Forecasting Volatility in Copper Prices Using Linear and Non-Linear Models

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***Abstract*—Copper is one of the oldest and highest traded commodities on the Indian commodity market. Its price is based on demand and supply. With the 'Make in India' and 'Smart Cities' project in process there is a large amount of copper requirement in speculation, which in turn shall cause a sudden increase in demand and bring volatility in copper prices. Therefore, there is a need to study the price behaviour of copper spot prices in India. The study uses data from April 2007 to September 2016 of copper spot prices on Multi-Commodity Exchange. We conduct Autoregressive Integrated Moving Average (ARIMA) method and Multi-layer Prediction (MLP) Artificial Neural Network (ANN) method for predicting volatility in copper prices. The study finds MLP neural network provides better forecasting accuracy compared to ARIMA on the basis of Root Mean Square (RMS) errors and forecast errors.**

***Index Terms*: volatility, ARIMA, artificial neural networks, MLP**

I. INTRODUCTION

Copper is one of the extensively used metals in India. In terms of usage and volume, the metal stands next to steel and aluminum. Per capita consumption of copper in India is as low as 0.5 kg compared to the world consumption of an average 2.7 kg. However, India is also one of the biggest producers of copper in the world. The recent trend shows that India will seek advantage with the falling prices of copper in international markets as it is one of the world's biggest importers of copper concerntrate, along with other nations such as China, Japan, South Korea and Germany. During the last few years, India has become the net exporter of refined copper.

This is due to upsurge in production by three Indian companies: Hindalco, Hindustan copper and Sterlite. The copper is mainly traded on four bourses- London Metal Exchange (LME), Chicago Mercantile Exchange (CME), Shanghai Futures Exchange (SHFE) and Multi Commodity Exchange of India (MCX) of which LME is used as a worldwide benchmark. It is also one of the highest traded commodities on the Indian commodity.

Copper is one of the most important metal which is used by India's Manufacturing sector after iron and steel. With 'Make in India' and 'Smart Cities' projects of our current Prime Minister, the country is investing more in power and infrastructure industries which is in turn boosting the usage of metals. High demand for copper comes from telecom sector and eletrical sector, 30% and 26% respectively. Other sectors consuming copper includes building, construction, transport and consumer durables. With the Make in India and smart cities project in process there is a large amount of copper requirement in speculation, which in turn can cause a sudden increase in demand and may most likely bring volatility in the copper spot prices. Hence, this is the motivation for the present study to understand the price behaviour of copper spot prices.

Most of the studies on International commodity futures markets are restricted to policy allied areas. Some of the major areas of research identified and investigated in Indian commodity futures are: the integration of spot markets, development of a contract and its terms, significance of warehousing and delivery facilities and policy areas like ceiling on cross-border movement of commodities, different kind of taxes, etc [1-3]. The literature on price discovery on Indian commodity futures markets is limited to regional exchanges, dated/small sample from the period prior to setting up of national exchanges. The Indian commodity futures markets have since then matured and have started playing a significant role in price discovery and risk management in the recent period. So, the present study focuses on forecasting the volatility in copper spot prices using both linear model (ARIMA) and non-linear model (artificial neural network). It will be helpful to producers, consumers, government and agents involved in copper mining business and also the investors of copper derivatives in order to understand and manage the price risk.

II. REVIEW OF LITERATURE

The prediction of price evolution is done by various methodologies: time series alone [4] or combined with other methodologies such as spectral analysis or wavelets [5] model forecasting [6] and Fourier transformations [7], etc. According to [8] ANN is a better method of forecasting that can be used in conditions when the linear model cannot solve the problem, or difficult to see relationships between events. [9] Perform forecasting and analyzes the behavior of copper prices in the New York Commodity Exchange (COMEX). They found that the performance levels of the MLP neural network and Elman RNN being higher than those achieved by ARIMA when analyzed in terms of RMSE.

