Gap Filling of Solar Radiation Data using Polynomial Fitting and Wavelet Transform Comparison

Dr.P.M.Beulah Devamalar[1] Dr.V.Thulasi Bai[2] D.Jahnavi[3] V.Vidhyawathy[4]
[1]Principal [2]Vice Principal [3]Assistant Professor [4]P.G. Scholar
[1,2,3,4]Department of Electronics & Communication Engineering
[1,2,3,4]Prathyusha Institute of Technology and Management, Tamil Nadu, India

Abstract— The amount of solar energy received is highly transient in nature, due to many meteorological conditions and needs to be analyzed for different applications like weather forecasting, resource assessment etc. The data captured using electronic data acquisition system is large, and thus there is a need to filter the data, to modify the data to be compact. Thus the data was filtered by using polynomial fitting method. This paper aims to fill the gaps of missing solar radiation data and to compare various wavelet transforms such as Haar wavelet, daubechies wavelet (D10) in compressing received solar radiation data.

Key words: polynomial fitting, global solar radiation data, Haar wavelet transform, daubechies wavelet transform

I. INTRODUCTION

The current aim is to provide an alternative energy resource. It is better to invest in the energy received from the sun. The solar radiation is an instantaneous power density measured in units of kW/m^2. In providing alternative energy sources and in electricity generation solar radiation prediction and forecasting plays a vital role [2]. The importance in developing solar radiation forecasting related technology is inevitable. In Karim et al. [3], compressing the solar radiation and prediction is done by using wavelet transform. Their work is based on symlet 6 wavelets and Meyer wavelets. Wavelets are been used in forecasting [7]. Besides, in solar radiation forecasting second generation wavelets construction with recurrent neural networks is been used for prediction [1]. In Karim et at. [4] the best polynomial fitting degree for solar radiation data is calculated using rmse (root mean square error) and r^2 value.

The rest of this paper is structured as follows. In section II fitting and prediction of solar radiation data using polynomial fitting is discussed. Section III presents the wavelet transforms. Results are discussed and summarized in Section IV. Finally, in Section V conclusions are drawn.

II. POLYNOMIAL FITTING

Polynomial data fitting is used for filtering and smoothening of global solar radiation data received in the stations. It was tested by various degrees of solar radiation data. Fig 1 shows the basic block diagram which describes the flow of polynomial data fitting method. As per the flow, the solar radiation data is obtained shown in Table 1 and it is represented graphically in Fig 2.

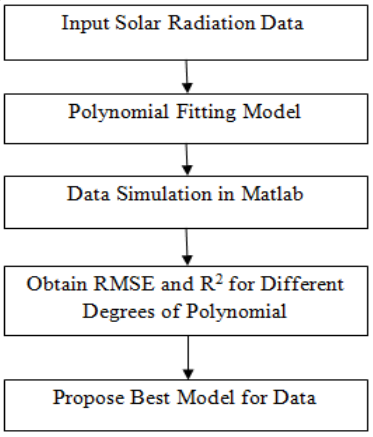

Fig. 1: Polynomial fitting framework

A. Solar Radiation Data Fitting:

There are various degrees of polynomial curve fitting such as linear polynomial, quadratic polynomial, cubic polynomial, 4^{th} degree polynomial, 5^{th} degree polynomial, 6^{th} degree polynomial and so on. These polynomials are applied on the received solar radiation data for a perfect fitting. All the polynomial coefficients are obtained under 95% confidence interval. The rmse and r^2 value is calculated for every degrees of polynomial. Table 2 shows all the polynomial fitting results.

