Analysis Data of Potassium Ion's Dynamics in KcsA Ion Channel

Fatemeh Shahzamani Varnosfaderani and Zahra Mousaei

November 20, 2020

Analysis data of Potassium ion's dynamics in KcsA ion channel

F. Sahzamani Varnosfaderani
Mathematical Sciences Isfahan University of Technology, Isfahan, Iran
and Z.mousai *
Mathematical Sciences Isfahan University of Technology, Isfahan, Iran

Abstract. Consider the speed of the ions at different temperatures. The ions speed was taken in 6 temperature groups of 5, 10, 100, 150, 250 and 300 at 50000 seconds. In fact, for each temperature, there are up to 50,000 speed data. The goal of this model is to predict other temperatures. After graphing the data, a linear model for six groups will be proposed.
Keywords: Ions speed, Predict, Bayesian, Linear model.
AMS Mathematical Subject Classification [2010]: 13D45, 39B42.

1. Introduction

A test used to compare the mean of a quantitative attribute in more than two groups is one-way analysis of variance. in the one-way ANOVA analysis, the initial assumption H_0 is that there is no difference between the mean of populations and, in contrast to the secondary assumption H_1, there is a significant difference between the mean of the two groups of populations.
If the H_0 assumption is accepted, the analysis ends, indicates that there is no difference between the mean of the groups. But if the H_0 assumption is rejected, it indicates the difference between the groups and we should look for differences.
The advantages of using the analysis of variance is that only by performing a single test, the difference between the mean of all the groups in the test is examined.

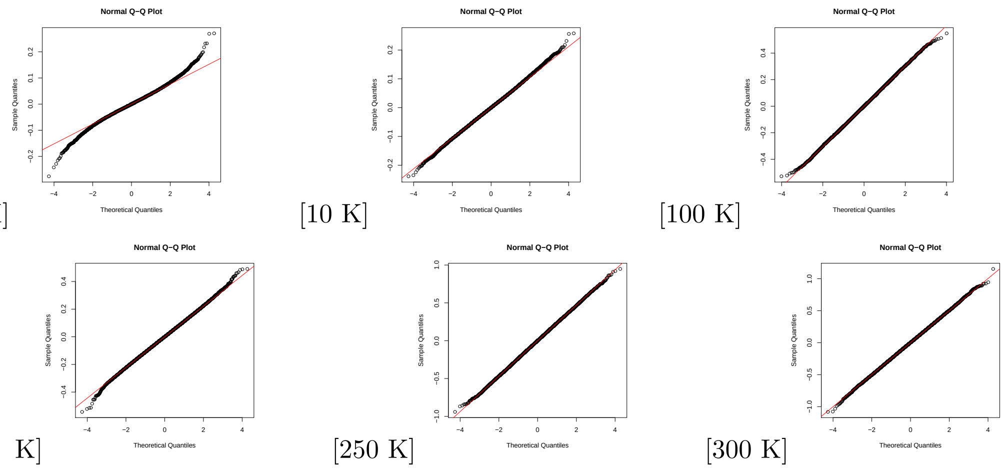
Remark 1.1. In one-way ANOVA, the following assumptions should be established:

(1) Independent random samples have been taken from each community. In other words, the dependent variable sizes in the variable factor levels are independent of each other.

(2) The traits examined in each community have normal distribution. That is, the dependent variable sizes at each level of the factor variable have a normal distribution.

The data we want to examine is obtained by simulating the ion speed at various temperatures of 5,10,100,200,250 and 300 Kelvin. for each temperature, we have about 50,000 speed variables depending on that temperature.We will review the conditions 1.1.
Clearly, the one condition is established. To make a second condition, use the of following tests and graphs.
Fig. 4 shows QQ-plot of quantile sample versus normal distribution, wherever the data is closer to the right line, it follows a normal distribution. According to Fig. 4, it is clear that the samples at different temperatures follow a normal distribution.

*speaker



[5 K] [10 K] [100 K] [200 K] [250 K] [300 K]

FIGURE 1. Q-Q plots of different temperatures.

The test, which is examined, is kolmogorovsmirnov test, the KolmogorovSmirnov test is a non-parametric test of the equality of continuous, one-dimensional probability distributions that can be used to compare a sample with a reference probability distribution, or to compare two samples. the KolmogorovSmirnov statistic quantifies a distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution, or between the empirical distribution functions of two samples. if the significance test, ie p was smaller than 0.05, it means that the distribution is not normal [?]. according to Table 1 in the appendix, almost all p-valu of the test statistic is greater than 0.05, and it rejects the assumption of kolmogorovsmirnov test, that is, the data follow the normal distribution.

Only data 5 Kelvin should be further reviewed. Figure 14 is a histogram of data 5 Kelvin, which indicates the normality of the data, and this fact can also be followed by the central limit theorem, when the data is highly selected the distribution of the data according to normal distribution.Now, with conditions A we want to check, is the average number of speeds between different temperatures the same or no?
First, Table 2 lists a descriptive index and plus a 95% confidence interval for the speed variable

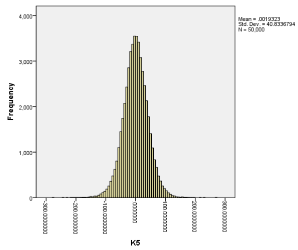


FIGURE 2. Histogram from 5 Kelvin

at each of the temperatures. If you look at the average speed at among temperatures, you will see that the mean is almost equal.

In Table 2, equality tests of variances were performed among six groups. You can see that with respect to the value of 0.00, the equality of variances is not accepted at the $\alpha = 0.05$ level.

Table 16 is an analysis table for variance with the value of Y equal to 0.969, which rejects the zero hypothesis. that's mean there is no difference between average speed between at the temperatures. Therefore, it can be said that the temperatures do not have a general relationship. The absence of a general relationship between temperatures means that if ion behavior is investigated at a particular temperature, we can not predict the behavior of this ion at other temperatures. Finally, according to the Tukey and Scheffe test, which is shown in Tables 20 and 5 of the appendix, we find that the temperatures do not have any relationship with each other. So, it can be said that temperatures do not have an outside group relationship and no intergroup relationship.

