

# Optimization Method Based MPPT for Wind Power Generators

Chun-Yao Lee , Yi-Xing Shen , Jung-Cheng Cheng , Chih-Wen Chang and Yi-Yin Li

**Abstract**—This paper proposes the method combining artificial neural network with particle swarm optimization (PSO) to implement the maximum power point tracking (MPPT) by controlling the rotor speed of the wind generator. With the measurements of wind speed, rotor speed of wind generator and output power, the artificial neural network can be trained and the wind speed can be estimated. The proposed control system in this paper provides a manner for searching the maximum output power of wind generator even under the conditions of varying wind speed and load impedance.

**Keywords**—maximum power point tracking, artificial neural network, particle swarm optimization.

## I. INTRODUCTION

THE power output of the wind power generator varies easily along with wind speed. To maintain maximum power output, all the time is a crucial task. Due to the wind energy system of non-linear form, it is difficult to establish the linear control method. Also, there are few studies related to the consideration of variations in wind speed and load impedance under the control mode of optimal operating point. Therefore, this study combines artificial neural network with PSO to adjust the controller parameters for maximum power output automatically. The power loss of wind power generator can achieve to a minimum value, which shortens time to attain maximum power point effectively, and decreases the energy loss ratio of wind power generator.

## II. THE STRUCTURE OF WIND POWER GENERATOR SYSTEM

For a typical wind power generator, the maximum power point can be found in the  $P_m-N$  curve, the output power and rotor speed characteristic curve, under a specific wind speed, as shown in Fig. 1. The maximum power output can be manipulated upon the control of the rotor speed of wind power generator [1] [2], which means the maximum power output will be raised from point B to point A. The structure of wind power system in this study is assumed, which the motor's rotor speed

of artificial wind field is controlled by the use of inverter to simulate natural wind speed variation. The coupling mode is adopted to drive the wind turbine with the permanent-magnet synchronous generator (PMSG) and the three-phase full bridge rectifier is connected to the generator's output terminal in order to transform AC voltage into DC voltage for delivering load impedance.

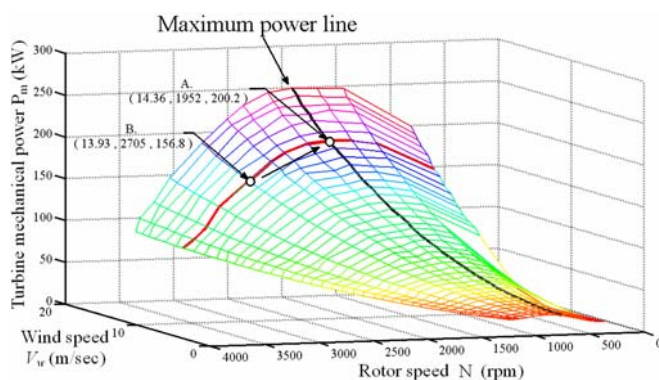


Fig. 1. Turbine power curves.

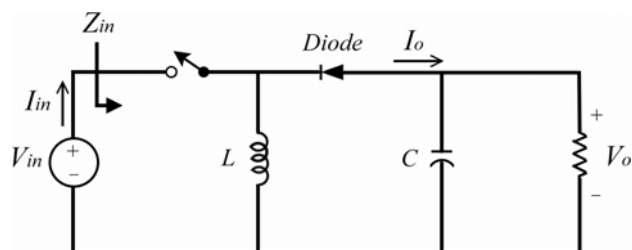


Fig. 2. Boost converter circuit.

Fig. 2 demonstrates a structure of boost converter circuit and the equivalent impedance  $Z_{in}$  can be calculated by (1), where  $R$  is the impedance of converter output terminal. Since the  $Z_{in}$  influences on rotor speed, the maximum power output is achieved by controlling duty cycle  $D$ .

$$Z_{in} = \frac{V_{in}}{I_{in}} = \frac{V_o(1-D)^2}{I_o} = R \times (1-D)^2 \quad (1)$$

## III. ARTIFICIAL NEURAL NETWORKS

This study adopts back-propagation artificial neural network and its structure is multilayer feed forward network. The study

