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# A Power Model for the Average Blood Glucose and SGPT Levels of Drug-Induced Diabetic Experimental Rats Treated With the Cissampelos Pareira L. (Menispermaceae) Root Extract

**Lalit Mohan Upadhyaya[1], Sudhanshu Aggarwal[2]**

[1]Department of Mathematics, Municipal Post Graduate College, Mussoorie, Dehradun, Uttarakahnd, India.
[2]Department of Mathematics, National Post Graduate College, Barhalganj, Gorakhpur, Uttar Pradesh, India.

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**Abstract -**We formulate a power model to look into the SGPT levels of the experimental diabetic rats of the group 4 Test (G4T) category in the recent experiments conducted by Ankit Kumar et al. (see, Ankit Kumar, Ravindra Semwal, Ashutosh Chauhan, Ruchi Badoni Semwal, Subhash Chandra, Debabrata Sircar, Partha Roy and Deepak Kumar Semwal, Evaluation of antidiabetic effect of Cissampelos pareira L. (Menispermaceae) root extract in streptozotocin-nicotinamide-induced diabetic rats via targeting SGLT2 inhibition, Phytomedicine Plus 2 (2022) 100374, 11pp., https://doi.org/10.1016/j.phyplu.2022.100374). This model excels a previous three dimensional model propounded by us for this purpose in the sense that it explains up to 99.66% variability of the observed levels of SGPT of the experimental animals as compared to the previous model which explained only about 95.71% of the variability of this variate.

**Keywords:** Diabetes, Cissampelos pareira, blood glucose, regression, SGPT, power model, covariance matrix.
**2020 Mathematics Subject Classification** 62J02, 62J05, 62J10, 62J99, 62P05, 62P20, 91B62, 91B74, 91B99, 91G70, 91G99.

## 1.INTRODUCTION

Serum Glutamic Pyruvic Transaminase (SGPT), which is also known by the names of 'serum glutamate pyruvate transaminase' and 'alanine transferase' is 'an enzyme found in liver and other tissues', whose elevated levels in blood may be indicative of liver damage, cancer or some other diseases [1]. In people suffering from type 2 diabetes for a long time, there is a higher risk of liver dysfunction with impairment of enzymatic activity in liver as was noted by Harris [2]. Significantly enhanced (highly significant) levels SGOT (Serum Glutamic Oxaloacetate Transaminase), SGPT and ALP (Alkaline Phosphatase) with P-Values <0.001 were also observed in her latest study by Kapoor [3, p. 127] among the diabetic male persons in the age bracket of 35-50 years. In fact she remarked that "the liver enzymes presently are found to be an important indicator of liver deterioration due to increased blood sugar" [3, p. 127]. A recent study Dundi et al. [4] has underscored the fact that with an advancing stage of diabetes, the incidences of liver dysfunction in diabetics rise steadily, therefore, a regular checkup of the liver function assessment should necessarily form the part of the clinical management of the complications of diabetes. Medical practitioners often advise their patients, who, in their view are prediabetic, or are on the verge of an early stage of type-2 diabetes, to keep a regular check on their Fasting Plasma Glucose (FPG) levels to prevent the occurrence of diabetes, because some studies like those conducted by Huang et al. [5], Bonnet et al. [6], Lee et al. [7] and Hong et al. [8] had shown the existence of a substantial degree of correlation between the liver enzyme levels and the FPG levels [7,8] in addition to the finding that raised liver enzyme

levels pointed to the beginning of type-2 diabetes, insulin resistance and a diminished insulin sensitivity [5,6,7]. There are chances of liver dysfunction in people suffering from long term uncontrolled diabetes because this ailment is intimately related to insulin resistance and the liver is considered to be an important organ of insulin clearance (see, Duckworth et al. [9]). The simultaneous effects of diabetes on the hepatic and renal functions are most recently studied in detail by Prakash et al. [10], where these authors have found a significant correlation with P-Value less than 0.005 between the hepatic and renal profile among 227 diabetic patients consisting of 132 (58.1%) male and 95(41.9%) female patients who attended the "medicine OPD of Janaki Medical College teaching hospital, Ramdiaya and Ram Janaki Hospital, Janakpur" at Janakpurdham, Nepal. The overall conclusion of this study is summed up by the authors of [10] in their own words as: "Among diabetic patients, there was a substantial correlation between the liver and renal profiles. The etiology of various forms of diabetes mellitus is significantly influenced by hepatorenal factors among diabetics." At the global level, diabetes is considered to be a major cause of morbidity among the developing economies by the World health Organization [11].

The above discussion, which we consider sufficient for the very limited purpose of our present study, shows that diabetes is a disease of great concern for human beings and efforts are continuously being made to discover more potent remedies for combating the menace of this ailment. Since it is clear from our discussion of the previous paragraph that diabetes in humans also affects the liver in the long run, therefore, to better understand the mechanism how we can control the potential damage to the liver in patients with a long history of diabetes, it becomes necessary to minutely understand the positive and negative effects on the liver of a possible drug under development for the treatment / management of diabetes. When such investigatory experimental studies are not possible on human subjects, then the investigations are required to be carried out on the animal models to study the various effects of the possible novel drugs to be developed for treating the ailments, here diabetes mellitus in the present context. Putting forth now our idea of writing this paper we reveal that as part of our ongoing previous studies [12 -17] of mathematical modeling based on the extensive mathematical tool of regression analysis [20-27], we postulate here a three dimensional power model for the SGPT levels of the diabetic experimental rats which were classified under the fourth group G4T in the experiments of Ankit Kumar et al. [18] with an aim to understand how the SGPT levels of these rats depended upon the number of days of the experiments of Ankit Kumar et al. [18] and the observed average blood glucose levels of these animals during the four weeks period of this study [18]. For the sake of introduction only we briefly mention here that in these experiments [18] diabetes was induced in the animal subjects by injecting them with streptozotocin-nicotinamide and the fourth group (test group) of rats were treated for a period of four weeks with an ethanolic extract of the roots of the climber Cissampelos pareira L. [19], which is a widely known traditional medicinal plant.

Outlining the structure of the paper, we elaborate that the second section mentions the secondary data which we analyze in this paper. The third section contains the complete details of the power model propounded by us to explain the variation of the values of SGPT of the experimental diabetic rats which formed the members of the test group G4T of the experiments of Ankit Kumar et al. [18] by considering their SGPT levels as a function of number of days of the experiment and the mean values of the measured blood glucose levels of these rats. In section 4 we analyze the covariance matrix of the power model developed by us and record some of its mathematical properties. The conclusions of the paper in the fifth section close the paper.