2. Two-Way ANOVA: Replications and Interaction

In the first section, the speed of different ions investigated on the temperature. in this section, we only consider the behavior of an ion at different temperatures. since it is believed that if we assign six different groups of speeds to each of the temperatures, the inherent feature of the ions may cause a difference. so, according to the data, we want to compare the six temperatures by means of variance analysis with Replications sizes. in Table 7, variable Factor Levels are reminded and in Table 8, the average and standard deviation of the speeds at each of the temperatures as well as the number of samples are given.

In Table 9, multivariate tests of factor levels are presented and Table Mauchly's Test 10 the test of uniformity of variance-covariance matrix with level of significance $\alpha = 0.00$ reasons for the non-uniformity of the variance-covariance matrix.

The most important table the analysis variance is Table Tests of Within-Subjects Effects 11. In the first row, level of significance of the ANOVA test is 0.965, that is, there is no significant difference between the temperatures. In the second to fourth row, more cautious tests were presented. These tests are for the assumption of the non-uniformity of the variance-covariate matrix the value of 0.05 these tests is due to the lack of discrepancy at various temperatures.

In Table 12, the avrage and standard deviation of the total, as well as the confidence interval 95%, are obtained for the average, and in Table 18, the average and standard deviation of the velocities for each of the temperatures as well as the 95% confidence interval for them are obtained.

Figure 3 also shows the difference between temperatures with a temperature of 300 Kelvin.

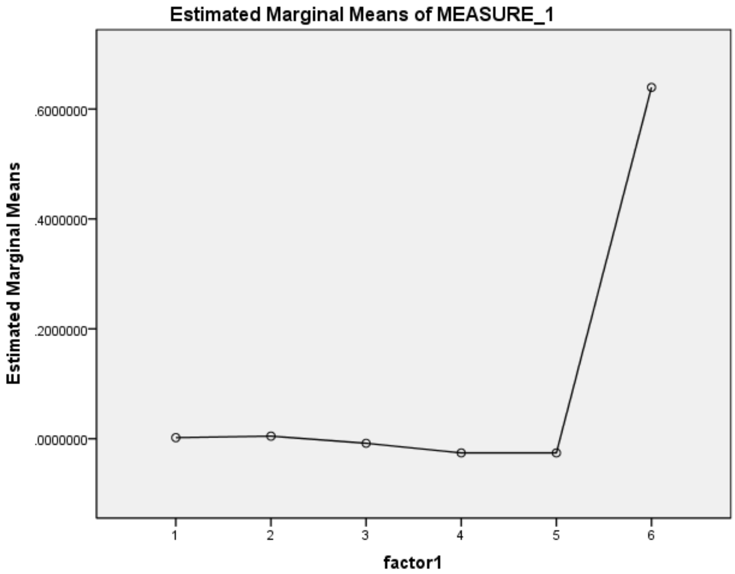


FIGURE 3. Average linear graph.

3. Time series

Introduction

A time series is a sequence of observation of data points measured over a time interval. The observations are ordered in time as successive observation may be dependent. Data must be equal at time interval and dependent on the variable also do not have missing data. The purpose of the time series is the describe, control and most importantly the predict. The difference in time series and other modeling methods, including regression, is that time series predict future values using previous data, while in other modeling methods, often, using independent variables, we try to predict the desired variable [**?**].

Static data

Staticity is a very important topic in time series modeling. Because many probability models of time series are based on the static series. If a series of times is static, it means that the series fluctuates randomly around a constant, and if the series is unstable, it means that the series has no stable mean. A trend series is a series of unsafe ones. Because its average is not constant and is rising or decreasing with time. Simply put, we can call a series of times static or mana if its statistical characteristics, such as its average and its variance, remain constant over time. The basic concept of static is that the laws governing the process do not change with time, that is, the process remains in statistical balance.

Model ARIMA(p, d, q) in time series analysis

Determining the appropriate model is one of the important issues in analyzing time series. In this paper, considering the general model of ARIMA, we study the effect of the difference value on the fit of the model. In the following sections, while introducing these models, we will examine the amount of differentiation.
Time series methods are used to analyze data that dependent on time. Two domains in the modeling of time series are the domain of time and domain of frequency.

The self-return model is one of the most time-consuming models. In this model, it is assumed that any value of the time series is returned to a certain and finite order such as p to the previous values of the series. In other words, each series value can be written in terms of a certain number of values before it, and the reason for naming this model is the same. For this model, the AR(p) symbol is usually used.
Model AR(p) is always invertible because it can be obtained in terms of its previous values.
In general, this model can be written as follows:

$$AR(p) : \psi(B)(Z_t - \mu_t) = a_t \tag{1}$$

In the 1 relation, the polynomial $\psi(B)$ is a ccording to backward operator B, which is

$$\psi(B) = 1 - \psi_1 B - ... - \psi_p B^p$$

Also Z_t indicates the amount of time series and a_t its noise.
The self-return model is not always static. Because it results from 1:

$$Z_t = \frac{1}{\psi(B)} a_t \tag{2}$$

In general, if you can get to convergethe coefficient a_t to the right of relation 2, then the model is convergent.
Therefore, convergence of the model is possible, for example, in the model AR(1), the coefficient B is smaller than one, in other words, the polynomial root $\psi(B)$ is greater than one. For higher levels of the model, the stationary determination depends on the solution of the differential return equation $\psi(B) = 0$ and places several conditions on the polynomial coefficients. Therefore, it is inevitable to determine the value of the $\psi(B)$ polynomial root for stationary diagnosis. If one or more of the roots of $\psi(B)$ is equal to one, then the model is not static. Since the convergence of the right coefficient of relation 2 does not exist. In this case, with the difference of the model it can be static:

$$ARI(p, d) : \psi(B)(1 - B)^d (Z_t - \mu_t) = a_t \tag{3}$$

In this model, the decomposition of the d rank of the AR(p) model is performed. This model is used when $\psi(B) = 0$ has a root d equal to one. In such cases, the difference in the model makes it standable.
Now, if any value of the Z_t series is in series, that is, a time series $\{a_t, t = 1, 2, ..., n\}$ to a certain and finite order such as q, then the resulting model is called the moving average model of the q-order and shown with the MA(q) symbol. The MA(q) moving average model can be shown as follows:

$$MA(q) : Z_t = \theta(B) a_t. \tag{4}$$

In Equation 4, $\theta(B)$ is equal to:

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q.$$

It is obvious that moving average models are always static. Both self-reversal and moving average models are in the realm of time. Now, if we consider the two models above, that is, any value of the time series is a function of its previous values and its constructive series, the ARMA(p,q) model is obtained.In general, this model can be written as follows:

$$ARMA(p, q) : \psi(B)(Z_t - \mu_t) = \theta(B) a_t. \tag{5}$$

Static ARMA(p,q) models are returned to the static part of the self-reversing part of the model.
In relation 5, if the model of the model is derived from the polynomial $\psi(B)$ root, then the model can be static with the difference of degree d. These models are represented by the ARIMA(p,d,q) symbol and are shown as follows:

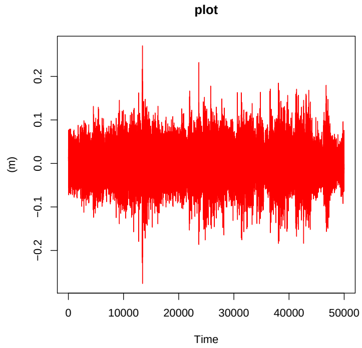
$$ARIMA(p, d, q) : \psi(B)(1 - B)^d (Z_t - \mu_t) = \theta(B) a_t.$$

That μ_t is the mean of the process corresponding to the desired time series. In these models, the values of d are natural numbers.

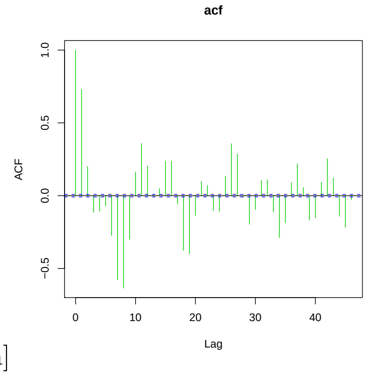
The data we have is data that is dependent to different temperatures at equal intervals. To predict the data, we use the following algorithm.

Algorithm (time series prediction)

Step one: Draw a time series graph.
Step Two: If the data are constant variance, we will go to the next step, otherwise by dividing the data we will go through the first step.
Step third: If the data is static, we go to the next step, otherwise by dividing the data we will go through the first step.
Step fourth: Using the graphs acf and pacf, we identify the model, we go to the next step.
Step Five: If the parameters are meaningful, we go to the next step, otherwise we will return to step four.
Step Six: If the residuals are independent and meaningful, we will go to the next step; otherwise, return to step four.
Step seventh: If the residuals is normal, we go to the next step otherwise, return to step four.
Step eEighth: We anticipate the next data.
Using the above algorithm, we examine the ion speeds at different temperatures. For each of the six temperatures of 5, 10, 100,200,250 and 300 Kelvin, we have 50,000 variable speeds $\frac{m}{s}$ depending on any temperature in the same range.
For each of the six temperature variables, we apply six time series models. The results are as follows.
Fig 4 is time series graph, acf and pacf at 5 K.



[Time series graph] [Acf



graph] [Acf graph]

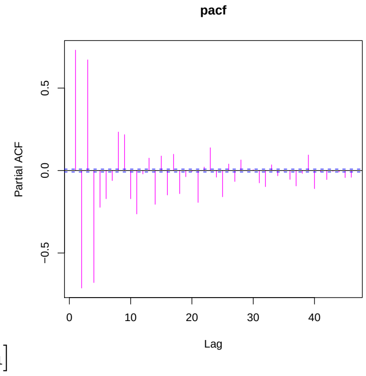
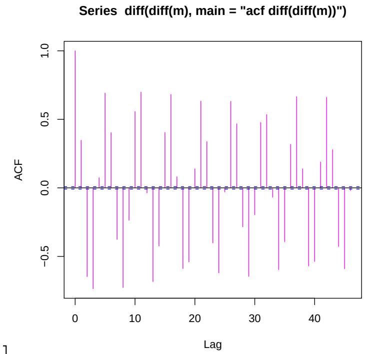


FIGURE 4. 5 kelvin temperatures.

The acf graph has a downward trend towards zero, so the 5 kelvin time series is not static [?]. By differentiating data and according to Figure 5, the data are static.



[Acf graph] [Pacf graph]

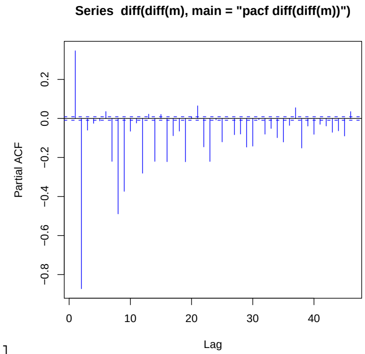


FIGURE 5. 5 kelvin temperatures.

Now, using the acf and pacf charts, we will identify models. For temperature 5 Kelvin, we approximate six models. Consider a model that is $p - value < 0.005$ and the residue has a white noise property, meaning that the residues are independent and meaningful and normal $(0, \sigma^2)$. In summary, the tested models are shown in Table 14.

