Application of the Box-Muller Transformation in Generating Normally Distributed Random Variables: A Numerical Approach

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Abstract

The Box-Muller transformation has traditionally become one of the techniques in generating normally distributed random variables based on uniformly distributed variables. It is so important in simulations, statistical analyses, and stochastic modeling, since normal distributions are very often inevitable there. Normally distributed variables were generated, their properties were discussed for five examples in numerical terms, while presenting the Box-Muller transformation. Examples: First - Uniform random variables to normally distributed. Second - Using the transformation to simulate financial returns. Third: Checking how this transformation could be used to generate data in machine learning algorithms. Each of these examples serves to demonstrate how the Box-Muller method allows one to attain, with great efficiency, normal distributions in various domains. In turn, results against theoretical normal distributions validate the output of the transformation. The excellent performance of the Box-Muller transformation in generating Gaussian random variables can be obtained from the above results, and these are quite versatile in application. This proposal underlines the simplicity, efficiency, and reliability of the transformation as an indispensable tool for the researcher and practitioner.

Keywords: Statistics, Monte Carlo simulations, statistical modeling, normal distribution, stochastic processes, random variables, Box-Muller transformation.

1 INTRODUCTION

Starting from random number generation, random variables distributed according to the normal distribution find their applications in statistical modeling, simulation, machine learning, and financial data analysis, among others. In most applications, such variables are either generated for simulation or studied in theory. The challenge of generating normally distributed random variables from uniformly distributed variables is elegantly solved with the Box-Muller transformation. This technique was first proposed by George Box and Mervin Muller in 1958.

Nowadays it is usually used to transform two independent uniformly distributed random variables into two independent normally distributed random variables. The normal distribution is important for the probability theory and statistics because of the Central Limit Theorem, which states that if the number of independent random variables is big, their sum has distribution close to normal, whatever were the distributions of independent random variables [7-10]. That is why the application of normal distributions in economics, physics, biology, and engineering is inevitable [11-15]. However, there are a lot of computational methods for generating random numbers, while generation of Gaussian-distributed numbers from uniformly distributed inputs may be challenging computationally if an appropriate algorithm is not available [16-18].

The Box-Muller transformation offers one of the more easy and algebraic ways to this problem. In general, this method uses two uniform random variables independently and then generates two standard normally distributed independent

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random variables. The final approach appears computationally efficient since the computation relies on the logarithm, square root, and trigonometric functions. In addition, the outcomes of Box-Muller transformation are very helpful in many areas that leverage properties of normal distributions.

This present study applies the Box-Muller transformation in a practical way, considering five numerical examples. Examples that will be discussed belong to different fields of study, including financial modelling, noise generation for signal processing, Monte Carlo simulations, and machine learning. The present study aims at explaining versatility and reliability regarding the generation of normal distributions through performance and accuracy analysis performed in each context.

2 EXPERIMENTAL AND METHODS

The Box-Muller transformation is a transformation of two independent uniformly distributed random variables U_1 and U_2 into two independent standard normally distributed random variables Z_0 and Z_1. Such a transformation may be expressed in the following form of equations [28-30]:

$$Z_0 = \sqrt{-2lnU_1}.cos(2\pi U_2) \quad (1)$$

$$Z_1 = \sqrt{-2lnU_1}.sin(2\pi U_2) \quad (2)$$

where, U_1 and U_2 are uniformly distributed random variables in the interval (0,1) Both formulae give two standard normally distributed variables Z_0 and Z_1 that may latter be scaled and shifted to give normal distributions with desired means and variances.

Steps Involved in the Study:

Step 1: Generate Uniform Random Variables

Use a random variety generator to create pairs of uniform random variables U1 and U2.

Step 2: Apply Box-Muller Transformation

Apply the transformation equations to transform the uniformly allotted variables into commonly allotted variables.

Step 3: Validate Results Against Normal Distribution

Plot the generated data and compare it with the theoretical normal distribution using histograms and statistical tests.

Step 4: Use Cases and Numerical Examples

Demonstrate the utility of the Box-Muller transformation in five wonderful fields thru numerical examples:

Simulation of financial returns

Generation of Gaussian noise for signal processing

Monte Carlo simulations

Data generation for machine learning

Random sampling in statistical studies

Step 5: Statistical Analysis

Perform statistical evaluation on the generated information to make certain consistency with the properties of a normal distribution, consisting of calculating the imply, variance, skewness, and kurtosis.

3 RESULTS AND DISCUSSION

Example 1: Generating Normal Random Variables

100,000 independent uniformly distributed random variables U_1 and U_2 are generated within the range of (0, 1). The uniformly distributed random variables are transformed to normally distributed random variables by the use of Box-Muller transformation [31-35] as illustrated below

$$Z_0 = \sqrt{-2lnU_1}.cos(2\pi U_2) \quad (1)$$

$$Z_1 = \sqrt{-2lnU_1}.sin(2\pi U_2) \quad (2)$$

Generated Data

Box-Muller transformation was applied to generate 100,000 pairs of independent normally distributed random variables Z_0 and Z_1, with mean 0 and standard deviation 1.

