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AN EXPERIMENTAL ESTIMATION OF HYBRID ANFIS-PSO BASED MPPT FOR PV GRID INTEGRATION UNDER FLUCTUATION SUN IRRADIANCE

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Abstract:

In this project to enhance the photovoltaic (PV) power-generation conversion, maximum power point tracking (MPPT)is the foremost constituent. This introduces an adaptive neuro - fuzzy inference system–particle swarm optimization (ANFIS–PSO)-based hybrid MPPT method to acquire rapid and maximal PV power with zero oscillation tracking. The inverter control strategy is implemented by a space vector modulation hysteresis current controller to get quality inverter current by tracking accurate reference sine-shaped current. The ANFIS–PSO based MPPT method has no extra sensor requirement for measurement of irradiance and temperature variables. The employed methodology delivers remarkable driving control to enhance PV potential extraction. An ANFIS– PSO - controlled Zeta converter is also modeled as an impedance matching interface with zero output harmonic agreement and kept between PV modules and load regulator power circuit to perform MPPT action. The attainment of recommended hybrid ANFIS– PSO design is equated with perturb and observe, PSO, ant colony optimization, and artificial bee colony MPPT methods for the PV system. The practical validation of the proposed grid-integrated PV system is done through MATLAB interfaced d space interface and the obtained responses accurately justify the proper design of control algorithms employed with superior performance.

***Index Terms* – ANFIS-PSO,MPPT, AURDINO NANO (micro controller), SOLAR PANEL,BATTERY,RPS,LDR, MOTOR ,MOTOR DRIVE.**

Introduction

By VIRTUE of depletion of traditional energy sources, the requisition and applications of renewable energy sources are booming globally. Amid entire renewable sources, the photovoltaic (PV) system has exceptional progression since the last decade. By means of nonlinear voltage/current features of PV modules, the transfiguration competency is limited. Maximum power point trackers (MPPTs) are imperative ingredients to warrant superlative PV energy generation under global power point tracking state. In many MPPT control strategies have been inspected in the literary work. Perturb and observe (P&O), Hill climbing (HC), and incremental conductance (INC) are reviewed as classical MPPT methods. The hardware implementation of P&O and HC methods is simpler, but it comprises high oscillations nearer to a maximum power point (MPP), which results in power losses.The INC method is accurate and flexible under fluctuating atmospheric situations. Nevertheless, it contains simulationand experimental complexities. However, the above-mentioned algorithms are not efficient under varying solar irradiance and for the calculation of correct perturbation size. Therefore, intelligent fuzzy logic control (FLC) and artificial neural network (ANN) techniques as MPPT trackers are selected to rectify classical MPPT algorithms' deficiency under fluctuating weather conditions. Various research teams are working to achieve low cost and improve tracking efficiency andreliability ofP V-based industrial sectors. In this regard, the fuzzy logic-based MPPT approach plays a vital role as it has simpler architecture and robust design that is able to solve uncertainties and nonlinearity problems of the PV power system. However, expert knowledge and design of rule base systems are the key challenges for FLC design. Compared to classical algorithms of MPPT techniques, the ANN method consisting of multi layered neurons is widely employed for fast PV power tracking under changing environmental conditions. However, using this method large data is required for proper training, periodically to achieve an accurate MPPT. After combining ANN and FLC, the hybrid algorithm comprises attractive learning abilities that provide trained membership for MPPT action. It is also noted that there is a requirement to calculate PV voltage and current to implement MPPT algorithms. However, some MPPT controllers failed because of high hardware complexity and noise calculations.

