World Academy of Science, Engineering and Technology
International Journal of Energy and Power Engineering
Vol:12, No:5, 2018

Optimization of Solar Tracking Systems

A. Zaher, A. Traore, F. Thiéry, T. Talbert, B. Shaer

***Abstract*—**In this paper, an intelligent approach is proposed to optimize the orientation of continuous solar tracking systems on cloudy days. Considering the weather case, the direct sunlight is more important than the diffuse radiation in case of clear sky. Thus, the panel is always pointed towards the sun. In case of an overcast sky, the solar beam is close to zero, and the panel is placed horizontally to receive the maximum of diffuse radiation. Under partly covered conditions, the panel must be pointed towards the source that emits the maximum of solar energy and it may be anywhere in the sky dome. Thus, the idea of our approach is to analyze the images, captured by ground-based sky camera system, in order to detect the zone in the sky dome which is considered as the optimal source of energy under cloudy conditions. The proposed approach is implemented using experimental setup developed at PROMES-CNRS laboratory in Perpignan city (France). Under overcast conditions, the results were very satisfactory, and the intelligent approach has provided efficiency gains of up to 9% relative to conventional continuous sun tracking systems.

***Keywords*—**Clouds detection, fuzzy inference systems, images processing, sun trackers.

I. Introduction

DUE to increasing demand for sustainable and green energy resources, solar energy technology has experienced phenomenal growth in recent years. The efficiency of all types of solar energy based technologies is influenced by the variation in solar resources due to weather changes. In this context, the Concentrated Solar Power efficiency IMProvement (CSPIMP) project has been initiated in 2013 in order to overcome the power system disturbances caused by the sudden changes in the weather and as a result to make concentrated solar power CSP, solar thermal collectors, and photovoltaic PV plants more efficient.

Considering the continuous change of the sun position, orientation of solar panels plays a key role in the total energy yield. There are two main ways to increase the efficiency of solar collectors. In the first way, collectors are fixed, or have a tilt that can be adjusted, monthly or seasonally [1]. In the second approach, they can always be pointed directly toward the sun using single or dual axis tracking system [2]. The most efficient of these driving techniques is the dual axis tracker that increases the capture of solar radiation by approximately 30% compared to the fixed mount and by 6% compared to the single axis tracker [3].

Considering weather conditions, most of global solar energy reaching earth's surface comes from the direct sunshine, and a small quantity is from diffuse solar energy in case of clear sky [4]. However, atmospheric components like clouds and pollution increase the percentage of diffuse radiation. Thus, during overcast conditions, tracking the sun is an ineffective method and the horizontal position becomes the ideal choice to capture this diffuse radiation that is isotopically-distributed over the whole sky [5]. In case of partly covered sky, diffuse radiations have anistropically-distribution and there are some zones of the sky dome which reflect more energy than others according to the position of clouds relative to the sun and clouds motion.

In the literature, satellite images are mostly used to study clouds distribution and features which constitute major factors in estimating and forecasting solar irradiance [6]. However, the low resolution of satellite images with respect to space and time is not adequate to satisfy the control requirements of solar energy systems. Thus, researchers have turned towards analyzing the images captured by ground-based sky camera systems in order to make up the deficiency of satellite cloud observations in terms of spatial and temporal resolutions [7].

Many detection algorithms have been implemented to separate pixels which represent clouds from those represent sky background. Indeed, all these approaches are segmentation methods adopting conditional rules based on the intensities of blue B and red R components of the RGB images to identify the pixels. Some researchers have divided the case of sky into three classes: opaque cloud, thin cloud, and clear sky by using one or two thresholds applied to the R/B ratio for the whole sky images WSI [8]. In the other works, the difference between R and B is considered to determine the case of pixels [9]. The last two approaches are combined by a hybrid thresholding algorithm that transforms the color images into normalized R/B ratio images (NRBR) and applying thresholding algorithm to the normalized images to identify the cloudy pixels [10]. However, most cloud classification algorithms encounter great uncertainties for cloud detection in the circumsolar and near-horizon zones. To overcome this problem, we propose a new cloud detection algorithm basing on fuzzy inference systems FIS.

Our work has two objectives; the first is to propose an intelligent method to detect the case of sky from ground-based images using fuzzy logic approach. The second aim is to imply the results of first part to point the solar panels in an optimal direction through which they can capture the maximum of the incident solar radiation. Under clear sky conditions, the solar panel is pointed towards the sun to

A. Zaher is with the Department of Sciences Exactes et Expérimentales, University of Perpignan Via Domitia, PROMES-CNRS Laboratory, Tecnosud, Rambla de la Thermodynamique, 66100 Perpignan, France (corresponding author, e-mail: ali.zaher@univ-perp.fr).

