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A Review of Solar Energy Tracker and Models

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Abstract: **Sun is one of the potential energy sources and an essential part of life. Importantly, solar-energy can be utilized as electric energy using a device called 'solar cell' or 'photovoltaic cell'. The challenge in this field of research is to improve efficiency of conversion of photo-to-electricity, thereby maximizing the utilization of the energy for the society. Use of a solar tracker is a promising strategy for improving the efficiency. The solar tracker is a device for operating a solar photovoltaic panel, especially in solar cell applications, require high degree of accuracy to ensure that the concentrated sunlight is dedicated precisely to the power device. Sun radiation falling on the tracker device gives information on how much of the sun's energy strikes a surface at a location on the earth during a particular time period. These data are needed for effective research in solar-energy utilization. In this article, a review is made on the solar energy tracker and its types, also the solar energy model are classified based on the basis of the surfaces(horizontal and tilt). Linear, nonlinear, artificial intelligence models for solar energy prediction have been discussed in this review.**

1. INTRODUCTION

Ancient Greeks and Romans saw great benefit in Ancient Greeks and Romans saw great benefit in what we now refer to as passive solar design. They learnt the use of architecture to make use of the suns capacity to light and heat indoor spaces. In 1861, Mouchout developed a steam engine powered entirely by the sun, but its high costs coupled with the falling price of English coal doomed his invention to become a footnote in energy history. Nevertheless, solar energy continued to intrigue and attracted European scientists through the 19th century.

An alternate and renewable source of power generation has become inevitable to meet the ever-increasing power demand. In this situation, solar-power generation has become the need of the day.

A Solar Energy Tracker is a device on which solar panels are fitted to track the motion of the sun across the sky so that the maximum sunlight strikes the panel throughout the day. Solar energy tracker was invented because solar panel is unable to move towards the sunlight when the sun moves from east to west. The Solar Energy Tracker will attempt to navigate to the best angle of exposure of light from the sun. In order to produce maximum power output, the solar energy tracker is designed with a motor so that the solar panel will move towards the position of the sun. It moves according to the sun's movement and is controlled by a microcontroller. Here, we present a review focusing on solar energy tracker, its types, and different models for its utilization to maximize the solar systems output.

2. TYPES OF SOLAR ENERGY TRACKER:

Trackers can be grouped into classes by the number and orientation of the trackers axes. Compared to a fixed mount, a single axis tracker increases annual output by approximately 30%, and a dual axis tracker an additional 6%. A tracker rotating in the east-west direction is known as a single-axis tracker. The sun also moves through 56 degrees north to south for 1 year period. The same panels set at the midpoint between the two local extremes will thus see the sun move 23° on either side, causing 8.3% of loss. A dual axis tracker is a tracker that accounts for both the daily and seasonal motions.

2.1. Single Axis Trackers

Single axis trackers have freedom of one degree that acts as the rotation axis. The rotation axis of single axis trackers is typically aligned along true North meridian. It is possible to align them in any principal direction with advanced algorithms of tracking. There are several common realization of single axis trackers. These are horizontal single axis trackers (HSAT), vertical single axis trackers (VSAT), tilted single axis trackers (TSAT) and polar aligned single axis trackers (PASAT). The orientation of the module with respect to the tracker axis is important when modeling performance.

2.1.1. Horizontal Single Axis Tracker (HSAT). The axis of rotation for horizontal single axis tracker is horizontal with respect to the ground. The posts of horizontal single axis tracker at either end of the axis of rotation can be shared between trackers. Field layouts are very flexible with horizontal single axis trackers.

The simple geometry refers by keeping all of the axis of rotation parallel to one another is all that is required for appropriately positioning the trackers with respect to one another. Appropriate spacing can maximize the ratio of energy production to cost, this being dependent upon local terrain and shading conditions and the time-of-day value of the energy produced. One means of computing the disposition of panels is backtracking. The trackers that are horizontal mostly have the face of oriented module parallel to the rotation axis . As module tracks, it sweeps the cylinder that is rotationally symmetric around rotation axis. Several manufacturers can deliver single axis horizontal trackers. In these, pylons or frames are used on which bearings are mounted for supporting a long horizontal tube. The tube axis is on a North-South line. Panels are installed on the tube, and the tube will revolve on its axis to track the observable motion of the sun through the day.