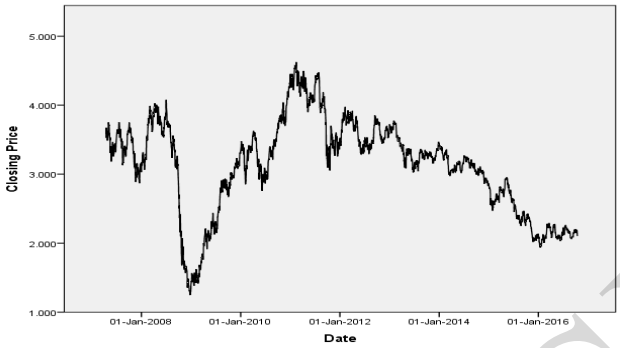
[10] Also compared the price behaviour and volatility of gold and silver using ARMA model and ANN techniques using data from 10 August 2007 to 11 March 2011. They

found performance of non-linear model better than linear technique in order to under price behaviour. Extant literature has used linear techniques only for forcasting volatility in metals [11-12] but later it was discovered that the commodity prices are usually non-linear in nature [13-16].

In India, non-linear techniques have been used mainly for prediction of stock market indices and returns such as [17] forecasted CNX S&P Nifty 50 index with high level of accuracy in a volatile market. They used Neural Network Architecture for the prediction.

III. DATA AND METHODOLOGY

The present research uses copper spot prices from the Investing.com (India) from 2nd April 2007 to 30th September 2016. The data set contains 2484 data points. The analysis has been conducted using the daily spot prices. Figure 3.1 shows the copper spot price for the period of study. The study uses Multi-Layer Perceptron (MLP) Model of Artificial Neural networks (ANN) and ARIMA model for the purpose of studying the price behaviour of copper in India.



Source: Own Contribution
Fig. 3.1: Copper Spot Prices from 2nd April 2007 to 30th September 2016

3.1 MLP Neural Networks

Multi-layer Perceptron (MLP) is a controlled learning procedure that learns a function

$$f(\cdot) : R^m \rightarrow R^o \quad \text{.....(1)}$$

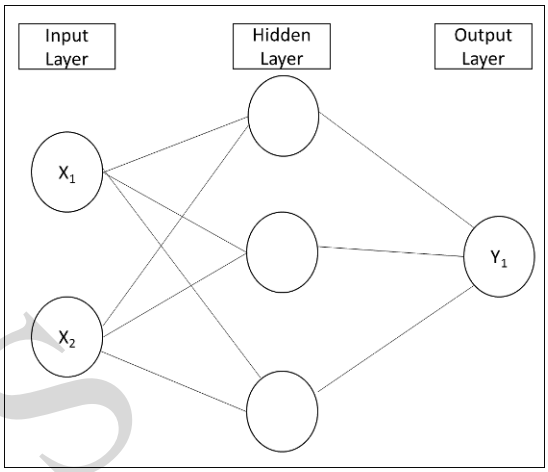
by training on a dataset, where m is the number of dimensions for input and o is the number of dimensions for output. It is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate outputs.

Given a set of features $X = x_1, x_2, \ldots, x_m$ and a target y, it can study a non-linear function approximator for either grouping or regression. It is different from logistic regression, in that between the input and the output layer, there can be one or more non-linear layers, called hidden layers.

The approach for the present study is detailed as follows:

a) Inputs: The inputs to the neural network are essentially the delayed coordinates of the time series. The number of inputs to the network is 4 i.e. close price (t-1), Open price (t-1), Low (t-1) and high (t-1). The output is the prediction of close price (t). The study uses standardized rescaling method for the covariates.

b) Network Structure: The study conducts Multi-Layer Perceptron neural network for the purpose of prediction. It essentially consists of three layers of nodes namely, input, hidden and output layers. The first layer consists of the input data. The last layer is the output layer, which consists of the target values. All layers between the input and the output layers are called as the hidden layers. Figure 3.2 shows a simple MLP feed forward network.



Source: Own Contribution
Fig. 3.2: A Simple MLP Network

c) Transfer functions: These functions map the neurons from input to an output, where the neuron is the link between the layers. The input functions are first multiplied by their respective weights, summed and then mapped to the output via the transfer function. The study uses the hyperbolic tangent transfer function.

3.2 ARIMA

ARIMA models are the most generic models for forecasting a time series. Such models can be stationarized by transformations such as differenciations and log. Lags of the differenced series appearing in the forecasting equation are called "auto-regressive" terms, lags of the forecast errors are called "moving average" terms, and a time series which needs to be differenced to be made stationary is said to be an "integrated" version of a stationary series. Moreover, random-walk and random-trend models, autoregressive models, and exponential smoothing models (i.e., exponential weighted moving averages) are all special cases of ARIMA models. In the present study, after collecting data it was tested for its suitability for time series analysis. For this purpose Durbin-Watson Test was carried out to analyze the nature of data.

