Complexity in Solar Irradiance From the Earth Radiation Budget Satellite

Mofazzal Hossain Khondekar, Member, IEEE, Dipendra Nath Ghosh, Koushik Ghosh, and Anup Kumar Bhattacharjee

Abstract—In this paper, a search is made to detect any sort of nonlinearity and chaos in the solar irradiance data from the Earth Radiation Budget Satellite during the time period from October 15, 1984 to October 15, 2003 in order to investigate the inherent complexity in it. In this paper, delay vector variance analysis has been applied to trace the nonlinearity; whereas 0–1 test, correlation dimension analysis, information entropy, recurrence plot, and recurrence quantification analysis have been used to explore the signature of chaos in the present time series. Present investigation reveals that though nonlinearity is significantly present in the signal, chaotic behavior is not really observed in it.

Index Terms—Chaos, geophysical signal processing, nonlinear dynamical systems, Sun.

I. INTRODUCTION

TOTAL solar irradiance (TSI) is the electromagnetic radiant energy released by the Sun over all the spectral frequencies (∼3 × 10⁻¹¹–6 × 10⁻¹⁷ Hz) [1] that falls per second on 1 m² outside the Earth’s atmosphere, where the highest frequencies are in the ultraviolet region of the spectrum, the intermediate frequencies are in the visible region, and the smaller frequencies are in the near-infrared region. TSI is the solar flux integrated over all frequencies to include the contributions from ultraviolet, visible, and infrared radiation. It has been established that the variation of the solar irradiance data obtained by the Earth Radiation Budget Satellite (ERBS) during the time period from October 15, 1984 to October 15, 2003 [2] is antipersistent [3], multiperiodic [4]–[6], and multifractal [7]. In this paper, an initiative has been taken to review the dynamics of the TSI fluctuations by searching for the evidence of nonlinearity and chaos in it.

The signature of chaos is very much analogous to call it the sensitivity to the initial conditions. Nonlinearity is a necessary condition for chaos. In a dynamical system, the opposite of the sensitivity to the initial conditions is said to be integrability, and if a dynamical system is integrable, then it must be multi-periodic. Sensitivity to the initial conditions basically kills the reductionism in a system. For a chaotic system, any small-scale uncertainty or perturbation in the initial conditions manifests an exponential growth over time. Eventually, this can generate so large a deviation that we will lose necessary information about the system. A complex system contains many interdependent constituents interacting nonlinearly. It possesses a structure spanning several scales, and it is capable of emerging behavior that may lead to self-organization. Complexity involves interplay between chaos and nonchaos and cooperation and competition between the constituent scales. The word “entropy” stands for the quantitative measure of the disorder of a system. The entropy remains increasing as long as the system evolves. If a system reaches its equilibrium and stops evolving, its entropy reaches a constant. In that sense, higher entropy indicates close to equilibrium, and this interprets less chaos as energy in the system in that case has been dissipated. On the other hand, lower entropy indicates more chaotic nature as, in this case, we have to add more energy to the system [8].

There are various methods to study the nonlinearity in a time series signal, such as the method of Kaplan [9], the method of Kennel et al. [10], δ−ε method [11], deterministic versus stochastic method [12], correlation exponents [13], etc. However, all these methods suffer from some serious statistical shortcomings [14]. In this paper, delay vector variance (DVV) [15] has been used to detect the linear or nonlinear nature of the TSI signals obtained from ERBS during the time period from October 15, 1984 to October 15, 2003. As a considerable amount of nonlinearity in the time series has been detected using DVV, there may be a likelihood of the presence of chaos in the signal. However, in this point, we need some rigorous tests. The presence of chaos for the signal has been tested using the 0–1 test [16]. The test result has been verified from the largest Lyapunov exponent based on the algorithm proposed by Rosenstein et al. [17] and the correlation dimension analysis based on the algorithm proposed by Grassberger and Procaccia [13], [18]. The correlation dimension analysis not only helps to detect the presence of chaos but also to determine the dimension of the chaos. This study reveals that chaos is not playing a role in the system. Recurrence plot (RP) and recurrence quantification analysis (RQA) have been also employed to explore the complexity in the signals [19]–[21].
II. THEORY

