Stock Market Data Analysis using Rescaled Range (R/S) Analysis Technique

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***Abstract*— Stock market related data analysis is attracting the focus of attention with the changing economic trends. Huge volumes are being traded and the turnover is growing exponentially. The unpredictable trends exhibited by the share prices posed challenges for interpretation and prediction of trends. Various approaches are adopted for data analysis and predictions in this area. We present Rescaled Range Analysis approach for analyzing share market data as this approach has capability of revealing long term and short term varying tendencies and issues like memory effect in price fluctuations. We present study of share prices for four companies to demonstrate the effectiveness of the R/S analysis approach in quantifying the trends present in the data that is apparently random. Details of data analysis and findings are presented.**

Keywords*— *Stock Market, Share Prices, Time Series, R/S Analysis, Fractal Dimension, persistence, memory effect.

I. INTRODUCTION

Randomly varying parameters pose difficulties in predicting trends and methods for accessing the fractal characteristics are found to be useful for non-stationary signals such as stock market[1 to 5] data. These apparently irregularly changing signals are considered to be driven by external non stationary factors. Standard methods such as Fourier analysis assume that the signals are stationary in temporal windows. Such an assumption does not strictly apply for stock market data as it changes constantly with an element of unpredictability. Such irregular phenomena are at times handled using the concept of fractals and fractal dimensions [6 to 8] whose characteristic is self similarity and scale invariance. Fractal based methods such as relative dispersional methods and rescaled range analysis does not impose the above assumption and therefore are better suited for the analysis. In this paper, we use rescaled range analysis [9 to 14] to analyze stock market data which gives statistical insight into the trends and tendencies of fluctuations. Share prices of four different companies from India over a period of (17 years) are studied and the findings are presented, it is shown that rescale range analysis can be used for assessing any trends of persistence or antipersistence that can be used for predicting future trends.

II. STOCK MARKET DATA

Share market is seen as fulcrum of economic trends in the market for ages and it has its own importance in establishing strength or weakness of companies that is reflected in the prices of their shares and the trends the share prices follow. With the introduction of online share trading [15] there has been a boom in the volumes traded and the turnover. Some experts look at it as share gambling and try to disconnect share prices with the performance of the corresponding companies. As huge funds are involved, the share market prices are carefully recorded and are available for users for their purpose most of the times investors use this information to forecast future trends in order to channelize their investments for higher profits.

Lot of standard software are available out there and investors use the software for planning their investments. Such software make use of a number of indicators proposed by experts who have analyzed the data over a period and proved that these parameter do help predicting the future trends of the share prices. All said and done, no one can exactly figure out as to what is going to be the price of a given share during the time to come. Most of the times, statistically based parameters fail drastically if the share prices drastically change due to economic events (also known as news) or issues like change of rule or Government, at times natural calamities and wars also shake the market drastically.

III. RESCALE RANGE ANALYSIS OF TIME SERIES

Hurst In 1951 introduced a method to study natural phenomena such as the flow of the Nile River in relation to long term correlation. This method was based on the statistical assessment of many observations of the natural phenomena. After studying 800 years of records, Hurst observed that the flow of the Nile River was not random, but patterned. He defined a constant, K, which measures the bias of the fractional Brownian motion. In 1968 Mandelbrot defined this pattern as fractal. There are many algorithms to calculate fractal characteristics such as fractal dimensions, which is a number that quantitatively describes how an object fills its space. He renamed the constant K to H in honor of Hurst. Rescaled range (R/S) analysis is a statistical method to analyse the records of natural phenomena. The theory of the rescaled range analysis was first given by Hurst. Mandelbrot and Wallis further elaborated the method. Feder (1988) gives an excellent review of the analysis of data using time series[16 , 17], history, theory and applications, and adds some more statistical experiments.

In this model Hurst exponent 'H' is calculated which tells that whether time series is random or non random. Hurst exponent is also related to the fractal dimension. There are different techniques for the estimation of Hurst Exponent. R/S analysis is a method usually used for distinguishing a completely random time series from a correlated time series.

IV. Methodology

The approach for estimation of the Hurst exponent 'H' follows simple statistical rules, for a time series like data, start with the whole observed data set that covers a total duration and calculate its mean over the whole of the available data.

for a given sequence of observations Z (t) the average is defined as

$$\langle Z \rangle_\tau = \frac{1}{\tau}\sum_{t=1}^{\tau} Z(t) \qquad \ldots\ldots\ldots\ldots\ 1$$

Then Sum the differences from the mean to get the cumulative total at each time point, $X(t,\tau)$, from the beginning of the period up to any time using

$$X(t,\tau) = \sum_{t=1}^{\tau}\left(Z(t) - \langle Z \rangle_\tau\right) \qquad \ldots\ldots\ldots\ldots 2$$

Then find the Xmax the maximum of X(t , τ) , Xmin the minimum of X(t,τ) and calculate the self adjusted range R(τ) defined as the difference between maximum and minimum accumulated influx X

$$R(\tau) = \max X(t,\tau) - \min X(t,\tau) \qquad \ldots\ldots\ldots\ldots\ldots 3$$

The standard deviation S, of the values, Z(t) of the observation over the period,

$$S(\tau) = \left(\frac{1}{\tau}\sum_{t=1}^{\tau}\left(Z(t) - \langle Z \rangle_\tau\right)^2\right)^{\frac{1}{2}} \qquad \ldots\ldots\ldots\ 4$$