According to Durbin-Watson test, statistic detects the presence of autocorrelation for its suitability for regression

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analysis. Autocorrelation is interrelated between the values with suitable time lag.

Durbin-Watson (DW) ≈ 2[1-ρ(1)], where ρ(1) is the 1st order auto-correlation……..(2)

According to [18], if DW value lies between 0 to 1.5 or between 2.5 to 4 then the data is longitudinal i.e. dependent on time, so time-series analysis can be done, but if DW value is between 1.5 to 2.5 then it is cross-sectional data i.e. independent of time hence regression analysis should be carried out on the collected data. Further, we need to compute autocorrelation and partial auto-correlation between the values of the data.

A. Autocorrelation

It is defined by ACF = corr(X_t , X_{t+k}) i.e. relationship between each other. Here X_t is the current observation and X_{t+k} is observation after k period. It ranges from -1 to +1.

B. Partial Auto-Correlation

Another distinctive feature is a partial autocorrelation function (PACF) which is conditional correlation of X_{t+k} with X_t. PACF is defined for positive lag only, their value also lies between -1 and +1. Both the statistics, ACF & PACF are equally important, but ACF is relatively easier to calculate than PACF.

A non-seasonal ARIMA model is classified as an "ARIMA (p,d,q)" model, where:

- p is the number of autoregressive terms,
- d is the number of nonseasonal differences, and
- q is the number of lagged forecast errors in the prediction equation.

Generally, a non-seasonal time series is a combination of past values and errors, which can be denoted as ARIMA (p,d,q) or expressed as the following form:

$$X_t = \theta_0+\varphi 1X_{t-1}+\varphi 2X_{t-2}+ +\varphi pX_{t-p}+ e_t -\theta 1e_{t-1} - \theta 2e_{t-2} - - \theta qe_{t-q} \quad \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where X_t and e_t are the actual value and random error at time t, respectively; φi (i=1, 2 ,…, p) and θj (j=1, 2 ,…, q) are model parameters. p and q are integers and often referred to as orders of autoregressive and moving average polynomials. Random errors are assumed to be independently and equally distributed with a mean of zero and a constant variance, σ2.

Similarly, a seasonal model can be represented as ARIMA (p,d,q). Basically, this method has three phases: model identification, parameters estimation and diagnostic checking. To identify the appropriate ARIMA model for a time series, you begin by identifying the order(s) of differencing needing to stationarize the series and remove the gross features of seasonality, perhaps in combination with a variance-stabilizing transformation such as logging.

IV. RESULTS AND DISCUSSION

4.1 Artificial Neural Network

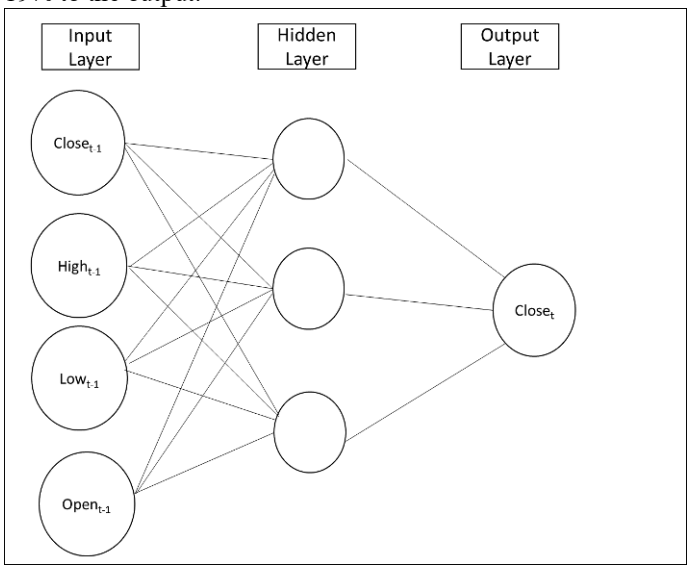
While conducting MLP neural networks method, out of the sample of 2484 observations, 1721 observations were used for training and 763 observations were used for testing. The architecture was selected using 4 input neurons, one hidden layer with 3 neurons in the hidden layer and one neuron in the output. Four input variablesi.e. Close price (t-1), Open price (t-1), Low (t-1) and high (t-1) that have been normalized were used as data in the input layer neurons. Data close (T) was normalized and was used as a data target/output. Figure 4.1 shows the archeitecture of MLP used in the present study.

