A Study on DSP Conrolled Photovoltaic System with Maximum Power Tracking

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ABSTRACT - The studies on the photovoltaic system are extensively exhaustible and broadly available resourse as a future energy supply. In this paper, a new maximum power point tracker(MPPT) using neural network theory is proposed to improve energy conversion efficiency. The boost converter and neural network controller(NNC) were employed so that the operating point of solar cell was located at the Maximum Power Point. And the back propagation algorithm with one input layer of two inputs(E, CE) and output layer(control value) was applied to train a neural network..
Simulation and experimental results show that the performance of NNC in MPPT of photovoltaic array is better than that of controller based upon the Hill Climbing Method.

I. INTRODUCTION

Generation of electrical energy faces many problems today. In a world of growing environmental awareness nuclear power plants find less and less acceptance, and conventional power plants are criticized because of their CO_2 exhaust. Thus renewable energy systems are becoming more important than ever.

One natural way of direct voltage generation is given by the photovoltaic.

To obtain maximum power output from an array of photovoltaic cells under changing insolation temperature and load conditions, it is necessary to use a circuit to optimize the electrical operating conditions of the array. This circuit, a MPPT, consists of a power section and a control section.

This power reports on a design of a complete MPPT comprising a PWM boost converter for power section, and a control section constructed with 32bit DSP(TMS320c31)

Generally, a hill climbing method is used to determine the maximum power point. The instantaneous current and voltage are sampled and multiplied to obtain the power. On the other hand, NNC is employed so that the operating point of solar cell was located at the Maximum Power Point. The back propagation algorithm with one input layer with two inputs; E (dp_{ph}/di_{ph}), CE(change of E) and output layer(control value) was applied to train a neural network. The proposed boost converter with MPPT system is implemented by 32 bit DSP (TMS320C31).

II. CHARACTERISTIC OF SOLAR ARRAY

The current-voltage-characteristic of solar cells and their combination to larger units (solar generators) is nonlinear and maybe described by the following equation under consideration of the interior series and shunt resistence[1][2].

$$I_L = I_{ph} - I_{sat}\left[\exp\left[\frac{q}{AKT}(V_L + I_L R_s)\right] - 1\right] \quad (1)$$

where I_L and V_L is the output current and output voltage of a solar array, respectively; I_{ph} is the generated current under a given insolation; I_{sat} is the saturation current of a solar array; q is the charge quantity of electron; K is the Boltzmann's constant. A is the ideality factor for a p-n junction. T is the temperature of a solar array (^oK); R_s is the intrinsic series resistance of a solar array, the value is very small usually. The simplified equivalent circuit of a solar array is shown in Fig. 1.

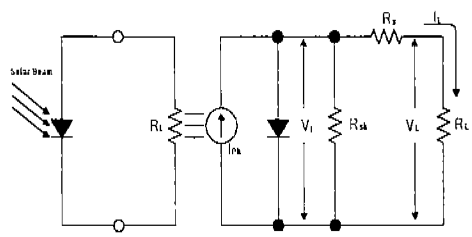

Fig. 1 Equivalent circuit of a solar array.

The saturation current I_{sat} of a solar array varies with temperature according to the following equation.

$$I_{sat} = I_{or}\left[\frac{T}{T_r}\right]^3 \exp\left[\frac{qE_{GO}}{KT}\left(\frac{1}{T_r} - \frac{1}{T}\right)\right] \quad (2)$$

where I_{or} is the saturation current at T_r; T is the temperature of a solar array (^oK); T_r is the reference temperature; E_{GO} is the band gap energy of the semiconductor used in the solar array.
Fig. 2 shows current, voltage and output power relation of a photovoltaic module used in the field.

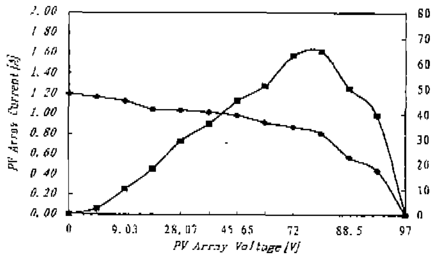

Fig. 2 Characteristics of a PV array used in the field [Ins-660 w/m^2, $T=52^oC$].