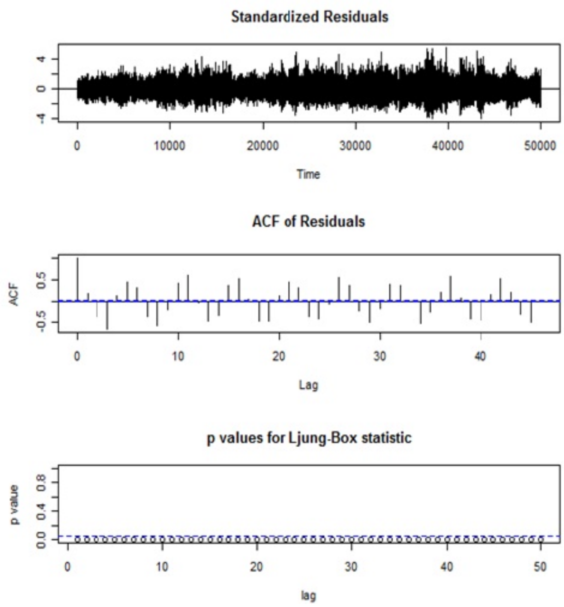
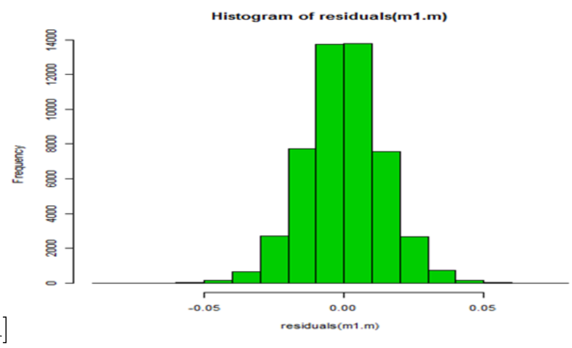
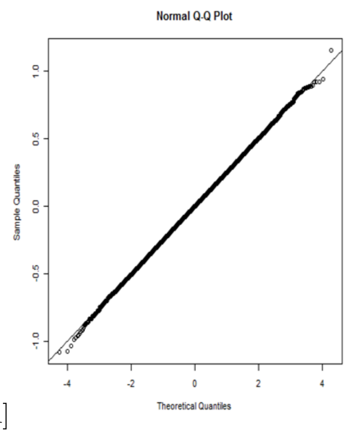


Figure 6. Time series graph, acf and pacf from residue 5 Kelvin for arima(3,3,3)



[Histogram from residue 5 Kelvin]

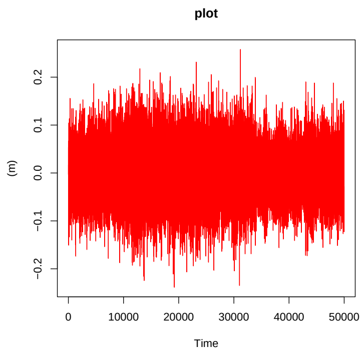


[QQ-plot from residue 5 Kelvin]

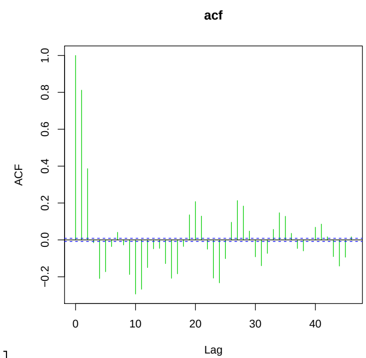
Figure 7. Investigating the Normality of Residues for Model arima(3,3,3).

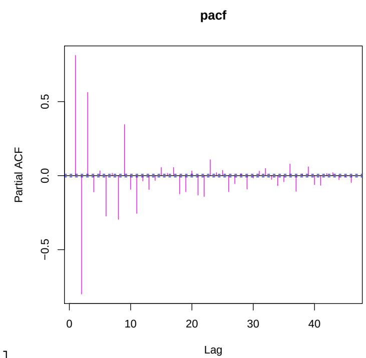
According to Table 14 and Chart Remnants 2 and 8 of model arima(3,3,3),this Model is acceptable, so the next data can be predicted. Table 15 predicts 20 data from a temperature of 5 Kelvin.

Similarly, model testing and detection of 10,100,200,250 and 300 Kelvin temperatures are presented below.



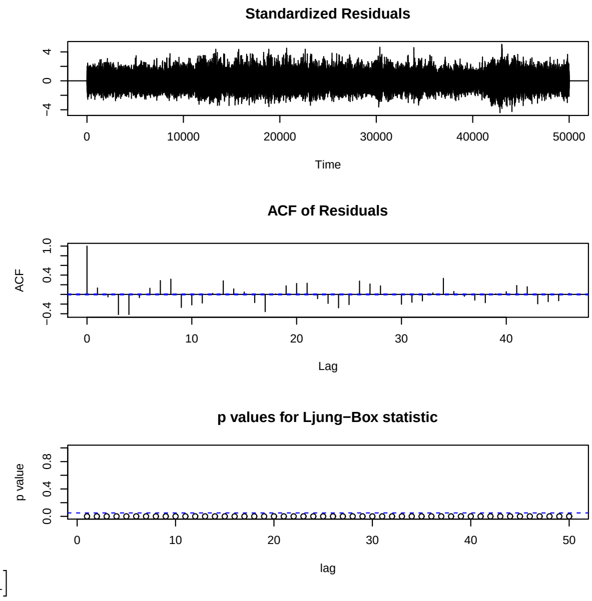
[Time series graph] [Acf



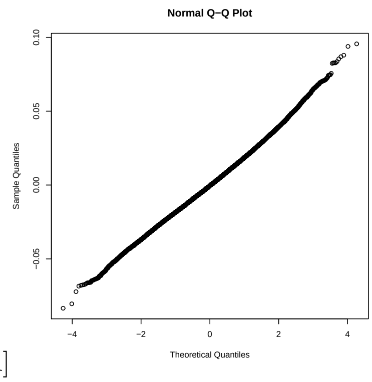


graph] [Acf graph]

FIGURE 8. 10 kelvin temperatures.



