Energy Conversion and Management 68 (2013) 305–312

Contents lists available at SciVerse ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

A benefits analysis for wind turbine allocation in a power distribution system

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ARTICLE INFO

Article history:
Received 7 September 2012
Received in revised form 25 December 2012
Accepted 25 December 2012
Available online 1 March 2013

Keywords:
Particle Swarm Optimization
Equivalent Current Injection
Wind turbine
Distribution system

ABSTRACT

This paper proposes an algorithm to analyze the long-term benefits of Wind Turbine (WT) allocation at the demand side of a power distribution system. The benefits are evaluated based on the wind electricity generation and the avoidance of CO_2 emissions. The objective function includes the investment cost, maintenance cost, and the cost of loss reduction, subjective to operating limits and line flow constraints. Taking load growth into account, Particle Swarm Optimization (PSO) with a power flow algorithm is proposed to solve this problem. To enhance the performance of the optimization approach, a load flow model with Equivalent Current Injection (ECI) is used to analyze the power flow of distribution systems. By considering the power generation of WTs, electricity prices, and carbon trading prices, the long-term benefits of the installation of wind turbines in different scenarios are evaluated. Examples of IEEE 69-bus systems are presented to illustrate the efficiency and feasibility of the proposed algorithm. Simulation results can help decision makers in selecting the proper installation sites for WTs, as well as in determining the tradeoff between optimal investment and environmental policy for future electricity and carbon markets.

1. Introduction

The greenhouse gas (GHG) emission of electric power sectors around the world is about 1/3 of the total world GHG emission, indicating the significance of electric power sectors in the global warming issue. In recent years, climate change due to greenhouse gas (GHG) emissions has become a focus of international organizations and governments. In order to reduce GHG emissions, the aim has been placed on finding more environmentally friendly alternatives for electricity power generation. Renewable Energy (RE) is required for local energy markets, as an important alternative energy production option in the near future [1]. RE technologies may include solar energy, wind, fuel cells, micro-turbines, etc. Due to advances in wind energy technologies, wind power is currently considered one of the most rapidly increasing resources [2]. There is no doubt that the benefit of WTs is beginning to attract many utilities in the electricity market [3,4].

Wind energy is expected to play an important role in the future global energy supply. The policy and challenges of wind power have been discussed in Taiwan for promoting the wind power technology industry [5]. Related issues, such as installation plans, financial incentives, feed-in tariffs, export credit subsidies, R&D, purchasing rates, and government tendering have been discussed to promote policy tools, and assist in the early steps of private investment. The development progress of wind power policy in China has many similarities to progress in Taiwan [6,7]. It is a universal problem that the investment of wind power technology requires support and incentives in most economies as long as prices for fossil fuels fail to reflect the negative externalities on the environment [8,9]. The characteristics of wind power include high capacity cost, and low CO_2 emissions as compared to fossil-fuel plants. If CO_2 emissions could be charged in the future electricity market, the environmental benefits of wind power can be increased significantly [10,11]. Wind Turbines (WTs) are small plants that are properly located to provide an incremental capacity to power systems [12,13]. The integration of WTs into an existing distribution system, depending on the allocation of WTs, can result in several advantages, such as line loss reduction, peak shaving, emission reduction, and increased system voltage profile [14]. Moreover, WTs can also relieve congestion and provide grid reinforcement. As a result, WTs have attracted more interests in the electricity industries.

In the electricity market, WTs are like small Independent Power Producers (IPPs), which intend to sell power to utilities for profit [15]. WTs need to maximize profit instead of minimizing operating cost. This problem emphasizes the importance of the price signal in the electricity market. Electricity prices are very volatile, varying with the level of use at various times of day, thus affecting the profits received by the IPPs when selling the power to the distribution network [16]. In addition, as WTs reduce CO_2 emissions due to the use of wind generated electricity, the reduced emissions will turn into revenues in the carbon market [17]. CO_2 emissions can be traded in the carbon market to gain further benefits [18]. This paper describes a benefit analysis when WTs are installed to meet

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0196-8904/$ - see front matter
http://dx.doi.org/10.1016/j.enconman.2012.12.022

load growth in a distribution system. A lifetime of 20 years is assumed for the wind-power installations. The benefits of WTs are evaluated by considering the power generation of WTs, electricity prices, and carbon trading prices.

