Power Management in Photovoltaic-Wind Hybrid System Based on Artificial Intelligence

***Mhusa N. J, Nyakoe G. N,**
Department of Mechatronic Engineering, Jomo Kenyatta University of Agricultural and Technology
Nairobi, Kenya
*Correspondence: mhusauk@gmail.com

Mgaya E. V
Department of Electrical Engineering, Arusha Technical College
Arusha, Tanzania

***Abstract*— This paper presents a control strategy for power management in standalone solar photovoltaic and wind hybrid power system based on Artificial intelligence techniques. Solar and wind energy are utilized as a primary sources of energy and a battery unit is considered as storage element to meet out the load demand in case of insufficient power generation from primary sources. To ensure efficiency optimization of sources the Adaptive Neural Fuzzy Inference System (ANFIS) strategy is employed to achieve the maximum power point (MPP) for photovoltaic (PV) panels and the Fuzzy Logic Control (FLC) strategy is employed to achieve the MPP of wind turbine. The fuzzy logic controller is developed to manage the power flow between the hybrid power sources and other devices in the system. The controller choose the optimal operating mode of power sources ensuring the continuous supply of the load and maintaining the battery state of charge (SOC) at acceptable levels. Proposed controller provides effective utilization of sources and minimizing usage of battery hence improves battery life. A complete mathematical modeling and MATLAB/Simulink model for the proposed system is implemented to track the system performance. Simulation results are presented to show the effectiveness of the proposed control system.**

Keywords*— *Artificial Neural Network (ANN); Fuzzy Logic Control (FLC); Maximum Power Point Tracker (MPPT); Adaptive Neural Fuzzy Inference System (ANFIS).

INTRODUCTION

Social, economic and industrial growth of any country requires energy. Fossil fuels are the major energy sources but still when over consumption takes place lead to disastrous effects such as air pollution and et cetera. Burning of fossil fuels releases harmful gases that have severe consequences on the habitats, also affect human health. They are non-renewable sources of energy as they are derived from pre-historic fossils and are no longer available if once used. Their source is limited and they are depleting at a faster rate. Renewable energy generation is the best option for protecting environment as well as solution towards the limited availability of fossil fuel.

The increasing of energy demand, high energy prices, as well as the increasing concern on over environmental aspects, health and climate change, has attracted many researchers and communities to move into alternative energy studies. Many studies have been done to make use of renewable energy sources (e.g. solar, biogas, wind, etc) that are stand alone. Among these, solar and wind energy are two of the most promising renewable power generation technologies. Solar power or wind power is normally used by remote off-grid areas where mains electricity supply is unavailable.

The disadvantage of standalone power systems using renewable energy is that the availability of renewable energy sources has daily and some have seasonal patterns which results in difficulties in regulating the output power based on the load. For example, the daily wind speed is not constant and solar irradiation cut-off at night and cloudy days, thus, the solar and wind system have low reliability and cannot supply the load throughout a day. Since neither the solar power nor wind power are available constantly throughout the day, month or year, exclusive solar or wind power systems cannot be used on standalone basis for electrical installations which require constant guaranteed power. Alternative to this is the installation of hybrid energy systems.

The major limitation for these hybrid systems is the control requirement for optimal efficiency. Conventional control algorithms require a mathematical model for the dynamic system to be controlled. The mathematical model is then used to construct a controller. In many practical situations, however, it is not always feasible to obtain an accurate mathematical model of the controlled system. Artificial intelligent (AI) control offers a way of dealing with modeling problems by implementing linguistic, non-formal control laws derived from expert knowledge [1]. Fuzzy logic control systems have benefits of replicating all desired features of human input, while maintaining all the advantages of closed-loop automation control. One of the major problems in the use of the fuzzy logic control is the difficulty of choice and design of membership functions to suit a given problem. A systematic procedure for choosing the type of membership function and the ranges of variables in the universe of discourse is still not available. Tuning of the fuzzy controller by trial and error is often necessary to get a satisfactory performance. However, the neural networks have the capability of identifying the characteristic features of a system that can be extracted from the input-output data. This learning capability of the neural network can be combined with the control capabilities of a fuzzy logic system resulting in a neuro-fuzzy inference system [1].

In this paper, MATLAB/Simulink software is used to model and develop controller that optimize energy efficiency and also manage the power distribution on PV-Wind hybrid system. The Adaptive Neural Fuzzy Inference System is used to estimate a reference voltage of a PV system which corresponds to the maximum power that can be produce by the PV system. The FLC is used to develop the MPPT of Wind turbine. Finally the FLC is designed in such a way it selects the best available energy source(s) and protects the battery against overcharge and excessive discharge.

Modeling of Hybrid System Components

In this section, the dynamic simulation model for the system is described. The system consists of several units, PV power and wind power units as primary sources of energy, battery bank unit as auxiliary source of energy, dc-dc and dc-ac converters, load unit and control unit. The function of controller unit is to ensure the management of the power, which is delivered by the hybrid system to satisfy the load and to charge the battery. The inverter unit is used to convert the DC generated power from renewable energy sources to feed the load with the required AC power. The excessive charge from the battery will be dumped to the dump load unit. The dump load in this case is the battery storage which can then be used to supply power to the load in case of insufficient power generated by primary sources. The block diagram describing the system components is shown in Fig. 1. The mathematical models describing the dynamic behavior of each of these components are given below.