The neural network is trained using Gradient descent optimization algorithm for both training and test data-sets. The learning rate for training and testing the data-set is 0.4 and momentum rate is 0.9. The training intervals are created at +- 0.5.

The study finds prediction accuracy of training data-set is 94.064 per cent and that of test data-set is 97.148 per cent, both significant at 1% level of significance. The RMS error for the training data-set is 0.0587 and that of the testing data-set is 0.0061. As the squared error is less of the test data-set, this indicates that the model fits the test pattern better than the training pattern.

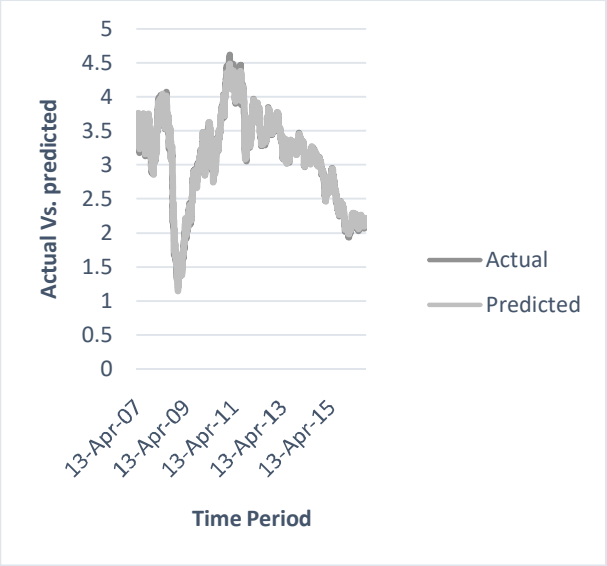
Moreover, the Forecast Error (FE) for all 2485 observations based on the formula: (Actual-Predicted)/Actual gave an average of -0.00032 with a minimum FE of -0.12173 and maximum FE of -139068. Figure 4.2 shows the plot of actual spot prices (in INR) compared to predicted values of copper using MLP neural networks.

Relative importance of each input on the output is also generated which shows high (t-1) (normalized relative importance: 100%) and close (t-1) (normalized relative importance: 97%) contributes most to the output while the low (t-1) adds 56% of the relative importance to the output. Open (t-1) has shown the least normalized relative importance of 19% to the output.



