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Forecasting of Wind Speed Using an Interval-Based Least Square Method

Muhammad Aslam and Mohammed Albassam*

Department of Statistics, Faculty of Science, King Abdulaziz University, Jeddah, Saudi Arabia

A new least square method (LSM) for time series analysis under indeterminacy is proposed in this work. The proposed LSM under indeterminacy is known as the neutrosophic least square method (NLSM). The NLSM is proposed to forecast wind speed when data are in the interval. The trended line under indeterminacy is introduced and applied using wind speed data. The time series plots under neutrosophic statistics are given. A comparative study shows that the proposed NLSM is more efficient and informative to apply for the forecasting of wind speed.

Keywords: wind speed, least square method, indeterminacy, forecasting, trend, neutrosophy

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****Correspondence:***
Muhammad Aslam
aslam_ravian@hotmail.com

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INTRODUCTION

In time series analysis, the least square method (LSM) is applied to study the relationship between the observed variable and the time factor variable. In such a model, the observed variable is taken as the dependent variable, and the time factor variable generated from the time span is taken as an independent variable. The LSM has been widely applied to the best fit of the data in hand. The LSM is applied in estimating future values based on the current data information. Among the other methods of time series analysis, the LSM method is free from personal bias as the mathematical model is applied to get the trend values. In addition, the LSM can be applied effectively in forecasting the values because of its mathematical function. Khalil and Moraes (1995) applied the LSM for methane time series data. Harris et al. (2003) and Ismail and Shabri (2014) applied the LSM for meteorology and lynx datasets, respectively. Yang et al. (2014) introduced genetic programming based on the LSM. More applications of series methods can be seen; see the work of Jebb and Tay (2017) for organizational research, Chatfield and Xing (2019) and McDowall et al. (2019) for time series analysis, and Feyrer (2019) and Kosiorowski et al. (2019) for geography.

The forecasting and estimation in energy areas are carried out using statistical models. For example, the time series model can be applied to estimate and forecast the wind speed for the next days or months. The statistical models have the ability to give a reasonable forecast based on the current or past data. Kavak Akpinar and Akpinar (2005) discussed the applications of statistics on the data obtained from the wind energy system. A statistical distribution was fitted on the wind speed data by Brano et al. (2011). Liu et al. (2016) discussed the forecasting using the LSM. The applications of several statistical distributions on wind speed data were given by Ali et al. (2018), Bidaoui et al. (2019), Alrashidi et al. (2020), and ul Haq et al., 2020. The applications of statistical techniques in the area of energy can be seen in the work of Ozay and Celiktas (2016), Katinas et al. (2018), Qing (2018), Wang et al. (2018), Akgül and Şenoğlu, 2019, Mahmood et al. (2020), and Zaman et al. (2020).

The existing LSM for time series analysis is applied for the forecasting of the wind speed by assuming certainty in the parameters and observations of the data. In practice, the wind speed data are recorded in intervals. Therefore, the existing LSM cannot be applied for the forecasting and estimation of wind speed. The statistical techniques under the fuzzy logic can be applied for the forecasting of the wind speed in this case. Song and Chissom (1993) and Sezer et al. (2020)

introduced time series when observations were not exact. The fuzzy-based analysis for various applications was introduced by Przemysław Grzegorzewski (2000), Montenegro et al. (2001), Przemysław Grzegorzewski (2009), von Storch and Zwiers (2013), and Grzegorzewski and Śpiewak, 2019.