Hurst used a dimension less ratio R/S where $S(\tau)$ is the standard deviation as a function of τ

$$(R/S) = (\tau/2)^H \qquad \ldots\ldots\ldots\ldots\ 5$$

Hurst exponent H can be found by plotting log (R/S) against log (τ /2), the slope of the resulting straight line is the Hurst exponent. The Hurst exponent gives a measure of the smoothness of a fractal object where H varies between 0 and 1. Low 'H' values indicate high levels of roughness or variability. High values of H indicate high levels of smoothness. We use H and D to analyze our stock market data as it has a broad applicability to signal processing due to its robustness. These parameters can be calculated by the rescaled range analysis method. It is useful to distinguish between random and nonrandom data points/time series. If H equals 0.5, then the data is determined to be random. If the H value is less than 0.5, it represents anti-persistence, meaning, if the signal is up/down in the last period then more likely it will go down/up in the next period (i.e. if H is between 0 and 0.5 then an increasing trend in the past implies a decreasing trend in the future and decreasing trend in past implies increasing trend in the future). If the H value varies between 0.5 and 1, this represents persistence which indicates long memory effects, where, if the signal is up/down in the last period, then most likely in the next period the signal will continue going up/down. This also means that the increasing trend in the past implies increasing trend in the future also or decreasing trend in the past implies decreasing trend in the future also. It is important to note that persistent stochastic processes have little noise whereas anti-persistent processes show, presence of high frequency noise.

The relationship between fractal dimensions Df and Hurst exponent H can be expressed as

$$D_f = 2 - H \qquad \ldots\ldots\ 6$$

From the Hurst exponent H of a time series, the fractal dimension of the time series can be found. When Df = 1.5, there is normal scaling. When Df is between 1.5 and 2, time series is anti-persistent and when Df is between 1 and 1.5 the time series is persistent. For Df =1, time series is a smooth curve and purely deterministic in nature and for Df = 1.5 time series is purely random.

4.Data Analysis:

From equation (1) to (4) We have a value of (R_N / S_N) for the time series, Z(t). t=1, 2,3,….N. Since we are interested in how (R / S) Varies with successive subintervals τ of N, we substitute τ for N in equation (1) to (4) .the Hurst exponent is obtained from equation

$$(R_\tau/S_\tau)_{Ave} = (\tau/2)^H \qquad \ldots\ldots\ldots\ 7$$

for example ,if 64 value of X(t) are available for time series , the R_N and S_N for N=64 are obtained .then data are broken into two parts , each with τ = 32 (1,2 …32 and 33,34…64).the value for R_{32} and S_{32} are obtained for the two parts . the two values of R_{32} / S_{32} are then averaged to give (R_{32} / S_{32})ave.the data set is then broken in four parts, each with τ = 16(1,2,…16;17,18…32;33,34…48;and49,50…64) .the value of (R_{16} / S_{16}) are obtained for the four parts and are averaged to give (R_{16} / S_{16})ave. this process is continued for τ = 8 and 4 to give (R_8 / S_8)ave and (R_4 / S_4)ave for τ = 2, the vlue for $R_2 = S_2$ so that (R_2 / S_2) =1 . the values of log (R_τ / S_τ)ave are plotted against log (τ /2) and the best fit straight line gives H from equation (7) .

V. R/S Analysis of Share Prices of ACC.

For the purpose of implementation of R/S analysis we grouped the data in four groups of 1024 points each for share prices of ACC, ACC1 (1 to 1024), ACC2 (1025 to 2048), ACC3 (2049 to 3072), ACC4 (3073 to 4096). This covers a period from 03/11/1994 to 27/04/2011, daily closing prices of the stocks are used. For ease of comparison all the sets are combined into one plot shown in Fig. 1. The axis of x shows the serial number of the trading day starting from 1 and running up to 1024 for each group of data set and the time span for the four sets is Mar-94 to Dec-98, Dec-98 to Jan-03, Jan-03 to Mar-07 and Mar-07 to Apr-11 respectively.

The first two groups show steady trend and the prices oscillate around 150 with random fluctuations and the two plots for set I (ACC1) and set II (ACC2). Over these 2048 working days no appreciable gross rise or fall is seen in the share prices except that ACC1 has a falling trend. For set III (ACC3) that corresponds to 24/01/2003 to 27/02/2007, the share prices show continuous increasing trend and start rising from a value of about 150 and reach a value close to 1200 showing an eight fold increase. The last set IV (ACC4) shows that the rising part is over and the prices strongly fluctuate around 900 with too much of variability.