Distribution system planners must ensure the adequate capacity that meets the load growth within the planning horizon year. They are obligated to provide service reliability through planning, operation, construction, and maintenance with limited resources [19]. In general, WTs are mostly installed in a demand system, and connected directly to distribution networks. Inappropriate locations of WTs may lead to greater system losses [20]. However, integration of WTs into the distribution systems is a major challenge to system operators and planners due to the high uncertainty and variability in the characteristics of WTs. In this paper, a Particle Swarm Optimization (PSO) [21] based approach is presented to optimally incorporate WTs into a distribution system. The proposed algorithm combines PSO with a power flow algorithm to find the best combination of locations. To enhance the performance of the new approach, a load flow model with Equivalent Current Injection (ECI) [22] is used to analyze the power flow of distribution systems. By considering the power generation of WTs, electricity prices, and carbon prices, the benefits of WTs in different scenarios are evaluated. The IEEE 69-bus distribution system [23] is used to validate the proposed method. Simulation results can help decision makers determining the proper installation locations of WTs in order to reduce system losses and maintain voltage profile. They can also determine the return of investment between cost and the environment for future electricity and carbon markets.

2. Problem formulation

2.1. WT integrate into a power distribution system

The WT is connected to a power distribution system at node i, as shown in Fig. 1. The substation (S/S) is equivalent to a voltage-source and transmission line, and is simplified to lump impedance $R + jX$. The load can be expressed by a constant power $P + jQ$. The injection characteristic of WT in power flow calculation is regarded as a PQ node, in which the output of real power can be determined as following Eq. (1) [24]:

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

where ρ is the air density, A the swept area of the rotor blades, and V_{wind} is the wind velocity. In this paper, the longitude of rotor blade is 10 m and the range of wind velocity is from 4 m/s to 20 m/s. The maximal real power output of WT is 200 kW when the wind velocity is above 13 m/s.

2.2. Objective function and constraints

In order to obtain the maximal benefit from the WT allocation, the suitable location and sizing must be determined before its installation. The WT real power output is continuous when WT is placed in a power distribution system. The optimal size of WT is determined by making the kW output of WT optimal in the objective function. The objective function of WT allocation is to find the optimal WT installation buses, in order to minimize the total line losses, thereby satisfying the load growth. Therefore, the objective problem is expressed as Eq. (2), and is incorporated into ECI to carry out load flow analysis, as described in Section 3.1. The optimal WT installation buses are determined by the PSO method, which will be described in Section 3.2. In Eq. (24), the position vector for each WT is optimized by minimizing the total line losses in:

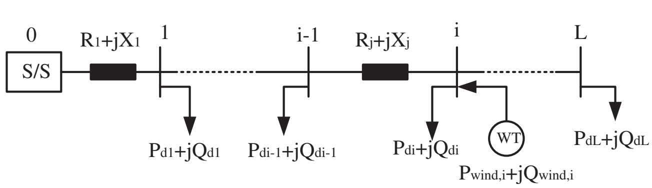

Fig. 1. The diagram of WT integrate into a power distribution system.

$$\text{Min} \quad P_{loss} = \frac{1}{2}\sum_{i=1}^{NB}\sum_{j=1}^{NB}\text{Re}[Y_{ij}][|V_i|^2 + |V_j|^2 - 2|V_i||V_j|\cos\theta_{ij}] \tag{2}$$

where P_{loss} is the total line losses, Y_{ij} the admittance of branch $i - j$, Re the real part of complex quantity, NB the total number of branches in the system,V_i the voltage of i-th bus, and $\theta_{ij} = \theta_i - \theta_j$ is the voltage phase angle difference between bus-i and bus-j.

From Eq. (1), the line losses could be reduced by lowering the branch currents in the distribution network. In order to reduce the current in certain parts of the network, WTs are introduced to the power distribution system.

The constraints considered are described as follows.

