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Simulation Methods of Multivariate Normal Distribution

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Abstract: In this paper, we are studying three simulation methods to generate observation for multivariate normal distribution, and these methods are: Matlab mvnrnd, decomposition and conditional methods, and we put simulation programs for each method by Matlab 2015a software, and comparison between these methods by depend on many criterions as MSE, AIC, skw, kur. As well as the run speed criterion for each method to get the best method.

1- Introduction:

Wolfgang Bischoff and Werner Fieger generalization the result of the Castillo and Galambos for multivariate random vectors [4], Patrick J., Matias, katarzyna [5], Chun-Chao Wang [6] and others wrote about the multivariate normal distribution and the simulation tests.

Multivariate distributions are studying with several variables (p)that is associated with each relationship and different degrees and thus dependent with a variance and covariance matrix Σ .[1] If Y has a multivariate normal distribution with mean vector μ and var-covariance matrix Σ , the density function is given by :

$$g(Y) = \frac{1}{\left(\sqrt{2\pi}\right)^p |\Sigma|^{\frac{1}{2}}} e^{-(Y-\mu)'\Sigma^{-1}(Y-\mu)/2}$$

Where μ :Length-p row vector, $\Sigma p \times p$ Matrix, $|\Sigma|$:Matrix determinant, and p is the number of variables. [2]

2- The concept of simulation

As a result of appearance several problems and statistical theories which are difficult find a logical analysis by mathematical proof, so it has been translated and transformation these theories to real societies, then they have chosen a number of independent random samples, To get the ideal solution for these problems, so practically these samples which are difficult find at the area because they Requires High cost, Time and effort hence some researchers have gone in the beginning of Twentieth century to apply technique the sampling experiment that which is known today simulation .The simulation process is a digital style to complete the experiments on the electronic calculator, which include types of logical and mathematical operations necessary to describe the behavior and structure of complex real system through a given time period.

3- Comparative criteria:

1) Mean squared error (MSE)

If T is (statistic) estimate for the parameter θ then we called that $E[(T - \theta)^2]$ is

$$MSE = E[(T - \theta)^2] - V(T) + [\theta]$$

 $= V(T) + [\theta - E(T)]^2$ Now when the estimate T be unbiased estimator then $\theta = E(T)$, which mean that

 $[\theta - E(T)]^2$ is equal to zero and

MSE = V(T).

There is another formula for these estimators specially (for joint estimator) of it as

$$MSE_{model} = det \frac{1}{Rep} \sum_{i=1}^{Rep} ((T - \theta) (T - \theta)')$$

Where Rep: Replication of experiment

2) Akaike information criteria (AIC)

The form of this criteria is either $AIC = -2 \log(MLE) + 2n$, or AIC = Nlog(MSE) + 2nWhere n: number of fitted parameters,

N: sample size.

3) Mardia's test statistic for skewness and kurtosis [6] [7]

If $X_1, X_2, ..., X_n$ random sample of independent and identical p-variate vectors with unknown mean μ and unknown covariance matrix \sum . Mardia (1970-1974) defined the measure of multivariate skewness and kurtosis as follows:

$$b_{1,p} = \frac{1}{n^2} \sum_{i,j=1}^{n} g_{ij}^{3}$$

Where

$$g_{ij} = (x_i - \overline{x})' S^{-1} (x_j - \overline{x})$$

And
$$b_{2,p} = \frac{1}{n} \sum_{i=1}^n \{ (x_i - \overline{x})' S^{-1} (x_i - \overline{x}) \}^2$$

Under normality of $X_1, X_2, ..., X_n$, asymptotically MVN, $A=nb_{1,p}$ /6 has a X^2 distribution with f=p(p+1)(p+2)/6degrees of freedom and the statistic $B = b_{2,p} - p(p+2)/\sqrt{8p(p+2)/n}$ has asymptotic standard normal distribution. Based on the statistic A and B, as test for multivariate normality jarque and bera (1987) proposed to use the statistic JB=A+B² which has asymptotic chi-square distribution with f+1 degrees of freedom. in addition, the distribution is symmetric (null of skewness) around the curve when the value of skewness is zero (sk=0), and the value of kurtosis for the normal distribution in univariate case is 3, while the Mardia's kurtosis is p(p+2) for the multivariate distribution of p- variables, which is ku=2(2+2)=8 when (p=2).but, the p_JB criterion has belong on the following hypothesis

 H_{\circ} : the data is belong to MVN If p-value <0.05 the hypothesis H_{\circ} is reject. Either p-value >0.05 the hypothesis H_{\circ} is not reject.