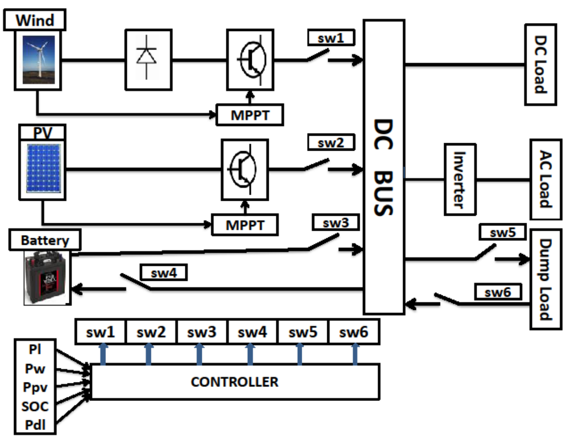

Fig. 1: Block diagram of PV-Wind Hybrid power system with controller

The Photovoltaic Module

The operation and the performance of PV generator depends to its maximum power, the models describing the PV module's maximum power output behaviors are more practical for PV system assessment. The following section describes the mathematical model for estimating the power output of PV. The equivalent circuit of a PV cell is shown in Fig 2. It includes a current source, a diode, a series resistance and a shunt resistance [2], [4].

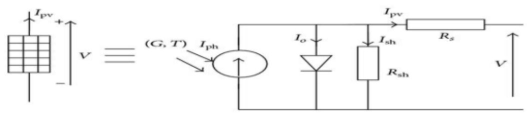

Fig. 2 The equivalent circuit of a PV cell

The current source I_{ph} represents the cell photocurrent. R_{sh} and R_s are the intrinsic shunt and series resistances of the cell, respectively. Usually the value of R_{sh} is very large and that of R_s is very small, hence they may be neglected to simplify the analysis. PV cells are grouped in larger units called PV modules which are further interconnected in a parallel-series configuration to form PV arrays. The photovoltaic panel can be modeled mathematically as given in equations below:

Module photo-current:

$$I_{ph} = [I_{SCr} + K_i\,(T - 298)] * G / 1000 \qquad (1)$$

Where I_{ph} is the light generated current in a PV module (A), I_{SCr} is the PV module short-circuit current at 25°C and 1000W/m^2, Ki is the short-circuit current temperature co-efficient at I_{SCr} = 0.0017A=°C, T is the module operating temperature in Kelvin, G is the PV module illumination (W/m^2) = 1000W/m^2

Module reverse saturation current - I_{rs}:

$$Irs = \frac{Iscr}{[exp^{\left(\frac{qVoC}{NskAT}\right)} - 1]} \qquad (2)$$

Where q is Electron charge = 1.610-19C, V_{oc} is the open circuit voltage, N_s is the number of cells connected in series, k is Boltzman constant = 1.3805*10 -23J/K, A = B is an ideality factor = 1.6,

The module saturation current I_0 varies with the cell temperature, which is given by

$$Io = Irs\left[\frac{T}{Tr}\right]^3 exp\left[\frac{q*Ego}{Bk}\left[\frac{1}{Tr} - \frac{1}{T}\right]\right] \qquad (3)$$

Where T_r is the reference temperature = 298 K, I_o is the PV module saturation current (A), E_{go} is the band gap for silicon = 1.1 eV.

The current output of PV module is

$$Ipv = Np * Iph - Np * Io\left[exp\left[\frac{q*(Vpv+IpvRs)}{NsAkT}\right] - 1\right] \qquad (4)$$

Where N_p is the number of cells connected in parallel, V_{pv} is output voltage of a PV module (V), I_{pv} is output current of a PV module (A), R_s is the series resistance of a PV module. Equations (1) - (4) are used to develop the PV model.

The Wind Turbine

Currently two types of configuration for wind turbine exist, which is the vertical-axis wind turbine (VAWT) configuration and the widely used horizontal-axis wind turbine (HAWT) configuration. HAWT have the ability to collect maximum amount of wind energy for time of day and season and their blades can be adjusted to avoid high wind storm. Wind turbines operate in two modes namely constant or variable speed. For a constant speed turbine, the rotor turns at constant angular speed regardless of wind variations. One advantage of this mode is that it eliminates expensive power electronics such as inverters and converters. Its disadvantage however, is that it constrains rotor speed so that the turbine cannot operate at its peak efficiency in all wind speeds. For this reason a constant wind speed turbine produces less energy at low wind speeds than does a variable wind speed turbine which is designed to operate at a rotor speed proportional to the wind speed below its rated wind speed [3]. The output power or torque of a wind turbine is determined by several factors. Among them are (i) turbine speed, (ii) rotor blade tilt, (iii) rotor blade pitch angle (iv) size and shape of turbine, (v) area of turbine, (vi) rotor geometry whether it is a HAWT or a VAWT, (vii) and wind speed. A relationship between the output power and the various variables constitute the mathematical model of the wind turbine. In this paper a model describing HAWT is proposed.

