A Novel MPPT Control Design for Wind-Turbine Generation Systems Using Neural Network Compensator

***Abstract*- This paper presents a novel maximum-power-point-tracking (MPPT) algorithm in wind-turbine generation systems using neural network compensator based on the slope of the wind-turbine mechanical power versus rotation speed to avoid the oscillation problem and effect of uncertain parameters. Because the characteristics of the wind-turbine rotation speed is determined by the wind speed and air density conditions, the technologies of changing the location of the maximum power point must be developed in the applications of MPPT control in order to make the wind-turbine generator get the optimal efficiency from wind energy at different operating conditions. In this study, the uncertainties in wind-turbine generation systems are compensated by a neural network, the duty cycle of dc/dc converter is determined by a PI controller, and the parameters is determined by a genetic algorithm with the help of MATLAB. From the simulation results, the validity of the proposed MPPT controller can be verified under variations of wind speed, air density, and the load electrical characteristics in wind-turbine generator systems.**

I. INTRODUCTION

Recently, environmental pollution and the increasing depletion of fossil fuels are main issues all over the world. Every country actively seeks renewable energy. Among the renewable energy, the wind or solar energy must be extracted by using electronic technology. Then through the power converter, the renewable energy can be converted to become a stable power supply. Due to the rapid growth in the semiconductor and power electronics techniques, wind energy becomes more and more interesting in electrical power applications. To increase the output efficiency of wind-turbine generators, the techniques of tracking the maximum power point for wind-turbine energy conversion systems are necessary. Many algorithms developed so far can be classified into three control methods, namely tip speed ratio (TSR) control [1]-[3], power signal feedback (PSF) control [4]-[6], and hill-climb search (HCS) control [7]-[15].

Among them, TSR control method was used to regulate the wind-turbine rotation speed in order to maintain an optimal value of TSR. In this method, the rotor speed and wind speed are either measured or estimated. PSF control method requires the knowledge of wind turbine maximum power curve which the control system tracks in order to deliver maximum power. HCS control method continuously searches for the peak power point of the wind turbine and delivers it at the output. Perturbation and observation method which can be seen as one of the HCS control method is often used for the MPPT problem because it is easy to implement [13]-[15]. However, it has some disadvantages such as slow tracking performance and continuous oscillations around an operating point.

The aforementioned methods can be further classified into deterministic approaches and intelligent approaches such as fuzzy logic or neural networks. Neural networks with multi-layer neurons are widely used to approximate an arbitrary input-output mapping of an uncertain system so as to have a faster convergence property [16]-[17].

Conventionally, wind energy conversion systems are composed of a wind-turbine generator, an ac/dc converter, a dc/dc converter, and a dc/ac inverter or batteries as the load. In this study, based on the slope of power versus the wind-turbine rotation speed, a novel MPPT algorithm using neural network compensator is proposed to avoid the oscillation problem and effect of uncertain parameters in wind-turbine generators. Practically, the characteristics of wind-turbine generator output voltage and output current are determined by the amount of the wind speed, ambient air density, and the load electrical characteristics, thereby the technologies of changing the location of the maximum power point must be developed in the applications of maximum-power-point-tracking (MPPT) control in order to make the wind-turbine generators get the optimal efficiency from wind energy at different operating conditions.

In this study, the proposed MPPT algorithm is based on the slope of the wind-turbine mechanical power versus rotation speed. The uncertainties of varying wind speed, ambient air density, and the load electrical characteristics in wind-turbine generator systems are compensated by a neural-network estimator and the duty cycle of dc/dc converter is determined by a PI controller. The parameters of the PI controller are determined off-line by a genetic algorithm (GA) with the help of MATLAB [18]-[19]. The control objective is to achieve MPPT for the wind-turbine generator systems despite of the variation of the wind speed, ambient air density, and the load electrical characteristics in wind-turbine generator systems. The main contribution of this paper is the new idea of transferring the maximum-power-point tracking problem into a unit-stepcommand PI control problem. From the simulation results, the validity of the proposed MPPT controller can be verified under variations of wind speed, ambient air density and the load electrical characteristics in wind-turbine generator systems.

