	_			_		-				_	_
L				_	9						$\mathcal{Y}_{\lambda l K}$
100		40	5	=	5	100	2	40	3	ē	5
20	L	U	oc	U	3	20	Ī	0	00	v	ı
0.012	0.010	0.01272	0.0106	0.01297	0.01081	0.0136	0.01133	0.01442	0.01201	0.0147	0.01225
0.0509		0.0514	0.0507	0.05161	0.0509	0.0537	0.05296	0.05695	0.05617	0.05718	0.0564
0.1043	l	0.1106	0.1071	0.1124	0,1088	0.1098	0.1063	0.1164	0.1127	0.1183	0.1145
_	0.011	0.0155	0.013	0.0165	0.0139	0.0148	0.0124	0.0175	0.0147	0.0187	0.0157
0.0521	0.0509	0.0525	0.0513	0.0534	0.0522	0.0577	0.0564	0.0581	0.0568	0.0591	0.0578
0.1099	0.106	0.1136	0.1096	0.1157	0.1116	0.1157	0.1115	0.1195	0.1153	0.1218	0.1174
0.015	0.0101	0.01604	0.0108	0.0169	0.0114	0.017	0.01145	0.01818	0.01224	0.01915	0.01292
0.0523	0.0502	0.05313	0.051	0.054	0.0518	0.05795	0.05562	0.05887	0.05651	0.05983	0.05739
0.1042	0.1009	0.1061	0.1026	0.1100	0.1063	0.1096	0.1062	0.1117	0.1080	0.1158	0.1119

Table (2): Empirical powers of g, g_{ML} , g_{LH} , g_{MK} , g_{BP} , and g_{AL} test statistics

أحصاءة	7			$\lambda = 0.5$			<i>∆</i> = 1			2-11	
[. <u>2</u>		73									
			$\alpha = 0.01$	$\alpha = 0.01$ $\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.1$ $\alpha = 0.01$	$\alpha = 0.05$ $\alpha = 0.1$ $\alpha = 0.01$	$\alpha = 0.1$	$\alpha = 0.01$	$\alpha = 0.05$ $\alpha = 0.1$	$\alpha = 0.1$
9,		(J	0.7121	0.7303	0.7552	0.6644	0.6814	0.7356	0.6887	0.7062	0.730
	15	s	0.698	0.7171	0.753	0.6513	0.6690	0.7023	0.675		0.728
	į	œ	0.758	0.7684	0.801	0.707	0.717	0.7472	0.7328	0.7431	0.774
	40	ō	0.7345	0.766	0.7726	0.6853	0.7147	0.7139	0.7102	0.7407	0.7471
		0	0.7776	0.8016	0.829	0.7255	0.7479	0.7735	0.7519	0.7752	0.8016
	100	20	0.7677	0.7740	0.7801	0.7163	0.7221	0.7278	0.7423	0.7485	0.7544
#1 0	5	u	0.804	0.8246	0.8527	0.7501	0.7694	0.8305		_	0.8246
		5	0.7881	0.8096	0.850	0.7353	0.7553	0.7930	0.7621	0.783	0.822

