A Review of Fuzzy Logic and Artificial Neural Network Technologies Used for MPPT

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Abstract: Solar electric power generating stations play a major role in meeting the growing demand for electric power. These generating stations make use of solar photovoltaic (PV) panels to perform the conversion of solar energy to electric energy. However, the solar panel output is highly unpredictable because the output is a function of number of factors; some of which are not in the control of humans like the weather conditions, and the output is also a function of the age of PV panel, dust and other debris collected on the panel, direction and angle of elevation and so on. The solar panels exhibit a low efficiency. Currently, a lot of research is going on to overcome these issues. This paper represents a review of two modern techniques used in solar photovoltaic systems which enhance the extraction of maximum output power in an efficient manner. The Artificial Intelligence Based MPPT Techniques for PV Applications, and, a Forecasting System of Solar PV Power Generation using Wavelet Decomposition and Bias-compensated Random Forest are reviewed and compared in this paper.

Keywords: Artificial Intelligence, Fuzzy-Logic, Neural Network, Solar Photovoltaic, Wavelet Decomposition.

1. Introduction

The most recent couple of years have seen enormous development in the utilization of sun powered vitality in the private, business, and modern segments. As indicated by [1], the aggregate limit of the worldwide solar based PV area achieved 178 GW in the year 2014, and is assessed for achieve 540 GW in the year 2019. An essential hurdle for coordinating solar based power with utility grids is the exceptionally discontinuous behavior of the sun based energy delivery, contingent upon the area and time as well as fast temperature changes, that results in a lower use of sun powered energy and the requirement of high capacity batteries because of the bungle between the power usage and the generation based on PV. Estimation of solar based power is fundamental not just for proficient administration of the power framework yet in addition for better use of sunlight based in private and business organizations. Sun oriented radiation comprises of immediate and diffuse sunlight-based radiation, the last getting dispersed, consumed, and reflected inside the air, for the most part by mists, yet in addition by particulate issue and gas particles [2]. Sunlight based PV determining procedures can be grouped into three classes dependent on figure skylines [3]: intra-hour, intra-day and days ahead forecasting. Solar energy is obtainable in abundance and to harness the radiations form sun into electricity, solar photovoltaic conversion is the most preferable one. So, we utilize a few methods with a goal to harness most energy at every moment will be successfully by using the photovoltaic framework.

The man-made consciousness-based techniques are powerful in nature and are observed to be valuable in such conditions [4]. The non-stationary, non-straight normal for sun-oriented radiations are grouped through four classes [5]: NWP (Numerical-Weather-Prediction), satellite sky imagers, nearby sky imagers and sensor exhibits, man-made and stochastic consciousness (Artificial Intelligence) procedures. Authors from [6], [7] likewise demonstrate and prove the last strategy has a better performance for a neighborhood intra-day gauge. Time Series procedures namely AR (Auto-Regressive) and ARX (Auto-Regressive with exogenous information) models are likewise been connected for Solar photovoltaic gauging [8]. Authors in [9] propose the principal basic determining strategy utilizing meteorological information and artificial intelligence to do the non-straight mapping from information factors to PV yield. The execution isn't enhanced since the decision of information factors and adjustments in the artificial intelligence models is missing. Authors form [10], numerous counterfeit neural system (ANN) procedures are assessed for anticipating of sun-powered radiation, for example, multilayer perception (MLP), repetitive neural systems (RNNs) and hereditary calculations, and so forth.

2. Modelling the Photo-Voltaic Module

The A single cell of PV consists of a p-n junction manufactured on a slight semiconductor wafer that changes approaching sun-based radiation into electricity by photo-electric impact. A photovoltaic cell displays nonlinear characteristics for current voltage and power which are a function of the insulation levels and the temperature. A photovoltaic module may be demonstrated with utilizing a single diode display, dual diode display or a triple diode display. For the majority of exploration, a solitary diode demonstrate is adequate. For the most part, a sunlight-based photovoltaic cell may be demonstrated using present energy source and a diode connected parallelly depicted in Figure 1. Arrangement obstruction speaks to obstacle that happens amid due to stream consisting of electric charge from n– p and the parallel opposition speaks to the spillage current [11]. A perfect sunlight based cell must have a Series opposition as zero and Parallel obstruction as endlessness.

$$I = N_p I_{ph} - N_p I_o \left(exp\left[\frac{q(V/Ns + IRs/Np)}{AkT}\right] - 1 \right) \quad (1)$$

$$- \frac{V + IR_s}{R_p}$$

where, I represents electric current, V as voltage across the photovoltaic panel, photo-current, reverse saturation current, the number of cells circuited in parallel configuration, and in series configuration, represents electron charge i.e., (1.6x10e-19C), k as Boltzmann's constant (1.38x10-23J/K), A as p-n junction with factor of ideality as, (1 <a < 2, a = 1 ideal value), and T is the temperature of photovoltaic module.