II. PROBLEM FORMULATION OF MAXIMUM POWER POINT TRACKING FOR WIND-TURBINE GENERATOR SYSTEMS

For a wind turbine, the wind power can be expressed by

$$P_{wind} = \frac{1}{2}\rho A V_W^3 \tag{1}$$

where ρ is the air density, A is the wind turbine blade sweep area, and V_W is the wind speed. The mechanical power of the wind turbine extracted from the wind power is then given by

$$P_m = P_{wind} C_p(\theta,\lambda) = \frac{1}{2}\rho A C_p(\theta,\lambda) V_W^3 \tag{2}$$

where $C_p(\theta,\lambda)$ is called the performance coefficient and is function of the blade pitch angle θ and the tip speed ratio λ. In (2), the tip speed ratio is defined as

$$\lambda = \frac{r\omega}{V_w} \tag{3}$$

where r is the wind-turbine blade length and ω is the wind turbine rotation speed. An example of the $C_p(\theta,\lambda)$ of a wind turbine is given as follows [20]:

$$C_p = 0.22\left(\frac{116}{\lambda_i} - 0.4\theta - 5\right)e^{\frac{-12.5}{\lambda_i}} \tag{4}$$

where

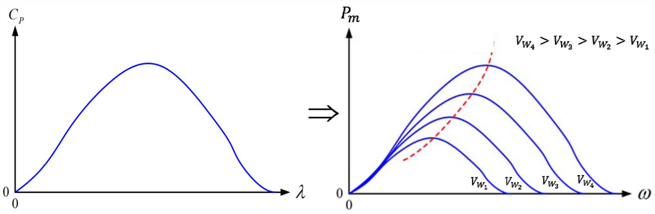
$$\lambda_i = 1/\left(\frac{1}{\lambda + 0.08\theta} - \frac{0.035}{\theta^3 + 1}\right) \tag{5}$$

Substituting (5) into (4) yields

$$C_p = 0.22\left(\frac{116}{\lambda + 0.08\theta} - \frac{4.06}{\theta^3 + 1} - 0.4\theta - 5\right)e^{-\left(\frac{12.5}{\lambda + 0.08\theta} - \frac{0.4375}{\theta^3 + 1}\right)} \tag{6}$$

In general, for a small wind turbine with output power less than 10 kW, its pitch angle θ is fixed. Thus, the plot of $C_p - \lambda$ curve is shown in Fig. 1(a), which implies the $P_m - \omega$ curves at different wind speed as shown in Fig. 1(b) according to (2) and (3). As can be seen form Fig. 1(b), at the maximum power points in different wind speed, we have

$$\frac{dP_m}{d\omega} = 0 \tag{7}$$



(a) (b)

Fig. 1 (a) $C_p - \lambda$ curve, (b) $P_m - \omega$ curves for different wind speed.

The purpose of this study is to develop a maximum power point tracking (MPPT) controller for wind-turbine generators. The conventional MPPT algorithms use Eq. (7) to obtain the maximum output power point. However, we can develop a novel adaptive MPPT algorithm based on Eq. (7) employing a neural network with the information of wind-turbine torque, which will be in terms of generator current, and rotation speed as the input variables of the neural network.

The wind-turbine torque and rotation speed are related to the output power as Eq. (8).

$$T = \frac{P_m}{\omega} \tag{8}$$

Thus, we have

$$\frac{dP_m}{d\omega} = \frac{d(\omega \times T)}{d\omega} = T + \omega\frac{dT}{d\omega} \tag{9}$$

Substituting Eq. (2) and Eq. (6) into Eq. (8), the wind-turbine torque T can be expressed as

$$T = (0.11)\rho A V_W^3 \left(\frac{116}{\frac{R}{V_W}\omega^2 + 0.08\theta\omega} - \frac{4.06}{\omega(\theta^3+1)} - \frac{0.4\theta + 5}{\omega}\right)e^{-\left(\frac{12.5}{\frac{R\omega}{V_W}+0.08\theta} - \frac{0.4375}{\theta^3+1}\right)} \tag{10}$$

and the derivative of the torque with repect to the rotation speed is

$$\frac{dT}{d\omega} = (0.11)\rho A V_W^3 e^{-\left(\frac{12.5}{\frac{R\omega}{V_W}+0.08\theta} - \frac{0.4375}{\theta^3+1}\right)} \times \left\{\left[\frac{-116\times\left(\frac{2R\omega}{V_W} + 0.08\theta\right)}{\left(\frac{R}{V_W}\omega^2 + 0.08\theta\omega\right)^2} + \frac{4.06}{\omega^2(\theta^3+1)} + \frac{0.4\theta+5}{\omega^2}\right] + \left[\left(\frac{116}{\frac{R}{V_W}\omega^2 + 0.08\theta\omega} - \frac{4.06}{\omega(\theta^3+1)} - \frac{0.4\theta+5}{\omega}\right)\frac{12.5}{\left(\frac{R\omega}{V_W}+0.08\theta\right)^2}\left(\frac{R}{V_W}\right)\right]\right\} \tag{11}$$