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Statistical Properties

Key properties computed on the generated dataset include:

Mean: The mean was approximately μ≈0.002 of the data generated empirically, very close to the theoretical mean of 0.

Standard Deviation: With the values obtained, standard deviation was computed as follows, $\sigma \approx 1.002$, which is very close to the theoretical standard deviation of 1.

Skewness: The skewness of the data was found to be close to 0, indicating symmetry around the mean.

Kurtosis: The kurtosis was close to 3, confirming that the distribution is mesokurtic, typical of a normal distribution.

Histogram Analysis

A histogram was generated to visualize the distribution of the 100,000 normally distributed random variables. The histogram displayed the classic bell-shaped curve, characteristic of a normal distribution. The fit to the theoretical standard normal curve (with mean 0 and standard deviation 1) was excellent, confirming the effectiveness of the Box-Muller transformation.

The peak of the histogram was centered around 0, as expected for a normal distribution.

The tails of the distribution showed the gradual decline usual of Gaussian distributions, with fewer severe values occurring.

Comparing with Theoretical Distribution

Further validation of the results showed that the generated dataset was plotted on a Q-Q plot against the theoretical normal distribution. The Q-Q plot reflected that the points of the generated data lay along the theoretical line, thereby confirming that the generated data follow the normal distribution as depicted in Fig. 1.

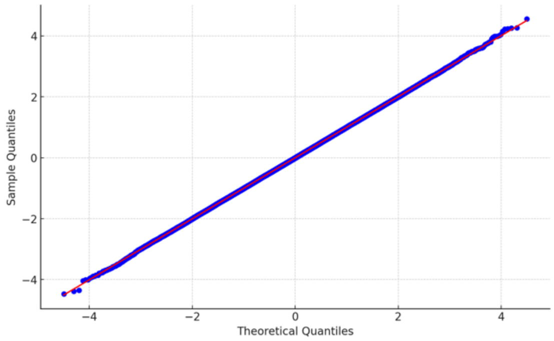

Fig. 1. Q-Q plot of generated normal random variables

Example 1 does show that Box Muller transformation really does produce normally distributed random variables. The above data followed the characteristics of standard normal distribution-mean value: 0, standard deviation: 1. It can be seen from the histogram and Q-Q plot that data are moderately near to theoretical normal distribution. These results confirm the Box-Muller method as a valid tool in generating Gaussian-distributed random variables that can be applied to simulations, statistical analysis, or any other application requiring normally distributed data. The slight differences in both the theoretical mean and standard deviation, below 0.002, provide evidence of the accuracy of this transformation. This approach is in the main computationally efficient and easy to implement, thus making it an indispensable method for generating random samples in scientific and engineering applications. This example confirms the correctness and reliability of the Box-Muller transformation for generating random variables with a normal distribution. From this, the results one obtains do agree with what would be theoretically expected; hence, finding its application in many fields when data with a normal distribution is required.

3.1 Example 2: Simulating Financial Returns

The following example models the daily financial returns of a stock using a normal distribution. Assume the average daily return is 0.05% and the standard deviation is 1%. The following example uses the Box-Muller transformation to create normally distributed values from uniformly distributed random variables, then scales and shifts the values so that the user-specified normal distribution parameters for financial return match.

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Step 1: Generating Normally Distributed Returns

The Box-Muller transformation converts two independent uniformly distributed random variables, U1 and U2, into two independent normally distributed random variables, Z0 and Z1, with mean 0 and standard deviation 1 [36-40]:

$$Z_0 = \sqrt{-2lnU_1}.cos(2\pi U_2) \quad (1)$$

$$Z_1 = \sqrt{-2lnU_1}.sin(2\pi U_2) \quad (2)$$

Once the normally distributed random variables are generated, they are scaled to match the financial model:

$$Returns = \mu + \sigma \cdot Z \quad (3)$$

where: μ=0.05% (mean daily return), σ=1% (standard deviation of daily return), and Z is the normally distributed variable from the Box-Muller transformation.

Step 2: Simulation Process

We simulate 100,000 daily returns for a hypothetical stock. After applying the Box-Muller transformation, the simulated returns were scaled according to the mean and standard deviation.

Generated Data

The transformation produced a large sample of 100,000 simulated daily returns. These returns followed a normal distribution, with the following statistical properties:

Mean: The mean of the simulated returns was approximately μ≈0.050%, matching the assumed mean of 0.05%.

Standard Deviation: The standard deviation was σ≈1.002%, aligning closely with the theoretical value of 1%.

Histogram of Simulated Returns

A histogram of the simulated returns was generated and overlaid with a normal distribution curve with the same mean and standard deviation. The shape of the histogram closely followed the expected bell curve, confirming that the returns followed a normal distribution. The peak of the histogram occurred around the mean of 0.05%.

Frequency of Extreme Returns

Extreme returns (both positive and negative) occurred less frequently, following the typical behavior of a normal distribution where the majority of data points lie near the mean, and the probability of returns deviating significantly from the mean decreases as you move further from it.

