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Research article

Simulating chi-square data through algorithms in the presence of uncertainty

Muhammad Aslam* **and Osama H. Arif**

Department of Statistics, Faculty of Science, King Abdulaziz University, Jeddah 21551, Saudi Arabia

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

Abstract: This paper presents a novel methodology aimed at generating chi-square variates within the framework of neutrosophic statistics. It introduces algorithms designed for the generation of neutrosophic random chi-square variates and illustrates the distribution of these variates across a spectrum of indeterminacy levels. The investigation delves into the influence of indeterminacy on random numbers, revealing a significant impact across various degrees of freedom. Notably, the analysis of random variate tables demonstrates a consistent decrease in neutrosophic random variates as the degree of indeterminacy escalates across all degrees of freedom values. These findings underscore the pronounced effect of uncertainty on chi-square data generation. The proposed algorithm offers a valuable tool for generating data under conditions of uncertainty, particularly in scenarios where capturing real data proves challenging. Furthermore, the data generated through this approach holds utility in goodness-of-fit tests and assessments of variance homogeneity.

Keywords: chi-square distribution; random numbers; simulation; classical statistics; neutrosophic statistics
Mathematics Subject Classification: 62A86

1. Introduction

Among the statistical distributions, the chi-square distribution is very popular and has been used in many areas, including medical science [1] and engineering [2]. This distribution has been widely used in the goodness of fit test to see whether the data series is independent or not. The chi-square distribution is also been used for testing the variation in the variance of the variable, see [3]. The chi-square random variable is the sum of squares of a standard normal random variable. Due to the complexity of the systems, it may not possible to note the real data. In such cases, there is a need to generate the simulated data that can be applied for estimation and forecasting. The analysis of the simulated data is very close to the real data phenomena. As mentioned by [4]. "The simulation depends on the application of the study on systems similar to the real systems, and then projecting these results if they are appropriate on the real system. The simulation based on generating a series of random numbers that are subject to a uniform probability distribution". In addition, [5] suggested generating random variables from the underlying statistical distributions. The random numbers are generated using algorithms that are based on statistical distributions. Monahan [6] worked on generating chi-square random numbers. Shmerling [7] used the rational probability function in generating the random variables. Ortigosa et al. [8] presented the algorithms for the modified chi-square distribution. Devroye [9] proposed the simple algorithm for many distributions. Devroye [10] discussed the methods to generate non-uniform random variates. Devroye [11] presented the algorithm for generalized inverse Gaussian distribution. Luengo [12] worked on Pseudo random variate from the gamma distribution. Yao and Taimre [13] proposed the method to generate mixed random variables. More algorithms can be seen in [14]. Pereira [15] presented the simple method to generate a Pseudo random variate.

Smarandache [16] introduced descriptive neutrosophic statistics to deal with the data having imprecise observations. Neutrosophic statistics is found to be more efficient than classical statistics in terms of information obtained from the analysis of imprecise data. The results obtained from the neutrosophic statistical analysis reduce to the results of classical statistics when no imprecise observation is found in the data. Neutrosophic statistics offers greater information richness compared to classical statistics by providing an additional measure known as the degree of indeterminacy. Smarandache [17] demonstrated the superior efficiency of neutrosophic statistics over interval statistics. Chen et al. [18] and [19] provided the methodology to analyze neutrosophic numbers in engineering. Aslam [20] provided the algorithm for neutrosophic DUS-Weibull distribution. Smarandache [21] showed that neutrosophic statistics is more efficient than interval statistics. Alhabib et al. [22] worked on some statistical distribution under neutrosophic statistics. Khan et al. [23] worked on the gamma distribution using neutrosophic statistics. Sherwani et al. [24] presented spine test using neutrosophic normal distribution. Granados [25] and Granados et al. [26] proposed several discrete and continuous distributions using the idea of neutrosophy. Various algorithms within neutrosophic statistics have been introduced in the literature. Guo and Sengur [27] introduced an algorithm for neutrosophic c-means clustering. Garg [28] proposed an algorithm incorporating clustering techniques along with a novel distance measure. Aslam [29] introduced algorithms utilizing sine-cosine and convolution methods within neutrosophic statistics. Aslam [30] presented an algorithm for generating imprecise data from the Weibull distribution. Aslam and Alamri [31] introduced an algorithm employing the accept-reject method to generate neutrosophic data.

The existing methods for generating chi-square random variates are limited to deterministic environments, rendering them unsuitable for complex scenarios or uncertainty simulations. A thorough review of the literature indicates a dearth of algorithms for generating chi-square variates using neutrosophic statistics. To address this gap, this paper will introduce the chi-square distribution within the framework of neutrosophic statistics. Additionally, algorithms for generating chi-square data under neutrosophic statistics will be presented. Simulation methods will be provided for scenarios with both small and large degrees of freedom, generating neutrosophic chi-square random variates across varying degrees of indeterminacy/uncertainty. Furthermore, the application of the generated data will be discussed. It is anticipated that the degree of uncertainty will significantly influence the computation of neutrosophic chi-square variates. The proposed neutrosophic chi-square variate is expected to find application in various fields where obtaining original data is impractical or prohibitively expensive.

2. Methods

In this section, we will introduce normal distribution, standard normal distribution and chi-square distribution under neutrosophic statistics.

