ANN BASED PEAK POWER TRACKING FOR PV SUPPLIED DC MOTORS

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF

Bachelor of Technology
In
Electrical Engineering

By

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CERTIFICATE

This is to certify that the Thesis Report entitled **ANN BASED PEAK POWER TRACKING FOR PV SUPPLIED DC MOTORS** submitted by **Deepak Singh Rajpoot (10502056)**,**Chiranjeeb Dutta(10502041) and Manoja kumar Biswal(10502042)** in partial fulfilment of the requirements for the award of Bachelor of Technology degree in **Electrical Engineering** during session 2008-2009 at National Institute Of Technology, Rourkela (Deemed University) and is an authentic work by them under my supervision and guidance.

Date

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ACKNOWLEDGEMENT

Contents

ABSTRACT

The report presents an application of an Artificial Neural Network(ANN) for the identification of the optimal operating point of a PV supplied separately excited dc motor driving two different load torques. A gradient descent algorithm is used to train the ANN controller for the identification of the maximum power point of the Solar Cell Array (SCA) a gross mechanical energy operation of the combined system. The algorithm is developed based on matching of the SCA to the motor load through a buck-boost power converter so that the combined system can operate at the optimum point. The input parameter to the neural network is solar insulation and the output parameter is the converter chopping ratio corresponding to the maximum power output of the SCA or gross mechanical energy output of the combined PV system. The converter chopping ratios at different solar insulations are obtained from the ANN controller for two different load torques and are compared with computed values.

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CHAPTER1

1. INTRODUCTION

The rapid trend of industrialization of nations, increased interest in environmental issues led recently to explore the use of renewable forms such as solar energy. Photovoltaic (PV) gene-ration is gaining increased importance as renewable source due to its advantages like absence of fuel cost, no noise and wear due to absence of moving parts and little maintenance etc. In particular PV systems are rapidly expanding and have increasing roles in electric power technologies, providing more secure power sources to the pumping systems, where it is not economically viable to connect the existing grid supply. Optimum operation of the SCA and a dc shunt motor is achieved by means of a switching procedure of the SCA modules, direct current transformers as well as controlling the motor fluxes. Appelbaum has analyzed the performance of dc motors (separately, series and shunt) supplied from PV sources. These studies reveal that the dc shunt motor powered by solar cells has an inferior performance and a separately excited dc motor driving a centrifugal pump is the best device / drive as far as better matching of the PV generator is concerned. Performance analysis (dynamic and steady state) of dc motors fed from PV supplies through intermediate power converter have been reported. Saied (1988) formulated guidelines to construct the motor v-characteristics for maximum daily gross mechanical energy output (GME) and to determine the optimal motor parameters to match the solar generator. Artificial Neural Networks are widely accepted as a technology offering an alternative way to solve complex problems and have been successfully applied in many areas. The power of the ANNs in modeling complex mappings and in system identification has been demonstrated. ANN based real time maximum power tracking controller for PV grid connected systems has been reported. The studies emphasize that the SCA operating point is shifted to its maximum power point by using a voltage control type inverter, which is identified by the ANN. Various methods of maximum power (MP) tracking have been reported in literature. The present paper brings out the identification of optimal point (corresponding to MP or GME operation) of the PV supplied separately

excited dc motor fed from intermediate power converter driving centrifugal pump or volumetric pump loads. The converter-chopping ratio is selected adaptively using ANN to get maximum power from SCA or GME output from the combined system. This on-line training approach avoids adjustment of optimal operating point through trail and error procedure and does not require high resolution sensors.

CHAPTER2

2. STATEMENT OF PROBLEM:

The problem is to design an adaptive controller by using Artificial Neural Network for obtaining the MP or GME operation of the PV supplied dc motor system. These MP or GME operations can be achieved at different solar isolations by controlling the power converter duty ratio, which is adjusted by the adaptive ANN controller.

CHAPTER 3

3. MATHEMATICAL MODEL OF THE SYSTEM:

The combined system mainly consists of Solar Cell Array, dc–dc converter, dc motor coupled to either centrifugal pump or volumetric pump load as in fig. Mathematical model for individual components and describing equations for MP, GME operations are derived in the following sections.

3.1PV GENERATOR MODEL

The PV generator is formed by the combination of many PV cells connected in series and parallel fashion to provide desired value of output voltage and current. This PV generator exhibits a non-linear insolation dependent v-i characteristic. The V-I characteristic with Ns cells in series and Np cells in parallel is,

$$V_g = -I_g R_s (N_s/N_p) + (N_s/A) \ln\{1 + (N_s I_{ph} - Ig/N_p I_o)\} \text{----------------(1)}$$

where $A = q / AKT$;

- q −electric charge;
- A−Completion factor
- K −Boltzmann constant
- T −Absolute temperature

