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APPLICATION OF INTELLIGENT CONTROL TECHNIQUES FOR GLOBAL MAXIMUM POWER POINT TRACKING OF SOLAR PHOTOVOLTAIC SYSTEM

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ABSTRACT

In this paper, a fuzzy logic based feedforward voltage method of global maximum power point (GMPP) tracking scheme is developed for the boost converter supplied Solar Photovoltaic (SPV) system. With the developed realistic model of SPV array and boost converter, the proposed controller has been simulated. The reference voltage is obtained from Artificial Neural Network (ANN). The ANN was trained for optimum values computed from Particle Swarm Optimization (PSO) technique. Fuzzy Logic Controller (FLC) is used to find the error in voltage and the output from FLC is fed to Pulse Width Modulator (PWM) to control the boost converter. Comparison studies have been made for Proportional plus Integral (PI) and FLC. From the simulation results, it is observed that the feedforward control strategy with fuzzy controller reduces error and it is a promising one with reference to GMPP tracking. Furthermore, it does not require any tuning of the parameters, unlike conventional PI controller, wherein the controller gain parameters needs to be changed when solar insolation changes.

Keywords: solar photovoltaic array, GMPP tracking, fuzzy logic controller, feed forward voltage method, ANN, PSO.

INTRODUCTION

SPV source provides a clean energy from sun and has more advantages compared to other non conventional energy sources. It directly converts solar energy into electricity. It has a nonlinear Voltage-Power characteristic and the characteristic becomes more complex when there is an existence of partial shading. Under partial shading multiple peaks occur in the V-P characteristics among which one is called Global maxima as shown in Figure-1 (Patel and Agarwal, 2008a; Patel and Agarwal, 2008b; Ramaprabha and Mathur, 2009; Silvestre *et al*., 2009). To track GMPP with respect to changes in solar insolation and temperature, an intelligent controller is proposed in this work. PSO method is used for power optimization of SPVA under partial shaded conditions, which provides accurate results as compared to other optimization methods (Kennedy and Eberhart, 1995; Chaturvedi *et al*., 2009; Chettih *et al*., 2009; Ramaprabha and Mathur, 2011). Boost converter is used to adjust the impedance between SPV source and load. Won *et al*. (1994) reported the application of FLC to track the MPP with boost converter under uniform insolation conditions. The studies show that the fuzzy control algorithm is capable of improving the tracking performance as compared with the conventional methods. Artificial neural network (ANN) based real time MPP tracking controller for SPV grid connected systems has been reported in the literature (Hiyama *et al*., 1995; De Medeiros Torres *et al*., 1998).

A boost converter is presented in this paper as an intermediate converter and for tracking the maximum power a fuzzy feed forward controller is developed. In the feed forward array voltage based tracking scheme, the MPP tracking depends on the adjustment of reference voltage for the feed forward loop that corresponds to the optimal array voltage at that solar insolation. If the solar insolation changes, then the optimal array voltage also changes. Therefore, an on-line estimation of the optimal array voltage is required for the MPP tracking control.

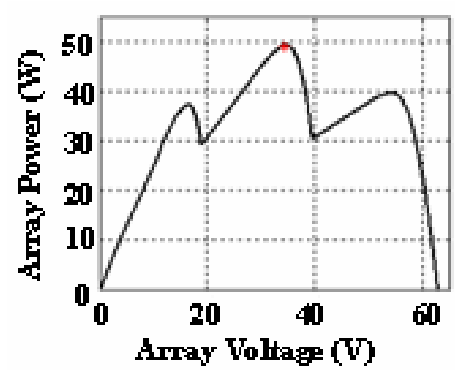

Figure-1. Voltage-power characteristics of SPV array under partial shaded conditions.