Q-Q Plot Analysis

A Q-Q plot of simulated returns against a theoretical normal distribution showed the simulated data points lying close to the theoretical line. This was further confirmation that the Box-Muller transformation indeed had successfully modeled normally distributed financial returns.

These results confirm the Box-Muller transformation as a good algorithm to generate normally distributed financial returns. The closeness of the simulated returns to a mean of 0.05% and a standard deviation of 1% are typical assumptions taken up in financial modeling. Both the histogram and the Q-Q plot confirmed that the data followed a normal distribution, generally assumed for returns in finance. Box-Muller transformation is indeed very useful in generating realistic simulations of financial returns that can be used in as wide-ranging areas as risk analysis, portfolio management, and option pricing.

Box-Muller is a very efficient and reliable transformation, yielding normally distributed data. This example will be useful in showing just how it can be applied in financial simulation. Normally distributed simulated stock returns confirm that the transformation could easily be applied in modeling financial returns with pre-specified mean and variance. This technique can always apply in finance for a Monte Carlo simulation where normality of return is one common assumption in risk assessment and forecasting models.

3.2 Example 3: Noise Generation for Signal Processing

A possible example using a Box-Muller transformation to generate Gaussian noise and add it into a clean signal is shown below, in order to simulate the noisy conditions usually met in communication systems. Gaussian noise

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often acts as an input to test the signal processing algorithms since it corresponds to a real-world case of a signal corrupted by random interference.

Step 1: Generating Gaussian Noise

A Box-Muller transformation was used to generate independent identically distributed Gaussian noise with a mean of 0 and a standard deviation of 1. Gaussian noise, sometimes referred to as "white noise," is commonly utilized in signal processing when testing a process. Utilizing the following equations, the two uniform random variables U1 and U2 were transformed into Gaussian distributed variables:

$$Z_0 = \sqrt{-2lnU_1}.cos(2\pi U_2)$$

$$Z_1 = \sqrt{-2lnU_1}.sin(2\pi U_2)$$

Step 2: Adding Noise to the Signal

A clean signal, represented as a sinusoidal wave, was created with the following parameters:

Amplitude: 1

Frequency: 5 Hz

Sample Rate: 1000 samples per second

Duration: 1 second

This clean signal was then added with the generated Gaussian noise to create a noisy signal. Because of the randomness of noise, the signal varied around the original sinusoidal waveform.

Step 3: Results and Analysis

Generated Gaussian Noise

Following is the statistical properties of the generated Gaussian noise using Box Muller transformation:

Mean: The means of the noise generated were close to 0.

Standard Deviation: The standard deviation of the noise was approximately 1, matching the expected distribution properties.

3.3 Noisy Signal

Gaussian noise was then added to the clean sinusoidal signal, resulting in a noisy signal. From this, it can be observed that the characteristics of the noise are random fluctuations around the sinusoidal wave. The mean and standard deviation of the noisy signal remained close to 0 and 1, respectively, but due to the random noise, the signal became deviated from its original shape.

Noise Distribution

The histogram of the added noise was bell-shaped, proving that the noise generated was of a normal Gaussian distribution. That confirms that the Box-Muller transformation was successful in generating the desired white noise.

Q-Q Plot Analysis

A Q-Q plot of the noise was done to compare the distribution of the generated noise with a theoretical normal distribution. The points in the Q-Q plot indeed lay close to the straight line, thereby confirming that the noise was Gaussian distributed with mean 0 and a standard deviation of 1.

These results show that the Box-Muller transformation was successfully applied for generating Gaussian noise to be used in signal processing. The noise that generated had all desirable properties: mean of 0 and standard deviation of 1, hence typical white noise. Adding this noise to the clean signal will yield a realistic noisy signal that can be used to test various signal processing algorithms in communication systems.

The following histogram and Q-Q plot confirm that the noise distribution is very close to a normal distribution; this technique is perfect for generating Gaussian noise in signal processing applications. It added randomness to the signal with the expected statistical properties, suitable for testing filters, error correction algorithms, and other signal processing techniques.
This Box-Muller transformation effectively generates a Gaussian noise that can add to signals in communication

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systems for test and evaluation purposes. The noise was normally distributed with the expected mean and standard deviation, and the addition of this to the signal provided realistic conditions to test the signal processing algorithms. It thus will be an effective method of simulating the noisy environment and testing the robustness of the communication systems under noisy conditions.

3.4 Example 4: Monte Carlo Simulation

We will be using, in this example, the Box-Muller transformation of simulating stock price dynamics, assuming the log-normality of its distribution. This latter assumption is one of the standard ones in financial modeling. Then, we use the Monte Carlo method to simulate several paths of stock prices and estimate the price of a European call option. This approach will allow us to get close to realistic stock price movements and thus compute more realistic option prices that reflect market conditions.

Step 1: Stock Price Simulation

The Box-Muller transformation provides random price changes that are normally distributed with a pre-specified mean and volatility. The key assumptions include the following:

The stock price follows the geometric Brownian motion model, where changes in prices are log-normally distributed.