Smarandache (1998) introduced the neutrosophic logic as an extension of the fuzzy logic. Smarandache (2015) proved the efficiency of the neutrosophic logic over the fuzzy logic and interval-based analysis. Later on, several people worked on the neutrosophic logic and applied it in various real-life problems; see, for example, the work of Broumi et al. (2017), Abdel-Basset et al. (2019), Smarandache (2019), and Nabeeh et al. (2019). Smarandache (2014) worked on the neutrosophic statistics (NS) and discussed the application and difference between NS and classical statistics (CS). According to Smarandache (2014), "Neutrosophic Statistics refers to a set of data such that the data or a part of it are indeterminate to some degree and to methods used to analyze the data. In classical statistics, all data are determined; this is the distinction between neutrosophic statistics and classical statistics." Neutrosophic statistics deals with analyzing the data having neutrosophic numbers. Classical statistics is a special case of neutrosophic statistics. The neutrosophic statistics reduces to classical statistics when only determinate numbers are in the data. Chen et al., 2017a and Chen et al., 2017b introduced a different method than Smarandache (2014) to analyze the neutrosophic data. Aslam (2020a) and Aslam (2020c) worked on the statistical tests under NS.

Aslam (2020b) introduced the semi-average method for time series analysis under neutrosophic statistics and applied it for wind forecasting. From the literature study, it can be noted that the existing LSM for time series analysis based on CS is unable to give information about the measure of indeterminacy. According to the best of knowledge, no work is available on the designing of the LSM for time under neutrosophic statistics. In this article, we will focus on presenting the neutrosophic least square method (NLSM) for time series analysis. The application of the proposed NLSM will be given using wind speed data. It is expected that the proposed NLSM can be used effectively to fit the model for wind speed data and forecasting the wind speed for the future.

LEAST SQUARE METHOD UNDER INDETERMINACY

As mentioned earlier, the least square method (LSM) has been widely used in practice to find the trend in time series. The existing LSM under CS is worked on the basis of the relationship of the observed value and time factor variables. The existing LSM is applied when observations in both variables are determined and exact. However, as mentioned before, in a complex process or when the data are in intervals, the existing LSM cannot be applied to find the trend values. Let $y_N = y_L + y_U I_{yN}; I_{yN}\varepsilon[I_{yL}, I_{yU}]$ and $x_N = x_L + x_U I_{xN}; I_{xN}\varepsilon[I_{xL}, I_{xU}]$ be neutrosophic forms of the observed variable $y_N\varepsilon[y_N, y_N]$ and time factor variable $x_N\varepsilon[x_L, x_U]$, respectively, of sample size $n_N\varepsilon[n_N, n_N]$. The variable $x_N\varepsilon[x_L, x_U]$ is a coded variable and generated from the given time span. Note here that $I_{yN}\varepsilon[I_{yL}, I_{yU}]$ and

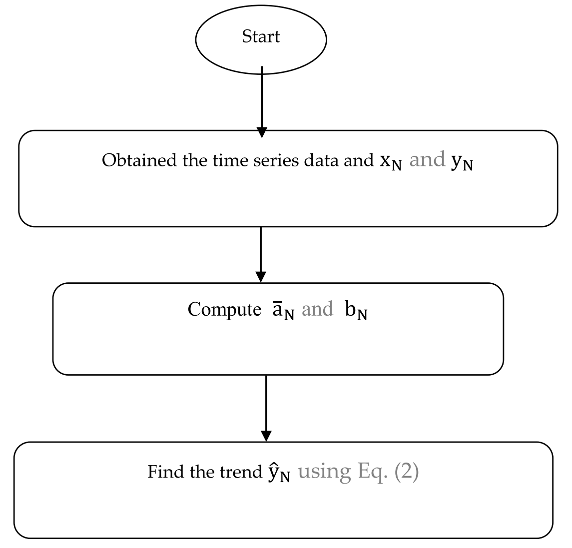

FIGURE 1 | The frame diagram of the proposed time series method.

TABLE 1 | Neutrosophic trended lines of wind speed data of 2019.