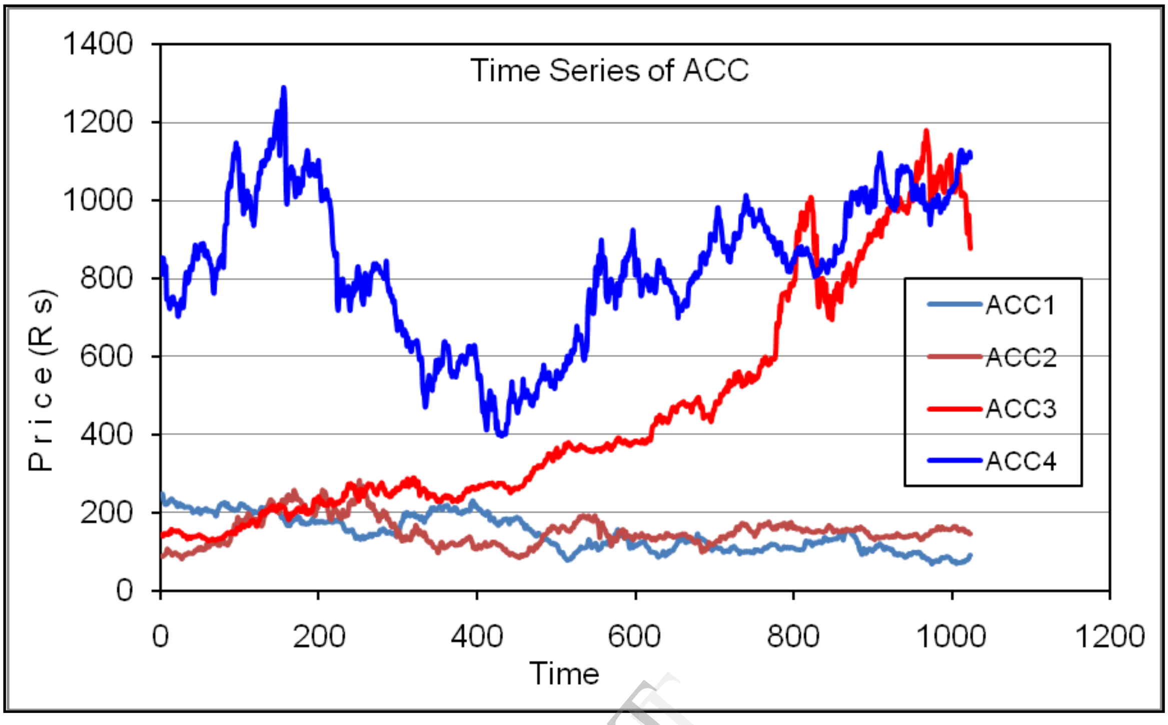

Fig 1: Share price Time series for ACC (03/11/1994 to 27/04/2011)

Rescale Range Analysis is implemented on these four groups (set of data) and the results are tabulated in Table – 1. The log log plot of R/S against τ/2 is shown in Fig. 2, it is interesting to note that all the four groups show that the slope of the straight line best fitting the data point lie between 0.5 and 1.0 indicating persistent trend indicating that the rising prices continue to rise and the falling prices continue to fall that is in agreement with what is seen from the plots, of course there is always a turning point where the prices show the trend and that is one point or two and rest of the points follow certain trend.

Table 1: Mean R/S and τ/2 for ACC data from (03/11/1994 to 27/04/2011)

LOG(T/2)	LOG(R/S)ave ACC1	LOG(R/S)ave ACC2	LOG(R/S)ave ACC3	LOG(R/S)ave ACC4
0.30103	0.005446	0.003503	0.005320	0.003813
0.60206	0.262744	0.232141	0.231109	0.226942
0.90309	0.52952	0.442189	0.460156	0.442443
1.20412	0.820543	0.676343	0.685421	0.661559
1.50515	1.104788	0.926805	0.949129	0.873644
1.80618	1.414900	1.236791	1.192731	1.078406
2.10721	1.671483	1.535594	1.558126	1.322828
2.40824	1.900050	1.859607	1.887482	1.695287
2.70927	2.306401	2.106191	2.204802	1.945591

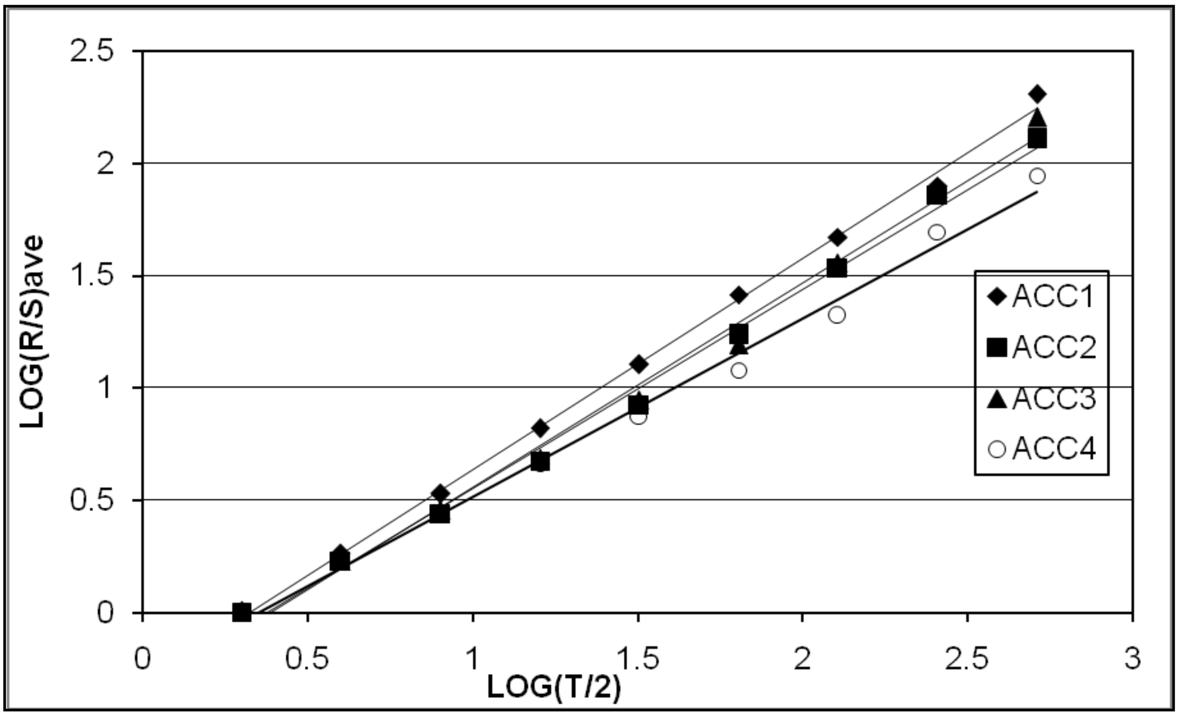

Fig. 2 Log-Log Plot of ACC data for 1to 1024, 1025 to 2048 2049 to 3072, 3073 to 4096 data points

The Hurst exponent estimated from the graph and the fractal dimension calculated from the Hurst exponent are tabulated in Table – 2 the values of R^2 are shown in the last column which indicated the least square fit applied line best describes the data as the points lie along this straight line. The fractal dimension for ACC1 and ACC3 are on the lower side indicating relatively less fluctuations and also they possess a falling and rising trend.