### 1.1 Abbreviations Used in the Paper

The following abbreviations are used by us in this work for clarity and conciseness. The abbreviations, like

SGPT, are borrowed from medical terminology and some of the abbreviations used by Ankit Kumar et al. [18] are used by us to ensure the concordance of this study with that precursor work [18].

| | |
|---|---|
| G4T: group 4 Test | BG: Blood Glucose |
| Day: Day of Experiment | G4BGm: Mean of the blood glucose levels of the G4T rats |
| SGPT: Serum Glutamic Pyruvic Transaminase | 1.2345E+03 = $1.2345\times10^{3}$ |
| 1.2345E-03 = $1.2345\times10^{-3}$ | G4SGPT: SGPT levels of the group G4T rats |

## 2. DATA FOR THE STUDY

The secondary data which we aim to examine in this work is reproduced below in Table 1 from the relevant entries of Table 3 and Table 4 on p. 6 of the previously published paper of Ankit Kumar et al. [18]. Our appreciation and thanks for this purpose are given ungrudgingly to all the learned authors of [18] and the Publisher of the Journal [18] which forms the original source of the data given in Table 1 below.

**Table -1:** Measurements of the average blood glucose levels in mg/dL and the SGPT levels in (U/L) of the experimental rats showing the effect of the Cissampelos Pareira Root Extract on it.

| S.No. | Day | G4BGm (mg/dL) | G4SGPT (U/L) |
|---|---|---|---|
| 1. | 0 | 303.9 | 36.25 |
| 2. | 7 | 288.54 | 37.17 |
| 3. | 14 | 250.24 | 37.98 |
| 4. | 21 | 225.35 | 38.64 |
| 5. | 28 | 198.56 | 60.39 |

Source: A. Kumar et al. [18]

## 3. A POWER MODEL FIT TO THE MEASUREMENTS OF THE SGPT LEVELS OF THE RATS OF THE GROUP G4T

We discuss the main part of our work in this section by formulating a power model to understand the trend of values of the SGPT levels of the experimental diabetic rats of the group G4T as shown in the dataset of Table 1. For this purpose, we treat the variates 'Day' and 'G4BGm' as our predictors and the variate G4SGPT as the response. The Power Model which we propose in this paper for the dataset of Table 1 is given precisely by the relation:

$$y = a + x_1^b x_2^c \quad (3.1)$$

in which $y$ denotes the response G4SGPT (measured in U/L) and the predictors $x_1$ and $x_2$ stand respectively for the predictors Day and G4BGm (measured in mg/dL). The model of (3.1) belongs to the general class of models termed as the Power Models. Here we have three regression parameters $a, b$ and $c$.

The details of our examinations made in this connection are displayed in Table 2(a) below. With two degrees of freedom and a coefficient of determination of 99.66%, the model seems highly reliable. The Akaike Information Coefficient (corrected) (AICc) [28] of the model is 3.707072. The covariance matrix of the model is depicted in Table 2(b). The plot of the surface for the model of (3.1) is shown in Fig. 1, while

Fig. 2 displays its residual plot, where the residuals of G4SGPT are plotted against the first predictor Day. Fig. 3 shows the residual plot of G4SGPT against the second predictor G4BGm. The Residual History Plot of the model is shown in Fig. 4, which shows that the residuals have attained a constancy after the eighth iteration and the residual change has fallen below the preset tolerance limit of $10^{-8}$ after the fourteenth iteration. It is evident from the Parameter Histories Plot of the model shown in Fig. 5 that the parameter $a$ has settled down to a steady value after the ninth iteration and the values of the parameters $b$ and $c$ attain stable values after the tenth iteration.

**Table -2(a):** Details of the Power Model of Error! Reference source not found.

| |
|---|
| Name:Power Model |
| Kind:Regression |
| Family:Power Models |
| No. of Independent Variables:2 |
| |
| Parameters: |
| $a$ =3.70977001622376E+01 |
| $b$ =7.49174907691743E+00 |
| $c$ =-4.12316004356692E+00 |
| |
| Parameter Value Std Err Range (95% confidence)<br>$a$ 37.097700 0.498052 34.954756 to 39.240645<br>$b$ 7.491749 1.661882 0.341249 to 14.642249<br>$c$ -4.123160 1.048274 -8.633520 to 0.387199 |
| |
| Standard Error: 8.42697330762444E-01 |
| Coefficient of Determination (r^2): 9.96634385557141E-01 |
| Correlation Coefficient (r): 9.98315774470754E-01 |
| DOF: 2 |
| AICc: 3.707072 |
| |
| Parameter Standard Deviations: |
| $a$ _stddev =4.98051920272345E-01 |
| $b$ _stddev =1.66188175730743E+00 |
| $c$ _stddev =1.04827412730645E+00 |

| |
|---|
| Parameter Uncertainties, 95%: |
| $a$ _unc =2.14294445439736E+00 |
| $b$ _unc =7.15050007986855E+00 |
| $c$ _unc =4.51035953555044E+00 |

**Table -2 (b):** Covariance matrix of the Power Model of (3.1)

| | $a$ | $b$ | $c$ |
|---|---|---|---|
| $a$ | 3.4930596431987976E-01 | 5.9133088864816874E-01 | -3.7523350454845933E-01 |
| $b$ | 5.9133088864811978E-01 | 3.8891706934018484E+00 | -2.4531258246235734E+00 |
| $c$ | -3.7523350454842846E-01 | -2.4531258246235739E+00 | 1.5474139132837086E+00 |

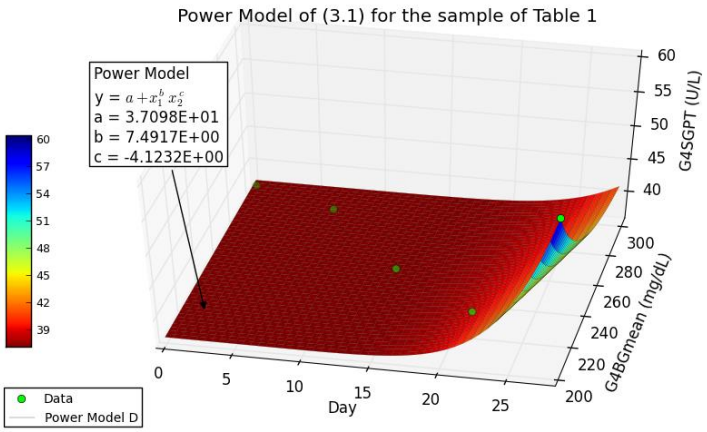


**Fig -1**:The Plot of the Power Model of (3.1) for the sample of Table 1.

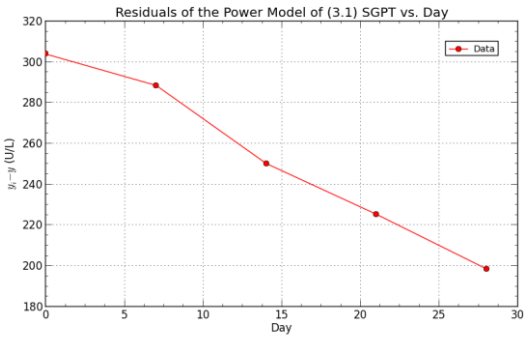


**Fig -2**:The Residual Plot of the Power Model of (3.1) G4SGPT vs. Day.

For the values of Day and G4BGm given in Table 1 above we have evaluated the value of G4SGPT from

(3.1) and the results of these calculations are shown by us in Table 3 below with the corresponding residuals and percentage errors. The reader may note that the percentage error in Table 3 for all the five pairs of the predictors mentioned in Table 1 is less than 5%, which shows that our model of (3.1) is highly reliable to predict the behavior of the pattern of G4SGPT as observed from Table 1 as a function of the predictors Day and G4BGm.