1. The equality constraints are the power flow equations in the power distribution system as follows:

$$P_{i,sch} = P_{wind,i} - P_{di}^n = |V_i|\sum_{j=1}^{NB}|V_j||Y_{ij}|\cos(\theta_i - \theta_j - \delta_{ij}) \tag{3}$$

$$Q_{i,sch} = Q_{wind,i} - Q_{di}^n = |V_i|\sum_{j=1}^{NB}|V_j||Y_{ij}|\sin(\theta_i - \theta_j - \delta_{ij}) \tag{4}$$

2. The inequality constraints are the voltage limits imposed on the power distribution system:

$$\left|V_i^{\min}\right| \leqslant |V_i| \leqslant |V_i^{\max}| \tag{5}$$

3. The inequality constraints with the WTs real power output are:

$$P_{wind,i}^{\min} \leqslant P_{wind,i} \leqslant P_{wind,i}^{\max} \tag{6}$$

δ_{ij} is the admittance phase angle of branch $i - j$, S_{ij} the line flow in branch $i - j$, $S_{ij}^{\max}$ the upper line flow in branch $i - j$, $P_{wind,i}^{\min}$, $P_{wind,i}^{\max}$ the lower and upper real power generation of WT at i-th bus, $P_{i,sch}$ the net real power at i-th bus, $Q_{i,sch}$ the net reactive power at i-th bus, $P_{wind,i}$ the real power generation for WT at i-th bus, $Q_{wind,i}$ the reactive power generation of WT at i-th bus, P_{di}^n the real power demand of i-th bus for n-th horizon year, Q_{di}^n the reactive power demand of i-th bus for n-th horizon year, and n is the number of year.

2.3. Benefit analysis of WTs allocation

The benefit of WTs over its lifetime is calculated when the WTs are allocated based on the load growth. The benefit of WTs installed is determined by the net change in the total cost of electricity generation before and after the installation. The costs include investment cost and maintenance cost, and the benefits include the profit of electricity sold, CO_2 emissions sold, and loss reduction. A better planning method is to locate the minimum cost solution where the total benefits can be maximized. Therefore, costs and benefits of WT allocation in the network can be expressed as follows, with the cash flows presented below in Fig. 2.

2.3.1. Investment cost

The investment cost of WT units can be formulated as the following equation:

$$C_1 = \sum_{i=1}^{m} Fix_i \tag{7}$$

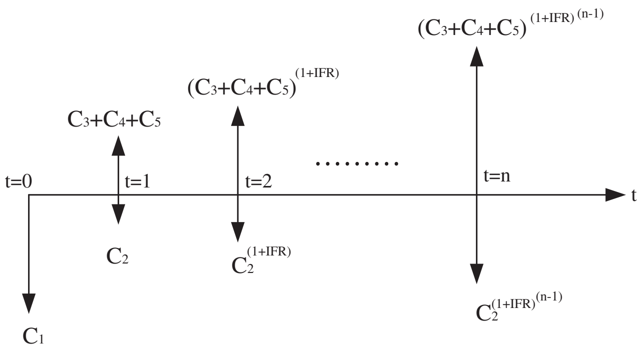

Fig. 2. Cash flows of the WT project.

2.3.2. Maintenance cost

The maintenance cost can be evaluated by:

$$C_2 = \sum_{i=1}^{m} CM_i \tag{8}$$

Present value of this annual cost considering inflation rate and interest rate [25,26] in the lifetime is calculated by:

$$PW(C_2) = C_2 \sum_{t=1}^{T} \frac{(1+IFR)^{t-1}}{(1+INR)^t} \tag{9}$$

2.3.3. The profit of WTs installed

The annual profit of WTs installed includes the profit of line loss reduction, C_3, the profit of power generation, C_4, and the profit of CO_2 sold, C_5. The formulation is calculated as follows:

$$C_3 = 8760 \times CF \times P^r_{loss} \times Cost_e \tag{10}$$

$$C_4 = 8760 \times CF \times \sum_{i=1}^{m} P_i \times Cost_e \tag{11}$$

$$C_5 = 8760 \times CF \times \sum_{i=1}^{m} P_i \times \phi \times Cost_c \tag{12}$$