A. Traore, F. Thiéry, and T. Talbert are with the Department of Sciences Exactes et Expérimentales, University of Perpignan Via Domitia, PROMES-CNRS Laboratory, Tecnosud, Rambla de la Thermodynamique, 66100 Perpignan, France (e-mail: traore@univ-perp.fr, thiery@univ-perp.fr, talbert@univ-perp.fr).

B. Shaer is with the high school of technology, 1100 rue Notre-Dame Ouest, Montreal QC H3C 1K3, Canada (e-mail: bassel.shaer.1@ens.etsmtl.ca).

capture the maximum of direct solar radiation under different weather conditions. Thus, this paper is organized as follows: the experimental setup is introduced in Section II. Section III describes the overall solar energy capture by solar panels according to weather conditions. The intelligent orientation method is presented in Section IV. Cloud detection algorithms are illustrated in Section V. Finally, a summary and suggestions for future research are shown in Section VI.

II. Experimental Setup

The intelligent approach proposed in this paper has been implemented on an experimental setup developed by PROMES-CNRS laboratory located in Perpignan City (Latitude = 42.700 N, Longitude= 2.900 E). As shown in Fig. 1, the setup comprises:

- Polycrystalline photovoltaic panels SUNSET-PX 60E.
- Two dual axis sun trackers of type SM34SPM+ equipped with microcontroller board. One tracks the sun continuously and the other is oriented optimally taking into account the case of sky.
- Computer with a data acquisition card NI-USB-6008.
- Ground-based sky camera system.

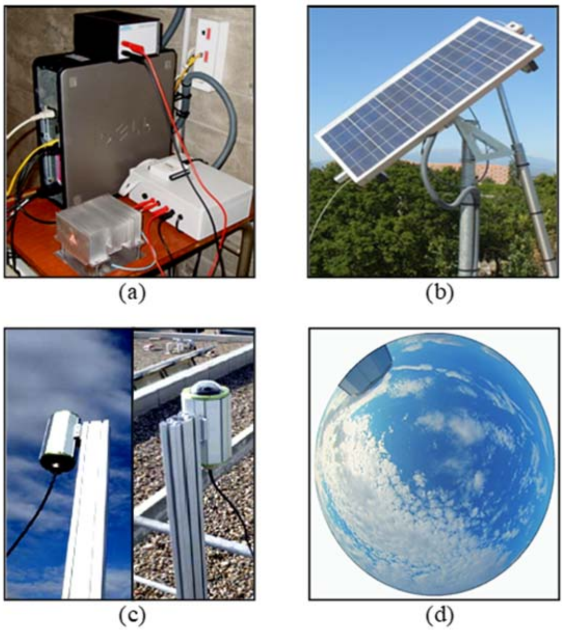

Fig. 1 Picture of the experimental setup: (a) Data acquisition system, (b) sun tracker, (c) PROMES-CNRS sky imager, and (d) Sample of images

The images used in this study are captured by a 5-megapixels ground-based sky camera with a color CMOS sensor. The camera, named 5481VSE-C and provided by IDS-imaging, is equipped with a Fujinon fisheye lens and protected by a waterproof enclosure manufactured by autoVimation. Images are collected every 20 seconds at a resolution of 1920 x 2560 pixels with 8 bits per channel. Since 2014, all captured images have been stored in data base in form of HDF5 files that organize the data and metadata in a hierarchical structure. In addition to the captured images, the HDF 5 files contain the meteorological measures like solar irradiance and the atmospheric turbidity factor. The great number of stored images allowed us to take into account all sky conditions in our experiments.

In practice, the intelligent algorithm detects the point of sky dome that emits the maximum of solar energy during the period Δt (fixed in this study at Δt = 15 minutes) and then, zenith and azimuth angles of the last point are calculated and transmitted to the microcontroller in the tracker via a RS232 serial communication.

III. Image-Based Orientation Method

The proposed method consists of several steps as demonstrated by the flow diagram presented in Fig. 2. Firstly, the image captured at the moment t is used to detect the case of sky. If the sky is clear, the solar panel will track the sun, and if overcast sky is detected, the collector must be pointed horizontally. In the case of partly covered sky, the solar panel must be oriented towards the center of gravity of the brightest area in the studied image $I(t)$. The process is repeated and the position is updated each Δt (time interval between two orientations).