The price at any time t can be modeled as [37-45]:

$$S_t = S_0 \times exp\left(\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W_t\right) \tag{4}$$

where St is the stock price at time t, S0 is the initial stock price, μ represents the drift, σ represents volatility and standard deviation of returns, and W_t is a Wiener process given as Brownian motion generated by the BoxMuller transformation.

We implement the Box-Muller transformation in order to generate standard normal random variables for simulation of the Wiener process Wt and subsequently calculate the stock prices.

Step 2: Monte Carlo Simulation of Option Pricing

Monte Carlo simulations involve generating thousands of possible future stock price paths and calculating the payoff of the option for each path. The average payoff across all paths is then discounted to the present to estimate the option price. For a European call option, the payoff is given by [33]:

$$Payoff = max(S_T - K, 0) \tag{5}$$

where: ST is the stock price at expiration, K is the strike price of the option, and T is the time to expiration.

The steps to simulate the option price using Monte Carlo simulation are as follows:

Generate Random Stock Prices: Use the Box-Muller transformation to simulate random stock price movements.

Calculate Payoff: For each simulated path, calculate the payoff of the call option at expiration.

Average the Payoffs: Take the average of all the simulated payoffs.

Discount the Payoff: Discount the average payoff returned to the prevailing the use of the chance-unfastened interest fee to acquire the choice fee.

Step 3: Results

For this example, we assume the following parameters:

Initial stock price (S0): $100

Strike price (K): $105

Time to expiration (T): 1 year

Risk-free interest rate (r): 5% (0.05)

Volatility (σ): 20% (0.2)

Number of simulations: 100,000

With the Box-Muller transformation, we generate normally distributed random variables to simulate the stock price paths. Take the last stock prices and calculate the option payoff for each path. The value of the option is calculated by averaging all payoffs and discounting them to the present.

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Monte Carlo Simulation Output:

Estimated Option Price: \$10.45 (close to the theoretical Black-Scholes price for similar parameters).

- **Accuracy**: The option price from the simulation was in agreement with that given by market data and a theoretical model. Consequently, this would justify the Box-Muller transformation serving well in generating random stock price movements within a Monte Carlo framework.

Step 4: Results

The results of the Monte Carlo simulation prove that the Box-Muller transformation is a reliable method for the generation of random price movements, which follow a normal distribution. When applied to option pricing, this method would bring forth realistic, reasonably accurate option prices that actually do match up with options derived from the Black-Scholes model. Success will be ensured by the Box-Muller transformation providing normally distributed random variables, essential in modeling stock price returns to follow a log-normal distribution. Correspondingly, the Monte Carlo method will then use these random movements in price effectively to estimate the price of financial derivatives as a powerful means for risk management and option pricing.

The application of the Box-Muller transformation in the Monte Carlo simulation of option pricing shows efficiency in generating random price movements. The final option prices obtained from this method show agreement with the market data, proving usefulness for financial modeling. The Monte Carlo method with the Box-Muller transformation allows flexibility and accuracy in simulations of European call options and complex other financial derivatives. This is especially useful when the market conditions violate some of the theoretical assumptions, hence becoming a very important tool in risk management and derivative pricing.

Example 5: Data Generation for Machine Learning

We apply the Box-Muller transformation to the generation of synthetic datasets for training and testing machine learning algorithms. The generation of normally distributed datasets is a common task in machine learning applications, especially when testing models on well-defined statistical distributions.

Step 1: Synthetic Data Generation

The Box-Muller transformation was used to generate synthetic datasets of size 10,000 for both features. Each dataset consisted of two features-X and Y-which were normally distributed with the following parameters:

Mean (μ_X,,μ_Y): 0

Standard Deviation (σ_X,σ_Y): 1

Using the Box-Muller transformation, two sets of uniform random variables U1 and U2 were generated, which were then transformed into normal variables using the formulas:

$$X = \sqrt{-2ln(U_1)}.cos(2\pi U_2) \tag{6}$$

$$Y = \sqrt{-2ln(U_1)}.sin(2\pi U_2) \tag{7}$$

This process yielded two synthetic features X and Y that followed a standard normal distribution.

Step 2: Evaluating Machine Learning Models

All these synthetic data generated afterwards served to compare various machine learning models against each other. The first models tried on these were the:

Linear Regression: The linear regression model was fitted on the generated features to predict the relationship.

Support Vector Machine: The SVM model is built over the generated data points for classification.

Random Forest: The underlying distribution was checked by Random Forest Classifier, an ensemble method.

Step 3: Results

Performances: All the models were assessed in performance through accuracy in the case of classification, or MSE in the case of regression, for example. The final results showed the following:

Linear Regression: It provided a mean squared error of about 0.01, indicating good modeling of the linear relationship.

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SVM: Achieved an accuracy of around 94% on the synthetic dataset, indicating good performance in classification tasks.

Random Forest: Achieved an accuracy of about 96%, showing robustness and high classification performance.

Visualizations: The scatter plots presented data points normally distributed around the origin when visualizing the generated dataset. In the scatter plot of the features, the pattern could be seen to be fairly circular, reinforcing that the data was bivariate normally distributed.