The equivalent circuit of PV generator structure is shown in Fig2 and its algorithm for designing an adaptor shows the output V-I,P-I characteristics of the solar cell array (insolations) which follow in the final section of this report.
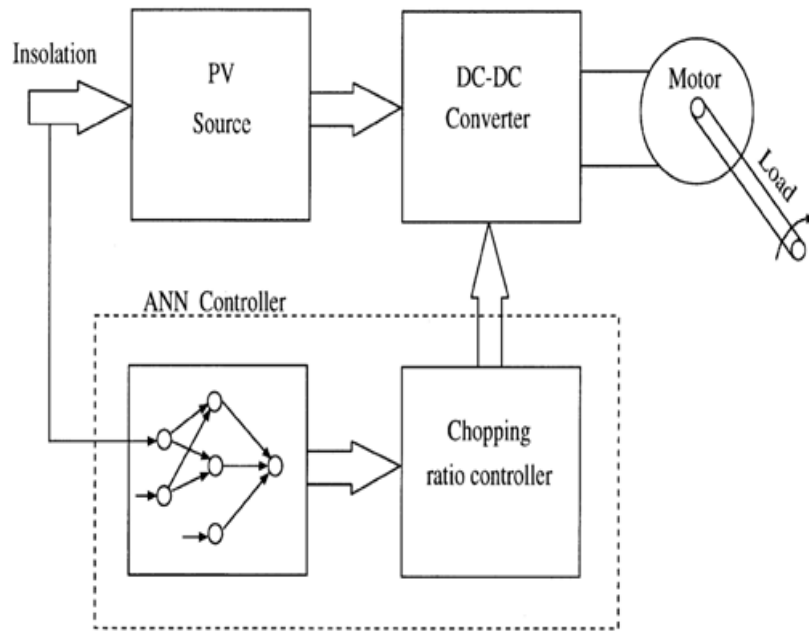
Figure1: Functional block of the system

Isolation of 1000 W/ m2 =100% insolation) with solar insolation as a parameter. In this figure Ig , Vg , and Pg are the output current, voltage and power of the solar array respectively. It is seen that in fig the maximum power point of the solar array shifts when the solar insolation is changing. The PV generator considered in these studies consists of 18 parallel paths and each path contains 324 cells in series. After substituting the cell constants in Eq. (1) and upon simplification the resulting v-I characteristic is where K_{ins} is percentage of isolation .

