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Application of artificial neural networks for the wind speed prediction of target station using reference stations data

Mehmet Bilgili, Besir Sahin*, Abdulkadir Yasar

Cukurova University, Faculty of Engineering and Architecture, Mechanical Engineering Department, 01330 Adana, Turkey

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Abstract

In this study, artificial neural networks (ANNs) were applied to predict the mean monthly wind speed of any target station using the mean monthly wind speeds of neighboring stations which are indicated as reference stations. Hourly wind speed data, collected by the Turkish State Meteorological Service (TSMS) at 8 measuring stations located in the eastern Mediterranean region of Turkey were used. The long-term wind data, containing hourly wind speeds, directions and related information, cover the period between 1992 and 2001. These data were divided into two sections. According to the correlation coefficients, reference and target stations were defined. The mean monthly wind speeds of reference stations were used and also corresponding months were specified in the input layer of the network. On the other hand, the mean monthly wind speed of the target station was utilized in the output layer of the network. Resilient propagation (RP) learning algorithm was applied in the present simulation. The hidden layers and output layer of the network consist of logistic sigmoid transfer function (logsig) and linear transfer function (purelin) as an activation function. Finally, the values determined by ANN model were compared with the actual data. The maximum mean absolute percentage error was found to be 14.13% for Antakya meteorological station and the best result was found to be 4.49% for Mersin meteorological station.

Keywords: Artificial neural network; Wind speed prediction; Reference stations

*Corresponding author. Tel.: +90 322 338 60 80; fax: +90 322 338 61 26.
E-mail address: bsahin@cu.edu.tr (B. Sahin).

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1. Introduction

The demand for electricity grows rapidly in Turkey as a result of social, economical and industrial development of country. Almost all types of oil and natural gas are imported from neighboring countries. Rapidly growing demand of energy forces Turkey to search for renewable energy sources such as wind energy. However, the potential sites of wind energy generation of the country have not been completely investigated in detail [1,2].

The amount of heat energy that is absorbed varies spatially as well as temporally because of the available solar radiation and cloudiness. This creates temperature, pressure and density (specific mass) differences that, in turn, create forces that move air from one place to another. It is evident that depending on the surface features of the earth, some areas are preferable to others for extracting kinetic energy from the wind in the atmospheric boundary layer [3]. Because of the fact that this kinetic energy varies directly proportional to the third grade power of the wind speed, the prediction of the wind energy is usually obtained using estimated wind speeds. Wind estimation is difficult due to the complex structures of parameters which affect wind strongly such as topographical properties of the earth, the rotation of the world, temperature and pressure difference.

Nowadays, renewable energy such as wind energy is one of the most attractive sources of energy. Researchers may need to prepare an inventory on the availability of wind energy in an area where there is no measured wind speed data. For this type of situation, it seems useful to predict the wind energy potential using the ANN method. Kalogirou et al. [4] stated that the predicted variations of meteorological parameters such as wind speed, relative humidity, solar radiation, air temperature, etc. are needed in the industry of renewable energy for design purposes, performance analysis and running cost estimation of renewable energy systems. In addition, they reported that for proper and efficient utilization of wind power, it is very important to know the statistical characteristics, persistence, availability, diurnal variation and prediction of wind speed. The values of wind power distributions are needed for site selection, performance prediction and planning of wind turbines. Moreover, prediction of wind speed is needed for any regional inventory wind energy studies in advance. In this sense, the establishment of a model for wind speed correlation in a region is of great importance in the management of wind energy resources for power generation as well as in other research fields related to energy conservation [5].

The objective of the present work is to apply the ANN method for the prediction of the wind speed of target station using neighboring measuring stations, in order to show that this method can be applied to predict the wind speeds for any locations around sampled measuring stations.