To cope with this situation an off-line ANN is proposed here to estimate the optimal array voltage variation with solar insolation and temperature. ANN is trained with a set of data optimized by PSO technique. For controlling the DC-DC converters several control strategies are reported in the literature. These controllers are simple to implement and easy to design. However, there are several drawbacks (So *et al*., 1994) that hinder the conventional controllers, such as performance dependent on the working point, necessity for tuning of control parameters against changes in supply voltage and load parameters, complex design of control parameters, and stabilization problems, etc. To overcome some of the disadvantages mentioned above, FLCs are coming up in industrial processes owing to their heuristic nature associated with simplicity and effectiveness for both linear

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and nonlinear systems. Fuzzy controller application has been successful in many areas, particularly in the field of power electronics to regulate the DC-DC converters and pulse width modulated inverters etc. (Gupta *et al*., 1997; Mattavelli *et al*., 1997; Raviraj and Sen, 1997). This fuzzy control is nonlinear and adaptive in nature, which gives it robust performance under parameter variation, load and supply voltage disturbances, etc. In this work, FLC has been applied to track the GMPP from the boost converter supplied SPV system. The control inputs to the FLC are voltage error and change of errors, while the output is the change of control signal for PWM generator. Use of FLCs for the SPV systems will relive the burden involved in the design of controller parameters. In addition to this, these controllers will improve the tracking performance as compared with conventional controllers.

BLOCK DIAGRAM OF THE PROPOSED INTELLIGENT CONTROLLER

The block diagram of the proposed intelligent controller for GMPP is shown in Figure-2. A feed forward GMPP tracking scheme is developed for the boost converter fed SPV system using fuzzy controller. The tracking algorithm changes the duty ratio of the converter such that the SPVA voltage equals the voltage corresponding to the GMPP at that solar insolation and temperature This is done by the feed forward loop, which generates an error signal by comparing the instantaneous array voltage and reference voltage. The reference voltage for the feed forward loop, corresponding to the GMPP, is obtained by an off-line trained neural network. The PSO optimized data is used for off-line training of the neural network, which employs back-propagation algorithm. The proposed fuzzy feed forward peak power tracking effectiveness is demonstrated through the simulation results, and is compared with the conventional PI controller based system.

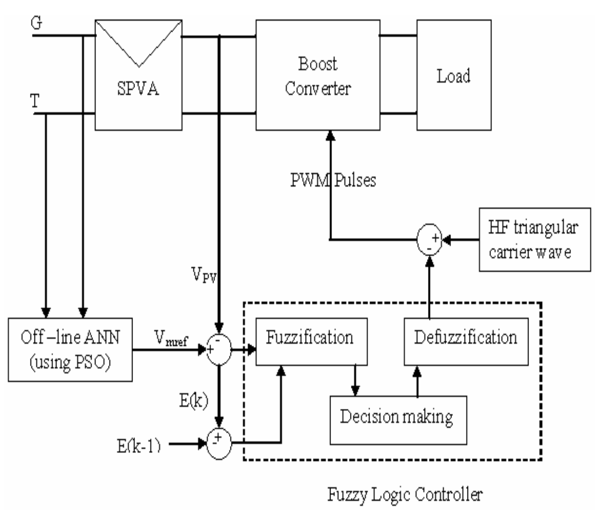

Figure-2. Block schematic of Fuzzy logic and ANN based controller.

The models for SPV array boost converter and other control blocks are explained in the following sections. The analysis of the system is carried out under the following assumptions:

- Switching elements (MOSFET and Diode) of the converter are assumed to be ideal, i.e., forward voltage drops and ON-state resistances of the switches are neglected.
- The equivalent series resistance of the capacitance and stray capacitances are neglected.
- Passive components of the converter (R, L and C) are assumed to be linear, time invariant, and frequency independent.
- The converter operates in the continuous inductor current mode.

MATHEMATICAL MODEL OF SOLAR PV SYSTEM

Model of SPV system is required to known to study the converter and other connected systems to it. Many models have been reported in the literature. A well known single diode model has been used in this work for its simplicity and well representation of mono crystalline silicon solar cells as in this work the same type is considered. The model with improved equations has been used (Villava *et al*., 2009; Ramaprabha and Mathur, 2010). The modelling equations are:

$$I_{PV} = I_{ph} - I_r\left[\exp\left\{\frac{V_{PV}+I_{PV}R_{se}}{V_t}\right\} - 1\right] - \frac{(V_{PV}+I_{PV}R_{se})}{R_{sh}} \quad (1)$$