Months	Neutrosophic trended lines
January	$\hat{y}_N$ = [0.13306,15.53629]+[−0.00242, −0.14758] x_N
February	$\hat{y}_N$ = [0.17734, 10.11823]+[0.01067, 0.05473] x_N
March	$\hat{y}_N$ = [0.00202, 10.71169]+[0.01492, 0.06653] x_N
April	$\hat{y}_N$ = [−0.21505, 12.79785]+[0.04472, 0.18176] x_N
May	$\hat{y}_N$ = [−0.21774, 15.21774]+[0.05323, 0.07581] x_N
June	$\hat{y}_N$ = [1.39785, 16.50108]+[−0.03893, 0.21602] x_N
July	$\hat{y}_N$ = [4.53226, 28.33871]+[−0.00968, −0.44839] x_N
August	$\hat{y}_N$ = [2.96573, 15.15524]+[−0.11169, 0.02621] x_N
September	$\hat{y}_N$ = [1.06022, 13.15054]+[−0.01335, −0.03337] x_N
October	$\hat{y}_N$ = [1.58669, 16.11089]+[−0.04556, −0.26331] x_N
November	$\hat{y}_N$ = [0.26452, 11.68387]+[−0.01135, −0.19199] x_N
December	$\hat{y}_N$ = [0.14516, 5.11895]+[−0.00323, 0.04153] x_N

$I_{xN}\varepsilon[I_{xL}, I_{xU}]$ are the indeterminate intervals associated with variables $y_N\varepsilon[y_L, y_U]$ and $x_N\varepsilon[x_L, x_U]$, respectively. The neutrosophic linear trend line is given by

$$\hat{y}_N = a_N + b_N x_N; \hat{y}_N\varepsilon\left[\hat{y}_L, \hat{y}_U\right] \quad (1)$$

The neutrosophic linear regression under indeterminacy can be expressed as

$$\hat{y}_N = (a_L + a_U I_{aN}) + (b_L + b_U I_{bN})(x_L + x_U I_{xN}); I_{aN}\varepsilon[I_{aL}, I_{aU}], I_{bN}\varepsilon[I_{bL}, I_{bU}] \quad (2)$$

where $I_{aN}\varepsilon[I_{aL}, I_{aU}]$ and $I_{bN}\varepsilon[I_{bL}, I_{bU}]$ are measures of indeterminacy associated and $a_N\varepsilon[a_L, a_U]$ is the neutrosophic intercept and $b_N\varepsilon[b_L, b_U]$ is the neutrosophic rate of change. The values of $a_N\varepsilon[a_L, a_U]$ and $b_N\varepsilon[b_L, b_U]$ can be computed by

$$\bar{a}_N = \bar{y}_N - b_N\,\bar{x}_N; \bar{a}_N\varepsilon\left[\bar{a}_L, \bar{a}_U\right] \quad (3)$$