2. Wind data analysis

In this study, hourly wind speed data, collected by the Turkish State Meteorological Service (TSMS) at 8 measuring stations such as Antakya, İskenderun, Samandağ, Dörtyol, Karataş, Yumurtalık, Adana and Mersin stations in the eastern Mediterranean region of Turkey, were used. The long-term wind data, containing hourly wind speeds, directions and related information, cover the period from the year 1992 to 2001. The mean monthly wind speeds were calculated from these hourly wind speed data. These data were divided into two parts. The first part of the data which covers the years between 1992 and 1999 was used for training procedure. The second part of the data which covers the years of 2000 and 2001 was utilized for testing procedure. The map of the region, the location of the stations and the dominant prevailing wind directions for each station are presented in Fig. 1. Stations are located between 36°.05″ and 36°.59″ north latitude, while the heights of stations above the sea level vary between 3 and 100 m. Except Adana and Antakya; all stations are located on the coastal site of the eastern Mediterranean region of Turkey. Dominant prevailing wind directions for Antakya, Samandağ and Karataş meteorological stations are 210° (SW). In these regions, southwestern winds are effective. For Adana, Yumurtalık, Dörtyol, İskenderun and Mersin, dominant prevailing wind directions are 0° (N), 30° (NE), 120° (ES), 300° (WN) and 330° (NW), respectively. The mean wind speeds and dominant prevailing wind directions of all stations are presented in Table 1. As seen in this table, the mean wind speed varies mainly from 0.8 m/s to a maximum of 4.0 m/s. Height of anemometer of all stations is 10 m above the ground level. Mediterranean climate is dominant in this region, usually hot and dry in summer, lukewarm and rainy in winter. But, climate properties vary depending on the level of the height above the sea level. On the slope of a mountain looking at the sea, an increase of terrestrial effects on

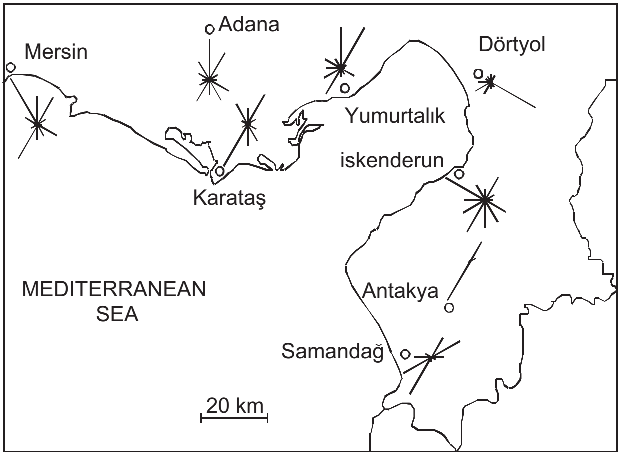

Fig. 1. Map of the region, location of the stations and dominant wind directions.

Table 1
Mean wind speeds and dominant prevailing wind directions of all stations

Station	Latitude	Longitude	Altitude (m)	Mean wind speed (m/s)	Dominant prevailing wind direction
Antakya	36°.12″	36°.10″	100	2.8	SW(210°), NE(30°)
İskenderun	36°.35″	36°.10″	4	2.6	WN(300°), SW(210°)
Karataş	36°.34″	35°.23″	22	2.7	SW(210°), NE(30°)
Yumurtalık	36°.46″	35°.47″	27	1.9	NE(30°), N(0°)
Dörtyol	36°.51″	36°.13″	28	0.9	ES(120°), WS(240°)
Samandağ	36°.05″	35°.58″	4	4.0	SW(210°), EN(60°)
Adana	36°.59″	35°.18″	28	0.8	N(0°), NE(30°)
Mersin	36°.49″	34°.36″	3	2.3	NW(330°), SW(210°)

Table 2
Correlation coefficients of wind speeds amongst stations

Station	Dörtyol	Antakya	Samandağ	Karataş	İskenderun	Yumurtalık	Adana	Mersin
Dörtyol	1	0.04	0.10	0.02	0.24	0.06	0.18	0.25
Antakya	0.04	1	0.46	0.40	0.66	0.44	0.14	0.91
Samandağ	0.10	0.46	1	0.76	0.74	0.69	0.41	0.31
Karataş	0.02	0.40	0.76	1	0.72	0.85	0.67	0.36
İskenderun	0.24	0.66	0.74	0.72	1	0.59	0.29	0.59
Yumurtalık	0.06	0.44	0.69	0.85	0.59	1	0.76	0.43
Adana	0.18	0.14	0.41	0.67	0.29	0.76	1	0.15
Mersin	0.25	0.91	0.31	0.36	0.59	0.43	0.15	1

climate is observed. However, the weather in this region does not show intense terrestrial climate due to the Mediterranean Sea effect.