For an object having mass m and velocity V under a constant acceleration, the kinetic energy Ww is given by

$$Ww = \frac{1}{2}mv^2 \tag{5}$$

The power Pw in the wind is given by the rate of change of kinetic energy, i.e

$$Pw = \frac{dWw}{dt} = \frac{1}{2}\frac{dm}{dt}{V_w}^2 \tag{6}$$

But the mass flow rate is given by

$$\frac{dm}{dt} = \rho A V_w \tag{7}$$

Where A is the swept area of the turbine, ρ is the density of air. With this expression equation (7) becomes

$$P_w = \frac{1}{2}\rho A {V_w}^3 \tag{8}$$

The actual mechanical power Pw extracted by the rotor blades in watts is the difference between the upstream and the downstream wind powers [3], i.e.

$$P_w = \frac{1}{2}\rho A V_w({V_u}^2 - {V_d}^2) \tag{9}$$

Where Vu is the upstream wind velocity at the entrance of the rotor blades in m/s and Vd is the downstream wind velocity at the exit of the rotor blades in m/s.

From the mass flow rate, the equation can be written as

$$\rho A V_w = \frac{\rho A(V_u + V_d)}{2} \tag{10}$$

Vw being the average of the velocities at the entry and exit of rotor blades of turbine. With this expression, equation (10) can be simplified and becomes

$$P_w = \frac{1}{2}\rho A {V_w}^3 \tag{11}$$

Where C_p is a fraction called the power coefficient. The power coefficient represents a fraction of the power in the wind captured by the turbine and has a theoretical maximum of 0.593. C_p is often called the Betz limit after the Germany physicist Albert Betz who worked it out in 1919. The power coefficient can be expressed by a typical empirical formula as

$$C_p = \frac{1}{2}(\lambda - 0.022\beta^2 - 5.6)e^{-0.17\lambda} \tag{12}$$

Where β is the pitch angle of the blade in degrees and λ is the tip speed ratio of the turbine, defined as

$$\lambda = \frac{V_w(mph)}{w_b(rads^{-1})} \tag{13}$$

Where Wb is the turbine angular speed. Equations (5) - (13) describe the power captured by the turbine and constitute the turbine model.

Energy storage system

The harnessing of renewable energies presents, however, a further set of technical and economic problems. Unlike fossil and nuclear fuels, which are concentrated sources of energy that can be easily stored and transported, renewable forms of energy are highly dilute and diffuse. Moreover, their supply can be extremely intermittent and unreliable. So, batteries are required to even out irregularities in the solar and wind power distributions. The development of battery behavior models has been the focus of researchers for many years. Based on the model given by Gu H et al [5] and incorporation of the diffusion precipitation mechanism studied by Ekdunge and Simonsson [6] in the reaction kinetics of the negative electrode, Kim and Hong [7] analyzed the discharge performance of a flooded lead acid battery cell using mathematical modeling. Bernardi and Carpenter [8] developed a mathematical model of lead acid batteries by adding the oxygen recombination reaction. Nguyen et al. [9] presented a model analogous to the flooded type and examined the dynamic behavior of the cell during discharge with respect to cold cranking amperage and reserve capacity. In general, these models are complex in terms of the expressions and number of parameters employed. Yang et al. [10] states that a lead acid battery is characterized by two indexes, i.e. the state of charge (SOC) and the floating charge voltage (or the terminal voltage). Extensive SOC determination methods have been introduced by Sabine Piller et al. [11]. It concluded that the most used modeling technique at this time for all systems is ampere-hour counting method because it is the most direct and transparent method and quite easily implemented with satisfyingly accurate results for short- time applications, especially if used in the range of low to medium SOC. The lead-acid battery is proposed in this paper for energy storage. The section below describes the mathematical formulation of lead acid battery model based on its state of charge.

At any hour the state of battery is related to the previous state of charge and to the energy production and consumption situation of the system during the time from t-1 to t. During the charging process, when the total output of PV and wind generators is greater than the load demand, the available battery bank capacity at hour t can be described by [12].

$$C_{bat}(t) = C_{bat}(t-1) * (1-\sigma) + \left(E_{pv}(t) + E_{WG}(t) - \frac{EL(t)}{\eta_{inv}}\right)\eta_{bat} \quad (14)$$

On the other hand, when the load demand is greater than the available energy generated, the battery bank is in discharging state. Therefore, the available battery bank capacity at hour t can be expressed as

$$C_{bat}(t) = C_{bat}(t-1) * (1-\sigma) - \left(\frac{EL(t)}{\eta_{inv}} - E_{pv}(t) + E_{WG}(t)\right) \quad (15)$$

Where $C_{bat}(t)$ and $C_{bat}(t-1)$ are the available battery bank capacity (Wh) at hour t and t-1, respectively, ηbat is the battery efficiency (During discharging process, the battery efficiency = 1) σ is self-discharge rate of the battery bank. $E_{pv}(t)$ and $E_{WG}(t)$ are the energy generated by PV and wind generators, respectively; $E_L(t)$ is the load demand at hour t and η_{inv} is the inverter efficiency [%]