2.1 Neutrosophic normal distribution

Let $x_{1N,}x_{2N,}x_{3N,},\ldots,x_{nN}$ be a neutrosophic normal variable of size n. Let $x_N = x_L + x_L I_{x_N}; I_{x_N}\epsilon[I_{x_L}, I_{x_U}]$ be a neutrosophic form of standard normal variate. Note that x_L presents the determinate part (classical statistics) with mean μ and variance σ^2, $x_L I_{x_N}$ presents the indeterminate part, and $I_{x_N}\epsilon[I_{x_L}, I_{x_U}]$ is the measure of indeterminacy. The expected value of the neutrosophic random variable is given by

$$E(x_N) = E(x_L) + I_{x_N}E(x_L) = \mu(1 + I_{x_N}). \tag{1}$$

The variance of neutrosophic random variable is given by

$$Var(x_N) = Var(x_L) + I_{x_N}^2 Var(x_L) = (1 + I_{x_N})^2\sigma^2. \tag{2}$$

Note that $I_{x_N}^2 = I_{x_N}$.

The neutrosophic probability distribution function (npdf) of the normal distribution is given by

$$f(x_N) = \frac{e^{-\left(\frac{x_N-\mu_N}{\sigma_N}\right)^2/2}}{\sigma_N\sqrt{2\pi}}, \tag{3}$$

where $\mu_N = \mu(1 + I_{x_N})$ and $\sigma_N = \sqrt{(1 + I_{x_N})^2\sigma^2}$.

2.2 Neutrosophic standard normal distribution

Suppose that $z_{1N,}z_{2N,}z_{3N,},\ldots,z_{kN}$ be neutrosophic standard normal variable. Let $z_{iN} = z_{iL} + z_{iL}I_{z_N}; I_{z_N}\epsilon[I_{z_L}, I_{z_U}]$ $(1 = 1,2,..,k)$ be a neutrosophic form of a standard normal variate. Note that z_{iL} presents the determinate part (classical statistics), $z_{iL}I_{z_N}$ presents the indeterminate part, and $I_{z_N}\epsilon[I_{z_L}, I_{z_U}]$ is the measure of indeterminacy.

When $L = U$, the neutrosophic standard normal variable can be expressed as

$$z_{iN} = z_{iL}(1 + I_{z_N}); I_{z_N}\epsilon[I_{z_L}, I_{z_U}]. \tag{4}$$

The neutrosophic mean of z_{iN} is given by

$$E(z_{iN}) = E(z_{iL}) + I_{z_N}E(z_{iU}) = 0. \tag{5}$$

The neutrosophic variance of z_{iN} is given by

$$Var(z_{iN}) = Var(z_{iL}) + Var(z_{iU})I_{z_N} = 1 + 1I_{z_N}. \tag{6}$$

Based on this information, the neutrosophic probability density function (npdf) of standard normal distribution is given by

$$\varphi(z_N) = \frac{e^{-z_N^2/2}}{\sqrt{2\pi}}. \tag{7}$$

2.3 Neutrosophic chi-square distribution

In the area of classical statistics, the chi-square distribution is denoted by χ^2 with degree of freedom k. Let χ_N^2 denotes the chi-square distribution for neutrosophic statistics with k_N a degree of freedom. As mentioned before, $z_{1N,}z_{2N,}z_{3N,} \dots, z_{kN}$ be neutrosophic standard normal variable, then $Q_N = \sum_{i=1}^{kN} z_{iN}^2$ is distributed as a neutrosophic chi-square distribution k_N degree of freedom. When $L = U$, $Q_N = \left(1 + I_{z_N}\right)^2 \sum_{i=1}^{kN} z_{iL}^2$. We will denote it as $Q_N{\sim}\chi_{kN}^2$. The neutrosophic pdf of a chi-square distribution is given by

$$f(Q_N) = \left[Q_N^{(k_N/2-1)}e^{-Q_N/2}\right] / \left[2^{k_N/2}\Gamma(k_N/2)\right];\ Q_N \geq [0,0]. \tag{8}$$

The mean of Q_N with k_N degree of freedom is given by

$$E(Q_N) = k_N\left(1 + I_{z_N}\right). \tag{9}$$

The $E(Q_N^2)$ will be computed as

$$E(Q_N^2) = \left(1 + I_{z_N}\right)^2 \int_0^\alpha (Q_L^2) f(Q_N) dQ_N. \tag{10}$$

$$E(Q_N^2) = k_N(k_N + 2)\left(1 + I_{z_N}\right)^2. \tag{11}$$

The variance of Q_N with k_N degree of freedom is given by

$$Var(\chi_{kN}^2) = 2k_N\left(1 + I_{z_N}\right)^2. \tag{12}$$

It is important to note that these distributions represent a generalization of those found in classical statistics. They revert to classical distributions in the absence of imprecise or uncertain values in the data. The proposed distributions operate on the premise that data is acquired within an uncertain environment, allowing for their utilization in scenarios where uncertainty is present during data recording.

3. Generating neutrosophic chi-square variate $(k_N < 30)$

In this section, we will present the routine and algorithm to generate neutrosophic chi-square variate when k_N is less than 30. The neutrosophic chi-square variate having k_N a degree of freedom will be generated by squaring and adding neutrosophic standard normal variables. The routine is explained as follows:

Step 1: fix the value of k_N.
Step 2: Generate k_N standard normal variable z_{iN}; for $i = 1$ to k_N.
Step 3: Fix the values of I_N.
Step 4: Compute the values of $Q_N = \left(1 + I_{z_N}\right)^2 \sum_{i=1}^{kN} z_{iN}^2$ random variate.
Step 5: Next i.
Step 6: Return Q_N.

The algorithm to generate neutrosophic chi-square random variate is also shown with the help of Figure 1.

