Mid-term Solar Forecast system based on Geostationary Satellite data

Zhenzhou Peng #1, Shinjae Yoo #2, Dantong Yu #3, Dong Huang *4

#*Stony Brook University*
100 Nicolls Road, Stony Brook, NY 11794
1zhenzhou.peng@stonybrook.edu

**Brookhaven National Laboratory*
50 Bell Avenue, Upton, NY 11973
2sjyoo@bnl.gov
3dtyu@bnl.gov
4dhuang@bnl.gov

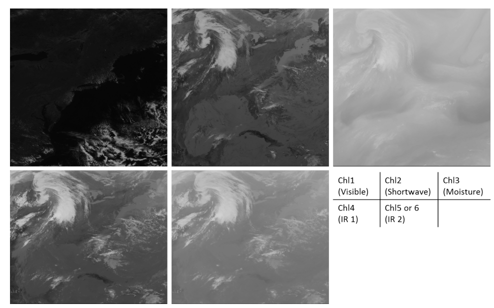
***Abstract*—Prediction of solar energy has become a significant concern in smart grid field. In this papar, a mid-term forecast system is designed with utilizing Optical Flow Motion Estimation on multi-channel geostationary data and Support Vector Regression(SVR) on solar radiation. Different from previous approaches, our system is trying to improve satellite model precision and fill the gap of forecasting in 30 minutes up to 5 hours. The experiment result shows that performance in both estimation and forecasting has been significantly improved.**

I. Introduction

With utilization and economy concern, planning and managing of control in advance acquires great importance in solar grids system. For the purpose of making decisions in near future, a forecast system is needed to provide information of solar energy tendency and distribution. Since operations of solar grids rely on accuracy of forecast outputs, especially hourly estimation, this system needs to assimilate local knowledge of cloud fraction and more importantly the atmospheric change in large scale.

Since the main source of irradiance fluctuation is cloud distribution and variation, we propose a new system based on geostationary satellite data and its correlation with solar irradiance. In general, the forecast system consists of two part: Estimation of solar irradiance based on current cloud information from satellite and forecast of cloud motion in near future. In the estimation procedure, we use Support Vector Machine(SVM) learning strategy to do regression on ground-based measurement and preprocessed multi-channel data to get estimated solar radiation. Then use optical flow motion estimation as cloud forecasting strategy to get view of cloud distribution in near future. The combination of forecast cloud distribution and time feature of radiation will generate final predicted solar irradiance.

Although solar energy estimation combined with satellite data has been well studied since 1970s, most of works are discussing the visible channel correlated with cloud coverage. These approaches are not capable of forecasting or fail to acquire good precision and resolution since, 1) Cloud coverage is hard to extract in visible channel with brightness variation, 2) Spacial resolution of satellite cloud information is larger than coverage of pyranometer ground-truth, 3) Prediction of coverage of cloud on satellite lack both spacial and temporal accuracy even with Numerical Weather Prediction(NWP) model. 4) More information atmospherical variables such as temperature, humidity are needed for clear sky model.



To these concerns, our novelties lie in data source, model selecting, and more importantly, cloud motion forecasting:

1) **integration of multi-channel** Besides visible channel, we import other 4 channels multi-channel data of Geostationary Operational Environmental Satellite(GOES) imaging system into satellite model. Since each channel can sense radiant and solar reflected energy in different spectrum range, cloud properties can be presented with combination of multi-channel images(Figure I).
2) **New preprocessing approache** Instead of using various meorological clear sky models as reference. discussed previous works[1] we use statistical clear sky model with import multi-channel data of Geostationary Operational Environemental Satellite(GOES) imaging system into satellite model.
3) **radiation feature with time** Radiation measured in ground station is a good miniature of microscale solar energy change. We propose to add the variation of solar radiation as another concerned feature so as to provide robustness with localized knowledge.
4) **Max-margin regression** In satellite model field, linear model is widely used with empirical correction for local variation[2]. We address model differently using the idea of max-margin regression to improve performance. In

experiment, we consider both linear and non-linear kernel cases of Support Vector Regression model(SVR).