Where

$$I_{ph} = \{I_{ph,ref}[1+\alpha(T-T_{ref})]\}\frac{G}{G_{ref}} \quad 1(a)$$

$$I_{ph,ref} = I_{sc,ref} \text{ and } I_{phref} = \frac{R_{sh}+R_{se}}{R_{sh}} \times I_{scref} \quad 1(b)$$

$$I_r = \frac{I_{sc,ref} + \alpha(T-T_{ref})}{\exp\dfrac{V_{oc,ref}+\beta(T-T_{ref})}{nV_t} - 1} \quad 2(a)$$

$$I_{r,ref} = \frac{I_{sc,ref}}{\exp\left(\dfrac{V_{oc,ref}}{V_{t,ref}}\right) - 1} \quad 2(b)$$

$$V_t = V_{tref}\frac{T}{T_{ref}} \text{ and } V_{tref} = \frac{n_{ref}kT_{ref}}{q} \quad (3)$$

$$R_{sh} = \frac{3.6}{G-0.086} \quad (4)$$

$$I_m = I_{mref} \times G \text{ and } V_m = V_{mref} + \{\beta(T-T_{ref})\} \quad (5)$$

$$R_{se}\frac{G}{G_{ref}} = \frac{V_{terf}}{I_{rref}}\exp\left[-\frac{V_{mref}+I_{mref}R_{seref}}{V_{tref}}\right]$$

$$+R_{seref} - \frac{G}{G_{ref}}\left(\frac{V_t}{I_r}\exp\left[-\frac{V_m + I_m R_{se}}{V_t}\right] + R_{se}\right) \tag{6}$$

$$n = n_{ref}\frac{T}{T_{ref}} \tag{7}$$

Equation (1) represents the practical SPV cell. Here the five parameters are I_{ph}, I_r, V_t, R_{se} and R_{sh}. It can be shown that the array parameters for series array consists of N_S cells in series: $I_{ph,array} = I_{ph}$, $I_{r,array} = I_r$, $V_{t,array} = N_S V_t$, $R_{se,array} = N_S R_{se}$ and $R_{sh,array} = N_S R_{sh}$. For parallel array consists of N_P cells in parallel: $I_{ph,array} = N_P I_{ph}$, $I_r = N_P I_r$, $V_{t,array} = V_t$, $R_{se,array} = R_{se}/N_P$ and $R_{ph,array} = R_{ph}/N_S$. The above equations have been simulated using MATLAB/SIMULINK.

DESIGN OF MAXIMUM POWER POINT TRACKER

Maximum Power Point Tracker (MPPT) can be realized using different converter topologies. In this paper boost converter is used due to its high efficiency. The MPPT design is explained below. The DC voltage transfer function is given by:

$$\frac{V_o}{V_s} = \frac{1}{1-D} \tag{8}$$

Where V_o = Output voltage, V_s = Source voltage, D = Duty cycle. The critical values of the inductance and capacitance can be calculated using the following equations,

$$L_b = \frac{(1-D)^2 DR}{2f} \tag{9}$$

$$C_{min} = \frac{D}{2fR} \tag{10}$$

f = frequency 10 kHz. The inductance and capacitance are calculated as L=100uH, C=220uF. The value of resistance used is 100 Ω.

FUZZY LOGIC CONTROLLER

In recent years, FLCs (Veerachary *et al*., 2002) have been widely used for industrial processes owing to their heuristic nature associated with simplicity and effectiveness for both linear and nonlinear systems. Advantages of FLCs over the conventional controllers are:

- They do not need accurate mathematical model;
- They can work with imprecise inputs;
- They can handle nonlinearity;
- They are more robust than conventional nonlinear controllers.

This section briefly describes the techniques used in FLC i.e., fuzzification, fuzzy knowledge base, and defuzzification. The basic structure of a fuzzy controller used in this work is shown in Figure-3. In the fuzzification process the numerical variable is converted into a linguistic variable. The following five fuzzy levels are chosen for the controlling inputs of the fuzzy controller (error: E, change of error: ΔE) in the fuzzification: NB-Negative Big, NS- Negative Small, ZE- Zero, PS-Positive Small and PB-Positive Big. Membership functions for controller inputs, i.e., E, ΔE, and incremental change in the controller output (ΔU) are defined on the common normalized range of [-1, 1]. In this work symmetric triangles with equal base and 50% overlap with other neighboring membership functions are considered. The final membership functions are shown in Figure-3.