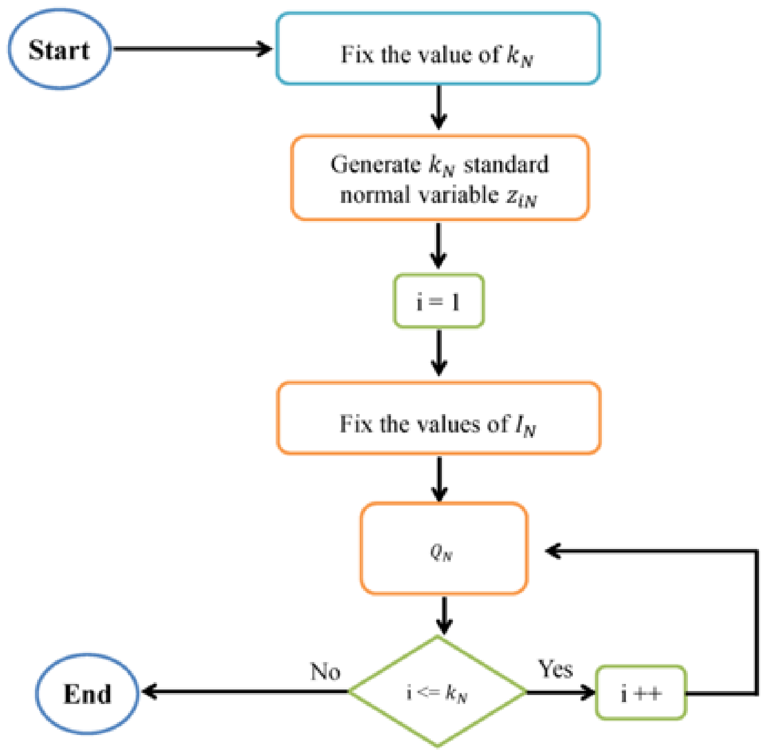

Figure 1. Algorithm to generate chi-square variate when $k_N < 30$.

By following the algorithm, the neutrosophic chi-square random variate for various values of k_N and I_N is presented in Tables 1–2. Table 1 presents the values of a neutrosophic chi-square random variate when k_N=3. Table 2 presents the values of a neutrosophic chi-square random variate when k_N=4. From Tables 1–2, it can be noted that as the measure of indeterminacy I_N increases, the values of neutrosophic chi-square random variate also increase. For example, from Table 1, when I_N=0.10, the neutrosophic chi-square random variate is 3.4578 and when I_N=0.80, the neutrosophic chi-square random variate is 9.2590. It is also interesting to note that when the values of k_N increases, we note the increasing trend in neutrosophic chi-square random variate. For example, when k_N=3 and I_N=0.20, neutrosophic chi-square random variate is 4.1151, and when k_N=4 and I_N=0.20, neutrosophic chi-square random variate is 8.8635.

Table 1. Chi-square values when $k = 3$.

I_N=0	I_N=0.10	I_N=0.20	I_N=0.30	I_N=0.40	I_N=0.50	I_N=0.60	I_N=0.70	I_N=0.80
2.8577	3.4578	4.1151	4.8295	5.6011	6.4299	7.3158	8.2588	9.2590
2.1893	2.6491	3.1526	3.6999	4.2910	4.9259	5.6046	6.3271	7.0934
0.7138	0.8637	1.0279	1.2063	1.3991	1.6061	1.8274	2.0629	2.3127
0.5115	0.6190	0.7366	0.8645	1.0026	1.1510	1.3096	1.4784	1.6574
0.6801	0.8230	0.9794	1.1494	1.3331	1.5303	1.7411	1.9656	2.2036
0.6463	0.7821	0.9307	1.0923	1.2668	1.4542	1.6546	1.8679	2.0941
3.0556	3.6973	4.4000	5.1639	5.9889	6.8751	7.8223	8.8306	9.9001
4.1798	5.0575	6.0189	7.0638	8.1924	9.4045	10.7003	12.0796	13.5425
4.1798	5.0575	6.0189	7.0638	8.1924	9.4045	10.7003	12.0796	13.5425
4.3789	5.2985	6.3056	7.4004	8.5827	9.8526	11.2100	12.6551	14.1877

Table 2. Chi-square values when $k = 4$.

I_N=0	I_N=0.10	I_N=0.20	I_N=0.30	I_N=0.40	I_N=0.50	I_N=0.60	I_N=0.70	I_N=0.80
6.1552	7.4478	8.8635	10.4023	12.0642	13.8492	15.7574	17.7886	19.9429
1.3329	1.6128	1.9194	2.2526	2.6125	2.9991	3.4123	3.8521	4.3187
9.2470	11.1889	13.3157	15.6275	18.1242	20.8058	23.6724	26.7239	29.9604
5.2438	6.3450	7.5511	8.8620	10.2778	11.7985	13.4241	15.1545	16.9899
6.1292	7.4163	8.8260	10.3583	12.0132	13.7906	15.6907	17.7133	19.8585
4.1976	5.0791	6.0446	7.0940	8.2273	9.4446	10.7459	12.1311	13.6003
3.3166	4.0131	4.7759	5.6050	6.5005	7.4623	8.4905	9.5849	10.7457
6.1028	7.3844	8.7880	10.3137	11.9615	13.7313	15.6231	17.6371	19.7730
5.8980	7.1366	8.4932	9.9677	11.5601	13.2705	15.0989	17.0453	19.1096
1.4373	1.7391	2.0696	2.4290	2.8170	3.2338	3.6794	4.1537	4.6567

