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Solar Forecasting Methodologies

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ABSTRACT: Use of photovoltaic (PV) panels in power generation is the most widely used renewable energy source today. But this solar power energy source is highly susceptible to fluctuations and easily affected by variations in weather conditions over the area. At such times, solar forecasting models play a key role for operators to manage the operations of generation units such as balancing the fluctuations and extracting, supplying and maintaining maximum output power. Maximum Power Point Tracking (MPPT) technique is the technique offently preferred in photovoltaic (PV) systems to extract the maximum power inspite of climatic variations. In this paper various solar forecasting methodologies are discussed. Out of the various MPPT methods, the perturbation and observation (P&O) method is widely used.

Keywords: Maximum Power Point Tracking (MPPT), Perturb and Observe (P & O) method, Solar forecasting.

INTRODUCTION

Best alternative to reduce the environmental hazards due to thermal power generation plants is the use of renewable energy in power generation. Developments in PV technologies today has increased the PV power generation plants on a large scale. Key component of PV power generation unit is the PV module. The solar PV panels transform the solar energy into required electrical energy. Hence the total output power depends on the incoming solar radiation, its intensity as well as the characteristics of utilised PV panels [1]. Major share of efficiency of the entire generation system is dependent on performance and efficiency of these modules alone. Environmental factors such as ambient temperature, irradiance levels, partial shading, climatic conditions etc are the major factors that a PV module relies on. All these environmental factors are subjected to fluctuations at every time instants. Here comes the need of solar power forecasting models which help balance the fluctuations and hence provide smooth output with maximum power. Few factors to be considered while designing solar forecasting models are the environmental condition, deep knowledge regarding the incident sun rays, possibility of scattering of sun rays and the various characteristics of the of the PV plant used to generate the power. Efficient use of generated energy, trading of energy and proper management of the electrical grid are a few advantages of using forecasting models in generation units [2].

Advancements are also made in MPPT control techniques to extract maximum output power and improve the system efficiency. Traditional methods such as short circuit current (SCC), open circuit voltage (OCV) and modern techniques such as perturb and observe (P&O), incremental conductance (INC) and hybrid techniques are some of the MPPT control algorithms. Advanced techniques include the use of soft computing techniques or artificial intelligence algorithms such as Fuzzy Logic Control (FLC), Artificial Neural Network (ANN), Variable Universe Fuzzy Logic Control (VUFLC) etc are also implemented in recent years. The major and common drawback is that maximum of the techniques only consider irradiance variation parameter of PV modules and eliminate its dependency on temperature. Advancements in microprocessors and microcontrollers makes it easy to implement techniques such as ANN, FLC, model predictive control (MPC), genetic algorithms etc. There are two main categories of MPC – finite set control model predictive control (FCS-MPC) and continuous control set model predictive control (CCS-MPC). For power converters, FCS-MPC helps achieve optimal switching state. To decide the application of next switching state, converter model is discretised.

This paper proposes a solar forecasting method for parameter monitoring, thus reducing the system cost and at the same time improving the accuracy and efficiency of the tracking system to extract maximum possible power from PV panels.

RELATED WORK

Authors presented a forecasting model for solar power generation using artificial intelligence. Artificial Neural Networks (ANN) and an Adaptive Neuro-Fuzzy Inference System (ANFIS) are used to design the prediction model [3]. Dong *et al.,* [4] presents a forecasting model based on regression and particle swarm optimisation (PSO). The design makes use of self-organised maps along with support vector regression and PSO for solar irradiance forecasting. A brief history and introduction of solar light intensity and PV power forecasting using text mining is discussed in [5].

A brief classification of existing solar forecasting conventional models is presented in [6]. Boost converter is controlled with the help of FCS-MPC along with P&O method. Value of capacitor voltage useful for MPC algorithm implementation is estimated using extended Kalman filter (EKF). A forecasting model using ANN is presented [7].

SOLARFORECASTING

Installation of solar parks, operation of PV generation units, scheduling and accuracy of dispatched power are few of the functions of solar power forecasting models. Factors such as irradiance, velocity of winds, coverage of clouds, temperature affect the quality and quantity of obtained solar power. Forecasting models are dependent on combination of various parameters such as solar irradiance, weather condition parameters, data obtained by monitoring the solar generation unit and the mathematical modelling involved in the system design. Improved quality of the energy supplied to the grid as well as reduction in system cost required for dealing with weather dependent parameters are the major advantages of implementing forecasting models.

Type of forecasting model to be designed is mainly dependent on time scale factor. Fig 1 briefs the classification of forecasting models based on time scale and the granularities. They are majorly classified as intra-hour, intra-day and day ahead forecasting models. Intra-hour forecasts consider a time span of 15 min to 2 hours maximum. Intra-day forecast models consider a time span ranging from one to six hours whereas, the day ahead forecast model covers up the time span of one to three days ahead. Very short-term time scale forecast includes the time scale ranging from several minutes to few hours. Live onsite data measurement is fairly enough for these forecasts. Ground based sky imagers are preferred for this model design. Considering a time frame ranging from 30 min to 6 hours approximately, best suited models are the satellite image-based forecasts. Talking about forecast models for grid integration, comparatively a longer forecast time span is preferred, say about two days or more. For such long-term forecasts, numerical weather prediction (NWP) models are used.