4- Formulation of Simulation Model

We are choose Matlab 2015a as a program for this study to write a simulation model to generate observation for multivariate normal distribution and selecting default value for the parameters $\mu = \begin{bmatrix} 2.6 \\ 4 \end{bmatrix}$, $\Sigma = \begin{bmatrix} 1 & -1 \\ -1 & 2 \end{bmatrix}$ of this distribution, in addition to select sample size n= 15, 50,100 and 200 respectively and choosing the number of replication as (R= 10000).

5- Simulation method

1- Matlab mvnrnd

This method depend on the following formula to get observation for multivariate normal distribution as

 $y = mvnrnd(mu, sigma_cov, sample size)$ Where mu: mean value vector for the distribution $sigma_cov$: variance and cov_variance for the variable and we wrote a complete program for this method in matlab software.

2- Decomposition method

To generate observation of multivariate normal distribution by this method must be generate the vector \underline{Z} from the relation $Z \sim N_p(0,1)$

and also generate the matrix T from the form *chol A* in matlab program, such that A is var_cov matrix ,then get the variable X as

 $X = \mu + T\underline{Z}$ that submit to this distribution.

3- Conditional method[3]

The idea of this method is

Generate x_1 from the marginal distribution of X_1 .

Generate x_2 from the conditional distribution of X_2 , given $X_1 = x_1$.

The suitability of this method for a given bivariate distribution depends on there being an efficient method for generating from the required univariate distributions.

Let $(X_1, X_2)'$ denote the bivariate normal vector with covariance matrix \sum .define

$$Y_{2} = \frac{(X_{1} - \mu_{1})/\sigma_{1}}{(X_{2} - \mu_{2}) - \frac{\sigma_{2}}{\sigma_{1}}(X_{1} - \mu_{1})\rho}{\sigma_{2}(1 - \rho^{2})^{1/2}}$$

Then Y_1 and Y_2 are two independent standard normal variables, and we can express it by

$$X_1 = \sigma_1 Y_1 + \mu_1$$

= $\sigma_2 \rho Y_1 + \sigma_2 (1 - \rho^2)^{\frac{1}{2}} Y_1 + \mu_1$

 $X_2 = \sigma_2 \rho Y_1 + \sigma_2 (1 - \rho^2)^2 Y_1 + \mu_2$ Univariate standard generators are widely available for this purpose. More generally, let $X \sim N(\mu, \Sigma)$, i.e, X is a p-dimensional multivariate normal random vector with mean vector μ and covariance matrix Σ , let L be the lower triangular matrix of the cholesky decomposition of Σ , i.e a matrix such that Σ =LL'. (routines for computing L are available in many computer software packages.) given ρ independent univariate standard variates, $Y' = (Y_1, \dots, Y_{\rho})$, transform them

$$X = LY + \mu$$

To achieve $N_p(\mu, \Sigma)$ distribution.

5- Result of simulation

After we show the special methods to generate observation for multivariate normal distribution, we review the results that obtained it from these methods as:

Sample size	μ	Σ	ρ	MSE	skw Sig. of skw	kur Sig. of kur	(P_JB)	time	AIC
15	[2.5975 4.0056]	[0.9971 1.9917]	-0.8330	3.1445	0.7875 0.7415	5.7207 0.1349	0.9483	0.9672	21.1848
50	[2.5996 3.9998]	[0.9997 1.9957]	-0.8064	0.0809	1.2377 0.0355	8.0727 0.4744	0.2818	0.9828	-121.6971
100	[2.5980 4.0029]	[0.9999 1.9970]	-0.5736	0.0101	0.1307 0.7031	7.5316 0.2791	0.6975	1.1076	-455.1037
200	[2.5994 3.9995]	[1.0003 2.0008]	-0.7019	0.0013	0.0201 0.9549	7.7267 0.3145	0.9884	1.2324	-1332.4

Table (3-1): Simulation result of multivariate normal distribution by mvnrnd method

Table (3-2): Simulation result of multivariate normal distribution by decomposition method