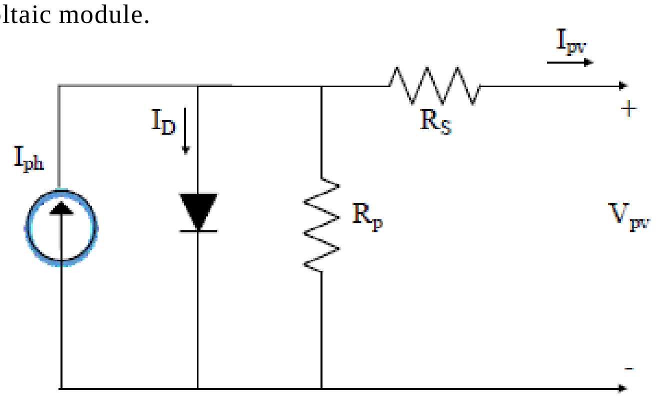


Figure 1: Electric equivalent model of solar photovoltaic cell

3. Mppt (maximum power point tracking)

To acquire the most extreme accessible energy for every moment, utilization of MPPT technology is of utmost importance. In the load line based maximum power point tracking methods, calculation faculties' current, voltage, or intensity of a photovoltaic Array and follow up on the ideal calculation. Be that as it may, in MPPT strategies based on AI, no confinement exists for detection of the required parameters. Understanding these important parameters, for example, Insulation, Temperature level and so forth and anticipate the voltage, current or power. To put it plainly, man-made consciousness based strategies need not require any information of the general PV framework. Be that as it may, if AI is connected in a similar way as if there should be an occurrence of burden line-based strategies, it may be observed as progressively productive.

3.1. MPPT based on Fuzzy Logic

MPPT technique based on Fuzzy Logic is one of the most important AI technology that is predominantly used because of the progressions in VLSI innovation. Additionally, the Fuzzy-logic-based frameworks do not require any accurate modeling of the photovoltaic module to structure a controller. The information factors are changed into a semantic variable dependent on fresh arrangements of enrollment work. The quantity of participation capacities utilized relies upon the exactness of the controller, yet it more often than not shifts somewhere in the range of 5 up to 7. Fuzzy logic control can be categorized in different dimensions, some of them are given as., Negative Big (NB), Negative Medium (NM), Negative Small (NS), Negative Zero (NZ), Zero (ZE), Positive Zero (PZ), Positive Small (PS), Positive Medium (PM) and Positive Big (PB) [12]–[15]. Yield of fuzzy rationale converter normally is an adjustment for the obligation proportion of a power-converter, ΔD, and an adjustment to the DC-connect for the reference voltage, ΔV. Standard-base, otherwise called principle-base query table or sometimes fuzzy guideline calculation, relates fuzzy yield to fuzzy data sources dependent on the utilized power converter. Benefits associated with the mentioned controllers are management of uncertain information sources without the requirement of precession scientific models with utmost care taken for the nonlinear behavior, are quick intermingling and negligible motions around the maximum power point. Moreover, these methods have been appeared to perform efficiently under advance variations in the illumination.

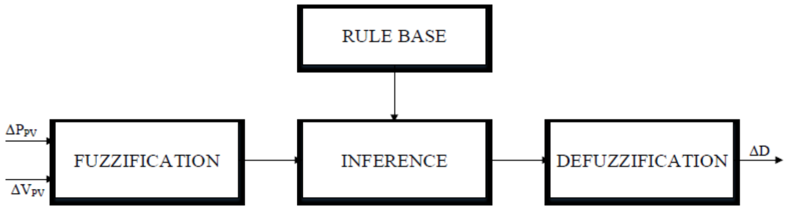


Figure 2: Controller based on Fuzzy Logic [24]

3.2. MPPT based on Neural Network

The Artificial Neural Network is a group of artificial (electrical) neurons associated dependent on different topology designs. One of the most widely recognized utilization of an Artificial Neural Network includes ID and displaying of framework utilizing non-linear and complex capacities. Amid the learning procedure followed by ANNs, the Weights associated with different connections (Wi) are resolved. ANN experiences an adjustment cycle, amid that the loads get refreshed up to the point when system achieves the balanced condition. So as to precisely recognize the maximum power point utilizing ANN's the (Wi) must be resolved suitably as a function of the connection across the information and the photovoltaic framework yield. Information flag for every neuron is the flag received from the neighboring neurons or the artificial neural network input factors related to the non-linear framework taken under examination [16]–[18]. In utilization of MPPT based on AI, information factors may be photovoltaic exhibit specifications such as VOC and ISC, climatic information such as solar irradiance and temperature, or maybe blend all. Yield of artificial neural