5) **New motion estimation algorithm** Unlike block-based template matching, we utilize the optical flow motion estimation as a tool to extract cloud motion with concern of gradient of greyscale change within smaller range.

In this paper, related works and models are discussed in Section 2. After introduction of each satellite model, Section 3 and Section 4 describes data preprocessing and strategy of SVM in new approach. Following our satellite pipeline, we present experiments results in Section 5 providing both estimation and forecast performance improvement. At last, in Section 6, a conclusion can be made for the mid-term prediction usage.

II. Background

As estimating solar radiation data from satellite images is more accurate than interpolating data measured by a modern radiometric network,[3], Many works regarding mesoscale range have been develop to do radiation estimation using satellite data. In early years, Satellite models are built up firstly to correlate cloud coverage with Global Horizontal Irradiance(GHI)[4], [5], [6]. Later works follows this idea by studying on linear relationship between Direct Normal Irradiance(DNI) and satellite visible channel[7], [8]. These models use "Cloud Index"(CI) as optical density derived from satellite data to indicate fraction or coverage. By using multiple empirical clear sky models, the local distribution of solar energy is derivable from satellite image[1], [9]. More recent works majorly follow this idea but with different concerns such as terrain factor[10], but with new ideas coming from knowledge of other fields such as statistical approach[11] and Artificial Neural Network(ANN) method[12], [13], moreover even without including meteorological data[14]. In fact, the biggest problem of framework of cloud coverage lies in untrusted and unstable visible channel image, since snow coverage and floating brightness of image with various zenith angle. Though Multispectral analysis is the most known and developed method to detect clouds, this work relies on heuristic thresholds for infrared and visible range are needed for cloud classification[15] and snow detection[16] Another drawback of previous works is that simple linear relation derived from cloud coverage has limitations in describing variation under cloudy condition. Therefore, a customized constant must be used as an estimation compensation to reduce linear biased influence [2].

On the topic of forecast using satellite, studies are mostly around cloud prediction. To describe cloud coverage in advance, cloud motion vector extraction is usually used for estimating cloud movement. As an import input parameter to feed satellite models. Cloud motion tracking algorithm is commonly generated from blockwise cross-correlation matching[17], [18]. It turns out to be highly senstive to block size and segmentation as it try to represent area of cloud in block unit. In fact, this methodology is based on a basic assumption that cloud motion is stable and identical with no deformation. But in reality, cloud on satellite image is more complicated as with rotation and shape changing. Therefore merging and splitting of cloud will be ignored due to fixed block size. Another extreme case is that when multilayer clouds appear, block matching will fail as its correlation only covers the texture information in a block. Therefore a lot of recent works tried evade the unsolved issue of cloud motion by integration of other source of information,e.g. radar ground measurement. One way to to predict cloud ahead is using ground radar to get continous radiation fluctuation trend[19]. Another work explores the time series feature of cloud statistically to do prediction[20]. The drawbacks of no-motion methodology is that cloud tracking is of low precision and forecast time can only be either minutes or up to 2 hours as they claimed. Though satellite approach is also in mesoscale, local information can be assimilated through adding ground-based pyranometer and multispectral views.Another drawback of current models is that the precision in both temporal and spacial aspect decrease rapidly with the longer forecast period. Due to the restriction of motion estimation algorithm, cloud

In our approach, we are targeting to use the ground-based pyranometer and satellite image to get estimated radiation in future. The local instrument can provide Direct Normal Irradiance(DNI) per second while satellite image has 30 minutes response time before next scanning. For pre-scheduling need, radiation forecast coverage starts from 30 minutes to 5 hours. Compared with pyranometer, satellite image has low spatial resolution(1 km x 1 km in VIS channel, 4km x 4km in Infrared channel), especially in multispectral and motion vector related applications. To meet to requirement of local forecast, pyranometer data is assimilated into satellite model as another feature.