We remark here that we examined in detail the pattern of the values of G4SGPT as mentioned in Table 1 and we arrived at a conclusion that all the five values of the response G4SGPT as recorded in Table 1, viz., 303.9 U/L, 288.54 U/L, 250.24 U/L, 225.35 U/L and 198.56 U/L follow a Normal Probability Distribution reasonably well based on the Kolmogorov-Smirnov D-Statistic test if we exclude the Johnson and Cauchy distributions. The inclusion of the Johnson and Cauchy Distributions into our considerations results into the conclusion that when we use the Kolmogorov-Smirnov D-Statistic test as our distinguishing test then the Johnson Distribution appears as the first choice, followed by the Cauchy Distribution as the second choice, which is then followed by the Normal Distribution as the third best choice. For our present discussion we decided to exclude the Johnson and Cauchy Distributions from our considerations, and then we found that the trend of values of the second predictor G4BGm in the dataset of Table 1 follows a Normal Distribution reasonably well, so we fitted a Normal Distribution with a mean of 253.318 mg/dL and a standard deviation of 43.5581 mg/dL to the predictor G4BGm of Table 1 and suitably obtained random numbers from that distribution, which we assigned to the predictor G4BGm for different values of the Day in such a manner that our assignment pattern remains more or less similar to that observed in the values of G4BGm as displayed in Table 1. Based on this method we computed the G4SGPT levels of the experimental animals on a daily basis for one month according to the Power Model of (3.1). These results of ours are tabulated in Table 4 below. The readers may observe the close and reasonably good agreement of our predictions at the seventh, fourteenth, twenty first and the twenty eighth day with the experimental values of Ankit Kumar et al. [18] as shown in Table 1.

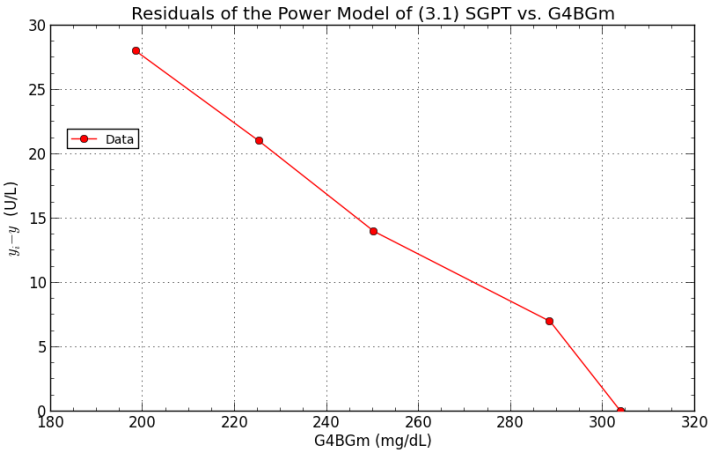


**Fig -3**:The Residual Plot of the Power Model of (3.1) G4SGPT vs. G4BGm.

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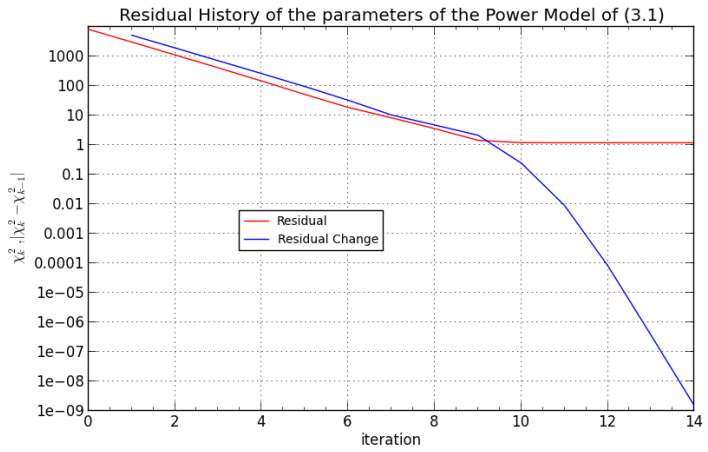


**Fig -4**:The Residual History Plot of the Power Model of (3.1).

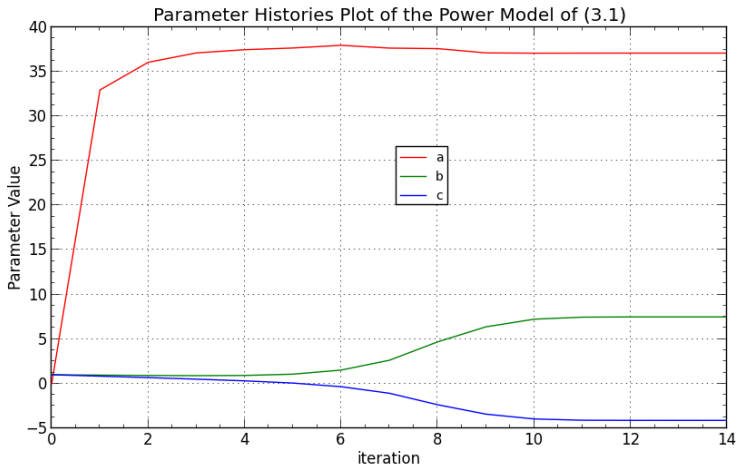


**Fig -5**:The Parameter Histories Plot of the Parameters of the Power Model of (3.1).

**Table -3:** Calculations from (3.1) for G4SGPT for the sample of Table 1.

| Day | G4BGm (mg/dL) | SGPT (U/L) | Calculated SGPT (U/L) from (3.1) | Residual (U/L) | Percentage Error |
|---|---|---|---|---|---|
| 0 | 303.9 | 36.25 | 37.0977 | -0.8477 | -2.33848 |
| 7 | 288.54 | 37.17 | 37.09785 | 0.072146 | 0.194097 |
| 14 | 250.24 | 37.98 | 37.14755 | 0.832446 | 2.191802 |
| 21 | 225.35 | 38.64 | 38.6992 | -0.0592 | -0.15321 |
| 28 | 198.56 | 60.39 | 60.38769 | 0.002308 | 0.003822 |