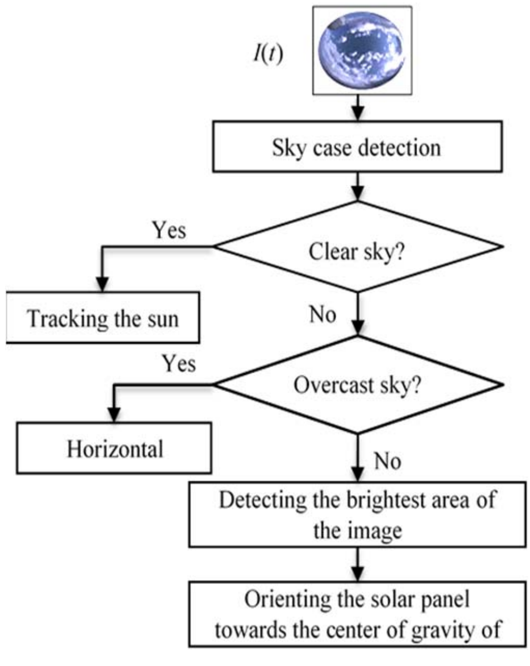

Fig. 2 Block diagram of intelligent sun tracking method

Sky Case Detection

Fuzzy inference systems (FIS) systems play a key role in situations where qualitative data and human expertise are introduced into the modeling, such as in our case, where meteorological variables as well as human perceptions and values are used. There are two main structures of fuzzy inference systems: Mamdani-type and Sugeno-type. Mamdani's fuzzy inference method expects the output membership functions to be fuzzy sets [11]. Sugeno -type can be used to model the systems in which the output membership functions are either linear or constant [12]. Here Sugeno -type inference system is used to classify the pixels into four categories: light cloudy, heavy cloudy, clear sky and circumsolar pixels depending upon the normalized components R, G, and B of each pixel. In fact, three main processes are required to build a fuzzy inference system: the fuzzification, the fuzzy rules base, and the defuzzification.

The aim of fuzzification process is to map the crisp values of input and output variables to values from 0 to 1 using fuzzy subsets. In this context, the range of variation of each variable is divided into sub-ranges associated with linguistic labels such as: "Small", "Big", "High", etc.

The last linguistic ratings can be characterized by different types of fuzzy membership functions like: triangular, sigmoid, trapezoidal, Gaussian, or singleton [13]. Selecting the right type of membership functions depends strongly upon the user experience [14]. As presented in Fig. 3, triangular and trapezoidal fuzzy membership functions are used for the sake of simplicity. In this figure, each of the input variables is normalized to be varied from 0 to 1 and then it is fuzzified into three membership functions with the associated linguistic labels L ("Low"), M ("Medium") and H ("high").

In the output, we defined four constant membership functions according to the five classes of pixels: 0.25 for light cloudy, 0.5 for heavy cloudy, 0.75 for circumsolar, and 1 for clear sky pixels.

The fuzzy rules have the following form:

If *R* is "L" And *G* is "L" **And** *B* is "H" **Then** the case of pixel is "clear sky pixel"

When fuzzy rules are applied to the fuzzified inputs, the outputs of all rules are aggregated to form one membership function. Then, the fuzzy output is converted to a crisp value using the defuzzification process. In this work, the weighted average is adopted:

$$Z_{Wa} = \frac{\sum_{i=1}^{m} \mu_A(z).z}{\sum_{i=1}^{m} \mu_A(z)} \tag{1}$$

where Z_{Wa} is the crisp output, $\mu_A(z)$ is the aggregated membership functions, and z is the centroid of each membership function.

After determining the class of each pixel, the case of sky can be determined depending upon the portion of clouds in the whole image. Fig. 4, shows the results obtained by the proposed identification method whereby cloudy pixels form 22% of the whole image, thus the sky is considered as partly covered.

Brightest Area Detection

Brightness of an object composed of group of pixels is an attribute assigned to the pixels in which the object appears to be radiating or reflecting light. In the other words, brightness is an indicator to the luminance of a visual object. To determine the brightest area, the true color image *I* is converted into a gray scale one I_g, and then, this grayscale image is transformed to binary image I_b by replacing all pixels in the input image with luminance greater than level with the value 1 (white) and by replacing all other pixels with the value 0 (black). Finally, the brightest area is that has the biggest number of white pixels (Fig. 5).

