

Solar Activity Explored With Wavelet 1-D And 2-D

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ABSTRACT

In recent years, the interest in solar energy has risen due to surging oil prices and environmental concern [1]. About 12.5 percent in urban households and 56.5 percent of rural households are still unelectrified. In order to fill up the gap, the ministry of new and renewable energy sources (MNRES) has embarked on a clear policy of substituting at least 10% of grid power by the deployment of renewable energy sources [2]. The country has an estimated energy potential of around 85,000 MW from renewable energy sources like wind, small hydro, and biomass to get the same or constant energy from the sun, by using PV array with MPPT. In order to improve the forecasts of the impact of solar activity on the terrestrial environment on time scales longer than days, improved understanding and forecasts of the solar activity are needed. The first results of a new approach of modelling and forecasting solar activity are presented. The nonlinear characteristics of solar activity have been studied with wavelet methods [4]. Wavelet voltage-time spectra are examined for one day i.e. the period 9 A.M to 5 P.M .This wavelet spectra is observed for both wavelet 1-D and 2-D similarly the one year solar cycle was further studied with these methods. The simulation results are discussed in this paper.

Keywords-- Solar panel, MPPT, wavelet toolbox, MNRES, STS, SP

I.INTRODUCTION

The solar energy is an energy source, which finds at least its importance in the isolated sites where grid power is unavailable and a big investment is needed to implement it. The solar energy is a source with no pollution, no noise and renewable [5]. But, its major problem resides in the initial cost of the system and how to choose the different components with little maintenance [6]. To reduce these problems; two ways can be used. The first is the cost utility. The second one is correct utilization of power. Wind energy and Renewable PV systems interface scheme with the electric hybrid utility are rapidly growing in recent years [7,8]. The scheme comprises of a PV array, DC link and line commutated inverter as the elements of this energy converter. The application of the photovoltaic systems is not limited to the isolated area; but it can be locally at the domestic level [9]. The PV systems are normally, non-linear power sources that need accurate on-line. Identification of the optimal operating point. Also, the power from PV array varies depending on the environmental factors such as insulation and cell temperature. Energy radiated by the sun converts to heat when it reaches earth. Some heat is reflected back through the atmosphere, while some is absorbed by atmospheric gases and radiated back to earth.

To operate at peak efficiency, solar panels should be aligned perpendicular to the sun. But since the sun's position in the sky is constantly changing, frequent manual alignment is not practical. While solar trackers, which automatically align the panels for the sun's daily east to west transition, are available, they are expensive and prone to failure. A less-expensive option is to mount the panels facing south, and to include an easy way to adjust the tilt in order to compensate for the position of the sun in the sky as the seasons change. While the summer sun appears almost directly overhead at mid-day, winter sun appears to the south. The drawing below shows the sun's position, and the approximate best angle for roof-mounted panels for the summer and winter seasons. While you probably don't want to change the angle every month, changing it two to four times per year will improve the performance of your array. Using data for my location, I've decided to use a 45 degree angle for spring and summer, and 50 degrees for fall and winter.

Photo voltaic arrays are used to provide energy from many electrical applications to get the maximum power from the pv array, a maximum power point tracker (MPPT) is used to control the variations in I-V characteristics of the solar cells .fig.2 shows the I-V curve will change depending on the temperature and illumination. Fourier transform is not suitable if the signal has time varying frequency, i.e., the signal is non-stationary. If only, the signal has the frequency component "f" at all times (for all "t" values), then the result obtained by the Fourier transform makes sense. Therefore for non stationary signals wavelet transform is applicable. The wavelet transform is a transform of this type. It provides the time-frequency representation. (There are other transforms which give this information too, such as short time Fourier transforms, Wigner distributions, etc.).

Since the solar activity can be described as a nonlinear chaotic dynamic system (Mundt et al., 1991) methods such as wavelet method is one of the suitable method (Lundstedt (1997); Lundstedt (2001)). Many have used wavelet techniques for studying solar activity. The fig.1 shows the block diagram without maximum peak power tracking (MPPT). From the fig.1 solar panel converts light energy into electrical energy with the help of photo voltaic cells. A 12v battery is used as an energy storage unit.