Sample size	û	Σ	ρ	MSE	skw Sig. of skw	kur Sig. of kur	(P_JB)	time	AIC
15	[2.5987 3.9979]	[0.9993 1.9968]	-0.7350	3.2092	0.4369 0.8955	5.7690 0.1401	0.9113	1.4508	21.4905
50	[2.5981 4.0010]	[0.9948 2.0012]	-0.7082	0.0848	0.2766 0.6799	6.0539 0.0427	0.6620	0.9672	-119.4022
100	[2.5986 4.0021]	1.0006 2.0010]	-0.7750	0.0101	0.2457 0.3933	7.6275 0.3207	0.5616	1.1856	-455.6912
200	[2.5992 4.0014]	[0.9999 2.0025]	-0.7266	0.0012	0.4234 0.0069	9.1161 0.0243	0.4155	2.3244	-1334.0

Sample size	μ	Σ	ρ	MSE	skw Sig. of skw	kur Sig. of kur	(P_JB)	time	AIC
15	[2.6010 4.0007]	[0.9973 1.9966]	-0.7484	3.2385	0.5520 0.8477	0.9016 0.1548	0.7903	0.9204	21.6265
50	[2.6007 3.9996]	[1.0028 1.9972]	-0.6849	0.0842	0.2019 0.7939	7.2519 0.2542	0.7057	0.9516	-119.7166
100	[2.6014 3.9989]	[0.9997 1.9997]	-0.7280	0.0104	0.2071 0.4852	8.2721 0.3669	0.1768	1.0296	-452.1387
200	[2.6001 4.0002]	[1.0006 1.9998]	-0.6959	0.0012	0.0445 0.8295	8.0473 0.4666	0.8811	1.2480	-1334.2

Table (3-3): Simulation result of multivariate normal distribution by conditional method

Table (3-4): Comparison between the results in table (3-1),(3-2)and (3-3)

		μ	$\widehat{\Sigma}$	$\hat{\rho}$	MSE	skw	kur		time	AIC
Sample	methods			_		Sig. of	Sig. of	(P_JB)		
size						skw	kur			
	Matlab	[2.5975	[0.9971	-0.8330	3.1445*	0.7875	5.7207	0.9483*	0.9672	21.1848*
	(mvnrnd)	4.0056]	1.9917]			0.7415	0.1349			
	Decomposition	[2.5987	[0.9993	-	3.2092	0.4369*	5.7690	0.9113	1.4508	21.4905
15		3.9979]	1.9968]	0.7350*		0.8955	0.1401			
	Conditional	[2 6010	[0 9973	-0 7484	3 2385	0.5520	5 9016*	0 7903	0 9204*	21 6265
		4 00071	1 9966]	-0.7404	5.2505	0.3320	0 1548	0.1705	0.7204	21.0205
			1.7700]			0.0477	0.1240	0.0010		
	Matlab	[2.5996	[0.9997	-0.8064	0.0809*	1.2377	8.0727*	0.2818	0.9828	
	(mvnrnd)	3.9998]	1.9957]			0.0355	0.4744			121.69/1*
50	Decomposition	[2.5981	[0.9948	-	0.0848	0.2766	6.0539	0.6620	0.9672	-119.4022
50		4.0010]	2.0012]	0.7082*		0.6799	0.0427			
	Conditional	[2.6007	[1.0028	-0.6849	0.0842	0.2019*	7.2519	0.7057*	0.9516*	-119.7166
		3.9996]	1.9972]			0.7939	0.2542			
	Matlab	[2.5980	[0.9999	-0.5736	0.0101*	0.1307*	7.5316	0.6975*	1.1076	-455.1037
	(mvnrnd)	4.0029]	1.9970]			0.7031	0.2791			
	Decemente	12 5096	1 0000	0.7750	0.0102	0.2457	7 (275	0.5(1(1 1056	
100	Decomposition	1 00211	2 00101	-0.7750	0.0102	0.2457	0.3207	0.5010	1.1050	-
		4.0021]	2.0010]			0.3935	0.3207			455.0912
	Conditional	[2 6014	[0 999 7	_	0.0104	0 2071	8 2721*	0 1768	1 0296*	-452 1387
		3.99891	1.9997]	0.7280*	0.0104	0.4852	0.3669	0.1700	1.0270	-452.1507
	Matlah	[2 5004	[1 0002		0.0012	0.0201*	7 7267	0 000 4 *	1 2224*	1222.4
	(mynrnd)	2.5994	2 00081	-	0.0015	0.0201	0.3145	0.9004*	1.2324*	-1352.4
		5.7775]		0.7013	0.0010	0.7349	0.3143	0.41.55	0.0044	1224.0
200	Decomposition			-0.7266	0.0012*	0.4234	9.1161	0.4155	2.3244	-1334.0
200		4.0014]	2.0025]			0.0069	0.0243			
	Conditional	[2.6001	[1.0006	-0.6959	0.0012*	0.0445	8.0473*	0.8811	1.2480	-1334.2*
		4.0002]	1.9998]			0.8295	0.4666			