At any hour, the storage capacity is subject to the following constraints:

Cbatmin ≤ Cbat(t) ≤ Cbatmax (16)

ENERGY MANAGEMENT AND CONTROL SYSTEM

ANN Based PV MPPT

A typical solar panel can converts only 30 to 40 percent of the incident solar irradiation into electrical energy. Maximum power point tracking technique is used to improve the efficiency of the solar panel. Therefore the MPPT of a photovoltaic array is an essential part of a PV system. As such, many maximum power point tracking (MPPT) techniques have been developed and implemented. Among these techniques, hill-climbing MPPT such as perturb and observe (P&O), which is a simple algorithm that does not require previous knowledge of the PV generator characteristics and is easy to implement with analogue and digital circuits. In this technique, first the PV voltage and current are measured and hence the corresponding power is calculated. Considering a small perturbation of voltage or perturbation of duty cycle of the dc/dc converter in one direction corresponding power is calculated. Is then compared with. If is more than, then the perturbation is in the correct direction; otherwise it should be reversed. In this way, the peak power point is recognized and hence the corresponding voltage can be calculated [13] [14]. The major drawbacks of P&O/hill-climbing are occasional deviation from the maximum operating point in case of rapidly changing atmospheric conditions, such as broken clouds. Also, correct perturbation size is important in providing good performance in both dynamic and steady-state response [15]. In addition, P&O technique may cause many oscillations around the MPP, and this slows down the response of the system.

Introduction of intelligent MPPTs in PV systems is very promising. They achieved very good performances, fast responses with no overshoot, and less fluctuations in the steady state for rapid temperature and irradiance variations [19]. FL-based MPPT do not require the knowledge of the exact PV model [16] [17]. Artificial Neural Network (ANN)-Based MPPT Technique operates like a black box model, requiring no detail information about the PV system [17]. For MPPT, ANN input can be PV array parameters like PV voltages and currents, environmental data like irradiance and temperature, or any combination of these, whereas the output signal is the identified maximum power or the duty cycle signal used to drive the electronic converter to operate at the MPP. The ANN input and output data are obtained from experimental measurement or model-based simulation results. After learning relation of with temperature and irradiance, ANN can track the MPP online [17].

In this paper, intelligent control technique using ANN is associated to an MPPT controller in order to increase the tracking response and consequently increase the tracking efficiency of the solar panel. The neural network control (NNC) has two inputs the solar irradiance and temperature. NNC is used to estimate the PV panel operating voltage (V_{ref}) which corresponds to the maximum power (P_{max}) at any given solar radiation and cell temperature. The network was trained to recognize the relationships between the input and output parameters. The developed PV model is used to collect the training data. The operating temperature is varied from 15 C to 65 C in a step of 5C and the solar irradiance level is varied from 100 W/m2 to 1000 W/m2 in a step of 50 W/m2, to get the training data sets for ANFIS. For each pair of operating temperature and irradiance level the reference voltage which corresponding to the maximum available power is recorded. Table1 shows a sample of training data set for ANFIS. Proposed ANN based MPPT of the PV system is shown in fig 3. The fig 4 shows the training errors versus epochs of the ANFIS, The ANFIS MPPT structure is shown in fig 5. Fig 6 and 7 shows the input membership function of the controller and Fig 8 and 9 shows rule view and surface view created by ANFIS.

Table 1: ANFIS Training Data

Irradiance	Temperature	Voltage (V)
100	15	21.22
150	15	21.69
200	15	22.00
250	15	22.21
300	15	22.37
350	15	22.49
400	15	22.58
450	15	22.65
500	15	22.71
550	15	22.74
600	15	22.77
650	15	22.79
700	15	22.80
750	15	22.80
800	15	22.80
850	15	22.79
900	15	22.78
950	15	22.76
950	15	22.74