II.LITERATURE REVIEW

A low-power low-cost highly efficient maximum power point tracker (MPPT) to be integrated into a photovoltaic (PV) panel is proposed. This can result in a 25% energy enhancement compared to a standard photovoltaic panel, while performing functions like battery voltage regulation and matching of the PV array with the load. Instead of using an externally connected MPPT, it is proposed to use an integrated MPPT converter as part of the PV panel. It is proposed that this integrated MPPT uses a simple controller in order to be cost effective. Furthermore, the power converter has to be very efficient, in order to transfer more energy to the load than a directly-coupled system. This is achieved by using a simple soft-switched topology. A much higher conversion efficiency at lower cost will then result, making the MPPT an affordable solution for small PV energy systems[6].

In order to improve the forecasts of the impact of solar activity on the terrestrial environment on time scales longer than days, improved understanding and forecasts of the solar activity are needed. The first results of a new approach of modeling and forecasting solar activity are presented. Time series of solar activity indicators, such as sunspot number, group sunspot number, F10.7, E10.7, solar magnetic mean field, mountwilson plage and sunspot index, have been studied with new wavelet methods; ampligrams and time-scale spectra. Wavelet power spectra of the sunspot number for the period 1610 up to the present show not only that a dramatic increase in the solar activity took place after 1940 but also that an interesting change occurred in 1990. The main 11-year solar cycle was further studied with ampligrams for the period after 1850. Time-scale spectra were used to examine the processes behind the variability of the solar activity. Several interesting deterministic and more stochastic features were detected in the time series of the solar activity indicators. The solar nature of these features will be further studied[4].

A practical step-by-step guide to wavelet analysis is given, with examples taken from time series of the El Niño–Southern Oscillation (ENSO). The guide includes a comparison to the windowed Fourier transform, the choice of an appropriate wavelet basis function, edge effects due to finite-length time series, and the relationship between wavelet scale and Fourier frequency. New statistical significance tests for wavelet power spectra are developed by deriving theoretical wavelet spectra for white and red noise processes and using these to establish significance levels and confidence intervals. It is shown that smoothing in time or scale can be used to increase the confidence of the wavelet spectrum. Empirical formulas are given for the effect of smoothing on significance levels and confidence intervals. Extensions to wavelet analysis such as filtering, the power Hovmöller, cross-wavelet spectra, and coherence are described. The statistical significance tests are used to give a quantitative measure of changes in ENSO variance on interdecadal timescales. Using new datasets that extend back to 1871, the Niño3 sea surface temperature and the Southern Oscillation index show significantly higher power during 1880–1920 and 1960–90, and lower power during 1920–60, as well as a possible 15-yr modulation of variance. The power Hovmöller of sea level pressure shows significant variations in 2–8-yr wavelet power in both longitude and time.

Wavelet analysis is becoming a common tool for analyzing localized variations of power within a timeseries. By decomposing a time series into time–frequency space, one is able to determine both the dominant modes of variability and how those modes vary in time. The wavelet transform has been used for numerous studies in geophysics, including tropical convection (Weng and Lau 1994), the El Niño–Southern Oscillation (ENSO; Gu and Philander 1995; Wang and Wang 1996), atmospheric cold fronts (Gamage and Blumen 1993), central England temperature (Baliunas et al. 1997), the dispersion of ocean waves (Meyers et al. 1993), wave growth and breaking (Liu 1994), and coherent structures in turbulent flows (Farge 1992).

A complete description of geophysical applications can be found in Foufoula-Georgiou and Kumar (1995), while a theoretical treatment of wavelet analysis is given in Daubechies (1992). Unfortunately, many studies using wavelet analysis have suffered from an apparent lack of quantitative results. The wavelet transform has been regarded by many as an interesting diversion that produces, yet purely qualitative results. This misconception is in some sense the fault of wavelet analysis itself, as it involves a transform from a one-dimensional time series (or frequency spectrum) to a diffuse two-dimensional time–frequency image. This diffuseness has been exacerbated by the use of arbitrary normalizations and the lack of statistical significance tests. In Lau and Weng (1995), an excellent introduction to wavelet analysis is provided. Their paper, however, did not provide all of the essential details necessary for wavelet analysis and avoided the issue of statistical significance.