$$V_g = -\ 0.9 I_g$$

$$+123.697 \ln\{\ 1.0 + 123.456\ (13.45\ K_{ins} - I_g)\} \ -----(2)$$

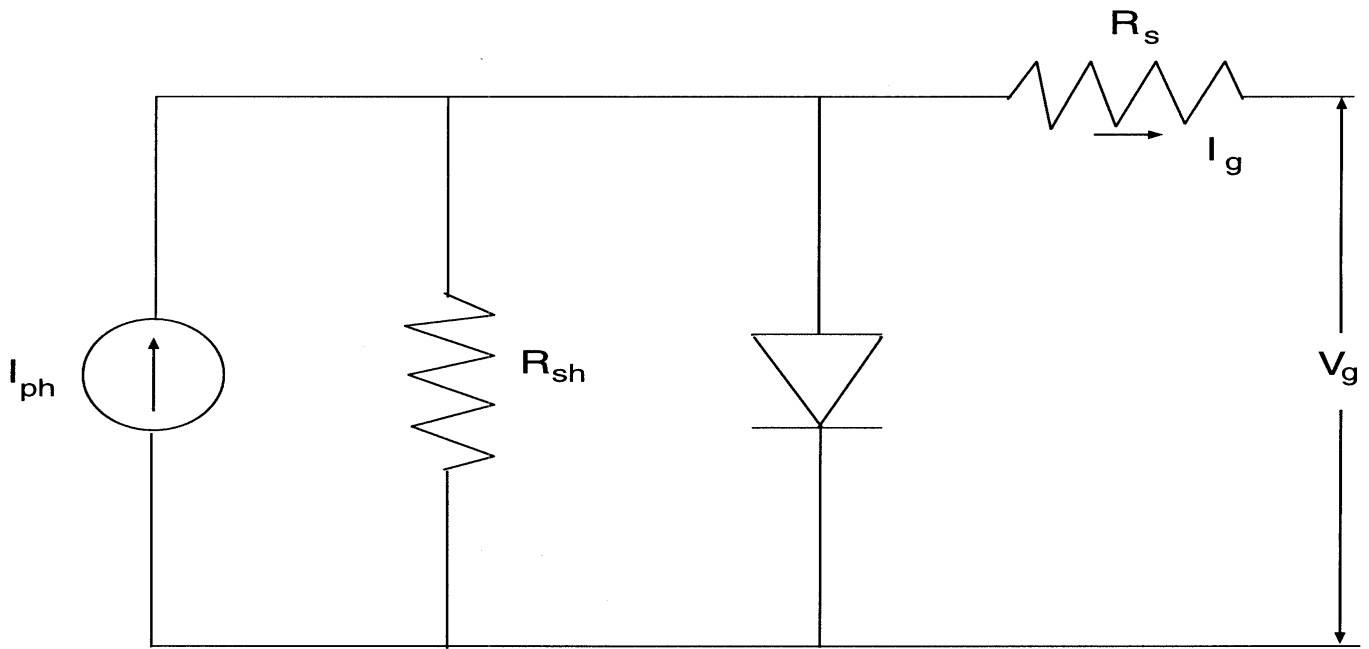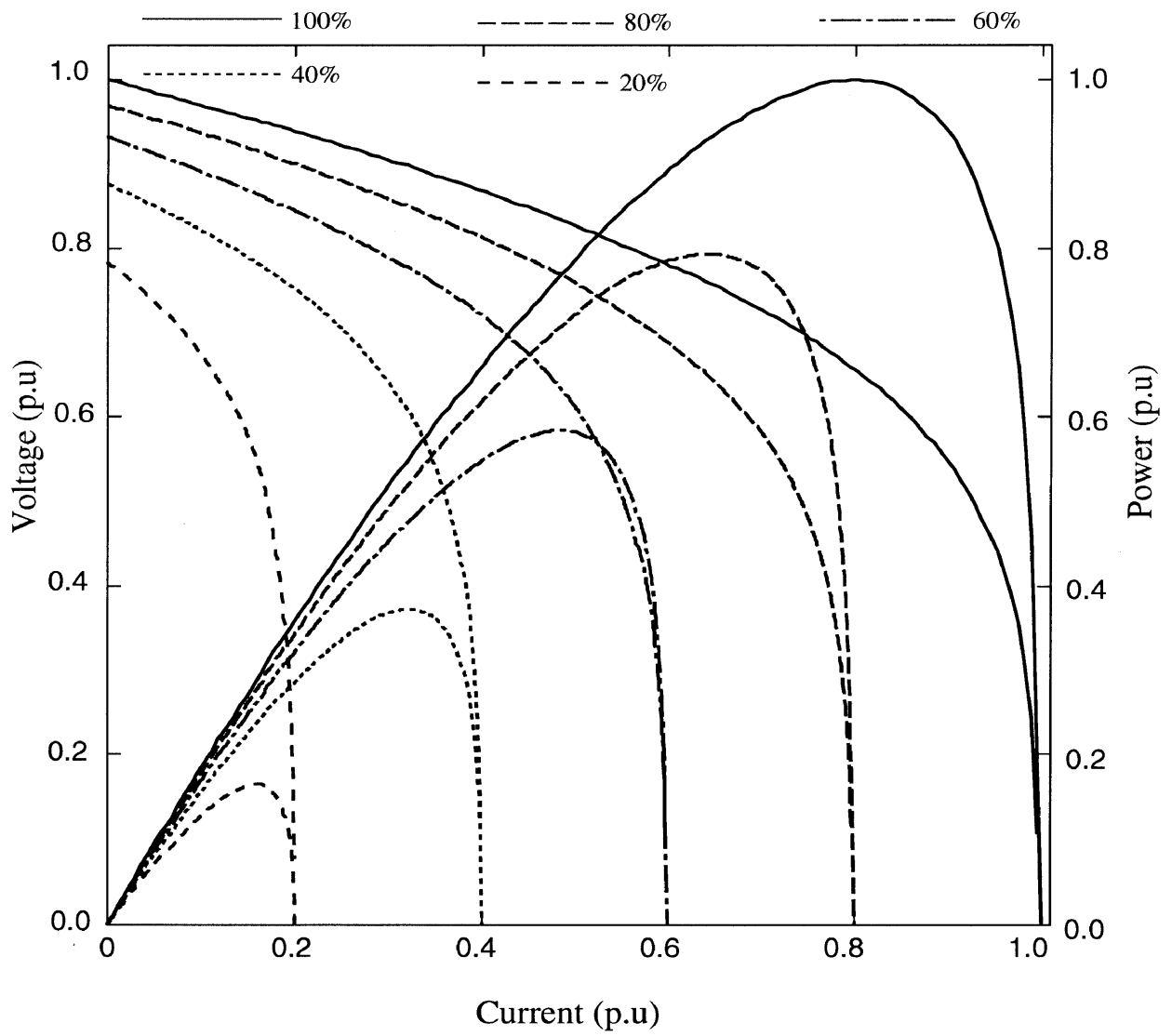**Figure 2: Equivalent circuit of the PV generator**

Figure 3:The V-I/P-I characteristics of PV generator at different solar insolation.

3.2 POWER CONVERTER MODEL

The intermediate dc–dc converter is a buck-boost converter with a variable duty or chopping ratio. This converter produces a chopped output dc voltage and controls the motor average voltage, current. Further, the converter continuously matches the output characteristic of the PV generator to the input characteristic of the motor so that maximum power is extracted from the SCA or the gross mechanical energy per day of the system is maximum.

Assuming the dc-dc converter is ideal, the output voltage and current of the converter for a duty ratio δ is related to the solar cell voltage(Vg),current(Ig)

$$V_{av} = \delta\, V_g / (1-\delta) \qquad\qquad \text{------------------------(3)}$$

$$I_{av} = I_g\, (1-\delta)/\, \delta \qquad\qquad \text{---------------------- (4)}$$

$$\delta = (t_{on}\, /T_P) \qquad\qquad \text{--------------------- (5)}$$

$$y = \delta\, /(1-\delta) \qquad\qquad \text{-----------------------(6)}$$

where d –duty ratio; Y –chopping ratio; T_p –switching period of the converter; d ,0.5 for buck operation and d .0.5 for boost operation.

