Fuzzy rule-based model for optimum orientation of solar panels using satellite image processing

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Abstract. In solar energy converting systems, a particular attention is paid to the orientation of solar collectors in order to optimize the overall system efficiency. In this context, the collectors can be fixed or oriented by a continuous solar tracking system. The proposed approach is based on METEOSAT images processing in order to detect the cloud coverage and its duration. These two parameters are treated by a fuzzy inference system deciding the optimal position of the solar panel. In fact, three weather cases can be considered: clear, partly covered or overcast sky. In the first case, the direct sunlight is more important than the diffuse radiation, thus the panel is always pointed towards the sun. In the overcast case, the solar beam is close to zero and the panel is placed horizontally to receive the diffuse radiation. Under partly covered conditions, the fuzzy inference system decides which of the previous positions is more efficient. The proposed approach is implemented using experimental prototype located in Perpignan (France). On a period of 17 months, the results are very satisfactory, with power gains of up to 23% compared to the collectors oriented by a continuous solar tracking.

1. Introduction
Considering the continuous change of the sun position, orientation of solar panels is an effective method to increase total energy yield. There are two main ways to increase the efficiency of photovoltaic systems (PV panels). In the first way, panels are fixed, or have a tilt that can be adjusted, monthly or seasonally [1]. In the second approach, solar panels can always be pointed directly toward the sun using single or dual axis tracking system [2]. The most efficient is the dual axis tracker that increases the incident solar radiation by approximately 30% compared to the fixed mount and by 6% compared to the single axis tracker [3].

The total radiation captured by the PV panel is composed of direct and diffuse components. The direct component is used to describe solar radiation traveling on a straight line from the sun down to the surface of the panel. On the other hand, diffuse radiation is the sunlight that has been scattered by molecules and particles in the atmosphere.

In case of clear sky, 90% of the global solar energy comes from the direct sunshine and the other 10% from diffuse solar energy [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].

METEOSAT satellite images (METEOSAT of Second Generation) are widely used for weather parameters forecasting. Mainly, these images have been useful to study solar radiation and clouds...
features in different locations around the world. A. Mefti et al. [6] derived global hourly solar radiation from the visible METEOSAT-5 images, while H. Escrig et al. [7] focused on cloud cover forecasting basing on cloud detection and cloud motion estimation techniques. The same images where used by A. Ghosh et al. [8] to determine different types of cloud coverage: overcast, partially covered and cloudless. METEOSAT 8 data were also used by J. Cermak et al. [9] to propose a method based on object-oriented techniques for fog and low stratus clouds detection.

In this work, the cloud cover index and cloud duration are two main parameters for the determination of the optimum position of solar panel. In this field, the limitations due to the resolution of METEOSAT images, induce incertitude in most of weather parameters estimation. Thus, the integration of fuzzy inference systems becomes an advantageous approach.

This paper is organized as follows. In the first part, the different components of solar radiation on inclined surfaces on cloudy days are studied in order to know the optimum orientation of solar panels under different meteorological conditions. The second part is dedicated to the intelligent decision-making system through which the cloud information is used to determine the optimum position over the time. The last part shows the experimental results and a comparative study between the proposed approach and the continuous solar tracking systems.

2. Maximizing the overall solar energy capture on cloudy days

Determination of incident global solar irradiance on the inclined plane relative to the ground, at different latitudes, requires mathematical models that use relationships between the global intensity of solar radiation on a horizontal plane and the inclined plane at an angle $\beta \neq 0$ [10].

The research works of Liu and Jordan [11] set the basis for the development of further decomposition models by several researchers, to fit datasets from different locations and chronological periods, which have been successful to varying degrees. In the Liu-Jordan isotropic model, with correction coefficients for all components, the diffuse part (scattered and reflected radiation) is isotropic in character and dispersed from the whole sky hemisphere. For a photovoltaic receiver facing south, a total solar radiation on a plane tilted $G_{\beta}$ at the $\beta$ angle is defined by the following relation [12]:

$$G_{\beta} = B \left( \frac{\cos(\theta_{z})}{\cos(\theta_{c})} \right) + D \left( \frac{1 + \cos \beta}{2} \right) + (B + D) \rho \left( \frac{1 - \cos \beta}{2} \right)$$  \hspace{1cm} (2.1)

Where: $B, D$ are the direct and diffuse horizontal solar irradiance, $\theta_{z}$ the solar zenithal angle, $\theta_{c}$ is the incidence angle of the beam radiation on the tilted surface and $\rho$ is the reflectance factor.

