



SOLAR POWERED BLDC MOTOR WITH ARTIFICIAL NEURAL NETWORK CONTROLLER

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ABSTRACT

In this paper, the artificial neural network (ANN) closed loop controlled with DC photovoltaic solar pump is implemented in MATLAB/Simulink using Boost converter. The simulated system consists of the photovoltaic (PV) module, the Boost converter, the ANN control, and the BLDC motor. The simulated parameters are voltage, current, power, speed, and mechanical torque. A modal/sensitivity analysis is also conducted on a liberalized model of the overall system, to characterize dynamic properties of the system, to evaluate robustness of the controllers, and to identify the nature of interactions between the PV system and the network/loads. And to maximize the efficiency of the proposed PV pumping system, compare the ANN and the classical proportional integral derivatives (PID) controller. Different tests have been carried to prove the effectiveness of the proposed control system. All simulations have been done in SIMULINK software of MATLAB.

Keywords: PV module, direct control method, - PID, ANN controller, Boost converter, DC BLDC motor

1 INTRODUCTION

Energy generated from cleans, efficient, and environmentally friends have become one of the major challenges for engineers and scientists. Among all renewable energy sources, photovoltaic

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power systems attract more attention while greenhouse emissions are reduced. Regarding the endless aspect of solar energy, it is worth saying that solar energy is a unique solution for energy crisis. However, despite all the aforementioned advantages of solar power systems, they do not present desirable efficiency. Many methods and controllers have been widely developed and implemented to track the maximum power point (MPP) [2-6]. Most control schemes use the Perturb and Observe (P&O) method which is based on iterative algorithms to track continuously the MPP, because it is easy to implement [2, 3] but the oscillation problem is unavoidable. In many references the effectiveness of a fuzzy logic controller is shown [2-5] compared to the (P&O) method. It improves control robustness and this control gives robust performance under parameters and load variation. Several authors present much attention to the study of the dynamic performance of the photovoltaic pumping systems. In this paper, we present a PV pumping water which includes photovoltaic array generator, DC/DC converter, DC/AC converter and induction motor coupled to a centrifugal pump. The FLC controller is applied to ensure a maximum operating of the photovoltaic array. And to improve the FLC controller, we make a comparison with the classical MPPT, the Perturb and Observe (P&O). The environmental effects such as temperature, irradiation, special characteristics of sunlight, dirt, shadow, and so on affect the performance of the photovoltaic (PV) system. The PV system has poor efficiency so it operates at the maximum power point tracking (MPPT). In this work ANN closed loop algorithm is recommended because of their simplicity and ease of implementation and compare with conventional PID closed loop controller through the MATLAB/SIMULINK software.

1. PV Module

The PV cell converts energy in the photons of sunlight into electricity by means of the photoelectric phenomenon found in certain types of semiconductor materials such as silicon and selenium [1]. It indicates an exponential and nonlinear relation between the output current and voltage of PV module. The main equation for the output current (I_o) of a module as flows

$$I = I_{sc} - I_o \left(\frac{e^{q(V+IxR_s)}}{nkT} - 1 \right) - (V + IxR_s/R_p) \quad (1)$$

Where I_{sc} is the short-circuit current that is equal to the photon generated current, I_o is the reverse saturation current of diode (A); q is the electron charge (1.602×10^{-19} C); V is the voltage across the PV cell (V); k is the Boltzmann's constant (1.38×10^{-23} J/K); T is the junction temperature in Kelvin (K). n is known as the ideality factor and takes the value between 1 and 2. R_s and R_p are series and parallel resistance respectively.