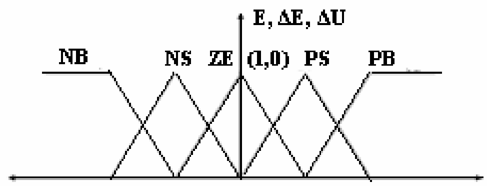

Figure-3. Membership functions for E, ΔE, ΔU.

Fuzzy knowledge base

The rule base that associates the fuzzy output to the fuzzy inputs is derived by understanding the system behavior. It basically contains the knowledge acquired by the designer as fuzzy rules and is expressed in the form of IF-THEN rules. The fuzzy rules are designed here to incorporate the following considerations keeping in view the overall control performance.

- When the SPVA terminal voltage is much greater than the GMPP voltage (V_{mref}), then change the duty ratio (increase) of the converter so as to bring the terminal voltage to V_{mref}.
- When the SPVA terminal voltage is less than the GMPP voltage, then the change of duty ratio is negative and it must be large so as to bring the terminal voltage to V_{mref}.
- When the array voltage is close to the V_{mref}, then incremental duty ratio is small.
- When the array voltage is near to GMPP voltage and is approaching it rapidly, then the change of duty ratio should be zero so as to prevent operating point deviation away from the MP point.
- When the array voltage is equal to the GMPP voltage, then the change of duty ratio should be maintained at zero.

Taking the above points into consideration the fuzzy rules are derived and rule base is given in Table-1. There are several possible combinations of the degree of supports with varying strengths to the corresponding rules, to satisfy different conditions. However, for the present problem one such combination for the degree of support, resulting in better tracking performance is 1.0, 0.5, 0.3 and 0.0.

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Table-1. Rule base table for FLC.

ΔU \ ΔE. E	NB	NS	ZE	PS	PB
NB	NB	NS	NS	NS	ZE
NS	NS	NS	NS	ZE	PS
ZE	NS	NS	ZE	PS	PS
PS	PS	ZE	PS	PS	PS
PB	ZE	PS	PS	PS	PB

Defuzzification

In the defuzzification process the crisp value of the change of duty cycle is obtained. The well-known center of gravity method for defuzzification is used here. It computes the center of gravity from the final fuzzy space, and yields a result which is highly related to all of the elements in the same fuzzy set. The crisp value of control output ΔU is computed by Equation (11).

$$\Delta U = \frac{\sum_{i=1}^{n} W_i \Delta U_i}{\sum_{i=1}^{n} W_i} \tag{11}$$

where n is the maximum number of effective rules, W_i is the weighting factor, and ΔU_i is the value corresponding to the membership function of ΔU. Using the steps mentioned above, the fuzzy controller is implemented in real-time for GMPP tracking. At each sampling time, the terminal and reference voltages have been sensed and error, $E = (V_{mref} - V_{PV})$ is calculated. Employing this error and change of error signals, fuzzy controller determines the control action required from the fuzzy knowledge base. Then it computes the required change in the control voltage for the PWM generator, which changes the duty ratio of the converter so as to bring the terminal voltage to the desired value. In the following sections the method of estimating the reference voltage for the feed forward loop using neural networks is discussed.

APPLICATION OF PSO FOR GMPP TRACKING

A Nonlinear optimization problem can be stated in mathematical terms as follows:

$$\text{Find } X = (x_1, x_2, \ldots.. x_n) \tag{12}$$

such that F(X) is minimum or maximum
Subject to:

$$g_j(X) \geq 0,\ j=1,2..m \text{ and } x_j^L \leq x_i \leq x_j^U,\ j=1,2..n, \tag{13}$$

Where F is the objective function to be minimized or maximized, x_j's are variables, g_j is constraint function, x_j^L and x_j^U are the lower and upper bounds on the variables.

In this work the objective function considered is:
F(X) =Maximization of SPVA power, P_{PV}
The variable x_i = SPVA current, I_{PV}
The constraint is $I_{PVmax} \geq I_{PV} \geq I_{PVmin}$.

Here, $x_j^U = I_{PVmax} = I_{sc}$, short circuit current of SPVA and $x_j^L = I_{PVmin} = 0$.