The model developed by Kasten et al. [13] is a total cloud based model comprising the calculation of direct beam radiation using:

$$B = G_{ex} e^{(-T \cdot x \cdot m)} (1 - C)$$  \hspace{1cm} (2.2)

Where: $G_{ex}$ the extraterrestrial solar radiation, $C$ is the cloud cover index and $T$ is the Linke turbidity. The previous equation shows that the direct radiation equals zero when the cloud cover index equals 1 during heavy cloudy days. So, under these conditions the equation 2.1 becomes:

$$G_{\beta} = D \left( \frac{1 + \cos \beta}{2} \right) + D \rho \left( \frac{1 - \cos \beta}{2} \right)$$  \hspace{1cm} (2.3)

If the reflected component is neglected the last relation can be written:

$$G_{\beta} = D \left( \frac{1 + \cos \beta}{2} \right)$$  \hspace{1cm} (2.4)

Regarding the last relation, to maximize the inlet solar power, the solar panel inclination angle $\beta$ must be zero and that refers to the horizontal position.
As a result, under clear sky the solar panel must be pointed towards the sun to capture the maximum of direct solar radiation. On the other hand, on cloudy days, the direct radiation is close to zero therefore, the PV panel must be oriented horizontally to collect the diffuse radiation which is generally pretty equally distributed throughout the sky.

3. Intelligent decision-making system

The flow diagram of the decision-making system is presented in Figure 1. In this diagram, the cloud cover index and the cloud duration are computed for the pixel \(P_0(x_0, y_0)\) which presents the studied zone. The cloud cover allows us to estimate the amount of solar energy acquired from direct solar radiation and the amount of scattered solar radiation at a moment \(t\). The cloud duration presents the number of cloudy cases which will be at the pixel \(P_0\) during a period \(\Delta t\) which is the orientation period.

When the cloud cover index and the cloud duration are calculated, they are treated by a fuzzy inference system (FIS) which decides if the PV panel must be pointed toward the sun or horizontally during the period of study \(\Delta t\).

![Decision-making system block diagram](image)

**Figure 1.** Decision-making system block diagram.

3.1. Cloud cover index

The METEOSAT sensor for the visible channel captures sunlight of the visible band reflected by an object back to the satellite. The fraction of solar radiation that is reflected back to space is called the albedo. The cloudy surfaces usually have a higher albedo than the other surfaces of the Earth. So clouds usually appear white, while land and water surfaces appear in darker gray scale levels.
To estimate the cloud cover index \( n \) for each pixel \( (x, y) \), the actual image \( I(t) \) is compared to the image obtained during perfectly clear weather \( I_C(t) \) and to the image taken on cloudy days \( I_O(t) \) as follows:

\[
n(x, y, t) = \frac{I(x, y, t) - I_C(x, y, t)}{I_O(x, y, t) - I_C(x, y, t)}
\]

The images \( I_C \) and \( I_O \) are obtained using an archive of images taken at the same moment \( t \) over \( N \) days using the two following equations:

\[
I_C(x, y, t) = \min(I(x, y, t, \text{day}), I(x, y, t, \text{day}-1), \ldots, I(x, y, t, N-1))
\]

\[
I_O(x, y, t) = \max(I(x, y, t, \text{day}), I(x, y, t, \text{day}-1), \ldots, I(x, y, t, N-1))
\]

### 3.2. Cloud duration

In this study, the cloud duration is defined as the number of cloudy cases, which present at the pixel \( P_0 (x_0, \ y_0) \) during the period \( \Delta t \). In fact, this number is the number of cloudy pixels, between the studied zone \( P_0 \) and the pixel \( P_i (x_i, \ y_i) \), divided by the distance (in pixels) between the two pixels as shown in figure 2. The location of the pixel \( P_i (x_i, \ y_i) \) can be determined using the following formula:

\[
x_i = x_0 - u.\Delta t \tag{3.4}
\]

\[
y_i = y_1 - v.\Delta t \tag{3.5}
\]

Where: \( \Delta t \) is the orientation period, \( u \) and \( v \) are velocity components of clouds between the pixels \( P_0 \) and \( P_i \).

**Figure 2.** Example shows the number of cloudy pixels between the pixel \( P_i \) and the Pixel \( P_0 \). 5 cloudy pixels, the distance equals 7 pixels.

Once the coordinates \( x_i \) and \( y_i \) are computed, the cloud duration \( CN \) can then be determined as follows:

\[
CN = \frac{\text{Number of cloudy pixels between } P_0 \text{ and } P_i}{\sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^2}} \tag{3.6}
\]

To compute the cloud duration, a robust algorithm is needed for the estimation of cloud motion field \((u, v)\) taking into account the semi-fluid behavior of clouds. Many approaches, such as block...
matching, pixel recursive and optical flow algorithms are used to compute the motion vectors in image sequences [14] and [15].

The method used in this article is based on Block Matching Algorithms combined with a best candidate block search for extracting cloud motion from satellite image sequence [16]. The basic concept of BMA is to divide the frame into small blocks then, the BMA finds the optimal motion vectors (MV) that minimize the difference between reference block of the current frame and candidate block from the search area of previous frame.