**Table -4:**Calculations from (3.1) for G4SGPT for given values of Day and G4SGPT.

| Day | G4BGm (mg/dL) | Calculated G4SGPT (U/L) from (3.1) |
|---|---|---|
| 0 | 309.028 | 37.0977 |
| 1 | 306.708 | 37.0977 |
| 2 | 302.593 | 37.0977 |
| 3 | 300.715 | 37.0977 |
| 4 | 297.209 | 37.0977 |
| 5 | 293.197 | 37.09771 |
| 6 | 290.72 | 37.09775 |
| 7 | 286.423 | 37.09786 |
| 8 | 281.475 | 37.09816 |
| 9 | 279.122 | 37.09886 |
| 10 | 275.074 | 37.10041 |
| 11 | 273.175 | 37.1034 |
| 12 | 269.977 | 37.10919 |
| 13 | 263.471 | 37.12084 |
| 14 | 258.993 | 37.14096 |
| 15 | 254.045 | 37.17625 |
| 16 | 248.417 | 37.23742 |
| 17 | 245.531 | 37.3286 |
| 18 | 242.788 | 37.46882 |
| 19 | 237.24 | 37.7098 |
| 20 | 229.925 | 38.1205 |
| 21 | 224.956 | 38.7108 |
| 22 | 222.47 | 39.49056 |
| 23 | 219.839 | 40.60401 |
| 24 | 213.235 | 42.5671 |
| 25 | 208.206 | 45.29172 |
| 26 | 205.866 | 48.61487 |
| 27 | 202.018 | 53.6145 |
| 28 | 199.231 | 60.06597 |
| 29 | 194.594 | 70.01861 |
| 30 | 191.26 | 82.67203 |

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## 4. ANALYSIS OF THE COVARIANCE MATRIX OF THE POWER MODEL FIT

Now we undertake an exploration of some spectacular features of the covariance matrix of the Power Model of (3.1) displayed in Table 2(b) above. Normally mathematics researchers are aware of the concepts of matrix analysis, linear algebra and integral transforms invoked by us in this section, and for the other interested researchers we refer them to the works [29-38] and the references therein for an understanding of concepts utilized by us below.

Noting that a covariance matrix is always symmetric, therefore, we rewrite the covariance matrix of the Power Model of (3.1), which is displayed in Table 2(b) in the following notation, which we utilize for our analysis in this section

$$A := \begin{bmatrix} 0.34930596431987976 & 0.5913308886481 & -0.3752335045484 \\ 0.5913308886481 & 3.8891706934018484 & -2.453125824623573 \\ -0.3752335045484 & -2.453125824623573 & 1.5474139132837086 \end{bmatrix}. \quad (4.1)$$

We confirm below that $A$ is a real symmetric positive definite matrix of rank 3 with an empty kernel. The value of its determinant by different methods of evaluation and its basis vectors are also shown in (4.2).

$$\begin{aligned} &\text{Rank}(A) = 3,\ \text{kern} := \text{NullSpace}(A) = \{\},\ \text{RowDimension}(A) = 3, \\ &\text{ColumnDimension}(A)=3,\ \text{Determinant}(A) = 0.000066105103, \\ &\text{Determinant}(A, \text{method} = \text{algnum}) = 0.00006610543972, \\ &\text{RowSpace}(A) = \left[[1.\ \ 0.\ \ 0.], [-0.\ \ 1.\ \ -0.], [0.\ \ 0.\ \ 1.]\right]; \\ &\text{ColumnSpace}(A) = \left[\begin{bmatrix} 1. \\ 0. \\ 0. \end{bmatrix}, \begin{bmatrix} -0. \\ 1. \\ -0. \end{bmatrix}, \begin{bmatrix} 0. \\ 0. \\ 1. \end{bmatrix}\right]; \text{IsDefinite}(A, \text{query} = \text{'positive\_definite'}) = \text{true}. \end{aligned} \quad (4.2)$$

The *orthogonal basis* for this matrix as given by the Gram Schmidt orthogonalization process is given as

$$\text{ord} := \left[\begin{bmatrix} 0.34930596431987976 \\ 0.5913308886481 \\ -0.3752335045484 \end{bmatrix}, \begin{bmatrix} -1.36302005335190 \\ 0.580701336401849 \\ -0.353711477623573 \end{bmatrix}, \begin{bmatrix} 4.0562016523360010^{-7} \\ 0.0000295406701154022 \\ 0.0000469301041978731 \end{bmatrix}\right] \quad (4.3)$$

and the corresponding orthonormal basis is given by

$$\text{orthnor} := \left\{\begin{bmatrix} -0.894837671194800 \\ 0.381236820579177 \\ -0.232215479246388 \end{bmatrix}, \begin{bmatrix} 0.00731440992442728 \\ 0.532696816347610 \\ 0.846274542838964 \end{bmatrix}, \begin{bmatrix} 0.4463315041 \\ 0.7555828756 \\ -0.4794608498 \end{bmatrix}\right\}. \quad (4.4)$$

We find the characteristic polynomial of $A$ in variable $\lambda$ as

$$\begin{aligned} &\text{CharacteristicPolynomial}(A, \lambda) \\ &= -0.0000661051035 + 1.408889552\lambda - 5.785890570\lambda^2 + \lambda^3, \end{aligned} \quad (4.5)$$

which on solving for $\lambda$, gives the following eigenvalues and eigenvectors of $A$

$$v,\ e := \text{Eigenvectors}(A) \Rightarrow$$

$$v := \begin{bmatrix} 5.53117477134287 + 0.I \\ 0.254668869882405 + 0.I \\ 0.0000469297801584362 + 0.I \end{bmatrix},$$

$$e := \begin{bmatrix} 0.133933358559622 + 0.I & 0.990963329768671 + 0.I & 0.00731672869028443 + 0.I \\ 0.838153615405838 + 0.I & -0.117213502690538 + 0.I & 0.532690821930636 + 0.I \\ -0.528734690035618 + 0.I & 0.0652125282503500 + 0.I & 0.846278295664101 + 0.I \end{bmatrix} \quad (4.6)$$

In (4.6) we specify that for the first eigenvalue $\lambda_1 = 5.53117477134287 + 0.I$ in the vector $v$, the corresponding eigenvector $v_1$ in the matrix $e$ is given by the first column of this matrix, thus,

$$v_1 = \begin{bmatrix} 0.133933358559622 + 0.I \\ 0.838153615405838 + 0.I \\ -0.528734690035618 + 0.I \end{bmatrix},\ I = \sqrt{-1}.$$

The Gaussian elimination of $A$ gives by the following upper triangular matrix

$$\text{GaussianElimination}(A)$$

$$:= \begin{bmatrix} 0.591330888648100 & 3.88917069340185 & -2.45312582462357 \\ 0. & -1.70604701861660 & 1.07385616456590 \\ 0. & 0. & 0.0000655269872430232 \end{bmatrix}. \quad (4.7)$$

Using the Gaussian elimination method if we perform the LU decomposition of $A$, we obtain he following permutation matrix $p$, the lower triangular factor $l$ and the upper triangular factor $u$ s.t. $plu = A$. Thus we have

$$p,\ l,\ u := \text{LUDecomposition}(A) \Rightarrow$$

$$p,l,u := \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \begin{bmatrix} 1.0 & 0. & 0. \\ 0.590711513681389 & 1.0 & 0. \\ -0.634557591615514 & -0.00866152210454603 & 1.0 \end{bmatrix}, \quad (4.8)$$

$$\begin{bmatrix} 0.591330888648100 & 3.88917069340185 & -2.45312582462357 \\ 0. & -1.70604701861660 & 1.07385616456590 \\ 0. & 0. & 0.0000655269872430232 \end{bmatrix}.$$