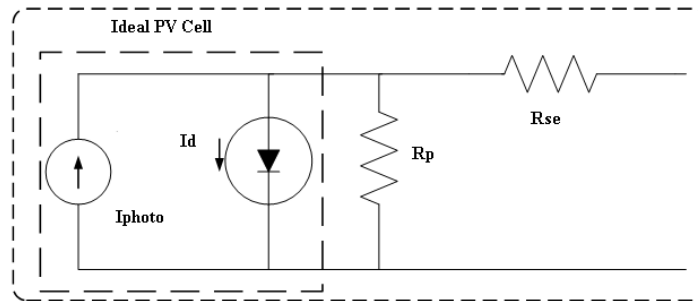


Figure 1 Equivalent model of the PV panel

The simple equivalent circuit of a PV cell consists of an ideal current source in parallel with an ideal diode is shown in Figure 1. Since a single PV cell produces an output voltage of less than 1 volt, it is necessary to string together a number of PV cell in series to achieve a desired output voltage. For simulation the LE24P315 PV module, which contains 72 cells, was chosen in this paper. The electrical parameters are tabulated in table 1, and the resultant curves are shown in Figure. (2) - (4). It shows the effect of varying weather conditions on location at $I-V$ and $P-V$ curves.

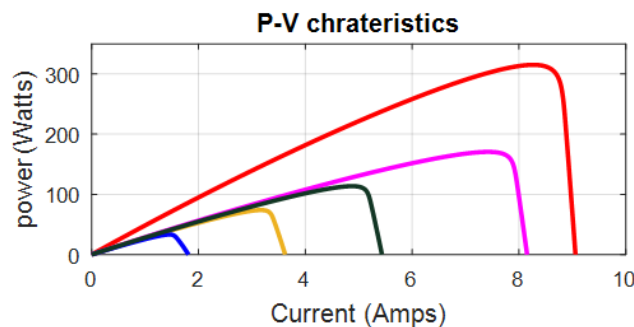


Figure 2 P-I curves of PV module at various irradiations

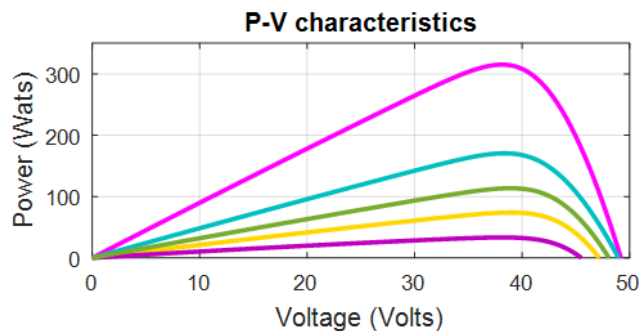


Figure 3 P-V curves at various irradiations

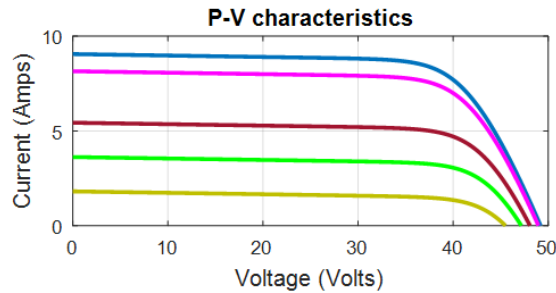


Figure 4 C-V curves at various irradiations

Table: 1 Parameters of Solar Module

ELECTRICAL CHARACTERISTICS	LE24P315
Maximum power at STC(P_{MAX})	315 watts
Open circuit voltage (V_{OC})	45.5 volts
Short circuit current (I_{SC})	9.06amps
Voltage at max power(V_{MAX})	38.23 v
Current at max power (I_{MAX})	8.24 amps
Maximum System Voltage (V for UL)	600V
Maximum System Voltage (V for IEC)	1000V

Table: 2 Types of cell

MULTI CRYSTALLINE	SI
Front Face	Tempered Glass And Low Iron
Encapsulate	Ethylene Vinyl Acetate
UL	Underwriter Lab
IEC	International Electrochemical Commission

2. BOOST CONVERTER

Controller design for any system needs knowledge about system behavior. This involves a mathematical relation between inputs to the system, state variables, and output called modeling of the system. Then PID controller is used to form closed loop converter. The State variable approach is a power technique for analysis of switching converters. The state model of a system consists of the state equation and output equation.