The sum of absolute differences SAD is used as matching criterion and it is given by [17] and [18]:

$$SAD(x_r, y_r) = \sum_{i=0}^{L-1} \sum_{j=0}^{M-1} |I_n(x_r + i, y_r + j) - I_{n-1}(x_r + i, y_r + j)|$$ (3.7)

Where: In(xr, yr) is the block of the current frame (n) and (xr, yr) is the coordinate of its upper left corner. Lr(x, y) is the block of the previous frame (n-1) and (x, y) is the coordinate of its upper left corner. Each of these blocks is of LxM pixels.

But in this method, the future evolution of the block is not taken into account, thus a big error occurs in the estimation. For this reason, (BMA) is combined with a best candidate block search [19]. In the last method, the BMA is applied and a list of the best candidates block is obtained by minimizing the cost function along the directions and consequently the estimation error increases.

The basic concept of BMA is to divide the frame into small blocks then, the BMA finds the optimal motion vectors (MV) that minimize the difference between reference block of the current frame and candidate block from the search area of previous frame.

$$C_c(x_c, y_c) = \sqrt{(x_c - x_r)^2 + (y_c - y_r)^2}$$ (3.8)

The criterion used to match the candidates to the reference block in the search zone is a cost function of the distance and the scores. This function is given by:

$$Cost = p.S_c + (1 - p)C_c$$ (3.9)

The best match is obtained by minimizing the cost function along the N-I image pairs using:

$$Match = \min_{n=1}^{N-1} \sum_{c=1}^{N-1} Cost_{n,c}$$ (3.10)

In the BMA algorithms, the performance is influenced by two main parameters: the research window size and the block size. Concerning the research window size, if this one is small, the amount of information inside the window is also small and the estimation is not reliable. In the other hand, if the size is too large, the number of matching candidates is big, thus the estimation can be wrong. In practice, the ideal size depends on the clouds displacement speed. For our experiments, the maximum displacement speed is 32 pixels per hour therefore; windows of 32x 32 pixels are adopted. The second important parameter of the block matching technique is the block size. If the size is too small, the number of matched blocks increases as well as the estimation error. On other hand, with a bigger block size, there is a high possibility that the block contains different objects moving in different directions and consequently, the estimation error increases.

The performance measure used to obtain the optimal block size is the peak-signal-to-noise-ratio (PSNR) [20]:

$$PSNR = 10 \log_{10} \left( \frac{255^2}{MSE} \right)$$ (3.11)

Where, MSE is the mean square error between the original image I and the reconstructed image I, using the estimated motion vectors. It is given by the relation:
\[ MSE = \frac{1}{m^2} \sum_{x=1}^{m} \sum_{y=1}^{m} (I_r(x, y) - I(x, y))^2 \]  

(3.12)

The bigger values of PSNR refer to a better performance of the algorithm. Figure 3 shows the PSNR versus the block size. Clearly, the PSNR is high for a block size of 4×4 pixels. So this size is used in the implementation.

![Figure 3. PSNR measured in decibels (dB) vs block size.](image)

3.3. Fuzzy inference system structure

Fuzzy inference systems (FIS) have a multidisciplinary nature and they have been successfully applied in a wide variety of fields, such as automatic control, data classification, decision analysis, expert systems, and computer vision. There are two main structures of fuzzy inference systems: Mamdani-type and Sugeno-type. Here, Mamdani’s fuzzy inference system [21] is used in order to decide the optimal position for the solar panel using the two inputs: the cloud cover index and the cloud duration.

The first step when making up a FIS is the fuzzification. Each of the cloud cover index, the cloud duration and the decision of orientation varies from 0 to 1. As presented in figure 4, Each of the input variables are fuzzified into three triangular membership functions with the associated linguistic labels \( S \) (“Small”), \( M \) (“Medium”) and \( B \) (“Big”). The decision of the PV panel position \( d \) is fuzzified using two triangular membership functions which are associated to the linguistic labels: \( T \) for the tracking mode and \( H \) for the horizontal position.

The Fuzzy rules that have been used in this work are given in the table below:

| Cloud cover index | Cloud duration | PV panel position |
|-------------------|----------------|-------------------|
| \( S \)           | \( S \)         | \( T \)           |
| \( M \)           | \( S \)         | \( T \)           |
| \( B \)           | \( S \)         | \( T \)           |
| \( S \)           | \( M \)         | \( T \)           |
| \( M \)           | \( M \)         | \( H \)           |
| \( B \)           | \( M \)         | \( H \)           |
| \( S \)           | \( B \)         | \( H \)           |
| \( M \)           | \( B \)         | \( H \)           |
| \( B \)           | \( B \)         | \( H \)           |
In the described fuzzy inference system, the fuzzy rule structure is predetermined by the interpretation of the characteristics of the variables and the membership functions are empirically tuned depending on the experimental data.

