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The MPPT of Photovoltaic Solar System by Controlled Boost Converter with Neural Network

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Abstract

The neural network can roughly be classified as the specialized control, indirect control and general schemes. Neural network is adopted for MPPT of solar array. And back propagation algorithm also is used to train neural network controller.

We investigate the possibilities of P_{max} control using the neural networks, and then we also examine about operating the solar cell at an optimal voltage comprise of temperature compensated voltage with boost converter.

Proposed boost converter of MPPT system is studied by simulation and is implemented by using a microprocessor(80c196kc) which controls duty ratio of the boost converter.

Keyword : Neural-Network, MPPT, Photovoltaic, Back-propergation, Boost-converter

I. Introdution

Photovoltaic is considered to be one of the most promising technologies which can greatly contribute to future energy supply because it is a pollution-free, essentially inexhaustible and broadly available resource-sunlight. Therefore, recent progress in photovoltaic make also possible its near-term practical application in some areas.[1]-[2]

The output characteristics of solar cell are nonlinear because it's affected with load, solar insolation, cell temperature. And then the tracking control of maximum power point is the complicated problem..

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Therefore, the PV systems need accurate on-line identification of the optimal operating points in order to yield maximum power supply from the systems.

Generally, a hill climbing method demonstrated by Boehringer(1971), Harashima(1987) is used to determine the maximum power point. The input source voltage is sampled to help the controller determine whether the operating point is to the left or right side of maximum power point of the solar array.[3]-[4]

In recent times, studies on artificial intelligence (A. I) have brought to light the possibility to use systems with learning capabilities for the imitation of patterned type of actions in incompletely defined situations. These systems are called artificial neural networks.[5]-[7] This study present neural networks (N.N) structure for compensating MPPT of solar array parameters variations and then controlling of duty ratios.

II. Thoery

2.1 Boost converter for MPPT

Boost converter was used from power of solar array to drive of load with aircondition system. The basic circuits for a boost converter are shown equivalent circuit and waveform in Fig.1, Fig.2 and Fig.3.

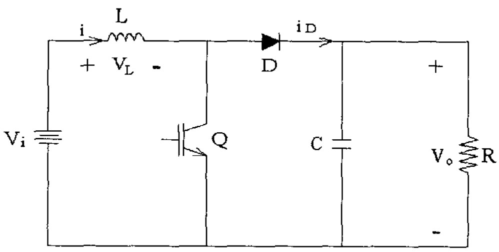
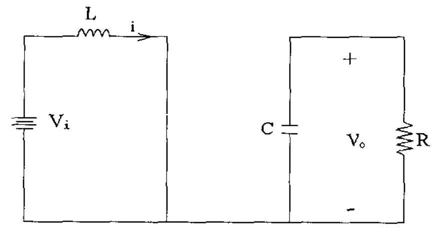
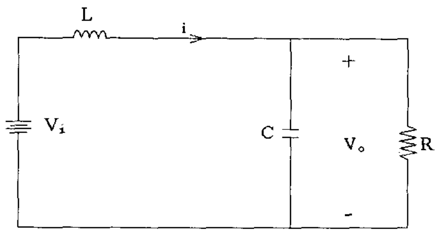


Fig. 1. Booster converter for MPPT.



(a) Q : ON



(b) Q : OFF

Fig. 2. Equivalent circuit of boost converter.

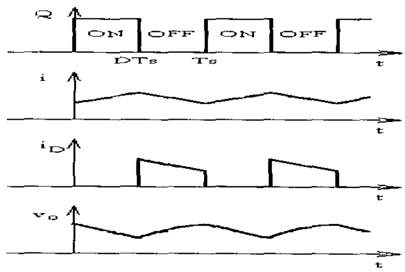


Fig .3. Waveforms of boost converter.

In Fig.2~3, i,i_D and Vo are inductor current ,diode current and ouput voltage of boost converter. The output voltage of boost converter has equation as follow

$$Vo = \frac{1}{(1-D)}\, Vi \qquad (1)$$

where V_i is input voltage or solar array output voltage , V_o is output voltage of boost and D is duty ratio.