From (4.8), we can verify the fact that the product of the matrices $p,l$ and $u$ is $A$. We confirm the same by the following computation

$$p.l.u := \begin{bmatrix} 0.349305964319880 & 0.591330888648100 & -0.375233504548400 \\ 0.591330888648100 & 3.88917069340185 & -2.45312582462357 \\ -0.375233504548400 & -2.45312582462357 & 1.54741391328371 \end{bmatrix} = A.$$

The Cholesky decomposition of $A$ is given by

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$$\text{LUDecomposition}(A, \text{method} = \text{'Cholesky'})$$

$$:= \begin{bmatrix} 0.591021120028616 & 0. & 0. \\ 1.00052412445002 & 1.69944760725224 & 0. \\ -0.634890178764224 & -1.06970222361422 & 0.00809487413388130 \end{bmatrix}. \quad (4.9)$$

The matrix exponential $\exp(A)$ of the covariance matrix $A$ of the model of (3.1) given by (4.1) computed as below

$$\text{MatrixExponential}(A) := \exp(A) \Rightarrow$$

$$\exp(A) = \begin{bmatrix} 5.79518855888863 & 28.1921765984550 & -17.7870548632656 \\ 28.1921765984550 & 177.641179298798 & -111.430701907795 \\ -17.7870548632656 & -111.430701907795 & 71.2940099770712 \end{bmatrix}. \quad (4.10)$$

In $\exp(A)$ if we treat the values in the second column as some function $f(x)$ in an unknown $x$ of the corresponding values in the first column of $\exp(A)$, i.e., if suppose,

$f(5.79518855888863) = 28.1921765984550$, $f(28.1921765984550) = 177.641179298798$,

$f(-17.7870548632656) = -111.430701907795$

then the quadratic polynomial interpolant function $f(x)$ fitted to the first and second columns of $\exp(A)$ is given by

$$f(x) = 0.0163562834182736x^2 + 6.11682073231883x - 7.80526579047413, \quad (4.11)$$

and the two dimensional plot of $f(x)$ given by (4.11) is shown in Fig. 6(a), while its two dimensional polar plot is exhibited in Fig. 6(b) below. Fig. 6(c) represents the three dimensional Conformal Plot of $f(x)$ and Fig. 6(d) gives the three dimensional Complex Plot of $f(x)$ given by (4.11).

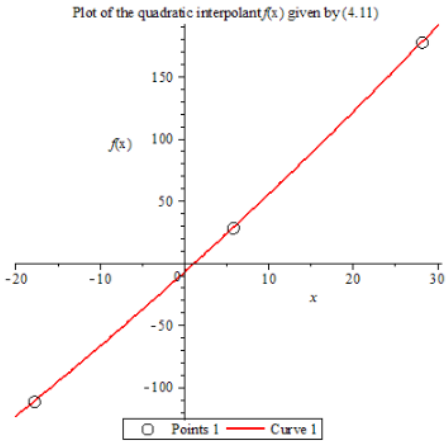


**Fig -6(a)**: Plot of the quadratic interpolant $f(x)$ of (4.11).

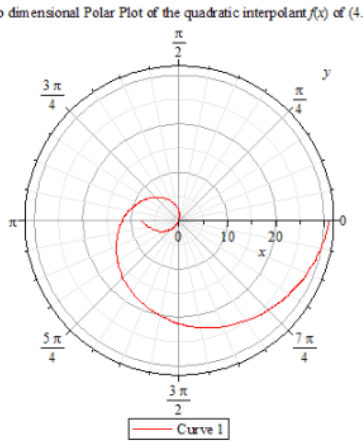


**Fig -6(b)**: Polar Plot of the quadratic interpolant $f(x)$ of (4.11).

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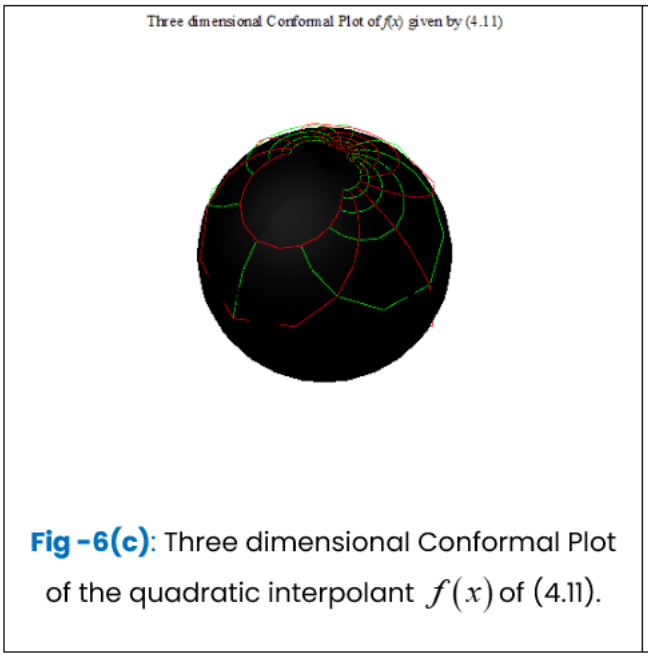


**Fig -6(c)**: Three dimensional Conformal Plot of the quadratic interpolant $f(x)$ of (4.11).

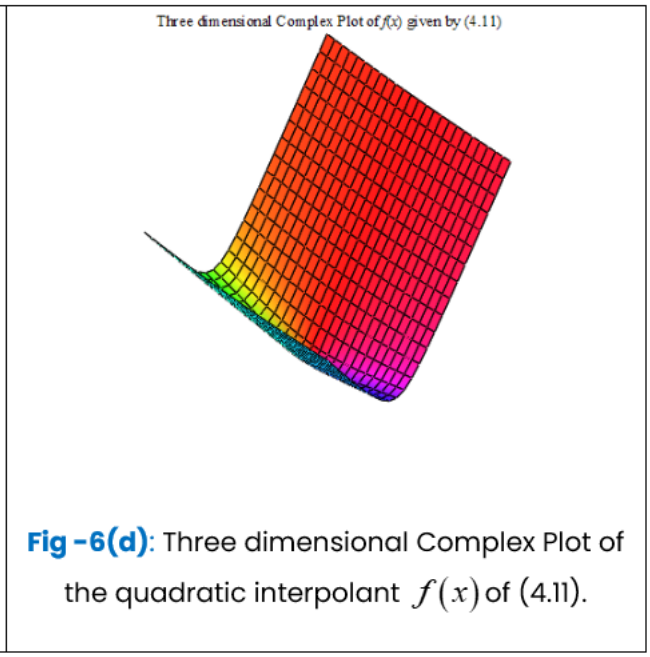


**Fig -6(d)**: Three dimensional Complex Plot of the quadratic interpolant $f(x)$ of (4.11).

As above in the matrix $\exp(A)$ given by (4.10), by assuming that the entries of its second column are some unknown function $g(x)$ of the corresponding entries $x$ of its first column, then a Thiele's continued fraction interpolant function $g(x)$ fitted to the first and second columns of $\exp(A)$ is given by

$$g(x) = 28.192176598455 + \frac{x - 5.79518855888863}{0.161535564513405 - 0.000414008973858033x}. \qquad (4.12)$$

Similarly in the matrix $\exp(A)$ given by (4.10), by treating the entries of the third column as some function of the corresponding entries of its second column and likewise, etc. we can compute similar interpolant functions.