Time (hours)	global solar radiation data (w/m2)
6.00	0
7.00	130
8.00	343
9.00	537
10.00	686
11.00	742
12.00	729
13.00	682
14.00	604
15.00	432
16.00	245
17.00	60
18.00	0

Table 1: Daily Average of Measured Global Solar Radiation Data (Thiruvallur- January 2010)

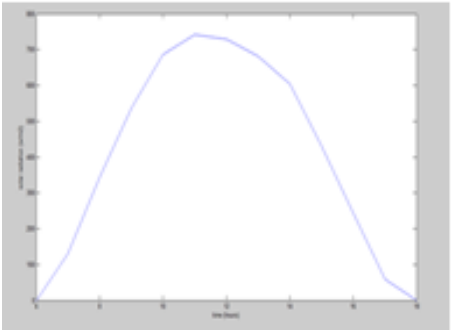

Fig. 2: Graphical representation (jan 2010)

All rights reserved by www.ijsrd.com

Rmse which gives an error value and r^2 (coefficient of distribution) gives the goodness of fitting of data. On analyzing, it can be clearly seen that for higher degrees of polynomial the fitting graphs will starts to wiggle thus higher degrees are omitted though they give a low rmse value and high r^2 value [4].Since higher degrees becomes unstable. Among the entire model 2nd, 3rd and 4th polynomial degree seems to give better results. From Wu and Chan [2], we believe the best model for the fitting of solar radiation data is quadratic polynomial shown in Fig 3. Since it gives better indication to the solar radiation data compare with other polynomial fitting model.

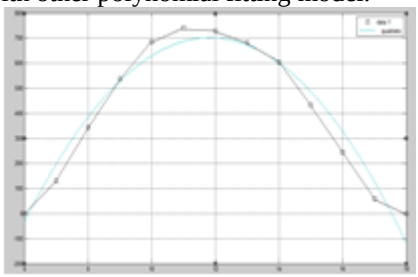

Fig. 3: Quadratic polynomial

Polynomial fitting	statistics	
	RMSE	R^2
Linear model Poly1: f(x) = p1*x + p2 Coefficients: p1 = -7.038 (-55.6, 41.53) p2 = 483.7 (-126.8, 1094)	297.7	0.009166
Quadratic polynomial: f(x) = p1*x^2 + p2*x + p3 Coefficients p1 = -21.58 (-24.83, -18.33) p2 = 510.8 (432, 589.6) p3 = -2321 (-2765, -1877)	65.29	0.9567
Cubic polynomial: f(x) = p1*x^3 + p2*x^2 + p3*x + p4 Coefficients p1 = 0.6533 (-0.3134, 1.62) p2 = -45.09 (-80.03, -10.16) p3 = 776.7 (376.2, 1177) p4 = -3254 (-4698, -1810)	61.32	0.9656
4th degree polynomial: f(x) = p1*x^4 + p2*x^3 + p3*x^2 + p4*x + p5 Coefficients p1 = 0.3878 (0.276, 0.4995) p2 = -17.96 (-23.34, -12.58) p3 = 276.3 (182.8, 369.7) p4 = -1575 (-2268, -882.1) p5 = 2872 (1031, 4713)	21.68	0.9962
5th degree polynomial: f(x) = p1*x^5 + p2*x^4 + p3*x^3 + p4*x^2 + p5*x + p6 Coefficients p1 = -0.003893 (-0.04438, 0.03659) p2 = 0.6214 (-1.811, 3.054) p3 = -23.39 (-80.18, 33.39) p4 = 337.2 (-305, 979.4) p5 = -1905 (-5414, 1604) p6 = 3556 (-3837, 1.095e+004)	23.09	0.9962
6th degree polynomial: f(x) = p1*x^6 + p2*x^5 + p3*x^4 + p4*x^3 + p5*x^2 + p6*x + p7 Coefficients p1 = 0.01432 (0.007997, 0.02064) p2 = -1.035 (-1.491, -0.5793) p3 = 30.78 (17.42, 44.14) p4 = -481.1 (-684.9, -277.4) p5 = 4132 (2432, 5833)	10.08	0.9994

Table 2: Polynomial Fitting

B. Prediction of Missing Data:

Solar radiation prediction is an important task for all engineers in providing the photo voltaic power generation. Using polynomial fitting, prediction of missing data is determined. From previous result, quadratic polynomial fitting in (1) can be used to predict the missing data in mathematical calculation also

$$f(x) = \sum_{i=0}^{2} a_i x^i \qquad (1)$$

With

a0= -21.58 , a1= 510.8 ,a2= -2321

where x=1 corresponds to 6.00 a.m and x=2 corresponds to 7.00 a.m.