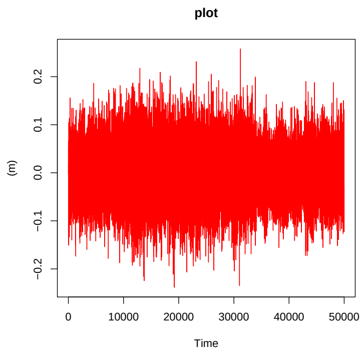
[Graph from residue 10 Kelvin]



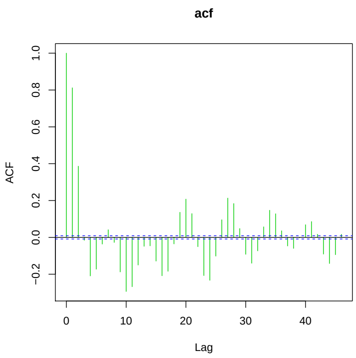
[QQ-plot from residue 10 Kelvin]

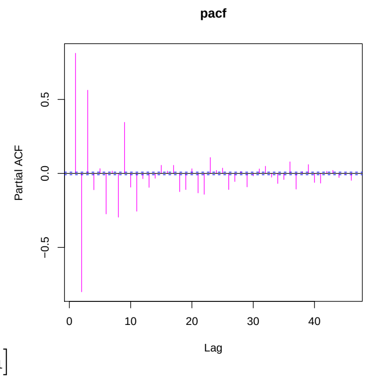
FIGURE 9. Investigating the Normality of Residues for Model arima(1,1,1).

Table 16 predicts 20 data from a temperature of 10 Kelvin.



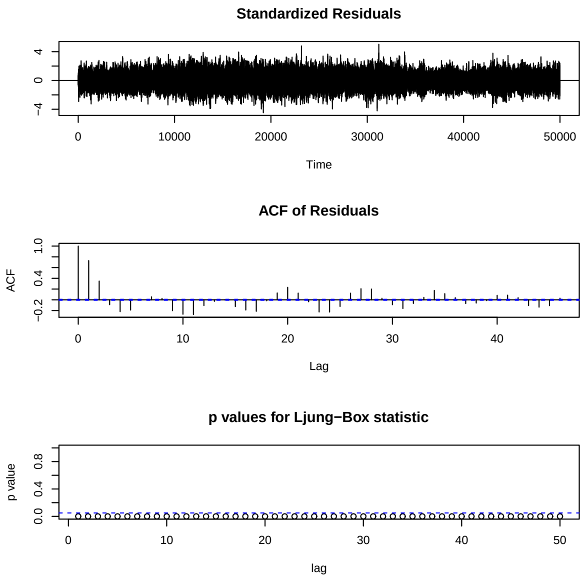
[Time series graph] [Acf



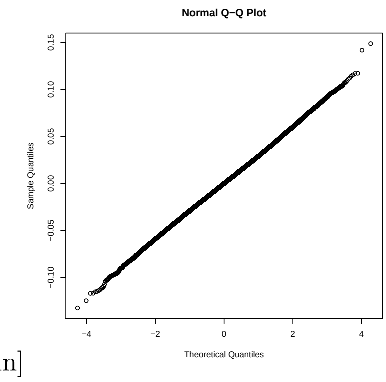


graph] [Acf graph]

FIGURE 10. 100 kelvin temperatures.



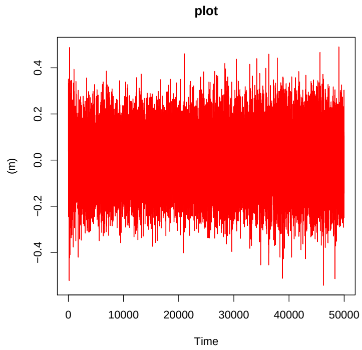
[Graph from residue 100 Kelvin]



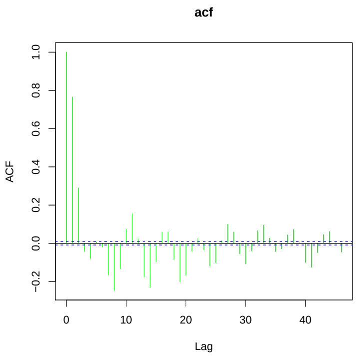
[QQ-plot from residue 100 Kelvin]

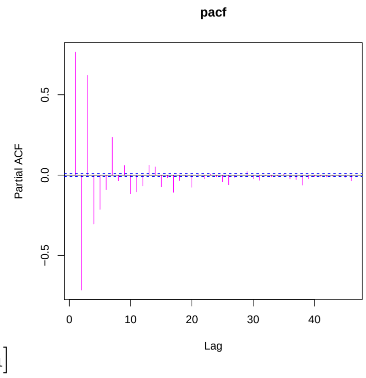
FIGURE 11. Investigating the Normality of Residues for Model arima(0,0,1).

Table 17 predicts 20 data from a temperature of 100 Kelvin.



[Time series graph] [Acf

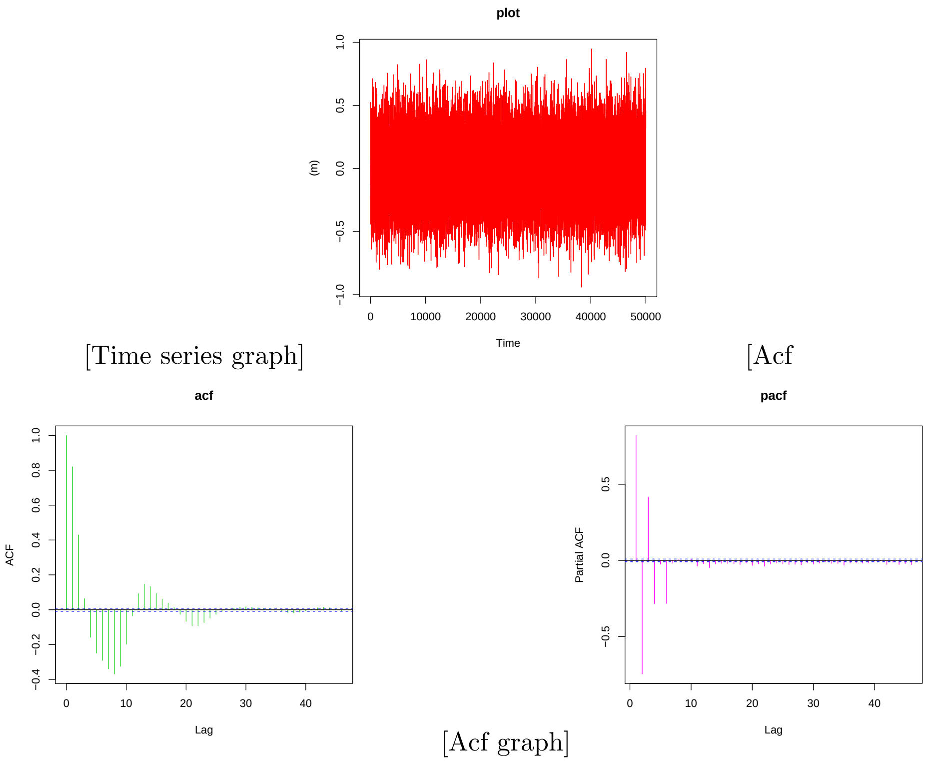




graph] [Acf graph]