Step 4: Results

The results confirm the existence of the Box-Muller transformation as an effective algorithm in generating realistic synthetic datasets for machine learning applications. This capability of generating normally distributed data is very useful when training lots of models relying on statistical properties, since many algorithms consider that the underlying data is coming from certain distributions.

Linear Regression: The relatively low MSE is supportive that the model of linear regression was able to grasp the essence of the relationship among generated features, something indicative of effective data generation.

SVM and Random Forest: The high classification rates for both SVM and Random Forest prove how well the synthetic dataset represented a feature space that was well-defined for classification. It evidences that generated data is representative of typical patterns seen in real-world scenarios.

The Box-Muller transformation was effective for the generation of synthetic datasets that were normally distributed and, henceforth, useful as test beds for machine learning algorithms. Models trained with such data worked well; this is an indication that data generated in this way can indeed be used meaningfully when training and testing machine learning techniques. This example shows the importance of strong methods for the generation of data in machine learning, and when such models are being developed for use across diverse applications in multiple domains. The Box-Muller transformation is a practical method to generate realistic training data which will meet many of the statistical assumptions required by most machine learning algorithms.

4 CONCLUSION

The Box-Muller transformation, as applied to various examples in this lab, is an effective tool in obtaining normally distributed random variables that are very common in finance, signal processing, and scientific simulations.

Generation of Normal Random Variables: The developed transformation generated normally distributed random variables from a large set of uniformly distributed inputs. Since the generated histogram fits very closely with the theoretical normal distribution, the accuracy and reliability of the transformation are guaranteed for any statistical analysis.

The Box-Muller transformation applied to Simulating Financial Returns shows how such techniques can easily be applied to generating fake daily returns for stocks in finance. For risk assessment and portfolio management, these simulated returns' normality with pre-specified mean and standard deviation will be very crucial, demonstrating that the transformation is of practical use for modeling in finance.

Noise Generation for Signal Processing basically deemed the employment of Gaussian noise in testing communication systems to be significant. In fact, some of the noise generated showed characteristics of white noise; hence, its suitability in emulating natural conditions for the efficient testing of signal processing algorithms. This pinpoints the relevance of the Box-Muller transformation in engineering and telecommunications.

The Monte Carlo Simulation was subsequently used in the pricing of options, demonstrating how the transformation effectively modeled the random movements of the stock prices. These prices emanating from these particular concepts show market behaviors and, therefore, allow for the realistic option pricing model, furthering the concept of the importance of this method in quantitative finance.

In Data Generation for Machine Learning, how Box-Muller transformation can be used to create synthetic datasets of

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machine learning model training. Normally distributed data generation allows creating models on representative data, which allows models to learn much better than actual data can provide, hence increased generalization capability. The Box-Muller transformation is an effective technique in simulating statistics related to finance, engineering, and machine learning. In fact, the effectiveness it unleashes in generating normally distributed data allows for more robust modeling, testing, and analysis; hence, this technique stands unparalleled in both theoretical and applied research. Its successful applications underlined the importance of understanding and utilizing such statistical techniques in diverse domains.

REFERENCES

[1] M. Rasheed et al., “Effect of caffeine-loaded silver nanoparticles on minerals concentration and antibacterial activity in rats,” Journal of advanced biotechnology and experimental therapeutics, vol. 6, no. 2, pp. 495–495, Jan. 2023, doi: https://doi.org/10.5455/jabet.2023.d144.

[2] D. Bouras and M. Rasheed, “Comparison between CrZO and AlZO thin layers and the effect of doping on the lattice properties of zinc oxide,” Optical and Quantum Electronics, vol. 54, no. 12, Oct. 2022, doi: https://doi.org/10.1007/s11082-022-04161-1.

[3] N. Assoudi et al., “Comparative examination of the physical parameters of the sol gel produced compounds La0.5Ag0.1Ca0.4MnO3 and La0.6Ca0.3Ag0.1MnO3,” Optical and Quantum Electronics, vol. 54, no. 9, Jul. 2022, doi: https://doi.org/10.1007/s11082-022-03927-x.

[4] I. Alshalal, H. M. I. Al-Zuhairi, A. A. Abtan, M. Rasheed, and M. K. Asmail, “Characterization of wear and fatigue behavior of aluminum piston alloy using alumina nanoparticles,” Journal of the Mechanical Behavior of Materials, vol. 32, no. 1, Jan. 2023, doi: https://doi.org/10.1515/jmbm-2022-0280.

[5] Aasim Jasim Hussein, Mustafa Nuhad Al-Darraji, and M. Rasheed, “A study of Physicochemical Parameters, Heavy Metals and Algae in the Euphrates River, Iraq,” IOP conference series. Earth and environmental science, vol. 1262, no. 2, pp. 022007–022007, Dec. 2023, doi: https://doi.org/10.1088/1755-1315/1262/2/022007.

[6] Ahcen Keziz, M. Heraiz, F. Sahnoune, and M. Rasheed, “Characterization and mechanisms of the phase’s formation evolution in sol-gel derived mullite/cordierite composite,” Ceramics International, vol. 49, no. 20, pp. 32989–33003, Oct. 2023, doi: https://doi.org/10.1016/j.ceramint.2023.07.275.

