AIMS Mathematics, 8(4): 7981–7989.
DOI: 10.3934/math.2023402
Received: 30 September 2022
Revised: 29 December 2022
Accepted: 10 January 2023
Published: 31 January 2023

http://www.aimspress.com/journal/Math

Research article

Neutrosophic test of linearity with application

Muhammad Aslam[1,*] and Muhammad Saleem[2]

[1] Department of Statistics, Faculty of Science, King Abdulaziz University, Jeddah 21551, Saudi Arabia
[2] Department of Industrial Engineering, Faculty of Engineering-Rabigh, King Abdulaziz University, Jeddah 21589, Saudi Arabia

* **Correspondence:** Email: aslam_ravian@hotmail.com.

Abstract: The existing F-test of linearity cannot be applied when data has indeterminacy and uncertainty. The present paper introduces the F-test of testing linearity under neutrosophic statistics. We will develop F-test under neutrosophic statistics and neutrosophic analysis of the variance (NANOVA) table. The application of the proposed test will be given using the data of dry bulb temperature and relative humidity. From the analysis and comparison studies, it is found that the proposed F-test under neutrosophic statistics gives the results in indeterminate intervals and measures of indeterminacy. In addition, the proposed test is more flexible, adequate, and more informative than the F-test under classical statistics.

Keywords: F-test; classical statistics; indeterminacy; regression; the level of significance
Mathematics Subject Classification: 62A86

1. Introduction

In regression theory, the relationship between independent and dependent variables is studied. It checked how the change in the independent variable affects the dependent variable. The regression models have been applied in various fields for the purposes of forecasting and estimation. Ghosal et al. [1] applied the regression model to estimate the deaths due to Covid-19. For this purpose, the existence of linearity between the independent variable and the dependent variable is tested first. The regression models can be applied for forecasting purposes if it is proved that the regression is linear. This testing is done under the assumption that the error terms are distributed normally and independently with mean zero and the two variables are also normally and independently distributed. For this purpose, the F-test for testing whether the two variables are linearly related or not are applied. This test is applied to test the null hypothesis that two variables are not linearly related vs. the alternative hypothesis that two variables are linearly related. Due to the importance of such an F-test, many people proposed tests for a variety of reasons. Biedermann and Dette [2] used the test using the Kernel-based methods. Panagiotidis [3] worked on the assumptions of the F-test. Niermann [4] proposed the test for the simple linear regression model. Wang and Cui [5] and Lan et al. [6] presented the generalization of the F-test for high-dimensional models. Li et al. [7] and Wang. and Cui [8] focused on the development of the test for partially linear models. More information about the test can be seen in [9,10].

The regression models have been applied to estimating energy consumption. Among other variables, the temperature and humidity also affect energy consumption, see [11]. Schoen [12] worked on temperature and humidity index. Ojobo et al. [13] studied the effect of temperature and humidity on human stress. Bastistella et al. [14] applied the regression for bioengineering applications. McKinnon and Poppick [15] presented the relationship between temperature and humidity using the spline approach. The details about this type of study can be seen in [16–18].

Due to the complexity of measuring the variables under study, it may not possible to record them accurately and precisely. In such situations, the data obtained may be intervals, fuzzy, or incomplete. For such data, the regression models designed using fuzzy logic is applied for forecasting purposes. Pourahmad et al. [19] applied a fuzzy regression in the medical field. Kovac et al. [20] presented the application of fuzzy regression in the manufacturing process. Tzimopoulos et al. [21] presented the application using the methodology data. Gkountakou and Papadopoulos [22] applied the fuzzy regression in predicting the cement strength. More applications can be seen in [21,23].

Smarandache [24] introduced the neutrosophic logic and discussed that fuzzy logic is a special case of it. Neutrosophic logic has advantages over fuzzy logic because it gives additional knowledge about the measure of indeterminacy. Now, the applications of neutrosophic logic have become significant in those fields where uncertainty and indeterminacy can influence the results, see, for example, [25–27]. Using the idea of neutrosophic logic, Smarandache [28] introduced neutrosophic statistics. In classical statistics, the uncertainty factor is always involved which is always ignored in the analysis and development of statistical methods. Classical statistics is a special case of neutrosophic statistics. The neutrosophic gives information about the measure of indeterminacy and is applied when the Neutrosophy is presented in the data. Chen et al. [29] and Chen et al. [30] presented the methods to deal with neutrosophic numbers. More details can be seen in [31–33]. More information on uncertainty handling related works can be seen in [34–36].