The purpose of this paper is to provide an easy-to use wavelet analysis toolkit, including statistical significance testing. The consistent use of examples of ENSO provides a substantive addition to the ENSO literature. In particular, the

statistical significance testing allows greater confidence in the previous wavelet- based ENSO results of Wang and Wang (1996). The use of new datasets with longer time series permits a more robust classification of interdecadal changes in ENSO variance.

III.CIRCUIT DETAILS

1. Block Diagram without MPPT:

The fig.1 shows the block diagram without maximum peak power tracking (MPPT).

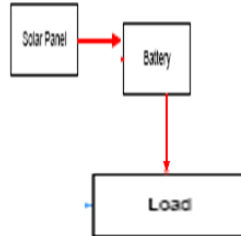


Fig .1 Block diagram without using MPPT

From the fig.1 solar panel converts light energy into electrical energy with the help of photo voltaic cells. A 12v battery is used as an energy storage unit. The PV generator characteristic is represented by an implicit non-linear equation,

$$I = I_g - I_{sat} \left[\exp(q(V + R_s I)/(AKT)) - 1 \right]$$

Where I_g is the light generated current, I_{sat} is the reverse saturation current, q is the electronic charge (1.6×10^{-19} C), A is a dimensionless factor, K is the Boltzmann's constant (1.3805×10^{-23} Nm/°K), T is the temperature in °K, R_s is the series resistance of the cell.

The PV system is composed firstly of a PV generator. It ensures a voltage and a variable direct current, knowing that the variance of the power is due to the changes in particular daily illumination, this climatic condition influences the extracted power [12] as shown in fig 8 and similarly voltage-time plot is examined for one day i.e. from 9.00am to 4pm is shown in fig 4.

2. Block Diagram with MPPT:

The concept of maximum power point tracking is best illustrated. MPPT is designed with AT89S52 MCU.Solar panel output is interfaced to Microcontroller through ADC. The controller continuously checks the voltage level of the panel and operates the stepper motor to attain maximum voltage. The fig.2 shows block diagram of MPPT.

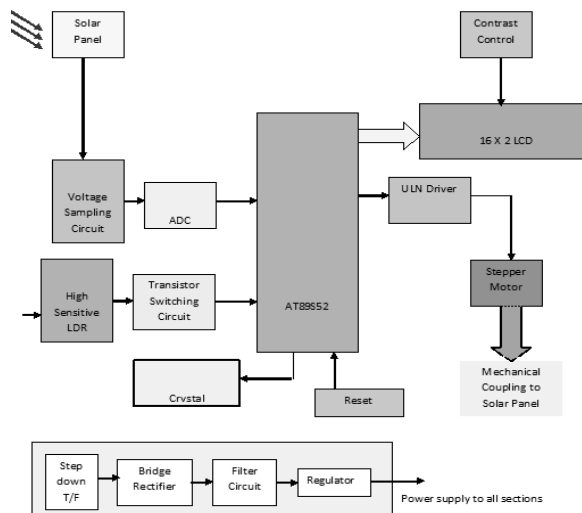
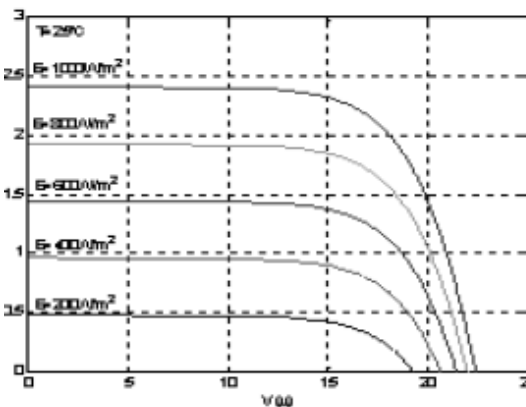


Fig 2 Block diagram With MPPT.