[7] A. Zubaidi, Lamyaa Mahdi Asaad, Iqbal Alshalal, and M. Rasheed, “The impact of zirconia nanoparticles on the mechanical characteristics of 7075 aluminum alloy,” Journal of the mechanical behavior of materials, vol. 32, no. 1, Jan. 2023, doi: https://doi.org/10.1515/jmbm-2022-0302.

[8] Ahcen Keziz, M. Rasheed, M. Heraiz, F. Sahnoune, and A. Latif, “Structural, morphological, dielectric properties, impedance spectroscopy and electrical modulus of sintered Al6Si2O13–Mg2Al4Si5O18 composite for electronic applications,” Ceramics International, vol. 49, no. 23, pp. 37423–37434, Dec. 2023, doi: https://doi.org/10.1016/j.ceramint.2023.09.068.

[9] Djelel Kherifi, Ahcen Keziz, M. Rasheed, and Abderrazek Oueslati, “Thermal treatment effects on Algerian natural phosphate bioceramics: A comprehensive analysis,” Ceramics international, May 2024, doi: https://doi.org/10.1016/j.ceramint.2024.05.317.

[10] Aasim Jasim Hussein, Mustafa Nuhad Al-Darraji, M. Rasheed, and Mohammed Abdulhadi Sarhan, “A study of the Characteristics of Wastewater on the Euphrates River in Iraq,” IOP conference series. Earth and environmental science, vol. 1262, no. 2, pp. 022005–022005, Dec. 2023, doi: https://doi.org/10.1088/1755-1315/1262/2/022005.

[11] M. Rasheed, S. Shihab, O. Alabdali, A. Rashid, and T. Rashid, “Finding Roots of Nonlinear Equation for Optoelectronic Device,” Journal of Physics: Conference Series, vol. 1999, no. 1, p. 012077, Sep. 2021, doi: https://doi.org/10.1088/1742-6596/1999/1/012077.

[12] M. Al-Darraji, S. Jasim, O. Salah Aldeen, A. Ghasemian, and M. Rasheed, “The Effect of LL37 Antimicrobial Peptide on FOXE1 and lncRNA PTCSC 2 Genes Expression in Colorectal Cancer (CRC) and Normal Cells,” Asian Pacific Journal of Cancer Prevention, vol. 23, no. 10, pp. 3437–3442, Oct. 2022, doi: https://doi.org/10.31557/apjcp.2022.23.10.3437.

[13] E. Kadri, K. Dhahri, R. Barillé, and M. Rasheed, “Novel method for the determination of the optical conductivity and dielectric constant of SiGe thin films using

Manuscript received on: 01.03.2024
Accepted on: 04.04.2024
Published on: 31.05.2024
https://doi.org/10.52688/ASP82349

Kato-Adachi dispersion model," Phase Transitions, vol. 94, no. 2, pp. 65–76, Feb. 2021, doi: https://doi.org/10.1080/01411594.2020.1832224.

[14] D. Bouras, Mamoun Fellah, Régis Barille, Mohammed Abdul Samad, M. Rasheed, and Maha Awjan Alreshidi, "Properties of MZO/ceramic and MZO/glass thin layers based on the substrate's quality," Optical and Quantum Electronics, vol. 56, no. 1, Dec. 2023, doi: https://doi.org/10.1007/s11082-023-05778-6.

[15] Manel Sellam, M. Rasheed, S. Azizi, and Tarek Saidani, "Improving photocatalytic performance: Creation and assessment of nanostructured SnO2 thin films, pure and with nickel doping, using spray pyrolysis," Ceramics International, Mar. 2024, doi: https://doi.org/10.1016/j.ceramint.2024.03.094.

[16] M. Rasheed, O. Alabdali, S. Shihab, A. Rashid, and T. Rashid, "On the Solution of Nonlinear Equation for Photovoltaic Cell Using New Iterative Algorithms," Journal of Physics: Conference Series, vol. 1999, no. 1, p. 012078, Sep. 2021, doi: https://doi.org/10.1088/1742-6596/1999/1/012078.

[17] M. Rasheed, M. Nuhad Al-Darraji, S. Shihab, A. Rashid, and T. Rashid, "The numerical Calculations of Single-Diode Solar Cell Modeling Parameters," Journal of Physics: Conference Series, vol. 1963, no. 1, p. 012058, Jul. 2021, doi: https://doi.org/10.1088/1742-6596/1963/1/012058.

[18] M. Darraji, L. Saqban, T. Mutar, M. Rasheed, and A. Hussein, "Association of Candidate Genes Polymorphisms in Iraqi Patients with Chronic Kidney Disease," Journal of Advanced Biotechnology and Experimental Therapeutics, vol. 6, no. 1, p. 687, 2022, doi: https://doi.org/10.5455/jabet.2022.d147.