Because the wind-turbine torque and the generator output current has the relationship as Eq. (12)

$$T = K_t i \tag{12}$$

where K_t is an equivalent torque constant. Substituting (11)-(12) into (9) yields

$$K_t i - (0.11)\rho A V_W^3 e^{-\left(\frac{12.5}{\frac{R\omega}{V_W}+0.08\theta} - \frac{0.4375}{\theta^3+1}\right)} \left\{\left[\frac{116\times\left(\frac{2R\omega}{V_W} + 0.08\theta\right)}{\omega\left(\frac{R\omega}{V_W} + 0.08\theta\right)^2} - \frac{4.06}{\omega(\theta^3+1)} - \frac{0.4\theta+5}{\omega}\right] - \left[\left(\frac{116}{\frac{R\omega}{V_W}+0.08\theta} - \frac{4.06}{\theta^3+1} - 0.4\theta - 5\right)\frac{12.5}{\left(\frac{R\omega}{V_W}+0.08\theta\right)^2}\left(\frac{R}{V_W}\right)\right]\right\} = 0 \tag{13}$$

Then, dividing by $K_t i$ on both sides of Eq. (13), at the maximum power point we have

$$1-\frac{0.11}{K_t i}\rho A V_W^3 e^{-\left(\frac{12.5}{\frac{R\omega}{V_W}+0.08\theta}-\frac{0.4375}{\theta^3+1}\right)}\left\{\left[\frac{116\times\left(\frac{2R\omega}{V_W}+0.08\theta\right)}{\omega\left(\frac{R\omega}{V_W}+0.08\theta\right)^2}-\frac{4.06}{\omega\left(\theta^3+1\right)}-\frac{0.4\theta+5}{\omega}\right]-\left[\left(\frac{116}{\frac{R\omega}{V_W}+0.08\theta}-\frac{4.06}{\theta^3+1}-0.4\theta-5\right)\frac{12.5}{\left(\frac{R\omega}{V_W}+0.08\theta\right)^2}\left(\frac{R}{V_W}\right)\right]\right\}=0 \quad (14)$$

III. A Novel Control Structure for Wind-Turbine Generators with MPPT

By observing Eq. (14), the parameters V_w (wind speed), ρ (air density), and K_t (equivalent torque constant) are uncertain terms. Let $V_W = V_{W0} + \Delta V_W$, $\rho = \rho_0 + \Delta\rho$, $K_t = K_{t0} + \Delta K_t$, where V_{W_0} , ρ_0 , and K_{t0} denote nominal terms and ΔV_W $\Delta\rho$, and ΔK_t denote perturbed terms for V_W , ρ , and K_t , respectively. Therefore, Eq. (14) can be rewritten as follows:

$$1-\left(x_0+\Delta x\right)=0 \quad (15)$$

where

$$x_0=\frac{0.11}{K_{t0} i}\rho_0 A V_{W_0}^3 e^{-\left(\frac{12.5}{\frac{R\omega}{V_{W_0}}+0.08\theta}-\frac{0.4375}{\theta^3+1}\right)}\left\{\left[\frac{116\times\left(\frac{2R\omega}{V_{W_0}}+0.08\theta\right)}{\omega\left(\frac{R\omega}{V_{W_0}}+0.08\theta\right)^2}-\frac{4.06}{\omega\left(\theta^3+1\right)}-\frac{0.4\theta+5}{\omega}\right]-\left[\left(\frac{116}{\frac{R\omega}{V_{W_0}}+0.08\theta}-\frac{4.06}{\theta^3+1}-0.4\theta-5\right)\frac{12.5}{\left(\frac{R\omega}{V_{W_0}}+0.08\theta\right)^2}\left(\frac{R}{V_{W_0}}\right)\right]\right\} \quad (16)$$