Although the F-test for testing the linearity under classical statistics is available in the literature it cannot be applied when the data is obtained from a complex process or the data has neutrosophy, uncertainty, and indeterminacy. In the literature study, we did find any work on the F-test of linearity under neutrosophic statistics. We will present the neutrosophic analysis of variance (NANOVA) table. We will introduce the F-test statistics under neutrosophic statistics. We will apply the proposed test for testing the linear relationship between the dry bulb temperature (ºC) and relative humidity (%). It is expected that the proposed F-test will be more informative, flexible, and adequate to be applied in an uncertain environment.

2. The proposed F-test under neutrosophic statistics

In this section, we will present the test of linearly between an independent variable and a dependent variable under neutrosophic statistics. The proposed test can be applied to test the linearity between variables when these variables are measured in intervals or have indeterminate observations. The proposed test has the ability to check whether linearity exists between two variables or not when indeterminacy is recorded in the data. The proposed test has the assumption that the variables $X_N \epsilon [X_N, X_N]$ and $Y_N \epsilon [Y_N, Y_N]$ of size $n_N \epsilon [n_L, n_U]$ have the neutrosophic normal distribution and are distributed independently. In addition, the error term under Neutrosophy has a neutrosophic normal distribution and is distributed independently with neutrosophic mean [0,0], see [28,37]. Let $\alpha_N \epsilon [\alpha_L, \alpha_U]$ and $\beta_N \epsilon [\beta_L, \beta_U]$ denote the neutrosophic intercept and neutrosophic slope of neutrosophic regression. The relationship between $X_N \epsilon [X_N, X_N]$ and $Y_N \epsilon [Y_N, Y_N]$ is expressed by

$$Y_N = \alpha_N + \beta_N X_{iN}. \tag{1}$$

The proposed test will be applied to test the following neutrosophic null (H_{0N}) and alternative hypothesis (H_{1N}).

$$H_{0N}: \beta_N = 0 \text{ vs. } H_{1N}: \beta_N \neq 0. \tag{2}$$

The neutrosophic null hypothesis states that no linear relationship exists between the two variables. The neutrosophic total sum of square (NTSS), say $TSS_N \epsilon [TSS_L, TSS_U]$ for the proposed test is given by

$$TSS_N = \sum y_{iN}^2 - (\sum y_{iN})^2 / n_N;\ TSS_N \epsilon [TSS_L, TSS_U]. \tag{3}$$

The neutrosophic form of $TSS_N \epsilon [TSS_L, TSS_U]$ is expressed as

$$TSS_N = TSS_L + TSS_U I_{NT}; I_{NT} \epsilon [I_{LT}, I_{UT}]. \tag{4}$$

Note here that $TSS_N \epsilon [TSS_L, TSS_U]$ has two parts, the first part TSS_L presents the total sum of square (TSS) under classical statistics and the second part $TSS_U I_{NT}$ presents the indeterminate part and $I_{NT} \epsilon [I_{LT}, I_{UT}]$ presents the indeterminacy interval associated with $TSS_N \epsilon [TSS_L, TSS_U]$. The proposed NTSS reduces to TSS when $I_{LT} = 0$.

The neutrosophic error sum of square (NESS), say $ESS_N \epsilon [ESS_L, ESS_U]$ is given by

$$ESS_N = \sum (y_{iN} - \bar{y}_N) - \beta_N^2 \sum n_{iN} (x_{iN} - \bar{x}_N)^2;\ ESS_N \epsilon [ESS_L, ESS_U]. \tag{5}$$

The neutrosophic form of $TSS_N \epsilon [TSS_L, TSS_U]$ is expressed as

$$ESS_N = ESS_L + ESS_U I_{NE}; I_{NE} \epsilon [I_{LE}, I_{UE}]. \tag{6}$$

Note here that $ESS_N \epsilon [ESS_L, ESS_U]$ has two parts, the first part ESS_L presents the error sum of square (ESS) under classical statistics and the second part $ESS_U I_{NE}$ presents the indeterminate part and $I_{NE} \epsilon [I_{LE}, I_{UE}]$ presents the indeterminacy interval associated with $ESS_N \epsilon [ESS_L, ESS_U]$. The proposed NESS reduces to ESS when $I_{LE} = 0$.

