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Optimization Method Based MPPT for Wind Power Generators

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***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.

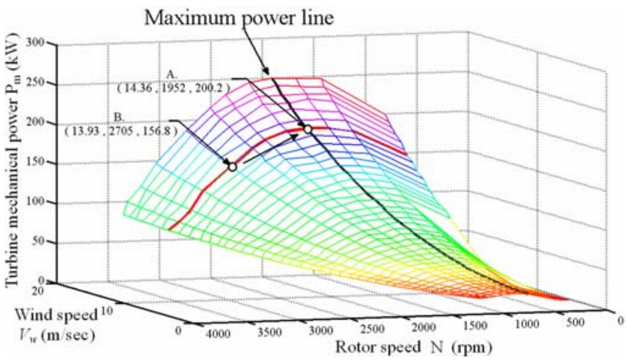

Fig. 1. Turbine power curves.

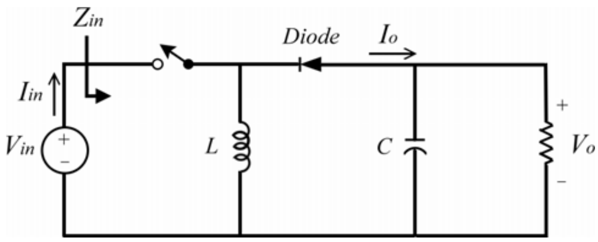

Fig. 2. Boost converter circuit.

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.

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

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, ω 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}.

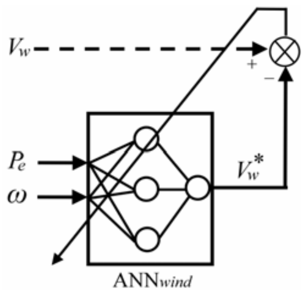

Fig. 3. Training scheme of ANN_{wind}.

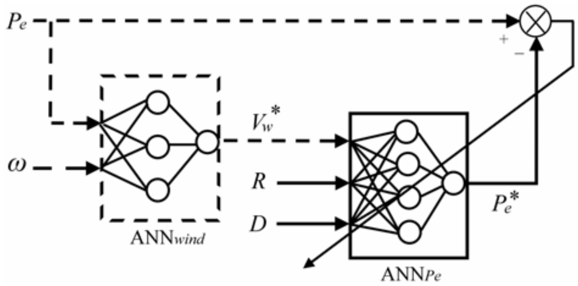

Fig. 4. Training scheme of ANN_{Pe}.

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, $X_i=(X_{i1},...,X_{ij},...,X_{ik})$, and V_i is the velocity of i-th particle in the searching space, $V_i=(V_{i1},...,V_{ij},...,V_{ik})$. 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 $\mathrm{Fit}(\cdot)$ is the fitness function for solving the maximum value, the optimal position of each particle is shown in (2).

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

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.

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

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

where

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

$Gbest = (Gbest_1,...,Gbest_j,....,Gbest_k)$

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

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:

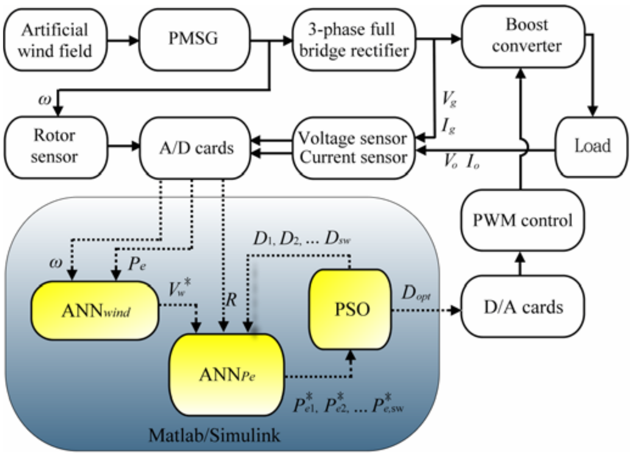

Fig. 5. Block diagram of the MPPT control Process.

A. The Module of Wind Estimated ANN$_{wind}$

The use of sensors extracts the analog signals, V_o, I_o, and ω, 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,…,D_{sw}), are designated as the input signal of the ANN$_{Pe}$, where ANN$_{Pe}$ is as the fitness function Fit(·) of PSO for searching the optimal duty cycle D_{opt}. In the searching process, the control system initializes D_i and ΔD_i, and loads the signals P_e, ω and R. The signals, P_e, ω 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, ΔD_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}^*,…, $P_{e,sw}^*$, are the fitness of particle position, D_1, D_2,…, D_{sw}, respectively. The control system accomplishes the MPPT by Matlab/Simulink, and the real-time control interface is shown in Fig. 6.

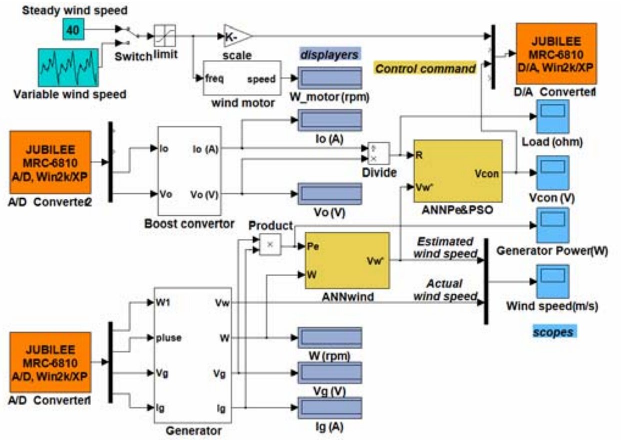

Fig. 6. Simulink structure of MPPT control.

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 (Ω) to 23.22 (Ω) 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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