4. Generating neutrosophic chi-square variate $(\boldsymbol{k_N \geq 30})$

In this section, we will discuss the routine and algorithm to generate neutrosophic chi-square random variate when k_N is larger than 30. The neutrosophic chi-square random variate with k_N degree of freedom will be generated with the help of approximation. When $k_N \geq 30$, due to the central limit theorem, the neutrosophic χ^2_{kN} distribution is shaped like the neutrosophic normal distribution that is $\chi^2_{kN} \sim N(k_N, 2\,k_N)$, see [3]. An approximation to α-percent χ^2_{kN} value is given by

$$\chi^2_{kN} \approx k_N + z_{\alpha_N}\sqrt{2k_N}, \tag{13}$$

where z_{α_N} is neutrosophic standard normal variables with $P\left(z_N > z_{\alpha_N}\right) = \alpha_N$. The approximation formulas used in practice is given by

$$\chi^2_{kN} = int\left(k_N + z_{\alpha_N}\sqrt{2k_N} + 0.5\right). \tag{14}$$

Based on the given information, the routine is stated as follows:
Step 1: fix the value of k_N.

Step 2: Generate k_N standard normal variable z_{iN}; for $i = 1$ to k_N.
Step 3: Fix the values of I_N.
Step 4: Compute the values $\chi^2_{kN} = int\left(k_N + z_{\alpha_N}\sqrt{2k_N} + 0.5\right)$ random variate using z_{iN} obtained in Step 3.
Step 5: Next i.
Step 6: Return χ^2_{kN}.

The algorithm to generate neutrosophic chi-square random variate is also shown with the help of Figure 2.

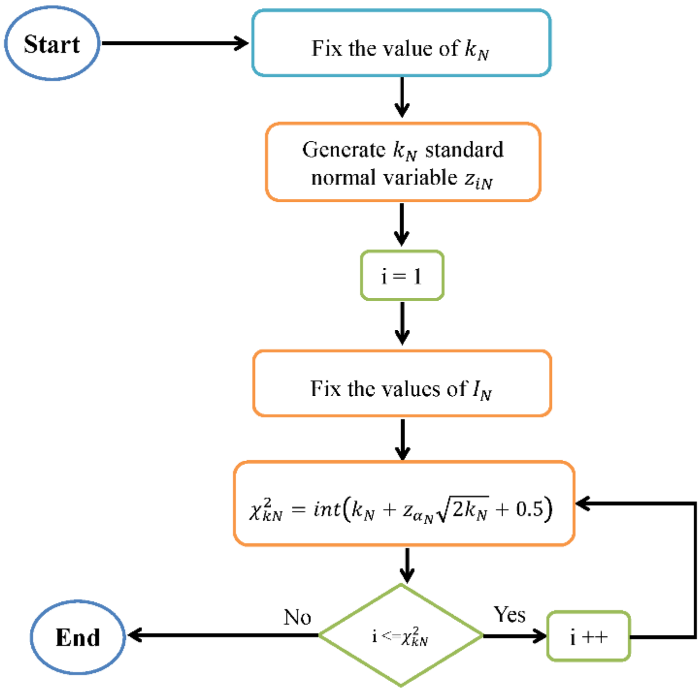

Figure 2. Algorithm to generate chi-square variate when $k_N \geq 30$.

By following the algorithm, the neutrosophic chi-square random variate for various values of k_N and I_N is presented in Tables 3–5. Table 3 presents the values of neutrosophic chi-square random variate when k_N=35. Table 2 presents the values of neutrosophic chi-square random variate when k_N=40. Table 3 presents the values of neutrosophic chi-square random variate when k_N=239. From Tables 3–5, it can be noted that as the measure of indeterminacy I_N increases, the values of a neutrosophic chi-square random variate also increase. For example, when I_N=0.10, from Table 3, the neutrosophic chi-square random variate is 39.427and when I_N=0.80, the neutrosophic chi-square random variate is 41.925. It is also interesting to note that when the values of k_N increases, we note the increasing trend in neutrosophic chi-square random variate. For example, when k_N=35 and I_N=0.20, neutrosophic chi-square random variate is 39.784, and when k_N=239 and I_N=0.20, the neutrosophic chi-square random variate is 250.694.

Table 3. Chi-square values when $k = 35$.

I_N=0	I_N=0.10	I_N=0.20	I_N=0.30	I_N=0.40	I_N=0.50	I_N=0.60	I_N=0.70	I_N=0.80
39.070	39.427	39.784	40.141	40.497	40.854	41.211	41.568	41.925
37.345	37.529	37.714	37.898	38.083	38.267	38.452	38.636	38.821
35.836	35.870	35.904	35.937	35.971	36.005	36.038	36.072	36.106
41.452	42.047	42.642	43.238	43.833	44.428	45.023	45.618	46.214
39.260	39.636	40.012	40.388	40.764	41.140	41.516	41.892	42.268
41.136	41.700	42.264	42.827	43.391	43.955	44.518	45.082	45.646
45.497	46.497	47.496	48.496	49.496	50.495	51.495	52.495	53.495
39.241	39.615	39.990	40.364	40.738	41.112	41.486	41.860	42.234
40.361	40.847	41.333	41.819	42.306	42.792	43.278	43.764	44.250
37.605	37.815	38.026	38.236	38.447	38.657	38.868	39.078	39.289

Table 4. Chi-square values when $k = 40$.