III. Preprocessing and modeling

In this section, we present the idea of preprocessing pipeline at the begining. This procedure is significant for data selecting and noise filtering. In general, preprocessing includes satellite multi-channel data and radiation data. The need of radiation data processing originates from ground measurement data nomalization and clear sky calculation. In later subsection, a new satellite model using SVR is introduced. Compared with previous linear approaches, we propose a new linear relation solution using SVR linear kernel. To utilize the SVR more, we also delevop non-linear solution to the forecast problem.

A. *Preprocessing*

In most cases, remote sensing techniques used in geostationary satellite are good enough to capture plate view in global scale. Whereas, due to unpredicted issues of radiometer scanning and postprocessing of raw data, there are several major issues that should be noted for satellite modeling: 1) In greyscale multispectral images, failure of sensing leave black rasters, 2) GOES data may have luminance change. Since most motion estimation algorithms are texture based, cloud tracking on images with these issues will be unreliable. One solution of this is to use filters such as mean filter and bad-frame filter to interpolate the gap or removing abnormal cases from dataset. The overview of preprocessing is shown in III-B.

Another key procedure of preprocessing is related to radiation output from ground measurement. Actually in our approach, radiation is used for not only output but also input representing local feature with time. Therefore, our goal is set to decrease the noise from other factors except cloud capture by satellite. In most clear sky models discussed in II, the calculation of solar direct normal irradiance is based on parameterization model. This model takes a lot of atmospheric input parameters such as O2, CO2, ozone, water vapour and aerosol optical thickness (AOT). The model building-up requires other instruments and esitmation model in forecasting step later. It means that more uncertainties of atmosphere conditions are imported into whole satellite system. As a result, prediction of radiation change becomes more chanllenging in terms of precision and resolution. In order to solve estimation problem but with less parameters involved, we develop a new statistical model on historical radiation data only for clear sky calculation. One advantage of this methodology is that local measurements of atmosphere are not necessary. In our experiment, 2-order polynomial regression is used for generation of monthly clear sky curve(figure III-A).

In final step of preprocessing, satellite data is combined with radiation data as input dataset feeding into SVR model. Integration between mesoscale data and microscale should cover both temporal and spaticial differences. In satellite dataset, as multi-channel images have different resolution in sensing coverage, coordinate mapping and interpolation are used for unifying pixel scale. While in radiation dataset, the sampling rate 1 per second whereas satellite update every 30 minutes(routine scan). Therefore, short-term fluctuation and noise in 30 minutes cannot be capture by satellite channels due to granularity issue of time. Then in the last preprocessing, we implement a method using the idea of integral and normalization. The solar radiation at time t is the fraction of integral over $2 * N$ minutes. The equation is 1 while CSI stands for clear sky irradiance calculated from clear sky model.

$$DNI_{norm} = \frac{\int_{t-N}^{t+N} DNI}{\int_{t-N}^{t+N} CSI} \tag{1}$$

Another key procedure of preprocessing is the radiation value from ground measurement. The basic idea of radiation processing is to remove noise and build up clear sky radiation estimation as a reference of no-cloud situation. The calculation of solar direct normal irradiance is based on parameterisation model. This model takes a lot of atmospheric input parameters such as O2, CO2, ozone, water vapour and aerosol optical thickness (AOT). It means that other instruments and esitmation model will be needed for forecast part. With more uncertainties of atmosphere conditions imported into forecasy system, it is more chanllenging to predict radiation change. Therefore we develop a new clear sky calculation model in preprocessing part with regression statistically. One advantage of this methodology is that local measurements of atmosphere are not necessary. The computation is only based on historical radiation data. Overview of algorithm structure is listed in III-B.

B. SVR modeling

With preprocessed input data of both multispectral images and radiation feature, we summarise modeling as a regression problem with a set of training patterns $(x_1, y_1), \ldots, (x_n, y_n)$, where $X_i \in R^N$, i=1,...,n. Specifically in our concern of satellite model, the idea is implemented as: $y_t \leftarrow x_t, x_t = \{Chl1_t, Chl2_t, Chl3_t, Chl4_t, Chl6_t, y_{t-\Delta t}\}$,where $Chln$ stands for satellite channel n, y is DNI value from preprocessing. If the relation is linearly formulated, the estimation output is a function of (w, b)2.

$$f_t(x) = \langle w, x_t \rangle + b, w \in R^N, b \in R \tag{2}$$

To solve the problem and import non-linear relation into estimation, we turn to use Support Vector Regression(SVR) on the basis of Support Vector Machine(SVM). In machine learning field, SVM has been widely used for classfication and labeling. The basic idea of SVM is formed in 1992[21]. In 1995, Corinna Cortes and Vladimir N. Vapnik expand the idea to modified maximum margin with cost function penalty on mislabeled examples[22]. As a extension of SVM for regression, SVR is firstly developed for various forecast problems in 1997[23].