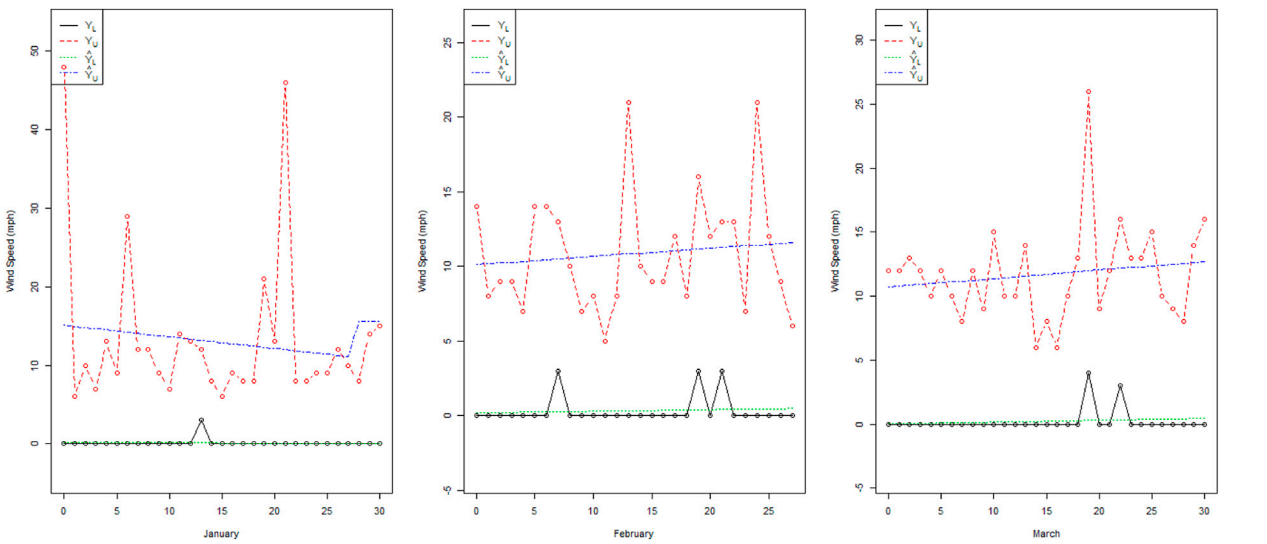

FIGURE 2 | Trended lines for January, February, and March.

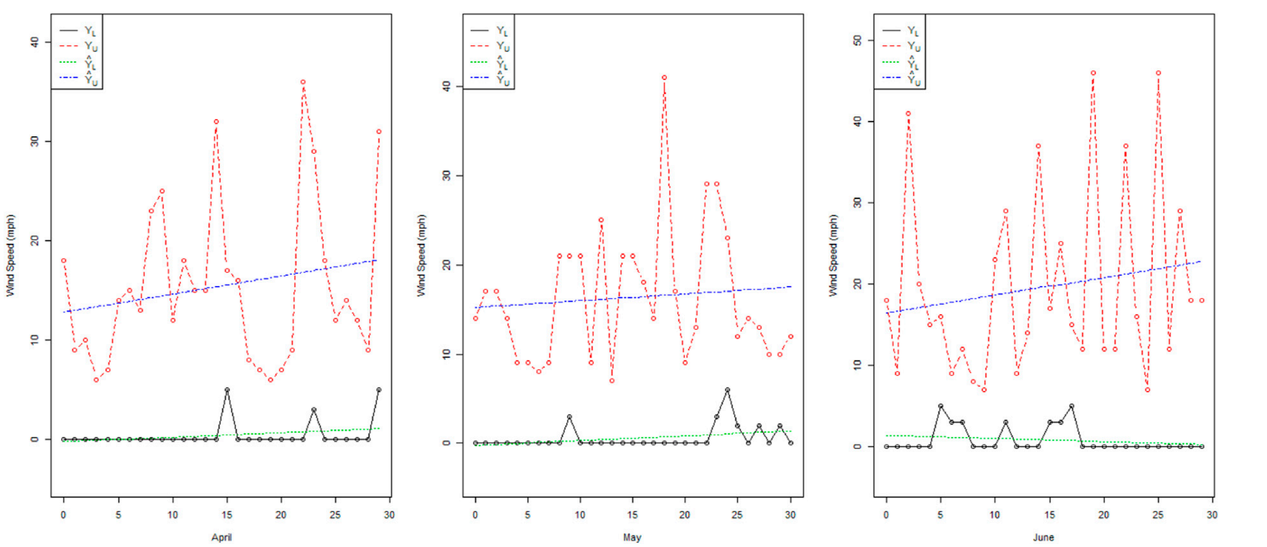

FIGURE 3 | Trended lines for April, May, and June.

where

$$b_N = \frac{n_N\left(\sum x_N y_N\right) - \left(\sum x_N\right)\left(\sum y_N\right)}{n_N\left(\sum x_N^2\right) - \left(\sum x_N\right)^2};\, b_N \varepsilon [b_L, b_U] \tag{4}$$

The frame diagram of the proposed method is shown in **Figure 1**.

APPLICATION USING WIND SPEED DATA

The application of the proposed time series method is given with the help of the wind speed data. The wind speed (mph) of the year 2019 is selected from the Metrology Department of Pakistan. Aslam (2020b) also used the wind speed data for forecasting purpose. The wind speed (mph) data are recorded in intervals, and experts are interested to forecast the wind speed (mph). As the wind speed (mph) data are in the interval, the use of the existing LSM may mislead the experts in forecasting the wind speed. As mentioned before, the methodology under the neutrosophic logic is better than the fuzzy logic and CS. Therefore, energy experts can apply the proposed LSM under NS. Using the proposed method, values of $a_N \varepsilon [a_L, a_U]$ and $b_N \varepsilon [b_L, b_U]$ are computed using **Eqs 3**, **4**. The neutrosophic trended lines using **Eqs 1**, **2** for each month of 2019 are shown in **Table 1**.