Table – 2 Hurst exponent and Fractal Dimension D_f for ACC.

SR No	Company	Hurst exponent	Fractal Dimension	R^2
1	ACC1 (1 to 1024)	0.94	1.06	0.998
2	ACC2 (1025 to 2048)	0.888	1.112	0.995
3	ACC3 (2049 to 3072)	0.911	1.089	0.991
4	ACC4 (3073 to 4096)	0.794	1.206	0.992

VI. R/S ANALYSIS OF SHARE PRICES OF HINDALCO.

Similar to the case of ACC discussed above the data of share prices of HINDALCO is divided into four groups (sets 1, 2, 3 and4). The four groups cover the data over a period of 03/11/1994 to 27/04/2011 the four sets contain the share prices of HINDALCO and are labeled serially from 1 to 1024, 1025 to 2048, 2049 to 3072 and 3073 to 4096 respectively, the serial number stands for the trading day starting from 03/11/1994 for convenience of associating it with time series. The four plots are shown in Fig. 3, similar to ACC, the first two sets show steady trend with sizable fluctuations around a value of 70. Set 3 and 4 show patterns similar to ACC, in fact this is the pattern of the whole market that is reflected in individual share prices.

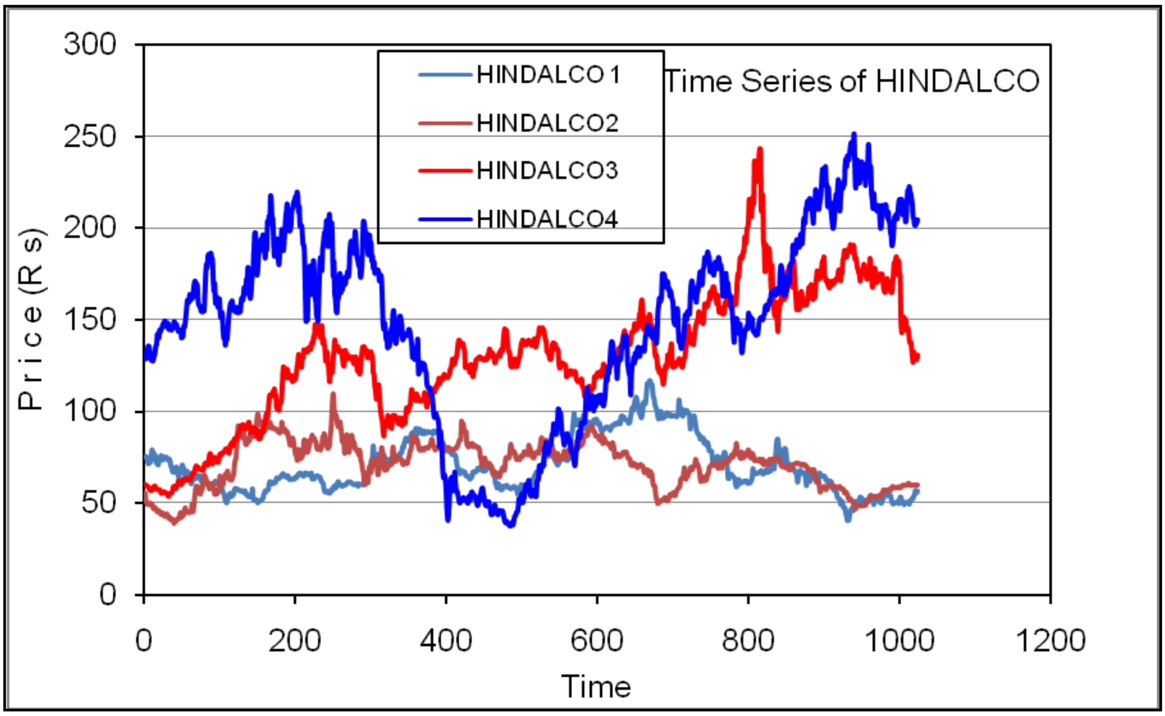

Fig 3 Share price Time series for HINDALCO (03/11/1994 to 27/04/2011).

The results of R/S analysis applied to the share prices of Hindalco are presented in Table – 3, the values or R/S for the four sets are shown against the τ/2 values. Log log plot of R/S against τ/2 is shown in Fig. 4. Coincidentally all the four plots almost overlap being very much identical in trends and patterns. All the data points best fit to a straight line as is indicated by the value of R^2 being close to unity.

Table – 3: Mean R/S and τ/2 for HINDALCO data from (03/11/1994 to 27/04/2011)

LOG(T/2)	LOG(R/S)ave HINDALCO1	LOG(R/S)ave HINDALCO2	LOG(R/S)ave HINDALCO3	LOG(R/S)ave HINDALCO4
0.30103	0.006429	0.007476	0.005247	0.006059
0.60206	0.258687	0.268426	0.262397	0.262892
0.90309	0.523515	0.525768	0.530063	0.535074
1.20412	0.80576	0.811681	0.810694	0.814873
1.50515	1.110915	1.091247	1.102543	1.101715
1.80618	1.410353	1.40747	1.41152	1.391751
2.10721	1.712778	1.707798	1.701374	1.726714
2.40824	2.018843	1.986353	2.014102	1.999655
2.70927	2.247461	2.27083	2.277203	2.312181