2.1 Modeling and Construction

The steps to obtain a state space modeling and simulation of Model Construction of DC-DC Switching power electronic converters are

- 1) Determine the state variables in the power converter e.g. inductor current and capacitor voltage.
- 2) Determine the modes of operation governing the states of the power semiconductors (Switch ON & OFF states)
- 3) Assume the main operating modes of the converter (continuous or discontinuous conduction)
- 4) Apply Kirchoff's laws and combine together to form state-space model
- 5) Implement the derived equations with "SIMULINK" blocks (open loop system simulation is then possible to check the obtained model).
- 6) Design a proper controller or compensator to overcome the deviation of the circuit operation from the desired nominal behavior.

Fig 5 Shows DC-DC boost converter with switching period T and the duty cycle (D). Consider continuous conduction mode of operation, when the switch is ON and OFF, the state space equations are as follows

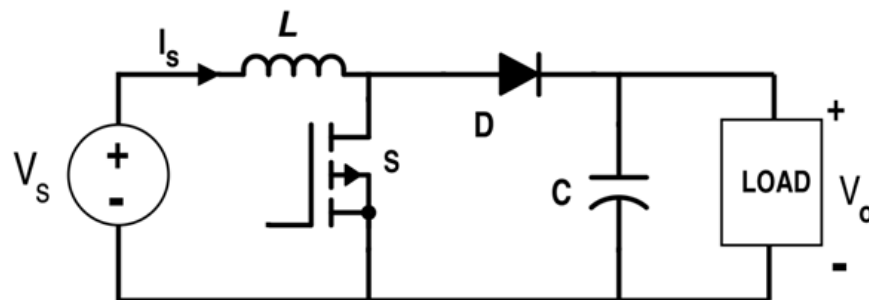


Figure 5 Boost converter

The ripple in the output voltage is

$$V_o = V_s \delta / fC$$

Where

$$f = 1/T \text{ is the frequency of the chopper.}$$

And the output current is given as,

$$I_o = (V_s \delta) / (fL)$$

The output average voltage is given as,

$$V_{0(av)} = V_s / (1 - \delta)$$

3. DC MONOBLOCK Pump

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Brushless DC (BLDC) Motor

A BLDC motor accomplishes commutation electronically using rotor position feedback to determine when to switch the current. The structure is shown in Figure 9(b). Feedback usually entails an attached Hall sensor or a rotary encoder. This permits the stator coils to be driven by a constant DC voltage (hence the name brushless DC), which simply switches from one stator coil to the next to generate an AC voltage waveform with a trapezoidal shape.

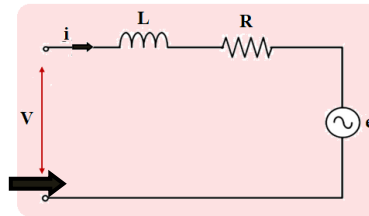


Figure 6 Per Phase equivalent circuit of Brushless DC motor

Using the equivalent circuit electrical equation can be obtained as in equation

$$V = Ri + L \frac{di}{dt} + e \quad (2.1)$$

Where,

V --- is applied phase voltage,

i --- is phase current,

e--- is back EMF voltage and

L ---is phase inductance.

4. PID CONROLLER:

4.1 Proportional Integral Derivatives

A PID controller is feedback loop controlling mechanism and corrects the error between a measured process value and a desired set point by calculating and then a corrective action adjust the process as per the requirement. The PID controller calculation involves three separate parameters, The Proportional value(P) determines the reaction to the current error, the Integral(I) determines the reaction based on the sum of recent errors and the Derivative (D) determines the reaction to the rate at which the error has been changing. DC converters are modeled using state space analysis which directly determines state variables like inductor current and capacitor voltage.

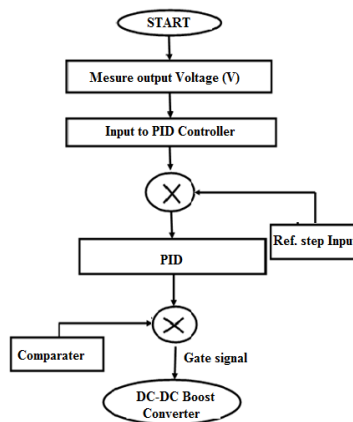


Figure 7 Flow chart of PID

Table: 3 PID PARAMTERS:

PARAMETERS	RANGE
Source	Internal
Proportional (P)	0.65
Integrator (I)	150
Differentiator	2.7e-06
Filter coefficient	100

$$\text{COMPENSATOR COEFFICIENT} = P + I \left(\frac{1}{s} \right) + D \left(N / \left(1 + N \left(\frac{1}{s} \right) \right) \right)$$

The PID controller calculation involves three separate parameters, The Proportional value(P) determines the reaction to the current error, the Integral(I) determines the reaction based on the sum of recent errors and the Derivative (D) determines the reaction to the rate at which the error has been changing. DC boost converters are modeled using state space analysis which directly determines PV voltage. Requirement is to obtain a constant output voltage for input disturbance and this can be achieved by directly tuning the integral value.

Table: 4

Parameter	Rise time	Over shoot	Settling time
K _P	Decrease	Increase	Small change
K _I	Decrease	Increase	Increase
K _D	Small change	Decrease	Decrease

5. ANN Controller

Artificial neural network has the potential to provide an improved method of deriving non-linear models which is complementary to conventional techniques. Neural networks have a self-adapting capability which makes them well suited to handle the parameter variations. The artificial neuron consists of input, activation function and output with respected weight. The higher a weight of an artificial neuron is the stronger the input which is multiplied by its weight. The weights of the artificial neuron are adjusted to obtain the outputs for the specific inputs.

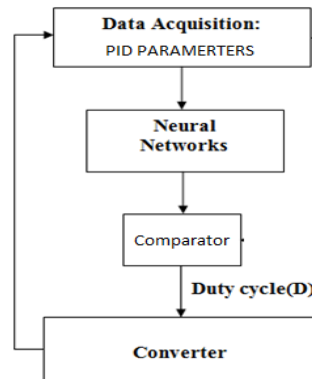


Figure 7 Flowchart of ANN

5.1 Feed-forward Neural Network

The feed-forward neural network is the first and simplest type of artificial neural network devised. The feed-forward neural network consists of several types. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. A single-layer perceptron network, which consists of a single layer of output nodes; the inputs are fed directly to the outputs via a series of weights. In this way it can be considered the simplest kind of feed-forward network.

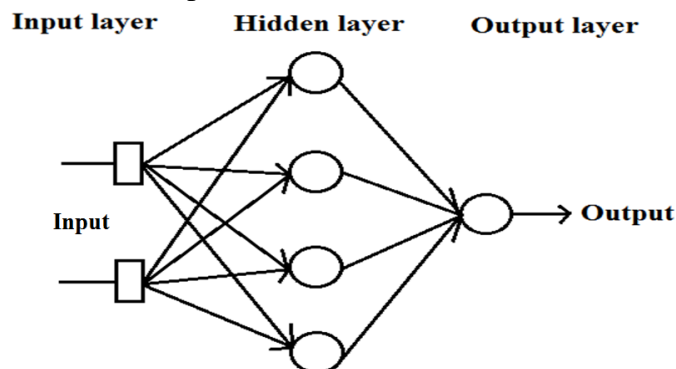


Figure 8 Architecture of Neural Network

A perception can be created using any values for the activated and deactivated states as long as the threshold value lies between the two. Most perceptions have outputs of 1 or -1 with a threshold of 0 and there is some evidence that such networks can be trained more quickly than networks created from nodes with different activation and deactivation values. Perceptions can be trained by a simple learning algorithm that is usually called the delta rule. It calculates the errors between calculated output and sample output data, and uses this to create an adjustment to the weights, thus implementing a form of gradient descent. This method performs a gradient descent on the error surface which is a function of the line current error. A gradient descent minimization can be performed on the error function. In this work online simulated PID controller 500 output voltage data and modulation index collected and trained using ANN MATLAB software as show in figure 10.