FIGURE 12. 200 kelvin temperatures.

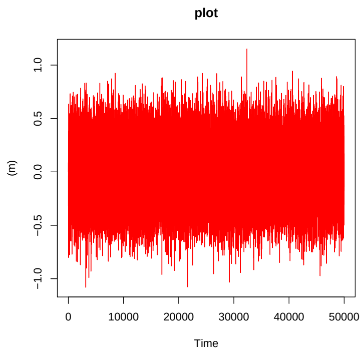
Table 18 predicts 20 data from a temperature of 200 Kelvin for model arima(1,1,1) .



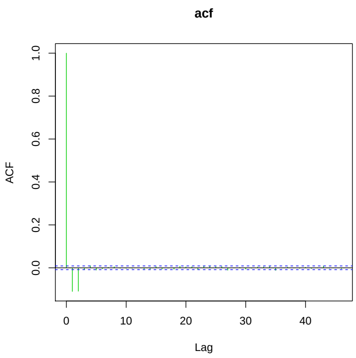
[Time series graph] [Acf graph] [Acf graph]

FIGURE 13. 250 kelvin temperatures.

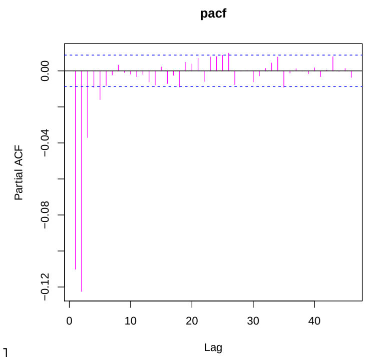
Table 19 predicts 20 data from a temperature of 250 Kelvin for model arima(1,2,1) .



[Time series graph] [Acf

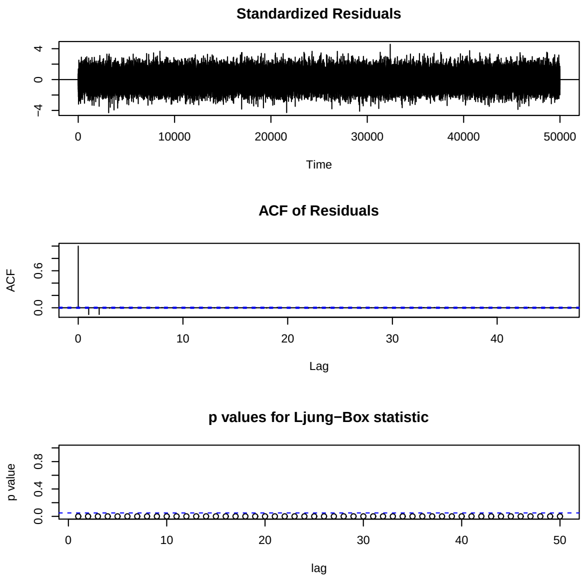


graph]

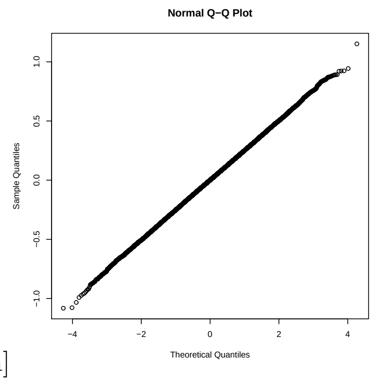


[Acf graph]

FIGURE 14. 300 kelvin temperatures.



[Graph from residue 300 Kelvin]



[QQ-plot from residue 300 Kelvin]

FIGURE 15. Investigating the Normality of Residues for Model arima(1,2,1).

Table 20 predicts 20 data from a temperature of 300 Kelvin.

Table 1. One-Sample Kolmogorov-Smirnov Test

	K_5	K_{10}	K_{100}
Number	50000	50000	50000
$Normal Parameters^{a,b}$ Mean	0.001932319	0.004717649	-0.008281157
Std. Deviation	40.8336794436	54.1247153816	148.6141327423
Most Extreme Differences Absolute	0.017	0.007	0.002
Positive	0.015	0.007	0.002
Negative	-0.017	-0.005	-0.002
Kolmogorov-Smirnov Z	3.746	1.550	0.492
Asymp. Sig. (2-tailed)	0.000	0.160	0.969
	K_{200}	K_{250}	K_{300}
Number	50000	50000	50000
$Normal Parameters^{a,b}$ Mean	-0.025794156	$-.025794156$	0.639499674
Std. Deviation	111.7119287029	111.7119287029	251.8141972986
Most Extreme Differences Absolute	0.004	0.004	0.004
Positive	0.004	0.004	0.002
Negative	-0.004	-0.004	-0.004
Kolmogorov-Smirnov Z	0.890	0.890	0.808
Asymp. Sig. (2-tailed)	0.407	0.407	0.532

a. Test distribution is Normal.
b. Calculated from data.