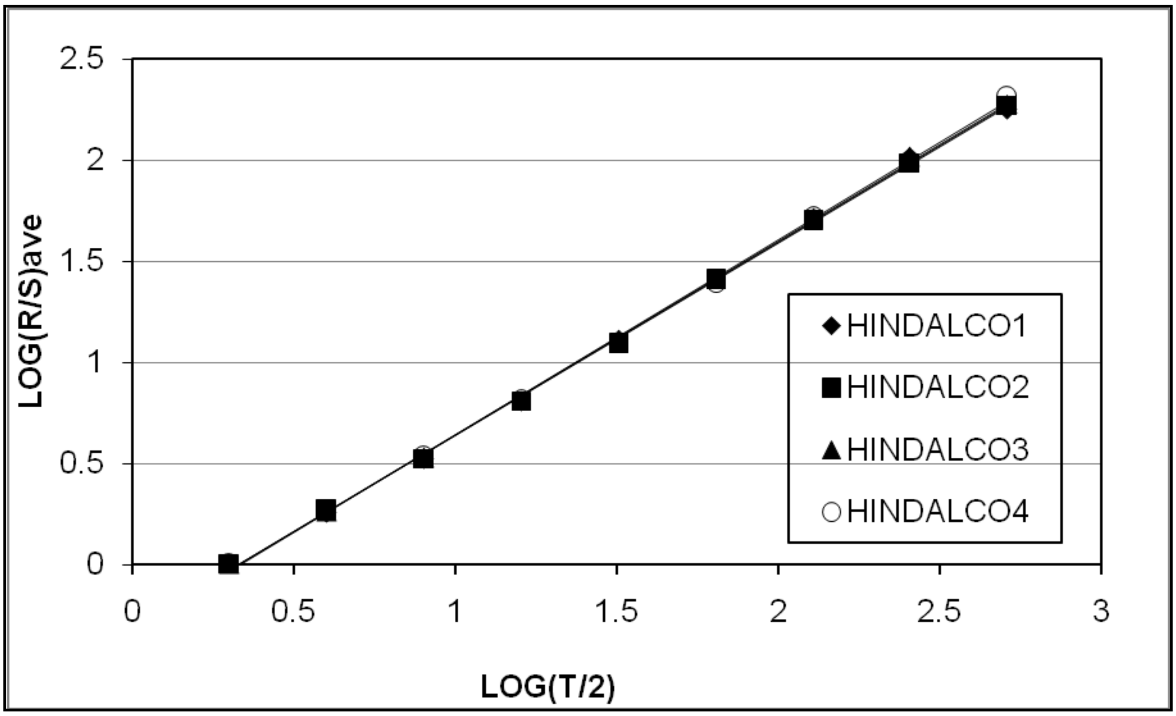

Fig 4 shows R/S analysis of HINDALCO for 1to 1024 & 1025 to 2048, 2049 to 3072 , 3073 to 4096 data points from 03/11/1994 to 27/04/2011

Table – 4 shows the summary of the R/S analysis in terms of the Hurst exponents obtained from the slope of the straight lines best fitting to the four sets of data points obtained by R/S analysis. The fractal dimension of the time series calculated from the Hurst exponent (D_f = 2 –H) is shown in the fourth column and the fifth column is the value of R^2 obtained while fitting the data to a straight line, all the values of R^2 lie close to unity indicating a good fit.

Table – 4: Hurst exponent and Fractal Dimension D_f for HINDALCO

SR. No	Company	Hurst exponent 'H'(Slope)	Fractal Dimension D_f=2-H	R^2
1	HINDALCO1 (1 to 1024)	0.953	1.047	0.999
2	HINDALCO2 (1025 to 2048)	0.95	1.05	0.999
3	HINDALCO3 (2049 to 3072)	0.957	1.043	0.999
4	HINDALCO4 (3073 to 4096)	0.963	1.037	0.999

Table 4 : Hurst exponent, Fractal dimension and R^2 for share Prices of HINDALCO.

VII. R/S ANALYSIS OF SHARE PRICES OF INFOSYS.

Following a procedure similar to the two earlier cases, the data of share prices of INFOSYS is divided into four groups (sets 1, 2, 3 and 4). The four groups cover the data over a period of 03/11/1994 to 27/04/2011 the four sets contain the share prices of INFOSYS and are labeled serially from 1 to 1024, 1025 to 2048, 2049 to 3072 and 3073 to 4096 respectively, this convention is used as the time scale for the trading day in Fig. 5, the serial number starts from 1 and run up to 1024 for each set. The four plots are shown in Fig. 5. The trends here are bit different, however the overall market trend is also preserved. The share prices cover a wide range starting from somewhere around 7 and exceed 3000. Set 1 shows a steady slow rise initially and a relatively fast rise near the end. Set 2 shows a fast initial rise followed by a fall and settles to fluctuations around 500. Set 3 shows steady about four fold rise with limited fluctuations and Set 4 has initial dips followed by a rise contributing to about two fold rise.