2.1.2. Vertical Single Axis Tracker (VSAT). The rotation axis for vertical single axis trackers is vertical with reference to the ground. These trackers revolve from East to West during the day. Such trackers at high latitudes are more effective than are horizontal axis trackers. Field designs should consider shade for avoiding unnecessary energy loss and to optimize utilization of land.

2.1.3. Tilted Single Axis Tracker (TSAT). All trackers with axes of rotation between horizontal and vertical are considered tilted single axis trackers. Tracker tilt angles are limited often to reduce the wind profile and decrease the elevated ends height off the ground. Field designs should consider shade for avoiding unnecessary loss and to optimize utilization of land. With backtracking, they can be packed without shading perpendicular to their axis of rotation at any density. However, the packing parallel to their axis of rotation is limited by the tilt angle and the latitude.

2.1.4. Polar Aligned Single Axis Tracker(PASAT). One scientifically interesting variation of a tilted single axis tracker is a polar aligned single axis trackers (PASAT). In this particular implementation of a tilted single axis tracker the tilt angle is equal to the latitude of the installation. This aligns the tracker axis of rotation with the earths rotation axis. These are deployed rarely due to their high wind profile.

2.2. Dual Axis Trackers

Dual axis trackers have two degrees of freedom that act as the rotation axis. These axis are typically perpendicular to one another. The axis fixed with reference to the ground can be considered as primary axis. The axis referenced to the primary axis can be referred as secondary axis. There are many realizations of dual axis trackers. They are categorized by the orientation of their primary axes with respect to the ground. Two common realizations are tip-tilt dual axis trackers (TTDAT) and azimuth-altitude dual axis tracker (AADAT). Dual axis trackers allow for optimum solar energy levels due to their ability to follow the sun vertically and horizontally. Dual axis trackers angle themselves to be in contact with the sun directly irrespective of sun's position in the sky.

2.2.1. Tip-Tilt Dual Axis Tracker (TTDAT). A tip-tilt dual axis tracker has its primary axis horizontal to the ground. The secondary axis is typically perpendicular to the primary axis. The support at both end of the primary rotation axis of this tracker can be occupied between trackers to minimize the costs of installation. Field designs with this dual axis trackers are quite flexible. The easy geometry means that by keeping the rotation axis parallel to each other in all that is required for suitably positioning the trackers with respect to one another. Likewise with backtracking, they can be packed without shading at any density.

2.2.2. Azimuth-Altitude Dual Axis Tracker (AADAT). An azimuth-altitude dual axis tracker has its primary axis vertical to the ground. The secondary axis is typically perpendicular to the primary axis. Field designs must consider shade for avoiding unnecessary energy loss and to optimize utilization of land. Also optimization for dense packing is deficient because of the shading nature over the course of a year. By using combinations of the two axis, any location in the upward hemisphere may be pointed. One axis is a vertical pivot shaft or horizontal ring set, that enables the device to be sway to a compass point. A horizontal elevation pivot is the second axis fixed upon the azimuth platform. According to the expected solar orientation such systems may be operated under computer control, or may use a tracking sensor to control motor drives that align the panels toward the sun.

3. SOLAR ENERGY MODELS

The solar energy is accepted as dependable and widely available renewable energy resources. Various types of solar energy models have been reviewed in the literature.

3.1. Modeling Solar Energy on a Horizontal Surface

Solar energy modeling on a horizontal surface can be done using linear models, nonlinear models and also using artificial intelligent techniques like artificial neural network(ANN), multi-layer feed forward neural network(MLFFNN) and feed forward MLP neural network model.