PSO is developed by Kennedy and Eberhart (1995). It was found to be reliable in solving non-linear problems with multiple optima. In PSO, a number of particles form a ‘‘swarm” that evolve or fly throughout the feasible hyperspace to search for fruitful regions in which optimal solution may exist. Each particle has two vectors associated with it, the position (Z_i) and velocity (V_i) vectors. In N-dimensional search space, $Z_i = [z_{i1}, z_{i2} \ldots z_{iN}]$ and $V_i = [v_{i1}, v_{i2}, \ldots v_{iN}]$ are the two vectors associated with each particle i. During their search, members of the swarm interact with each others in a certain way to optimize their search experience. There are different variants of particle swarm paradigms but the most commonly used one is the gbest model where the whole population is considered as a single neighborhood throughout the flying experience. In each iteration particle with the best solution shares its position coordinates (gbest) information with the rest of the swarm. Each particle updates its coordinates based on its own best search experience (pbest) and gbest according to the (14) and (15).

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \left(pbest_i^k - z_i^k\right) + c_2 rand_2 \left(gbest_i^k - z_i^k\right) \tag{14}$$

$$z_i^{k+1} = z_i^k + v_i^{k+1} \tag{15}$$

where c_1 and c_2 are two positive acceleration constants, they keep balance between the particle's individual and social behavior when they are set equal; $rand_1$ and $rand_2$ are two randomly generated numbers with a range of [0, 1] added in the model to introduce stochastic nature in particle's movement; and w is the inertia weight (equation 16) and it keeps a balance between exploration and exploitation. In our case, it is a linearly decreasing function of the iteration index.

$$w(k) = w_{max} - \left(\frac{w_{max} - w_{min}}{iter_{max}}\right) \times iter \tag{16}$$

where $iter_{max}$ is the maximum number of iteration, ‘iter’ is the current iteration number, w_{max} is the initial weight and w_{min} is the final weight. In conclusion, an initial value of *w* around 1, with a gradual decline toward 0 is considered as a proper choice. The most important factor that governs the PSO performance in its search for optimal solution is to maintain a balance between exploration and exploitation. Exploration is the PSO ability to cover and explore different areas in the feasible search space while exploitation is the ability to concentrate only on promising areas in the search space and to enhance the quality of potential solution in the fruitful region. Exploration requires bigger step sizes at the beginning of the optimization process to determine the most promising areas then the step size is reduced to focus only on that area. This balanced is usually achieved through proper tuning of PSO parameters (Chaturvedi *et al.*, 2009). The

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tuned PSO parameters for the proposed scheme are listed in Table-2.

Table-2. PSO parameters.

Number of design variables	1
Number of particles	20
Acceleration constants	$c_1 = 1.5$
	$c_2 = 1.5$
Inertia weight	$w_{max} = 0.9$
	$w_{min} = 0.4$
Maximum iterations, $Iter_{max}$	50

ARTIFICIAL NEURAL NETWORK

ANNs are widely accepted as a technology offering an alternative way to solve complex problems. Particularly, in recent years the application of ANN models in various fields is increasing because, these ANNs operate like a black box model, requiring no detailed information about the system. They learn the relationship between the input and output variables by studying the previously recorded data. Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters. These trained ANNs can be used to approximate an arbitrary input-output mapping of the system.

In the voltage based peak power tracking scheme, the reference voltage to the feedforward loop is to be adjusted such that it is equal to the GMPP voltage at that solar insolation and temperature (De Medeiros Torres *et al*., 1998). Since the solar insolation is varying, the corresponding reference voltage (V_{ref}=V_m) for the feed forward loop should also change according to the insolation variation. Therefore, for GMPP tracking control, an on-line estimation of the reference voltage for the feed forward loop is essential. Since the GMPP voltages are nonlinearly related to the solar insolation and temperature the linear function approximation techniques were not suitable. Further, it may not be possible to find a closed form relationship between V_m and G. Even if it is not able to find the relationship between these variables for a limited range, employing curve fit methods, they may not result in true GMPP voltages for the whole range of operation. Thus, the conventional curve fit methods were not suitable to realize the true peak power trackers. Under these circumstances, the ANNs provide a viable solution for the on-line estimation of the insolation-dependent reference voltage. In these studies a three layer feed forward neural network with sigmoid activation function is considered for the on-line estimation of reference voltage.

Among the available training algorithms, the back-propagation algorithm is one of the most widely used, because it is stable, robust, and easy to implement. In this work the feedforward neural network consisting of a single hidden layer with sigmoid activation function is considered. The input vectors G = (G_1, G_2, G_3….GN) ^{T} and T = (T_1, T_2, T_3….T_N) ^{T} are applied to the input layer of the network as shown in Figure-4.