2.2 Temperature compensation theory

We took up the theory of the temperature compensated equation and Becom transducer of pf-type about solar array as follow theory.

· <u>Optimum voltage(In case, compensated temperature)</u>

$$V_m(T) = V_m(1 + \gamma(T-25) - \delta(100-L))[\mathrm{V}] \qquad (2)$$

V_m : Optimum voltage at the standard condition [V]

$V_m(t)$: Optimum voltage at the optional test condition [V]

γ : Temperature coefficient of optimum voltage (-0.00462/℃)

δ : Irradiance coefficient of optimum voltage (0.000094 (mW/㎠))

T : Temperature(effected by compensate transducer) T=((V_o-1) · (140/4))-40

· Maximum output power

$$Pm = 100Pm(T)/L[1+\alpha(T-25)] \text{ (W)} \qquad (3)$$

Pm : Maximum output power at the standard condition (Cell temperature : 25℃, Irradiance : 100mW/㎠) (W)

$Pm(T)$: Maximum output power at the optional test condition (W)

L : Irradiance at the optional test condition (100mW/㎠)

T : Cell temperature at the optional test condition (℃)

α : *Temperature coefficient* (-0.00510/℃)

· Short circuit current

$$I_{SC} = 100I_{SC}(T)[1-\beta(T-25)]/L \text{ (A)} \qquad (4)$$

I_{SC} : Short circuit current at the standard condition (A)

$I_{SC}(T)$: Short circuit current at optional test condition (A)

β : Temperature coefficient of short circuit current (0.000505/℃)

· Open circuit voltage

$$V_{OC} = V_{OC}(T)/[1+\gamma(T-25)-\delta(100-L)] \text{ (V)} \qquad (5)$$

V_{OC} : Open circuit voltage at the standard *condition* (V)

$V_{OC}(T)$: Open circuit voltage at optional test condition (V)

γ : Temperature coefficient of open circuit voltage (-0.00377/℃)

δ : Irradiance *coefficient* of *open* circuit voltage (0.000475(mW/㎠))

Optimum voltage (In case, uncompensated temperature)

$$V_m(T) = V_m(1+\gamma(T-25)-\delta(100-L)) \qquad (6)$$

T : Atmosphere Temperature(℃)

2.3 Neural Network controller for MPPT

The neural network controller is composed of MPPT control in photovoltaic system. And then the control object is to track and extract maximum power from the PV arrays for a given solar insolation level. Normally a DC-DC converter is utilized between the input source and the load for the purpose of MPPT.

The actual voltage and current of PV array can be measured via A/D converter of 80c196kc microprocessor and the power can be calculated. In discrete system, single input and single output system is represented as follow

$$y(k+1) = f(y(k), y(k-1), \cdots y(k-m+1), x(k), x(k-1), \cdots x(k-m+1)) \qquad (7)$$

At first, actual output of plant $y(k+1)$ can follow the output for reference x(k). In photovoltaic system, the application of neural network at parameters tracking, a recursive training algorithm and the back propagation method is used. In Fig.4, the block diagram for training the neural network is shown.

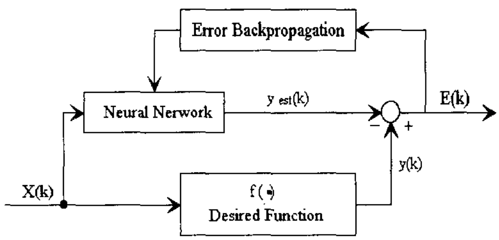


Fig. 4. Back propagation method.