I_N=0	I_N=0.10	I_N=0.20	I_N=0.30	I_N=0.40	I_N=0.50	I_N=0.60	I_N=0.70	I_N=0.80
44.316	44.698	45.079	45.461	45.843	46.224	46.606	46.987	47.369
42.472	42.670	42.867	43.064	43.261	43.458	43.656	43.853	44.050
40.860	40.896	40.932	40.968	41.004	41.040	41.076	41.111	41.147
46.863	47.499	48.136	48.772	49.408	50.044	50.681	51.317	51.953
44.520	44.922	45.324	45.725	46.127	46.529	46.931	47.333	47.735
46.526	47.128	47.731	48.333	48.936	49.538	50.141	50.744	51.346
51.187	52.256	53.325	54.393	55.462	56.531	57.600	58.668	59.737
44.500	44.900	45.300	45.700	46.099	46.499	46.899	47.299	47.699
45.697	46.216	46.736	47.256	47.775	48.295	48.815	49.334	49.854
42.750	42.975	43.200	43.425	43.650	43.875	44.100	44.325	44.550

Table 5. Chi-square values when $k = 239$.

I_N=0	I_N=0.10	I_N=0.20	I_N=0.30	I_N=0.40	I_N=0.50	I_N=0.60	I_N=0.70	I_N=0.80
248.828	249.761	250.694	251.626	252.559	253.492	254.425	255.358	256.290
244.321	244.803	245.285	245.767	246.250	246.732	247.214	247.696	248.178
240.379	240.467	240.555	240.643	240.731	240.819	240.907	240.995	241.083
255.054	256.609	258.164	259.720	261.275	262.830	264.386	265.941	267.496
249.325	250.308	251.291	252.273	253.256	254.238	255.221	256.203	257.186
254.229	255.702	257.175	258.648	260.120	261.593	263.066	264.539	266.012
265.624	268.236	270.848	273.461	276.073	278.686	281.298	283.910	286.523
249.277	250.254	251.232	252.210	253.187	254.165	255.143	256.120	257.098
252.203	253.473	254.743	256.014	257.284	258.554	259.825	261.095	262.365
245.000	245.550	246.100	246.650	247.200	247.751	248.301	248.851	249.401

5. Comparative study

The effect of the degree of uncertainty/indeterminacy on the chi-square variate will be discussed now. The chi-square variates under classical statistics are given in Tables 1–5. The chi-square variates under classical statistics when $k_N < 30$ are reported in Tables 1 and 2. The chi-square variates under classical statistics when $k_N \geq 30$ are reported in Tables 3–5. From Tables 1–5, we note that the values of chi-square variates are higher for the classical statistics. In general, there is an increasing trend in neutrosophic chi-square variates. For example, when k_N=35 and I_N=0, the chi-square variate under classical statistics provides the value that is 39.070. On the other hand, k_N=35, and I_N=0.10, the neutrosophic chi-square variate is 39.427. The trends in chi-square variates under classical statistics and neutrosophic statistics are given in Figures 3–6. Figures 3 and 4 show the curves of chi-square variates when $k_N < 30$. From Figures 3 and 4, it can be observed that the curve of chi-square variates under classical statistics is lower than the neutrosophic chi-square variates at various values of I_N. Figures 5 and 6 present the curves of chi-square variates when $k_N \geq 30$. From Figures 5 and 6, it can be observed that the curve of chi-square variates under classical statistics is lower than the neutrosophic chi-square variates at various values of I_N. In addition, it can be noted that when the values of k_N is larger than 30, the neutrosophic chi-square variates are close to k_N. This statistical analysis highlights significant disparities between the data generated from the chi-square distribution under uncertainty and that obtained from the chi-square distribution under classical statistics. It is evident that the degree of indeterminacy/uncertainty significantly influences data generation. Consequently, based on this study, it is concluded that decision-makers should exercise caution when employing existing algorithms rooted in classical statistics for generating chi-square data. The utilization of such algorithms in uncertain contexts may lead to misleading outcomes in decision-making processes.

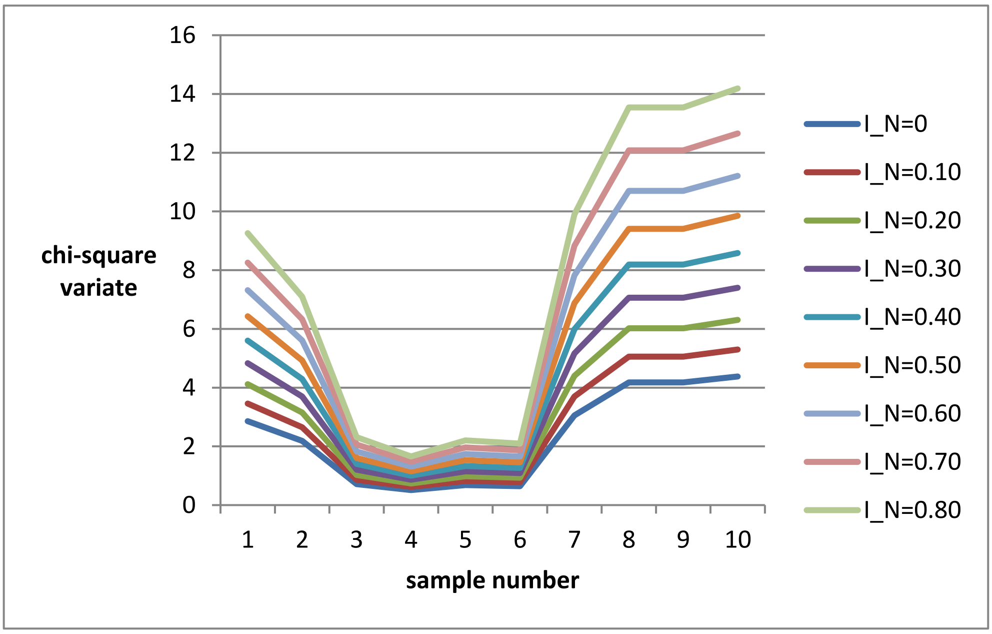

Figure 3. The chi-square variates when k_N=3.