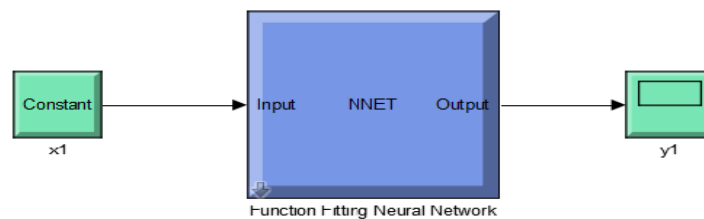


Fig. 9 Simulation Circuit of Proposed System

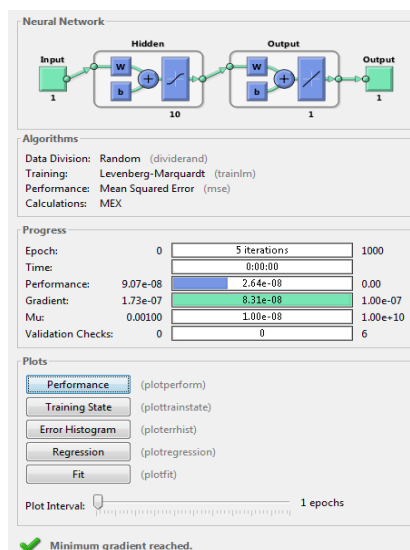


Fig 10 ANN Training structure

In the proposed system the solar panel is connected with the boost converter. The temperature and radiation is given to the solar panel. Normally the solar panel works on 1000w/m^2 and 25° . The output voltage and the current is taken from the PV system. The closed loop ANN controller used with the neural network controller and produced the duty cycle to track the maximum power point. Technique used to improve the efficiency of the system.

7. Simulation Results

The direct control method is implemented with ANN Controller using Boost converter and the simulation is performed under the linearly increasing irradiance varying from 24.71W/m^2 to 30.26W/m^2 . The relationship between the output power of converter and its duty cycle, the maximum output power is 315W at duty cycle $(\) = 4.5$. Fig. 11(d) shows the current and voltage relationship of converter output. Since the load is DC submersible pump, the current and voltage increase linearly with the slope of $1/R_{load}$ on the $I-V$ plane. It shows that maximum output current is 5A at 30V . The curve of flow rate of submersible pump vs time is shown in Fig. 11(e) which shows that in the starting the flow rate increases with time and then constant at 12L/hr . D