MPPT input stage followed by a single boost converter, which would bring a nominally 12 V solar panel up to the necessary 230 V DC. Using two boost converters in tandem was briefly considered but eventually discarded as excessively difficult to control and inelegant. 12 V nominal input voltage was not feasible since, at 300 W, this corresponds to a current of almost 42 A. Not only would this converter have heavy losses but it would be very difficult to test with available laboratory equipment. Thus, it was decided that the input voltage would be 12V, 24V, 48V, 36V nominally [11], fig 3



shows the V-I characteristics of MPPT.
 V-I characteristics of MPPT

Fig 3

IV. METHODOLOGY

Wavelet analysis is a powerful tool both to find the dominant mode of variation and also to study how it varies with time, by decomposing a nonlinear time series into time-frequency space. The wavelet transform of a function $y(t)$ is given by

$$w(a, b) = a^{-1/2} \int_{-\infty}^{\infty} y(t) g^* \left(\frac{t-b}{a} \right) dt$$

where a is the scale dilation, i.e. the compressing and stretching of the wavelet g , b is the translation parameter, i.e. the shifting of g , and g^* the complex conjugate of g . The Morlet wavelet is defined as a complex sine wave, localized with a Gaussian and given by

$$g(t) = \exp \left(i \omega_0 t - \frac{t^2}{2} \right)$$

where ω_0 is a phase constant. To analyze a discrete signal $y(t_i)$ we need to sample the continuous wavelet transform on a grid in the time-scale plane (b, a) . By setting $a=j$ and $b=k$ the wavelet coefficients $w_{j,k}$ are

$$w_{j,k} = j^{-1/2} \int_{-\infty}^{\infty} y(t) g^* \left(\frac{t-k}{j} \right) dt$$

When the wavelet coefficient magnitudes (WCM) are plotted for the scale and the elapsed time. Wernik et al. (1997) introduced a method to study this, based on non-linear filtering of the wavelet coefficients. The deterministic strong part is obtained by setting to zero all wavelet coefficients less than a certain threshold. The inverse wavelet transform is then used to calculate the corresponding time series. The stochastic weak part is obtained by setting to zero all wavelet coefficients greater than that threshold level. The inverse wavelet transform is then used to calculate the corresponding time series. New wavelet spectra are finally calculated for each partial time series.

Ampligrams and time-scale spectra (Liszka, 2003) can be looked upon as a generalization of the above technique, a kind of band-pass filtering in the WCM domain analogous to Fourier analysis is in a frequency domain. They can be used to separate independent components of the signal, assuming that the different components are characterized by different wavelet coefficient magnitudes (spectral densities). Ampligrams are constructed in the following way: The maximum magnitude ($|W|$) among the wavelet coefficients is first found. L magnitude intervals are then defined,

$$I_l = [(l-1)\Delta w, l\Delta w], l=1,2,\dots,L \text{ with } \Delta w = |W|/L$$

From that we construct L matrices $W_l, l=1,2,\dots,L$ such that $j,$

$$w_{j,k}^{(l)} = \begin{cases} w_{j,k} & \text{if } |w(l)j, k| \in I_l \\ 0 & \text{otherwise} \end{cases}$$

Inverse the wavelet transform to get a new time-signal $y_l(t_i), l=1, \dots, L$. Each $y_l(t_i)$ is what the signal should have looked like if only a narrow range of wavelet coefficient amplitude would be present in the signal. After that an $L \times N$ matrix Y is constructed with $y_l(t_i)$ as rows. This matrix Y is the ampligram of the original time-signal $y_1(t_i)$. Finally to construct the time-scale spectra each row of the ampligram matrix Y is first wavelet transformed, which results in L matrices. We then time-average these matrices (average along rows) leading to L arrays \bar{w}_l with J elements. Finally, an $L \times J$ matrix \bar{Y} is constructed, with \bar{w}_l as rows. This matrix \bar{Y} is the time-scale spectrum of the ampligram.

Continuous wavelet transform analogy:

The continuous wavelet transform was developed as an alternative approach to the short term fourier series transform to overcome the resolution problem [13]. Similar to window function in the STFT, and the transform is computed separately for different segments of the time domain signal. However, there are two main differences between the STFT and CFT:

1. The fourier transforms of wavelet signals are not taken, and therefore single peak will be seen corresponding to a sinusoid, i.e., negative frequencies are not compared.
2. The width of the window is changed as the transform is computed for every single spectral component, which is probably the most significant characteristic of the wavelet transform.