Among different types of SVR methodologies, the most commonly used is ϵ-SVR which consider a ϵ-sensitivity tube by a regularization technique that considers ϵ deviation from y_t at the same time flatness of regression[24]. In detail, points that lie outside certain bound that defined by ϵ-sensitivity tube from regression are penalized in ojective funtion. With slack variables imported, the satellite model regression will be formalted as an optimization problem:

$$f(x) = 1+ \\ g(x) \tag{3}$$

$$minimize \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) subject\, to \quad \begin{cases} y_i - \langle w, x_i \rangle - b \leq \epsilon \\ \langle w, x_i \rangle - y_i + b \leq \epsilon \\ \xi_i, \xi_i^* \geq 0 \end{cases} \tag{4}$$

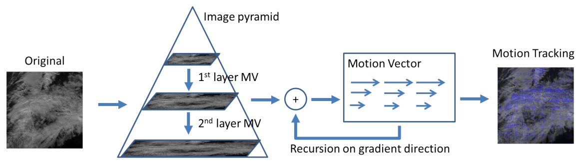
IV. MOTION ESTIMATION AND FORECASTING

In this section, forecasting is discussed in detail. As our approach of prediction rely on images only, an Optical Flow(OF) motion estimation methodology is introduced. Compared with block matching algorithm, Optical Flow is more stable in motion tracking and able to capture changes in pixel scale.

A. Optical Flow Motion Estimation

Motion estimation techniques are widely used for video coding and compressing in image processing field. The common goal has been set to reduce temporal redundancies so as to get predicted image with lower cost in both storage and computational time. Thus feature based methods such as block-matching are widely used to meet criteria of minimum cost. Whereas, in satellite forecast application, the focus is more on accurary of motion vector extraction.

In feature or region based motion tracking, algorithms use different criteria as similarity measurement between regions or blocks. In general all the methods rely on an assumption of consistence of region and luminance. Although normalized



cross correlation has been applied to avoid luminance bias, they performance are not stable as proper segmentation of regions are required. On satellite images, Relying on cloud detection may have contrary influence on cloud motion tracking since detection and classification introduce other uncertainties, eg. differtiation of snow and cloud.

Optical Flow estimation is a branch of methodology that utilize the gradient of image. The core of algorithm is the assumption of constant illuminance. Displacement of images will be presented and estimated through ingredient change. Just like different criteria in region based motion tracking, various Optical Flow methods implements ingradient in unique way. In this paper, the most common method named Lucas-Kanade Optical Flow(LKOF) is implemented. In order to improve accurary of motion vector extraction, the tracking is recursive following the ingredient change. As suggested in image processing filed, motion estimation process also implement the tuning of pyramid of image(multi layer images) and ingredient windows size.

Different from texture based matching us

Optical Flow Motion Estimation algoritm is developed based on an assumption of is a scheme used

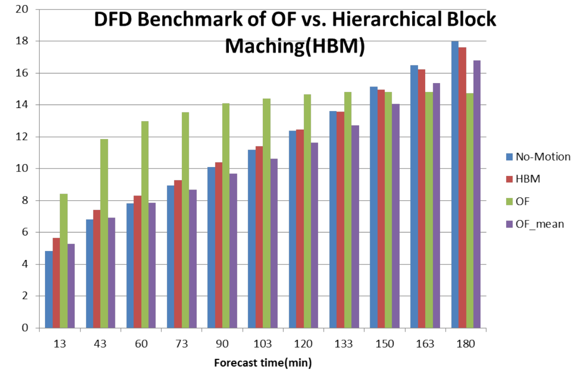
In order to The major challenge to feature based algorithms is the segmentation and cloud extraction