A. DVV Analysis

A time series \( x(i) \) of length \( N \) can be represented in “phase space” by embedded time delay lag \( \tau \) and embedded dimension \( m \) to obtain a set of delay vectors (DV’s) \( x(k) = [x_{k−mτ}, . . . , x_{k−τ}] \) and \( k = 1, 2, . . . , N \). Within a certain Euclidean distance \( \tau_d \) to DV \( x(k) \), the DV’s are grouped, which is denoted by \( \lambda_k(\tau_d) \). For an optimal embedding dimension \( m \), the mean target variance \( \sigma^{-2} \), which is a measure of unpredictability, is computed over all sets of \( \lambda : k = 1, 2, . . . , N \). The embedding dimension \( m \), which yields minimum target variance \( \sigma^{-2} \), has been selected as the optimal one. The variation of the standardized distance enables the complete range of pairwise distances to be examined [15], [22].

In order to standardize the distance axis, \( \tau_d \) is replaced by \( (\tau_d − \mu_d)/\sigma_d \), which will have zero mean and unit variance. \( \mu_d \) and \( \sigma_d \) are the mean and the standard deviation, respectively, of each DV. The “DVV plots” are obtained by plotting target variance \( \sigma^{-2}(\tau_d) \) as a function of the standardized distance. The minimum value of the target variance \( \sigma^{-2}_{\text{min}} = \min \{\sigma^{-2}(\tau_d)\} \) gives the measure of noise present in the time series. The quantity of noise is predominant in the stochastic component, and hence, the stochastic component will have large \( \sigma^{-2}_{\text{min}} \). The presence of one strong deterministic component will lead to a small value of \( \sigma^{-2}_{\text{min}} \). As all the DVs are in the same set and the variance of the targets is equal to the variance of the time series for maximum span, the DVV plots converge to unity.

The DVV plots of a number of surrogate time series (generated using the iterated amplitude adjusted Fourier transform method [23], [24]) are obtained using the optimal embedding dimension of the original time series. Since the distance axis has been standardized, a “DVV scatter diagram” is obtained by plotting the target variance \( \sigma^{-2}(\tau_d) \) of the original time series along the horizontal axis and the mean of that of the surrogate time series. The deviation of the DVV scatter diagram from the bisector line is a sign of nonlinearity and can be quantified as the root-mean-square error (RMSE) between the \( \sigma^{-2}(\tau_d) \) of the original time series and the mean \( \sigma^{-2}(\tau_d) \) of the surrogate time series, i.e.,

\[
\text{RMSE} = \sqrt{\text{mean} \left\{ \sigma^{-2}(\tau_d) - \frac{\sum_{k=1}^{N_s} \sigma^{-2}_{s,k}(\tau_d)}{N_s} \right\}^2}
\]  

where \( \sigma^{-2}_{s,k}(\tau_d) \) is the target variance at span \( \tau_d \) for the \( k \)th surrogate, and the mean is taken over all span of \( \tau_d \) that is valid in all surrogate and DVV plots [14].

B. 0–1 Test for Chaos

This is a binary test introduced and modified by Gottwald and Melbourne [16], [25], which takes the time series vector as the input and gives the output of “0” or “1” if the dynamics input vector time series is “nonchaotic (i.e., regular)” or “chaotic.” The test is not only simple to implement and reliable [26] but also robust for the detection of deterministic chaos in a noisy time series [27] and experimental data [28]. A Fourier transformed series \( p_n \) is constructed for the time series \( x(k) \) for \( k = 1, 2, . . . , N \) as [29]

\[
p_n = \sum_{k=1}^{n} x(k)e^{i\lambda k}
\]  

for several values \( \lambda \) randomly chosen. Here, 100 random values of \( \lambda \) between \( [\pi/5, 4\pi/5] \) are chosen.