The continuous wavelet transform is defined as follows:

$$CWT_{\tau, s}(t, s) = \frac{1}{\sqrt{|s|}} \int x(t) \psi \left(\frac{t-\tau}{s} \right) dt$$

where $\psi(t)$ is a continuous function in both the time domain and the frequency domain called the mother wavelet and $*$ represents operation of complex conjugate. The main purpose of the mother wavelet is to provide a source function to generate the daughter wavelets which are simply the translated and scaled versions of the mother wavelet. To recover the original signal $x(t)$, inverse continuous wavelet transform can be exploited.

$$x(t) = \int_0^\infty \int_{-\infty}^\infty \frac{1}{a^2} X_w(a, b) \frac{1}{\sqrt{|a|}} \tilde{\psi} \left(\frac{t-b}{a} \right) db da$$

$\tilde{\psi}(t)$ is the dual function of $\psi(t)$. And the dual function should satisfy

$$\int_{-\infty}^\infty \int_{-\infty}^\infty \frac{1}{|a^3|} \psi \left(\frac{t_1-b}{a} \right) \tilde{\psi} \left(\frac{t-b}{a} \right) db da = \delta(t-t_1).$$

Sometimes

$$\tilde{\psi}(t) = C_\psi^{-1} \psi(t),$$

Where

$$C_\psi = \frac{1}{2} \int_{-\infty}^{+\infty} \frac{|\tilde{\psi}(\zeta)|^2}{|\zeta|} d\zeta$$

is called the admissibility constant and $\hat{\psi}$ is the Fourier transform of ψ . For a successful inverse transform, the admissibility constant has to satisfy the admissibility condition:

$$0 < C_{\psi} < +\infty.$$

It is possible to show that the admissibility condition implies that $\hat{\psi}(0) = 0$, so that a wavelet must integrate to zero. As seen above equation, the transformed signal is a function of two variables, τ and s , the translation and scale parameters, respectively, $\Psi(t)$ is the transforming function, and it is called mother wavelet. The term mother wavelet gets its name due to two important properties as explained below:

The term wavelet means small wave. The smallness refers to the condition that this function is of finite length. The wave refers to the condition that this function is oscillatory. The term mother implies that the function with different region of support that are used in the transformation process are derived from one main function, or the mother wavelet. In other words, the mother wavelet is a prototype for generating the window functions.

$$m_k = \int t^k \psi(t) dt.$$

if $m_0 = m_1 = m_2 = \dots = m_{p-1} = 0$

we say $\psi(t)$ has p vanishing moments.

The term translation is used in the same sense as it was used in the STFT; it is related to the location of the window, as the window is shifted through the signal. This term, obviously, corresponds to time information in the transform domain. However, we do not have a frequency parameter, as we had before for the STFT. Instead, we have scale parameter which is defined as (1/frequency). The term frequency is reversed for the STFT.

V. RESULTS AND DISCUSSIONS

The wavelet analysis for voltage time curve and voltage-current curves for wavelet 1-D and wavelet 2-D with compressed images. In wavelet 1-D by loading the signal we can observe the wavelet coefficients where as in wavelet 2-D by loading the image we can observe the compressed image.

The purpose of wavelet 1-D is to show how to analyze, denoise or compress a multisignal, and then to cluster different representations or simplified versions of the signals composing the multisignal.

In this example, the signals are first analyzed and different representations or simplified versions are produced:

- * Reconstructed approximations at given levels,
- * Denoised versions,
- * Compressed versions.

Denoising and compressing are two of the main applications of wavelets, often used as a preprocessing step before clustering. The fig 4 shows voltage time curve. fig 5 shows continuous wavelet 1-D representation.