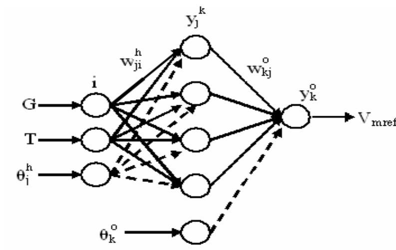

Figure-4. Feedforward neural network.

The net input of the jth hidden unit is given as (17).

$$net_j^h = \sum_{i=1}^{n} w_{ji} x_i + \theta_j^h \tag{17}$$

Where, w_{ji} is the weight on the connection from the ith input unit, θ_j^h for j =1, 2… represents the bias for hidden layer neurons, which is mainly used to improve the learning speed during network training process. Now, the output of the neurons in the hidden layer is written as in (18).

$$y_j^h = f\left(\sum_{i=1}^{n} w_{ji} x_i + \theta_j^h\right) \tag{18}$$

and the net input to the neurons in the output layer becomes:

$$net_k^o = f\left(\sum_{j=1}^{N_h} w_{kj} y_j^h + \theta_k^o\right) \tag{19}$$

Where, θ_k^o represents the bias for neurons in the output layer. Finally, the output of the neurons (reference voltage for the feedforward loop, V_{mref}) in the output layer is given by (20).

$$y_k^o = f\left(\sum_{j=1}^{N_h} w_{kj} y_j^h + \theta_k^o\right) \tag{20}$$

The learning stage of the network is performed by updating the weights and biases using back-propagation algorithm with the gradient descent method in order to minimize a mean squared error performance index E_p as given by equation (21).

$$E_p = \frac{1}{2}\left(V_{mref}(n) - V_{PV}(n)\right)^2 \tag{21}$$

The synaptic weights updating expressions are given by equations (22) and (23).

$$w_{ji}(n+1) = w_{ji}(n) - \eta\left(\frac{\partial E_p}{\partial w_{ji}(n)}\right) + \alpha \Delta w_{ji}(n) \tag{22}$$

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$$\Delta w_{ji}(n) = w_{ji}(n) - w_{ji}(n-1) \tag{23}$$

where η, α are learning and momentum factors respectively. The network training is performed repeatedly until the performance index $E_p = (V_{mref}-V_{PV})^2$ reduce below a specified value, ideally to zero. In other words when $E_p \rightarrow 0$ leads to $(V_{mref} - V_{PV})^2 \rightarrow 0$, then the trained neural network connecting weights are adjusted in such a way that the estimated array voltage is identically equal to the GMPP voltage.

With the above equations in the forward direction, the ANN training is performed. The steps involved in the training process are as follows.

Step 1: Initialize the network synaptic weights with small random values.
Step 2: Apply an input vector (solar insolation) to the network and calculate the corresponding output values.
Step 3: Compare the actual outputs with the desired outputs (reference voltage) and determine the measure of error (evaluating function).
Step 4: Determine the amount by which each weight is to be changed and update all the connection weights.
Step 5: Repeat steps 2 to 4 with all training vectors until the error for the vectors in the training set is reduced to an acceptable value.

SIMULATION RESULTS

Comprehensive simulation studies (http://www.mathworks.com) were made to investigate the GMPP tracking capability of the proposed controller. The off-line ANN sets the reference voltage to the feed forward loop from the known solar insolation equivalent voltage signal. At a given solar insolation for MPP operation of SPVA, the array operating voltage must be made equal to the optimum voltage V_{mref} by changing the converter duty ratio. The duty ratio is controlled by means of a PWM generator control signal (V_c), obtained from the fuzzy controller. This fuzzy controller works based on the controlling inputs, error (E) and change of error (ΔE) signals, generated with the help of feed forward loop. The error signal generated by feed forward loop depends on the instantaneous array voltage (V_{PV}) and the reference voltage (V_{mref}). Estimating this reference voltage by means of an off-line ANN is given in the following lines.