Table 2. Descriptives

Temperature (K)	Mean	Std. Deviation	95% Confidence Interval for Mean	
			Lower Bound	Upper Bound
5	0.001932	40.8336794	-0.355993	0.359857
10	0.004718	54.1247154	-0.469709	0.479144
100	-0.008281	148.6141327	-1.310949	1.294386
200	-.025794	111.7119287	-1.004998	0.953409
250	-0.025794	111.7119287	-1.004998	0.953409
300	0.639500	251.8141973	-1.567761	2.846761

Table 3. Test of Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
26298.072	5	299994	0.000

Table 4. Test of Homogeneity of Variances

	Sum of Squares	df	Mean Square	F	Sig
Between Groups	17654.884	5	3530.977	0.184	0.969
Within Groups	$5.753e^9$	299994	19175.422		
Total	$5.753e^9$	299999			

4. CONCLUSION

5. ACKNOWLEDGMENTS

6. Appendix

Table 5. Multiple Tukey Model Comparison

			Statistics				
			Mean			95% Confidence Interval	
Test	(I) V2	(J) V2	Difference (I-J)	Std. Error	Sig	Lower Bound	Upper Bound
Tukey HSD	1	2	-.0027853	.8757950	1.000	-2.498559	2.492989
		3	.0102135	.8757950	1.000	-2.485560	2.505987
		4	.0277265	.8757950	1.000	-2.468047	2.523500
		5	.0277265	.8757950	1.000	-2.468047	2.523500
		6	-.6375674	.8757950	.979	-3.133341	1.858207
	2	1	.0027853	.8757950	1.000	-2.492989	2.498559
		3	.0129988	.8757950	1.000	-2.482775	2.508773
		4	.0305118	.8757950	1.000	-2.465262	2.526286
		5	.0305118	.8757950	1.000	-2.465262	2.526286
		6	-.6347820	.8757950	.979	-3.130556	1.860992
	3	1	-.0102135	.8757950	1.000	-2.505987	2.485560
		2	-.0129988	.8757950	1.000	-2.508773	2.482775
		4	.0175130	.8757950	1.000	-2.478261	2.513287
		5	.0175130	.8757950	1.000	-2.478261	2.513287
		6	-.6477808	.8757950	.977	-3.143555	1.847993
	4	1	-.0277265	.8757950	1.000	-2.523500	2.468047
		2	-.0305118	.8757950	1.000	-2.526286	2.465262
		3	-.0175130	.8757950	1.000	-2.513287	2.478261
		5	.0000000	.8757950	1.000	-2.495774	2.495774
		6	-.6652938	.8757950	.974	-3.161068	1.830480
	5	1	-.0277265	.8757950	1.000	-2.523500	2.468047
		2	-.0305118	.8757950	1.000	-2.526286	2.465262
		3	-.0175130	.8757950	1.000	-2.513287	2.478261
		4	.0000000	.8757950	1.000	-2.495774	2.495774
		6	-.6652938	.8757950	.974	-3.161068	1.830480
	6	1	.6375674	.8757950	.979	-1.858207	3.133341
		2	.6347820	.8757950	.979	-1.860992	3.130556
		3	.6477808	.8757950	.977	-1.847993	3.143555
		4	.6652938	.8757950	.974	-1.830480	3.161068
		5	.6652938	.8757950	.974	-1.830480	3.161068

TABLE 6. Multiple Scheff Model Comparison

			Statistics				
			Mean			95% Confidence Interval	
Test	(I) V2	(J) V2	Difference (I-J)	Std. Error	Sig	Lower Bound	Upper Bound
Scheffe	1	2	-.0027853	.8757950	1.000	-2.916781	2.911210
		3	.0102135	.8757950	1.000	-2.903782	2.924209
		4	.0277265	.8757950	1.000	-2.886269	2.941722
		5	.0277265	.8757950	1.000	-2.886269	2.941722
		6	-.6375674	.8757950	.991	-3.551563	2.276428
	2	1	.0027853	.8757950	1.000	-2.911210	2.916781
		3	.0129988	.8757950	1.000	-2.900997	2.926994
		4	.0305118	.8757950	1.000	-2.883484	2.944507
		5	.0305118	.8757950	1.000	-2.883484	2.944507
		6	-.6347820	.8757950	.991	-3.548778	2.279214
	3	1	-.0102135	.8757950	1.000	-2.924209	2.903782
		2	-.0129988	.8757950	1.000	-2.926994	2.900997
		4	.0175130	.8757950	1.000	-2.896483	2.931509
		5	.0175130	.8757950	1.000	-2.896483	2.931509
		6	-.6477808	.8757950	.990	-3.561776	2.266215
	4	1	-.0277265	.8757950	1.000	-2.941722	2.886269
		2	-.0305118	.8757950	1.000	-2.944507	2.883484
		3	-.0175130	.8757950	1.000	-2.931509	2.896483
		5	.0000000	.8757950	1.000	-2.913996	2.913996
		6	-.6652938	.8757950	.989	-3.579289	2.248702
	5	1	-.0277265	.8757950	1.000	-2.941722	2.886269
		2	-.0305118	.8757950	1.000	-2.944507	2.883484
		3	-.0175130	.8757950	1.000	-2.931509	2.896483
		4	.0000000	.8757950	1.000	-2.913996	2.913996
		6	-.6652938	.8757950	.989	-3.579289	2.248702
	6	1	.6375674	.8757950	.991	-2.276428	3.551563
		2	.6347820	.8757950	.991	-2.279214	3.548778
		3	.6477808	.8757950	.990	-2.266215	3.561776
		4	.6652938	.8757950	.989	-2.248702	3.579289
		5	.6652938	.8757950	.989	-2.248702	3.579289

TABLE 7. Within-Subjects Factors

factor1	Dependent Variable
1	K5
2	K10
3	K100
4	K200
5	K250
6	K300

Table 10. $Mauchly'sTestofSphericity^b$

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[a]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
factor1	.000	.	14	.	0.448	0.448	0.200

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.
a. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.
b. Design: Intercept
Within Subjects Design: factor1

Table 8. Within-Subjects Factors

	Mean	Std. Deviation	N
K5	0.001932319	40.8336794436	50000
K10	0.004717649	54.1247153816	50000
K100	-0.008281157	148.6141327423	50000
K200	-0.025794156	111.7119287029	50000
K250	-0.025794156	111.7119287029	50000
K300	0.639499674	251.8141972986	50000