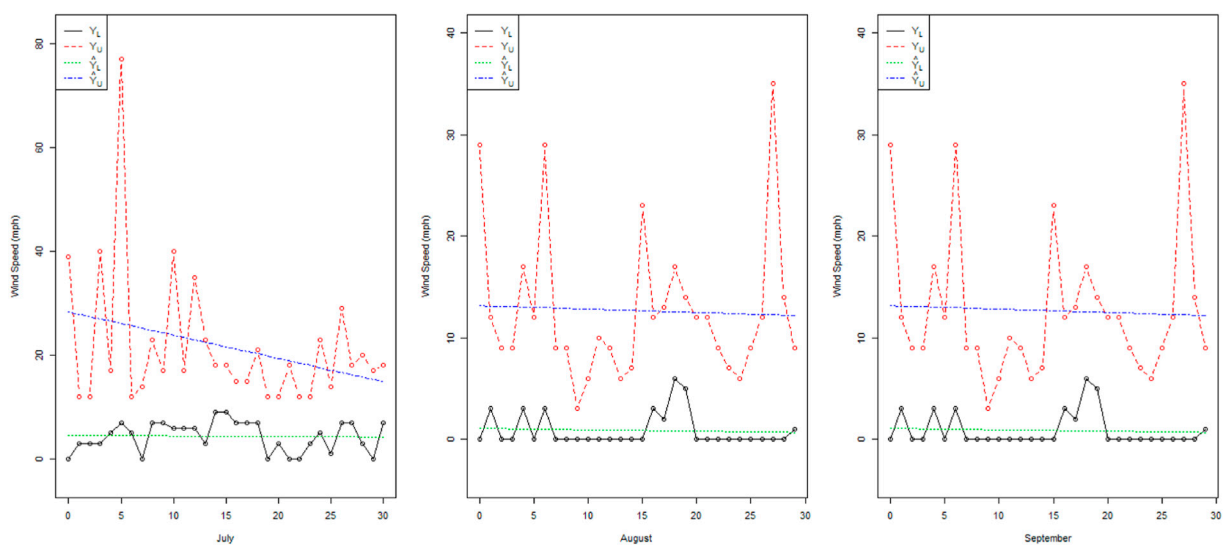

FIGURE 4 | Trended lines for July, August, and September.