B. Optical Flow vs. Block-based matching

To illustrate the improvement of Optical Flow Motion Estimation, we design a experiment between traditional block matching algorithm. In image processing field, Displaced Frame Difference(DFD) is widely used as benchmark for motion estimation evaluation. DFD is calculated by sumation over difference on predicted image(original image with displacement). In pratical usage, DFD value is calculated with average over all pixels to make sure DFD streching from 0 to 255. With u,v standing for motion vector in x,y direction and N as total number of pixels, the equation of average DFD is described in 5.

$$DFD_{avg} = \frac{\sum_{i,j} |I_t(i,j) - I_{t-\Delta t}(i + u_{i,j}\Delta t, j + v_{i,j}\Delta t)|}{N} \tag{5}$$

To decrease noise influence on small blocks, our experiment use hierarchical block-matching on two satellite images. This method is more robust than common region matching as small blocks(10 x 10 pixels) are represented by (50 x 50 pixels) using normalized cross correlation as similarity. On the other side, LKOF algorithm is a pixel-scale estimation technique therefore the prediction using motion vector will leave lots of black holes as information lost. We use mean filter to fill the holes to make image continous and smooth.



The test result of DFD is shown in Figure. IV-B. What should be noted about DFD is that to some extent, it has the ability to show motion estimation precision in general. But One common drawback of DFD benchmark is that it is passive in prediction. In other words, no motion will be encouraged in short term to preserve good performance in average errors. From the test of DFD, the optical flow with mean filter is better in motion tracking in mesoscale application. This is also proved when using SVR model as another benchmark in VI. As a make-up to DFD criteria, SVR model is local scale measurement of goodness of motion estimation algorithms verified by ground-truth radiation.

V. Radiation Prediction Models

As mentioned in III-B, satellite model is to solve the problem of In $y_t \leftarrow x_t, x_t = \{Chl1_t, Chl2_t, Chl3_t, Chl4_t, Chl6_t, y_{t-\Delta t}\}$. this section, 7 of satellite forecast models are introduced covering both linear and non-linear regression. 5 of them stick With linear relation while 2 of them use SVR RBF kernel to model non-linear trend.

In linear relation, the most common approach is single-channel as cloud coverage, or Cloud Index(CI). In this model, visible channel needs normalization as CI which has linear relation with radiation. But since CI uses the dynamic range of channel value with time to do normalization, the influence of solar angle may not be presented well. Starting from this concern, Linear Regression is developed to 1) Normalize channel value with zenith, 2) Remove compensation constant added to decrease deviation in CI. Another non-SVR approache named as Aggregate Linear Regression(ALR) is an multispectral extension of LR. In other words, linear relation is generated with 5-dimensional regression.

In 4 SVR models, ϵ-SVR is used for setting up sensitivity range. To simplify the forecast problem, Linear kernel firstly in 2 different ways. One linear relation($SVR - Li$) is similiar with ALR approach using 5-dimension training dataset. distinction of SVR-Li lies in the regularization and ϵ-tube. Another SVR linear kernel($SVR - Li_{rad}$) uses 6-dimension dataset with 30 minutes radiation as another input dimension. $SVR_L i_{rad}$ also consider the abnormal cases of overestimated output. Due to the high dimension and quality of motion estimation, prediction output can be noisy and outbound. In our experiment, all the radiation is normalized by integral of clear sky values. But over-estimation will lead to output beyond upper bound or below lower bound. Therefore, in $SVR-Li_{rad}$, output threshold is implemented to remove abnormalities. As characterics of SVR, non-linear relation is easy to implement through kernels. In our approach, non-linear relation is generated through common optimization of SVR linear kernel but with kernel mapping at the begining. Thus, the other two methods,$SVR-RBF$ and $SVR-RBF_{rad}$,are non-linear extensions of $SVR-Li$ and $SVR-Li_{rad}$.