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uses the superiority of learning capacity to construct two modules of artificial neural network's wind estimation  $ANN_{wind}$  and power estimation  $ANN_{Pe}$  so as to estimate wind speed and output power. Many studies indicated that artificial neural network is capable of approaching any function if the neurons are enough [3]. Therefore, the study firstly uses a hidden layer, and then in order to make the error within the tolerance, the number of neurons gradually increases until it achieves to a sufficient number.  $ANN_{wind}$  and  $ANN_{Pe}$  referring to two structures of multilayer feedforward neural network are applied to estimate wind speed and power respectively. Both of them correct the network weight by employing back-propagation algorithm. The training input and output of network will be illustrated in the following paragraph.

The  $ANN_{wind}$  module is a two-input to one-output network structure, as shown in Fig. 3, where  $V_w$  is the actual wind speed by anemometer,  $P_e$  is the output power of generator,  $\omega$  is the rotor speed of wind turbine, and  $V_w^*$  is estimated wind speed by  $ANN_{wind}$ . The  $ANN_{Pe}$  module is a three-input to one-output network structure, as shown in Fig. 4, where  $R$  is load impedance,  $D$  is the duty cycle, and  $P_e^*$  is the estimated output power of generator by  $ANN_{Pe}$ .  $P_e$  is not only the input signal of  $ANN_{wind}$  module but also the target in the training process of  $ANN_{Pe}$ . Therefore, before training the  $ANN_{Pe}$ , we must train  $ANN_{wind}$  until the accurate rate of  $V_w^*$  achieves the expectation, and then implement the training process of  $ANN_{Pe}$ .

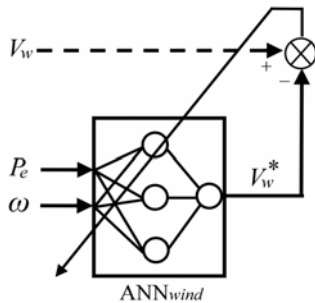


Fig. 3. Training scheme of  $ANN_{wind}$ .

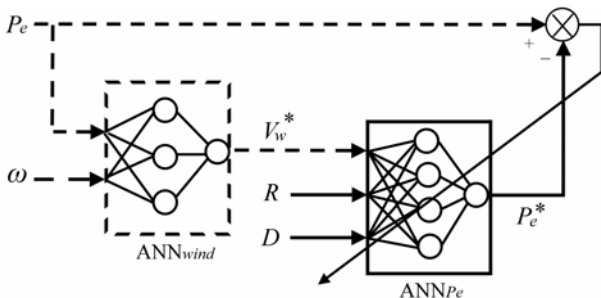


Fig. 4. Training scheme of  $ANN_{Pe}$ .

#### IV. PARTICLE SWARM OPTIMIZATION

PSO is a population-based searching algorithm. PSO randomly produces  $n_{popu}$  particles in searching space, and each particle includes position  $X_i$  and velocity  $V_i$  [4] [5], where  $X_i$  is the position of  $i$ -th particle in the searching space,

$X_i = (X_{i1}, \dots, X_{ij}, \dots, X_{ik})$ , and  $V_i$  is the velocity of  $i$ -th particle in the searching space,  $V_i = (V_{i1}, \dots, V_{ij}, \dots, V_{ik})$ . The position  $X_i$  of  $i$ -th particle represents a solution of the problem and the velocity  $V_i$  of  $i$ -th particle represents its displacement in the searching space.  $Pbest_i$  is the optimal position that the  $i$ -th particle has experienced and  $pbest_i$  is the optimal fitness that the  $i$ -th particle has experienced.  $Gbest$  is the optimal position that all particles have experienced and  $gbest$  is the optimal fitness that all particles have experienced. As  $Fit(\cdot)$  is the fitness function for solving the maximum value, the optimal position of each particle is shown in (2).

$$Pbest_i(t+1) = \begin{cases} Pbest_i(t) & \text{for } Fit(X_i(t+1)) \leq Fit(Pbest_i(t)) \\ X_i(t+1) & \text{for } Fit(X_i(t+1)) > Fit(Pbest_i(t)) \end{cases} \quad (2)$$