We compute the Matrix Exponential $\exp(Ax) = I + Ax + \frac{A^2x^2}{2!} + \cdots$ of the covariance matrix $A$ of the model of (3.1) given by (4.1) as follows

$$B = \text{MatrixExponential}(A,\ x) := [C_1, C_2, C_3], \qquad (4.13)$$

where,

$$C_1 = \frac{0.00005353466628e^{0.00004692978016x} + 0.9820083212e^{0.2546688699x} + 0.01793814452e^{5.531174771x}}{-0.1161542815e^{0.2546688699x} + 0.003897553982e^{0.00004692978016x} + 0.1122567287e^{5.531174771x}},$$
$$0.06462322349e^{0.2546688699x} + 0.006191989142e^{0.00004692978016x} - 0.07081521280e^{5.531174771x}$$

$$C_2 = \frac{0.1122567286e^{5.531174771x} - 0.1161542824e^{0.2546688699x} + 0.003897553562e^{0.00004692978016x}}{0.2837595086e^{0.00004692978016x} + 0.7025014829e^{5.531174771x} + 0.01373900693e^{0.2546688699x}},$$
$$-0.4431608920e^{5.531174771x} - 0.007643791911e^{0.2546688699x} + 0.4508046843e^{0.00004692978016x}$$

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$$C_3 = \begin{matrix} -0.07081521280e^{5.531174771x} + 0.06462322393e^{0.2546688699x} + 0.006191988508e^{0.00004692978016x} \\ -0.4431608919e^{5.531174771x} - 0.007643793271e^{0.2546688699x} + 0.4508046829e^{0.00004692978016x} \\ 0.7161869542e^{0.00004692978016x} + 0.2795603723e^{5.531174771x} + 0.004252673157e^{0.2546688699x} \end{matrix}.$$

The characteristic polynomial of the matrix $B$ of (4.13) in the variable $\lambda$ is given by

$$\begin{aligned} &\text{CharacteristicPolynomial}(B,\lambda) \\ &= -1.835\cdot10^{-10}e^{5.531268631x} + 4.6343\cdot10^{-9}e^{0.2547627295x} - 4.45084\cdot10^{-9}e^{0.00009385956032x}\lambda \\ &-4.61\cdot10^{-9}e^{0.5093846696x} - 0.9999999975e^{0.00004692978016x}\lambda^2 + 3.367910^{-9}e^{6.040512511x} \\ &-1.000000001e^{0.2546688699x}\lambda^2 - 1.0\cdot10^{-10}e^{11.06234954x}\lambda - 0.9999999997e^{5.531174771x}\lambda^2 \\ &+5\cdot10^{-12}e^{11.06239647x} + 1.013912\cdot10^{-10}e^{11.31701841x} + 1.24\cdot10^{-9}e^{0.5093377398x}\lambda \\ &-1.000000002e^{5.785890571x} + 1.000000002\lambda e^{5.531221701x} + 1.000000002\lambda e^{0.2547157997x} \\ &+0.9999999964\lambda e^{5.785843641x} - 5.781589\cdot10^{-15}e^{0.0001407893405x} - 8.72856\cdot10^{-15}e^{0.7640066097x} \\ &+5.50568975\cdot10^{-13}e^{16.59352431x} + \lambda^3. \end{aligned} \tag{4.14}$$

A three-dimensional plot of the characteristic polynomial of the matrix $B$ given by (4.14) for the range $-5 \le x \le 5, -5 \le \lambda \le 5$ is shown in Fig. (7a), and Fig. 7(b) displays a two-dimensional gradient plot for the same. Likewise, we draw an implicit plot in two-dimensions for the characteristic polynomial (4.14) of $B$ in Fig. 7(c) and a two-dimensional contour plot for it in Fig. 7(d).

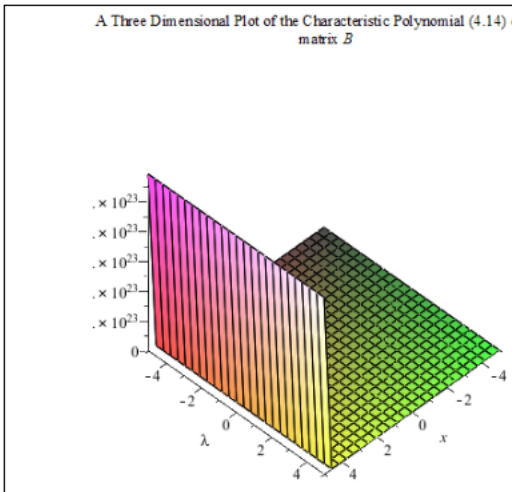


**Fig -7(a)**: A Three Dimensional Plot of the Characteristic Polynomial (4.14) of the matrix $B$.

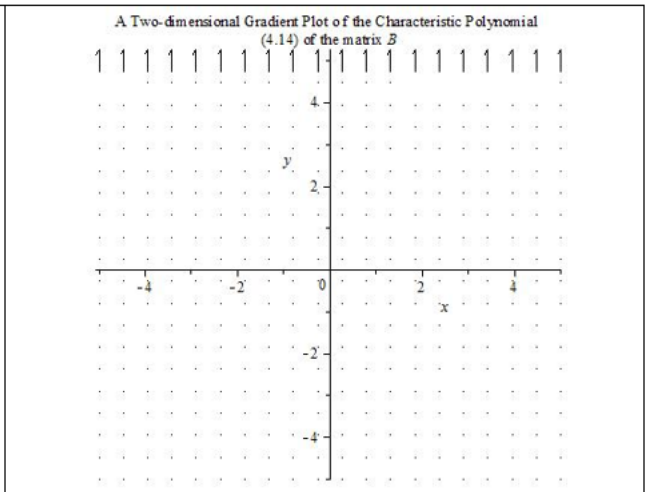


**Fig -7(b)**: A Two Dimensional Gradient Plot of the Characteristic Polynomial (4.14) of the matrix $B$.

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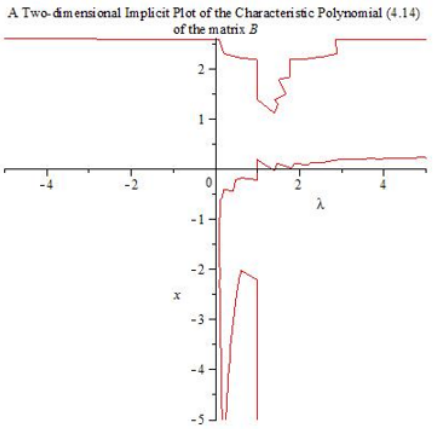