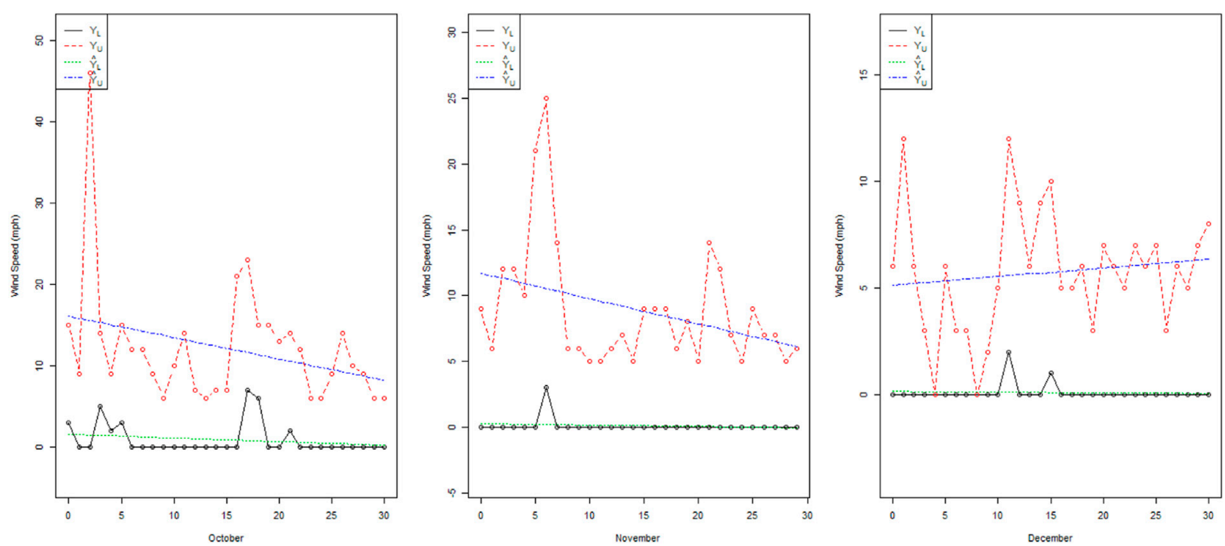

FIGURE 5 | Trended lines for October, November, and December.

From **Table 1**, it can be seen that the intercept of trend lines for the month of April and May is negative. The values of $b_N \varepsilon [b_L, b_U]$ for the months of January, July, September, October, and November are negative. The trend lines using the proposed LMS under indeterminacy can be interpreted as follows: for example, for the month of January, the wind speed (mph) will be from 0.13306 mph to 15.53 (mph) when $x_N = 0$. For a unit change in x_N, the wind speed will reduce from 0.00242 (mph) to 0.14758 (mph). The actual values of wind speed (mph) and the trended values of wind speed (mph) for each month of 2019 are obtained and plotted in **Figures 2–5**.

From **Figure 2**, we note that there is high indeterminacy between the trended values of February and March. The actual values of wind speed (mph) for the month of March have less fluctuation than those for January and February. **Figure 3** shows that in June, there are many variations in the wind speed as compared to April and May. From **Figure 4**, it can be noted that the wind speed in July has fewer variations as compared to the wind speed in August and October. From **Figure 5**, it can be seen that the wind speed in November has fewer variations as compared to that in October and December. From **Figures 2–5**, it can be seen that the trended values are in intervals rather than the exact trend values in the existing LSM. Therefore, the proposed NLSM is quite adequate, effective, and reasonable to apply for the forecasting of wind speed. In

TABLE 2 | Neutrosophic form and measure of indeterminacy.