In this study, a model was developed to estimate wind speed of any target station utilizing wind speeds of the reference measuring stations. Firstly, the mean monthly wind speed obtained at 8 measuring stations in the eastern Mediterranean region of Turkey were compared with each other and the correlation coefficients between them two by two were determined. The accuracy of the result depends on the cross-correlation level between the two stations' wind speed, which is related to the morphology of the surrounding area [5]. Thus, the relation amongst stations was defined and reference stations were determined for any target station. For the mean monthly wind speed between 1992 and 2001 the correlation coefficients of wind speeds amongst stations are presented in Table 2. As seen in this table, Antakya, İskenderun, Karataş, Mersin, Samandağ and Yumurtalık were defined as target stations sequentially except Adana and Dörtyol stations due to a high rate of correlation factors.

3. Artificial neural networks (ANNs)

Kalogirou [6] stated that during the past years there has been a substantial increase in the interest on the ANNs. Researches have been applying the ANN method successfully in various fields of mathematics, engineering, medicine, economics, meteorology, psychology, neurology, in the prediction of mineral exploration sites, in electrical and thermal load predictions and in adaptive and robotic control and many other subjects. This method learns from given examples by constructing an input–output mapping in order to perform predictions [7]. In other words, to train and test a neural network, input data and corresponding output values are necessary [8]. ANNs can be trained to overcome the limitations of the conventional approaches to solve complex problems that are difficult to model analytically [9].

Fundamental processing element of a neural network is a neuron. The network usually consists of input layers, hidden layers and output layer [9]. The model of a neuron is shown in Fig. 2.

A neuron j may be mathematically described with the following pair of equations [10]:

$$u_j = \sum_{i=0}^{p} w_{ji} y_i$$

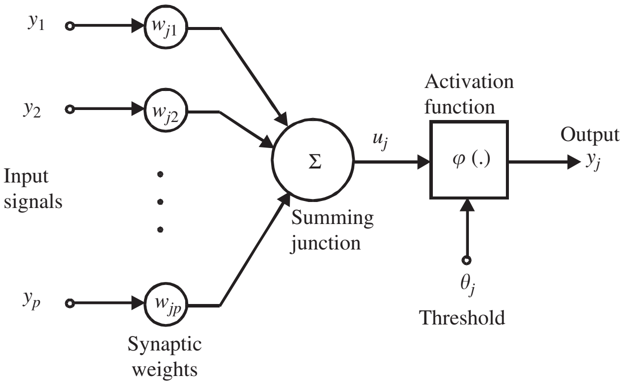

Fig. 2. Nonlinear model of a neuron [10].

and

$$y_j = \varphi(u_j - \theta_j).$$

The artificial neuron receives a set of inputs or signals y with weight w, calculates a weighted average of them (u) using the summation function and then uses some activation function φ to produce an output y. The use of threshold θ has the effect of applying *an affine transformation* to the output u of the linear combiner in the model of Fig. 2 [10,11]. The sigmoid logistic nonlinear function is described with the following equation:

$$\varphi(x) = \frac{1}{1+^{-x}}.$$

4. ANN architecture

ANN architecture used in this study for Karataş meteorological station which is selected as a target station is shown in Fig. 3. This network consists of an input layer, two hidden layers and an output layer. The mean monthly wind speeds of reference stations and corresponding month were used in the input layer of the network. İskenderun, Yumurtalık, Adana and Samandağ stations were selected as reference stations. The most significant point in the selection of these reference stations is that there is a good relation with high correlation coefficient between the target and reference stations. The mean monthly wind speed of Karataş which is a target station was used in the output layer of the network. For other target stations, the reference stations in the input layer of the network, the number of the neurons in the hidden layers of the network and the number of patterns in the training and testing procedures are given in Table 3. Resilient propagation (RP) learning algorithm was used in the present simulation. Neurons in the input layer have no transfer function. Logistic sigmoid transfer function (logsig) and linear transfer function (purelin) were used in the hidden layers and output layer of the network as an activation function, respectively. Simulations were performed to estimate the mean monthly wind speed of target station. In each layer, every neuron is connected to a neuron of adjacent layer having different weights. Each neuron as indicated in Fig. 3, receives signals from the neurons of the previous layer weighted by the interconnect values between neurons except