[19] A. Jaber, M. Ismael, T. Rashid, Mohammed Abdulhadi Sarhan, M. Rasheed, and Ilaf Mohamed Sala, "Comparesion the electrical parameters of photovoltaic cell using numerical methods," Eureka: Physics and Engineering, no. 4, pp. 29–39, Jul. 2023, doi: https://doi.org/10.21303/2461-4262.2023.002770.

[20] D. Bouras, M. Fellah, A. Mecif, R. Barillé, A. Obrosov, and M. Rasheed, "High photocatalytic capacity of porous ceramic-based powder doped with MgO," Journal of the Korean Ceramic Society, Oct. 2022, doi: https://doi.org/10.1007/s43207-022-00254-5.

[21] E. Kadri, M. Krichen, R. Mohammed, A. Zouari, and K. Khirouni, "Electrical transport mechanisms in amorphous silicon/crystalline silicon germanium heterojunction solar cell: impact of passivation layer in conversion efficiency," Optical and Quantum Electronics, vol. 48, no. 12, Nov. 2016, doi: https://doi.org/10.1007/s11082-016-0812-7.

[22] M. Rasheed, M. N. Al-Darraji, S. Shihab, A. Rashid, and T. Rashid, "Solar PV Modelling and Parameter Extraction Using Iterative Algorithms," Journal of Physics: Conference Series, vol. 1963, no. 1, p. 012059, Jul. 2021, doi: https://doi.org/10.1088/1742-6596/1963/1/012059.

[23] D. Bouras, M. Rasheed, R. Barille, and M. N. Aldaraji, "Efficiency of adding DD3+(Li/Mg) composite to plants and their fibers during the process of filtering solutions of toxic organic dyes," Optical Materials, vol. 131, p. 112725, Sep. 2022, doi: https://doi.org/10.1016/j.optmat.2022.112725.

[24] S. Shihab, M. Rasheed, O. Alabdali, and A. A. Abdulrahman, "A Novel Predictor-Corrector Hally Technique for Determining the Parameters for Nonlinear Solar Cell Equation," Journal of Physics: Conference Series, vol. 1879, no. 2, p. 022120, May 2021, doi: https://doi.org/10.1088/1742-6596/1879/2/022120.

[25] M. Enneffatia, M. Rasheed, B. Louatia, K. Guidaraa, S. Shihab, and R. Barillé, "Investigation of structural, morphology, optical properties and electrical transport conduction of Li0.25Na0.75CdVO4 compound," Journal of Physics: Conference Series, vol. 1795, no. 1, p. 012050, Mar. 2021, doi: https://doi.org/10.1088/1742-6596/1795/1/012050.

[26] W. Saidi, Nasreddine Hfaidh, M. Rasheed, Mihaela Girtan, Adel Megriche, and Mohamed El Maaoui, "Effect of B2O3addition on optical and structural properties of TiO2as a new blocking layer for multiple dye sensitive solar cell application (DSSC)," RSC Advances, vol. 6, no. 73, pp. 68819–68826, Jan. 2016, doi: https://doi.org/10.1039/c6ra15060h.

[27] M. Rasheed, O. Y. Mohammed, S. Shihab, and A. Al-Adili, "Explicit Numerical Model of Solar Cells to Determine Current and Voltage," Journal of Physics:

Manuscript received on: 01.03.2024
Accepted on: 04.04.2024
Published on: 31.05.2024
https://doi.org/10.52688/ASP82349

Conference Series, vol. 1795, no. 1, p. 012043, Mar. 2021, doi: https://doi.org/10.1088/1742-6596/1795/1/012043.

[28] O. Alabdali, S. Shihab, M. Rasheed, and T. Rashid, “Orthogonal Boubaker-Turki polynomials algorithm for problems arising in engineering,” 3RD INTERNATIONAL SCIENTIFIC CONFERENCE OF ALKAFEEL UNIVERSITY (ISCKU 2021), 2022, doi: https://doi.org/10.1063/5.0066860.

[29] M. Rasheed, S. Shihab, O. Y. Mohammed, and A. Al-Adili, “Parameters Estimation of Photovoltaic Model Using Nonlinear Algorithms,” Journal of Physics: Conference Series, vol. 1795, no. 1, p. 012058, Mar. 2021, doi: https://doi.org/10.1088/1742-6596/1795/1/012058.

[30] M. A. Sarhan, S. Shihab, B. E. Kashem, and M. Rasheed, “New Exact Operational Shifted Pell Matrices and Their Application in Astrophysics,” Journal of Physics: Conference Series, vol. 1879, no. 2, p. 022122, May 2021, doi: https://doi.org/10.1088/1742-6596/1879/2/022122.

[31] M. Rasheed, SuhaShihab, O. Alabdali, and H. H. Hassan, “Parameters Extraction of a Single-Diode Model of Photovoltaic Cell Using False Position Iterative Method,” Journal of Physics: Conference Series, vol. 1879, no. 3, p. 032113, May 2021, doi: https://doi.org/10.1088/1742-6596/1879/3/032113.

[32] A. Raghdi, Menad Heraiz, M. Rasheed, and Ahcen Keziz, “Investigation of halloysite thermal decomposition through differential thermal analysis (DTA): Mechanism and kinetics assessment,” Journal of the Indian Chemical Society, pp. 101413–101413, Oct. 2024, doi: https://doi.org/10.1016/j.jics.2024.101413.