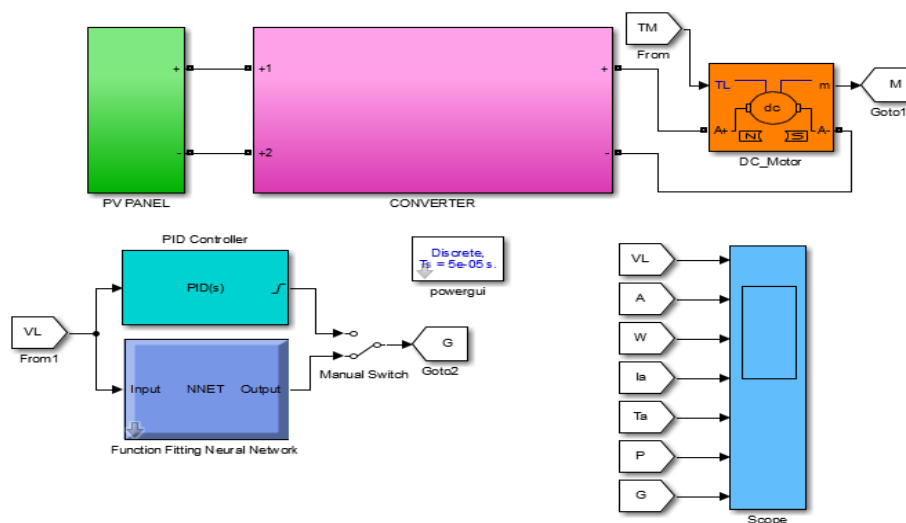


Fig 11 Simulation diagram of DC motor with ANN & PID

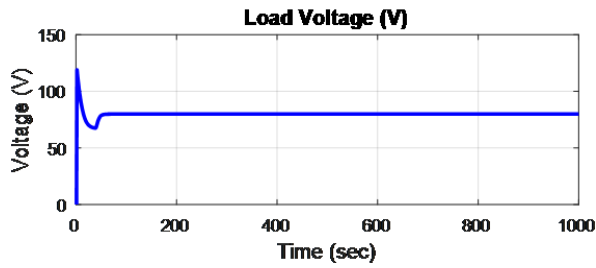


Fig.11(a) Load voltage of PID

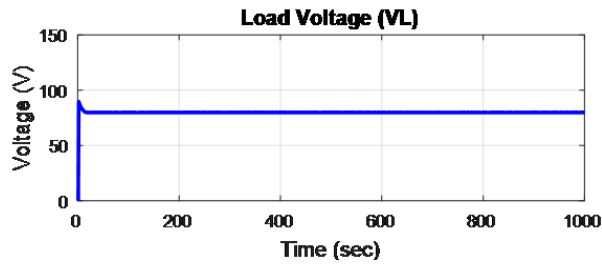


Fig. 11(b) Load Voltage of ANN

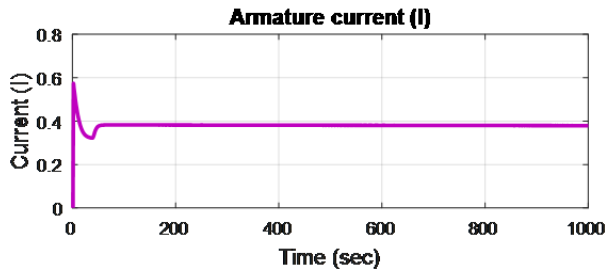


Fig.11(c) Armature current of PID

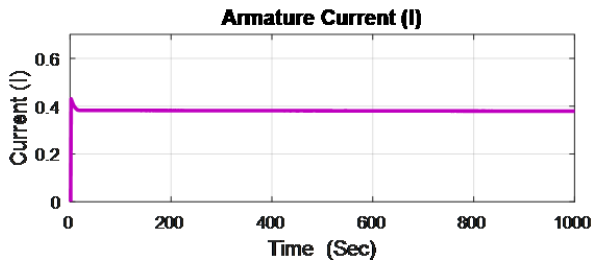


Fig. 11(d) Armature Current of ANN

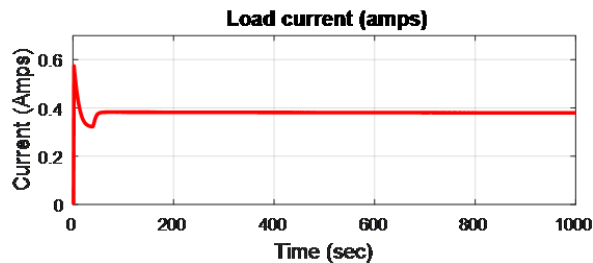


Fig 11(e). Load Current of PID

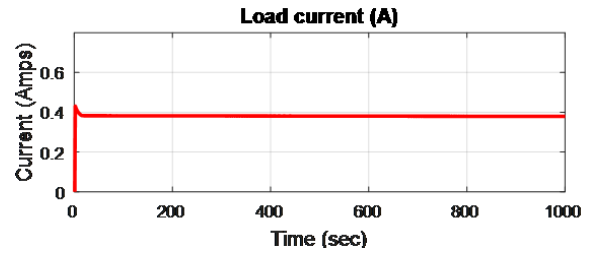


Fig 11(f). Load Current of ANN

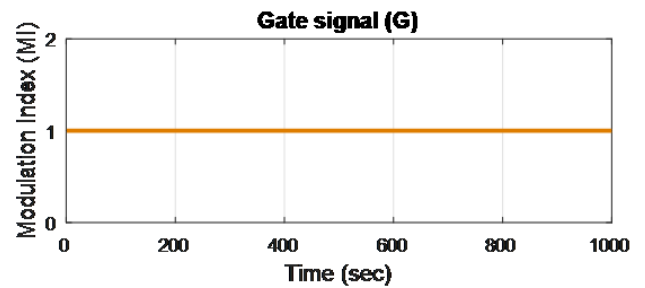


Fig 11(g) Gate Signal of PID

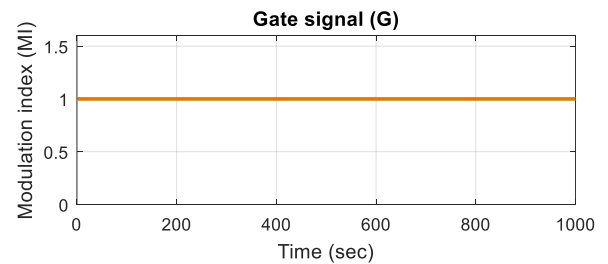


Fig 11(h). Gate Signal of ANN

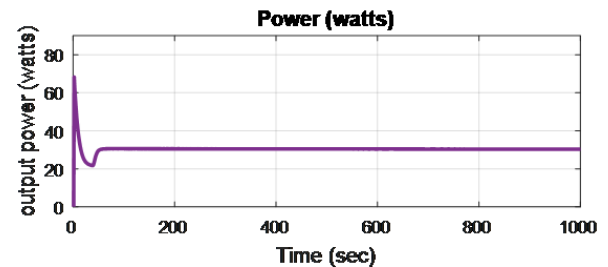


Fig 11(I). Power of PID

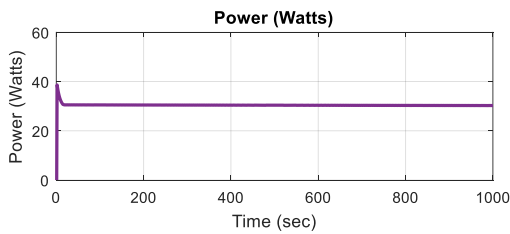


Fig 11(j).power of ANN

SIMULATION RESULT:

Table: 6

DESCRIPTION	PID	ANN
Source Voltage (Vs)	39.95	39.95
Load Voltage (VL)	72.05	79.84
Load Current (IL)	0.34	0.379
Power (P)	24.71	30.26
RPM	10.01	13.46

9. Conclusion