and

$$\Delta x=\frac{0.11}{K_t i}\rho A V_W^3 e^{-\left(\frac{12.5}{\frac{R\omega}{V_W}+0.08\theta}-\frac{0.4375}{\theta^3+1}\right)}\left\{\left[\frac{116\times\left(\frac{2R\omega}{V_W}+0.08\theta\right)}{\omega\left(\frac{R\omega}{V_W}+0.08\theta\right)^2}-\frac{4.06}{\omega\left(\theta^3+1\right)}-\frac{0.4\theta+5}{\omega}\right]-\left[\left(\frac{116}{\frac{R\omega}{V_W}+0.08\theta}-\frac{4.06}{\theta^3+1}-0.4\theta-5\right)\frac{12.5}{\left(\frac{R\omega}{V_W}+0.08\theta\right)^2}\left(\frac{R}{V_W}\right)\right]\right\}-x_0 \quad (17)$$

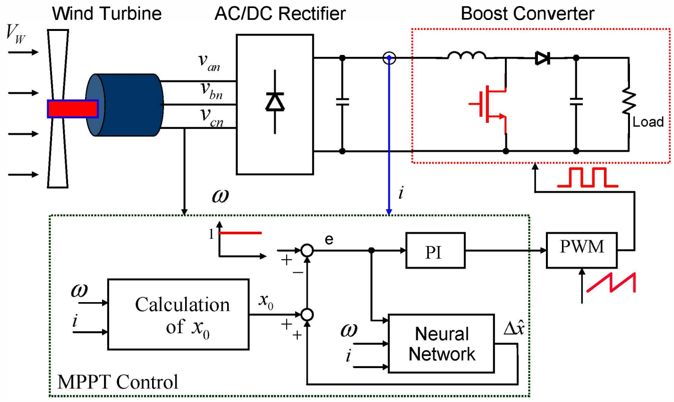


Fig. 2 The structure of the proposed controller.

From above analysis, x_0 is determined by the nominal value of the parameters in wind-turbine system and Δx is function of the uncertain parameters V_W , ρ , and K_t . This study proposes a novel controller for the MPPT problem to compensate the uncertainty Δx using neural networks as follows.

The structure of the proposed controller is shown in Fig. 2. Define a tracking error as Eq. (18)

$$e = 1-(x_0+\Delta\hat{x}) \quad (18)$$

where $\Delta\hat{x}$ is the output of the neural network and is an estimate of the uncertainty Δx . The inputs of the neural network are generator output current i and rotation speed ω , and the weightings in the neural network are adjusted by the tracking error e . At the same time, the duty cycle of the boost dc/dc converter is regulated by a PI controller, the parameters of which are to be determined by a genetic algorithm (GA) [18]. The purpose of the proposed controller is to make $1-(x_0+\Delta\hat{x})$ approach zero, which is equivalent to achieving MPPT control for the wind-turbine generation system.

IV. The Structure of the Proposed Recurrent Neural Networks

In this study, a recurrent neural network is adopted to compensate the uncertainties in the wind-turbine generation system. The structure of the proposed neural network compensator is shown in Fig. 3.

The model of recurrent neural networks including input layer, hidden layer, and output layer is described as follows:

A. *Input layer:*

There are two inputs in this study, which are i and ω, respectively. The outputs of the i^{th} node in the input layer are defined as

$$O_i(N)=\frac{1}{1+e^{-x_i(N)}},\ i=1,2 \quad (19)$$

where $x_1 = i$ and $x_2 = \omega$, respectively. N denotes the iteration number.

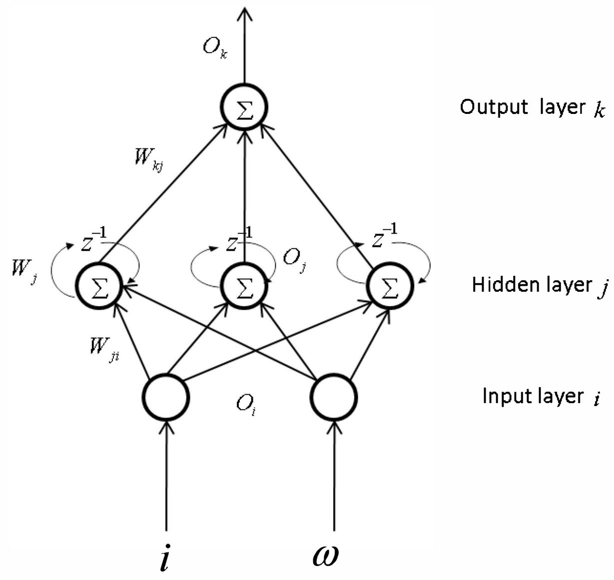


Fig. 3 The structure of recurrent neural networks.