The defuzzification produces the numerical result of the fuzzy inference system. Many ways can be used to achieve this task. In this work, the center of area is adopted. This method, proposed by Sugeno and also known as center of gravity \( [22] \), is given by:

\[
Z_{COG} = \frac{\int \mu_A(z)z\,dz}{\int \mu_A(z)\,dz}
\]  \hspace{1cm} (3.13)

Where \( Z_{COG} \) is the crisp output, \( \mu_A(z) \) is the aggregated membership function and \( z \) is the output variable.

![Input and output membership functions and the fuzzy decision surface of the FIS.](image1)

a. First input  
b. Second input  
c. Output decision  
d. Fuzzy decision surface

**Figure 4.** Input and output membership functions and the fuzzy decision surface of the FIS.
4. Implementation and results

4.1. Experimental process

The described decision-making system has been implemented on an experimental process located in PROMES laboratory in Perpignan City ((latitude = 42.700 N, longitude= 2.900 E). As shown in figure 5, the set-up comprises: a polycrystalline photovoltaic panel SUNSET-PX 50E, a dual axis sun tracker SM34SPM+ equipped with a microcontroller board and a computer with a data acquisition card NI-USB-6008.

In practice, the intelligent algorithm computes the optimum position of the PV panel during the period $\Delta t$ (fixed in this study at $\Delta t = 1$ hour) and then, the new position angles are sent to the microcontroller in the tracker via a RS232 serial communication.

For the present study, the cloud cover index and the cloud duration are computed using the MSG (Meteosat Second Generation) images from the channel 0.6 $\mu$m taken over the central Europe every 15 minutes. These images are provided by the European Organization for the Exploration of Meteorological Satellites (EUMETSAT). The normal resolutions for VIS channels are 3×3 km².

The following parameters are used to estimate the clouds velocity:

- Number of visible images used in each sequence (4 images)
- Block size (4×4 pixels)
- Research window (32×32 pixels)

![Picture of the experimental process](image)

**Figure 5.** Picture of the experimental process

4.2. Results and discussion

Let's note that the aim of this work is to increase the efficiency of classical solar trackers, taking into account different weather conditions. The proposed approach was evaluated by comparing daily mean global solar radiation captured by classical methods (continuous solar tracking systems) to that obtained with the proposed intelligent approach. The results presented in figures 6 and 7 cover the period from January 2015 to May 2016.
The results presented in these figures show that we get a bigger value of the global solar power by using the intelligent approach and that indicates a significant improvement of sun tracker efficiency.

To analyze the performance of our approach under different weather conditions, a classification in three cases has been considered and presented in Table 2.
Table 2. Sky classification

| Cloud cover index (n) | Sky class  |
|-----------------------|------------|
| n < 0.1               | Clear      |
| 0.1 < n < 0.5         | Partly covered |
| n > 0.5               | Overcast   |

For each class of sky, the gain (g) of captured solar power is computed using the following formula:

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

(4.1)

Where: $E_i$ (w/m²), is the solar power captured by the PV using the intelligent orientation method and $E_c$ (w/m²), is the solar power captured by the PV using the classical sun tracking method (continuous solar tracking systems).

The results are presented in figure 8. Regarding this figure, one can note that, under clear sky conditions, the gain of solar power equals to zero and this is normal since the intelligent system decides to track the sun as the classical sun tracker. In case of partly covered sky, the performance of the proposed approach increases and the gain is approximately 14%. Under overcast sky situations, by inducing a horizontal position, the intelligent approach produces a gain of about 23%.

![Figure 8. Gain of solar power vs sky class.](image)

5. Conclusion

In this paper, an intelligent procedure is proposed to optimize the orientation of solar PV panel taking into account weather conditions. This intelligent approach is based on METEOSAT satellite images processing and fuzzy inference systems. In this context, the cloud cover index is computed by comparing the considered visible image to a reference image under clear sky. At the same time, the block matching algorithm is used for the detection of cloud motion vectors. Once the motion vectors are computed, the cloudy duration is evaluated. The cloud cover index and the cloudy duration are then treated by a fuzzy inference system, to decide the optimal position of the PV panel. To evaluate the performance of this method, it was implemented using an experimental process and the obtained results over 17 months, show that the power gain reaches about 14% and 23% respectively in the case of partly covered and overcast sky. Consequently, the proposed orientation strategy is efficient in all seasons. The immediate continuation of this work will be the integration of other kinds of images such as infra-red and/or water vapor ones to perform the control system. It will also be interesting to apply the developed algorithm in zones with other kind of climate. In this sense, collaborations are being developed with research teams in Côte d’Ivoire and Spain.
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