I. Here, a hybrid adaptive neuro-fuzzy inference system (ANFIS) occupying peak power tracker is adopted, that subsists the benefit of couple algorithms. The training and updation of ANFIS specifications are a challenging task for the designers. The recent artificial intelligent algorithms, such as particle swarm optimization (PSO), firefly algorithm, artificial bee colony (ABC), and ant colony optimization (ACO), are used to solve optimized problems. The FLC and ANN provide better PV tracking ability under uniform variation of Sun insolation level. However, under changing weather conditions where multiple peaks are present and it is very difficult to obtain the MPP region, PSO provides an optimal solution as it requires very few parameters for adjustment. Compared to the mentioned optimization algorithms, the PSO method has a low sampling point, simpler mathematical analysis, easy hardware implementation, and economical computing estimation and provides fast and accurate PV power tracking under varying operating conditions. In contrast to the gradient techniques, the PSO provides simpler and rapid updation convergence velocity. Moreover, the PSO does not need initial parameter calculation and there is no requirement to flearning rate. It delivers rapid convergence velocity, simpler construction, and easy employment with utmost PV tracking efficiency utilization. This research work delivers effective, simpler, and robust hardware implementation of MPPT circuitry. When equated with the classical dc–dc converter, a Zeta converter provides low voltage ripple in voltage yield. Compared toother power converters, the Zeta converter has attractive characteristics as it transforms power in a single stage, consists of naturally isolating design, provides power factor corrections, and works in the step-up/down mode of operation. It is also termed as the fourth-order nonlinear power converter working in continuous/discontinuous modes.

II. ANFIS (Adaptive Neuro-Fuzzy Inference System)

An **Adaptive Neuro-Fuzzy Inference System** or **Adaptive Network-Based Fuzzy Inference System** (**ANFIS**) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. The technique was developed in the early 1990s. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Hence, ANFIS is considered to be a universal estimator. For using the ANFIS in a more efficient and optimal way, one can use the best parameters obtained by genetic algorithm. It has uses in intelligent situational aware energy management system.

ANFIS architecture

It is possible to identify two parts in the network structure, namely premise and consequence parts. In more details, the architecture is composed by five layers. The first layer takes the input values and determines the membership functions belonging to them. It is commonly called fuzzification layer. The membership degrees of each function are computed by using the premise parameter set, namely {a,b,c}. The second layer is responsible of generating the firing strengths for the rules. Due to its task, the second layer is denoted as "rule layer". The role of the third layer is to normalize the computed firing strengths, by dividing each value for the total firing strength. The fourth layer takes as input the normalized values and the consequence parameter set {p,q,r}. The values returned by this layer are the defuzzificated ones and those values are passed to the last layer to return the final output.

Fuzzification layer

The first layer of an ANFIS network describes the difference to a vanilla neural network. Neural networks in general are operating with a data pre-processing step, in which the features are converted into normalized values between 0 and 1. An ANFIS neural network doesn't need a sigmoid function, but it's doing the preprocessing step by converting numeric values into fuzzy values.