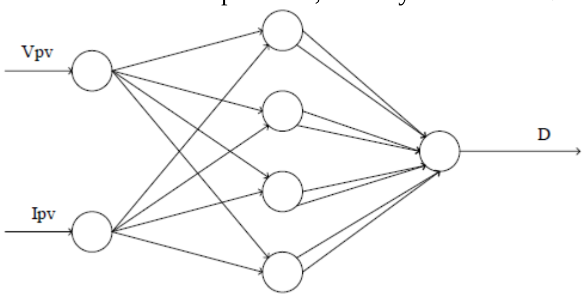


Figure 3: Neural Network Neuron [24]

network is normally one of a few reference flags, the most well-known of which is the obligation cycle flag used to drive the power converter to work at or near the MPP.

Execution of Neural Network depends on the capacities utilized through the shrouded layers and the design efficiency of the neural network. All the connections between the nodes are weighted specifically. For the MPP to accomplish the task of maximum power extraction precisely, the data consisting of examples and results are recorded over an extensive timeframe in the neural network.

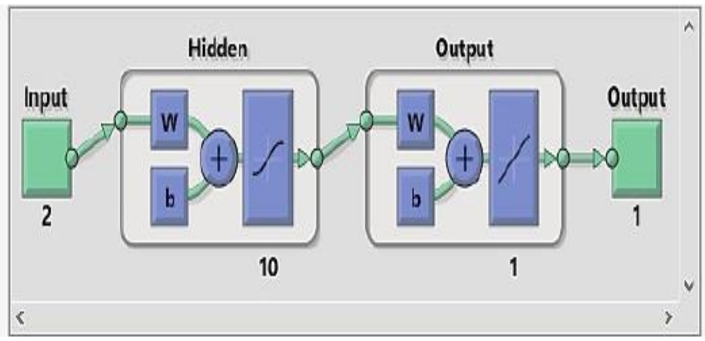


Figure 4: Diagram for Neural Network [24]

3.3. MPPT based on ANFIS

ANFIS (Adaptive Neuro-Fuzzy Inference System) coordinates artificial neural systems and fuzzy systems rationale. Fuzzy rationale systems exhibit capacity to change the etymological quantities into numerical qualities utilizing fuzzy tenets and enrollment capacities. Anyway, establishing the right fuzzy guidelines and enrollment capacities which very are a function of framework conduct can wind up task of testing. ANFIS consolidates neural network system and fuzzy rationale systems to conquer downsides of the individual strategies and appropriately tuned MPPT based on ANFIS framework may follow MPP with higher exactness than some other strategy.

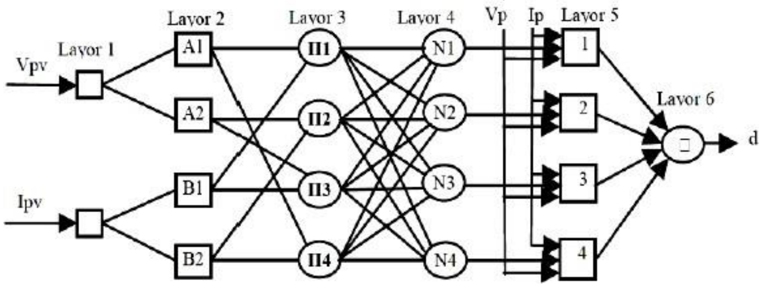


Figure 5: MPPT based on ANFIS [24]

Versatile ANFIS combines the upside associated with fuzzy rationale and neural network systems in a single system and thus, generates a streamlined fuzzy based derivation framework installing the entire information of the framework conduct (following task). The outputs of photovoltaic cells rely upon various climatic parameters. Temperature and Insulation are among the most vital variables based on which the power delivered from the photovoltaic cluster is dependent upon.

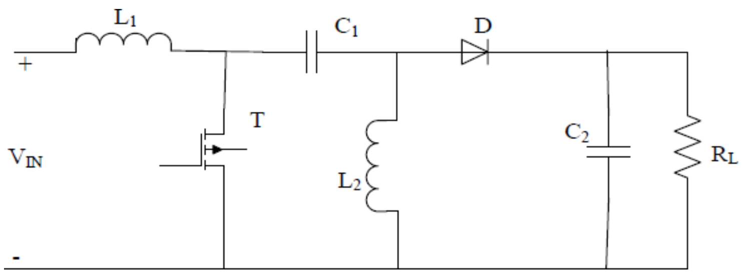
The preparation information is same as that utilized for Neural based framework. The required participation capacities are produced in the wake of preparing with the assistance of 'anfisedit' device in Matlab\Simulink. Like NN, ANFIS can likewise have diverse data sources, for example, VOC and ISC or Irradiance and Temperature levels.

