from the explanation above that, the smaller the error value, the greater the level of accuracy. Vice versa, the greater the error value of eating the greater the level of error. From the comparison above, the writer takes the forecasting result from the error value, and the smallest error value from the two methods is the ANN forecasting error value with an error rate of 12% which means that the drainage rate is 88%. With these results, the author takes the results of forecasting from the ANN method which will be applied to the planned development of PLTB in the city of Bandung.

3.4. Plan for the application of a power plant in Bandung

The use of wind turbines is divided into several heights and capacities, namely large, medium, small and micro scale. The larger the scale, the greater the capacity that wind turbines can produce. Figure 9 is the type of wind turbine based on its height and capacity.

![Figure 9. Type of wind turbine based on its height and capacity [10].](image)

In choosing the type of blade that needs to be shown is Cp and Tip Speed Ratio (TSR). Cp is the level of efficiency of the blade. The greater the efficiency, the greater the ability of a turbine to extract the energy it receives (energy conversion). TSR is the ratio of blade tip speed to wind, the greater the TSR the greater the rotation. Of the various types of wind turbines, type 3 propeller blades are the most suitable to use, because the value of efficiency is ideal (the coefficient reaches 40%) and can also be used for high speed, Figure 10 is the display of 3 Blade Propeller turbines [10].

![Figure 10. Blade Propeller type 3 turbines [10].](image)
In the plan for applying Wind Power in Bandung, average wind speed is only 1.7 (m / sec). If you want to plan the construction of this power plant, the turbine used is type 3 blade propeller with a micro scale. Some of the reasons this micro scale is more suitable to be applied in Indonesia are:

- Economically, prices and operating costs are lower.
- The technology is easier to master and develop.
- In practice, management in remote areas will be easier to develop.
- Socially easier to be accepted by society.
- Small impact and burden on the environment.

| Wind Speed | 2.2 (m/s) | 4.5 (m/s) | 10 (m/s) | 20 (m/s) |
|------------|-----------|-----------|---------|----------|
| Blade diameter 1 m | 1 Watt | 6 Watt | 70 Watt | 560 Watt |
| Blade diameter 2 m | 3 Watt | 25 Watt | 280 Watt | 2300 Watt |
| Blade diameter 3 m | 7 Watt | 60 Watt | 630 Watt | 5000 Watt |
| Blade diameter 4 m | 12 Watt | 100 Watt | 1120 Watt | 9000 Watt |

In Table 15 it can be concluded that the greater the wind speed, the greater the power produced. Seeing the average wind speed in the city of Bandung in 2016 - 2020 is only 1.7 (m / sec), the city of Bandung is not feasible to establish a micro-scale power plant though. Because the wind speed is below the minimum scale to establish a PLTB.

4. Conclusion
Input data used Exponential Smoothing and Artificial Neural Network (ANN) methods, namely Bandung city wind speed values from 2000 - 2015, Bandung air temperature values from 2000 - 2015, Bandung air pressure values from 2000 - 2015. The results of the analysis of forecasting value with Exponential Smoothing method is the average value of forecasting the most optimal value is in experiment 1 with Dumping Factor 0.1 with a minimum value occurring in 2017 which is 3.08 (m / sec) and value the maximum occurs in 2020 which is equal to 5.09 (m / sec) with an average wind speed of 3.58 (m / sec) with an error rate of 13.98%. The analysis of forecasting value using the Artificial Neural Network (ANN) method is the value of forecasting in training 3, the maximum value of wind speed occurs in 2020 at 2.34 (m / sec) and the minimum value occurs in 2016 which is 1.22 (m / sec). For the average value of forecasting wind speed in training 3 is 1.7 (m / sec) with an error rate of 12%. Comparative results of the two approaches, the smaller the error value, the greater the accuracy. Vice versa, the greater the error value of eating the greater the level of error. From the results of the comparison the author takes the forecasting results based on the error value, and the smallest error value of the two methods is the ANN forecasting error value with an error rate of 12% which means that the drainage rate is 88%. The relationship between wind speed and PLTB is the greater the wind speed, the greater the power produced. Seeing the average wind speed in the city of Bandung in 2016 - 2020 is only 1.7 (m / sec), the city of Bandung is not feasible to establish a micro-scale power plant though. Because the wind speed is below the minimum scale to establish micro-scale power plants.

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