The smoothed mean square displacement \( D_c(n) \) is obtained as

\[
D_c(n) = \frac{1}{N-m} \sum_{k=1}^{N-m} |p_{k+n} - p_k|^2 - \langle x \rangle^2 \frac{1 - \cos ne}{1 - \cos c}
\]  

where \( \langle x \rangle \equiv (1/N) \sum_{k=1}^{N} x(k) \) is the average of the given time series, and \( n \leq m = N/10 \ll N \). If the underlying dynamics of \( x(k) \) is deterministic chaos, then \( D_c(n) \) linearly scales with \( n \) (i.e., \( D_c(n) \sim n \)) and \( p_n \) will present a Brownian motion in the complex plane. If the underlying dynamics is regular, then \( D_c(n) \) is a bounded function of \( n \), i.e., \( D_c(n) \) should not increase with \( n \) and \( p_n \) will present a bounded motion in the complex plane. To make the test more robust to the presence of noise, \( D_c(n) \) has been modified to \( D_c^*(n) \) as

\[
D_c^*(n) = D_c(n) + \alpha V_{\text{damp}}(n)
\]  

where \( V_{\text{damp}}(n) = \langle x \rangle^2 \sin(\sqrt{2}n) \).

The amplitude \( \alpha \) of the term \( V_{\text{damp}}(n) \) controls the sensitivity of the test to weak noise and, simultaneously, to weak chaos. In order to assess the strength of the linear growth, the asymptotic growth rate \( K_c \) is obtained, which is defined as

\[
K_c = \text{corr} (n, D_c^*(n))
\]  

This quantity measures the strength of the correlation of \( D_c^*(n) \) with linear growth. The binary output of the test is given by the value of \( K \), which is given by

\[
K = \text{median}(K_c)
\]  

If the value of \( K \) is close to 0, the time series signal may be judged as regular, whereas if the value is close to 1, the signal may be judged as chaotic [30].

C. Correlation Dimension Analysis

Grassberger and Procaccia [13], [18] introduced the correlation dimension \( D \) to describe the ability of a time series to fill the phase space with the embedding dimension \( m \) and the embedding lag \( \tau \). \( D \) is obtained by covering the phase space with boxes of a given size \( r \) and then computing the probability of having a point of the phase space in the \( k \)th box. The correlation dimension is defined as

\[
D(r, m) = \lim_{r \to 0} \sum_k \frac{\log(C(r, m))}{\log(r)}
\]
where $C(r, m)$ is the correlation integral and is given as

$$
C(r, m) = \lim_{N \to \infty} \frac{1}{N^2} \{ \text{Number of pairs of points with separation } r \}
$$

$$
= \lim_{N \to \infty} \frac{1}{N^2} \sum_{j=1}^{N} \sum_{i=j+1}^{N} H(r - |X_i - X_j|) \quad (8)
$$

where $H$ is the Heaviside function, which acts as a counter of the number of pairs of points (let $i$th and $j$th points be with coordinates $X_i$ and $X_j$ in the phase space) with separation $|X_i - X_j| < r$.

$D(r, m)$ is estimated for $m = 1, 2, 3, \ldots, L$, where $L \leq 10$ is generally used. Let $D(m)$ be the average of $D(r, m)$ taken over all the possible values of $r$. If $D(m)$ increases with $m$ continuously, then this suggests that the time series is stochastic. For many of the stochastic dynamics, $D(m)$ tends to infinity [31]. On the other hand, if the time series is generated from a deterministic process (chaotic or regular), then as $m$ increases, $D(m)$ also increases until it reaches a plateau value at some relatively small $m$. The value of the plateau gives the value of $D(m)$. For a trustworthy measurement of $D(m)$, the thumb rule is that $D(m) \leq 2 \log_{10} N$ [32]. Thus, any plateau in the plot of $D(m)$ versus $m$ at values of $D(m) > 2 \log_{10} N$ is discarded as artifacts of the finite data size. The correlation dimension can be therefore used to distinguish true stochastic processes from deterministic processes.