B. Hidden layer:

For simplicity of implementation, there are three nodes (j=1,2,3) in the hidden layer. The outputs of the j^{th} node in the hidden layer are defined as

$$O_j(N) = \frac{1}{1+e^{-net_j(N)}} \tag{20}$$

where $net_j(N) = W_j \times O_j(N-1) + \sum_i \{W_{ji} \times O_i(N)\}$ and the updating of the weights, W_{ji}, W_j, and W_{kj}, in the neural network are defined as follows:

$$W_j(N+1) = W_j(N) + \Delta W_j(N) \tag{21}$$

$$\Delta W_j(N) = \eta_j \delta_k W_{kj} \times P_j(N) \tag{22}$$

In (15), the propagation error

$$\delta_k = e \tag{23}$$

and

$$P_j(N) = f_j'(net_j(N))[O_j(N-1) + W_j \times P_j(N-1)] \tag{24}$$

In (17), we have

$$f_j'(net_j(N)) = \frac{\partial O_j(N)}{\partial (net_j(N))} = \frac{e^{-net_j(N)}}{(1+e^{-net_j(N)})^2} \tag{25}$$

$$W_{ji}(N+1) = W_{ji}(N) + \Delta W_{ji}(N) \tag{26}$$

$$\Delta W_{ji}(N) = \eta_{ji} \delta_k W_{kj} \times Q_{ji}(N) \tag{27}$$

$$W_{kj}(N+1) = W_{kj}(N) + \Delta W_{kj}(N) \tag{28}$$

$$\Delta W_{kj}(N) = \eta_{kj} \delta_k O_j(N) \tag{29}$$

$$Q_{ji}(N) = f_j'(net_j(N))[O_i(N) + W_j \times Q_{ji}(N-1)] \tag{30}$$

where η_j, η_{ji}, and η_{kj} are learning rate.

C. Output layer:

There is only one output in the output layer (k=1 only). The output node in the output layer is defined as

$$O_k(N) = \sum_j \{W_{kj} \times O_j(N)\} \tag{31}$$

V. PI-Controller Designed by GA Algorithm and Simulation Verification

To illustrate the effectiveness of the proposed controller, the simulation block diagram of the proposed MPPT controller for the wind-turbine generation system with the boost converter switching frequency of 10 KHz and neural network updating rate of 100 Hz using MATLAB is shown in Fig. 4. The neural network compensator has two input nodes (i=1,2) for the two input variables i and ω, three hidden nodes (j=1, 2, 3) and one output node (k=1) for the $\Delta\hat{x}$. Initially, the simulation block is linked to a MATLAB function file in Fig. 5 by the "sim" function and gets the performance index which is defined as

$$J = \int_0^{t_0} e^2 dt \tag{32}$$

in which the integration time interval t_0 is set to be 0.04 seconds. This MATLAB function file in Fig. 5 is then called by the main program of our GA algorithm via a "degademo" function, which is shipped with MATLAB, to find the parameters of PI controller by minimizing the performance index in Eq. (32).

To find the optimal value of the performance index function using GA, we set the maximum number of generation to be 50 and confine the search domain of the parameters k_p and k_i within a squared area of $[10^{-7}\ 10]\times[10^{-7}\ 10]$. Every generation in our GA contains 50 pairs of data (k_p and k_i). Fig. 6 is the plot of the performance index which is convergent on about the twenty-second generation. Executing the MATLAB main program file also reports the values of the PI controller parameters, which are:

$$k_p = 0.0957 \tag{33}$$

and

$$k_i = 0.0304 \tag{34}$$

The above parameters of PI controller are then passed over to the simulation block in Fig. 4 for the overall simulation verification of the proposed MPPT controller performance.

Fig. 7 shows the simulated results for the wind speed with sudden changes from 10 m/s to 13 m/s, and down to 10 m/s. As can be seen, the wind turbine performance coefficient C_p is nearly at its maximum value of 0.35 for the wind speed with sudden changes. As also can be seen, the tracking error is approaching to zero despite of the variations of the wind speed. This is equivalent to achieving MPPT for the wind-turbine generation system.