1) **Cloud Index(CI)** we implement the CI framework mentioned in [2] as performance benchmark for all other models. It uses normalized visible channel value as cloud index. The equation of estimation is

$$CI = \frac{X_1 - bound_{min}}{bound_{max} - bound_{min}} \tag{6}$$

$$f(x) = w(1 - CI) + b \tag{7}$$

2) **Linear Regression(LR) on single channel** To avoid linear relation with compenstaion in CI-based approach, more reliable method is linear regression.

$$f(x) = w(x_1) + b \tag{8}$$

3) **Aggregate Linear Regression(ALR) on multi-channel** 5 GOES channel are used for linear regression for radiation. This is an extension of single channel linear relation.

$$f(x) = \langle w, x \rangle + b \tag{9}$$

4) **SVR using Linear kernel**($SVR-Li$) This model use ϵ-SVR method using linear relation as kernel function.

$$Objective function: \quad f_t(x) = \langle w, x_t \rangle + b, w \in R^5 \tag{10}$$

5) **SVR using Radial Basis Function kernel**($SVR-RBF$) The RBF funtion is used for kernel mapping in SVR before linear optimization.

$$Objective function: \quad f_t(x) = \langle w, x_t \rangle + b, w \in R^5 \tag{11}$$

6) **SVR using Linear kernel with radiation** ($SVR-Li_{rad}$) Different from SVR-Li, this model uses previous radiation as another input feature. A 0 1 threshold of is applied to forecast output to generate normalized prediction.

$$Objective function: \quad f_t(x) = \langle w, x_t \rangle + b, w \in R^5 \tag{12}$$

7) **SVR-Radial Basis Function kernel with radiation** ($SVR-RBF_{rad}$) Same as $SVR-Li_{rad}$ but with RBF kernel as non-linear mapping to linear space.

$$Objective function: \quad f_t(x) = \langle w, x_t \rangle + b, w \in R^5 \tag{13}$$

VI. Experiment Results

A. Dataset

The time range of our satellite dataset is from April 1st 2012 to November 1st 2012, covering partial Spring ,Summer, and most autumn. All the raw satellite multi-channel data is from public FTP server from GOES project[]. The radiation data is from pyranometer on-site measurement. As satellite data from GOES has routine scan(30 min) and rapid scan(15 min), Span between two images is not fixed and motion vector extraction also takes this into account for later forecasting. For both satellite images and pyranometer measurement, raw input has been preprocessed by removing data points which have 1) bad-frame of multi-channels 2) failure of ground radiation sensor 3) timestamp mismatch 4) low solar angles. In total, the dataset has 8477 frames for each satellite channel that are continous in single day but may not in month. and 8477 normalized radiation data with interal of 15 minutes at.

The experiment covers:1) **Estimation** 2

VII. Conclusion

References

[1] S. Janjai, J. Laksanaboonsong, M. Nunez, and A. Thongsathitya, "Development of a method for generating operational solar radiation maps from satellite data for a tropical environment," *Solar Energy*, vol. 78, no. 6, pp. 739–751, 2005.

[2] R. Perez, K. Moore, M. Kmiecik, C. Chain, P. Ineichen, R. George, and F. Vignola, in *PROCEEDINGS OF THE SOLAR CONFERENCE*. AMERICAN SOLAR ENERGY SOCIETY; AMERICAN INSTITUTE OF ARCHITECTS, 2002, pp. 315–322.

[3] A. Zelenka, R. Perez, R. Seals, and D. Renné, "Effective accuracy of satellite-derived hourly irradiances," *Theoretical and Applied Climatology*, vol. 62, no. 3-4, pp. 199–207, 1999.

[4] D. Cano, J.-M. Monget, M. Albuisson, H. Guillard, N. Regas, and L. Wald, "A method for the determination of the global solar radiation from meteorological satellite data," *Solar Energy*, vol. 37, no. 1, pp. 31–39, 1986.

[5] R. Stuhlmann, M. Rieland, E. Raschke, *et al.*, "An improvement of the igmk model to derive total and diffuse solar radiation at the surface from satellite data." *Journal of Applied Meteorology*, vol. 29, no. 7, pp. 586–603, 1990.