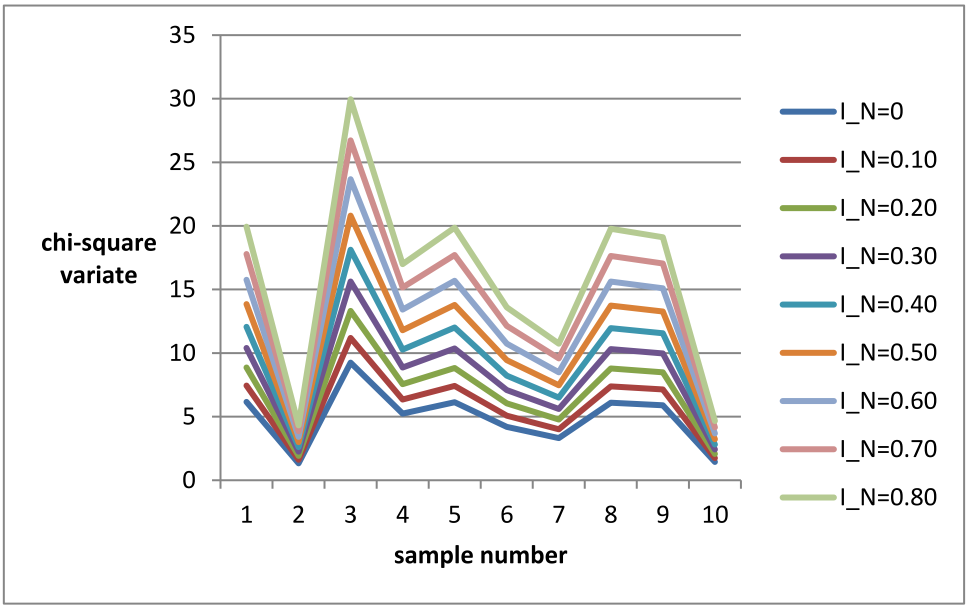

Figure 4. The chi-square variates when k_N=4.

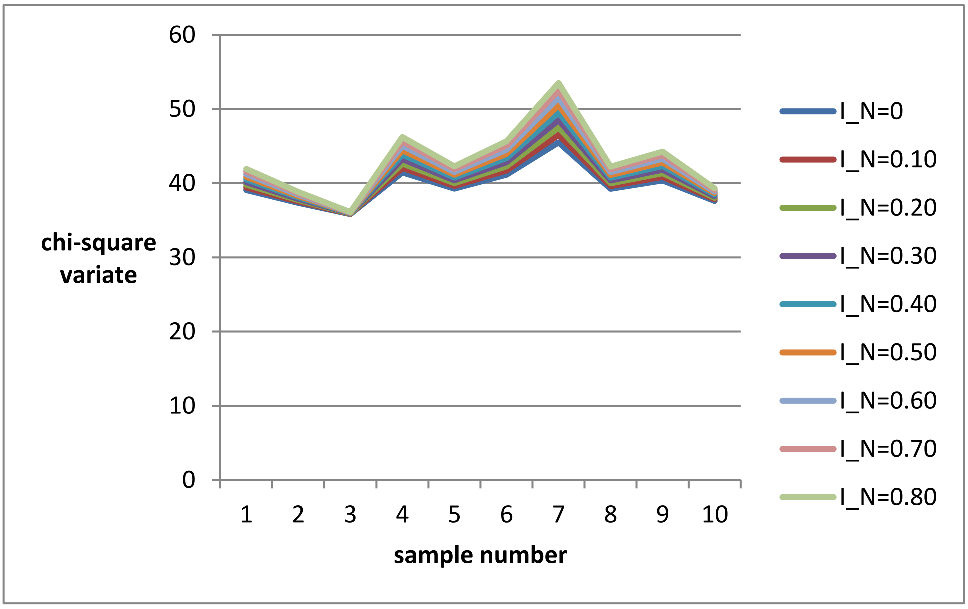

Figure 5. The chi-square variates when k_N=35.