Source: Own Contribution

Fig 4.1 MLP Archeitecture

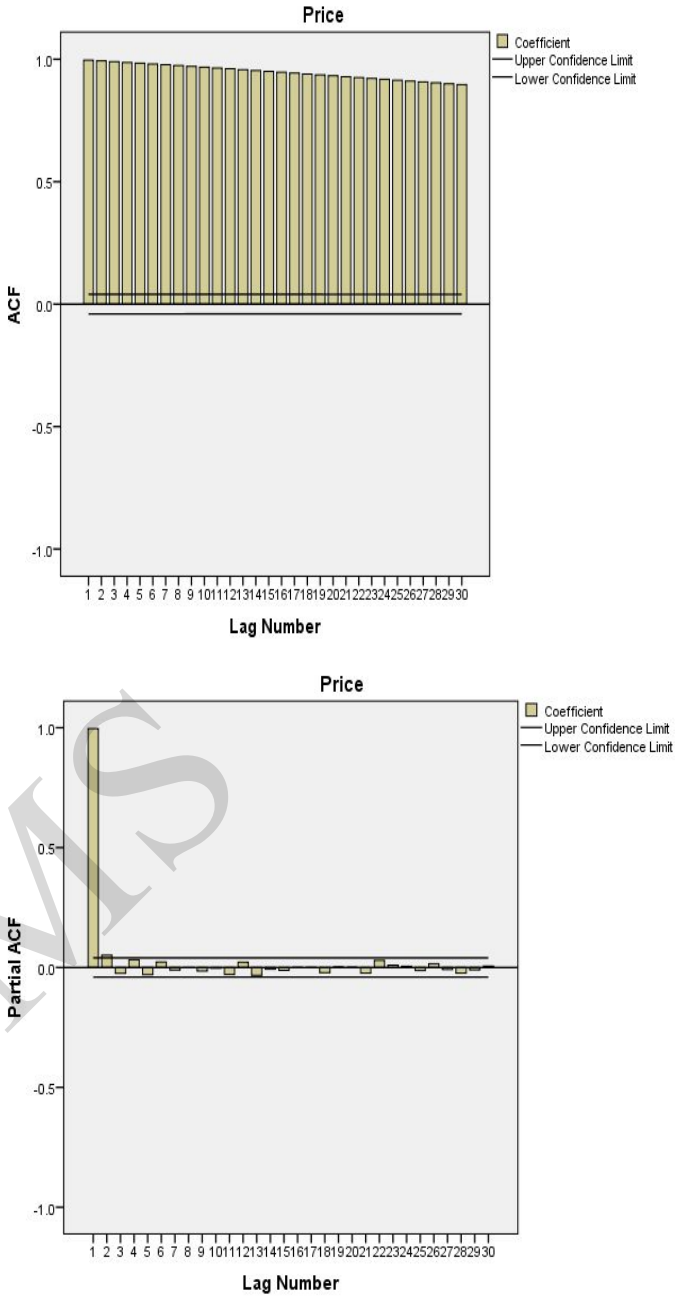


Source: SPSS Package

Fig 4.2 Actual Vs Predit values of copper spot prices

4.2 ARIMA

The ARIMA model was developed using copper spot closing prices of the entire data-set of 2484 observations. Figure 3.1 shows that the time series is non-stationary. Durbin Watson statistic is 1.005. As DW ≈ 2[1-ρ(1)], the results clearly indicate copper prices show high first order autocorrelation. The ACF and PACF correlograms was plotted to identify the model of ARIMA. Further, ARIMA Expert Modeler was run on SPSS which gave best model (p,d,q) as (1,1,0).

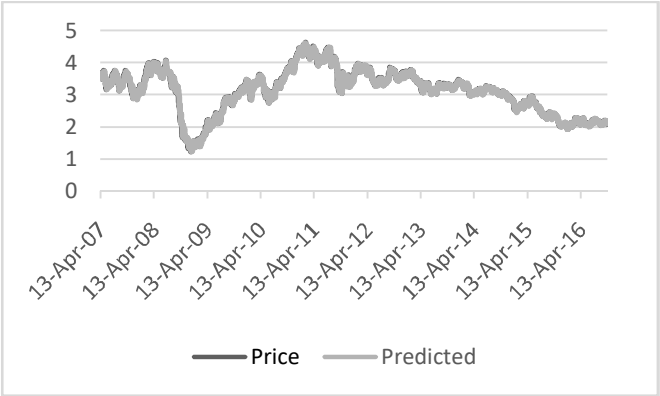


Source: SPSS Package

Fig 4.3 ACF and PACF

Also, Ljung-Box statistic was used to check the adequacy of the model [19]. The p-value for the Ljung-Box statistic was 0.68 which clearly states that there is no correlation among the residuals of the ARIMA model. The RMS error for the model (2484 observations) is 0.063 and the forecast error on an average is -0.00040 with a maximum of 0.112506 and minimum of -0.12245. Figure 4.4 shows the plot of actual spot prices (in INR) compared to predicted values of copper using ARIMA (1, 1, 0) model.

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Source: SPSS Package

Fig 4.4 Actual Vs Predit values of copper spot prices

V. CONCLUSION

The present study aims at understanding the price behaviour of copper spot prices on MultiCommodity Exchange for a period of April 2007 to September 2016 using linear model of ARIMA and a non-linear model of arificial neural network. It can be stated that the performance of the MLP neural network is higher than that of the ARIMA model in terms of RMS error and also the forecast error. Hence, our study is also in line with the extant literature that artificial neural network provide better prediction accuracy as compared to ARIMA model.