**D. Largest Lyapunov Exponent $\lambda_{\text{max}}$ Method**

For a dynamical system, Lyapunov exponents quantify the sensitivity to initial conditions and provide the measure of predictability. It is a measure of the exponential separation of the neighboring orbits averaged over all points of an orbit around an attractor. If $X_0$ and $X_0 + \Delta x_0$ are the two points in space, which are functions of time and each of which generate an orbit in that space using some equations, then the separation between the two orbits $\Delta x$ will be also a function of time and the location of the initial value, i.e., $\Delta x(X_0, t)$. For a chaotic time series, $\Delta x(X_0, t)$ randomly varies at every time.

Mathematically, Lyapunov exponent $\lambda$ can be expressed by

$$
\lambda = \lim_{t \to \infty} \frac{1}{t} \ln \frac{\Delta x(X_0, t)}{\Delta x_0}. \quad (9)
$$

From the preceding equation, a negative exponent implies that the orbits converge to a common fixed point. A zero exponent means that the orbits maintain their relative positions, i.e., they are on a stable attractor. Finally, a positive exponent implies that the orbits are on a chaotic attractor; thus, the presence of a positive Lyapunov exponent indicates chaos.

Though there are various methods to calculate the Lyapunov exponent, we have used the algorithm proposed by Rosenstein et al. [17], which is fast, easy to implement, and robust to changes in the embedding dimension, size of data set, embedding lag, and noise level. This method looks for the nearest neighbor of each point in phase space and tracks their separation over a certain time evolution.

**E. IE**

Núñez et al. [33] proposed a technique to detect the nature of complexity of a system using the information entropy (IE). The time series $x(i)$ of length $N$ having embedded time delay (lag) $\tau$ and embedded dimension $m$ will have $m$ number of variables (dimensions) denoted by $X_k$, where $k = 1, 2, \ldots, m$ each of length $N' = N - (m - 1)\tau$. The IE $I(X_1, \ldots, X_m)$ for the system with $m$ number of variables is defined as

$$
I(X_1, \ldots, X_m) = H(X_1, \ldots, X_m) - \text{mean} \left( \sum_{j=1}^{m} H_j \right) \quad (10)
$$

where $H_j$ is the joint entropy of all the variables, except the $j$th variable, i.e., $X_j$ and $H$ are the joint entropy of all the variables. The joint entropy is calculated using the concept described in the paper by Núñez [33, eqs. (10), (11a), and (11b)]. The IE at any time $n$ (where $n = 2, \ldots, N'$) can be obtained on taking the variables up to the length $n$, which implies that the IE has values from time 2 to $N'$. If $x(i)$ is regular, then $X_1, \ldots, X_m$ are strongly correlated for all time $n$ and $I(n) \approx 0$. On the other hand, if $x(i)$ is chaotic, then $X_1, \ldots, X_m$ will be uncorrelated and $I(n) > 0$ for a span of time [33].

**F. RP and RQA**

**RP:** The graphical depiction of the matrix of all those times at which a state of the dynamical system recurs is the RP of the system. Eckmann et al. [34] pioneered a mean to picture the recurrence of states $s_i$ in a phase space. It allows us to inspect the $m$-dimensional phase space trajectory through a 2-D representation of its recurrences. Such recurrence of a state at time $i$ at a different time $j$ is marked within a 2-D squared matrix with black and white dots representing ones and zeros, where both axes are time axes. This illustration is called the RP. Such an RP can be mathematically expressed as

$$
\text{RP}_{i,j} = H(\varepsilon_i - ||s_i - s_j||), \quad x_i \in \mathbb{R}^d, i, j = 1, \ldots, N \quad (11)
$$

where $\text{RP}_{i,j}$ is the RP, $N$ is the number of considered states $s_i$, $\varepsilon_i$ is a threshold distance, and $H(\ast)$ is the Heaviside step function. The RP thus obtained will have very long diagonal lines for periodic signals, will have very short diagonal lines for chaotic signals, and will have no diagonal lines at all but homogeneous distribution for stochastic signals.

**RQA:** Beyond the visual inspection of RPs, some measures of complexity based on the recurrence point density, diagonal and vertical structures in the RP have been proposed in [19] and [35]–[37] and are known as RQA.