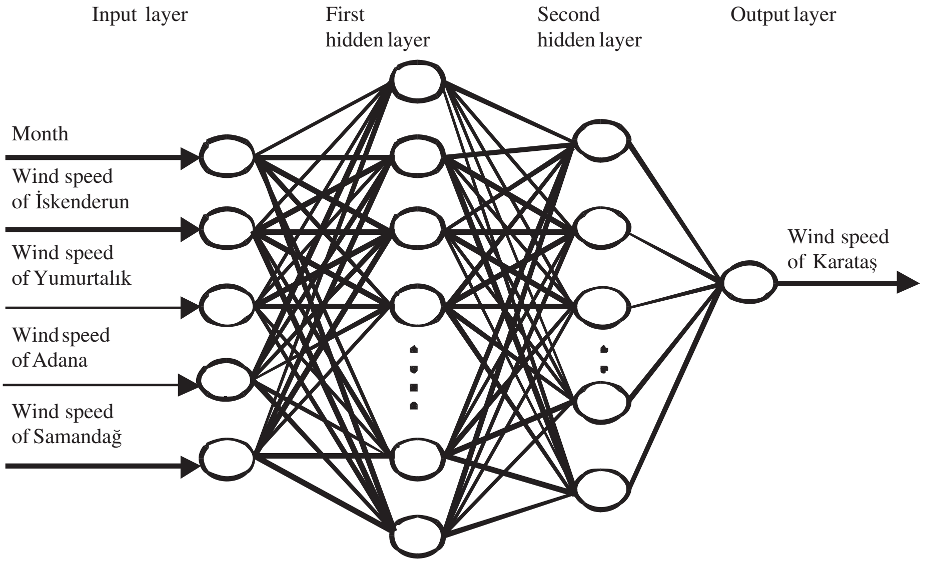

Fig. 3. ANN architecture.

Table 3
Reference stations and number of neurons in the hidden layers of the network for target stations

Target station	Reference stations	Number of neurons in hidden layers	Number of patterns in training	Number of patterns in testing
Antakya	İskenderun, Mersin	6–6	95	24
İskenderun	Yumurtalık, Mersin, Antakya, Samandağ, Karataş	12–6	75	24
Karataş	İskenderun, Yumurtalık, Adana, Samandağ	10–5	73	24
Mersin	Antakya, İskenderun	6–3	95	24
Samandağ	Karataş, İskenderun, Yumurtalık	8–4	75	24
Yumurtalık	Adana, Samandağ, Karataş, İskenderun	10–5	73	24

input layer. Neurons then produce an output signal by passing the summed signal through an activation function [12]. Mohandes et al. [7] state that during the training procedure, the weights of the connections between neurons are adjusted in order to achieve the desired input/output relation of the network. This procedure goes on until the difference between the actual output of the network and the desired output is equal with a specified remainder value. Here, the criterion is put forward as the network output which should be closer to the value of desired output. This training procedure has to be repeated for the rest of the input–output pairs existing in the training data.

5. Results and discussion

In the present study, it is realized that ANN is a convenient method to apply for the prediction of the wind speed. The mean absolute percentage error (MAPE) was used to see the convergence between the target and the output values. This parameter is defined as follows [9]:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{abs}\left(\frac{o_i - t_i}{o_i}\right) \times 100.$$

In addition, the coefficient of correlation between the target value and output value is defined as follows [13]:

$$R = \frac{\overline{to} - \bar{t}\bar{o}}{\sqrt{\left[\overline{t^2} - (\bar{t})^2\right]\left[\overline{o^2} - (\bar{o})^2\right]}},$$

where t is the target value, o the output value, n the total number of months, $\bar{t}$ the mean of the t_is, $\bar{o}$ the mean of o_is and $\overline{to}$ the mean of t_io_is.