			_		1		_		-			-										,,					
				ς.	a,					MK	۱					M	۵					MI.	٩				
100		40		10		100		40		10		100		40		-0		100		40		01		100	į	40	
20	5	5	∞	2	w	20	5	5	œ	S	w	20	- 0	5	œ	w	w	20	5	ō	œ	S	w	20	ō	5	×
0.926	0.938	0.886	0.914	0.842	0.859	0.8343	0.8451	0.7983	0.8235	0.759	0.774	0.614	0.622	0.5874	0.606	0.5582	0.5695	0.8741	0.8855	0.8364	0.8628	0.795	0.811	0.8667	0.878	0.8293	0.8555
0.9337	0.967	0.924	0.927	0.865	0.881	0.8413	0.8713	0.833	0.8352	0.7794	0.7938	0.619	0.6411	0.6126	0.6146	0.5735	0.584	0.8814	0.9128	0.8723	0.8751	0.8166	0.8317	0.874	0.9051	0.8649	0.8677
0.941	0.978	0.932	0.966	0.908	0.911	0.848	0.901	0.84	0.8704	0.8181	0.8208	0.624	0.663	0.618	0.6405	0.602	0.604	0.8883	0.944	0.880	0.9119	0.8572	0.860	0.881	0.936	0.872	0.9042
0.8640	0.8752	0.8266	0.8528	0.7856	0.8014	0.7785	0.7886	0.7448	0.7684	0.7078	0.7221	0.573	0.5803	0.5480	0.5654	0.5208	0.5313	0.8156	0.8262	0.7803	0.805	0.7416	0.7565	0.8087	0.8192	0.7737	0.7982
0.8711	0.9022	0.8621	0.8649	0.807	0.8220	0.7849	0.8129	0.7768	0.7793	0.7271	0.7406	0.5775	0.5982	0.5716	0.5734	0.535	0.545	0.8223	0.8517	0.8138	0.8165	0.762	0.7760	0.8153	0.8444	0.8069	0.8095
0.8779	0.9330	0.8612	0.9013	0.8472	0.8873	0.7910	0.8406	0.7759	0.8121	0.7633	0.80	0.582	0.6186	0.5710	0.5976	0.5617	0.5883	0.8287	0.8808	0.813	0.8510	0.8000	0.8376	0.8217	0.8733	0.8061	0.8436
0.8954	0.9070	0.8568	0.8840	0.8142	0.8307	0.8068	0.8172	0.7720	0.7965	0.7336	0.7485	0.5937	0.6013	0.5681	0.5861	0.5332	0.5508	0.8453	0.8562	0.809	0.8345	0.7686	0.7842	0.8381	0.849	0.802	0.8274
0.9029	0.9351	0.8935	0.8964	0.8365	0.8519	0.8135	0.8425	0.8050	0.8077	0.7537	0.7676	0.5986	0.6200	0.5924	0.5943	0.5546	0.5648	0.8523	0.8827	0.8435	0.8462	0.7900	0.8042	0.8451	0.8753	0.8363	0.839
0.9100	0.967	0.9012	0.934	0.878	0.881	0.82	0.8713	0.812	0.8415	0.7911	0.7938	0.6033	0.6411	0.5975	0.6192	0.5821	0.5841	0.859	0.9128	0.8507	0.8817	0.829	0.8317	0.852	0.9051	0.8435	0.874