The first recurrence variable is $\%\text{REC}$. $\%\text{REC}$ quantifies the percentage of recurrent points falling within the specified threshold, i.e., it basically counts the black dots in the RP. This variable can range from 0% (no recurrent points) to 100% (all points recurrent). The expression for $\%\text{REC}$ is as follows:

$$
\text{REC}(\varepsilon_i) = \frac{1}{N^2} \sum_{i,j=1}^{N} \text{RP}_{i,j}(\varepsilon_i). \quad (12)
$$
The second recurrence variable is %DET or predictability, which measures the ratio of recurrence points forming diagonal structures to all recurrence points, as expressed in (14). Diagonal line segments must have a minimum length defined by the line parameter, lest they be excluded. For a periodic signal, %DET is close to 100%, and for a stochastic signal, it tends toward 0% value, whereas for a chaotic signal, its value varies in between that of periodic and stochastic signals. Now, if we define

\[ D_{i,j} = \begin{cases} 
1, & \text{if } (i,j) \text{ and }(i+1,j+1) \text{ or }(i-1,j-1) \text{ are recurrent} \\
0, & \text{otherwise} 
\end{cases} \]

then

\[ \%\text{DET} = \frac{\sum_{i,j=1}^{N} D_{i,j}}{\sum_{i,j=1}^{N} R_{i,j}} \]  

(14)

The third recurrence variable is linemax, i.e., %LMAX, which is simply the length of the longest diagonal line segment in the plot, excluding the main diagonal line of identity, where \( i = j \). Eckmann et al. [34] suggested that it inversely scales with the most positive Lyapunov exponent. Thus, for the shorter linemax, the signal can be judged as more chaotic (less stable).

If \( N_i \) is the number of diagonal lines and we let \( l_i \) be the length of the \( i \)th diagonal line, then

\[ \text{LMAX} = \max(l_i) \]

where \( i = 1, \ldots, N_i \).

The fourth recurrence variable is entropy, i.e., ENTR, which is the Shannon IE of all diagonal line lengths distributed over integer bins in a histogram. It is the probability to find a diagonal line of exactly length \( l \) in the RP, thus

\[ \text{ENTR} = - \sum_{l=1}^{N_i} p(l) \ln p(l) \]  

(16)

where \( p(l) \) is the distribution of diagonal line lengths, and ENTR is a measure of signal complexity and is calibrated in units of bits per bin. High entropy is typical of periodic behavior, whereas low entropy indicates chaotic behavior. For simple periodic systems in which all diagonal lines are of equal length, the entropy can be expected to be 0.0 bins/bin [22].

III. RESULTS

Fig. 1(a) represents the original signal of the solar irradiance (from October 15, 1984 to October 15, 2003), and Fig. 1(b) represents the optimal values of the embedding dimensions \( m \), where the target variances \( \sigma^2 \) are minima for the data series. In the preceding figures, the optimal value of the embedding dimensions is 12.

Fig. 2(a) and (b) represents the DVV plot and the DVV scatter diagram for the time series, respectively. In Figs. 1(b) and 2(a), the minimum value of the target variance \( \sigma^2 \) for the solar irradiance time series obtained is \( 4.6459 \times 10^{-1} \), and in Fig. 2(b), the RMSE of the series obtained is \( 1.201 \times 10^{-1} \).

Fig. 3 gives the \( D_c(n) \) versus \( n \), \( p_n \) in the complex plane, \( D^*_c(n) \) versus \( n \), and \( K_c \) versus \( c \) for TSI data signals while performing the 0–1 test for chaos. The binary output of the “0–1 test” for this signal is \(-0.0044\), which is very close to 0.

The correlation dimension \( D(m) \) of the data using the Grassberger and Procaccia algorithm (GPA) [13], [18] is plotted with respect to the embedding dimension \( m \) in Fig. 4.

The correlation dimension, as found using the GPA, for the signal is 0.99527.