In recent years it is very important to concentrate on renewable energy resources. In renewable energy resources solar energy is most reliable and cheap in cost. In power system, it is important to get optimum power from the system.

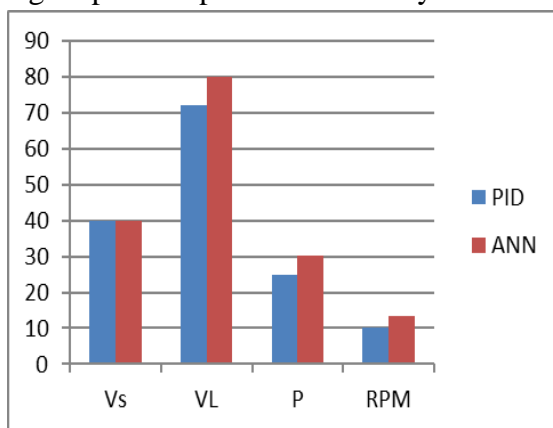


Fig 12

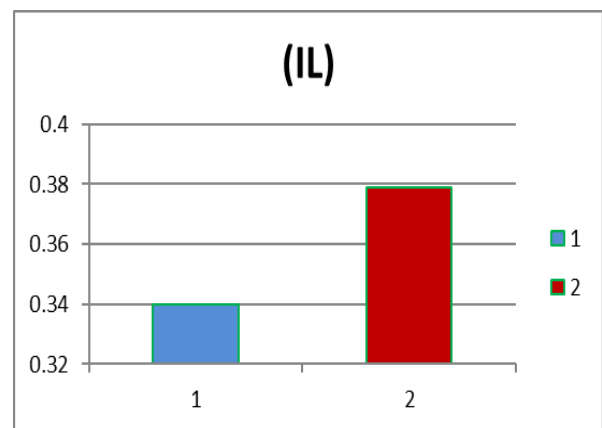


Fig 13

The DC monoblock pump is very useful for pumping ground water for irrigation in the rural areas where lack of electricity. In this paper the authors concentrate the method which is helpful to get MPP. In recent years the ANN (MPPT) algorithm plays vital role to achieve MPP. Hence in this paper direct control method (ANN controller with duty cycle adjustment) is implemented.

Simulation results of DC monoblock solar pump are obtained using MATLAB simulation for different values of irradiance by adjusting duty cycle of the dc-dc converter (Boost converter). It is observed that the curves obtained by direct control method are better than simple ANN controller for PV module.

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