3.3 Model of the DC motor

When the dc separately excited motor is supplied from a PV source through an intermediate power modulator, the motor voltage and torque equations under steady-state are

$$V_{av} = E_b + I_{av}\, R_a \qquad\qquad \text{-------------- (7)}$$

$$T_e = C_e\, I_{av} \qquad\qquad \text{-------------- (8)}$$

$$E_b = C_e\, \omega \qquad\qquad \text{--------------- (9)}$$

3.4 Model for the pump-loads

Pumps may be volumetric or centrifugal types having different head–vs.–flow characteristics. These pump loads will develop speed dependent torques. The speed–torque characteristics of centrifugal (T_{L1}) and volumetric pump (T_{L2}) loads including friction torque are given by

$$T_{L1} = A_1 + B_1 \omega + C \omega^{\wedge 1.8} \qquad \text{---------------- (10A)}$$

$$T_{L2} = A_1 + B_1 \omega \qquad \text{----------------- (10B)}$$

3.5 Maximum power operation of SCA

For the maximum utilization of the SCA, a power converter is introduced in between SCA and motor. The duty ratio of the converter is changed accordingly to match the motor load to SCA. Assuming the power converter is ideal (all of the array power is delivered to the motor) at maximum power point, the power absorbed by the motor is equal to the power delivered by the SCA i.e.

$$P_m = V_{av} I_{av} = V_m = I_m \qquad \text{--------------------- (11)}$$

Where Vav,Iav are the motor armature voltage,current;Vm,Im are the SCA voltage,current respectively at maximum power point of SCA.The motor armature voltage and currents are expressed in terms of SCA voltage,current at maximum power point as

$$V_{av} = \delta_{mp} V_m \qquad \text{---------------------------(12)}$$

$$I_{av} = I_m / \delta_{mp} \qquad \text{---------------------------(13)}$$

$$V_{av} = E_b + I_{av} R_a \qquad \text{- ---------------------------(14)}$$

From Fig.4 transforming the motor equivalent circuit to SCA side by substituting eq.(12)and Eq. (13) in Eq. (14) then the motor armature voltage equation (in terms of SCA voltage, current) is

$$V_m = (E_b / \delta_{mp}) + I_m (R_a / \delta_{mp}{}^\wedge 2) \qquad \text{-------------------- (15)}$$

Rearranging the above equation

$$V_m \delta_{mp}{}^\wedge 2 - E_b \delta_{mp} - I_m R_a = 0 \qquad \text{-------------------- (16)}$$

or the above equation two solutions exist .Since the duty ratio never be negative, expression which gives positive duty ratio is

$$\delta_{mp} = E_b / 2V_m + ((E_b / 2V_m)^2 + (I_m R_a / V_m))^{1/2} \text{ --------(17)}$$

For a given SCA maximum power, the motor armature current is obtained from the following equations

$$P_m = E_b I_{av} + I_{av}^2 Ra \qquad\qquad \text{----------------- (18)}$$

$$R_a I_{av}^2 + Eb\ Iav - Pm = 0$$

$$Iav = -Eb / 2\ Vm + ((Eb / 2Vm)^2 + (Pm / Ra))^{1/2} \qquad \text{----------------(19)}$$