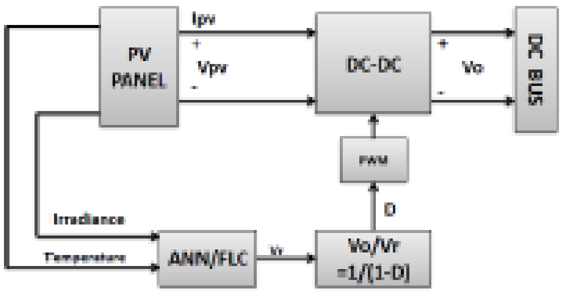

Fig.3 Proposed ANN based MPPT of the PV system

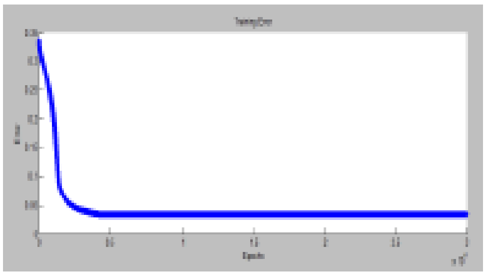

Fig.4 Training errors versus epochs of the ANFIS

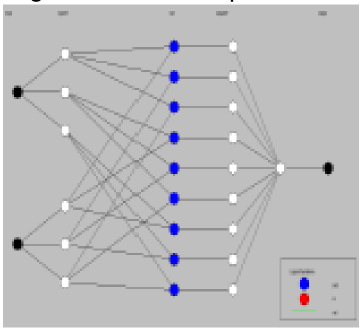

Fig.5 The ANFIS MPPT structure

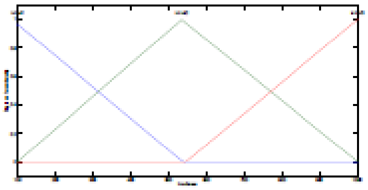

Fig.6 Solar irradiance membership function

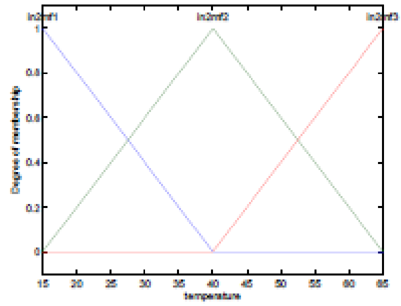

Fig.7 Temperature membership function

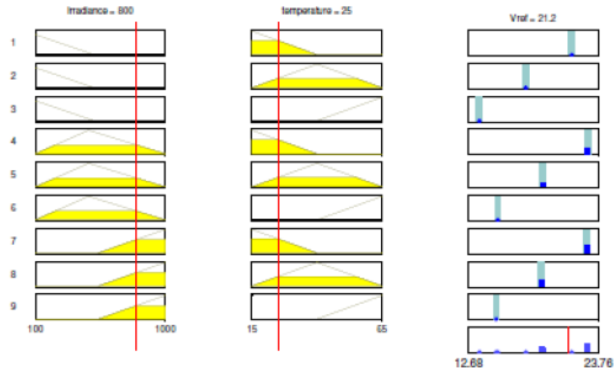

Fig.8 Rule view at 800 irradiance and 25 temperature

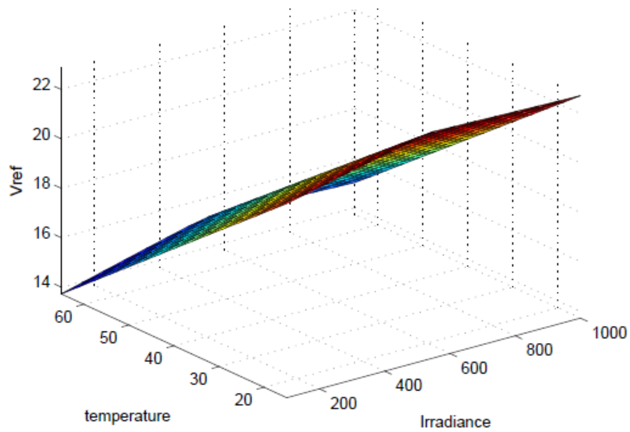

Fig.9 Surface view created by ANFIS

FLC Based Wind MPPT

The FLC was used to develop a wind turbine MPPT based on equation 13. From the relationship between Tip Speed Ratio (TSR) and Cp, it is possible to devise a control strategy that ensures that the wind turbine operates around or at the peak point of the curve. This can be done by varying the generator angular speed. This paper adapt the FLC based MPPT developed by Lina [18]

FLC Based Power Management

The Fuzzy Logic Controller is used to control the power generated by wind source, PV source, Battery and dump load. Depending on the load demand and available power, the controller selects individual source or combination of sources that will meet the load demand. It will also control the battery state of charge (SOC) by activating the charger control switch when there is excess power from primary sources and activates the discharging switch in case of primary sources do not meet the load demand. The controller has four inputs named as Load Power (Pl), Wind turbine power (Pw), Solar PV Power (Ppv) and Battery Power (Pb). The outputs for controller are Wind power switch (SW1), PV power switch (SW2), Battery power switch (SW3), Charger controller switch (SW4), dump load charging switch (SW5) and dump load discharging switch (SW6). All four inputs has three(3) triangular membership function such as Low, Medium and High L,M,H and all output have two membership function (ON and OFF).

The FLC relates the outputs to the inputs using a list of if-then statements called rules. The if-part of the rules describes the fuzzy sets (regions) of the input variables. In this paper, the fuzzy variables Pw, Pl, Pw and Pb are described by fuzzy singleton, i.e. the measured values of these variables are used in the interface process without being fuzzified. Specifically, the fuzzy rules are in the form:

Rule i: IF Pl is Ai and Ppv is Bi and Pw is Ci and Pb is Di, THEN sw1 is Ei and SW2 is Fi and SW3 is Gi and SW4 is Hi and SW5 Ii and SW6 is Ji.

Where Ai, Bi, Ci and Di are fuzzy subsets in their universes of discourse, and Ei, Fi, Gi, Hi, Ii and Ji are fuzzy singletons. Each universe of discourse is divided into three fuzzy subsets: L (Low), M (Medium), and H (High) and all outputs have two membership function ON and OFF. For the inputs low is defined from 0-200W, medium range from 200-600W and high considered to range from 600-1000w. All selector switches will be ON when any of the sources is low. The battery state of charge is limited from 20% to 80% which means the battery charging switch will be ON only when the state is below 80% and the discharging switch will be ON only when the SOC is above 20%. This paper proposes Sugeno type of fuzzy inference system.