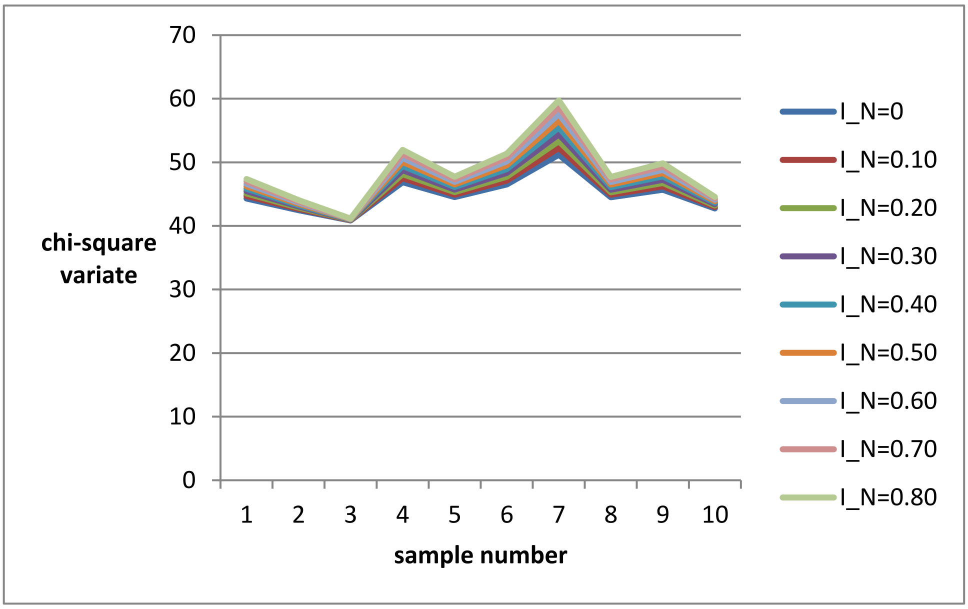

Figure 6. The chi-square variates when k_N=40.

6. Application using big data in transportation

In this section, we will discuss the application of the neutrosophic chi-square test for big data of transportation. [32] used the uncertainty based chi-square for the big data. According to [33], uncertainty is always presented in big data, therefore, it is always expected uncertainty or impression in transportation data. According to (https://www.mongodb.com/big-data-explained/examples) "Airplanes generate enormous volumes of data, on the order of 1,000 gigabytes for transatlantic flights. Aviation analytics systems ingest all of this to analyze fuel efficiency, passenger and cargo weights, and weather conditions, with a view toward optimizing safety and energy consumption". Suppose that there is uncertainty in this transportation data with a degree of uncertainty that is 0.10. Let the degree of freedom is 239. Let us define the null hypothesis H_0: Flight operation is efficient vs. the alternative hypothesis H_1: Flight operation is not efficient. From Table 5, the value of χ^2_{kN} is 249.761. Suppose that level of significance $\alpha = 0.10$, the tabulated value of the chi-square test is 267.412. By comparing χ^2_{kN} with the tabulated value, we will not reject the null hypothesis that the flight is efficient. Based on the analysis, it can be concluded that the flight operation is efficient. For the same level of significance $\alpha = 0.10$, the chi-square value under classical statistics is χ^2_k=248.828. By comparing χ^2_k=249.761 with the tabulated value, again, we do not reject the null hypothesis. But, from this comparison, it can be seen that the χ^2_k=249.761 is close to 267.412 as compared to χ^2_{kN}=248.828. The study suggests that the proposed test can effectively be applied to test hypotheses concerning flight efficiency within the transportation sector.

7. Concluding remarks

The algorithms to generate chi-square random numbers were presented in this paper. The methods to generate random variables were presented when the degree of freedom is small and large. The results were presented by implementing the proposed algorithms. The results showed that the measure of indeterminacy plays an important role in determining chi-square random numbers. From the tables, it was concluded that as the measure of indeterminacy increases, the values of chi-square random numbers also increase. This random number generator can be used to generate chi-square random numbers under uncertainty. The proposed method holds applicability for generating chi-square random numbers across diverse domains such as medical science, engineering, quality control, and reliability analysis. Additionally, it can facilitate the application of goodness-of-fit tests and tests of variance homogeneity across a variety of fields. The proposed study has a limitation in that the data generated from the proposed algorithm is exclusively applicable within uncertain environments. Moreover, the proposed neutrosophic chi-square distribution is suitable solely for modeling imprecise data. Future research could explore modifications to the simulation method, incorporating alternative statistical distributions or sampling schemes. Furthermore, the potential application of the proposed test in handling large datasets within metrology and healthcare warrants investigation in future studies. Additionally, there is scope for further research into the proposed algorithm utilizing the accept-reject method.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflicts of interest.

References

1. P. Schober, T. R. Vetter, Chi-square tests in medical research, *Anesth. Analg.*, **129** (2019), 1193. https://doi.org/10.1213/ANE.0000000000004410
2. M. V. Koutras, S. Bersimis, D. L. Antzoulakos, Improving the performance of the chi-square control chart via runs rules, *Methodol. Comput. Appl. Probab.*, **8** (2006), 409–426. https://doi.org/10.1007/s11009-006-9754-z
3. N. T. Thomopoulos, *Essentials of Monte Carlo simulation: Statistical methods for building simulation models*, New York: Springer, 2013. https://doi.org/10.1007/978-1-4614-6022-0
4. M. A. Jdid, R. Alhabib, A. A. Salama, Fundamentals of neutrosophical simulation for generating random numbers associated with uniform probability distribution, *Neutrosophic Sets Sy.*, **49** (2022), 92–102. https://doi.org/10.5281/zenodo.6426375
5. M. A. Jdid, R. Alhabib, A. A. Salama, The static model of inventory management without a deficit with Neutrosophic logic, *International Journal of Neutrosophic Science*, **16** (2021), 42–48. https://doi.org/10.54216/IJNS.160104