The purpose of wavelet 2-D is to show how to compress an image using two-dimensional wavelet analysis. Compression is one of the most important applications of wavelets. Like de-noising, the compression procedure contains three steps:

- * Decompose: Choose a wavelet, choose a level N. Compute the wavelet decomposition of the signal at level N.
- * Threshold detail coefficients: For each level from 1 to N, a threshold is selected and hard thresholding is applied to the detail coefficients.
- * Reconstruct: Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

The fig 6 shows wavelet 2-D representation, fig 7 shows wavelet 2-D compressed image representation for voltage-time curve and Fig 8 represents the V-I curve. and fig 9 shows the continuous wavelet 1-D representation. fig 10 shows wavelet 2-D representation for V-I curve and fig 11 represents compressed image for voltage-current characteristics.

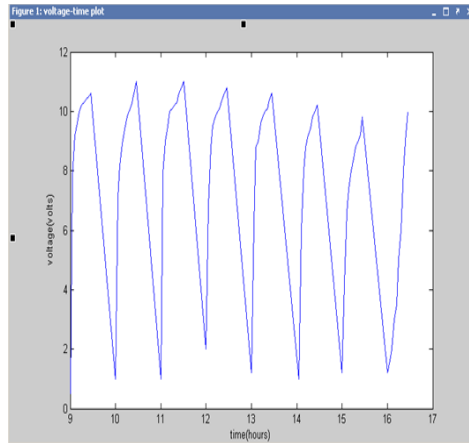


Fig 4 voltage time curve

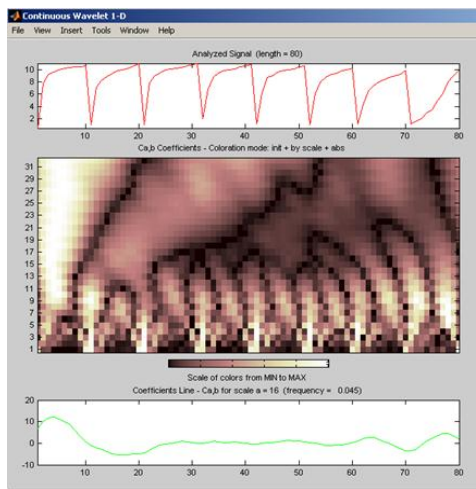


Fig 5 Continuous wavelet 1-D representation.

