The Nucleus **47**, No. 4 (2010) : 295-299

The Nucleus
A Quarterly Scientific Journal of Pakistan Atomic Energy Commission
NCLEAM, ISSN 0029-5698

CHARACTERIZING THE MODELING STRATEGIES OF SOLAR FLARE DURATION FOR PAKISTAN ATMOSPHERIC REGION

*S. A. JILANI and [1]M.A.K.YOUSUF ZAI

Department of Physics, University of Karachi, Karachi-75270, Pakistan

[1]Department of Applied Physics, University of Karachi, Karachi-75270, Pakistan

(Received October 30, 2010 and accepted in revised form November 02, 2010)

This paper presents the significance of solar flare according to their duration. The characterization in the variability of flares has been developed using modeling techniques. It is desirable to develop such models which predict at least a day or so ahead, when solar flare influence on terrestrial system may be expected. For that purpose, future aspects of these flares are investigated by stochastic analysis. After doing residual analysis a proper ARIMA model is developed to forecast the Solar Flare Duration (SFD). These investigations are the part of work connecting solar flare activity with ozone layer depletion which is one of the solar-terrestrial relationships.

Keywords: Solar flare variability, Solar flare duration, Stochastic analysis, Simulation

1. Introduction

The monthly average solar flare duration was obtained from SUPARCO, HQ Karachi. These are the interceptions in the ionosphereic layer recorded by Digisonde at the time of solar flare. The analyses are computed for the period from March 1979 to March 2006.

Solar flares occur when strong magnetic fields extending high into the sun's atmosphere above sunspots or other portions of the photosphere, suddenly collapse and then recombine. In such case the oppositely directed magnetic field lines come together and partially annihilate each other. A largest solar flare has total energy emissions equal that released by two and a half thousand million hydrogen bombs [1, 7].

The field of solar physics is important because of its complexities and effects on terrestrial environment. The effects of high-energy particles emitted during the flare normally last for hours to days after the augmentation in radiative flux. These particles are lethal for astronauts in space [2].

Other effects include partial or total blackout of radio waves communication, ozone layer depletion, polar cap absorption, magnetic storms, interruptions in electronic system of satellite and its orbital drag. Navigation systems are adversely affected and the accuracy and reliability of Global Positioning System (GPS) decreases [4, 6, 8].

Impulsive flares are of short duration and at most they are not associated with coronal mass ejection (CME) and solar proton events (SPE), whereas gradual flares are of long duration and mostly associated with these events. Sometimes CMEs can originate also in quiet parts of the sun [5].

Solar Flares which have marked effects on near earth are also interrelated with sunspots at the time especially while they are decaying [3]. These evidences signify the need of a proper model that can be used to forecast the behavior of solar flares. It has been known that a model is the prediction of the variation of basic parameters. These we obtained by stochastic or time series analysis in which the arrangement of the data is in accordance with the time of occurrence [15].

2. Examine Stationarity

As the autocorrelation of the original series does not drop to or near zero quickly, instead it decays exponentially and upto lag 15 it remain

* Corresponding author : saifjilani@yahoo.com

positive indicates non-stationarity. On the other hand the partial autocorrelation indicates stationarity because it drops near to zero quickly after the first value [11].

It, therefore, concludes that the data have partially non-stationary behavior.

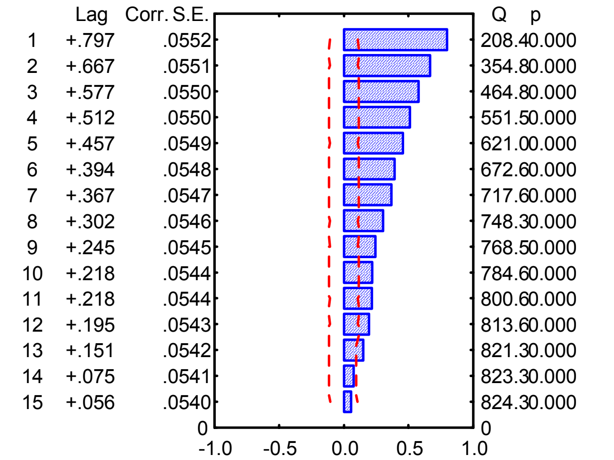

Figure 1. Autocorrelation for SFD exhibit non-stationary behavior.