~	Methods								
Sample size	Matlab (mvnrnd)	Decomposition	Conditional						
15	3	2	2						
50	3	1	3						
100	3	1	3						
200	4	0.5	2.5						
Total of each method	13	4.5	10.5						
Ratio	47%	16%	37%						

Table (3-5): Number times of excellence for each method and the total ratio to excellence

Table (3-6): The average of all parameters and criterion of each method

Methods	mean1	mean2	var1	var2	roh	MSE	skw	kur	P_JB	time	AIC
Matlab	2.600	4.002	0.999	1.996	-	0.809	0.544	7.263	0.729	1.073	-
(mvnrnd)					0.714						472.004
Decomposition	2.599	4.001	0.999	2.000	-	0.826	0.346	7.142	0.638	1.482	-
_					0.736						471.901
Conditional	2.603	4.000	1.000	1.998	-	0.834	0.251	6.118	0.638	1.037	-
					0.718						471.107

Table (3-7): Number times of excellence for each method and the total ratio to excellence according to the average of each method

Methods	Matlab (mvnrnd)	Decomposition	Conditional
Total of each method	6	1	4
Ratio	55%	9%	36%

6- Discussion of the Results

Form the above tables we can discuss the following result:

1- We can see in the tables (3-1),(3-2) and (3-3) that the value of $\hat{\mu}$ and $\hat{\Sigma}$ are approach to the default value ,which $\mu = \begin{bmatrix} 2.6 \\ 4 \end{bmatrix}$, $\Sigma =$

 $\begin{bmatrix} 1 & -1 \\ -1 & 2 \end{bmatrix}$ when the sample size are increasing from the smaller (15) to greater (200) in all three methods .

- 2- Note that the criterion MSE, AIC in all simulation results in the tables (3-1), (3-2) and (3-3) above are inversely proportional to the sample size, which mean ,when sample size is increasing the criterion MSE, AIC are decreasing .but the values of criterion skewness (sk) are approach to zero when the sample size is increasing in each method, also the values of kurtosis criterion(ku) are nearly from (8) in each method when the sample size start to be increasing, in addition, the values of the joint criterion (p_JB) in every method and in all cases of sample size are greater than (0.05) then we accept the hypothesis H_{\circ}, which H_o: the data is belong to MVN If p-value <0.05 the hypothesis H_o is reject. Either p-value >0.05 the hypothesis H_o is not reject.
- 3- The table (3-4) shown the comparison between the simulation result of these methods ,such that the best value to the criterion MSE,AIC when sample size is(15),(50) is matlab (mvnrnd) method ,and when sample size increasing (100) the best value of MSE is in the same method above but AIC in decomposition method, also when sample size is more increasing (200) we can see the same (0.0012)to MSE value criterion in decomposition ,conditional method ,respectively and criterion AIC is just in conditional method.

- 4- In same table (3-4) of comparison the best value of criterion skewness when sample size is (100) and (200) in matlab (mvnrnd) method, but in decomposition when sample size is (15) while in conditional method when sample size is (50).
- 5- In table (3-5) we make a comparison to know the number of times of excellence and total ratio of excellence($ratio = \frac{sub \ number}{total \ number} * 100$) for each method and we get that the upper ratio to the matlab (mvnrnd) method (47%), while the second method (decomposition) have got on (37%), and so be the matlab (mvnrnd) method is the best method to generate observation of multivariate normal distribution.
- 6- After that we put table (3-6) to get the average of all the parameter and criterion of each method, this average got from accumulated the four values of parameter and criterion in addition to correlation in all case of sample size after that we divided it by four, for example to get the value (2.600) of mean 1 in the same table, we do that

Mean1=

(2.5975+2.5996+2.5980+2.5994)/4=2.600,

And so on for all other values, in addition to the table (3-7) contain the comparison of number of the times of excellence and the ratio to table (3-6), and finally we deduced that the best method is matlab (mvnrnd)method because it get (55%) as a better ratio.