To improve the convergence,  $gbest$  and  $Gbest$  are selected by comparing with the experiences of others. Therefore, each particle is guided to its previous velocity,  $Pbest_i$ , and  $Gbest$ . The inertia weight method, shown as in (3) and (4), is applied to update velocity and position of the particles.

$$V_{ij}^{new} = w \cdot V_{ij} + c_1 \cdot rand1 \cdot (Pbest_{ij} - X_{ij}) + c_2 \cdot rand2 \cdot (Gbest_j - X_{ij}) \quad (3)$$

$$X_{ij}^{new} = X_{ij} + V_{ij} \quad (4)$$

where

$$Pbest_i = (Pbest_{i1}, \dots, Pbest_{ij}, \dots, Pbest_{ik})$$

$$Gbest = (Gbest_1, \dots, Gbest_j, \dots, Gbest_k)$$

$$w = w_{max} - iter \cdot (w_{max} - w_{min}) / iter_{max}$$

$c_1, c_2$  acceleration coefficient

$w$  coefficient of the inertia weight

$w_{min}$  minimum coefficient of the inertia weight

$w_{max}$  maximum coefficient of the inertia weight

$iter$  current iteration number

$iter_{max}$  maximum iteration number

Given the above description of PSO, the process of the PSO is shown as the following steps:

- Step 1) Generate equivalent  $n_{popu}$  quantity of position and velocity randomly, and record  $Pbest_i$ ,  $pbest_i$ ,  $gbest$  and  $Gbest$ .
- Step 2) Calculate each fitness value of particles.
- Step 3) If stopping criterion is satisfied (e.g., maximum iteration number), the procedure would go to the end; otherwise, proceed to step (4).
- Step 4) Update the  $Pbest_i$  and  $pbest_i$ .
- Step 5) Update the  $gbest$  and  $Gbest$ .
- Step 6) Update particles position and velocity by applying (3) and (4), and then go back to step (2).

### V. THE STRUCTURE OF MPPT CONTROL

The structure of MPPT control constructs the software and hardware communication environment through sensors and AD/DA cards. This study implements the artificial neural network and PSO. The process of MPPT control is shown in Fig. 5, where the wind estimation  $ANN_{wind}$  and the estimated  $ANN_{pe}$ -PSO of duty cycle are introduced as follows:

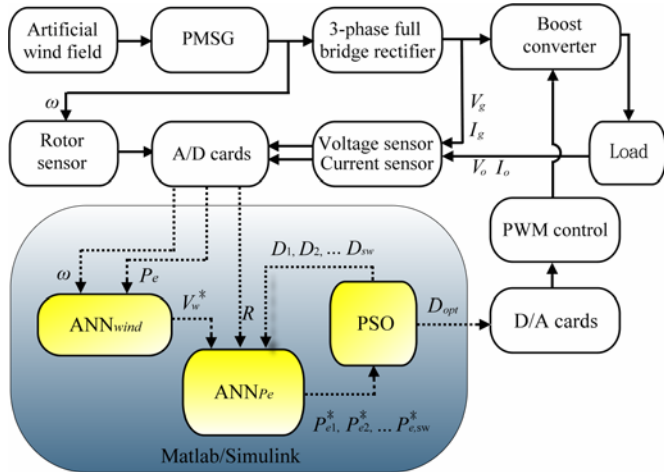


Fig. 5. Block diagram of the MPPT control Process.

#### A. The Module of Wind Estimated $ANN_{wind}$

The use of sensors extracts the analog signals,  $V_o$ ,  $I_o$ , and  $\omega$ , where  $V_o$  and  $I_o$  are the output voltage and current of boost converter respectively. By applying AD/DA cards, the analog signals are transformed into digital signals which are as an input signal of  $ANN_{wind}$  for estimating wind speed and further delivering to  $ANN_{pe}$ .