**Fig -7(c)**: A Two Dimensional Implicit Plot of the Characteristic Polynomial (4.14) of the matrix $B$.

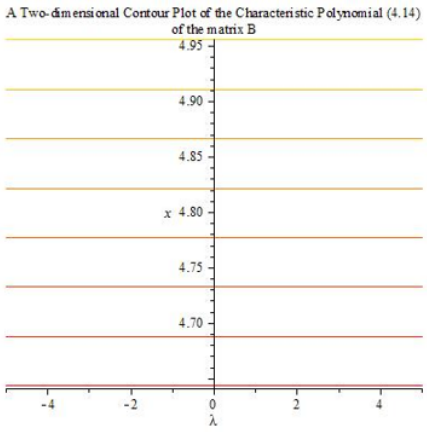


**Fig -7(d)**: A Two Dimensional Contour Plot of the Characteristic Polynomial (4.14) of the matrix $B$.

The Laplace transform of (4.14) with respect to the variable $x$ and the parameter $s$ is given in Fig. 8. For this Laplace transform we draw a three-dimensional plot in Fig. 9(a) for the range $-5 \le s \le 5, -5 \le \lambda \le 5$ and a two-dimensional implicit plot in Fig. 9(b). Similarly a three-dimensional implicit plot for the Laplace transform of the characteristic polynomial (4.14) of the matrix $B$ is shown in Fig. 9(c). Fig. 9(d) shows a two-dimensional contour plot, Fig. 9(e) a two-dimensional vector-gradient plot and Fig. 9 (f) depicts a two-dimensional density plot for the same function of Fig. 8.

$$-\frac{0.1835000000}{(1.000000000\,10^{9}\,s-5.531268631\,10^{9})^{1.}}+\frac{9.268600000}{(2.000000000\,10^{9}\,s-5.095254591\,10^{8})^{1.}}-\frac{6954.437500\,\lambda}{(1.562500000\,10^{12}\,s-1.466555631\,10^{8})^{1.}}-\frac{5.762500000}{(1.250000000\,10^{9}\,s-6.367308371\,10^{8})^{1.}}-\frac{3.124999992\,10^{12}\,\lambda^{2.}}{(3.125000000\,10^{12}\,s-1.466555631\,10^{8})^{1.}}+\frac{3.367900000}{(1.000000000\,10^{9}\,s-6.040512511\,10^{9})^{1.}}-\frac{1.000000001\,10^{10}\,\lambda^{2.}}{(1.000000000\,10^{10}\,s-2.546688699\,10^{9})^{1.}}-\frac{0.005000000000\,\lambda}{(5.000000\,10^{7}\,s-5.531174771\,10^{8})^{1.}}-\frac{9.999999997\,10^{8}\,\lambda^{2.}}{(1.000000000\,10^{9}\,s-5.531174771\,10^{9})^{1.}}+\frac{0.0005000000000}{(1.000000000\,10^{8}\,s-1.106239647\,10^{9})^{1.}}+\frac{0.01013912000}{(1.000000000\,10^{8}\,s-1.131701841\,10^{9})^{1.}}+\frac{6.200000000\,\lambda}{(5.000000000\,10^{9}\,s-2.546688699\,10^{9})^{1.}}-\frac{1.000000002\,10^{9}}{(1.000000000\,10^{9}\,s-5.785890571\,10^{9})^{1.}}+\frac{1.000000002\,10^{9}\,\lambda}{(1.000000000\,10^{9}\,s-5.531221701\,10^{9})^{1.}}+\frac{1.000000002\,10^{10}\,\lambda}{(1.000000000\,10^{10}\,s-2.547157997\,10^{9})^{1.}}+\frac{9.999999964\,10^{8}\,\lambda}{(1.000000000\,10^{9}\,s-5.785843641\,10^{9})^{1.}}-\frac{0.01156317800}{(2.000000000\,10^{12}\,s-2.815786810\,10^{8})^{1.}}-\frac{0.00008728560000}{(1.000000000\,10^{10}\,s-7.640066097\,10^{9})^{1.}}+\frac{0.00005505689750}{(1.000000000\,10^{8}\,s-1.659352431\,10^{9})^{1.}}+\frac{\lambda^{3.}}{s^{1.}}$$

**Fig -8**: The Laplace transform of the Characteristic Polynomial (4.14) of the matrix $B$.

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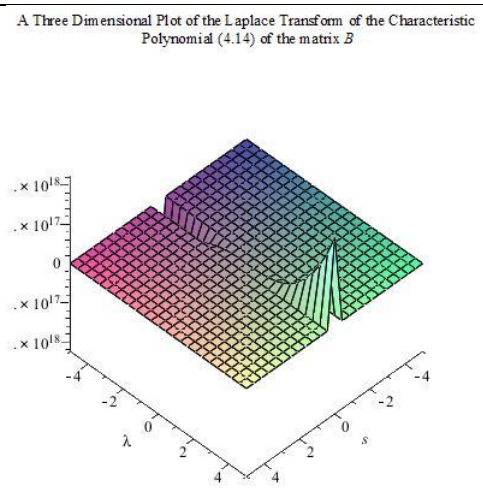


**Fig -9(a)**: A three-dimensional plot for the Laplace transform of the characteristic polynomial (4.14) of the matrix $B$.

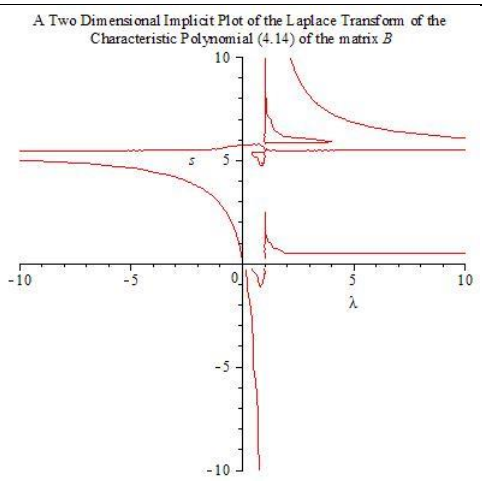


**Fig -9(b)**: A two-dimensional implicit plot for the Laplace transform of the characteristic polynomial (4.14) of the matrix $B$.

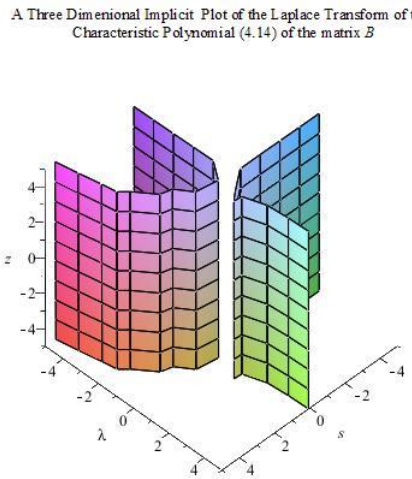


**Fig -9(c)**: A three-dimensional implicit plot for the Laplace transform of the characteristic polynomial (4.14) of the matrix $B$.