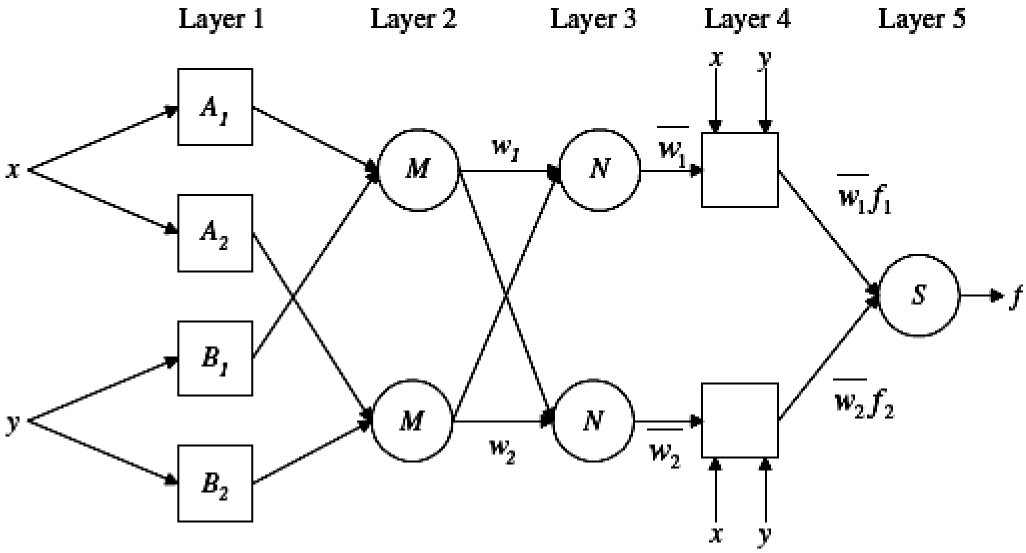


Fig-1 FUZZY LAYERS

III. BLOCK DIAGRAM

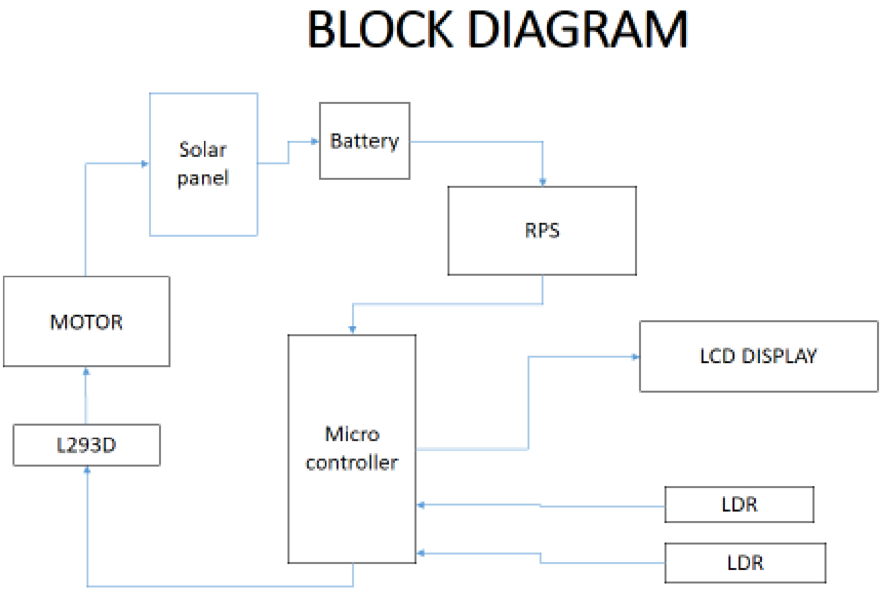


Fig 2: BLOCK DIAGRAM

IV. PSO (Particle Swarm Optimization)

particle swarm optimization (**PSO**) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. It solves a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formula over the particle's position and velocity. Each particle's movement is influenced by its local best known position, but is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

PSO is originally attributed to Kennedy, Eberhart and Shi and was first intended for simulating social behaviour, as a stylized representation of the movement of organisms in a bird flock or fish school. The algorithm was simplified and it was observed to be performing optimization. The book by Kennedy and Eberhart describes many philosophical aspects of PSO and swarm intelligence. An extensive survey of PSO applications is made by Poli. Recently, a comprehensive review on theoretical and experimental works on PSO has been published by Bonyadi and Michalewicz.

PSO is a metaheuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. Also, PSO does not use the gradient of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classic optimization methods such as gradient descent and quasi-newton methods. However, metaheuristics such as PSO do not guarantee an optimal solution is ever found.

PSO can be related to molecular dynamics.

V. MPPT(Maximum Power Point Tracking)

Maximum power point tracking (**MPPT**) or sometimes just **power point tracking** (**PPT**) is a technique used with variable power sources to maximize energy extraction as conditions vary. The technique is most commonly used with photovoltaic (PV)

solar systems, but can also be used with wind turbines, optical power transmission and thermophotovoltaics.