where Eb is given by Eq. (9). The duty ratio of the converter (Eq. (17)) depends on the motor back emf, which in turn depends on the motor load. When the dc motor coupled centrifugal or volumetric pump-load) the back emf at a given SCA power (Pm) is obtained by solving (Te= TL) eqn(8), (10-A), and Eqn. (19) in case of centrifugal pump load and Eqn. (8), Eqn. (10-B), and Eqn. (19) for volumetric pump load.once back emf is calculated corresponding to Pm,the duty ratio of the conveter is obtained from eqn.(17).these computed values are taken as reference patterns for training the neural network.
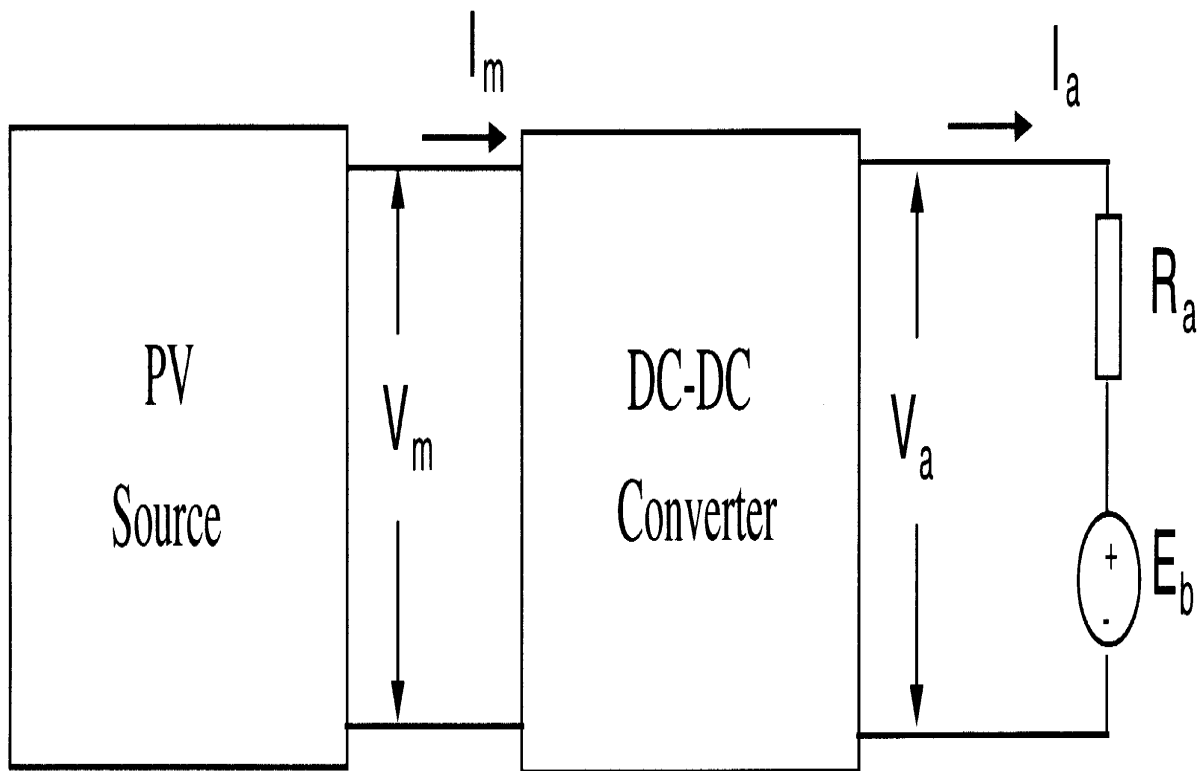
Figure 4 Equivalent Circuit of the Combined System
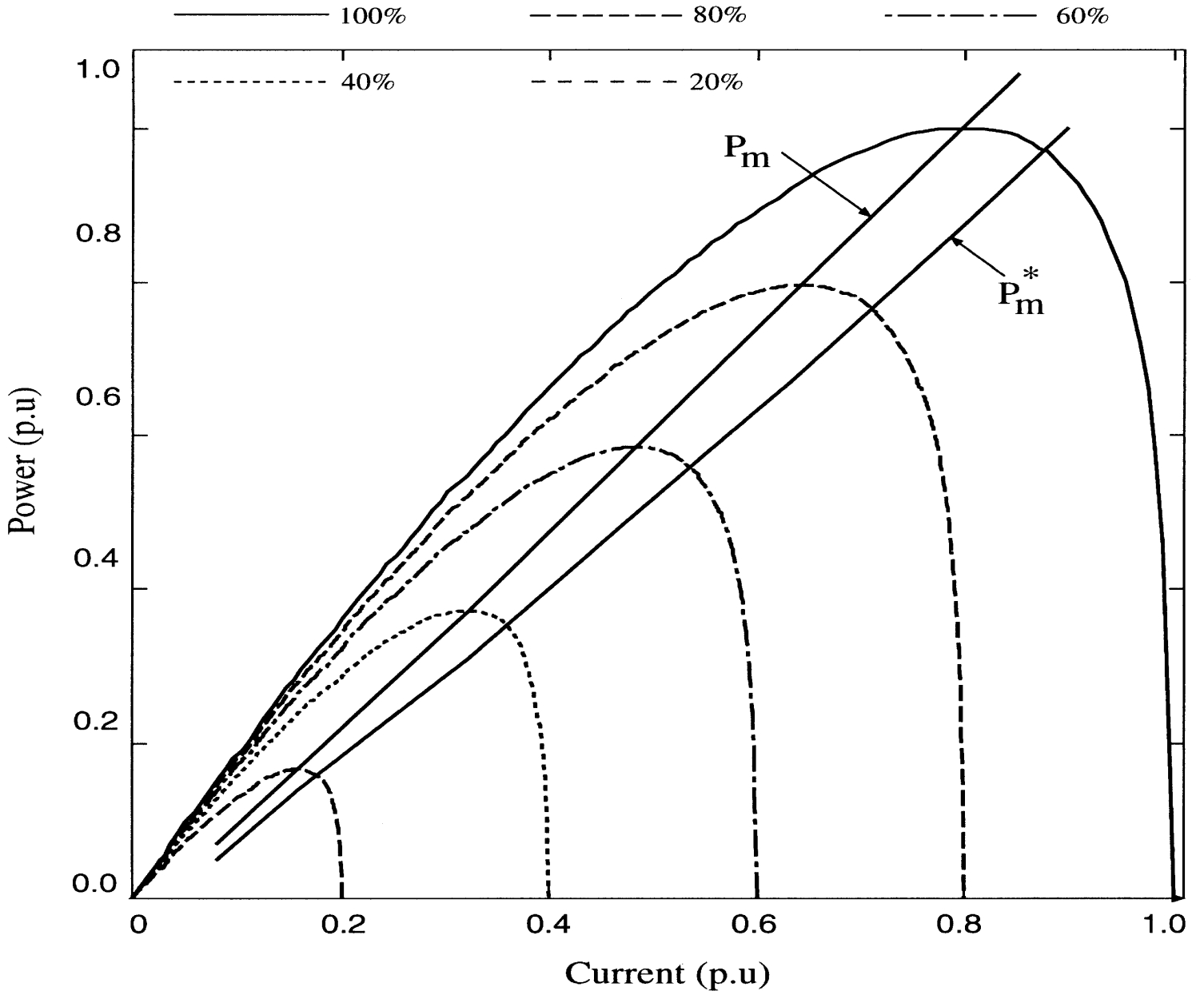
Figure 5 Mp And Gme Operating Points Trajectory Of SCA At Different Solar Insolation