The power output of a pv array depends significantly on the array characteristics and the loading conditions. Typical I-V and P-I characteristics of a solar cells are shown in Fig. 3. It is seen that the power output from a solar cell is maximum only if the load is operated at maximum power point(MPP). The MPP is not a fixed point. The I-V characteristics of solar cell shift with changes in insolation (solar radiation in kw/m^2) and the cell temperature. Hence MPP also becomes a function of insolation and cell temperature[3].

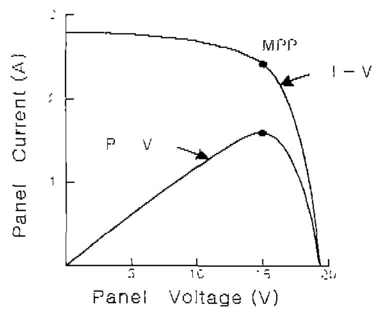

Fig. 3 I-V characteristics of a PV panel.

Ⅲ. Neural Network Controller

The objective of the control section is to track and extract maximum power from the PV arrays for a given solar insolation.
Normally a DC-DC converter is utilized between the input source and the load for MPPT.
In this paper, to control DC-DC converter for MPPT, an adaptive feedforward control system including a neural network control is proposed. It also provides the path of error backpropagation for a neural network adaptive control system. The NN shown in Fig. 4 consists of input layer with two inputs, one hidden layer with five hiddens and output layer with one output.

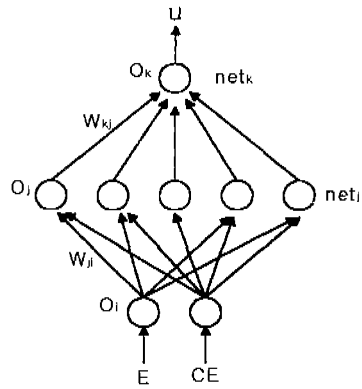

Fig. 4 The used NN architecture.

The backpropagation algorithm with one input layer of two inputs; E(dp_{ph}/di_{ph}), CE(change of E) and output layer(control value) was applied to train a neural network.
For choosing the weights of network, training procedure is required to secure an expected input-output relationship. The network, before training, have only random initial weights. So erroneous plant input will cause an erroneous output. A plant output is compared with the reference signal to calculation error signal between a plant output and reference signal. Then, error signal is used to training weights in the network through error back propagation algorithm. A plant output traces to the reference input signal by repetitive training and the network is made mature. Eventually the plant output error will decrease to zero. The error in the output layer of the NNC should be clarified in order to adjust the weights of the network through the back propagation algorithm. the subscripts i , j and k match to input, hidden and output layers, respectively, and the output of the k-th node in the output layer is

$$O_k = f(net_k) \tag{3}$$

Input net_k to k-th node in the output layer is

$$net_k = \sum W_{kj} O_j \tag{4}$$

and w_{kj} is the weight from unit j in the hidden layer to unit k in the output layer. Similarly, the output of the j-th node in the hidden layer is

$$O_j = f\ (net_j) \tag{5}$$

where $f(x)$ is sigmoid function given by

$$f(x) = \frac{1}{1+\exp(-x)}.$$

Squared error function on input patterns is

$$E_p = \frac{1}{2}\sum_k (t_{pk} - O_{pk})^2 \tag{6}$$

and. Average value of error square is

$$E = \frac{1}{2}\sum_p \sum_j (t_{pj} - O_{pj})^2 \tag{7}$$

the derivative the backpropagation algorithm for a specific pattern p is driven , that is, find a minimizing sequence of E_p.

Using the generalized delta rule for the net with backpropagation of error[3][4]. the deltas are given by the following expressions

$$\delta_k = O_k(1-O_k)(\tau_k - O_k) \tag{8}$$

$$\delta_j = O_j(1-O_j)\sum_k \delta_k w_{kj} \tag{9}$$

for the output layer and hidden layer, respectively, where τ_k is the target. In order to avoid a shallow local minimum momentum is added to backpropagation learning by making weight changes equal to sum of a fraction of the previous weight change and the new change suggested by the backpropagation rule:

$$\Delta w_{kj}(t+1) = \eta\, \delta_k O_j + \alpha \Delta w_{kj}(t) \tag{10}$$

$$\Delta w_{ji}(t+1) = \eta\, \delta_j O_i + \alpha \Delta w_{ji}(t) \tag{11}$$

where η is the learning rate, α is the momentum constant which determines the effect of past connection weight changes on the current direction of movement in connection weights space, and t is the iteration step for which a set of input patterns are presented to the net.