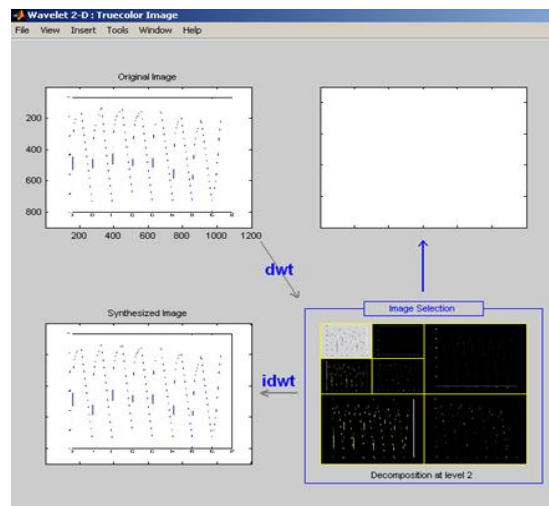


Fig 6 wavelet 2-D representation

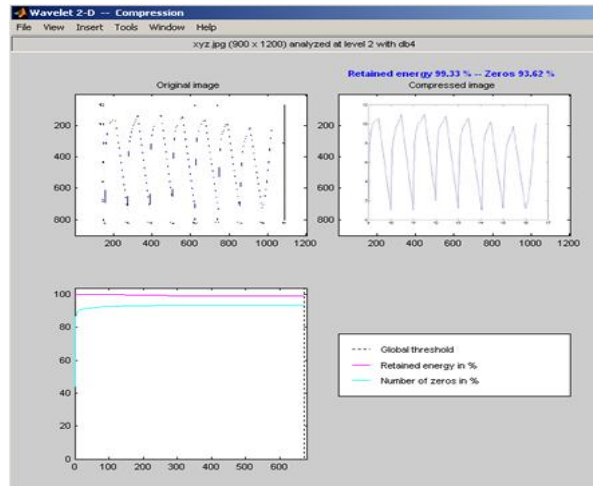


Fig 7 Wavelet 2-D compressed image representation

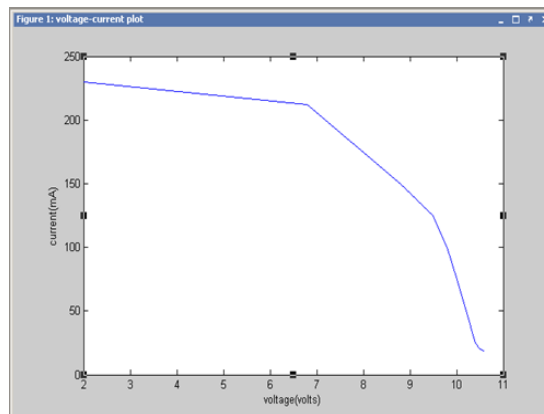


Fig 8

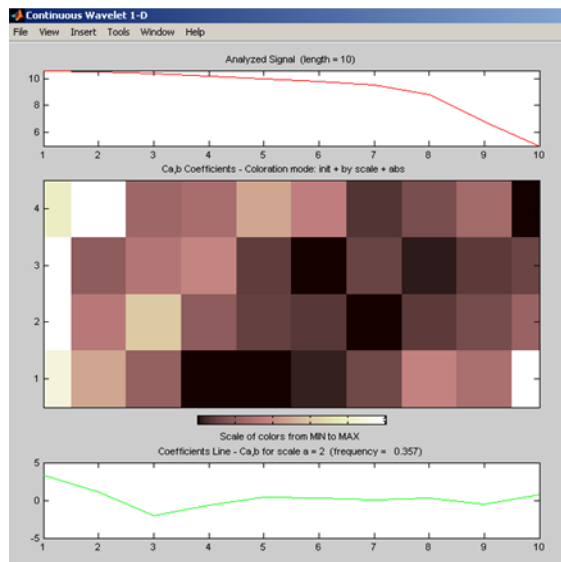


Fig 9 continuous wavelet 1-D representation

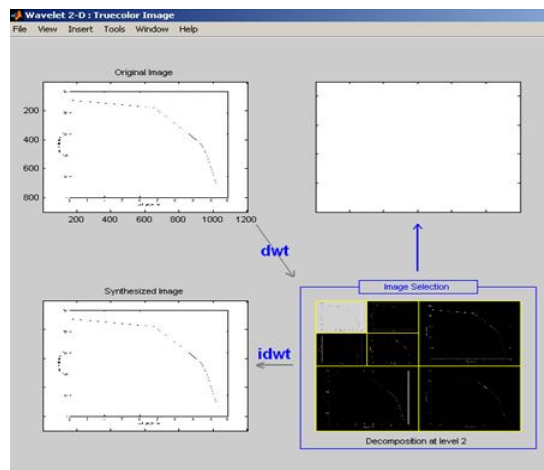


Fig 10. Wavelet 2-D representation for V-I curve

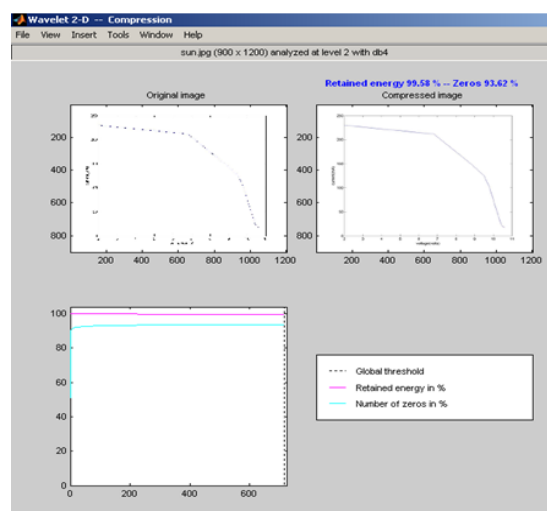


Fig 11. Compressed image for V-I characteristics.

VI. CONCLUSION

This paper presented the results of new approach of forecasting solar activity. New wavelet methods were used to explore the non-linear solar activity. It is difficult to observe the maximum voltage where it will present in one day duration .so by using wavelet it shows where the peak voltage is appeared .similarly is currently working as at the one year solar cycle was further studied with these methods wavelet 1-D and 2-D.

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