ANNs have a two-step procedure; these are called training and testing procedures. They are initially trained and then their accuracy is checked with the testing database. ANN can give different results for each test using algorithm constructed in the present work. Therefore, 10 tests were performed for each meteorological station separately and for the most appropriate result, average values of these tests were taken. The performance values for all stations, such as MAPE and R for training and testing procedures are given in Table 4. The MAPE values, ranging from 4.49% to 14.13%, differ from the actual value for all stations and testing procedure. The maximum MAPE was found to be 14.13% for Antakya station in the testing procedure, while the best result was found to be 4.49% for Mersin station in the testing procedure. The maximum correlation coefficient between the target and output values was found to be 0.97 for testing procedure of Mersin station, while the minimum correlation coefficient was found as 0.67 for Yumurtalık station. Moreover, another significant point in this table, the performance values of the training procedure are better than the performance values of the testing procedure.

In the present study, 2 years i.e. 24 months of hourly wind speed data from the year 2000 to 2001 were taken for comparison. As seen in Figs. 4–9, prediction of ANN follows the variation of actual data exactly. In the case of Antakya meteorological station, there are

Table 4
The performance values for training and testing procedures

Station	Training procedure		Testing procedure	
	MAPE	R	MAPE	R
Antakya	5.53	0.97	14.13	0.96
İskenderun	1.48	0.99	9.97	0.87
Karataş	1.7	0.97	6.66	0.72
Mersin	3.44	0.96	4.49	0.97
Samandağ	3.07	0.95	8.83	0.83
Yumurtalık	2.56	0.97	13.25	0.67

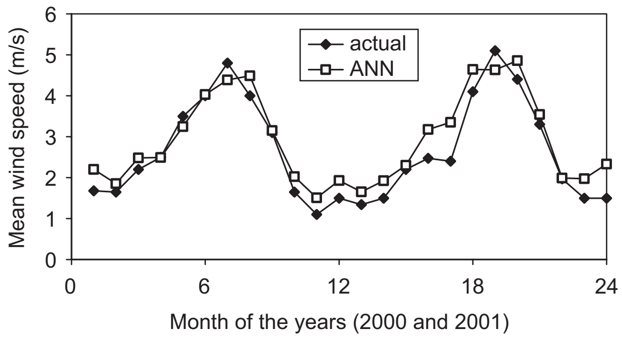

Fig. 4. Comparison between prediction of ANN and actual results for Antakya meteorological station.

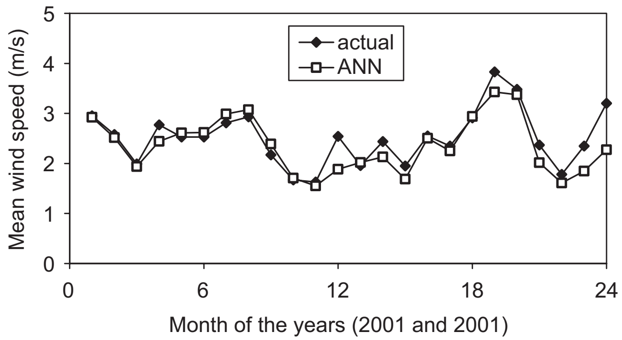

Fig. 5. Comparison between prediction of ANN and actual results for İskenderun meteorological station.

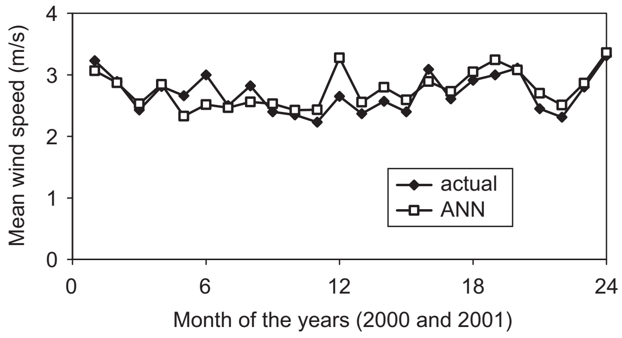

Fig. 6. Comparison between prediction of ANN and actual results for Karataş meteorological station.

two sharp points with a level of 5 m/s which correspond to the month of July, whereas the lowest level of wind speed is with a level of 1.1 m/s which corresponds to the months of November and December as indicated in Fig. 4, even though, the prediction of ANN agrees well with the actual value. On the other hand, actual mean wind speed of İskenderun meteorological station presented in Fig. 5 varies rapidly from month to month,