SIMULATION RESULTS AND DISCUSSION

Evaluation of proposed MPPT

The proposed PV MPPT model has been designed and simulated by MatLab/Simulink software. Fig 10 shows the Simulink model for the ANN MPPT. Table 2 compares the maximum output voltage and power produced by the proposed ANN MPPT with the classical P&O Algorithm. Simulation results demonstrate the efficiency of proposed ANN MPPT.

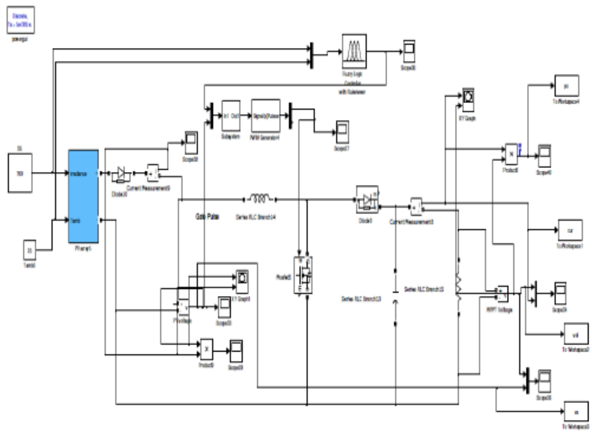

Fig. 10 Simulink model for the ANN MPPT

Table 2: 200W capacity PV power output at 25 degree and various solar irradiance

Irradiance	Actual PV generated	Boost converter output voltage with P& O (V)	Boost converter output voltage with FLC (V)	Current in amps	Power in watt
600	18.2	69	71	2.62	162
800	19.1	82	86	3.06	194
1000	20.0	89	92	3.21	206

FLC Power Management

Simulation model of PV-Wind hybrid system with battery storage and Fuzzy Logic controller is developed using MATLAB/Simulink software. Rating of hybrid system components is given in table 3. This section present simulation results of few selected cases.

Table 3: Rating of hybrid system components

Component	Rating (W)
Wind Power	1000
PV Power	1000
Battery Power	2000
DC Load	500
AC Load	500

Case 1

Consider the case where all of the renewable sources are sufficient to run the load. The solar selector switch SW1, the wind selector switches SW2, charge control switches (SW4 and SW5) are activated and the other selector switches are turned off. The fuzzy rule that satisfies this condition is:

If (Pl is L/M/H) and (Ppv is M/H) and (Pw is M/H) and (Pb is M/H) then (SW1 is ON) and (SW2 is ON) and (SW3 is OFF) and (SW4 is ON) and (SW5 is ON) and (SW6 is OFF).

Table 4 show fuzzy rules formed that satisfies this condition.

Table 4: Fuzzy rules

Ppv	Pw	Pb	Pl	SWI	SW2	SW3	SW4	SW5	SW6
M	M	M	L	ON	ON	OFF	ON	ON	OFF
M	M	M	M	ON	ON	OFF	ON	ON	OFF
M	M	M	H	ON	ON	OFF	ON	ON	OFF
M	M	H	L	ON	ON	OFF	ON	ON	OFF
M	M	H	M	ON	ON	OFF	ON	ON	OFF
M	M	H	H	ON	ON	OFF	ON	ON	OFF
M	H	M	L	ON	ON	OFF	ON	ON	OFF
M	H	M	M	ON	ON	OFF	ON	ON	OFF
M	H	M	H	ON	ON	OFF	ON	ON	OFF
M	H	H	L	ON	ON	OFF	ON	ON	OFF
M	H	H	M	ON	ON	OFF	ON	ON	OFF
M	H	H	H	ON	ON	OFF	ON	ON	OFF
H	M	M	L	ON	ON	OFF	ON	ON	OFF
H	M	M	M	ON	ON	OFF	ON	ON	OFF
H	M	M	H	ON	ON	OFF	ON	ON	OFF
H	M	H	L	ON	ON	OFF	ON	ON	OFF
H	M	H	M	ON	ON	OFF	ON	ON	OFF
H	M	H	H	ON	ON	OFF	ON	ON	OFF
H	H	M	L	ON	ON	OFF	ON	ON	OFF
H	H	M	M	ON	ON	OFF	ON	ON	OFF
H	H	M	H	ON	ON	OFF	ON	ON	OFF
H	H	H	L	ON	ON	OFF	ON	ON	OFF
H	H	H	M	ON	ON	OFF	ON	ON	OFF
H	H	H	H	ON	ON	OFF	ON	ON	OFF

Case 2

Consider the case where any of the renewable sources is sufficient to run the load (i.e. solar alone is sufficient to run the load). The solar selector switch (SW1) is activated and the other selector switches are turned off. In the event that the solar power supplied is more than the load demand, the excess power is need to charge the battery through SW4. The excess power thus activates the charge control SW4. The fuzzy rule that satisfies this condition is:

If (Pl is L/M/H) and (Ppv is M/H) or (Pw is M/H) and (Pb is M/H) then (SW1 is ON) and (SW2 is ON) and (SW3 is OFF) and (SW4 is ON) and (SW5 is ON) and (SW6 is OFF)

Case 3

Consider the case where all of the renewable sources are insufficient to run the load. The discharge selector switch (SW3) is activated and the other selector switches are turned off. The fuzzy rule that satisfies this condition is:

If (Pl is L/M/H) and (Ppv is L) and (Pw L) and (Pb is M/H) then (SW1 is OFF) and (SW2 is OFF) and (SW3 is ON) and (SW4 is OFF) and (SW5 is OFF) and (SW6 is OFF)

Case 4

Consider the case where any of the renewable sources and battery is sufficient to run the load (i.e wind and battery). The wind and discharge selector switches (SW2 and SW3) are activated and the other selector switches are turned off. The fuzzy rule that satisfies this condition is:

If (Pl is L/M/H) and (Ppv is M/H or Pw is M/H) and (Pb is M/H) then (SW1 is OFF/ON) and (SW2 is OFF/ON) and (SW3 is ON) and (SW4 is OFF) and (SW5 is OFF) and (SW6 is OFF).

Case 5

Consider the case where all of the renewable sources and battery are insufficient to run the load. The dump load discharge selector switch (SW6) is activated and the other selector switches are turned OFF. The fuzzy rule that satisfies this condition is:

If (Pl is L/M/H) and (Ppv is L) and (Pw L) and (Pb is L) then (SW1 is OFF) and (SW2 is OFF) and (SW3 is OFF) and (SW4 is OFF) and (SW5 is OFF) and (SW6 is ON)

Case 6

Consider the case where all of the renewable sources, battery and dump load are insufficient to meet the load. All the selector switches are turned OFF. The fuzzy rule that satisfies this condition is:

If (Pl is L/M/H) and (Ppv is L) and (Pw L) and (Pb is L) then (SW1 is OFF) and (SW2 is OFF) and (SW3 is OFF) and (SW4 is OFF) and (SW5 is OFF) and (SW6 is OFF)

Case 7

Consider the case where all of the renewable sources produces high power (PV and Wind is H), battery is (H) and dump load is (H) and load (L/M/). The discharge selector switch (SW3) is activated and the other selector switches are turned OFF. The fuzzy rule that satisfies this condition is:

If (Pl is L/M/H) and (Ppv is H) and (Pw is H) and (Pb is H) then (SW1 is OFF/) and (SW2 is OFF) and (SW3 is ON) and (SW4 is OFF) and (SW5 is OFF) and (SW6 is OFF).

Simulation results of few selected cases is shown in figure 11 to 13.

Case 1.

Fig 11 shows the output of controller when Pv and Wind supplies load. (Note: 1=ON, 0=OFF)

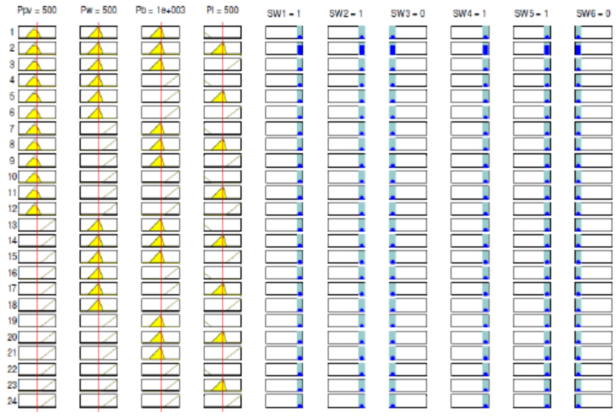

Fig. 11 Simulation result of the HPS when solar and wind supplies load

Case 3.

Fig 12 shows the output of controller when solar and Wind are insufficient to supplies load, only battery meet the load.

Case 5.

Fig 13 shows the output of controller when solar, Wind and battery are insufficient to supplies load, only dump load battery meet the load.