The neutrosophic regression sum of square (RESS), say $RSS_N \epsilon [RSS_L, RSS_U]$ is given by

$$RSS_N = \beta_N \left(\sum x_{iN} y_{iN} - \frac{1}{n_N} (\sum x_{iN})(\sum y_{iN}) \right);\ RSS_N \epsilon [RSS_L, RSS_U]. \tag{7}$$

The neutrosophic form of $RSS_N \epsilon [RSS_L, RSS_U]$ is expressed as

$$RSS_N = RSS_L + RSS_U I_{NR}; I_{NR} \epsilon [I_{LR}, I_{UR}]. \tag{8}$$

Note here that $RSS_N \epsilon [RSS_L, RSS_U]$ has two parts, the first part RSS_L presents the regression sum of square (ESS) under classical statistics and the second part $RSS_U I_{NR}$ presents the indeterminate part and $I_{NR} \epsilon [I_{LR}, I_{UR}]$ presents the indeterminacy interval associated with $RSS_N \epsilon [RSS_L, RSS_U]$. The proposed RESS reduces to RSS when $I_{LE} = 0$.

The neutrosophic mean square error (NMSE) can be obtained by the neutrosophic sum of squares by their corresponding neutrosophic degree of freedom (NDF). The proposed neutrosophic statistic $F_N \epsilon [F_L, F_U]$ can be obtained by the ratio of the mean regression sum of square (MRSS) to the mean error sum of square (MESS). The neutrosophic analysis of variance (NANOVA) for the proposed test is given in Table 1.

Table 1. The NANOVA table.

Source	NDF	NSS	NMSE	F_N
RSS_N	$[1,1]$	$RSS_L + RSS_U I_{NR}; I_{NR} \epsilon [I_{LR}, I_{UR}]$	$RSS_N/[1,1]$	$\frac{MRSS_N}{MESS_N}$
ESS_N	$[n_N - 2]$	$ESS_L + ESS_U I_{NE}; I_{NE} \epsilon [I_{LE}, I_{UE}]$	$ESS_N/[n_N - 2]$	
TSS_N	$[n_N - 1]$	$TSS_L + TSS_U I_{NT}; I_{NT} \epsilon [I_{LT}, I_{UT}]$	$TSS_N/[n_N - 1]$	

The proposed test will be implemented in the following steps.
Step-1: State the null hypothesis and alternative hypothesis as $H_{0N}: \beta_N = 0$ vs. $H_{1N}: \beta_N \neq 0$.
Step-2: Choose the level of significance α.
Step-3: Compute the statistic $F_N \epsilon [F_L, F_U]$.
Step-4: Determine the neutrosophic p-value for $(1, n-2)$ degree of freedom and α.
Step-5: Do not accept H_{0N} if the maximum neutrosophic p-value is less than $\alpha = 0.05$, see [38].
The operational process of the proposed test can be seen in Figure 1.

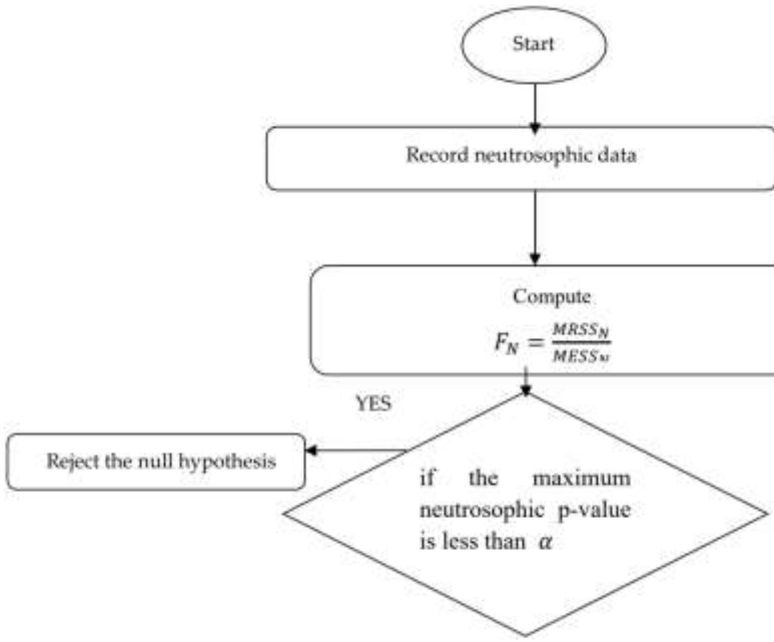

Figure 1. The operational process of the proposed test.