3.5 SIMULATION:

* The v-I/p-I characteristics of PV generator at different solar insolation can be plotted by the following "MATLAB" program

```
clc
close all
clear all
Ig=0:.01:1;
Kins=.2:.2:1;
for i=1:5;
 Vg=(-0.9*Ig)+(23.679)*log(1.0+123.456*(13.45*Kins(i)-Ig));
 Pm=Vg.*Ig;
 figure(1)
 hold on
 plot(Ig,Vg)
 hold off
 figure(2)
 hold on
 plot(Ig,Pm)
 hold off
 end
```

* The duty ratio and the chopping ratio of the converter for different types of motor loads is calculated by the following MATLAB program:

```
clc
clear all
close all
% Te=Ce*Iav;
% Tl1=A1+B1*w+C1*w^1.8;
% Tl2=A1+B1*w;
A1=0.00039;
B1=0.0023;
C1=0.5;
w=(2*3.14*1500)/60;
Ce=0.6626;
Vm=120;
Ra=1.5;
Pm=10*10^3;
Data=cell(5,5)
i=1;
Tl1=A1+B1*w+C1*w^1.8;
Tl2=A1+B1*w;

Data(i,1)={'Pm'};
Data(i,2)={'DELTAmp1'};
Data(i,3)={'DELTAmp2'};
Data(i,4)={'Y1'};
Data(i,5)={'Y2'};

for Pm=10*10^3:10^3:15*10^3

Iav1=Tl1/Ce;
```

```
Eb1=(2*Vm)*((Pm/(2*Iav1*Ra))-(Iav1/2));


Iav2=Tl2/Ce;
Eb2=(2*Vm)*((Pm/(2*Iav2*Ra))-(Iav2/2));


Im=Pm/Vm;
DELTAmp1=(Eb1/(2*Vm))+((Eb1/(2*Vm))^2+(Im*Ra/Vm))^0.5;
DELTAmp2=(Eb2/(2*Vm))+((Eb2/(2*Vm))^2+(Im*Ra/Vm))^0.5;
i=i+1;
Y1=DELTAmp1/(1-DELTAmp1);
Y2=DELTAmp2/(1-DELTAmp2);
Data(i,1)={Pm};
Data(i,2)={DELTAmp1};
Data(i,3)={DELTAmp2};
Data(i,4)={Y1};
Data(i,5)={Y2};
end
Data
```

3.5.1OUTPUT

Data =

'Pm'   'DELTAmp1'   'DELTAmp2'   'Y1'   'Y2'

[10000] [1.5396e-004] [1.2219e+004] [1.5399e-004] [1.5399e-004]

[11000] [1.6936e-004] [1.3441e+004] [1.6939e-004] [1.6939e-004]

[12000] [1.8476e-004] [1.4663e+004] [1.8480e-004] [1.8480e-004]

[13000] [2.0016e-004] [1.5885e+004] [2.0020e-004] [2.0020e-004]

[14000] [2.1556e-004] [1.7107e+004] [2.1561e-004] [2.1561e-004]

[15000] [2.3096e-004] [1.8329e+004] [2.3102e-004] [2.3102e-004]

Table-1 Machine data

V	120 volts
I	9.2 A
Speed	1500 RPM
R_a	1.5Ohm
L_a	0.02 H
C_e	0.66260
J	0.02360
A_1	0.00039
B_1	0.00238
C_1	0.50000

CHAPTER 4

4. ARTIFICIAL NEURAL NETWORKS

ANN is widely accepted as a technology offering an alternative way to solve complex and ill defined problems. These are the gross simplification of real biological networks and mimic somewhat the learning process of a human brain. The capacity of neural network is of little utility unless accompanied by useful generalizations to patterns that are not presented during training. In fact generalization is not needed, we can simply store the associations in a look of table and thus neural networks may be of little importance.