#### B. The Module of Duty Cycle Estimated $ANN_{pe}$ -PSO

The use of sensors extracts the analog signals, voltage  $V_o$  and current  $I_o$ . The analog signals transform into the digital signals by applying AD/DA cards. The  $R$ ,  $V_w^*$  and duty cycle ( $D_1, D_2, \dots, D_{sw}$ ), are designated as the input signal of the  $ANN_{pe}$ , where  $ANN_{pe}$  is as the fitness function  $Fit(\cdot)$  of PSO for searching the optimal duty cycle  $D_{opt}$ . In the searching process, the control system initializes  $D_i$  and  $\Delta D_i$ , and loads the signals  $P_e$ ,  $\omega$  and  $R$ . The signals,  $P_e$ ,  $\omega$  and  $R$ , are considered constants until the stopping criterion is satisfied and the control voltage  $V_{con}$  is delivered to PWM circuit, where  $V_{con}$  is the DC voltage level, 0~10V, for adjusting duty cycle. Since the control system adjusts duty cycle in order to reach  $D_{opt}$  by PWM circuit, the equivalent impedance makes the generator operate at the maximum power point. Where  $D_i$ ,  $\Delta D_i$  and  $sw$  are the position of the  $i$ -th particle, the speed of the  $i$ -th particle and the number of PSO respectively. The output signals of  $ANN_{pe}$ ,  $P_{e1}^*$ ,  $P_{e2}^*$ , ...,  $P_{esw}^*$ , are the fitness of particle position,  $D_1$ ,  $D_2, \dots, D_{sw}$ , respectively. The control system accomplishes the MPPT by Matlab/Simulink, and the real-time control interface is shown in Fig. 6.

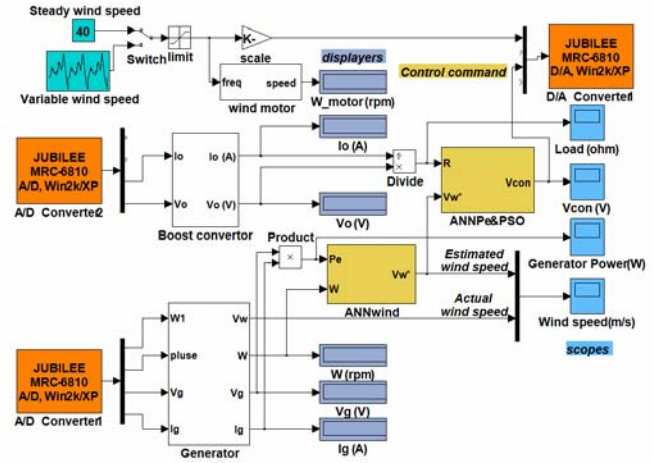


Fig. 6. Simulink structure of MPPT control.

### VI. NUMERICAL RESULTS

#### Wind Speed and Load Impedance Variation

The assumed actual wind speed is controlled for the arbitrary variation by the inverter. If the load impedance instantly varies from 50.03 ( $\Omega$ ) to 23.22 ( $\Omega$ ) at 150 (sec), the control voltage  $V_{con}$  of the control system has to vary along with the estimated wind speed and load impedance. The rotor speed is adjusted by the control system due to the variation of  $V_{con}$ . The results of output power under three specific wind speed (7.6 m/s, 10.6 m/s, and 13.0 m/s) are simulated before and after load impedance varies in Table I and II, respectively.

TABLE I  
Instantaneous Output Power before Load Varying

Wind speed (m/s)	Expected power (W)	Increase (W)	Decrease (W)	Absolute error (%)
7.6	38.6	28.9	43.4	6.34
10.6	88.5	82.3	110.1	8.70
13.0	167.5	156.9	175.8	2.57

TABLE II  
Instantaneous Output Power after Load Varying

Wind speed (m/s)	Expected power (W)	Increase (W)	Decrease (W)	Absolute error (%)
7.6	38.6	26.8	50.3	0.13
10.6	88.5	71.3	119.1	7.57
13.0	167.5	140.9	190.6	1.04

## VII. CONCLUSION

The study proposed a method based on artificial neural network and particle swarm optimization for tracking the maximum power point of wind power generator. The numerical results of this paper demonstrated that the estimated wind speed not only replaces the measurement of anemometer but also solves the problems such as aging anemometer and moved position. Considering the simultaneous variation of load and wind speed, artificial neural network and PSO are applied to estimate and control the optimal rotor speed so as to obtain the maximum power output of wind power generator. Furthermore, considering the condition of wind speed and load variation, the maximum output power can be tracked.

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