Table 9. $MultivariateTests^b$

Effect		Value	F	Hypothesis df	Error df	Sig
factor1	Pillai's Trace	0.000	0.080[a]	4.000	49996.000	0.988
	Wilks' Lambda	0.000	0.080[a]	4.000	49996.000	0.988
	Hotelling's Trace	0.000	0.080[a]	4.000	49996.000	0.988
	Roy's Largest Root	0.000	0.080[a]	4.000	49996.000	0.988

a. Exact statistic
b. Design: Intercept
Within Subjects Design: factor1

Table 12. Grand Mean

Mean	Std. Error	95% Confidence Interval	
		Lower Bound	Upper Bound
0.098	0.280	-0.450	0.646

Table 13. factor1

factor1	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	0.002	0.183	-0.356	0.360
2	0.005	0.242	-0.470	0.479
3	-0.008	0.665	-1.311	1.294
4	-0.026	0.500	-1.005	0.953
5	-0.026	0.500	-1.005	0.953
6	0.639	1.126	-1.568	2.847

Table 11. Tests of Within-Subjects Contrasts

Source	factor1	Type III Sum of Squares	df	Mean Square	F	Sig.
factor1	Linear	6770.670	1	6770.670	0.252	0.616
	Quadratic	6738.163	1	6738.163	0.248	0.618
	Cubic	3347.532	1	3347.532	0.166	0.684
	Order 4	723.475	1	723.475	0.106	0.745
	Order 5	75.044	1	75.044	0.007	0.933
Error(factor1)	Linear	$1.343e^9$	49999	26856.967		
	Quadratic	$1.357e^9$	49999	27146.186		
	Cubic	$1.007e^9$	49999	20147.541		
	Order 4	$3.417e^8$	49999	6833.621		
	Order 5	$5.310e^8$	49999	10620.512		

Table 15. Predicts 20 data from a temperature of 5 Kelvin.

N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$
1	0.030528	6	0.030527	11	0.030528	16	0.030526
2	0.030529	7	0.030529	12	0.030526	17	0.030527
3	0.030528	8	0.030529	13	0.030527	18	0.030527
4	0.030528	9	0.030528	14	0.030529	19	0.030527
5	0.030529	10	0.030529	15	0.030529	20	0.030529

Table 14. Model identification for a temperature of 5 Kelvin

Model	ar1	ar2	ar3	ma1	ma2	ma3
arima(1,2,1)	0.123			0.7982		
s.e.	0.0052			0.03		
arima(3,1,2)	1.0342	-1.0814	0.3297	0.3419	0.1629	
s.e.	0.0156	0.012	0.0126	0.0162	0.096	
arima(1,1,1)	0.3298			0.8808		
s.e.	0.0042			0.0091		
arima(1,1,0)	0.41818					
s.e.	0.0039					
arima(3,2,3)	1.0300	-1.0782	0.3265	-0.6535	-0.1810	-0.1654
s.e.	0.0159	0.123	0.128	0.0164	0.0092	0.0094
arima(3,3,3)	0.0202	-0.4468	-0.5685	-0.4258	-0.6251	0.0051
s.e.	0.0024	0.0156	0.0226	0.00256	0.0276	0.0042

Table 16. Predicts 20 data from a temperature of 10 Kelvin.

N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$
1	0.0189146	6	0.1271956	11	0.1887945	16	0.2348891
2	0.047400	7	0.1415878	12	0.1988690	17	0.2430617
3	0.0719922	8	0.1547150	13	0.2084579	18	0.250968
4	0.0929962	9	0.1668402	14	0.2176252	19	0.2586333
5	0.1111697	10	0.1781533	15	0.2264217	20	0.2660777

Table 17. Predicts 20 data from a temperature of 100 Kelvin.

N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$
1	0.0854351	6	0.1187241	11	0.1187242	16	0.1187243
2	0.1187243	7	0.1187242	12	0.1187241	17	0.1187242
3	0.1187241	8	0.1187242	13	0.1187244	18	0.1187241
4	0.1187242	9	0.1187243	14	0.1187243	19	0.1187241
5	0.1187242	10	0.1187242	15	0.1187241	20	0.1187241

Table 18. Predicts 20 data from a temperature of 200 Kelvin.

N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$
1	0.050079	6	0.278764	11	0.401364	16	0.49469
2	0.116548	7	0.307205	12	0.421633	17	0.511058
3	0.168667	8	0.333244	13	0.440971	18	0.527126
4	0.211115	9	0.357395	14	0.459496	19	0.542718
5	0.247144	10	0.380016	15	0.477303	20	0.557875

Table 19. Predicts 20 data from a temperature of 250 Kelvin.

N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$
1	0.1272352	6	0.1272352	11	0.1272351	16	0.1272352
2	0.1272352	7	0.1272351	12	0.1272352	17	0.1272353
3	0.1272351	8	0.1272351	13	0.1272352	18	0.1272353
4	0.1272352	9	0.1272352	14	0.1272351	19	0.1272352
5	0.1272353	10	0.1272353	15	0.1272353	20	0.1272354

TABLE 20. Predicts 20 data from a temperature of 300 Kelvin.

N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$	N	speed $\frac{m}{s}$
1	0.2518092	6	0.2518090	11	0.2518091	16	0.2518091
2	0.2518092	7	0.2518092	12	0.2518091	17	0.2518090
3	0.2518091	8	0.2518092	13	0.2518092	18	0.2518090
4	0.2518090	9	0.2518091	14	0.2518091	19	0.2518091
5	0.2518092	10	0.2518091	15	0.2518092	20	0.2518091

References

1. Congdon, Peter. Bayesian statistical modelling. *John Wiley & Sons*, **704** (2007) 109-132.

E-mail: fatemehshahzamany@yahoo.com
E-mail: f.shahzamani@alumni.iut.ac.ir
E-mail: zahramousaei5@gmail.com
E-mail: z.mousaei@math.iut.ac.ir