PSO method has been applied to the developed accurate model of SPVA, and the GMPP point voltages (V_{mref}) were determined for different shading scenario. Taking these values as reference patterns, the feed forward ANN is trained. Gradient descent algorithm is used in training, as it improves the performance of the ANN, reducing the total error by changing the weights along its gradient. The learning rate parameter is 0.5 and momentum factor of 0.9 is used for satisfactory performance. The training result for ANN is shown in Figure-5. The accuracy of this trained ANN is verified by considering test points (different shading patterns), which include both trained and untrained values. The test results are also plotted in Figure-6 and they are in close agreement with the results obtained from PSO method. Now this trained ANN is combined with the peak power tracking scheme for on-line estimation of the reference voltage to the feed forward loop at different solar irradiance levels. The reference voltage variation with different shading patterns, estimated from the off-line trained ANN.

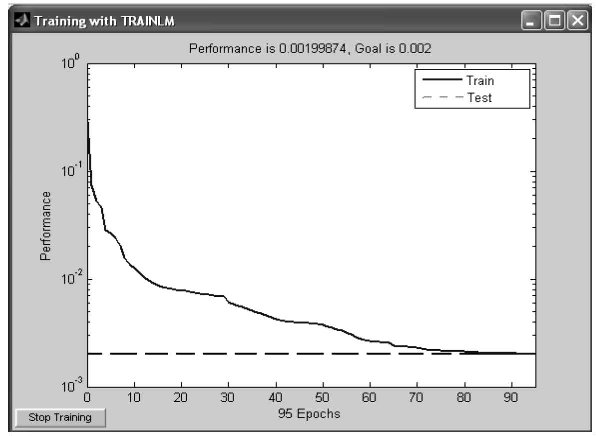

Figure-5. Training result of ANN block.

The developed scheme tracks the GMPP continuously by adjusting the SPVA terminal voltage to MPP voltage. Studies are made to observe the effectiveness of the developed tracking scheme for changing shading patterns.

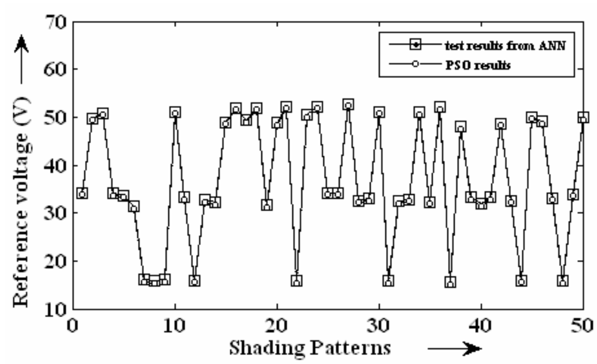

Figure-6. Feed forward loop reference voltage variation with different shading patterns.

The simulation result of tracking characteristics using proposed controller from shading pattern-2 to shading pattern-6 is shown in Figure-7 in comparison with PI controller. To illustrate the tracking capability of the developed converter system, shading pattern is changed after 0.2 sec. Under this condition, the SPVA power output changes and settles to a new MPP. For simulation purpose, three modules connected in series receiving unequal irradiance, G_1, G_2 and G_3 with temperatures T_1, T_2 and T_3 respectively, has been considered. The shading patterns are tabulated in Table-3 with GMPP location. For verification of GMPP points of SPVA, experiments were conducted on the SPVA by connecting electronic load

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(Ramaprabha and Mathur, 2010) with artificial shading patterns. The experimental global peak points are also mentioned in Table-3.