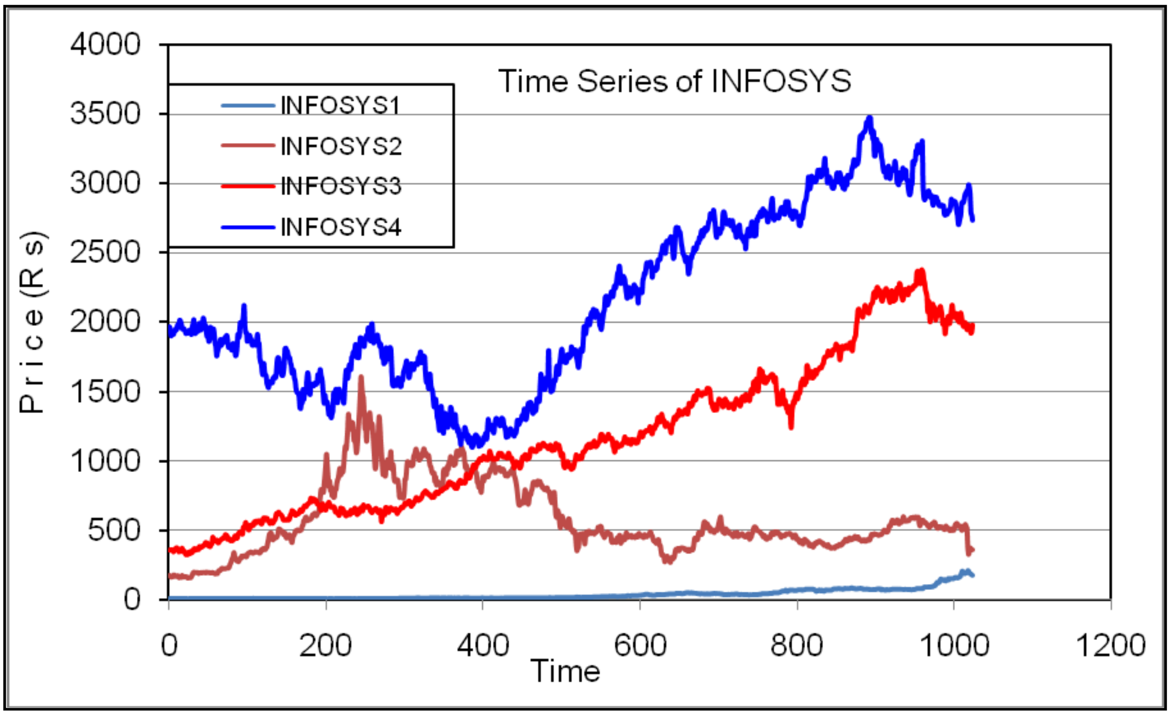

Fig 5: Share price Time series for INFOSYS (03/11/1994 to 27/04/2011).

Results of R/S analysis implemented on these four groups (set of data) are shown in Table – 5. The log log plot of R/S against τ/2 is shown in Fig. 6, it is interesting to note that all the four groups almost superimpose and the slopes of the straight line best fitting the data point are close to unity and lie between 0.5 and 1.0 indicating persistent trend indicating that the rising prices continue to rise and the falling prices continue to fall that is in agreement with what is seen from the plots, of course there is always a turning point where the prices show trend reversal.

Table – 5: Mean R/S and τ/2 for INFOSYS data from (03/11/1994 to27/04/2011).

LOG(T/2)	LOG(R/S)ave INFOSYS1	LOG(R/S)ave INFOSYS2	LOG(R/S)ave INFOSYS3	LOG(R/S)ave INFOSYS4
0.30103	0.022523	0.009149	0.018376	0.028633
0.60206	0.262748	0.262278	0.265636	0.267843
0.90309	0.526276	0.521773	0.527337	0.520680
1.20412	0.80852	0.796526	0.794235	0.810939
1.50515	1.091456	1.096231	1.087065	1.095966
1.80618	1.399698	1.384183	1.385468	1.388677
2.10721	1.68312	1.654109	1.738678	1.714285
2.40824	2.007188	1.960200	2.021213	1.989714
2.70927	2.308393	2.340942	2.335765	2.306935

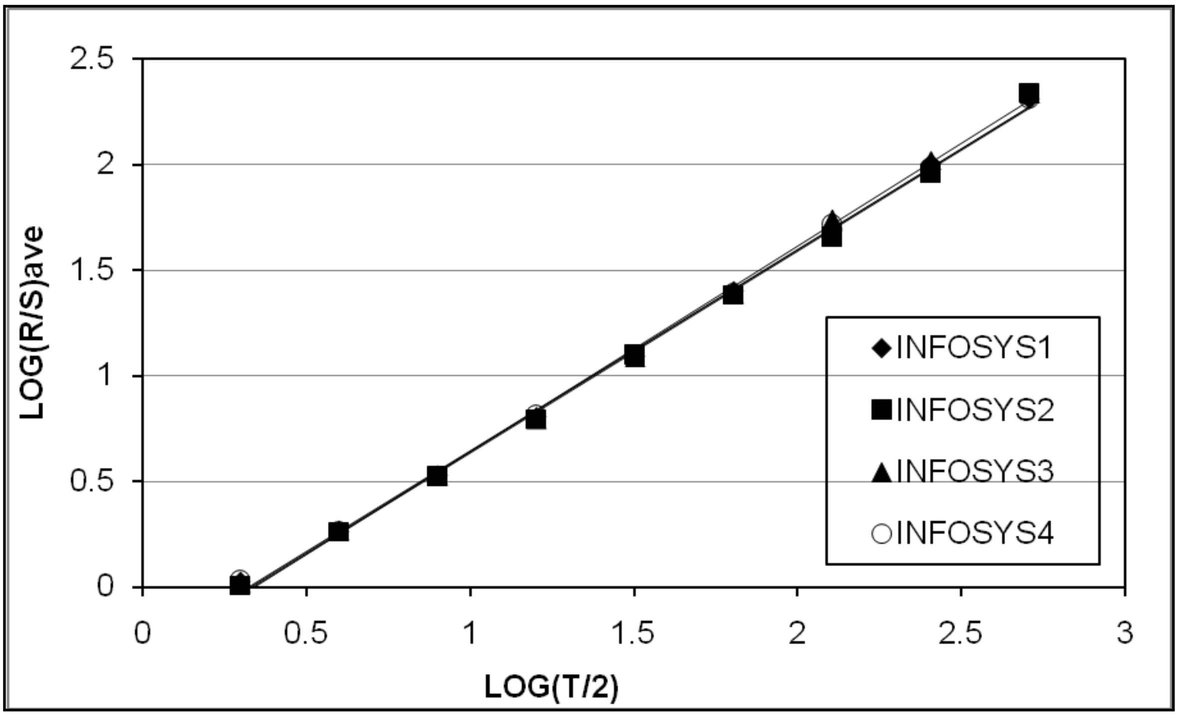

Fig. 6 R/S analysis of Time series Data of INFOSYS for 1 to 1024 & 1025 to 2048, 2049 to 3072, points from 3073 to 4096 data 03/11/1994 to 27/04/2011.