7- Appendixes (Programs)

```
clear all;num=1;
         while num<4
        num=input('number of program 1 cond. 2 Dec.
        3 Matlab?');
        switch num
        case 1
        % program 1 Generate observation of
        Multivariate Normal by conditional with
        Box_Muller Method
        disp('Result of conditional method')
        n=input('sample size?');% n is sample size.
        Rep=input('R of Rep.?');% number of
        replications
        t0=cputime();rand('seed',n);
        s_m=0;ssme =[0 0];ssva=[0 0];SS_MS=0;
        mu=[2.6; 4];sigma=[1-1;-12];
        rho=sigma(1,2)/(sigma(1,1)*sigma(2,2))^{0.5};
        l=length(mu);
        for r=1:Rep
        U=unifrnd(0,1,2,n);U1=U(1,:);U2=U(2,:);ph=2
        *(pi)*U1;R=(-2*log(U2)).^0.5;
          z1=R.*cos(ph);z2=R.*sin(ph);
             x1=mu(1,1)+z1*sigma(1,1)^{0.5};
             y2=rho*z1+sqrt(1-(rho)^2)*z2;
             x2=mu(2,1)+sigma(2,2)^0.5*y2;
             x=[x1;x2]';me=mean(x);
             ssme=ssme+me;ssva=ssva+var(x);
             SS_MS=SS_MS+(me'-mu)*(me'-mu)';
        end
          me=ssme/Rep
          var=ssva/Rep
          MSE=det(SS_MS)/(n-1)/Rep
          % MSE criterion for model
           AIC = n*log(MSE)+2*l
          % AIC criterion for model
           co=corr(x);rho_h=co(1,2)
          X=x;
        [n,p] = size(X); alpha = 0.05;
        difT = [];
        for j = 1:p
          difT = [difT,(X(:,j) - mean(X(:,j)))];
        end:
        S = cov(X);
                        % Variance-covariance matrix
        D = difT * inv(S) * difT'; \% Mahalanobis'
        distances matrix
b1p = (sum(sum(D.^3))) / n^2; \% Multivariate
skewness coefficient
b2p = trace(D.^2) / n; % Multivariate kurtosis
coefficient
v = (p^{*}(p+1)^{*}(p+2)) / 6;
                            % Degrees of freedom
g1 = (n*b1p) / 6;
                         % Skewness test statistic
(approximates to a chi-square distribution)
P1 = 1 - chi2cdf(g1,v); % Significance value of
skewness
```

g2 = (b2p-(p*(p+2))) / ...% Kurtosis test statistic (sqrt((8*p*(p+2))/n));(approximates to a unit-normal distribution) P2 = 1-normcdf(abs(g2)); % Significance value of kurtosis sk=b1p ku=b2p stats.Ps = P1 stats.Pk = P2ks=skewness(X);ku=kurtosis(X)-3; kwen=ks*ks';kur=ku*ku'; jb=n/6*(kwen+kur/4) p_jb=1-chi2cdf(jb,v) Mean_Ku=p*(p+2)*(p+1+n)/ntime=cputime()-t0 case 2 % program 2 Generate observation of Multivariate Normal by decomposition with inverse Method disp('Result of Dec. method') n=input('sample size?'); Rep=input('R of Rep.?'); t0=cputime();rand('seed',n); s_m=0;ssme =[0 0];ssva=[0 0];SS_MS=0; mu=[2.6; 4];sigma=[1-1;-12];l=length(mu);A=sigma; T=chol(A); for r=1:Rep u=rand(n,2);Z=norminv(u,0,1);Y=Z*T; for i=1:n for j=1:2X(i,j)=mu(j)+Y(i,j);end end me=mean(X);ssme=ssme+me;ssva=ssva+var(X); SS_MS=SS_MS+(me'-mu)*(me'-mu)'; end me=ssme/Rep var=ssva/Rep MSE=abs(det(SS_MS))/(n-1)/Rep % MSE criterion for model AIC = n*log(MSE) + 2*l% AIC criterion for model co=corr(X);rho_h=co(1,2) [n,p] = size(X); alpha = 0.05;difT = [];for j = 1:pdifT = [difT,(X(:,j) - mean(X(:,j)))];end: S = cov(X); % Variance-covariance matrix D = difT * inv(S) * difT';% Mahalanobis' distances matrix $b1p = (sum(sum(D.^3))) / n^2; \%$ Multivariate skewness coefficient b2p = trace(D.^2) / n; % Multivariate kurtosis coefficient $v = (p^{*}(p+1)^{*}(p+2)) / 6;$ % Degrees of freedom g1 = (n*b1p) / 6;% Skewness test statistic (approximates to a chi-square distribution)