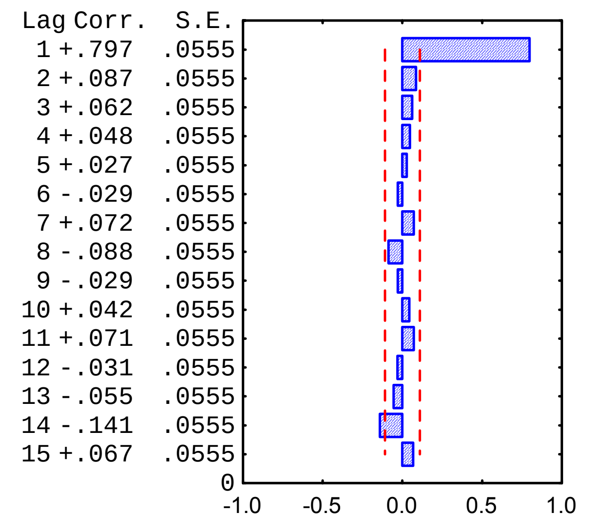

Figure 2. Partial Autocorrelation for SFD exhibit stationary behavior.

Another test of stationarity can be obtained by observing spectral density of the series. To be a series to stationary the spectral density cannot change with time [10].

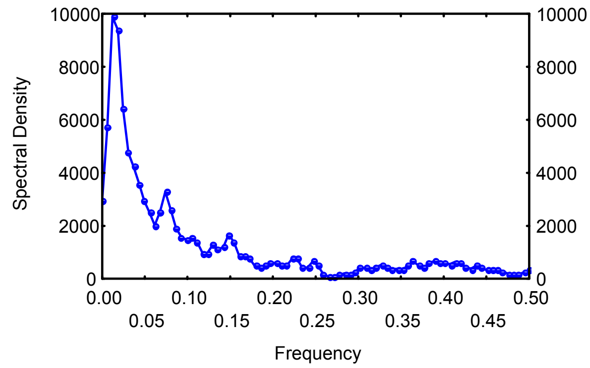

Figure 3. Spectral analyses for the first half data series of SFD.

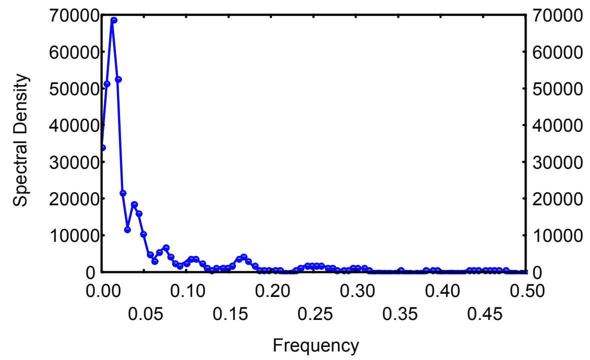

Figure 4. Spectral analyses for the second half data series of SFD.

For the case of SFD the first half of a time series had component oscillations of peak frequency, f = 0.0123 and for the second half this frequency found to be uniform. This indicates stationary series.

Although the mean of SFD seems to be uniform but the variance is far from constant and indicates partially non-stationary behavior [9] .

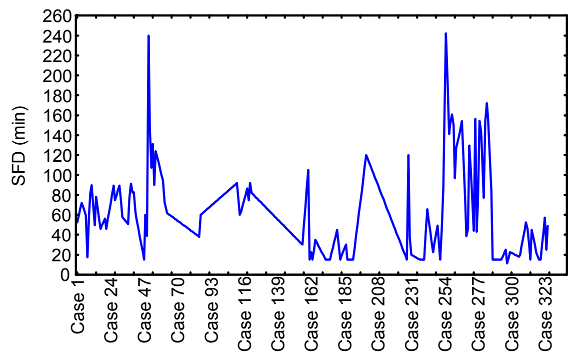

Figure 5. Average monthly observed SFD.

3. Examine Seasonality

A seasonal component in a series if it exists, can also be identified with the help of correlogram.