Table (1): Empirical significant levels of g^* , g_{vir}

		_	7	7-	\top	$\overline{}$	_	$\overline{\tau}$	7	_	7=	7	ī	┯	_	==	- -		$\overline{}$		_					
		$\alpha = 0.1$	0.0571	0.0551	0.058	0.0561	0.06	0.0581	01068	0.1105	0.1030	99010	0.1013	0 1047	0.1046	01103	0.1029	0.1064	0.1011	0.1045	0.0510	0.0493	0.0510	0.0501	0.050	0.000
$\lambda = 1.1$		$\alpha = 0.05$	0.0285	0.0297	0.0281	0.02923	0.0298	0.02877	0.06211	0.06474	0.06115	0.0637	0.06019	0.06271	0.05322	0.05549	0.0524	0.0546	0.05158	0.05374	0.0216	0.02071	0.02192	0 07104	0.0223	0.02137
		$\alpha = 0.01$	0.00763	0.00513	0.00815	0.0055	0.0086	0.0058	0.01302	0.0193	0.01233	0.01831	0.01153	0.01713	0.01254	0.01859	0.01188	0.01764	0.011111	0.0165	0.00675	0.00455	0.00722	0.00486	0.00761	0.00513
		$3 \alpha = 0.1$	0.0601	0.058	0.0621	0.0599	0.0632	0.061	0.1121	0.1162	0.1101	0.1141	0.1065	0.1104	0.1119	0.1160	0.1099	0.1139	0.1063	0.1102	0.0537	0.0518	0.0555	0.0536	0.0566	0.0546
		$\alpha = 0.0$	0.0287	0.0294	0.0282	0.0289	0.028	0.0286	0.0594	0.0640	0.0615	0.0629	0.0610	0.0624	0.0536	0.0548	0.0527	0.0539	0.0523	0.0535	0.0215	0.021	0.0217	0.0212	0.022	0.0215
	 	$\alpha = 0.01$	0.0055	0.0051	0.0085	0.0078	0.0068	0.0066	0.0158	0.0188	0.0148	0.0177	0.0125	0.0149	0.0152	0.0182	0.0143	0.0170	0.0121	0.0144	0.0058	0.0049	0.0069	0.0058	0.0074	0.0062
		$\alpha = 0.1$	0.057	0.0552	0.0604	0.0585	0.0614	0.059	0.1093	0.1129	0.1076	0.1111	0.1014	0.1048	0.1091	0.1127	0.1074	0.1109	0.1012	0.1046	0.051	0.0494	0.0541	0.0524	0.0549	0.0532
ごロニア		<0.0 = α	0.0280	0.0284	0.0299	0.0283	0.0296	0.028	0.058	0.05881	0.05777	0.05857	0.0572	0.058	0.0523	0.05303	0.05209	0.05281	0.05158	0.0523	0.021	0.02071	0.0212	0.02092	0.0213	0.021
	,	$\alpha = 0.01$	0.0068	0.0066	0.00689	0.00647	0.00668	0.0061	0.01234	0.01481	0.0121	0.01452	0.01142	0.0137	0.0119	0.01427	0.01166	0.014	0.011	0.0132	0.0054	0.0045	0.00472	0.00477	0.00584	0.00486
	ш		m	w.	œ ;	2	01	07	m]	S	x	2	10	20	m	S	œ	2 ;		50	m	v,	∞	2	9	20
~				10	·	40	9	3	•	01	Ş	9	1	99		01		040	-	907	 ,	=	_ 1.	9		100
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	(1) (1) (1) (1) (1) (1) (1) (1) (1) (1)	$\mathcal{C} = \mathcal{C} = \mathcal{C}$	$\lambda = 0.05$ $\alpha = 0.05$ $\alpha = 0.01$ $\alpha = 0.03$ $\alpha = 0.01$ $\alpha = 0.03$ $\alpha = 0.01$ $\alpha = 0.05$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$																

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- 3) The values of T are taken to be 10 (small sample size), 40 (moderate sample size) and 100 (large sample size).
- 4) All simulation experiments were based 0n R=1000 replications.
- 5) The a_i 's generated as zero mean, unit variance white noise.
- 6) The values of significant level lpha are taken to be 0.1, 0.05 and 0.01.
- 7) The values of m are taken to be m=3.5 for (T=10), m=8.10 for (T=40) and m=10.20 for (T=100).

In order to obtain some information concerning the validity of the asymptotic performance of \mathcal{G}_{BP} , \mathcal{G}_{LB} , \mathcal{G}_{ML} , \mathcal{G}_{M} , \mathcal{G}_{MK} and \mathcal{G}^{*} test statistics, a Visual Basic program was written by the author to calculate empirical significance levels and empirical powers of the test statistics under consideration.

Our results are reported in table (1) and table (2) respectively.