PV solar systems have varying relationships to inverter systems, external grids, battery banks, and other electrical loads. The central problem addressed by MPPT is that the efficiency of power transfer from the solar cell depends on the amount of available sunlight, shading, solar panel temperature and the load's electrical characteristics. As these conditions vary, the load characteristic that gives the highest power transfer changes. The system is optimized when the load characteristic changes to keep power transfer at highest efficiency. This optimal load characteristic is called the *maximum power point* (MPP). MPPT is the process of adjusting the load characteristic as the conditions change. Circuits can be designed to present optimal loads to the photovoltaic cells and then convert the voltage, current, or frequency to suit other devices or systems.

Solar cells' non-linear relationship between temperature and total resistance can be analyzed based on the Current-voltage (I-V) curve and the power-voltage (P-V) curves.MPPT samples cell output and applies the proper resistance (load) to obtain maximum power.MPPT devices are typically integrated into an electric power converter system that provides voltage or current conversion, filtering, and regulation for driving various loads, including power grids, batteries, or motors. Solar inverters convert DC power to AC power and may incorporate MPPT.

The power at the MPP (P_{mpp}) is the product of the MPP voltage (V_{mpp}) and MPP current (I_{mpp}).

In general, the P-V curve of a partially shaded solar array can have multiple peaks, and some algorithms can get stuck in a local maximum rather than the global maximum of the curve.

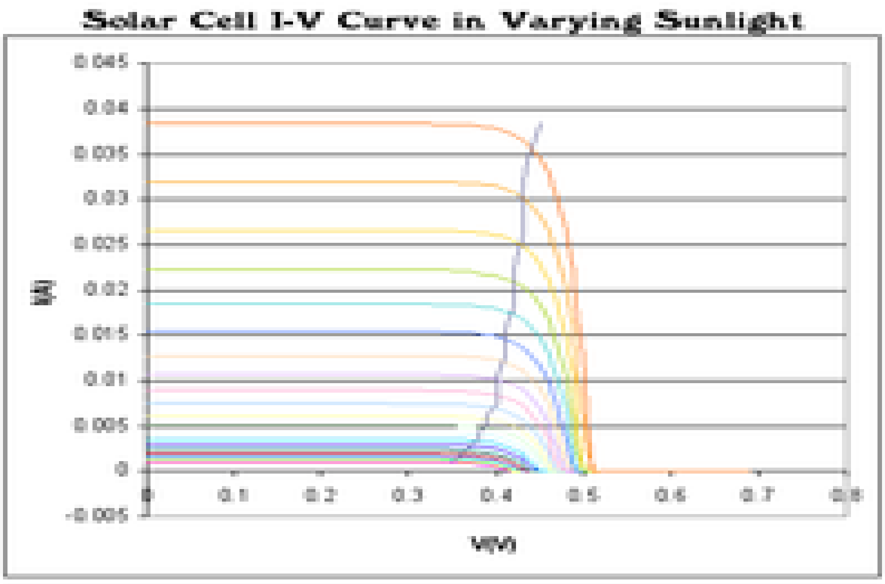


Fig 3 Solar Cell I-V Curve

Photovoltaic cells have a complex relationship between their operating environment and the power they produce. The fill factor (FF) characterizes the cell's non-linear electrical behavior. Fill factor is defined as the ratio of the maximum power from the cell to the product of open circuit voltage V_{oc} and short-circuit current I_{sc}. Tabulated data is often used to estimate the maximum power that a cell can provide with an optimal load under given conditions:

For most purposes, FF, V_{oc}, and I_{sc} are enough information to give a useful approximate view of the cell's electrical behavior under typical conditions.

For any given set of conditions, cells have a single operating point where the values of the current (*I*) and voltage (*V*) of the cell allow maximum power output. These values correspond to a particular load resistance, which is equal to *V* / I as specified by Ohm's law. The power P is given by:

.