Table 3 shows the original global solar radiation on january 2010 and with assumption of two missing data . Using polynomial curve fitting the missing data can be found and can be verified with the non-missing original data set of January 2010. The missing of data's are been represented as zero (0). Now inserting the previous year data on the missing values we can plot a polynomial fitting curve.

GLOBAL SOLAR RADIATION DATA				
TIME (HOURS)	ORIGINAL	MISSED DATA	PREVIOUS YEAR DATA	INSERTED DATA
6	0	0	0	0
7	130	130	130	130
8	343	343	343	343
9	537	537	534	537
10	686	686	678	686
11	742	742	765	742
12	729	729	778	729
13	**682**	**0**	**725**	**725**
14	**604**	**0**	**594**	**594**
15	432	432	468	432
16	245	245	261	245
17	60	60	63	60
18	0	0	0	0

Table 3: Missing Of Data 0n January 2010

Quadratic polynomial fitting is applied to the missing data. Prediction of missing data on the quadratic polynomial curve fitting gives the approximated original data which is been verified with the received data, shown in Fig 4(a) & (b).

The main drawback is that high-degree fits can become unbalanced. Within the given range polynomial fitting can give a good fit but can vary widely outside that range.

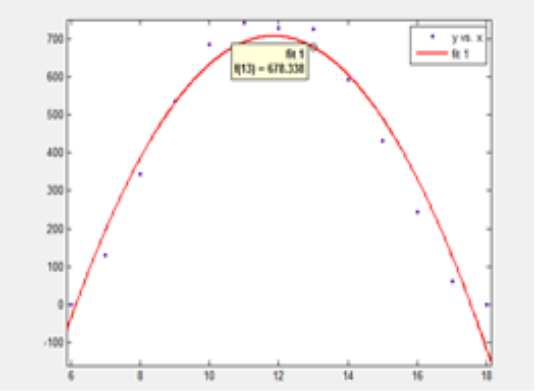

Fig. 4 (a): Prediction of Value at 13 (678.338)

All rights reserved by *www.ijsrd.com*

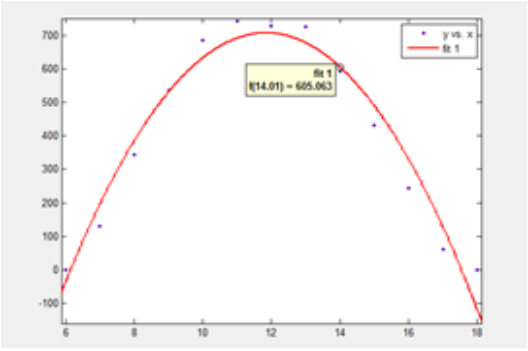

Fig. 4 (b): Prediction of value at 14 (605.063)

III. WAVELET TRANSFORM AND DATA COMPRESSION

Wavelet based filtering approach is based on applying low pass and high pass filter to obtain detail and approximation coefficients. Then by applying threshold method the detail coefficient which contains unwanted information is cut down to get a desired filtered value. The wavelet transforms are applied to values shown in Fig 2. And obtain compressed signals to compare haar and daubechies wavelet transform.

A. Haar Wavelet Transform:

It is the simplest type of wavelet that decomposes a signal into two sub signals of half its length. One sub signal is an average and other is a difference. It pairs up input values by storing differences and passing the sum. Fig 5 shows the compressed signal using haar wavelet transform.