P1 = 1 - chi2cdf(g1,v); % Significance value of skewness g2 = (b2p-(p*(p+2))) / ...(sqrt((8*p*(p+2))/n));% Kurtosis test statistic (approximates to a unit-normal distribution) P2 = 1-normcdf(abs(g2)); % Significance value of kurtosis stats.Ps = P1 stats.Pk = P2sk=b1p ku=b2p ks=skewness(X);ku=kurtosis(X)-3; kwen=ks*ks';kur=ku*ku'; jb=n/6*(kwen+kur/4) p_jb=1-chi2cdf(jb,v) time=cputime()-t0 case 3 % program 3 Generate observation of Multivariate Normal by Matlab function disp('Result of MATLAB method') n=input('sample size n?'); % n is sample size. Rep=input('R of Rep.='); t0=cputime();randn('seed',n); s m=0;ssme =[0 0];ssva=[0 0];SS MS=0; mu=[2.6; 4];sigma=[1-1;-12];l=length(mu); for r=1:Rep x=mvnrnd(mu,sigma,n);me=mean(x); ssme=ssme+me;ssva=ssva+var(x); SS_MS=SS_MS+(me'-mu)*(me'-mu)'; end me=ssme/Rep var=ssva/Rep MSE=det(SS_MS)/(n-1)/Rep % MSE criterion for model AIC = n*log(MSE) + 2*l% AIC criterion for model $co=corr(x);rho_h=co(1,2)$ X=x;[n,p] = size(X); alpha = 0.05;difT = [];for j = 1:pdifT = [difT,(X(:,j) - mean(X(:,j)))];end: S = cov(X);% Variance-covariance matrix D = difT * inv(S) * difT'; % Mahalanobis' distances matrix $b1p = (sum(sum(D.^3))) / n^2;$ % Multivariate skewness coefficient b2p = trace(D.^2) / n; % Multivariate kurtosis coefficient $v = (p^{*}(p+1)^{*}(p+2)) / 6;$ % Degrees of freedom g1 = (n*b1p) / 6; % Skewness test statistic (approximates to a chi-square distribution) P1 = 1 - chi2cdf(g1,v); % Significance value of skewness $g2 = (b2p-(p^*(p+2))) / ...$

% Kurtosis test statistic (sqrt((8*p*(p+2))/n));(approximates to a unit-normal distribution) P2 = 1-normcdf(abs(g2)); % Significance value of kurtosis sk=b1p ku=b2p stats.Ps = P1 stats.Pk = P2ks=skewness(X);ku=kurtosis(X)-3; kwen=ks*ks';kur=ku*ku'; jb=n/6*(kwen+kur/4) p_jb=1-chi2cdf(jb,v) $Mean_Ku=p*(p+2)*(p+1+n)/n$ time=cputime()-t0 otherwise disp('End of select') break end

end

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طرائق محاكاة للتوزيع الطبيعي متعدد المتغيرات

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المستخلص:

تم في هذا البحث، دراسة ثلاث طرائق محاكاة لتوليد مشاهدات تخضع للتوزيع الطبيعي متعدد المتغيرات وهي: Matlab mvnrnd ،التجزئة والطريقة الشرطية وبناء برامج محاكاة لكل طريقة بأستخدام برنامج Matlab 2015a ، وتم مقارنة هذه الطرائق الثلاث بالاعتماد على عدة مقاييس منها مقياس معدل مربع الخطأ MSE ،مقياس اكاكي ومقياس الالتواء والتفرطح kur, skw، على التوالي بالاضافة الى مقياس سرعة التنفيذ لكل طريقة.