A photovoltaic cell, for the majority of its useful curve, acts as a constant current source.[11] However, at a photovoltaic cell's MPP region, its curve has an approximately inverse exponential relationship between current and voltage. From basic circuit theory, the power delivered to a device is optimized (MPP) where the derivative (graphically, the slope) *dI/dV* of the I-V curve is equal and opposite the *I/V* ratio (where d*P/dV*=0) and corresponds to the "knee" of the curve.

A load with resistance *R=V/I* equal to the reciprocal of this value draws the maximum power from the device. This is sometimes called the 'characteristic resistance' of the cell. This is a dynamic quantity that changes depending on the level of illumination, as well as other factors such as temperature and cell condition. Lower or higher resistance reduces power output. Maximum power point trackers utilize control circuits or logic to identify this point.

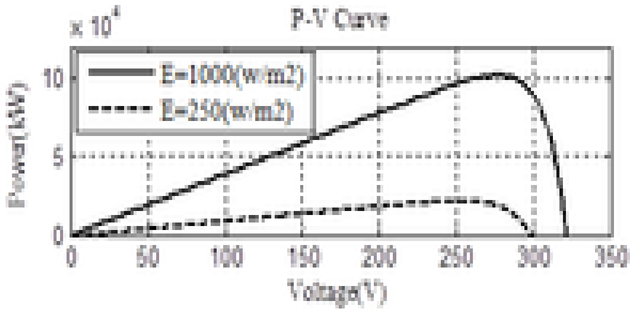


Fig 4 Power voltage(p-v curve)

VII. ARDUINO NANO (Micro controller)

The Arduino Nano, as the name suggests is a compact, complete and bread-board friendly microcontroller board. The Nano board weighs around 7 grams with dimensions of 4.5 cms to 1.8 cms (L to B). This article discusses about the technical specs most importantly the pinout and functions of each and every pin in the Arduino Nano board.

Arduino Nano has similar functionalities as Arduino Duemilanove but with a different package. The Nano is inbuilt with the ATmega328P microcontroller, same as the Arduino UNO. The main difference between them is that the UNO board is presented in PDIP (Plastic Dual-In-line Package) form with 30 pins and Nano is available in TQFP (plastic quad flat pack) with 32 pins. The extra 2 pins of Arduino Nano serve for the ADC functionalities, while UNO has 6 ADC ports but Nano has 8 ADC ports. The Nano board doesn't have a DC power jack as other Arduino boards, but instead has a mini-USB port. This port is used for both programming and serial monitoring. The fascinating feature in Nano is that it will choose the strongest power source with its potential difference, and the power source selecting jumper is invalid.