Supposing that the desired function which has to be imitated by the net is given, a series of test inputs are applied several times both to the desired function and to the neural network. At each training step k, the prediction error vector $E(k)=y(k)-y_{est}(k)$ is computed. The training algorithm adjusts weight rates of the neural network through the back propagation of E(k) to minimize the quadratic error $Q(k)=0.5E^T(k)E(k)$. Basically, the back propagation training algorithm consists of the adjustment of the neural network weights, layer by layer, minimizing the output quadratic error. It means that the error for plant output $e(k)=(x(k)-y(k+1))$ is minimized by learning. But the other possible shapes for the neuron output function are given in Fig.5.

The parameters of $x(k),y(k),y_{est}(k)$, e(k),desired function imply the value in solar cell array output voltage, optimum voltage ,training voltage, the error voltage and relationship duty ratios of boost converter.

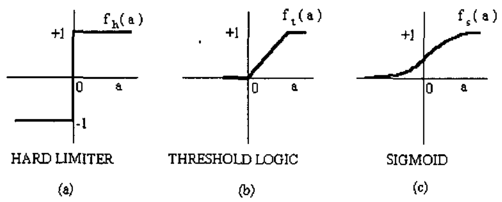


Fig. 5. Example of nonlinear functions used as neuron output functions.

Sigmoid functions are adopted for neuron output function, and it represents a equation as follow.

$$f(x) = \frac{1}{1+e^{-\alpha x}} \qquad (8)$$

Where α and x are represents gradients and summation of output stimulus.

Ⅲ. Simulation Results

We employed PV module 12s(series)×2p(parallel) (Module type SSM-60). The main characteristics of a photovoltaic module used in the field are as indicated below :

Open circuit voltage	:	21.1 [V]
Short circuit current	:	3.8 [A]
Voltage at load	:	17.1 [V]
Current at load	:	3.5 [A]
Maximum power	:	60 [W]

The results of the PV array characteristic were shown in Fig.6 with PSPICE(V-I curves and Maximum Power Point).

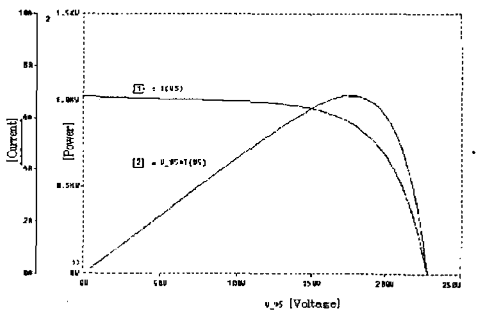


Fig. 6. The voltage-current characteristic curve and maximum power point curve of PV array.

The results of temperature characteristic are shown as follow by maximum output power, short current, open voltage, optimum voltage. The power ,voltage and current of solar array are obtained 1020[W],230[V],6[A].

Fig.7 represents the characteristics of maximum output power. When temperature is increasing, the maximum output power deceased linearly and the large value of insolation has steep slope characteristic.

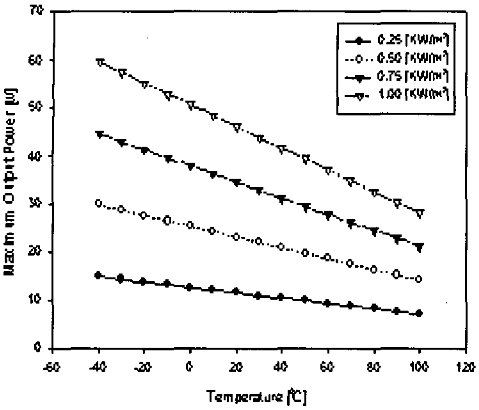


Fig. 7. The characteristics of maximum output power according to the solar insolation.

Fig.8 represents configuration of neural network. For the application of neural network in photovoltaic system parameters tracking, a recursive training algorithm, the back propagation method is used. In the simulation, the controller has 3 input layer neuron, 4 hidden layer neuron, 1 output layer neuron-it's affected by duty ratios.