3. Application using temperature and humidity data

In this section, we will apply the proposed test to test the linearity of regression between the dry bulb temperature (ºC) and relatively humidity (%). It is a well-known theory that determining the relatively humidity depends on the measurement of the dry-bulb temperature. Usually, these variables are measured having the minimum value and maximum value. The data is taken from (Signor, Westphal, & Lamberts, 2001). But, the maximum value of relatively humidity (%) is simulated. Therefore, to test the linearity of regression between the dry bulb temperature (ºC) and relatively humidity (%), the proposed test can be used more effectively than the test under classical statistics. Let $X_N\epsilon[X_N, X_N]$ be a neutrosophic independent variable and $Y_N\epsilon[Y_N, Y_N]$ represents the neutrosophic dependent variable. The aims of this study to test that $X_N\epsilon[X_N, X_N]$ and $Y_N\epsilon[Y_N, Y_N]$ are linearly related or not. The neutrosophic data along with descriptive neutrosophic statistics is reported in Table 2. We would like to whether the relationship between dry bulb temperature and relatively humidity is linear or not. The null hypothesis H_{0N} and the alternative hypothesis H_{1N} are stated as follows

$$H_{0N}: \mu_{iN} = \alpha_N + \beta_N X_{iN} \text{ or } H_{0N}: \beta_N = 0 \text{ vs. } H_{1N}: \beta_N \neq 0,$$

where $\alpha_N\epsilon[\alpha_L, \alpha_U]$ and $\beta_N\epsilon[\beta_L, \beta_U]$ denote the neutrosophic intercept and rate of change of neutrosophic regression. Under the null hypothesis $H_{0N}: \beta_N = 0$, the NTSS, NESS and NRSS for the given data are computed as

$\text{NTSS} = \sum y_{iN}^2 - (\sum y_{iN})^2/14 = [1405.42,439.21]$

$\text{NESS} = \sum(y_{iN} - \bar{y}_N) - [1.02,1.92]\sum[14,14](x_{iN} - \bar{x}_N)^2 = [400.08,227.40]$

$\text{NRSS} = [1.02,1.92]\left(\sum x_{iN}y_{iN} - \frac{1}{[14,14]}(\sum x_{iN})(\sum y_{iN})\right) = [1005.35,211.80].$

The ratio of mean squares with (1,12) a degree of freedom is given by

$$F_N = [30.15,11.17].$$

For $\alpha = 0.05$, (1,12) the degree of freedom, and $F_N = [30.15,11.17]$, the neutrosophic p-value is $[0.000138,0.005865]$. By (Smarandache, 2014), the null hypothesis will not be accepted if the maximum neutrosophic p-value is less than $\alpha = 0.05$. We note that $0.005865 < 0.05$, therefore, $H_{0N}: \beta_N = 0$ will not be accepted in favor of $H_{1N}: \beta_N \neq 0$. From this study, it is concluded that the variables dry bulb temperature (ºC) and relatively humidity (%) have a linear relation. In addition, energy experts can forecast the values of relatively humidity using the information on dry-bulb temperature.

Table 2. The data along with neutrosophic descriptive statistics.

Observation	X_N	Y_N	X_N^2	Y_N^2	$X_N.Y_N$
1	[20,35]	[44,90]	[400,1225]	[880,8100]	[880,3150]
2	[6.1,32.8]	[16,100]	[37.21,1075.84]	[97.6,10000]	[97.6,3280]
3	[–2.2,31.1]	[28,85]	[4.84,967.21]	[–61.6,7225]	[–61.6,2643.5]
4	[2.2,36.1]	[26,100]	[4.84,1303.21]	[57.2,10000]	[57.2,3610]
5	[20,32.2]	[39,91]	[400,1036.84]	[780,8281]	[780,2930.2]
6	[15.6,35]	[40,100]	[243.36,1225]	[624,10000]	[624,3500]
7	[18.9,32.8]	[42,88]	[357.21,1075.84]	[793.8,7744]	[793.8,2886.4]
8	[1.1,36.7]	[20,100]	[1.21,1346.89]	[22,10000]	[22,3670]
9	[19.4,31.7]	[53,89]	[376.36,1004.89]	1028.2,7921]	[1028.2,2821.3]
10	[12.8,38.3]	[32,100]	[163.84,1466.89]	[409.6,10000]	[409.6,3830]
11	[21.1,35]	[40,88]	[445.21,1225]	[844,7744]	[844,3080]
12	[20.6,35]	[44,95]	[424.36,1225]	[906.4,9025]	[906.4,3325]
13	[2.2,36.1]	[26,99]	[4.84,1303.21]	[57.2,9801]	[57.2,3573.9]
14	[11.1,35.6]	[34,100]	[123.21,1267.36]	[377.4,10000]	[377.4,3560]
Sum	[168.9,484.4]	[484,1325]	[2986.49,16748.2]	[18138,125841]	[6815.8,45860.3]