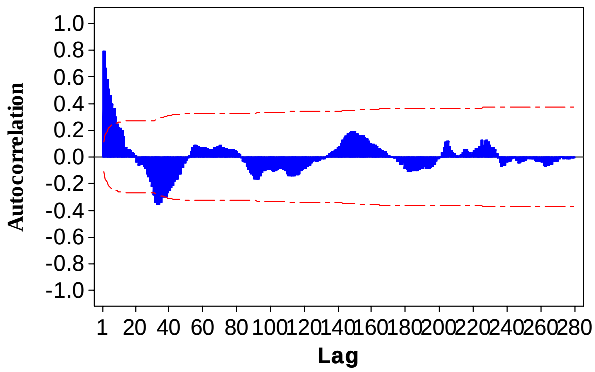

Figure 6. Autocorrelation Function for SFD .

The above figure depicts lack of seasonal component in the data set because peaks exist at lags 1, 33, 91, 149 etc. There was no apparent periodicity.

4. Model Estimation

The first thing to note is that most of time series are non-stationary, and the Autoregressive (AR) and Moving Average (MA) aspects of an ARIMA model refers only to a stationary time series. A time series is said to be stationary if there is no systematic change in mean (no trend) which is according to our data. However, some evidences indicate non-stationarity. For that purpose, we developed ARIMA models, some with differencing and other without differencing. After doing residual analysis we validated the model by comparing the predicted values with real observations of the last year. The models specified, are ARMA (2, 1) ARIMA (2, 1, 1), ARIMA (3, 1, 0), ARIMA (2, 1, 0) and AR (3).

An autoregressive process will only be stable if the parameters are within a certain range: for example, if there is only one autoregressive parameter then it must fall within the interval of $-1 < x_t < 1$ [9].

5. Residual Analysis

i. For a good model residuals are expected to be random and close to zero. For AR (3) only lag 14 existing outside the confidence band. Hence AR (3) may be an appropriate model.

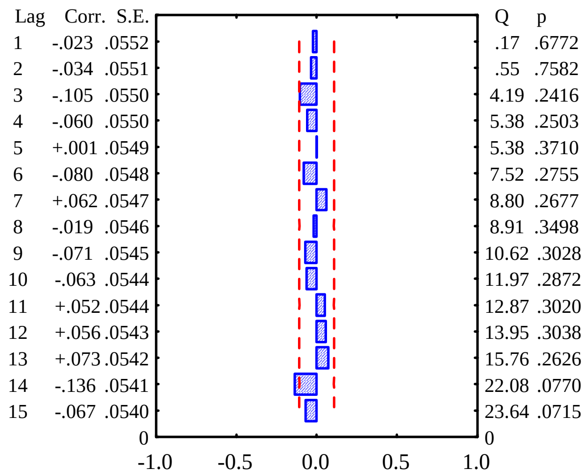

Figure 7. Autocorrelation of AR (3) shows serial dependence except at lag 14.

ii. One of the statistics which is used for testing residual is the Durbin-Watson statistic i.e. $d \cong 2(1-r_1)$. For a true model to be fitted, $r_1 \cong 0$ and $d \cong 2$ [12].

iii. The test suggested by Box and Pierce (1970) for the independence of the residuals is given by the expression: $R = n\sum_{j=1}^{k} r_j^{\ 2}$ where R is distributed as χ^2_{k-p-q} where k is usually at least 20. The r_j's are calculated on the residual series. If the residual series has N observations and the original series was fit by an ARIMA (p, d, q) model, then n = N – d. A significant chi-square indicates model inadequacy [13].
AR (1) model; R=33.70; χ^2_{19} = 30.14.
AR (2) model; R=30.45; χ^2_{18} = 28.87.
AR (3) model; R=24.86; χ^2_{17} = 27.59 at 5 % level of significance.

Hence AR (3) is an adequate model.

iv. The conditional or static aspect of the ARMA (n, m) model is exactly a linear regression model; therefore F-test can be used to check the adequacy of the model as follows.
$F = \frac{A_1 - A_o}{s} \div \frac{A_o}{N-r}$; where A_o is the (smaller) sum of squares of the unrestricted model A_1 is the (larger) sum of squares of the restricted model with s and $N-r$ degree of freedom [10].