Our main conclusions are:

- 1) As is it to be expected, as sample size increases, the performance of the different test statistics improve dramatically.
- 2) If the series obeys to the random walk process $(\lambda=1)$, the performance of the different test statistics will be less than their performance for stationary and non stationary models.
- 3) The performance of the different test statistics for stationary models better than their performance for non stationary models .
- 4) The goodness of performance of the test statistics under consideration, are as follows, respectively, \mathcal{G}^* , \mathcal{G}_{ML} , \mathcal{G}_{LB} , \mathcal{G}_{MK} , \mathcal{G}_{BP} , and finally \mathcal{G}_{M} .

where $\hat{F}_a(w) = \frac{1}{n}$ (number of w, less than or equal to w) and $\eta = 2\pi/\varepsilon$ represent the number of points which will be taken , to calculate $\hat{F}_a(w)$, i.e. $i = 1, 2, ..., \eta$ and ε an arbitrary number, like 0.01.

Now, to test the hypothesis in (11), we can use the kolmogorov - smirnov one sample test, with the following test statistic,

$$D = Max \left| \hat{F}_a(w_i) - F_a(w_i) \right| , i = 1, 2, ..., \eta ----(12)$$

where the sampling distribution of D under H_o is known [10], and a lot of references give critical values from that sampling distribution.

Intuitively, There are some advantages for the above procedure:

- 1) It deal with the frequency domain, which provides an alternative way of viewing the process. For some applications, the frequency domain analysis
 - may be more illuminating than the time domain analysis [3].
- 2) Since the test based on non parametric statistic, then the advantages of non Parametric statistical tests will be risen.

III- An Empirical study

A monte Carlo study was conducted to generate sets of observations from the Markov model $y_i = \lambda y_{i-1} + a_i$, under the following assumptions:

- 1) The initial value y_a equal to zero.
- 2) The values of Markov model parameter λ are taken to be 0.5 (to generate stationary process), 1 (to generate random walk process, i.e. a process has a boundary value problem) and 1.1 (to generate non stationary process).

Nasir conclused that almost all time, the null hypothesis is accepted and that the statistics \mathcal{G}_{BP} , \mathcal{G}_{LB} , \mathcal{G}_{M} and \mathcal{G}_{MK} have nearly the same performances at large sample sizes.

II- Another point of view

Since a white noise process has a flat spectral density function $f_a(w)$ as in (7), we can simply represent the problem under consideration by the hypothesis,

$$H_{a}: \hat{f}_{a}(w) = f_{a}(w)$$

$$vs$$

$$H_{1}: \hat{f}_{u}(w) \neq f_{u}(w)$$

$$----(9)$$

where

$$\hat{f}_a(w) = \frac{1}{2\pi} \sum_{v=-M}^{M} \hat{r}_v k_M(v) \cos(vw)$$
 , $-\pi \le w \le \pi$ $----(10)$

is a consistent estimator of $f_a(w)$, i.e. the frequencies obtained from the actual performance of an experiments.

where M is the truncation point parameter, $k_M(v)$ is the lag window and \hat{r}_v is the sample autocorrelation function, defined as in (2).

Since, the hypothesis tested is how good the observed frequencies $\hat{f}_a(w_i)$ fit a given pattern $f_a(w_i) = 1/2\pi$, we can rewrite the hypothesis in (9) in terms of cumulative spectrum as follows:

$$H_{o}: \hat{F}_{a}(w) = F_{o}(w)$$

$$vs$$

$$H_{1}: \hat{F}_{a}(w) \neq F_{a}(w)$$

$$----(11)$$

are replaced by the sample autocorrelations of the squared data, \tilde{r}_k , giving,

$$\theta_{ML} = T(T+2)\sum_{k=1}^{m} (T-k)^{-1} \tilde{r}_{k}^{2} \qquad ----(5)$$

The hypothesis of iid data is then rejected at level α if the observed value of \mathcal{G}_{ML} is larger than the $1-\alpha$ quantile of the χ^2_{m-p-q} distribution.

Monti 1994 [7] proposed another portmanteau test, based on the partial autocorrelation function of residuals,

$$\mathcal{G}_{M} = T(T+2) \sum_{k=1}^{m} (T-k)^{-1} \hat{\phi}_{kk} \qquad ----(6)$$

The \mathcal{G}_{M} statistic is asymptotically distributed as χ^{2}_{m-p-q} also.