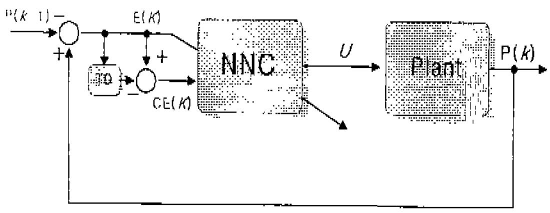

Fig. 5 Neural network controller

Proposed neural network controller has two inputs(error, chang error) and an output to plant input value in Fig. 5.

IV. PHOTOVOLTAIC SYSTEM WITH BOOST CONVERTER

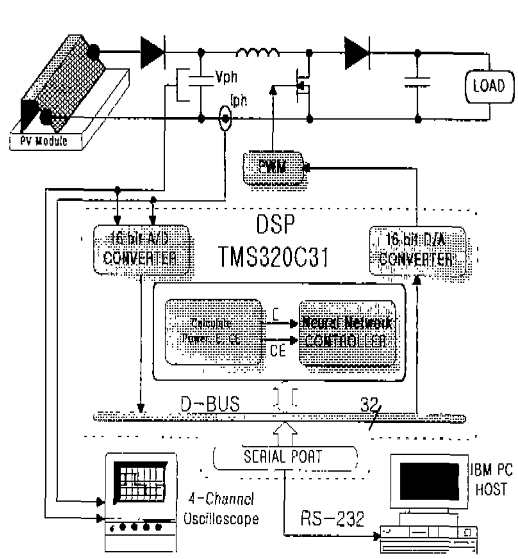

Fig. 6 Boost converter for MPPT.

Fig. 6 shows total diagram of boost converter for MPPT. A/D converter is converted to digital from analog of solar cells voltage and current.

Actually, PV array voltage and current, which are measured continuously by voltage divider and Hall senser, become input data 16 bit A/D converter of DSP(TMS320C31) and PV array power can be calculated by it. We have focused on SISO plant, which control is determined on two critera relating to two input variables of proposed controller, namely error(E) and changing error(CE) at a sampling instant k. The variable E and CE are expressed as follows :

$$E(k) = \frac{P_{ph}(k) - P_{ph}(k-1)}{i_{ph}(k) - i_{ph}(k-1)} \tag{12}$$

$$CE(k) = E(k) - E(k-1) \tag{13}$$

where $P_{ph}(k)$ and $i_{ph}(k)$ are the power and current of the PV array, respectively. Therefore, E(k) is zero at maximum power point of a PV array.

V. SIMULATION RESULTS

For simulation of PV array system, Eq.(1) is used. All elements (MOSFET, diode, inductor,capacitor) of boost converter is assumed to be ideal. Fig. 7 - Fig. 9 show the simulation results of the conventional hill climbing method. And, Fig. 10 - Fig. 12 show the simulation results of proposed controller in the field. It confirms that the Neural Network Controller shows a good performances compared with conventional method.

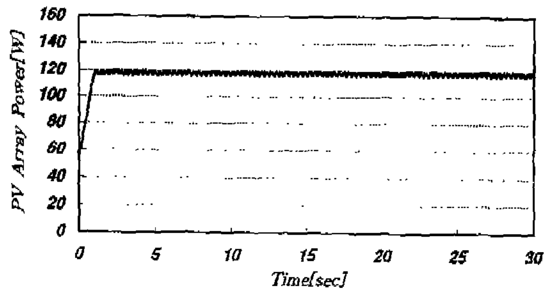

Fig. 7 PV array power in the field.[Ins=1016 w/m^2]

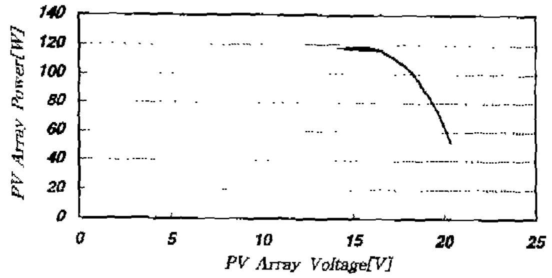

Fig. 8 The power versus voltage loci in the field for MPPT[Ins=1016 w/m^2].