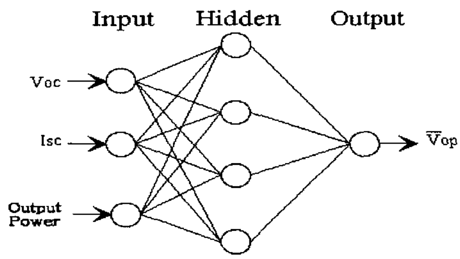
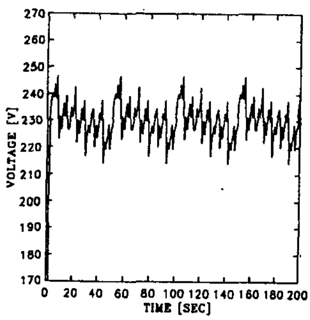


Fig. 8. Configuration of Neural Network.

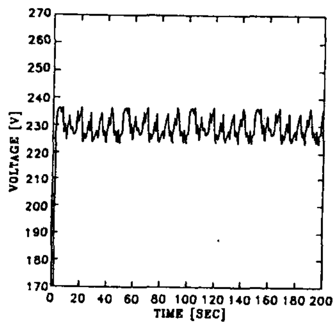
where is

Voc	:	Open circuit voltage [V]
Isc	:	Short circuit current [A]
Vop	:	Optimal operating voltage [V]

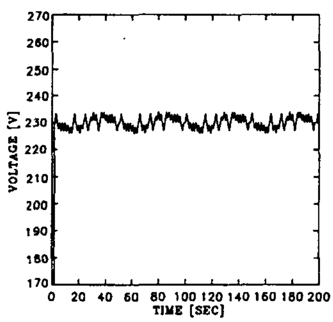
The simulation output voltage with general controller(PI),neural controller and neural +transducer controller is shown in Fig. 9. The output voltage of PV has a characteristic of variation with load, solar insolation, cell temperature in field. Among the controllers, the neural+transducer controller has a advantage of stable voltage.



(a) general controller



(b) neural controller



(c) neural +transducer controller

Fig. 9. The output voltage with general controller, neural controller, neural+transducer controller.

Ⅳ. Experiments Results

Fig.10 is showed block diagram of proposed PV energy conversion scheme with neural networks. The control program is down-loaded from host computer (IBM-PC) to 80c196kc via RS232C port. CMOS-12 buffered multiplying DAC (AD7545) with setting time of 140[nsec] used to display power. PF-type tranducer is used for the experiment.

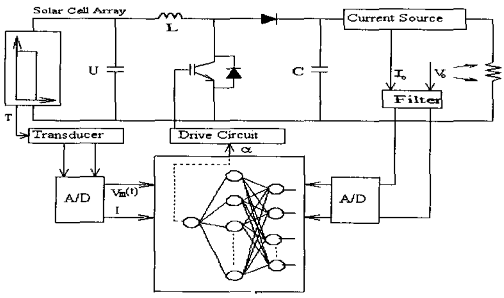
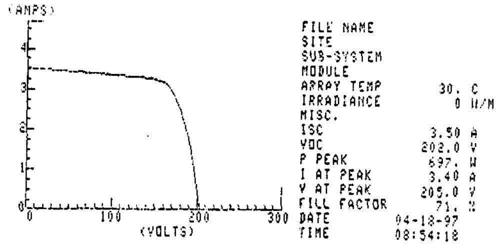


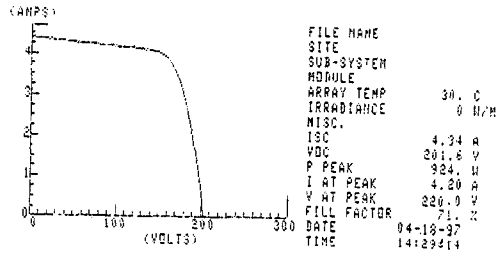
Fig. 10. Block diagram of proposed PV energy conversion scheme with neural networks.

Fig.11 is shown V-I curve of solar array with insolation and temperature by SPI-ARRAY TESTER TM 750

In the morning, the current is 3.4[A] and the voltage is 205[V]. But in the afternoon, the current is 4.2[A] and the voltage 220[V]. When the insolation increases ,the current increases. On the other side, change of voltage is small. Fig.12 is shown the waveform of inductor current and input signal switching elements. The switching mode has operating continuous mode.