[6] J. Schmetz, "Towards a surface radiation climatology: Retrieval of downward irradiances from satellites," *Atmospheric Research*, vol. 23, no. 3, pp. 287–321, 1989.

[7] P. Ineichen and R. Perez, "Derivation of cloud index from geostationary satellites and application to the production of solar irradiance and daylight illuminance data," *Theoretical and Applied Climatology*, vol. 64, no. 1-2, pp. 119–130, 1999.

[8] A. Hammer, D. Heinemann, C. Hoyer, R. Kuhlemann, E. Lorenz, R. Müller, and H. G. Beyer, "Solar energy assessment using remote sensing technologies," *Remote Sensing of Environment*, vol. 86, no. 3, pp. 423–432, 2003.

[9] F. Martins, E. Pereira, and S. Abreu, "Satellite-derived solar resource maps for brazil under swera project," *Solar Energy*, vol. 81, no. 4, pp. 517–528, 2007.

[10] R. Perez, P. Ineichen, M. Kmiecik, K. Moore, D. Renne, and R. George, "Producing satellite-derived irradiances in complex arid terrain," *Solar Energy*, vol. 77, no. 4, pp. 367–371, 2004.

[11] L. F. Zarzalejo, J. Polo, L. Martín, L. Ramírez, and B. Espinar, "A new statistical approach for deriving global solar radiation from satellite images," *Solar Energy*, vol. 83, no. 4, pp. 480–484, 2009.

[12] L. F. Zarzalejo, L. Ramirez, and J. Polo, "Artificial intelligence techniques applied to hourly global irradiance estimation from satellite-derived cloud index," *Energy*, vol. 30, no. 9, pp. 1685–1697, 2005.

[13] O. Şenkal and T. Kuleli, "Estimation of solar radiation over turkey using artificial neural network and satellite data," *Applied Energy*, vol. 86, no. 7, pp. 1222–1228, 2009.

[14] O. Şenkal, "Modeling of solar radiation using remote sensing and artificial neural network in turkey," *Energy*, vol. 35, no. 12, pp. 4795–4801, 2010.

[15] E. Ricciardelli, F. Romano, and V. Cuomo, "Physical and statistical approaches for cloud identification using meteosat second generation-spinning enhanced visible and infrared imager data," *Remote Sensing of Environment*, vol. 112, no. 6, pp. 2741–2760, 2008.

[16] R. Perez, S. Kivalov, A. Zelenka, J. Schlemmer, and K. Hemker Jr, "Improving the performance of satellite-to-irradiance models using the satellites infrared sensors," in *Proc. of American Solar Energy Societys Annual Conference, Phoenix, AZ*, 2010.

[17] J. A. Leese, C. S. Novak, and V. Ray Taylor, "The determination of cloud pattern motions from geosynchronous satellite image data," *Pattern Recognition*, vol. 2, no. 4, pp. 279–292, 1970.

[18] D. Heinemann, E. Lorenz, and M. Girodo, "Forecasting of solar radiation," *) Solar energy resource management for electricity generation from local level to global scale. Nova Science Publishers, New York*, 2006.

[19] U. Görsdorf, A. Seifert, V. Lehmann, and M. Köhler, "Cloud statistics and nwp-model validation based on long term measurements of a 35 ghz radar," in *35th Conference on Radar Meteorology*, 2011, pp. 26–30.

[20] D. Yang, P. Jirutitijaroen, and W. M. Walsh, "Hourly solar irradiance time series forecasting using cloud cover index," *Solar Energy*, 2012.

[21] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers," in *Proceedings of the fifth annual workshop on Computational learning theory*. ACM, 1992, pp. 144–152.

[22] C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning*, vol. 20, no. 3, pp. 273–297, 1995.

[23] H. Drucker, C. J. Burges, L. Kaufman, A. Smola, and V. Vapnik, "Support vector regression machines," *Advances in neural information processing systems*, pp. 155–161, 1997.

[24] V. Vapnik, *The nature of statistical learning theory*. springer, 1999.