Neutrosophic form January	Neutrosophic form February
$\hat{y}_N = 0.13306 + 15.09355\ I_N; I_N \varepsilon [0, 0.9912]$	$\hat{y}_N = 0.17734 + 10.11823\ I_N; I_N \varepsilon [0, 0.9825]$
$\hat{y}_N = 0.13064 + 14.94597\ I_N; I_N \varepsilon [0, 0.9913]$	$\hat{y}_N = 0.18801 + 10.17296\ I_N; I_N \varepsilon [0, 0.9815]$
$\hat{y}_N = 0.12822 + 14.79839\ I_N; I_N \varepsilon [0, 0.9913]$	$\hat{y}_N = 0.19868 + 10.22769\ I_N; I_N \varepsilon [0, 0.9806]$
$\hat{y}_N = 0.1258 + 14.65081\ I_N; I_N \varepsilon [0, 0.9914]$	$\hat{y}_N = 0.20935 + 10.28242\ I_N; I_N \varepsilon [0, 0.9796]$
$\hat{y}_N = 0.12338 + 14.50323\ I_N; I_N \varepsilon [0, 0.9915]$	$\hat{y}_N = 0.22002 + 10.33715\ I_N; I_N \varepsilon [0, 0.9787]$
$\hat{y}_N = 0.12096 + 14.35565\ I_N; I_N \varepsilon [0, 0.9916]$	$\hat{y}_N = 0.23069 + 10.39188\ I_N; I_N \varepsilon [0, 0.9778]$
$\hat{y}_N = 0.11854 + 14.20807\ I_N; I_N \varepsilon [0, 0.9917]$	$\hat{y}_N = 0.24136 + 10.44661\ I_N; I_N \varepsilon [0, 0.9769]$
$\hat{y}_N = 0.11612 + 14.06049\ I_N; I_N \varepsilon [0, 0.9917]$	$\hat{y}_N = 0.25203 + 10.50134\ I_N; I_N \varepsilon [0, 0.9760]$
$\hat{y}_N = 0.1137 + 13.91291\ I_N; I_N \varepsilon [0, 0.9918]$	$\hat{y}_N = 0.2627 + 10.55607\ I_N; I_N \varepsilon [0, 0.9751]$
$\hat{y}_N = 0.11128 + 13.76533\ I_N; I_N \varepsilon [0, 0.9919]$	$\hat{y}_N = 0.27337 + 10.6108\ I_N; I_N \varepsilon [0, 0.9742]$
$\hat{y}_N = 0.10886 + 13.61775\ I_N; I_N \varepsilon [0, 0.9920]$	$\hat{y}_N = 0.28404 + 10.66553\ I_N; I_N \varepsilon [0, 0.9734]$
$\hat{y}_N = 0.10644 + 13.47017\ I_N; I_N \varepsilon [0, 0.9921]$	$\hat{y}_N = 0.29471 + 10.72026\ I_N; I_N \varepsilon [0, 0.9725]$
$\hat{y}_N = 0.10402 + 13.32259\ I_N; I_N \varepsilon [0, 0.9922]$	$\hat{y}_N = 0.30538 + 10.77499\ I_N; I_N \varepsilon [0, 0.9717]$
$\hat{y}_N = 0.1016 + 13.17501\ I_N; I_N \varepsilon [0, 0.9923]$	$\hat{y}_N = 0.31605 + 10.82972\ I_N; I_N \varepsilon [0, 0.9708]$
$\hat{y}_N = 0.09918 + 13.02743\ I_N; I_N \varepsilon [0, 0.9924]$	$\hat{y}_N = 0.32672 + 10.88445\ I_N; I_N \varepsilon [0, 0.9700]$
$\hat{y}_N = 0.09676 + 12.87985\ I_N; I_N \varepsilon [0, 0.9925]$	$\hat{y}_N = 0.33739 + 10.93918\ I_N; I_N \varepsilon [0, 0.9692]$
$\hat{y}_N = 0.09434 + 12.73227\ I_N; I_N \varepsilon [0, 0.9926]$	$\hat{y}_N = 0.34806 + 10.99391\ I_N; I_N \varepsilon [0, 0.9683]$
$\hat{y}_N = 0.09192 + 12.58469\ I_N; I_N \varepsilon [0, 0.9927]$	$\hat{y}_N = 0.35873 + 11.04864\ I_N; I_N \varepsilon [0, 0.9675]$
$\hat{y}_N = 0.0895 + 12.43711\ I_N; I_N \varepsilon [0, 0.9928]$	$\hat{y}_N = 0.3694 + 11.10337\ I_N; I_N \varepsilon [0, 0.9667]$
$\hat{y}_N = 0.08708 + 12.28953\ I_N; I_N \varepsilon [0, 0.9929]$	$\hat{y}_N = 0.38007 + 11.1581\ I_N; I_N \varepsilon [0, 0.9659]$
$\hat{y}_N = 0.08466 + 12.14195\ I_N; I_N \varepsilon [0, 0.9930]$	$\hat{y}_N = 0.39074 + 11.21283\ I_N; I_N \varepsilon [0, 0.9652]$
$\hat{y}_N = 0.08224 + 11.99437\ I_N; I_N \varepsilon [0, 0.9931]$	$\hat{y}_N = 0.40141 + 11.26756\ I_N; I_N \varepsilon [0, 0.9644]$
$\hat{y}_N = 0.07982 + 11.84679\ I_N; I_N \varepsilon [0, 0.9933]$	$\hat{y}_N = 0.41208 + 11.32229\ I_N; I_N \varepsilon [0, 0.9636]$
$\hat{y}_N = 0.0774 + 11.69921\ I_N; I_N \varepsilon [0, 0.9934]$	$\hat{y}_N = 0.42275 + 11.37702\ I_N; I_N \varepsilon [0, 0.9628]$
$\hat{y}_N = 0.07498 + 11.55163\ I_N; I_N \varepsilon [0, 0.9935]$	$\hat{y}_N = 0.43342 + 11.43175\ I_N; I_N \varepsilon [0, 0.9621]$
$\hat{y}_N = 0.07256 + 11.40405\ I_N; I_N \varepsilon [0, 0.9936]$	$\hat{y}_N = 0.44409 + 11.48648\ I_N; I_N \varepsilon [0, 0.9613]$
$\hat{y}_N = 0.07014 + 11.25647\ I_N; I_N \varepsilon [0, 0.9938]$	$\hat{y}_N = 0.45476 + 11.54121\ I_N; I_N \varepsilon [0, 0.9606]$
$\hat{y}_N = 0.06772 + 11.10889\ I_N; I_N \varepsilon [0, 0.9939]$	$\hat{y}_N = 0.46543 + 11.59594\ I_N; I_N \varepsilon [0, 0.9599]$
$\hat{y}_N = 0.0653 + 15.53629\ I_N; I_N \varepsilon [0, 0.9958]$	—
$\hat{y}_N = 0.06288 + 15.53629\ I_N; I_N \varepsilon [0, 0.9960]$	—
$\hat{y}_N = 0.06046 + 15.53629\ I_N; I_N \varepsilon [0, 0.9961]$	—