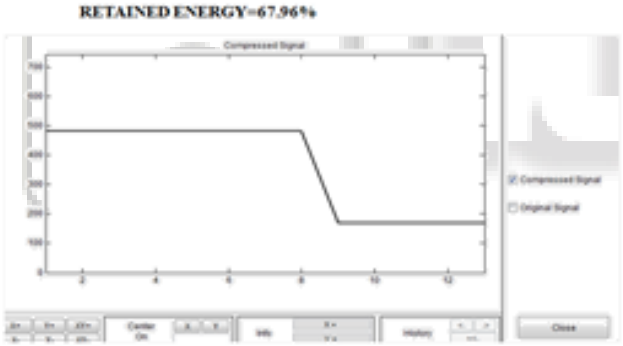

Fig. 5: Compression using Haar wavelet transform

B. Daubechies Wavelet Transform:

It is as same as haar wavelet by computing the averages and differences via scaling products with scaling signals the only difference is how the scaling signals are defined. Daubechies wavelet has about 10 levels. We use D10 for compressing the signal. Fig 6 shows the compressed signal using daubechies wavelet transform.

Retained Energy=81.08%

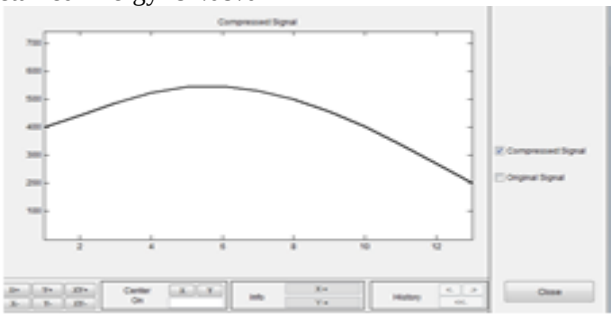

Fig. 6: Compression using Daubechies wavelet transform

IV. RESULTS AND DISCUSSION

The drawback in polynomial fitting is that higher degrees can become unbalanced. And within the range it provides a good fit but varies widely outside the range. Thus filtering method is moved towards wavelet transform which gives a detailed view of analysis. From table 4, it is given that the haar wavelet has a retained energy of about 67.96% and daubechies wavelet transform has a retained energy of about 81.08% for same thresholding value. Thus the obtained results shows daubechies wavelet transform provides better results than haar wavelet transform.

PROPERTIES	HAAR WAVELET TRANSFORM	DAUBECHIES WAVELET TRANSFORM
RETAINED ENERGY	67.96%	81.06%
NO. OF ZEROS	86.67%	73.91%

Table 4: Comparison of wavelet Transform

V. CONCLUSION

In this paper global solar radiation data prediction using polynomial fitting gives approximate values but it may vary for other data sets due meteorological condition changes. Thus daubechies D(10) wavelet transform which gives higher retained energy can be used for prediction of missing data.

REFERENCES

[1] G. Capizzi, C. Napoli, and F. Bonanno, "Innovative second-generation wavelets construction with recurrent neural networks for solar radiation forecasting," IEEE Transactions on Neural Networks and Learning Systems, vol. 23, no. 11, pp. 1805–1815, 2012.

[2] Wu, J. and Chan, C.K. Prediction of hourly solar radiation using a novel hybridmodel of ARMA and TDNN. Solar Energy 85:808-817, 2011.

[3] Karim, S.A.A., Singh, B.S.M., Razali, R. and Yahya, N. Data Compression Technique for Modeling of Global Solar Radiation. In Proceeding of 2011 IEEE International Conference on Control System, Computing and Engineering (ICCSCE) 25-27 November 2011, Holiday Inn, Penang, pp. 448-35,(2011a).

[4] Samsul Ariffin Abdul Karim and Balbir Singh Mahinder Singh,'' Global Solar Radiation Modeling Using Polynomial Fitting'' Applied Mathematical Sciences, Vol. 8, 2014, no. 8, 367 – 378.2012.

[5] Antoniadis, A. "Wavelets methods in statistics: some recent developments and their applications," Statistics Surveys, vol. 1, pp. 16-55, 2007.

[6] Daubechies, I. (1992). "Ten Lectures on Wavelets", Vol. 61, CBMSNSF Reg. Con. Ser. Appl. Math., Society for Indutsrial Appliied Maths (SIAM), Philadelphia, PA.

[7] Chui, C. K. An Introduction to Wavelets. Academic Press, New York, (1992)

All rights reserved by *www.ijsrd.com*