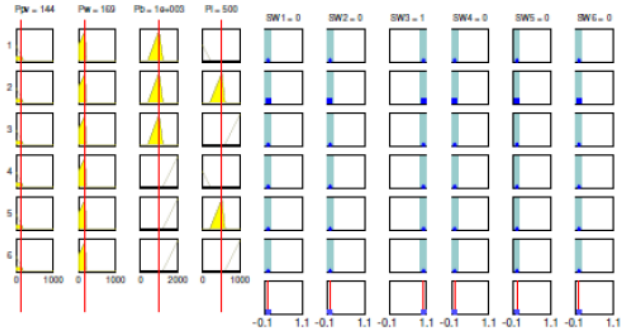

Fig.12 Simulation result of the system when battery alone supplies load

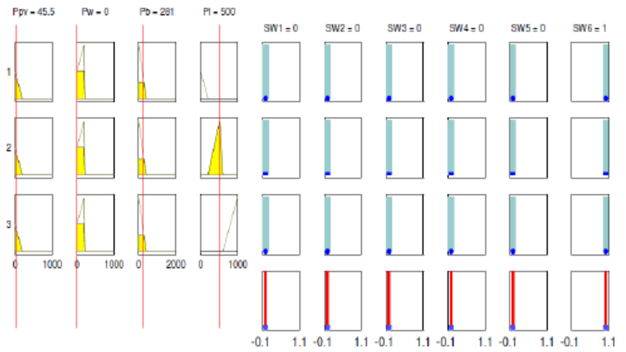

Fig.13 Simulation result of the system when dump load supplies load

Conclusion

The photovoltaic and wind hybrid power system is simulated using MATLAB/Simulink software. ANN and FLC MPPT Control is applied for solar and wind sources to make the system efficient. The performance of the MPPT was compared with the classical P& O technique. Results indicate that the ANN-based model developed in this work can predict the MPP for a PV panel with high accuracy. Moreover the simulation results of the developed Fuzzy logic based Power Management shows that the controller provides uninterrupted power, effective utilization of sources, minimizing usage of battery and hence improve battery life. It was found that the hybrid topology exhibits excellent performance under various operating conditions, and maintain the battery SOC between 20 – 80%. It can be concluded that the controller can satisfactory manage energy supply in a PV-Wind hybrid power system.

References

[1] Witold P, Fuzzy control and Fuzzy systems",Second,extended,edition, 1993.

[2] Huan-Liang Tsai, Ci-Siang Tu, Yi-Jie Su, Development of Generalized Photovoltaic Model Using MAT-LAB/SIMULINK, Proceedings of the World Congress on Engineering and Computer Science WCECS, San Francisco, USA, 2008.

[3] Manyonge,R. M. Ochieng1, F. N. Onyango and J. M. Shichikha; Mathematical Modelling of Wind Turbine in a Wind Energy Conversion System: Power Coe_cient Analysis,Applied Mathematical Sciences, Vol. 6, 2012, no. 91, 4527 - 4536

[4] M.G.Villalva, J.R.Gazol, and E.R.Filho, Comprehensive Approach to Modeling and Simulation of Photo-voltaic Arrays", IEEE trans. on Power Electronics, vol.24, no.5, pp.1198-1208, 2009.

[5] Gu H, Nguyen TV, White RE; "A Mathematical model of a lead acid cell: discharge, rest, and charge.",J Electrochem Soc ;134(12):2953-60,1987.

[6] Ekdunge P, Simonsson D. "The discharge behaviour of the porous lead electrode in the lead-acid battery. Experimental investigations.",J Appl Electrochem ;19(2):127-35,1989.

[7] Kim SC, Hong WH. "Analysis of the discharge performance of a

ooded lead-acid cell using mathematical modeling. ",J Power Sources ;77(1): 74-82,1999.

[8] Bernardi DM, Carpenter MK. "A mathematical model of the oxygen recombination lead-acid cell. ",J Electrochem Soc ;142(8):2631-41,1995.

[9] Nguyen TV, White RE, Gu H. "The eect of separator design on the discharge performance of a starved lead-acid cell. ",J Electrochem Soc ;137(10):2998-3004,1990.

[10] Yang HX, Lu L, Zhou WREN21, "A novel optimization sizing model for hybrid solar-wind power generation system",Solar energy ;81(1):76-84,2007.

[11] Piller S, Perrin M, Jossen A. "Methods for state-of-charge determination and their applications.",J Power Sources ;96(1):113-20,2001.

[12] Bogdan, S. B. and Salameh, Z. M. 1996. "Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system", IEEE Transactions on Energy Conv. 11(2), 367-375.

[13] G. de Cesare, D. Caputo, and A. Nascetti, Maximum power point tracker for photovoltaic systems with resistive like load, Solar Energy, vol. 80, no. 8, pp. 982988, 2006.

[14] Y. H. Lim and D. C. Hamill, Simple maximum power point tracker for photovoltaic arrays, Electron. Lett., vol. 36, no. 11, pp. 997999, 2000.

[15] F. Liu, Y. Kang, Y. Zhang, and S. Duan, Comparison of p&o and hill climbing MPPT methods for grid-connected PV generator, in Proc. 3rd IEEE Conf. Industrial Electron. Applicat., Singapore, Jun. 35, 2008.

[16] A. Mathew and A. I. Selvakumar, New MPPT for PV arrays using fuzzy controller in close

cooperation with fuzzy cognitive network, IEEE Trans. Energy Conv., vol. 21, no. 3, pp. 793803, Sep. 2006.

[17] C.-S. Chiu, T-S fuzzy maximum power point tracking control of solar power generation systems, IEEE Trans. Energy Conv., vol. 25, no. 4, pp. 11231132, Dec. 2010.

[18] Owino Lina Atieno, "Optimization of fuel consumption in hybrid Wind-Diesel system using fuzzy logic controller" Msc Thesis JKUAT 2013.

[19] Bidyadhar Subudhi and Raseswari Pradhan, "A Comparative Study on Maximum Power Point Tracking Techniques for Photovoltaic Power Systems" IEEE transaction on sustainable energy, VOL. 4, NO. 1, JANUARY 2013.