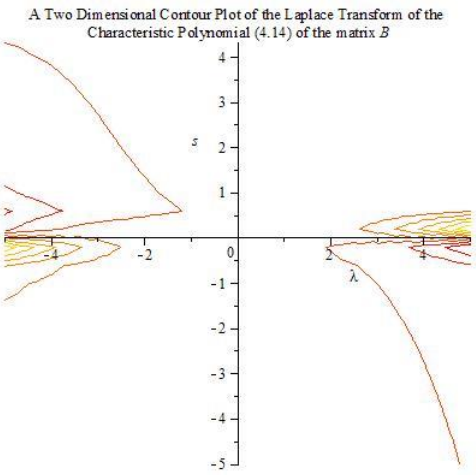


**Fig -9(d)**: A two-dimensional contour plot for the Laplace transform of the characteristic polynomial (4.14) of the matrix $B$.

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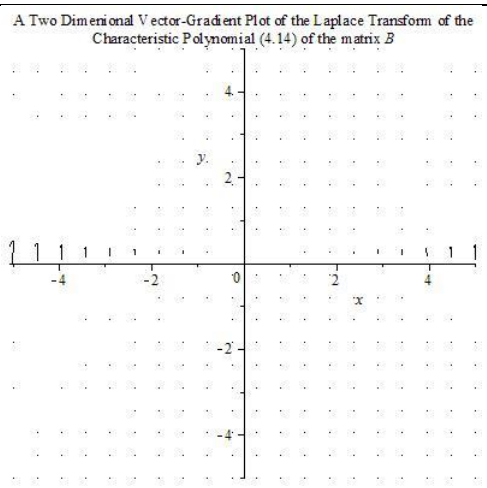


**Fig -9(e)**: A two-dimensional vector-gradient plot for the Laplace transform of the characteristic polynomial (4.14) of the matrix $B$.

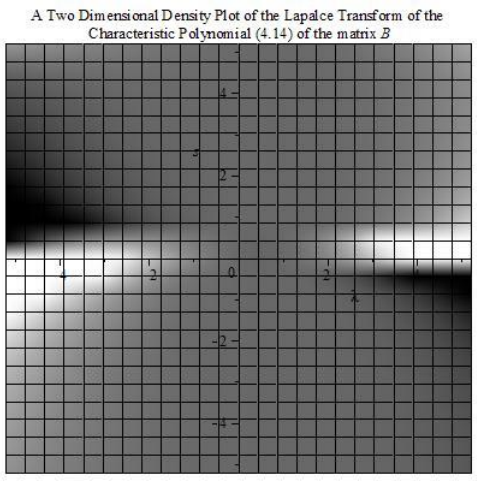


**Fig -9(f)**: A two-dimensional density plot for the Laplace transform of the characteristic polynomial (4.14) of the matrix $B$.

The upper Hessenberg form matrix $A1$ of the matrix $A$ of (4.1) is given by

$$A1 := \text{HessenbergForm}(A) \Rightarrow$$

$$A1 := \begin{bmatrix} 0.349305964319880 & -0.700337349286061 & -5.5511151231257810^{-17} \\ -0.700337349286061 & 5.43648398899572 & -0.0147131162442060 \\ 0. & -0.0147131162442062 & 0.000100617689835422 \end{bmatrix} \quad (4.15)$$

Before finishing this section we visualize the matrix plot of the matrix $A$ of (4.1) and its upper Hessenberg form $A1$ of (4.15) and some of the combinations of these two matrices. Figs. 10(a) and 10(b) show the matrix plots of the matrices $A$ and $A1$. The matrix plot of the product of these matrices is shown in Fig. 10(c) and Fig. 10(d) displays the matrix plot of the sum of these two matrices in histogram form.

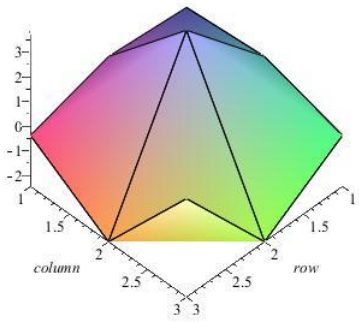


**Fig -10(a)**: The matrix plot of the matrix $A$ of (4.1).

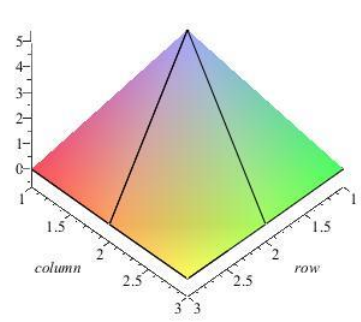


**Fig -10(b)**: The matrix plot of the upper Hessenber form matrix $A1$ of (4.15).

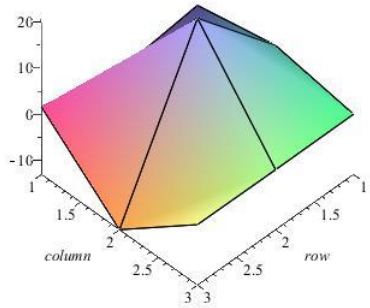


**Fig -10(c)**: The matrix plot of the product of the matrices $A$ and $A1$.

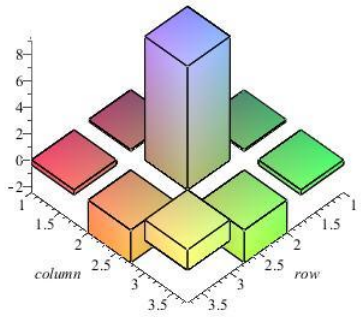


**Fig -10(d)**: The matrix plot in histogram form of the sum of the matrices $A$ and $A1$.

## 3. CONCLUSIONS

We formulated a Power Model to account for the observed variation of the SGPT levels of the experimental rats belonging to the group G4T with their observed blood glucose levels (G4BGm) and the number of days of the experiment (Day) as shown in Table 1 which are the findings of the experiments of Ankit Kumar et al. [18]. The surface plot of the enunciated model and its residual plot were shown and by exploring that the observed pattern of the measurement of G4BGm in Table 1 reasonably well follows a Normal Probability Distribution with a mean of 253.318 mg/dL and a standard deviation of 43.5581 mg/dL, we predicted the SGPT levels of the animals for given values of Day and G4BGm based on computations carried out by us from (3.1). These computations show that our predictions agree almost very well with the actual experimental results shown in Table 1. The covariance matrix of the model of (3.1) was also analyzed mathematically for its various features. In our next communication we propose to discuss a still

better model to predict the variation of the values of G4SGPT with those of the Day and G4BGm as presented in Table 1 above.

## ACKNOWLEDGEMENTS

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