3.1.1. Global Solar Energy Models. Linear or nonlinear models can be used to calculate the global solar energy in terms of the sun shine hours. Sopian and Othman gave a linear model of global solar energy has been developed using the solar radiation data for three locations in Malaysia and linear regression analysis [1]. The developed solar energy model using the monthly solar radiation for eight locations in Malaysia is based on the least square linear regression analysis had been discussed by Janjai [2]. Sben and Tan gave a simple linear model for global and diffuse solar radiation done for Bangkok, Thailand [3]. Linear modeling of global solar radiation given by Chineke was done by using the Angström model for the northwestern part of Turkey [4]. Two global solar energy models using the Angström model and the Hargreaves model have been developed for the three zones in Nigeria by Yohanna [5]. The author(s) who gave global solar energy model for Malaysia has been developed using the Angström model [6]. A simple regression model for global solar radiation in terms of clearness and diffuse indices for North Sinai, Egypt has been presented by Trabea [7]. A nonlinear model was used for modeling the global solar radiation in terms of sunshine ratio for Istanbul, Turkey by Top [8]. El-Sebaii gave a linear and nonlinear forms of Angström model employed to model the global solar radiation on horizontal surfaces in Jeddah, Saudi Arabia [9]. The global solar radiation is in terms of ambient temperature, relative humidity and sunshine hours. For modeling the global solar energy on a tilt surface, the Liu and Jordan model was used.

3.1.2. Diffuse Solar Energy Model. The relationship between the average daily diffuse and global solar radiations incident on a horizontal surface and the sky clearness index can be found from direct meteorological observations or through an empirical relationship given by Collare-Pereira(1979) [10]. A linear regression model has been applied for modeling diffuse solar radiation in Guangzhou, China [11]. The developed model is in terms of ambient temperature, global solar radiation, sunshine ratio, clearness index and relative humidity. An extraterrestrial solar radiation model in terms of the same parameters has been developed and compared with other linear and nonlinear models that do not take into account temperature and humidity.

3.1.3. Solar Energy Model Using Artificial Intelligent Techniques. Intelligent solutions, based on artificial intelligence (AI) technologies to solve complicated practical problems in various sectors, have received much popularity these days. AI-based systems are being developed and employed worldwide in myriad applications, mostly because of their flexibility, explanation capabilities and symbolic reasoning.

An artificial neural network (ANN) was used to estimate the global solar radiation for selected sites in Saudi Arabia [12]. Data from 41 stations were obtained to develop the ANN based solar energy model. The ANN model employed is the multi-layer feed forward neural network (MLFFNN) and the training algorithm is based on the back propagation algorithm. The developed MLFFNN consists of 4 input neurons, 10 neurons in the hidden layer and 1 output neuron . The inputs to the MLFFNN are the longitude, latitude, sunshine duration and altitude. A MLFFNN exercised by the back propagation algorithm was also developed to predict the global solar radiation for sites in Oman in terms of location, month, mean pressure, temperature, vapor pressure, relative humidity and sunshine duration had been discussed by Alawi and Hinai [13]. MLFFNN with back propagation algorithm was employed for estimating the total solar radiation in Greece had been given by Mihalakakou [14]. A multilayer recurrent neural network with back-propagation training algorithm was applied for predicting the solar radiation in Cyprus [15]. Here, the ANN input variables are the month, day of month, Julian day, season, mean ambient temperature and mean relative humidity. However, the disadvantages of the developed ANN method are that it is not accurate because it uses short term data and considers monthly average solar energy that does not help in designing accurate solar energy systems which require daily or hourly average solar energy. Fadare gave a feedback propagation neural network model that has been developed using 195 cites data for Nigeria. Here, the ANN input variables are the latitude, longitude, altitude, month, sunshine ratio, temperature and relative humidity. The developed ANN model is then used for obtaining solar maps of Nigeria for all months [16].

ANN has also been applied for predicting global solar radiation in terms of sunshine hours and ambient temperature in Algeria as given by the author(s) [17]. Similarly, Reddy and Ranjan gave an ANN model using the back propagation training algorithm has been developed for estimating the monthly, daily and hourly global solar radiation for selected sites in India [18]. The input parameters to the ANN that have been considered for estimating the solar radiation for each city are latitude, longitude, altitude, month, time, air temperature, wind speed, relative humidity and rainfall. The radial basis function neural network model is used to model the global solar radiation in Al-Madinah, Saudi Arabia [19]. The input parameters to the ANN are the air temperature, sunshine ratio and relative humidity. The global solar radiation results show that there is a strong correlation between the global solar radiation and the sunshine ratio compared to the temperature and humidity.