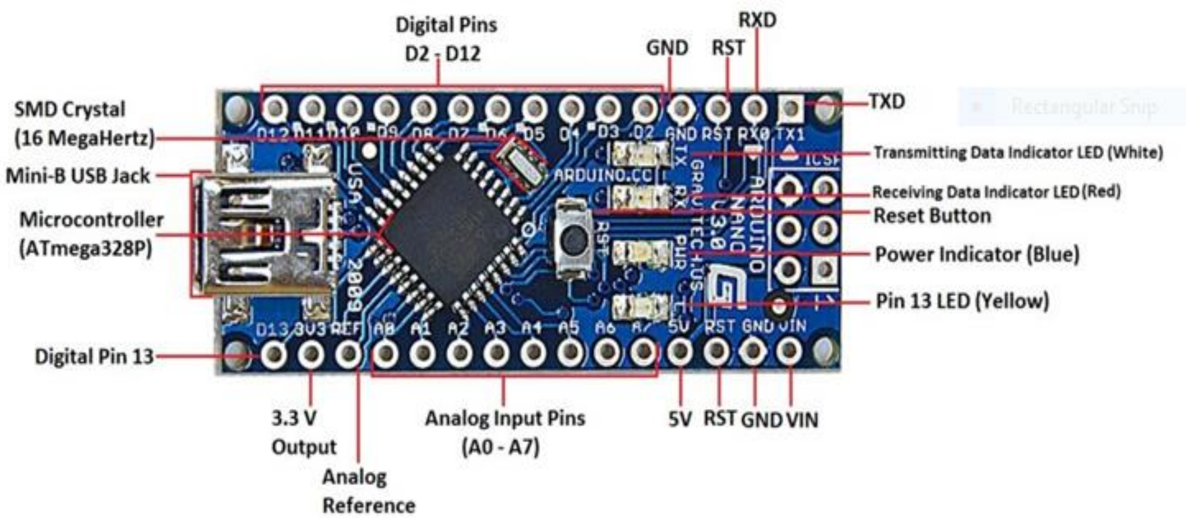


Fig 5 Arduino nano Board

Arduino Nano – Specification

Arduino Nano	Specifications
Analog I/O Pins	8
Architecture	AVR
Clock Speed	16 MHz
DC Current per I/O Pins	40 milliAmps
Digital I/O Pins	22
EEPROM	1 KB
Flash Memory	32 KB of which 2 KB used by Bootloader
Input Voltage	(7-12) Volts
Microcontroller	ATmega328P
Operating Voltage	5 Volts
PCB Size	18 x 45 mm
Power Consumption	19 milliAmps
PWM Output	6
SRAM	2KB
Weight	7 gms

Table: Specifications of the Arduino Nano

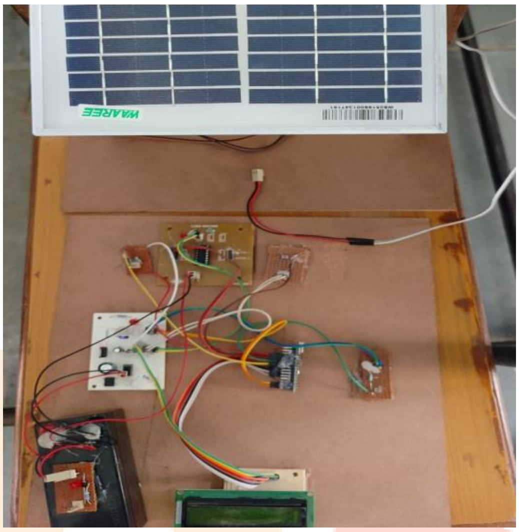
VI. Code used in project

```
#include <Wire.h>
#include <LiquidCrystal.h>
LiquidCrystal lcd(7, 6, 5, 4, 3, 2);
void setup()
{
  Serial.begin(9600);
  pinMode(A1,INPUT);
  pinMode(A2,INPUT);
  pinMode(13,OUTPUT);
  pinMode(A0,INPUT);
  pinMode(A3,INPUT);
  lcd.begin(16, 2);
  lcd.setCursor(0,0);
  lcd.print("Solar Tracker");
  lcd.setCursor(0,1);
  lcd.print("Power generation ");
  delay(2000);
  lcd.clear();

}

float vol;
float cur;
int Ldr1, Ldr2;
void loop()
{
 cur = analogRead(A3);
  cur = 1023 - cur;
  cur = (cur * 10)/512;
  int a = analogRead(A0);
  int b = analogRead(A3);
  float v1=a*(2.8/(4095.00))*30;
  float c1=b*(2.8/(8095.00))*30;
  float v2=a*(2.8/(4095.00))*35;
  float c2=b*(2.8/(8095.00))*35;
  String s = "V1:" + String(v1) + " C1:" + String(c1);
  String s1 = "V2:" + String(v2) + " C2:"+ String(c2);
```