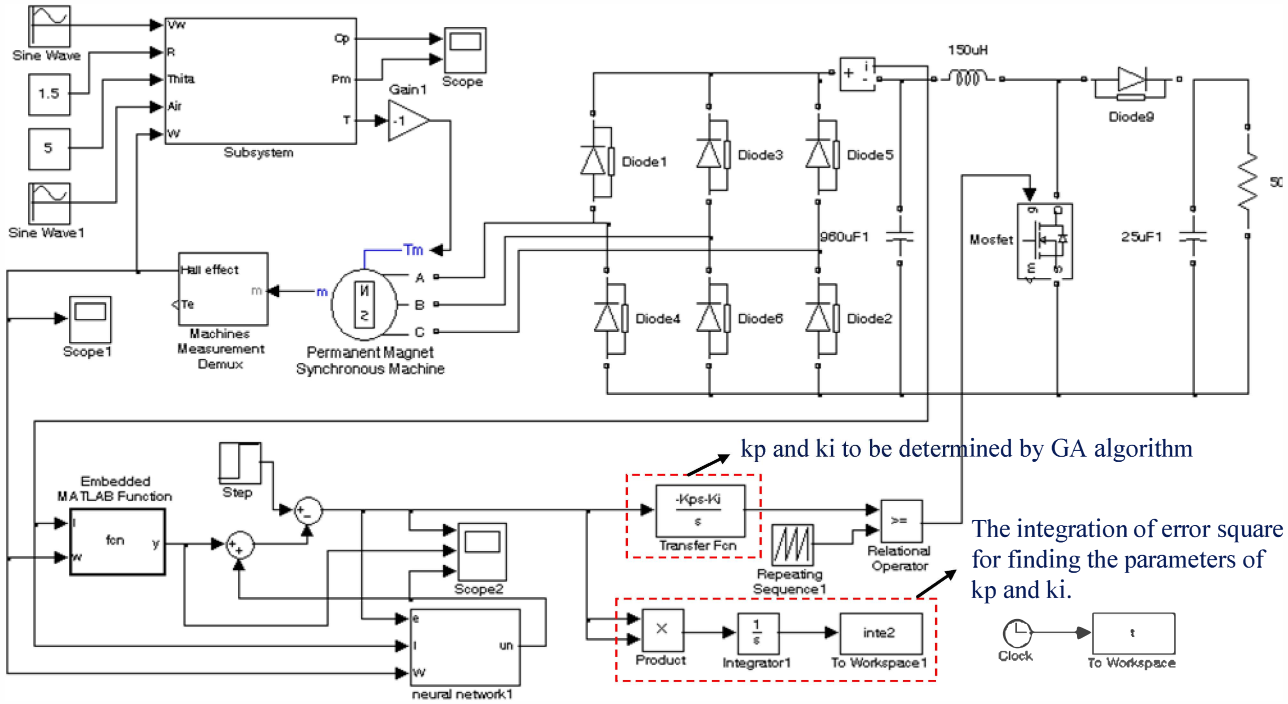


Fig. 4 The simulation block diagram of the proposed MPPT controller for the wind-turbine system.

```
function f = gaexcost(xyData)
global Kp Ki
[Nxy,Mxy]=size(xyData);
for i=1:Nxy
    Kp  =  xyData(i,1)
    Ki  =  xyData(i,2)
  If ((Kp>10^(-7) & Ki>10^(-7)) & (Kp<10 & Ki<10))
        [t,inte2]=sim('IwindKpKi_GA',[0 0.04]);  %% link to Simulink
        n=length(t);
        z(i)=-inte2(n)
  else
        z(i)=-10000;  % given an arbitrary large cost.
  end
end
f = z';
```

Fig. 5. The MATLAB function linked to the SIMULINK simulation file.

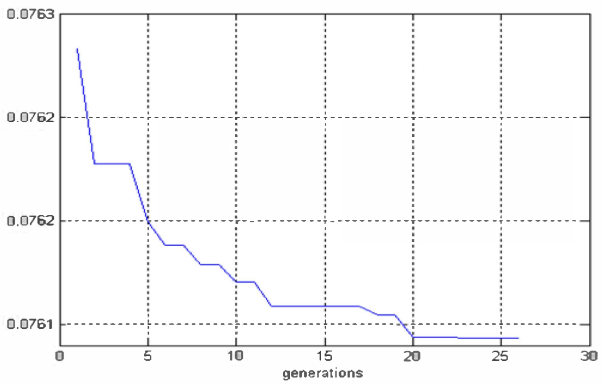


Fig. 6 The curve of performance index with respect to the generations.