The feed forward MLP neural network model considering four inputs and one output has been developed to predict the global solar radiation [20]. The inputs to the ANN are the latitude, longitude, day number and sunshine ratio while the output is the clearness index. Data from 28 weather stations were considered for the development of the ANN model in which data from 23 stations were used for training and data from 5 stations were used for testing the ANN. Author(s) gave a multi-layer perceptron (MLP) neural network using the back propagation training algorithm applied for modeling hourly solar radiation for seven sites in Spain [21]. This model is used for generating a time series of hourly solar radiation for sites at which no measuring devices are available. Zarzalejo gave an ANN and fuzzy logic which were used to predict the hourly global solar radiation in fifteen Spanish terrestrials using the satellite images and cloud index [22]. For predicting the global solar radiation, the cleanness index which is a function of the cloud index has to be estimated using four alternative models, namely, simple regression model, extended regression model, fuzzy logic model and ANN model. It is proven that the fuzzy logic and ANN models give accurate prediction of the clearness index compared to the regression models. Fuzzy logic was also applied for predicting solar energy where there are ambiguities and vagueness in solar energy and sunshine duration records in a day [23]. The main advantage of the fuzzy logic model is that it can be devised for handling uncertainties in estimating the solar radiation.

A detailed description of the fuzzy sets and fuzzy logic implementation for solar energy estimation had been given by Sen [23]. In the fuzzy logic implementation, the solar energy variables which are sunshine duration and solar energy are described in terms of linguistic variables such as small, high, short and long.

ANN model has been developed for estimating the diffuse solar energy in which the inputs of the model are latitude and longitude coordinates and cleanness index, day number [6]. Two MLP neural networks with the back propagation training algorithm are used for predicting the hourly and daily diffuse solar radiation for selected sites in Egypt had been given by author(s) [24]. The ANN model for predicting the hourly diffuse radiation has six inputs which are the hour, day, month, year, hourly global radiation and hourly extraterrestrial solar radiation.

Meanwhile, the ANN model for predicting the diffuse solar radiation has three inputs, namely, global solar radiation, extraterrestrial solar radiation and sun shine ratio. The results of the study showed that the ANN based models are more accurate in predicting the diffuse radiation compared to the linear regression models. A MLP neural network was also developed for predicting the direct solar radiation for selected sites in India had been given by Alam [25].

3.2. Modeling Solar Energy on a Tilt Surface

The solar energy models that have been described in the previous sections are for solar energy on horizontal surface, but here models of solar energy on tilt surface are considered. The aim of modeling of solar energy on a tilt surface is to find the optimum tilt angle of a solar collector in a specific region. As a matter of fact, the alignment and the tilt of a solar panel strongly affect the amount of the collected yield. Therefore, solar panels must be skewed and aligned at an ideal angles so as to gather the maximum solar energy available in a specific region. The best method to enhance the alignment and tilt of a solar panel is by using an active sun tracker. Active sun trackers are pure mechanical or electromechanical devices that keep changing the alignment and tilt of a solar panel systematically during the day. However, it utilizes energy during tracking and hence the principal cost of such a system is high [26].

To forecast the solar energy on a surface, the solar energy on horizontal surface and geometrical models are considered. Therefore, the components of incident global solar radiation on a tilt surface examine the global, diffuse, direct (beam) and reflected solar energy on a tilt surface.

3.2.1. Isotropic Diffuse Solar Energy Model. Isotropic solar energy models are based on the assumption that despite of the direction of measurement, isotropic radiation has the same strength, and an isotropic field utilizes the same action despite of how the test particle is aligned. It scatters in all directions from a an isotropic radiator. One of the most well-known isotropic diffuse solar models is the Liu and Jordan model.

3.2.2. Anisotropic Solar Energy Models. Anisotropy as compared to isotropy is the property of being directionally dependent, which indicates identical properties in all directions. Hence, anisotropic solar energy models are based on the assumption that anisotropic radiation depending on the direction of measurement has different strength and it scatters in all directions non uniformly.

4. CONCLUSION

A review focusing on solar energy trackers, its different types, and solar energy models have been presented comprehensively. In this review the solar energy tracker are classified into two types, the types are further divided into different types. Furthermore, different models for solar energy classified based on the basis of the surfaces (horizontal and tilt), linear, nonlinear and artificial intelligence models have been discussed.

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