4. Single ended primary inductor converter (sepic)

Core of almost any MPPT framework can be considered to be a converter (DC to DC), it is on the grounds that it is the converter obligation proportion that coordinates the fluctuating impedance of source of the photovoltaic board so as to accomplish most of the extreme power. Practically any DC to DC converter may be utilized, for such kind of applications, here a SEPIC converter is being utilized. It is important to utilize a converter with buck type support, on the grounds that on occasion we may require a kicking activity regardless of whether the framework is displayed for the purpose of boosting. From various experimental results, a SEPIC has been found to extricate to some degree more power contrasted with different techniques. A resistive load is driven by a Sepic converter, is shown in Figure 6. The authors in this work, have introduced the obligation proportion having an estimation of 0.5 and (75 to 125) V being the information variety. The shifting of yield voltage may range from (40 to 400) V.

Figure 6: Single Ended Primary Inductor Converter [24]

From the figure, the output current and the voltage are given by the following equations:



$$\frac{V_O}{V_i} = \frac{D}{1 - D} \quad (2)$$

$$\frac{I_O}{I_S} = \frac{1 - D}{D} \quad (3)$$

The design equations are given by

$$L_1, L_2 = \frac{V_{dc} D}{\Delta I_1 f} \quad (4)$$

$$C_1 = \frac{I_O(D)}{\Delta V_{C1} f} \quad (5)$$

$$C_2 = \frac{I_O(D)}{0.5\, \Delta V_{C2} f} \quad (6)$$

5. Theoretical Background and Proposed Technique

5.1. Random Forests

Subsequent to the application of wavelet decay, conceivably repetitive and insignificant highlights may exist. Thus, the artificial intelligence calculations must be strong and immune to this type of repetitiveness and highlights. Arbitrary timberlands were picked in [19], that are turned out to be strong with the repetitiveness and superfluous highlights [16]. Further, arbitrary timberlands have only two primary specifications that need to be tuned and it isn't touchy to such specifications [20], that enhance the use of this proposed procedure to a generalized solar based photovoltaic gauge issue.

5.2. Wavelet Decomposition

For the separation of genuine fundamental variety in photovoltaic control, the authors in [21] have utilized the stationary wavelet change exploiting its multi-resolution structure. Despite the fact that Fourier investigation is a customary instrument to the examination of worldwide frequencies of power present in the flag, it needs transient goals when managing varying procedures. Some recurrence goals in the Fourier examination may be traded to show signs of improvement time goals, that may be performed by characterizing brief length waves called mother wavelet works so the given flag for investigation is anticipated on this premise work. Wavelet decay gives an advantageous method to isolating the genuine basic pattern in signs from the false short vacillations [16][22]–[25]. In conventional Fourier change, the information is anticipated on sinusoidal premise capacities which stretch out through the range of time area. The wavelet premise work is parameterized by the interpretation parameter b and enlargement parameter [20].

Dual networks examined wavelets are by and large orthonormal. Utilizing the premise work in [26], DWT can be communicated as the internal item between the sunlight based PV flag x(t) and the premise work as.

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\, \psi_{m,n}(t) dt, \quad (7)$$

$-\infty$

$T_{m,n}$ is the coefficient of wavelet at level (or enlargement) m and area (or interpretation) n, and gives the detail (fine data) introduced in the flag. The scaling capacity at level m and move related with flag smoothing and has comparative multi-resolution structure as the wavelet. It is given by

$$\phi_{m,n}(t) = 2^{-\frac{m}{2}}\phi(2^{-m} \cdot t - n), \tag{8}$$

$$\int_{-\infty}^{\infty} \phi_{\mathrm{m,n}}(t)dt = 1 \tag{9}$$

6. Conclusion

In this paper the main point of focus are the techniques used for extraction of maximum power from a solar photovoltaic system. After reviewing many techniques, the techniques based on fuzzy logic, machine learning, and artificial intelligence seem to be most promising and beneficial in this process since the output of solar photovoltaic is highly dependent on weather conditions which are not predictable over a long period of time[21], [27], [28]. The artificial intelligence techniques learn the weather patterns over the course of time and develop patterns so as maximum power is extracted from the system. This technique also helps to predict the random nature of weather conditions with higher accuracy than any other methods. Thus, artificial intelligence techniques are a good choice for solar photovoltaic systems to attain higher efficiency along the long-term goals. Still a lot of research is needed to be conducted in this field so as we attain the system which has the ability for maximum power extraction from the most abundant solar photovoltaic systems.

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