Table – 6 shows the summary of the R/S analysis in terms of the Hurst exponents obtained from the slope of the straight lines best fitting to the four sets of data points obtained by R/S analysis. The fractal dimension of the time series calculated from the Hurst exponent (D_f = 2 –H) is shown in the fourth column and the fifth column is the value of R^2 obtained while fitting the data to a straight line, all the values of R^2 lie close to unity indicating a good fit.

Table – 6 Hurst exponent and Fractal Dimension D_f for INFOSYS.

SR. No	Company	Hurst exponent 'H'(Slope)	Fractal Dimension D_f=2-H	R^2
1	INFOSYS1 (1 to1024)	0.956	1.044	0.997
2	INFOSYS2 (1025 to 2048)	0.956	1.044	0.997
3	INFOSYS3 (2049 to 3072)	0.997	1.003	0.999
4	INFOSYS4 (3073 to 4096)	0.954	1.046	0.998

VIII. R/S ANALYSIS OF SHARE PRICES OF STATE BANK OF INDIA(SBI).

Using similar procedure, the data of share prices of State Bank of India(SBI) is divided into four groups (sets 1, 2, 3 and 4). The four groups cover the data over a period of 03/11/1994 to 27/04/2011 the four sets contain the share prices of SBI and are labeled serially from 1 to 1024, 1025 to 2048, 2049 to 3072 and 3073 to 4096 respectively, this convention is used as the time scale for the trading day in Fig. 7, the serial number starts from 1 and run up to 1024 for each set. The four plots are shown in Fig. 7. The patterns here are bit different, however the overall market trend is also preserved. The share prices cover a wide range starting from somewhere around 190 and reach a value around 3000. The patterns of price variations are much similar to that of ACC shown in Fig. 1.

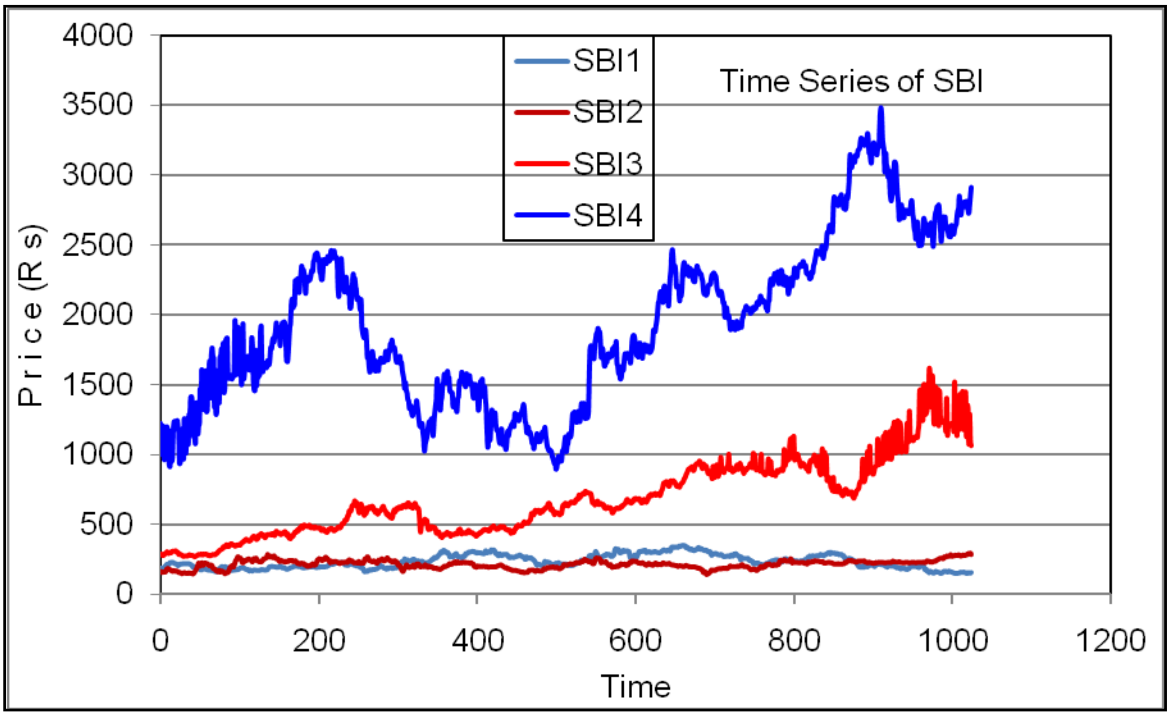

Fig. 7 Share price Time series for State Bank of India (SBI) from 03/11/1994 to 27/04/2011.

Table – 7: Mean R/S and τ/2 for SBI data from (03/11/1994 to 27/04/2011).

LOG(T/2)	LOG(R/S)ave SBI1	LOG(R/S)ave SBI2	LOG(R/S)ave SBI3	LOG(R/S)ave SBI4
0.30103	0.003335	0.006483	0.006117	0.025119
0.60206	0.258126	0.262348	0.252786	0.26264
0.90309	0.535348	0.528424	0.503545	0.51904
1.20412	0.822716	0.816325	0.787003	0.792297
1.50515	1.09962	1.106514	1.073719	1.063895
1.80618	1.408492	1.370796	1.387473	1.406932
2.10721	1.712339	1.627714	1.72353	1.701692
2.40824	1.98145	1.982918	2.007452	1.996964
2.70927	2.299325	2.182068	2.300784	2.248591

Table – 7 shows the results of R/S analysis implemented on these four sets of data and log log plot of R/S against τ/2 is shown in Fig. 8. It is interesting to note that the share price changing patterns being identical to that of ACC shown in Fig. 1 the four lines are close to each other and have similar slopes and thus Hurst exponent and fractal dimension, again the persistence of trend is visible from the values of Hurst exponent.