The study is important for producers as well as the consumers of copper as they can forecast the price behaviour of copper using the technique giving better prediction accuracy and manage to reduce the price risk associated to their operations. It is also beneficial for the investors to understand the price behaviour and take a price advantage from the market.

For future research, it shall be interesting to look at various hybrid techniques for statistical forecasting and other artifical neural network methods for understanding the price behaviour of commodities.

REFERENCES

[1] F. Pattarin and R. Ferretti, "The Mib30 Index and Futures Relationship: Economic Analysis and Implications for Hedging," Applied Financial Economics, 2004,Vol. 14, No. 18, pp. 1281-1289. doi:10.1080/0960310041233131357 8

[2] H. J. Ryoo and G. Smith, "The Impact of Stock Index Futures on the Korean Stock Market," Applied Financial Economics, 2004, Vol. 14, No. 4, pp. 243-251. doi:10.1080/0960310042000201183

[3] D. G. MacMillan, "Cointegrating Behaviour between Spot and forward Exchange Rates," Applied Financial Economics, 2005,Vol. 15, No. 6, pp. 1135-1144.

[4] G. Dooley and H. Lenihan,"An assessment of time series methods in metal price forecasting", Resources Policy, 2005, vol. 30, pp 208–217.

[5] T. Kriechbaumer,A. Angus,D. Parsons, R. Casado, "An improved wavelet–ARIMA approach for forecasting metal prices." Resources Policy, 2014,vol.39, pp. 32–41. http://dx.doi.org/10.1016/j.resourpol.2013.10.005

[6] B. A. Goss, S. G. Avsar, "Simultaneity, forecasting and profits in London copper futures." Australian Economics. Papers, 2013, vol. 52 (2), pp. 79–96. http://dx.doi.org/10.1111/1467- 8454.12008

[7] A. A. Khalifa, H. Miao, S. Ramchander,"Return distributions and volatility forecasting in metal futures markets: evidence from gold, silver, and copper" Journal of Futures Market, 2011,vol.31 (1), pp. 55–80. http://dx.doi.org/10.1002/fut.20459.

[8] G. Tkacz and S. Hu, "Forecasting GDP Growth Using Artificial Neural Networks", 1999, Working Paper pp. 99-3, Bank of Canada.

[9] F Lasheras, F. Juez, A. Sánchez, A. Krzemień, P. Fernández , "Forecasting the COMEX copper spot price by means of neural networks and ARIMA models," Resources Policy, 2015, vol. 45, pp 37-43.

[10] C. L. Dunis and A. Nathani,"Quantitative trading of Gold and Silver using non-linear models", Neural network world, 2007, vol. 2, pp. 93-111.

[11] L. Abdullah, "ARIMA model for gold bullion coinselling prices forecasting," International Journal of Advances in Applied Sciences,2012, vol. 1, no. 4, pp. 153-158.

[12] M. G. Deepika, G. Nambiar and M. Rajkumar, "Forecasting price and analysing factors influencing the price of gold using ARIMA model and multiple regression analysis",International Journal of Research in Management, Economics and Commerce, 2012, 2(11).

[13] G. Grudnitski and L. Osburn, "Forecasting S &P and Gold Futures Prices: An Application of Neural Networks", The Journal of Futures Markets, 1993, vol. 13(6) pp. 631-643.

[14] F. Parisi, A. Parisi and J. L. Guerrero, 'Rolling and Recursive Neural Network Models: The Gold Price', 2003, Working Paper, Universidad de Chile.

[15] M. Frank and T. Stengos, 'Measuring the Strangeness of Gold and Silver Rates of Return', Review of Economic Studies, 1989, vol. 56 (188), pp. 553-567.

[16] A. Chatrath, B. Adrangi and T. Shank, "Nonlinear Dependence in Gold and Silver Futures: Is it Chaos?", The American Economist, 2001, vol. 45 (2), pp. 25-32.

[17] M. Majumder and A. Hussian, "Forecasting of Indian Stock market Index using Artificial Neural Network", 2009, NSE Working Paper, pp 1-21.

[18] D. Banerjee, "Forecasting of Indian stock market using time-series ARIMA model," in Proc. Conference Paper, ICBIM-14, 2014.

[19] Ljung, G.M. and G.E.P. Box, On a measure of lack of fit in time series models, Biometrika,1978, vol. 65,pp 297-303.

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