The largest Lyapunov exponent \( \lambda_{\text{max}} \) calculated for this time series signal using the algorithm proposed by Rosenstein et al. [17] is 0.0425 \( \approx 0 \).

The IE of the data series for the time \( N' \) has been calculated and shown in Fig. 5.

The RP for entire time series under investigation is shown in Fig. 6.

The RP and the RQA are obtained using cross recurrence plot toolbox 4.3 by Marwan (http://tocsy.agnld.uni-potsdam.de/).
Fig. 3. (a) $D_c(n)$ versus $n$, (b) $p_n$ in the complex plane, (c) $D^*_c(n)$ versus $n$, and (d) $K_c$ versus $c$ for solar irradiance data signals.

Fig. 4. $D(m)$ versus $m$ for the solar irradiance signal.

Fig. 5. IE versus time for the solar irradiance signal.

In the RQA computation, two studies have been made for the TSI signal: In the first case (global), the RQA variables have been computed for the entire time series; in the second case (local), the whole time series has been split into subseries, and the variables in each subseries (called an epoch) have been calculated. Each epoch is 500 days long and regularly shifted by 75 days, in such a way that each epoch overlaps the next one by 425 days. If $N_e$ is the length of each epoch and $d_e$ is the shift, the epoch $i$ corresponds in the time series to the days starting in $t = (i - 1)d_e + 1$ and ending in $t = (i - 1)d_e + N_e + 1$ [38]. The first investigation has been devised in view of comparing global effects due to structures in subseries, whereas the computation for various epochs has been made to emphasize the changes in state inside the whole time series.

The results corresponding to the variables computed on the global basis taking the whole time series into account are presented in Table I, whereas Fig. 7 corresponds to the variables computed on epochs for the TSI signal.

The threshold distance $\varepsilon_i$ has been selected to be 0.8, which is nearly 5% of the maximal phase space diameter of the signal [39].

<table>
<thead>
<tr>
<th>RQA variables</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>$%REC$</td>
<td>18.4522</td>
</tr>
<tr>
<td>$%DET$</td>
<td>99.4816</td>
</tr>
<tr>
<td>$LMAX$</td>
<td>1629.000</td>
</tr>
<tr>
<td>$ENTR$</td>
<td>3.7085</td>
</tr>
</tbody>
</table>
IV. DISCUSSION

From the DVV plot of the time series, the value of the corresponding target variance $\sigma^2$ is coming to be low, which signifies that this time series has deterministic components. The DVV scatter diagram and the corresponding RMSEs there clearly depict that the signal is appreciably nonlinear. Though the signal is nonlinear, there is no such significant sign of the existence of chaos in it, and this can be confirmed after noticing the following points.

1) The binary outputs of the 0–1 test for both signals are very close to 0, which proves the absence of chaos.
2) $D_c(n)$ and $D^*_c(n)$ do not linearly scale with $n$, as observed in Fig. 3(a) and (c), rather they are found to exhibit a bounded oscillatory function of $n$.
3) $p_n$ exhibits a bounded motion in the complex plane for the signals, as shown in Fig. 3(b). The preceding two points can be only noticed if the underlying dynamics of the signal is regular.
4) The stable converging fractional value of the correlation coefficient $D(m)$, as observed in Fig. 4, advocates in favor of the claim that the signals are not stochastic but rather deterministic.
5) The value of the largest Lyapunov exponent for the signal being close to zero seals the claim that the signal has a regular and stable behavior. A physical system with this nearly zero exponent is conservative. Such systems exhibit Lyapunov stability.

The IE, as shown in Fig. 5, states that though initially it has a nonzero value for a small span of time, later it tends toward zero. This is again a vote in favor of the nonchaotic (regular) dynamics of the solar irradiance.

The RP of the time series reveals that the signal is not stochastic or chaotic. The nonhomogeneity in the RP of the signal shows that the signal is nonstationary. The dominance of white bands in the RP of the signal signifies that there is abundance in the number of states, which are rare or far from normal.