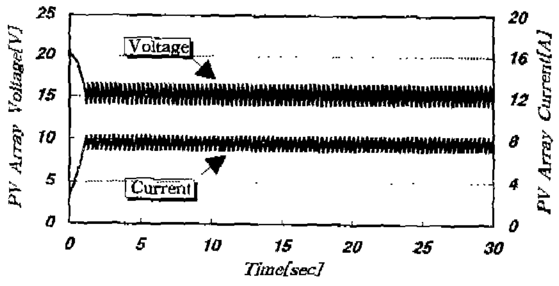

Fig. 9 Time-PV array voltage & current relation in the field[Ins=1016 w/m^2].

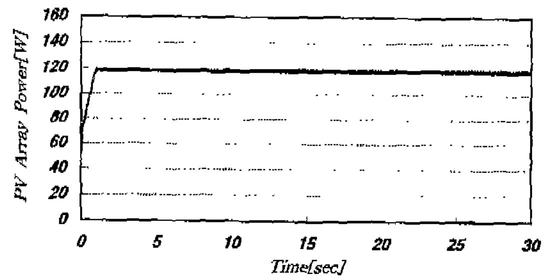

Fig. 10 PV array power in the field[Ins=1016 w/m^2].

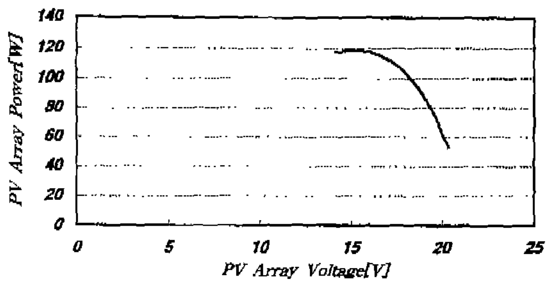

Fig. 11 The power versus voltage loci in the field for MPPT[Ins=1016 w/m^2].

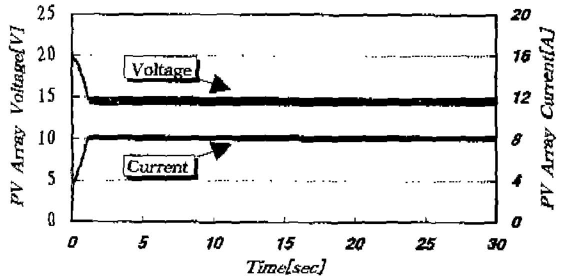

Fig. 12 Time-PV array voltage & current relation in the field[Ins=1016 w/m^2].

Ⅵ. EXPERIMENTAL RESULTS

Fig. 2 shows that the sign of E(error) is positive on the left hand side of maximum power point while negative on the right hand side and zero at maximum power point. For a boost converter, therefore, duty ratio should be decreased for the negative E and should be increased for positive E so as to shift the operating point towards the maximum point.
In this paper, experiments are implemented in the field photovoltaic modules in parallel. The PV array current and voltage are measured by Hall sensor(100A/10V), Resistor divider.
Fig. 13 - Fig. 15 show the experimental results of the conventional hill climbing method in the field[Ins = 450-500 w/m^2, Load=20Ω]. Also, Fig. 15 - Fig. 17 show the experimental results proposed controller in the field[Ins = 450-470 w/m^2, Load=20Ω].

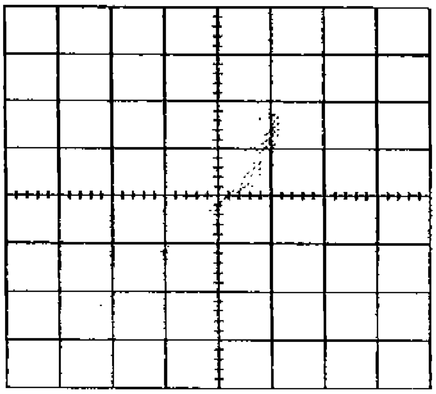

Fig. 13 PV array voltage versus power loci at hill climbing method
(Ins = 450-500 w/m^2, X: 5V/div, Y: 5W/div).