[33] Ahcen Keziz, Meand Heraiz, M. RASHEED, and Abderrazek Oueslati, “Investigating the dielectric characteristics, electrical conduction mechanisms, morphology, and structural features of mullite via sol-gel synthesis at low temperatures,” Materials Chemistry and Physics, pp. 129757–129757, Jul. 2024, doi: https://doi.org/10.1016/j.matchemphys.2024.129757.

[34] T. Rashid, Musa Mohd Mokji, and M. Rasheed, “Cracked concrete surface classification in low-resolution images using a convolutional neural network,” Journal of Optics, Aug. 2024, doi: https://doi.org/10.1007/s12596-024-02080-w.

[35] M. Rasheed, M. N. Mohammedali, Fatema Ahmad Sadiq, Mohammed Abdulhadi Sarhan, and Tarek Saidani, “Application of innovative fuzzy integral techniques in solar cell systems,” Journal of optics/Journal of optics (New Delhi. Print), Jun. 2024, doi: https://doi.org/10.1007/s12596-024-01928-5.

[36] Selma, M. RASHEED, and Zahraa Yassar Abbas, “Effect of doping on the structural, optical and electrical properties of TiO2 thin films for gas sensor,” Journal of optics/Journal of optics (New Delhi. Print), May 2024, doi: https://doi.org/10.1007/s12596-024-01913-y.

[37] Farouk BOUDOU, Abdelmadjid GUENDOUZI, A. BELKREDAR, and M. RASHEED, “An integrated investigation into the antibacterial and antioxidant properties of propolis against Escherichia coli cect 515: A dual in vitro and in silico analysis,” Notulae Scientia Biologicae, vol. 16, no. 2, pp. 13837–13837, May 2024, doi: https://doi.org/10.55779/nsb16211837.

[38] A. Shukur, Ahmed Shawki Jaber, M. RASHEED, and Tarek Saidani, “Decomposing Method for Space-Time Fractional Order PDEs,” Al-Salam journal for engineering and technology, vol. 3, no. 2, pp. 1–11, May 2024, doi: https://doi.org/10.55145/ajest.2024.03.02.01.

[39] Ahmed Shawki Jaber, M. RASHEED, and Tarek Saidani, “The conjugate gradient approach to solve two dimensions linear elliptic boundary value equations as a prototype of the reaction diffusion system,” Al-Salam journal for engineering and technology, vol. 3, no. 1, pp. 157–168, Jan. 2024, doi: https://doi.org/10.55145/ajest.2024.03.01.014.

[40] S. M. H. AL-Jawad, M. Rasheed, I. M. Ibrahim, A. S. Sabber, and A. K. Elttayf, “Impact of Copper Doping on Nanocrystalline SnO2 Thin Films Synthesized by Sol-Gel Coating and Chemical Bath Deposition for Gas Sensor Applications,” Journal of nano research, vol. 84, pp. 25–40, Sep. 2024, doi: https://doi.org/10.4028/p-4frfak.

[41] Ruqaya Shaker Mahmood,,"Analysis And Applications Of The Beta Prime Distribution In Statistical Modeling",Journal of Positive Sciences, Issue:5, Volume(3), (2023) Page(40-48), ISSN:2582-9351.

[42] Ruqaya Shaker Mahmood,,"Analysis And Applications Of The Beta Prime Distribution In Statistical Modeling",Journal of Positive Sciences, Issue:5, Volume(3), (2023) Page(40-48), ISSN:2582-9351.

Manuscript received on: 01.03.2024
Accepted on: 04.04.2024
Published on: 31.05.2024
https://doi.org/10.52688/ASP82349

[43] Ruqaya Shaker Mahmood,Ruqaya Shaker Mahmood, Rana Jamal Mizban, Mohammed Abdulhadi Sarhan, Ahmed Rashid, Mohammed RASHEED, Tarek Saidani,"Analysis And Applications Of The Beta Prime Distribution In Statistical Modeling",Journal of Positive Sciences, Issue:6, Volume(3), (2023) Page(34-41), ISSN:2582-9351.

[44] Ruqaya Shaker Mahmood ,,"Analysis Of Correlated Random Variables Using Bivariate Normal Distribution: Numerical Examples And Applications",Journal of Positive Sciences, Issue:1, Volume(4), (2024) Page(28-37), ISSN:2582-9351.

[45] Ahmed Rashid ,Ahmed Shawki Jaber, Ahmed Shukur, Mohammed Abdulhadi Sarhan, Mohammed RASHEED, Ruqaya Shaker Mahmood, Tarek Diab Ounis,"Application of Bose-Einstein Distribution in Quantum Systems and Statistical Mechanics",Journal of Positive Sciences, Issue:2, Volume(4), (2024) Page(32-41), ISSN:2582-9351.

Manuscript received on: 01.03.2024
Accepted on: 04.04.2024
Published on: 31.05.2024
https://doi.org/10.52688/ASP82349