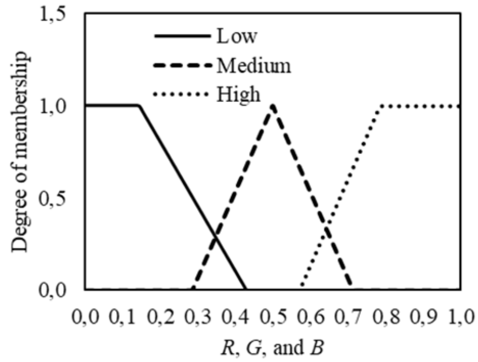

Fig. 3 Fuzzification of input variables

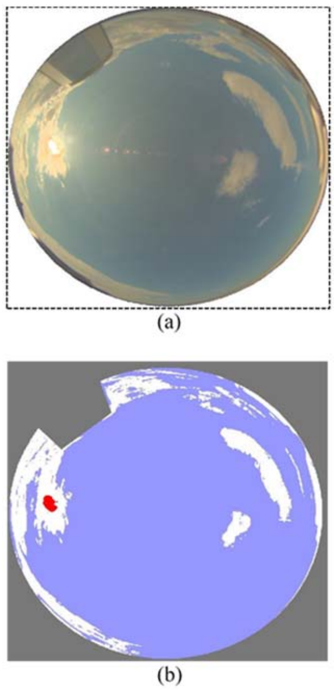

Fig. 4 Results of classification process: (a) original image and (b) segmented image through which clear sky pixels, cloudy pixels and circumsolar pixels are colored in Blue, White, and Red, respectively

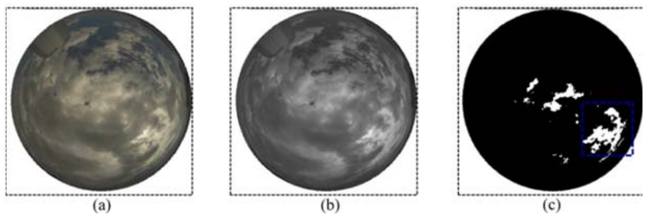

Fig. 5 Brightest area detection: (a) true color image, (b) gray scale image, and (c) binary image in which the brightest area surrounded by Blue line

IV. Results and Discussion

Our goal in this work is to increase the efficiency of continuous sun trackers taking into account different weather conditions. Thus, the proposed approach was evaluated by measuring and comparing the energy yield of a solar panel mounted on classical continuous sun tracker to that obtained from another solar panel mounted on intelligent sun tracker over 2016. The results, presented in Fig. 6, show that the solar panel driven by the intelligent tracker generates more energy than that driven by classical one over the whole experimental period, and that indicates a significant improvement of sun tracker efficiency.

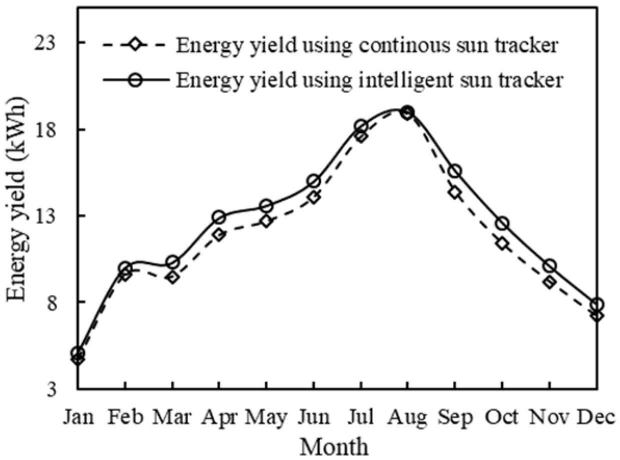

Fig. 6 Energy yield of the solar panel using continuous and intelligent sun trackers in 2016

TABLE I
Gain of Energy Yield Obtained by the Intelligent Sun Tracking Approach Relative to That Obtained by the Conventional Continuous Sun Tracking System in 2016

Month	Sunshine Duration (h)	Gain (%)
Jan	99	7.8
Feb	165	7.8
Mar	174	7.7
Apr	227	7.8
May	231	6.6
Jun	253	6
Jul	306	3.3
Aug	332	0.5
Sep	260	7.7
Oct	176	9.5
Nov	141	8.9
Dec	126	8.9

Now to analyze the performance of our approach under different weather conditions, the gain of energy (g) is computed for each month using:

$$g = \frac{\sum(E_i - E_c)}{\sum E_i} \tag{2}$$

where E_i (kWh) is the energy produced by the PV using the intelligent orientation method and Ec (kWh), is the energy produced by the PV using the classical sun tracking method (continuous solar tracking systems).