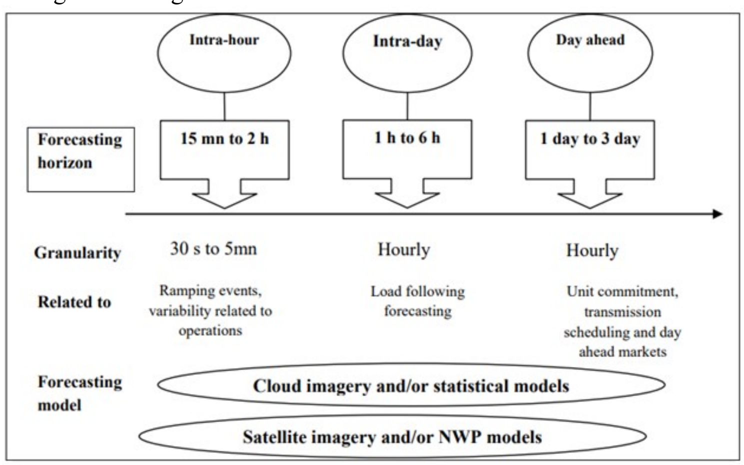

Fig. 1. Forecasting approaches based on prediction time scale.

Solar forecasting methodologies:

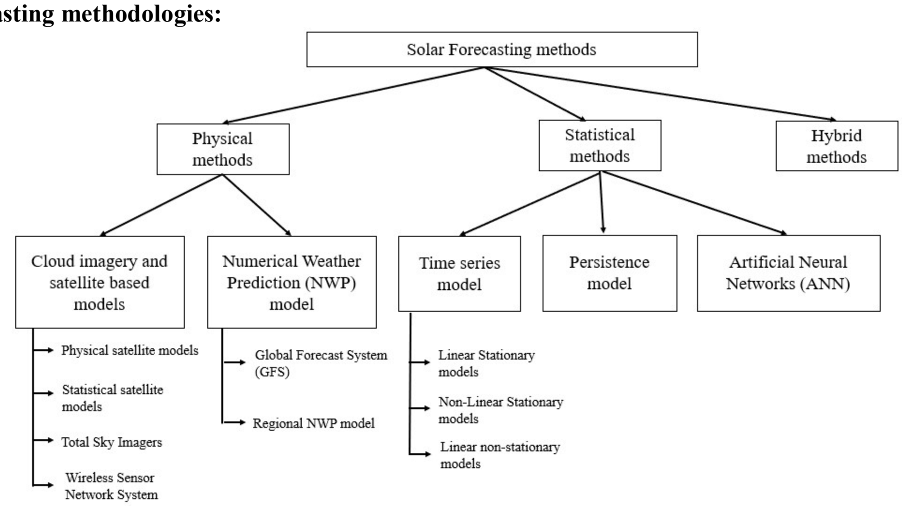

Fig. 2. Classification of solar forecasting methods.

Briefly the forecasting methods for solar power generation units are classified in three categories namely, the physical methods, the statistical methods and the hybrid methods. Fig 2 represents the classification of forecasting models. Following is a brief description of each of the said category.

A. Physical Methods

This method includes the use and dependency of physical data such as humidity, pressure, temperature and the cloud coverage of that area. Depending on variation in use of data, they are further classified as satellite-based models, numerical weather prediction (NWP) and Total Sky Imager (TSI).

(i) Cloud imagery and satellite-based models. This model mainly works on analysing clouds. High spatial resolution which is capable of deriving the information based on cloud motions is used to deal with the satellite imageries. Locating the cloud position makes it easier to predict the solar irradiance.

(ii) Physical Satellite models. This model wholly depends on the interaction of environmental components like solar radiation, aerosols, gases present etc. Local meteorological data is considered for this. This method helps eliminate the dependency of the system on solar irradiance parameter.

(iii) Statistical Satellite models. Satellite instruments provide the sensed data in the form of digital counts. This model is designed considering the basic principle of regression between the digital counts and solar irradiance level at ground surface measured using pyranometer. Cloud cover index, current brightness, minimum and maximum pixel brightness, transmissivity of atmosphere, solar zenith angle are some of the parameters required for forming the equations of regression. There are certain drawbacks of this technique, of which the two major being the measurement technique difference and the errors while localising the ground sites on satellite maps. Few researchers conclude that such errors can be minimised by increasing the satellite resolution.

(iv) Total Sky Imagers. Total Sky Imager (TSI) is an instrument manufactured by Yankee Environmental Systems, with an motive of providing an alternative to NWP and satellite imaging forecasting models, by imaging the ground-based local meteorological data. This technique is capable of providing information regarding fluctuations in solar radiance at much higher frequencies. This requires spatial as well as temporal resolution. This method makes use of digital processing of CCD image obtained to detect the cloud positions in the sky. Forecasting is done by forward propagating the cloud image.