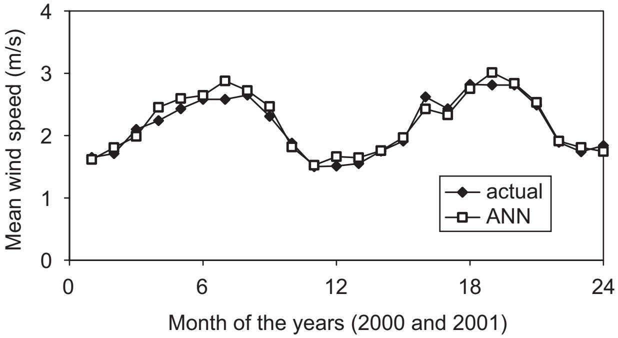

Fig. 7. Comparison between prediction of ANN and actual results for Mersin meteorological station.

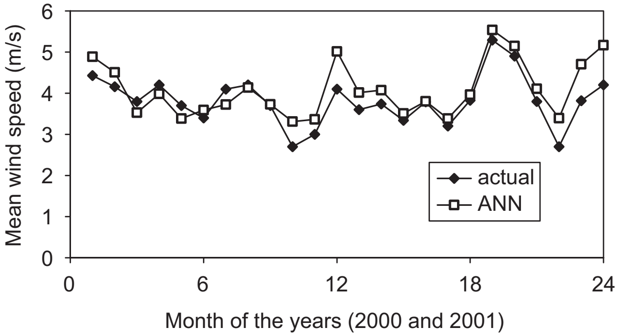

Fig. 8. Comparison between prediction of ANN and actual results for Samandağ meteorological station.

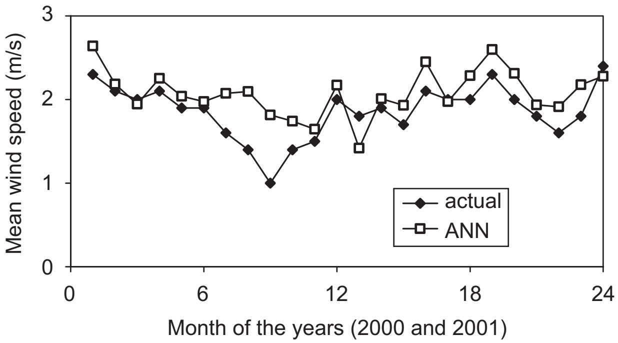

Fig. 9. Comparison between prediction of ANN and actual results for Yumurtalık meteorological station.

though, the prediction of ANN for most of the months agrees well with the actual values. It seems that as long as the necessary data are utilized for training and testing procedures of the ANN method, it is possible to estimate an accurate result. It can be concluded that the ANN looks promising in predicting the wind speed of a target station depending on the selection of the reference measuring stations.

6. Conclusion

In order to improve the accuracy of the simulations of ANN method one must select wind speed measuring stations having similarity correlation factors of 0.59. According to this statement, there is no good relation amongst the relative stations for Dörtyol meteorological station, because of the fact that the biggest correlation coefficient is 0.25 between Dörtyol and Mersin meteorological station. On the other hand, selecting Antakya meteorological station as a target station, it seems that İskenderun and Mersin meteorological stations should be chosen as reference stations due to the high rate of correlation coefficient between the target and reference stations. That is to say, the value of the mean monthly wind speed of İskenderun and Mersin meteorological stations can be utilized to estimate the mean monthly wind speed of Antakya meteorological station. Similarly, selecting Samandağ meteorological station as a target station, it seems that Karataş, İskenderun and Yumurtalık stations should be chosen as reference stations due to the high rate of correlation coefficient between the target and reference stations. In addition, İskenderun, Yumurtalık, Adana and Samandağ stations were chosen as reference stations to predict the mean monthly wind speed of Karataş meteorlogical station as a target station. Yumurtalık, Mersin, Antakya, Samandağ and Karataş stations can be used to estimate wind speed of İskenderun meteorological station. On the other hand, İskenderun and Antakya stations can be used to predict wind speed of Mersin meteorological station.

It can be concluded that the ANN method seems to be a powerful tool in predicting the missing wind speed of target station depending on the correlation between the target and reference stations. The advantage of this model is that as long as the required wind speed data of the reference stations are available, the future wind speed of target station can also be predicted straightaway and satisfactorily without the use of any topographical details or other meteorological data.

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