(a) In the morning



(b) In the afternoon

Fig. 11. The photovoltaic I-V characteristic curve.

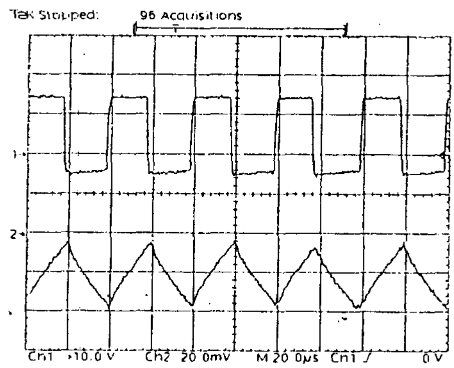


Fig. 12. Waveform of inductor current and input signal switching elements.

Fig.13 and Fig.14 are shown the input, output current, voltage and power of photovoltaic system. It was concluded that neural networks + transducer methods are more stable than other methods.

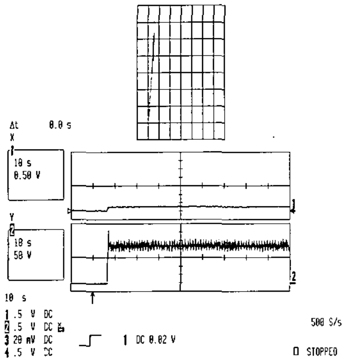
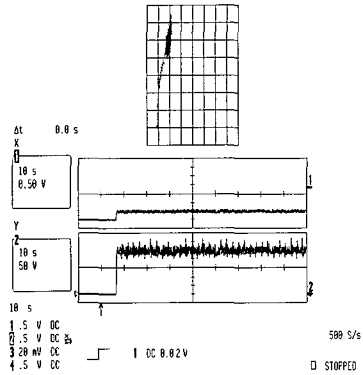
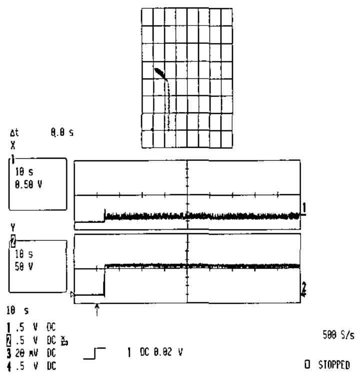


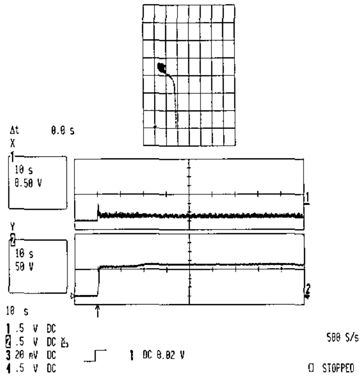
Fig. 13. The input current(middle), voltage(below) and power(top) of photovoltaic system.



(a) general controller



(b) neural networks



c) neural networks + transducer

Fig. 14. The output current(middle),voltage(below) and power(top) of photovoltaic system.

V. Conclusion

We took up neural networks with back propagation algorithm. The back propagation algorithm is utilized to general application of forward multi-layer neural networks. It holds that the power obtained from photovoltaic system with constant voltage by boost converter.

When the insolation has change,and then the voltages ,current and power ,the current has a excessive change. The difference of temperature compensated and uncompensated effect power of photovoltaic has affected the input voltage, output voltage and duty ratio of boost converter. It means that correct MPPT control must

be considered temperature compensated. From the results of experimental data, we attain more stable voltage and MPPT with transducer+neural controller method. These results will be brought effective data to control system for MPPT.

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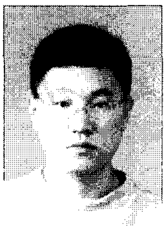

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