4. Comparative study

Now we compare the efficiency of the proposed test over the existing test under neutrosophic statistics in terms of a measure of indeterminacy. According to [30], in the neutrosophic theory, a method that provides the results in indeterminacy interval is better than classical statistics. Neutrosophic statistics is the generalization of classical statistics. The theory of neutrosophic statistics reduces to the theory of classical statistics when no indeterminacy is found in recording the data. We present the neutrosophic forms along with the measures of indeterminacy for NTSS, NESS, and NRSS, and F_N in Table 3. From the neutrosophic forms, it is clear that these neutrosophic forms reduce to classical statistics when $I_N = 0$. Note here that the first values in the neutrosophic forms represent the values of TSS, ESS, RSS, and F test under classical statistics. The second values of neutrosophic forms represent indeterminate values. The measures of indeterminacy are also shown along with these sums of the square. From Table 2, it can be noted that all values of the proposed test can be presented in the indeterminate interval. For example, the neutrosophic form of F_N is $F_N = 30.15 - 11.17 I_N; I_N \epsilon [0,1.6991]$. From this neutrosophic form, it can be noted that values of statistics F_N range from 30.15 to 11.17 with the measure of indeterminacy 1.6991. Based on this information, the proposed test is interpreted as the chance of accepting $H_{0N}: \beta_N = 0$ is 0.95, the chance of committing a type-I error is 0.95 and the chance of indeterminacy about $H_{0N}: \beta_N = 0$ is 1.6991. From this study, it can be seen that the proposed test gives the neutrosophic in neutrosophic form and provides information about the measure of indeterminacy that the existing test cannot provide. Therefore, the proposed test has advantages over the existing test under classical statistics. Based on this study, it can be concluded that the proposed test is informative, flexible, and reasonable to apply when dry bulb temperature and relatively humidity data are given in intervals.

Table 3. Neutrosophic form.

	Neutrosophic form
NTSS	$1405.42 - 439.21 I_N; I_N \epsilon [0,2.1998]$
NESS	$400.08 - 227.40 I_N; I_N \epsilon [0,0.7593]$
NRSS	$1005.35 - 211.80 I_N; I_N \epsilon [0,3.7466]$
F_N	$30.15 - 11.17 I_N; I_N \epsilon [0,1.6991]$

5. Conclusions

The F-test under neutrosophic statistics was introduced in the paper. The NANONA was also introduced to apply the F-test. The proposed test was the generalization of the F-test of linearity under classical statistics. The application of the proposed test is given on real data. From the analysis of dry bulb temperature and relatively humidity data, it is found that both variables are linearly related. The regression model can be applied for forecasting humidity on the basis of dry bulb temperature data. In addition, from the analysis and comparative studies, it is concluded that the proposed test gives information about the measure of indeterminacy additionally as compared to the existing control chart. The proposed F-test can be applied in business, medical and social sciences to check the linearity between the variables under study. The application of the proposed test for big data can be considered for future research.

Acknowledgements

The authors are deeply thankful to the editor and reviewers for their valuable suggestions to improve the quality and presentation of the paper.

Conflict of interest

The authors declare that they have no conflict of interest.