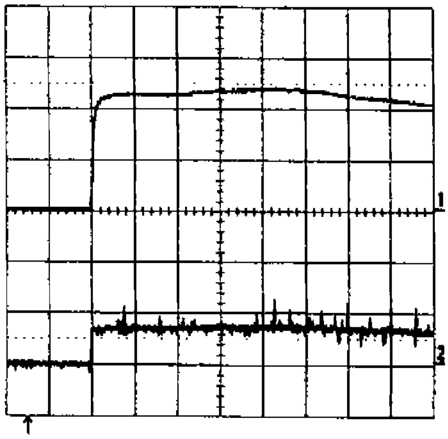

Fig. 14 Experimental results of V_{ph}, I_{ph} (upper:voltage, lower:current, 10V/div,2A/div).

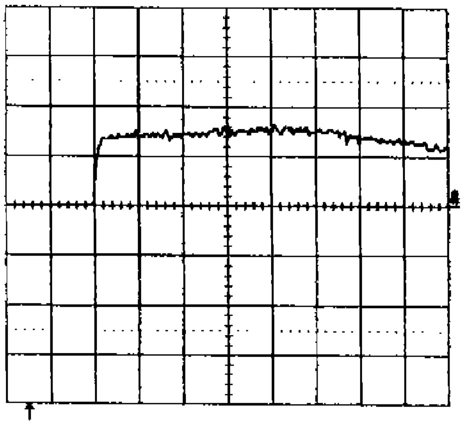

Fig. 15 PV array power(20W/div).

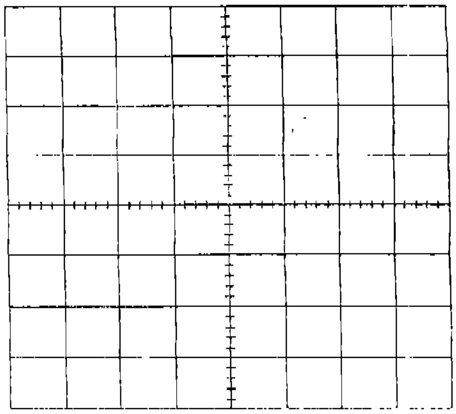

Fig. 16 PV array voltage versus power loci at neural network method
(Ins=450-470 w/m^2, X: 10W/div, Y: 10V/div).

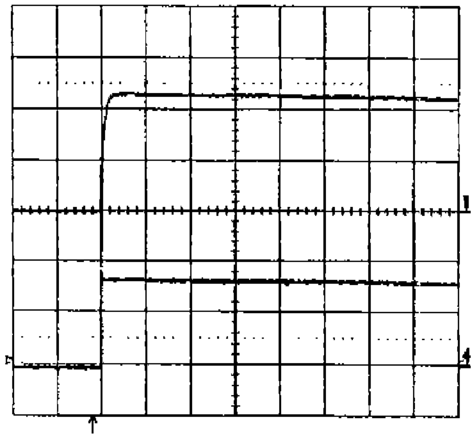

Fig. 17 Experimental results of V_{ph}, I_{ph} (upper:voltage, lower:current, 10V/div,1A/div).

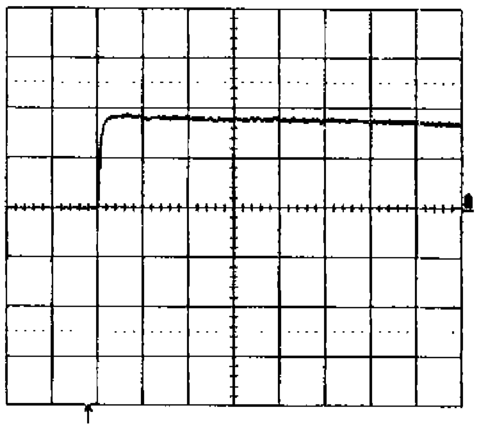

Fig. 18 PV array power in neural network method (10W/div).

Ⅶ. CONCLUSIONS

In this paper, a new Maximum Power Point Tracker using Neural Network Controller is proposed and applied to boost converter.

The photovoltaic array conversion system in the field is studied with proposed control algorithm by simulation. From the action results, the field test is studied with proposed algorithm by experiment and is implemented by using 32bit DSP(TMS320C31).

We are confirmed to superiority of new control method compared with the hill climbing method.

As a results, the proposed controller is more efficient than conventional controller on energy conversion.

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