The high value of the $\%\text{REC}$ for the signal, as obtained in Table I, indicates that there is regularity (may be periodic). The epoch numbers 6 (from day 376 to day 876), 18 (from day 1276 to day 1776), and 25 (from day 1801 to day 2301) have maximum $\%\text{REC}$ for the signal; whereas the epoch numbers 46 (from day 3376 to day 3876), 60 (from day 4426 to day 4926), 62 (from day 4576 to day 5076), and 66 (from day 4876 to 5376) have minimum $\%\text{REC}$.

From the high values of the $\%\text{DET}$ for the entire time series, it can be argued about the deterministic behavior of the signals. These variables remain high for all the epochs nearly up to 30, i.e., roundly up to day 2676. The inhomogeneity of the RP and the high values of RQA variables reveal events that can be interpreted as a thermodynamic phase transition.

High values of LMAX indicate that the process is periodic, and low values indicate that the process is chaotic. Table I shows a high value of LMAX, which indicates a probable periodic regularity in the TSI series. LMAX is nearly high for all epoch, except at epoch numbers 40 (from day 2926 to day 3426) and 58 (from day 4276 to day 4776).

The low entropy recommends in favor of the presence of chaos within the signal, whereas the high entropy indicates the regularity in the signal. As shown in Table I, ENTR has, more or less, a high value of 3.71 for the entire signal, which advocates for the regular dynamics of the signal. It has been observed that all the RQA parameters have high values up to epoch 30 (i.e., up to day 2676).

V. CONCLUSION

This study has revealed that the solar irradiance data have a stable, nonlinear, and more or less deterministic and regular dynamics. The absence of chaos in the present signal supports
the earlier observed multiperiodic nature [4–6] in it. The absence of chaos also advocates for the forecastability of the present time series both in short scale and long scale. As chaos is not taking part in the system, there is no such possibility of interplay between chaos and nonchaos [8]. Thus, the governing system for the present solar irradiance data can be considered with less complexity.

The predictability of the solar irradiance and its less complexity can be a pivotal breakthrough into the area of research in the fields like design of photovoltaic (PV) plants, solar thermal power plants, and Earth weather forecasting. Solar thermal and PV electricity productions are two optimistic climate-friendly technologies with mammoth prospective to oversatisfy the present global requirement for electricity consumption. Solar irradiance consists of direct and diffuse irradiance. Diffuse irradiance is only available in cloudy skies. Solar thermal power plants (which use large cylindrical parabolic mirrors that concentrate the sunlight on a line of focus) can only employ direct irradiance for power generation, whereas PV plants (which use semiconductor-materials-based PV solar cells) can extract electrical energy from the diffuse irradiance as well. The information regarding the solar irradiance signal complexity is important for the integration of PV plants into an electrical grid.

Proper knowledge of solar irradiance characteristics may help in the forecasting of the PV production, which in turn chiefly facilitates the grid operators to better accommodate the variable generation of electricity in their scheduling, dispatching, and regulation of power and thus lend a hand to optimize the electricity production and/or to trim down extra expenses by planning a suitable strategy. In the same way, to have an optimized production of electrical energy from the solar thermal power plants, the understanding of the intricacies of the solar irradiance signal may assist the engineers to design the plants accordingly.

Raychaudhuri [40] indicated that a small persistent variation in TSI may play an important role in climate changes. Rind et al. [41] also strongly established that there is a sturdy link between the Earth’s climate pulsation and TSI variation. In this regard, they stated that “Total solar irradiance changes, though of small magnitude, do appear to affect sea surface temperatures (SSTs), most obviously at latitudes where cloud cover is small and irradiance is abundant, such as the Northern Hemisphere subtropics during summer. The increased SSTs then help intensify circulations spiraling away from the sub-tropics, again favoring reduced rainfall near the equator and to the south, as well as northern mid-latitudes. Hence, both the TSI along with UV forcings produce similar effects, with the former helping to sharpen the response” [41]. Thus, proper awareness about the nature of the TSI signal will surely assist the climatologists and meteorologists to read and forecast the climate in short time scale and, hence, to analyze the weather in larger perspective.

REFERENCES

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