The results are presented in Table I. Considering this table, the gain of energy is affected by the sunshine duration. When the last parameter is short, the gain is big and vice versa. And this is normal because direct solar radiation and sunshine duration, in case of partly covered and overcast sky, are seriously reduced as a result of the increased scattering by particulates in the atmosphere, which makes tracking the sun ineffective.

V. Conclusion

In this paper, an intelligent sun tracking approach is proposed to optimize the conventional dual axis sun trackers under different weather conditions. The intelligent approach is mainly based on sky images processing and fuzzy inference systems. In this context, pixel identification algorithm is used to detect the case of sky and to compute clouds size presented in the whole image. While, block matching algorithms BMAs are used for estimating clouds motion. The size and the speed of clouds are then introduced to a fuzzy inference system, to decide the optimal position of the PV panel. To evaluate the performance of our method, it was implemented using an experimental setup, and the obtained results over one-year show that the energy yield increases proportionally with cloud duration. The immediate continuation of this work will be to apply the developed algorithm in zones with other kind of climate.

References

[1] M. Despotovic, and V. Nedic, “Comparison of optimum tilt angles of solar collector determined at yearly, seasonal and monthly levels”, Energy Conversion and Management, vol. 97, pp.121–131, 2015.
[2] H. Mousazadeh, A. Keyhani, A. Javadi, H. Mobli, K. Abrinia, and A. Sharifi “A review of principle and sun-tracking methods for maximizing solar systems output”, Renewable and Sustainable Energy Reviews, vol. 13, pp. 1800–1818, 2009.
[3] R. C. Neville,” Solar energy collector orientation and tracking mode”, Solar Energy, vol. 20, pp. 7–11, 1978.
[4] N. A. Kelly, and T. L. Gibson, “Improved photovoltaic energy output for cloudy conditions with a solar tracking system”, Solar Energy, vol. 83, pp. 2092–2102, 2009.
[5] N. A. Kelly, and T. L. Gibson, “Increasing the solar photovoltaic energy capture on sunny and cloudy days”, Solar Energy, vol. 85, pp. 111–125, 2011.
[6] R. Marquez, H. T. C. Pedro, and C. F. M. Coimbra, “Hybrid solar forecasting method uses satellite imaging and ground telemetry as inputs to ANNs”. Solar Energy, vol. 92, pp. 176–188, 2013.
[7] R. Marquez, and C. F. M. Coimbra, “Intra-Hour DNI forecasting based on cloud tracking image analysis”. Solar Energy, vol. 91, pp. 327–336.
[8] C. N. Long, J. M. Sabburg, J. Calbo, and D. Pagés, “Retrieving cloud characteristics from ground-based daytime color all-sky images”, J. Atmos. Ocean. Tech., vol. 23, pp. 633–652, 2006.
[9] A. Heinle, A. Macke, and A. Srivastav, “Automatic cloud classification of whole sky images”, Atmos. Meas. Tech., vol. 3, pp. 557–567, doi:10.5194/amt-3-557-2010, 2010.
[10] Q. Li, W. Lu, and J. Yang, “A hybrid thresholding algorithm for cloud detection on ground-based color images”, J. Atmos. Ocean. Tech., vol. 28, pp. 1286–1296, 2011.
[11] E. H. Mamdani, and S. Assilian, “An experiment in linguistic synthesis with a fuzzy logic controller”, Int. J. Man-Machine Studies, vol. 7, pp. 1-13,1975.
[12] T. Takagi, and M. Sugeno, “Fuzzy identification of systems and its applications to modeling and control”, IEEE Trans Syst Man Cybern, vol. 15, pp. 116-32, 1985.

[13] L. Suganthi, S. Iniyan, and A. A. Samuel, "Applications of fuzzy logic in renewable energy systems–a review". Renewable and Sustainable Energy Reviews, vol. 48, pp. 585-607, 2015.

[14] A. Ghanem and A. Zaher, "Fuzzy rule-based model for optimal management of marine protected areas: a case study on the marine reserve Cerbère-Banyuls", International Journal of Research-GRANTHAALAYAH, vol. 5, pp. 239-251. 2017.