6. J. F. Monahan, An algorithm for generating chi random variables, *ACM T. Math. Software*, **13** (1987), 168–172. https://doi.org/10.1145/328512.328522
7. E. Shmerling, Algorithms for generating random variables with a rational probability-generating function, *Int. J. Comput. Math.*, **92** (2015), 2001–2010. https://doi.org/10.1080/00207160.2014.945918
8. N. Ortigosa, M. Orellana-Panchame, J. C. Castro-Palacio, P. F. de Córdoba, J. M. Isidro, Monte Carlo simulation of a modified Chi distribution considering asymmetry in the generating functions: Application to the study of health-related variables, *Symmetry*, **13** (2021), 924. https://doi.org/10.3390/sym13060924
9. L. Devroye, A simple algorithm for generating random variates with a log-concave density, *Computing*, **33** (1984), 247–257. https://doi.org/10.1007/BF02242271
10. L. Devroye, Nonuniform random variate generation, *Handbooks in Operations Research and Management Science*, **13** (2006), 83–121. https://doi.org/10.1016/S0927-0507(06)13004-2
11. L. Devroye, Random variate generation for the generalized inverse Gaussian distribution, *Stat. Comput.*, **24** (2014), 239–246. https://doi.org/10.1007/s11222-012-9367-z
12. E. A. Luengo, Gamma Pseudo random number generators, *ACM Comput. Surv.*, **55** (2022), 1–33. https://doi.org/10.1145/3527157
13. H. Yao, T. Taimre, Estimating tail probabilities of random sums of phase-type scale mixture random variables, *Algorithms*, **15** (2022), 350. https://doi.org/10.3390/a15100350
14. T. H. Cormen, C. E. Leiserson, R. L. Rivest, C. Stein, *Introduction to algorithms*, Massachusetts: MIT Press, 2022.
15. D. H. Pereira, Itamaracá: A novel simple way to generate Pseudo-random numbers, *Cambridge Open Engage*, 2022. https://doi.org/10.33774/coe-2022-zsw6t
16. F. Smarandache, *Introduction to neutrosophic statistics*, Craiova: Romania-Educational Publisher, 2014.
17. F. Smarandache, Neutrosophic statistics is an extension of interval statistics, while Plithogenic Statistics is the most general form of statistics (second version), *International Journal of Neutrosophic Science*, **19** (2022), 148–165. https://doi.org/10.54216/ IJNS.190111
18. J. Q. Chen, J. Ye, S. G. 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
19. J. Chen, J. Ye, S. G. Du, R. Yong, Expressions of rock joint roughness coefficient using neutrosophic interval statistical numbers, *Symmetry*, **9** (2017), 123. https://doi.org/10.3390/sym9070123
20. M. Aslam, Truncated variable algorithm using DUS-neutrosophic Weibull distribution, *Complex Intell. Syst.*, **9** (2023), 3107–3114.
21. F. Smarandache, Neutrosophic statistics is an extension of interval statistics, while Plithogenic statistics is the most general form of statistics, *Neutrosophic Computing and Machine Learning*, **23** (2022), 21–38.
22. R. Alhabib, M. M. Ranna, H. Farah, A. A. Salama, Some neutrosophic probability distributions, *Neutrosophic Sets Sy.*, **22** (2018), 30–38.
23. Z. Khan, A. Al-Bossly, M. M. A. Almazah, F. S. Alduais, On statistical development of neutrosophic gamma distribution with applications to complex data analysis, *Complexity*, **2021** (2021), 3701236. https://doi.org/10.1155/2021/3701236

24. R. A. K. Sherwani, M. Aslam, M. A. Raza, M. Farooq, M. Abid, M. Tahir, Neutrosophic normal probability distribution–A spine of parametric neutrosophic statistical tests: properties and applications, In: *Neutrosophic operational research*, Cham: Springer, 2021, 153–169. https://doi.org/10.1007/978-3-030-57197-9_8
25. C. Granados, Some discrete neutrosophic distributions with neutrosophic parameters based on neutrosophic random variables, *Hacet. J. Math. Stat.*, **51** (2022), 1442–1457. https://doi.org/10.15672/hujms.1099081
26. C. Granados, A. K. Das, B. Das, Some continuous neutrosophic distributions with neutrosophic parameters based on neutrosophic random variables, *Advances in the Theory of Nonlinear Analysis and its Application*, **6** (2023), 380–389.
27. Y. H. Guo, A. Sengur, NCM: Neutrosophic c-means clustering algorithm, *Pattern Recogn.*, **48** (2015), 2710–2724. https://doi.org/10.1016/j.patcog.2015.02.018
28. H. Garg, Nancy, Algorithms for single-valued neutrosophic decision making based on TOPSIS and clustering methods with new distance measure, *AIMS Mathematics*, **5** (2020), 2671–2693. https://doi.org/10.3934/math.2020173
29. M. Aslam, Simulating imprecise data: sine-cosine and convolution methods with neutrosophic normal distribution, *J. Big Data*, **10** (2023), 143. https://doi.org/10.1186/s40537-023-00822-4
30. M. Aslam, Uncertainty-driven generation of neutrosophic random variates from the Weibull distribution, *J. Big Data*, **10** (2023), 177. https://doi.org/10.1186/s40537-023-00860-y
31. M. Aslam, F. S. Alamri, Algorithm for generating neutrosophic data using accept-reject method, *J. Big Data*, **10** (2023), 175. https://doi.org/10.1186/s40537-023-00855-9
32. M. Catelani, A. Zanobini, L. Ciani, Uncertainty interval evaluation using the Chi-square and Fisher distributions in the measurement process, *Metrol. Meas. Syst.*, **17** (2010), 195–204. https://doi.org/10.2478/v10178-010-0017-5
33. R. H. Hariri, E. M. Fredericks, K. M. Bowers, Uncertainty in big data analytics: survey, opportunities, and challenges, *J. Big Data*, **6** (2019), 44. https://doi.org/10.1186/s40537-019-0206-3