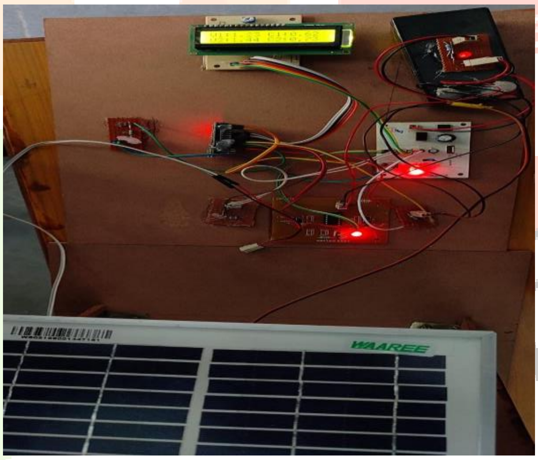
```
  lcd.clear();
  lcd.setCursor(0, 0);
  lcd.print(s);
  lcd.setCursor(0, 1);
  lcd.print(s1);
  delay (500);
Ldr1 = analogRead(A1);
  Ldr2 = analogRead(A2);

  if((Ldr1 < Ldr2) && (Ldr1 < 280))
   {
     digitalWrite(8,HIGH);
     digitalWrite(9,LOW);
     delay(100);
     digitalWrite(8,LOW);
     digitalWrite(9,LOW);
     delay (300);
   }

  else if((Ldr2 < Ldr1) && (Ldr2 < 300))
   {

     digitalWrite(8,LOW);
     digitalWrite(9,HIGH);
     delay(100);
     digitalWrite(8,LOW);
     digitalWrite(9,LOW);
     delay (500);
   }

  else
   {
     digitalWrite(8,LOW);
     digitalWrite(9,LOW);
     delay (500);

   }
}
```

VII. RESULT

The behaviour of an ANFIS-PSO MPPT algorithm has been tested under strong solar insolation profile presented. The power tracking ability of the proposed PV system with hybrid ANFIS-PSO MPPT control under the strong intensity of the un irradiance profile. An ANFIS-PSO MPPT tracking period, zero oscillation around MPP,and lo power losses. Also, the behaviour of the ANFFIS-PSO MPPT algorithm has been tested under weak solar insolation profile. Comparing to the gradient approach,the PSO technique provides rapid simpler, and fast convergence for updating of ANFIS paraameters.Moreover, the gradient method requires initial parameters for the calculation of learning rate. Practical results reveal that the proposed hybrid ANFIS-PSO method has better responses for complex non linear system equated with the conventional PSO method.



OFF Period



ON Period

VIII. CONCLUSION AND FUTURE SCOPE

In this project justification of a hybrid ANFIS– PSO and SVMHCC inverter control has been provided for the achievement of PV MPPT as well as injection of sinusoidal current to the electric grid. Compared to execution periods to obtain the least RMSE using PSO, ACO, and ABC, the proposed hybrid ANFIS–PSO has the least execution time (0.30 s), which justifies the acceptance of MPPT controller design. Inverter-fed sinusoidal current with low total harmonic distortion (THD) followed the IEEE 519 standard. A Zeta converter provides zero ripple output with MPPT functions using the proposed hybrid methodology. The performance of the proposed

MPPT is commensurate with P&O, ACO, and ABC MPPT methods that provide rapid, precise, and accurate PV tracking under fluctuating weather conditions. It is revealed that the PV power system is functioning with zero steady-state error and has rapid PV tracking convergence velocity under highly fluctuating Sun insolation, which is validated through practical responses. Compared to other training techniques such as PSO,ACO, and ABC, the proposed hybrid ANFIS–PSO has better power tracking ability, least RMSE execution period, and free derivation for finding antecedent parameters for proper training under uniform, nonuniform, and partial shading conditions. The obtained experimental results correspond to standard grid codes for the grid-tied PV system. The main contributions to academic field knowledge and industrial sectors' experience on the real platform are to obtain the best MPPT configuration based on the hybrid ANFIS–PSO algorithm and have the least execution time, which justifies the acceptance of MPPT controller design. Moreover, the obtained experimental results explain achievement of PVMPPTas well as injection of sinusoidal current to the electric grid and that the PV power system is functioning with zero steady-state error and has rapid PV tracking convergence velocity under highly fluctuating Sun insolation. The implemented work can be extended with multilevel inverter topology as well as the Internet of Things-based MPPT control strategies as a future scope.

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