(v) Wireless Sensor Networks Systems. This technique uses multiple readings obtained from distributed networks to design forecasting model to predict the power output of distributed network. This technique supports intra-minute forecasting wherein the time span varies between 20-50 seconds. This is achieved using spatial cross-correlations. Use of wireless sensor network helps reduce the system cost enhancing its accuracy at the same time.

(vi) Numerical Weather Prediction models. These models are designed considering only the current atmospheric condition data *i.e.* somehow similar to live monitoring. The data obtained via current observations is processed for future prediction. Processing of data and obtaining output in the form of meteorological data such as wind, temperature, irradiance is achieved using assimilation process with the help of super computers. NWP is widely used to design forecast models for one to multiple days ahead predictions. Data prediction is done using assimilation whereas statistical post processing of data obtained in previous performance of system is used for error correction. It is capable of predicting transient cloud variations and widely used for scheduling of PV power generation units.

(vii) Global Forecast System (GFS). Global Forecast System (GFS) is the most widely preferred NWP model. National Oceanic and Atmospheric Administration (NOAA) introduced this technique. This model is run every six hours. It is capable of producing forecasts upto 16 days i.e. 384 hours considering a global domain grid of 28 × 28 km. This technique can also estimate the wavelength attenuation of diffused radiations based on scattering/absorbing phenomena.

(viii) Regional Numerical Weather Prediction (NWP) model. This is rarely used technique only considered as a sub-domain of global forecasting model.

B. Statistical Methods

Statistical methods make use of previous historical solar radiation data for forecasting. They are further classified as statistical methods and learning methods.

Time series models. As said earlier time series models gives the result based on the historical data. These models work on random stochastic observation process which is time dependent, *i.e.* observations made on hourly, daily, weekly basis. Major requirement is the data patterns obtained via observations. These patterns need to be very precise and clear as well as easily identifiable for proper forecasting.

Linear stationary model. Observation data patterns thus obtained can be either stationary or non-stationary. Stationary series are static irrespective of their shape. Fluctuations may be random or specifically ordered in nature.

Non-linear stationary model. Name itself suggests that such models are mainly used for systems having complex non-linear nature. Saturation effects, chaos, hysteresis and combination of various such non-linear issues are some of the system non-linearities. This model is mostly preferred in the field of artificial networks wherein it is used to parameterize the networks.

Linear non-stationary model. In order to use this model one needs to be very particular about the variations in time series, as it includes analyses of a non-stationary time series.

Persistence models. Also named as naïve predictor, this is the simplest forecasting model among all its types. This model makes predictions assuming the future value to be equal to the previous value. This model finds its application in intra-hour forecasts where the time span of few minutes is considered. It can be preferred where there are few weather pattern fluctuations.

Artificial Neural Networks (ANN). Artificial neural networks belong to artificial intelligence domain wherein the allotted tasks are performed either by regression or pattern recognition. Both techniques can prove helpful for solar forecasting. Both these are applied in solar irradiance forecasting. Input-output are mapped in non-linear fashion using regression technique. Here one needs the historical data as an input to ANN model whose output is in the form of irradiance levels. ANN computes the weights of neurons in training phase whereas computes the forecast based on these weights obtained from training phase. Pattern recognition technique constitutes of training and testing phases. Here instead of forecasted irradiance, a number representing object classification is the output of ANN model.

Hybrid Methods

Enhancement in forecast accuracy can be further obtained by hybrid/combined models. Combining two models will definitely combine and increase the advantages of both models at same time decreasing their individual drawbacks and minimising the forecasting errors. Combination of two linear or two non-linear or one linear and one non-linear model can be made possible. There are various researches proving the enhanced performance of integrated forecast models over the individual forecast models.

This research focusses on designing a short-term power forecasting model without using any historical data. This helps reduce the system dependency and cost. Short-term power forecasting models can be installed in various areas of power system such as

— Control
— Unit Commitment
— Security Assessment
— Optimum planning and scheduling of power generation
— Energy exchange
— Integration of Grid

CONCLUSION AND FUTURE WORK

Balancing the load and generation of power are the key requirements in economic scheduling of electricity market trades and power generation units. Now-a-days use of clean, sustainable renewable energy sources for power generation is on high demands. Power generation from renewable sources always suffer uncertainty issues. Energy forecasting can hence prove best solution in solving challenges arising due to use of uncertain resources. PV plants being the abundantly used renewable resource for power generation, solar power forecasting is matter of attraction to the researchers. A combination of FCS-MPC and Kalman filter is used to draw maximum power from solar panels. Conventional MPPT technique based on FCS-MPC use three sensors for monitoring. Extracting maximum power using different MPPT tracking techniques along with other filters or using machine learning algorithms can be tried as future scope.

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