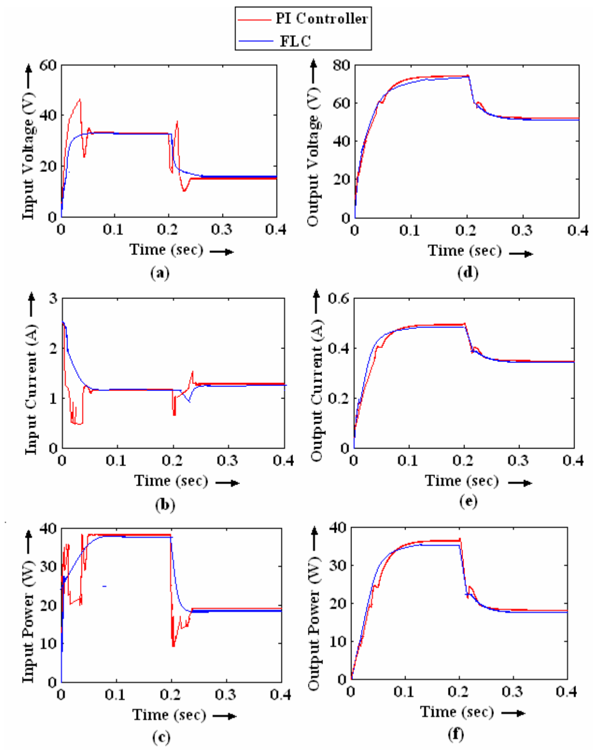

Figure-7. Tracking characteristics: From (a) to(f) show input voltage, output voltage, input current, output current, input power and output power of the converter when solar insolation suddenly changes from shading pattern-2 to shading pattern-6 after 0.2 sec.

From the simulation results and Table-3, it can be concluded that the proposed feed forward control method is capable tracking GMPP for different environmental variations and also capable of moving the operating point in any direction to track real peak point. The proposed fuzzy controller based scheme is evaluated by comparing its tracking performance with that of a conventional PI controller based scheme (Figure-8).

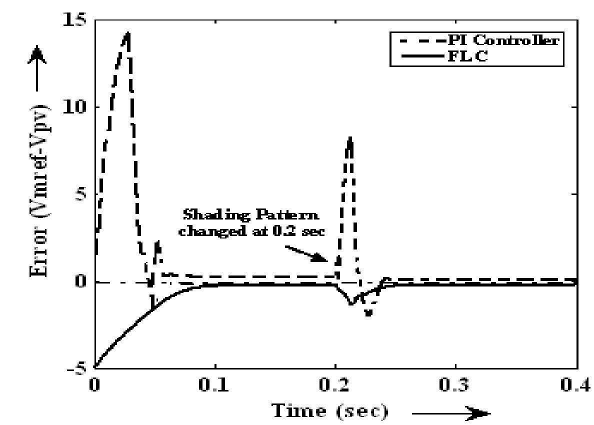

Figure-8. Error in SPVA terminal voltage tracking for Figure-7.

Table-3. Shading patterns and experimental GMPP values.

Shading pattern	Irradiance level (W/m^2)			Location of GMPP in the graph	Experimental GMPP value (W)
	G_1	G_2	G_3		
1	1000	1000	1000	Right side	112.4
2	1000	200	500	Centre	42.13
3	1000	700	500	Right side	64.71
4	1000	200	100	Left side	37.47
5	200	100	100	Right side	11.94
6	600	200	100	Left side	22.95
7	200	200	100	Centre	15.10

The performance comparison is presented in terms of Integral Square Error (ISE) for tracking voltage in Table-4. M-file code has been written for calculating ISE using trapezoid rule of integration. Results are presented in Table-4.

Table-4. Performance comparison of PI and FLC in terms of tracking error.

ISE in SPVA terminal voltage tracking	
PI	**FLC**
0.287	0.03

It can be noticed from the characteristics and Table-4 that, fuzzy controller improves the tracking performance over the conventional PI controller based SPV system. For different shading patterns the performance of the proposed intelligent controller system has been simulated. In particular, under shaded conditions the fuzzy controller provides better performance compared with PI controller. Under variable solar insolation conditions, if conventional PI controller is used for achieving the optimum tracking performance, it requires tuning of the controller gains appropriately depending on the solar insolation. From the simulation results, it is observed that the feed forward control strategy with fuzzy controller is a promising one with reference to GMPP tracking. Furthermore, it does not require any tuning of the parameters, which is the case with conventional PI controller, wherein the controller gain parameters needs to be changed when solar insolation changes.

CONCLUSIONS

The fuzzy feedforward voltage based GMPP tracking scheme has been developed for the boost converter supplied SPV system. With the developed realistic model of SPVA and boost converter the proposed controller has been simulated. An off-line ANN, trained using back-propagation algorithm, is utilized for on-line estimation of reference voltage for the feedforward loop. Its estimation accuracy is verified. GMPP tracking capability of the proposed scheme was demonstrated through simulation results. Further, it is also demonstrated that the fuzzy control improves the tracking performance compared with the conventional PI controller and thus avoids the tuning of controller parameters. Using the proposed intelligent controller improved SPVA performance is achieved under partial shaded conditions.

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