Since each frequency in the spectrum of white noise process contributes equally to the variance of the process, then the white noise process has a flat spectral density function

$$f_a(w) = 1/2\pi$$
 , $-\pi \le w \le \pi$ $---(7)$

Mokkadem 1994 [9] derived another portmanteau test statistic based on the hypothesis $H_a: f_a(w) = c$ vs $H_1: f_a(w) \neq c$, where c is any constant. The formula of Mokkadem statistic is:

$$\mathcal{G}_{MK} = Ln\left(\frac{\hat{R}_{o}}{2\pi}\right) - \frac{1}{2\pi} \int_{-\pi}^{\pi} Ln \left|\hat{f}_{a}(w)\right| dw$$

$$\cong \sum_{k=1}^{m} \hat{r}_{k}^{2} \qquad \qquad ----(8)$$

Al-Nasir 2000 [1], generated sets of observations from the markov process for comparison among test statistics θ_{BP} , θ_{LB} , θ_{M} and θ_{MK} . Al-

$$\hat{r}_{v} = \frac{\sum_{t=v+1}^{T} \hat{a}_{t} \hat{a}_{t-v}}{\sum_{t=1}^{T} \hat{a}_{t}^{2}} , \quad k = 1, 2, \dots \qquad ----(2)$$

Box and Pierce 1970 [2] show that, under the correct model specification (null hypothesis) provided that m is moderately large, the statistic

$$\mathcal{G}_{BP} = T \sum_{k=1}^{m} \hat{r}_k^2 \qquad \qquad ----(3)$$

is asymptotically distributed as χ^2 with (m-q-p) degrees of freedom. Tests of model adequacy based on this statistic are generally called portmanteau tests.

It has been shown by David , Triggs and Newbold 1977 [5] that , for sample sizes commonly found in practice , the actual significance levels of $\theta_{\rm BP}$ can be considered lower than those predicted by asymptotic theory . However , a simple modification , studied by Ljung and Box 1978 [6]

$$\theta_{I,B} = T(T+2) \sum_{k=1}^{m} (T-k)^{-1} \hat{r}_{k}^{2} ----(4)$$

appears to have a distribution very much closer to the asymptotic χ^2 with (m-p-q) degrees of freedom .

Davis and Newbold 1979 [4] concentrated on the behavior of the modified statistic \mathcal{G}_{LB} , and in particular investigated the frequency with which it detects misspecification, relating this to the increase in forecast error variance resulting from use of the incorrect model.

Another portmanteau, formulated by Mcleod and Li 1983 [8], can be used as a farther test for the *iid* hypothesis, since if the data are *iid*, then the squared data are also *iid*. It is based on the same statistic used for the Ljung and Box test, except that the sample autocorrelations of the data

On The Lack Of Fit In Time Series Models

د.صلاح حمزة عبد

Summary

In this paper, we present another test for lack of fit in time series models. A simulation study was conducted to compare among model adequacy tests. Our conclusion is that the proposed statistic achieves a high level of success to detect time series model misspecification, at all situations considered.

I- Introduction

Consider a discrete time series $\{y_i\}$ generated by a stationary autoregressive-moving average process

$$y_i = \lambda_1 y_i + ... + \lambda_t y_{i-p} + a_i + \beta_1 a_{i+1} - ... - \beta_q a_{i+q} - ... - (1)$$

and $\{a_i\}$ is a sequence of zero mean , finite variance , independent and identically distributed random deviates .

The y_i 's can in general represent the d-th difference or some other suitable transformation of a non stationary series $\{z_i\}$.

After a model of this form has been fitted to a series $y_1, y_2, ..., y_I$, it is useful to study the adequacy of the fit by examining the residuals $\hat{a}_1, \hat{a}_2, ..., \hat{a}_I$ and in particular, their autocorrelations