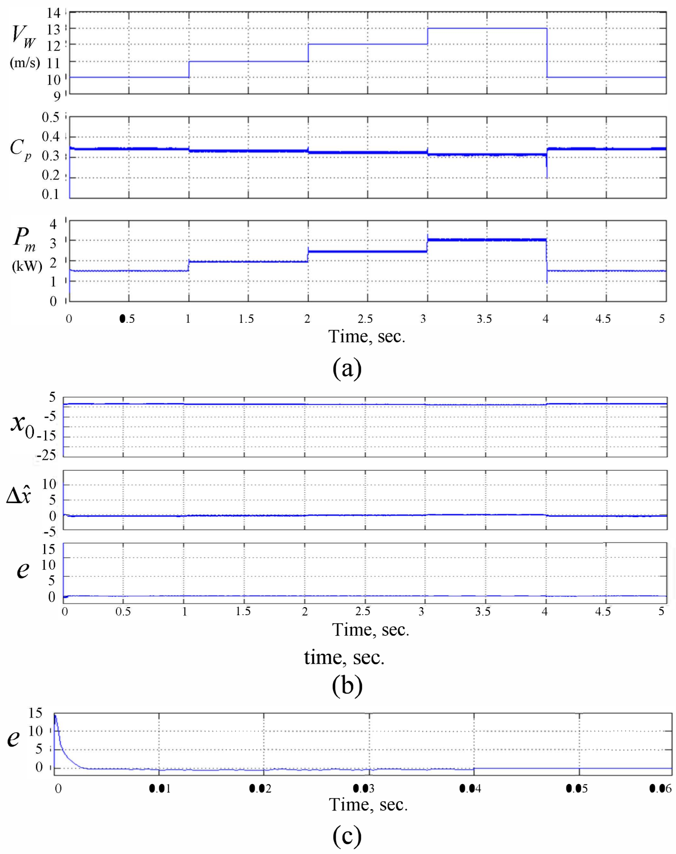


Fig.7 Simulation results in the case of the wind speed with sudden changes.

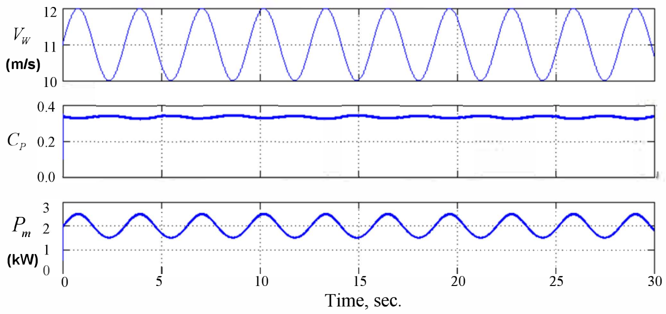


Fig. 8 Simulation results in the case of variations of the wind speed and air density.

As shown in Fig. 8, persistent perturbation of the wind speed and the air density with $V_W = 11 + \sin t$ and $\rho = 1.25 + \sin 0.01t$ also makes the performance coefficient C_p be kept nearly at its maximum value of 0.35.

VI. CONCLUSIONS

In this study, based on the slope of the wind-turbine mechanical power versus rotation speed, a novel MPPT algorithm using neural network compensator is proposed to avoid the oscillation problem and effect of uncertain parameters in wind-turbine generation systems. Naturally, the characteristics of the wind-turbine rotation speed is determined by the wind speed and air density conditions, thereby the technologies of changing the location of the maximum power point must be developed in the applications of maximum-power-point-tracking (MPPT) control in order to make the wind-turbine generator get the optimal efficiency from wind energy at different operating conditions. In this study, the uncertainties in wind-turbine generation systems are compensated by a neural network and the duty cycle of the boost dc/dc converter is determined by a PI controller, the parameters of which is determined by a genetic algorithm (GA) with the help of MATLAB. From the simulation results, the validity of the proposed MPPT controller can be verified under variations of wind speed, ambient air density, and the load electrical characteristics.