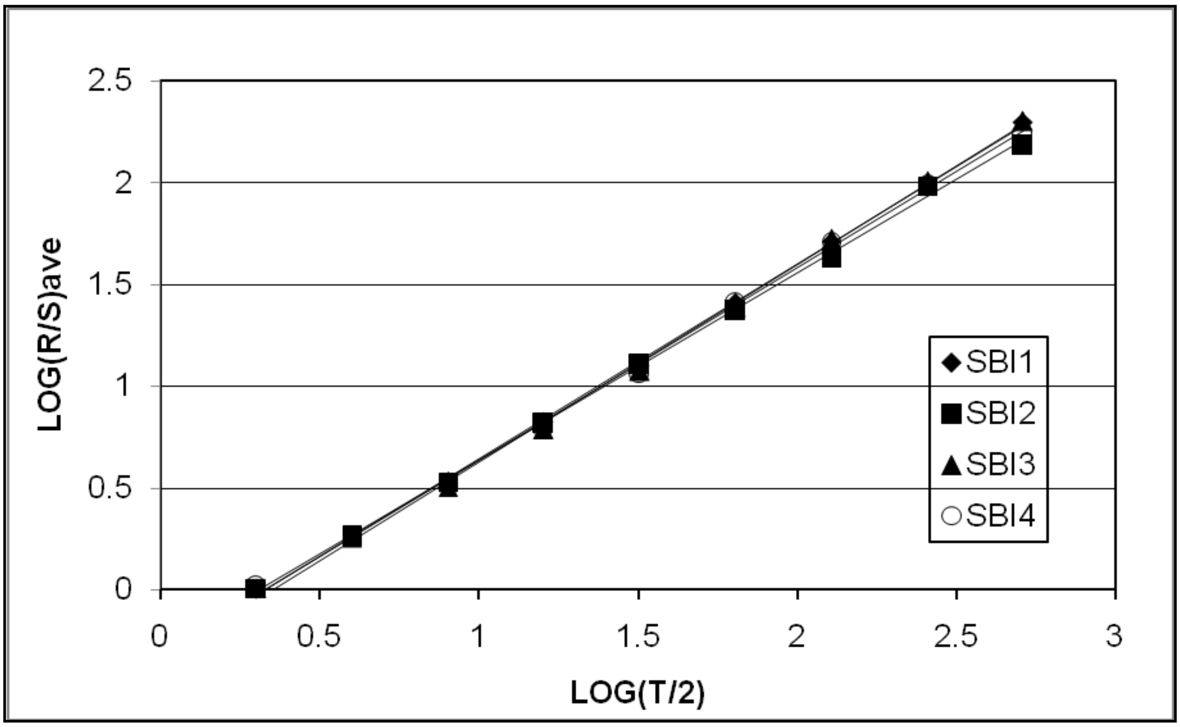

Fig. 8 R/S analysis of Time series Data of SBI for 1 to 1024 & 1025 to 2048, 2049 to 3072, points from 3073 to 4096 data 03/11/1994 to 27/04/2011.

Summary of the R/S analysis in terms of the Hurst exponents obtained from the slope of the straight lines best fitting to the four sets of SBI data obtained by R/S analysis is presented in Table –8. The fractal dimension of the time series calculated from the Hurst exponent is shown in the fourth column and the fifth column is the value of R^2 obtained while fitting the data to a straight line, all the values of R^2 lie close to unity indicating a good fit.

Table – 8: Hurst exponent and Fractal Dimension D_f for SBI.

SR. No	Company	Hurst exponent 'H'(Slope)	Fractal Dimension D_f=2-H	R^2
1	SBI1 (1to1024)	0.957	1.043	0.997
2	SBI2 (1025 to 2048)	0.92	1.080	0.997
3	SBI3 (2049 to 3072)	0.968	1.032	0.999
4	SBI4 (3073 to 4096)	0.945	1.055	0.998

IX. Comparison of Hurst Exponent:

A comparison of Hurst exponent for the four companies obtained for the four time slots Set-1, 2, 3 and 4 for the periods Mar-94 to Dec 98, Dec-98 to Jan 03, Jan-03 to Mar-07 and Mar-07 to Apr-11is shown in Table – 9 below. Higher values of Hurst exponent indicate higher degree of fluctuations, turbulence and noise where as lower values correspond to a lower degree of fluctuations, turbulence and noise. This is an index to the turbulence and volatility of share prices.

Table – 9: Hurst exponent 'H' for the four shares during four time slots.

Company	Value of H during period			
	Mar-94 to Dec-98	Dec-98 to Jan-03	Jan-03 to Mar-07	Mar-07 to Apr-11
ACC	0.940	0.888	0.911	0.794
HINDALCO	0.953	0.950	0.957	0.963
INFOSYS	0.956	0.956	0.997	0.954
SBI	0.957	0.920	0.968	0.945

X. RESULTS AND DISCUSSION:

Hurst exponent is an indicative of the presence of noise or fluctuations in the data which in turn gives information on the volatility of the share prices and turbulence in the trading of that share. It is seen from the first row of Table – 9 for ACC that the values of H are lowest compared to the rest of the three shares that are equally sound. Lower the value of H, higher is the noise or fluctuation and vice versa. This shows that over the entire period studied the volatility of the ACC was more compared to the rest of three. Also the turbulence and volatility was higher during 07 – 11 and it was lowest during 94 – 98. Trading in shares with higher value of H is risky as compared to those with lower values of H, however calculated trading in volatile shares with higher values of H may give higher returns in a shorter time. HINDALCO, INFOSYS and SBI exhibit relatively lower variability, turbulence and fluctuations over the entire period studied as the values of H are on the higher side, similar are the conclusions derived on the basis of fractal dimensions D_f as they are closely related ($D_f = 2 - H$).

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