This test can be utilized here to find the appropriateness of AR (3) or ARIMA (3, 1, 0) against ARMA (2, 1). As the F- computed value 3.10 is slightly greater than the value 3.00 obtained from the F-distribution table. It may conclude that the ARMA (2, 1) model is also adequate at 5 % level of significance.

The coefficient of determination (R^2) can be obtained by the relationship as,

$$R^2 = 1 - \frac{SS_E}{SS_Y} \quad [14]$$

SS_E = Residual sum of squares

SS_Y = Total sum of squares

Table 2.1. Summary.

	DWS	R^2	BPQS
AR(3)	2.046	0.614	24.86
ARIMA (2,0,1)	2.032	0.622	17.77
ARIMA (2,1,1)	2.018	0.637	28.87
ARIMA (2,1,0)	2.030	0.615	27.72
ARIMA (3,1,0)	2.018	0.619	22.00

Table 2.2. Forecast from AR (3).

Period	Forecast	Lower	Upper	Std. Error
		95.0 %	95.0 %	
326	46.0	6.6	85.4	23.8
327	41.9	-8.1	91.9	30.3
328	41.1	-15.5	97.8	34.3
329	39.9	-22.8	102.8	38.0
330	38.5	-29.6	106.6	41.3

Table 2.3. Forecast from ARMA (2. 1).

Period	Forecast	Lower	Upper	Std. Error
		95.0 %	95.0 %	
326	44.0	-8.1	83.0	23.6
327	41.0	-2.4	90.2	29.8
328	39.0	-15.8	93.9	33.2
329	37.7	- 21.1	96.5	35.6
330	36.7	-25.0	98.5	37.4

Table 2.4. Parameter estimation.

Model / Order	p (1)	p (2)	p (3)	q (1)	MS
AR(3)	0.78	0.06	0.11	-----	570
ARMA(2, 1)	1.58	- 0.5	-----	0.82	559
ARIMA(2,1,1)	0.73	0.09	-----	0.99	538
ARIMA(2,1,0)	- 0.2	- 0.1	-----	-----	569
ARIMA(3,1,0)	- 0.2	- 0.1	- 0.1	-----	564

6. Conclusion

i. A proper ARIMA model has been selected to forecast the SFD of solar flares. After doing residual analysis AR (3) is recommended. ARMA (2, 1) is also appropriate but since one of its parameters is greater than one, it consider unstable.

ii. The time series of SFD have partially non-stationary behavior but not much enough required for differencing.

References

[1] P.O. Taylor, Observing the Sun, Cambridge University Press (1991).

[2] E.N. Parker, F.C. Kennel, J.L. Lanzerotti, Solar System Plasma Physics Vol.1, North-Holland Publishing Company (1979).

[3] S. Glasstone, Sourcebook on the Space Science, D.Van Nostrand Company, Inc. Princeton, New Jersy (1965).

[4] J.H.K Phillips, Guide to the Sun, Cambridge University Press (1992).

[5] B.N. Dwivedi and E.N. Parker, Dynamic Sun, Cambridge University Press (2003).

[6] K.R. Lang, The Cambridge Encyclopedia of the Sun, Cambridge University Press (2001).

[7] G.D. Holman, The Mysterious Organize of Solar Flare, Scientific American, April (2006).

[8] J.R. Herman and R.A. Goldberg, Sun, Weather, and Climate, Dover Publication, Inc. N.Y (1985).

[9] G. Bradawl, Statistics of Earth Science Data, Springer-Verlag Berlin Heidelberg N.Y (2003)

[10] S.M. Pandit and S.M. WU, Time Series and System Analysis with Applications, John Wiley & Sons (1983).

[11] S. Makridakis, S.C. Wheelwright, V.E. McGee, Forecasting: Methods and Applications, Second Edition, John Wiley & Sons (1983).

[12] C. Chatfield, Analysis of Time Series (1988)

[13] J.M. Gottman, ‘Time Series Analysis, Cambridge University Press (1981).

[14] P.G. Mathews, Design of Experiments with MINITAB, Pearson Education, Singapore PTE Ltd. Indian Branch (2005).

[15] M.A.K. Yousuf Zai, ‘Ph.D. Thesis’ Institute of Space and Planetary Astrophysics, University of Karachi (2003).