References

1. S. Ghosal, Prediction of the number of deaths in India due to SARS-CoV-2 at 5–6 weeks, *Diabetes Metab. Synd.*, 2020.
2. S. Biedermann, H. Dette, Testing linearity of regression models with dependent errors by kernel based methods, *Test*, **9** (2000), 417–438. https://doi.org/10.1007/BF02595743
3. T. Panagiotidis, Testing the assumption of linearity, *Econ. B.*, **3** (2002), 1–9.
4. S. Niermann, Testing for linearity in simple regression models, *AStA-Adv. Stat. Anal.*, **91** (2007), 129. https://doi.org/10.1007/s10182-007-0025-2
5. S. Wang, H. Cui, Generalized F test for high dimensional linear regression coefficients, *J. Multivariate Anal.*, **117** (2013), 134–149. https://doi.org/10.1016/j.jmva.2013.02.010
6. W. Lan, P. S. Zhong, R. Li, H. Wang, C. L. Tsai, Testing a single regression coefficient in high dimensional linear models, *J. Econometrics*, **195** (2016), 154–168. https://doi.org/10.1016/j.jeconom.2016.05.016
7. N. Li, X. Xu, P. Jin, Testing the linearity in partially linear models, *J. Nonparametr. Stat.*, **23** (2011), 99–114. https://doi.org/10.1080/10485251003615574
8. S. Wang, H. Cui, Generalized F-test for high dimensional regression coefficients of partially linear models, *J. Syst. Sci. Complex.*, **30** (2017), 1206–1226. https://doi.org/10.1007/s11424-017-6012-0
9. D. Martin, A spreadsheet tool for learning the multiple regression F-test, t-tests, and multicollinearity, *J. Stat. Educ.*, **16** (2008). https://doi.org/10.1080/10691898.2008.11889573
10. D. C. Montgomery, E. A. Peck, G. G. Vining, *Introduction to linear regression analysis*, **821** (2012), John Wiley & Sons.
11. R. Signor, F. S. Westphal, R. Lamberts, *Regression analysis of electric energy consumption and architectural variables of conditioned commercial buildings in 14 Brazilian cities*, In Seventh International IBPSA Conference, Rio de Janeiro, Brazil, 2001.
12. C. Schoen, A new empirical model of the temperature-humidity index, *J. Appl. Meteorol.*, **44** (2005), 1413–1420. https://doi.org/10.1175/JAM2285.1
13. H. Ojobo, B. U. Wakawa, A. Umar, Influence of temperature and humidity on the physiological indices of stress in the obudu mountain landscape environment, Nigeria, *Environ. Nat. Resour. Res.*, **7** (2017). https://doi.org/10.5539/enrr.v7n1p11
14. L. Bastistella, P. Rousset, A. Aviz, A. Caldeira-Pires, G. Humbert, M. Nogueira, Statistical modelling of temperature and moisture uptake of biochars exposed to selected relative humidity of air, *Bioengineering*, **5** (2018), 13. https://doi.org/10.3390/bioengineering5010013
15. K. A. McKinnon, A. Poppick, Estimating changes in the observed relationship between humidity and temperature using noncrossing quantile smoothing splines, *J. Agr. Biol. Environ.. Stat.*, **25** (2020), 292–314. https://doi.org/10.1007/s13253-020-00393-4