addition, it is concluded that the presence of high indeterminacy may affect wind speed forecasting.

COMPARATIVE STUDIES BASED ON WIND SPEED DATA

As noted in the previous section, the trended values are in intervals, and indeterminacy is also presented. Therefore, the information about the measure of indeterminacy will be very helpful in forecasting decision making. In this section, we will present the trended values in the neutrosophic form and evaluate the measure of indeterminacy. To save space, the neutrosophic forms along with the measure of indeterminacy are presented only for January and February. The neutrosophic forms of other months can be obtained using the Excel sheet available with the author upon request. From **Table 2**, it can be noted that the measure of indeterminacy is greater than 0.95 for each day of the 2 months. The first values (determined) of neutrosophic forms denote the results of the wind speed forecasting for the existing LSM under CS. The second values show the values of indeterminate parts. For example, in neutrosophic form $\hat{y}_N = 0.13306 + 15.09355\ I_N; I_N \varepsilon [0, 0.9912]$, the value 0.13306 presents the forecasting value under CS when $I_L = 0$. The value 15.09355 is an indeterminate part of wind speed forecasting value. It means, for this day, the energy experts can expect the wind speed forecasting from 0.13306 mph to 15.09355 mph. From this study, it can be inferred that the proposed NLSM under indeterminacy provides the forecasting values in the interval while the existing LSM under CS provides only the determined forecasting wind speed. In addition, the proposed method gives information about the measure of indeterminacy. Therefore, the proposed method is desirable to find the forecasting values of wind speed.

CONCLUDING REMARKS

A new least square method (LSM) for time series analysis under indeterminacy was proposed in this manuscript. The proposed LSM under indeterminacy was known as the neutrosophic least square method (NLSM). The NLSM was proposed to forecast the wind speed when the data were in the interval. The trended line under indeterminacy is introduced and fitted using wind speed data. The time series plots under neutrosophic statistics were given. The analysis of wind speed (mph) data showed that the trended values of the wind speed are in intervals rather than the exact numbers. The comparative study showed that the proposed NLSM is quite effective and informative than the existing LSM under classical statistics. Therefore, the proposed NLSM is flexible and more informative than the existing LSM under CS. However, the proposed method has some limitations; it can be used only when the data follow the normal distribution and have imprecise observations. By applying the proposed NLSM, the energy experts can forecast the wind speed under an indeterminate environment. Other time series methods can be developed to analyze the interval data as future research. In addition, the proposed method using Pythagorean fuzzy uncertain environments can be studied as future research; see the work of Wang and Garg (2021).

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

MuA and MoA wrote the article.

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