ANN operates like a black box model requiring no detailed information about the system. Instead, they learn the relations between the input parameter, controlled and uncontrolled variables by studying previously recorded data and similar to the way nonlinear regression might perform. Another advantage of using ANN is their ability to handle large and complex system with man interrelated parameters. They seem to simplify, ignore, excess input data that are of minimal significance and concentrate on the more important input. This trained ANN can be used to approximate an arbitrary input output mapping of the system.
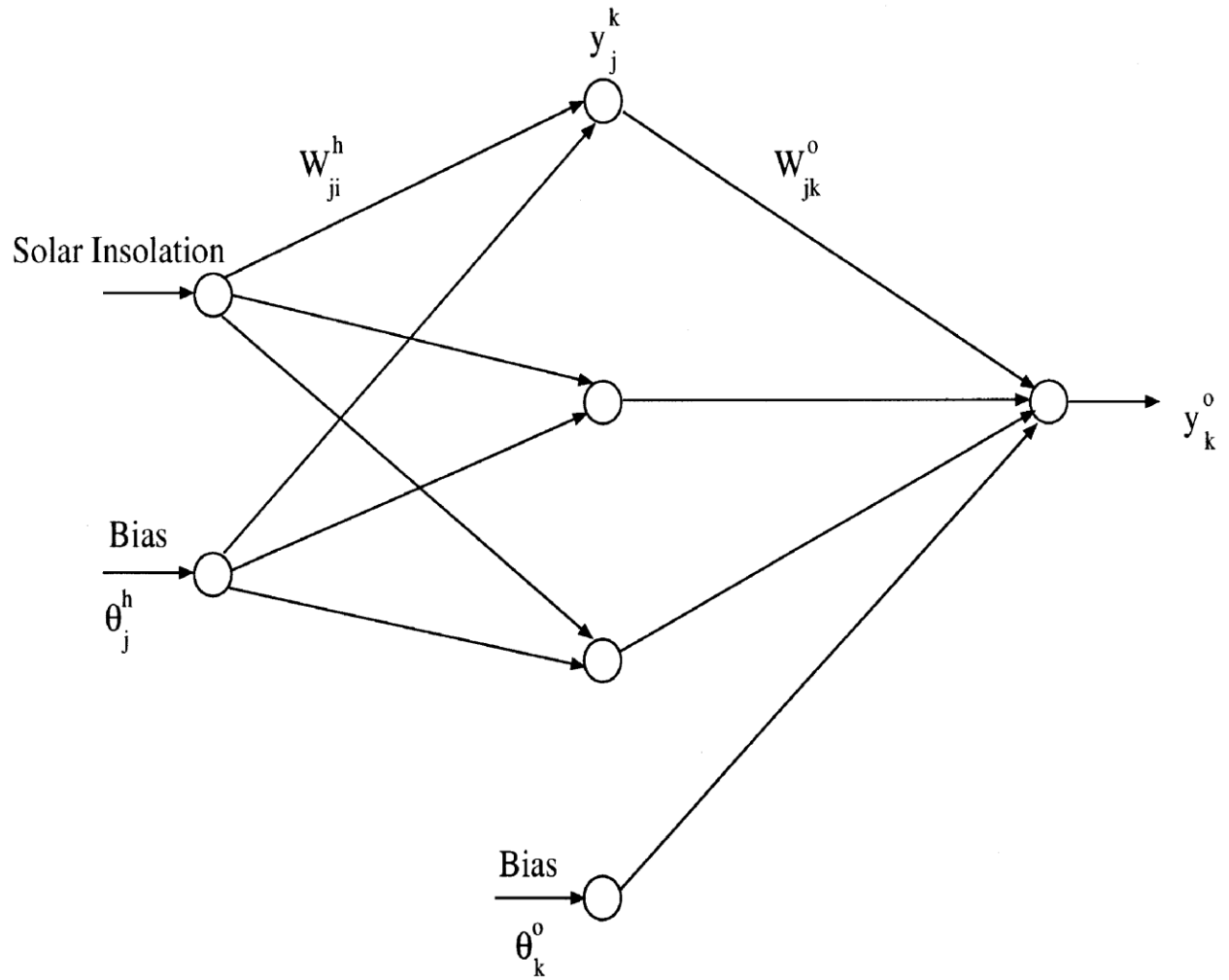
Figure 6 Schematic Diagram Of An Artificial Neural Network

An input vector, $x = (x_1, x_2, x_3 \ldots x_n)^t$ is applied to the input layer of the network. The net input of the hidden 'j' unit is:

$$net_j^h = \sum_{i=1}^{n} w_{ji}\, x_i + \theta_j^h$$

Where W_{ji}^h is the weight on the connection from ith input unit, θ_j^h for j=1, 2... N_h represents the bias for hidden layer neurons. Now output of the neurons in the hidden layer may be written as

$$y_j^h = f\left(\sum_{i=1}^{n} w_{ji}\, x_i + \theta_j^h\right)$$

And the net input to the neurons in the output layer becomes

$$net_k^0 = \sum_{j=1}^{Nh} w_{kj}\, y_j^h + \theta_k^0$$

Where θ_k^0 represents the bias for neurons in the output layer. Finally the output of the neurons in the output layer is

$$y_k^0 = f\left(\sum_{i=1}^{Nh} w_{kj}\, y_j^h + \theta_k^0\right)$$

With the above equations in the forward direction the error propagation rule is used in the following steps.

Step 1:

Construct the network and initialize the synaptic weights and random values.

Step 2:

Apply an input vector to the network and find the corresponding output value.

Step 3:

Compare the actual outputs with the desired outputs and find error.

Step 4:

Determine the amount by which each weight is to be changed and make necessary corrections.

Step 5:

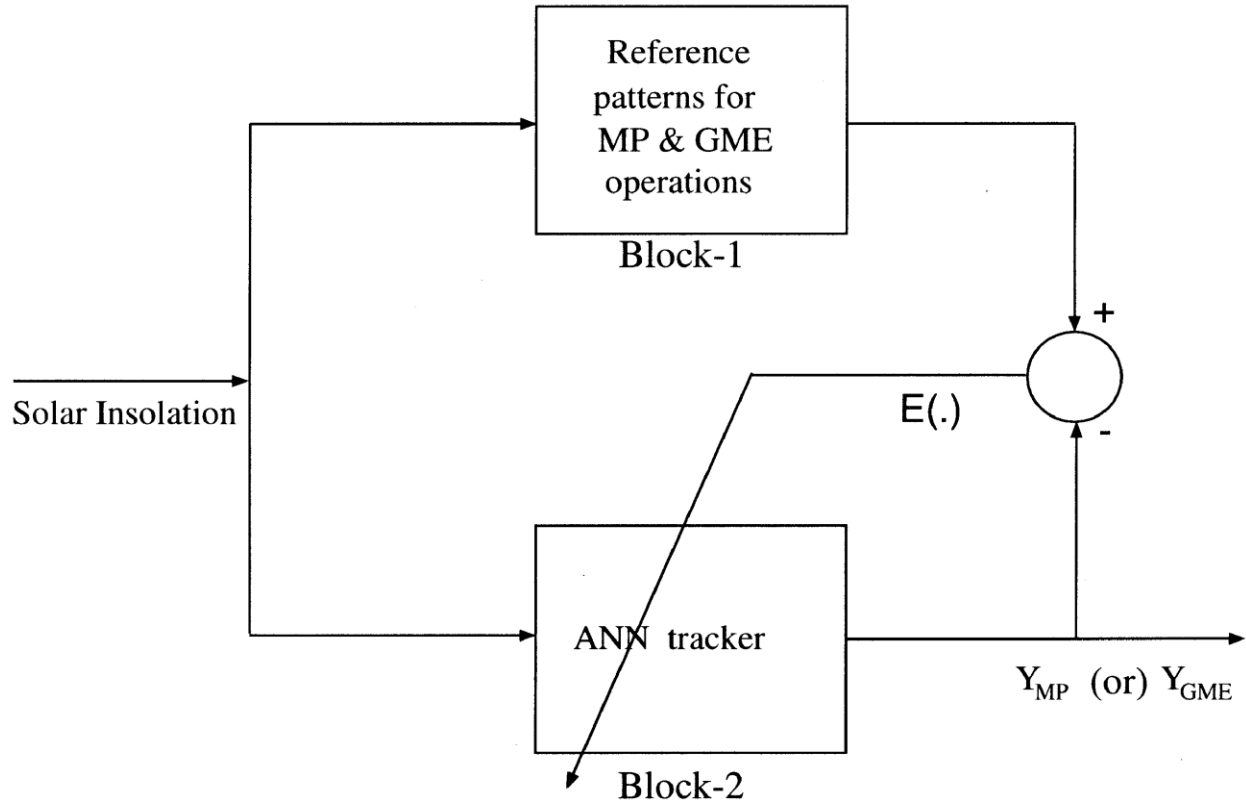Repeat the steps until acceptable error is attained.

Figure 7 Block Diagram for ANN training

The ANN training block diagram or MP or GME operation is shown in the figure. Using the mathematical models in section 3.5 and 3.6 the reference patterns for MP and GME operation are computed.Block-1 represents these reference patterns. The ANN training is performed by initially assigning random values to the weight terms. Gradient descent algorithm is used in the training, as it improve the performance of the ANN by reducing the total error by changing the weights along its gradient. The learning rate is 0.55 and momentum factor 0.80 is selected for satisfactory training. The training process was terminated as and when the mean square error E (.) is less than the specified value.

4.1 SIMULATIONS

```
clc;

%Script PC.2

%System Identification

close all;

% Define initial values

y(1)=0; y(2)=0;

%Create 500 random value data from input space [-2,2]

% and obtaining training patterns

N=500;

for k=2:N

f(k)=y(k)*(y(k-1)+2)*(y(k)+2.5)/(8.5+y(k)*y(k)+y(k-1)*y(k-1));

u(k)=(rand-0.5)*4;

y(k+1)=f(k)+u(k);

end

for k=1(N-1)

Input(1,k)=y(k+1);

Input(2,k)=y(k);

Target(k)=f(k+1);

End

%Build the initial NN and train

HN=10;

net=newff(minmax(Input),[HN 1],{'tansig','purelin'});

net.trainParam.goal=0.005;

net=train(net,Input,Target);
```

```
%Test the NN

for k=1:200,u(k)=2*cos(2*pi*k/100); end

for k=201:500 u(k)=1.2*sin(2*pi*k/20);end

yp(1)=0;yp(2)=0;ycap(1)=0;ycap(2)=0;

%yp-from direct calculation

for k=2:500

 yp(k+1)=yp(k)*(yp(k-1)+2)*(yp(k)+2.5)/(8.5+ yp(k)*yp(k)+yp(k-1))+u(k);

ycap(k+1)=sim(net,[ycap(k);ycap(k-1)])+u(k);

end

figure(2)

plot(1:501,yp,'r',1:501,ycap,'g');
```

OUTPUT

'DELTAmp1 ANN'	'DELTAmp2 ANN'
'1.6174e-004'	'1.2815e+004'
'1.7525e-004'	'1.3954e+004'
'1.8865e-004'	'1.5001e+004'
'2.0478e-004'	'1.6204e+004'
'2.1804e-004'	'1.7412e+004'
'2.3245e-004'	'1.8504e+004'

CHAPTER 5

CONCLUSIONS

A 120V, 9.2A, 1500 rpm PV supplied dc separately excited motor driving (i) centrifugal pump load (ii) volumetric pump load is considered in these studies. The parameters of the machine, PV generators are given in Table 1.Based on the mathematical models developed in the preceding Sections, the converter chopping ratios are computed are (i) maximum power operation of SCA and (ii) gross mechanical energy output operation at different corresponding output values solar insolations for two load torques mentioned above. The computed values for the above case is tabulated.

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