16. J. Almedeij, Modeling pan evaporation for Kuwait by multiple linear regression, *The Scientific World J.*, **2012** (2012). https://doi.org/10.1100/2012/574742
17. H. Guan, S. Beecham, H. Xu, G. Ingleton, Incorporating residual temperature and specific humidity in predicting weather-dependent warm-season electricity consumption, *Environ. Res. Lett.*, **12** (2017), 024021. https://doi.org/10.1088/1748-9326/aa57a9
18. B. Oliveiros, L. Caramelo, N. C. Ferreira, F. Caramelo, Role of temperature and humidity in the modulation of the doubling time of COVID-19 cases, *medRxiv*, 2020. https://doi.org/10.1101/2020.03.05.20031872
19. S. Pourahmad, S. M. T. Ayatollahi, S. M. Taheri, Z. H. Agahi, Fuzzy logistic regression based on the least squares approach with application in clinical studies, *Comput. Math. Appl.*, **62** (2011), 3353–3365. https://doi.org/10.1016/j.camwa.2011.08.050
20. P. Kovac, D. Rodic, V. Pucovsky, B. Savkovic, M. Gostimirovic, Application of fuzzy logic and regression analysis for modeling surface roughness in face milliing, *J. Intell. Manuf.*, **24** (2012), 755–762. https://doi.org/10.1007/s10845-012-0623-z
21. C. Tzimopoulos, C. Evangelides, C. Vrekos, N. Samarinas, *Fuzzy linear regression of rainfall-altitude relationship*, In multidisciplinary digital publishing institute proceedings, 2018. https://doi.org/10.3390/proceedings2110636
22. F. Gkountakou, B. Papadopoulos, The use of fuzzy linear regression and ANFIS methods to predict the compressive strength of cement, *Symmetry*, **12** (2020), 1295. https://doi.org/10.3390/sym12081295
23. U. T. Khan, C. Valeo, A new fuzzy linear regression approach for dissolved oxygen prediction, *Hydrolog. Sci. J.*, **60** (2015), 1096–1119. https://doi.org/10.1080/02626667.2014.900558
24. F. Smarandache, *Neutrosophy neutrosophic probability, set, and logic, ProQuest information and learning*, Ann Arbor, Michigan, USA, **105** (1998), 118–123.
25. M. Abdel-Basset, M. Mohamed, M. Elhoseny, L. H. Son, F. Chiclana, A. E. H. Zaied, Cosine similarity measures of bipolar neutrosophic set for diagnosis of bipolar disorder diseases, *Artif. Intell. Med.*, **101** (2019), 101735. https://doi.org/10.1016/j.artmed.2019.101735
26. M. Abdel-Basset, N. A. Nabeeh, H. A. El-Ghareeb, A. Aboelfetouh, Utilising neutrosophic theory to solve transition difficulties of IoT-based enterprises, *Enterp. Inform. Syst.*, 2019, 1–21. https://doi.org/10.1080/17517575.2019.1633690
27. N. A. Nabeeh, F. Smarandache, M. Abdel-Basset, H. A. El-Ghareeb, A. Aboelfetouh, An integrated neutrosophic-topsis approach and its application to personnel selection: A new trend in brain processing and analysis, *IEEE Access*, **7** (2019), 29734–29744. https://doi.org/10.1109/ACCESS.2019.2899841
28. F. Smarandache, *Introduction to neutrosophic statistics,* Infinite Study, 2014.
29. J. Chen, J. Ye, S. Du, Scale effect and anisotropy analyzed for neutrosophic numbers of rock joint roughness coefficient based on neutrosophic statistics, *Symmetry*, **9** (2017), 208. https://doi.org/10.3390/sym9100208
30. J. Chen, J. Ye, S. Du, R. Yong, Expressions of rock joint roughness coefficient using neutrosophic interval statistical numbers, *Symmetry*, **9** (2017), 123. https://doi.org/10.3390/sym9070123
31. M. Aslam, M. Sattam, Analyzing alloy melting points data using a new mann-whitney test under indeterminacy, *J. King Saud Univ.-Sci.*, **32** (2020), 2831–2834. https://doi.org/10.1016/j.jksus.2020.07.005
32. M. Aslam, Design of the Bartlett and Hartley tests for homogeneity of variances under indeterminacy environment, *J. Taibah Univ. Sci.*, **14** (2020), 6–10. https://doi.org/10.1080/16583655.2019.1700675

33. M. Aslam, On detecting outliers in complex data using Dixon's test under neutrosophic statistics, *J. King Saud Univ.-Sci.*, **32** (2020), 2005–2008. https://doi.org/10.1016/j.jksus.2020.02.003
34. P. Singh, A neutrosophic-entropy based adaptive thresholding segmentation algorithm: A special application in MR images of Parkinson's disease, *Artif. Intell. Med.*, **104** (2020) 101838. https://doi.org/10.1016/j.artmed.2020.101838
35. P. Singh, S. S. Bose, Ambiguous D-means fusion clustering algorithm based on ambiguous set theory: Special application in clustering of CT scan images of COVID-19, *Knowl.-Based Syst.*, **231** (2021), 107432. https://doi.org/10.1016/j.knosys.2021.107432
36. P. Singh, A type-2 neutrosophic-entropy-fusion based multiple thresholding method for the brain tumor tissue structures segmentation, *Appl. Soft Comput.*, **103** (2021), 107119. https://doi.org/10.1016/j.asoc.2021.107119
37. G. K. Kanji, *100 statistical tests*, Sage, 2006. https://doi.org/10.4135/9781849208499
38. F. Smarandache, *Introduction to neutrosophic statistics*, Romania-Educational Publisher, Columbus, Ohio, USA, **123** (2014).