Present value of this annual profit is calculated by:

$$BPW(B) = (C_3 + C_4 + C_5) \sum_{t=1}^{T} \frac{(1+IFR)^{t-1}}{(1+INR)^t} \tag{13}$$

The benefits of WTs can be calculated as:

$$Benefit = BPW(B) - C_1 - PW(C_2) \tag{14}$$

m is the number of WTs installed, T the lifetime of WTs (20 years), IFR the annual inflation rate, INR the annual interest rate, P_i the rated real power output of WTs (kW), $Cost_e$ the electricity price (NT\$), P^r_{loss} the loss reduction after WTs are installed (kW), φ the carbon exhaust coefficient (0.612 kg CO_2 e/kW h) [27], $Cost_c$ the carbon trading price (NT\$/ton), *Fix* the investment cost of WTs installed (NT\$$5.2 \times 10^8$/unit) [27], CM the maintenance cost of WTs (NT\$ 1.35×10^7/year) [27], and CF is the capacity factor of WTs.

The factors influencing the energy produced by a WT at a given location over a period are (1) the power response of the turbine to different wind velocities, (2) the strength of the prevailing wind regime, and (3) the distribution of wind velocity within the regime. The total energy generated by WT over a period can be computed by summing the energy corresponding to all possible wind speeds in the regime, at which the system is operational. Hence, along with the power characteristics of the WT, the probability density corresponding to different wind speeds is included in the energy calculation.

Various probability functions are fitted with the field data to identify suitable statistical distributions for representing wind regime. The Weibull and Rayleigh distributions can be used to describe the wind variations in a regime with an acceptable accuracy level [26]. Wind energy in Taiwan has been assessed according to the Weibull function by Cheng [28] using Particle Swarm Optimization method to find the Weibull parameters. Capacity factor is one of the important indices for assessing the field performance of a WT. The capacity, CF, of a WT at a given site is defined as the ratio of the energy actually produced by the system to the energy that could be produced by it, if the machine has operated at its rated power throughout the time period [26]. In [28], yearly statistical wind potential for three wind power stations in Penghu, Dayuan and Hengchun, was assessed; the capacity factors for the three stations were 0.518, 0.487 and 0.358, respectively. In this paper, the capacity factor is introduced into Eqs. (10)–(12) to calculate the energy output as well as profits evaluation of WT.

It should be noted that *INR* is the inflation-free interest rate (or the so-called real interest rate), which is given by the difference between the market interest rate and the inflation rate, *IFR*, if either the real interest rate or the inflation rate is relatively small. The interest rate, *INR*, is usually larger than the inflation rate, *IFR*. It is rare for the inflation rate to be higher than the interest rate, although this *hyperinflation* can sometimes arise, for example in countries where political instability, overspending by government, and/or weak in international trade balances, are present [29].

The benefits of WTs installed are evaluated on the basis of reduced profit loss, electricity trading profit, and carbon trading profit. In deregulated markets, the electricity and carbon prices vary in the energy market. To account for these volatilities, the benefits of WTs installed are calculated in different scenarios.

3. Proposed methodology

3.1. Load flow model with Equivalent Current Injection

Two basic power load flow techniques used in the industrial application are the Gauss–Seidel and Newton–Raphson based algorithms. The Gauss–Seidel algorithm is a slow convergence, and uses a full matrix which directly defines the problem to be solved. The Newton–Raphson algorithm is a gradient technique where the line parameters are stored in a Jacobian matrix. Ref. [30] presented a bi-factorized complex *Y*-admittance matrix Gauss–Seidel method, which is based on the Equivalent Current Injection, ECI, and the power components can be modeled in the *Y* matrix or converted into ECI. In this paper, the load flow with the Newton–Raphson method is proposed based on ECI.

For the power-based Newton–Raphson (NR) method, the mismatch function can be written in the rectangular form as:

$$\begin{bmatrix} \Delta P_i \\ \Delta Q_i \end{bmatrix} = \begin{bmatrix} \frac{\partial P_i}{\partial e_i} & \frac{\partial P_i}{\partial f_i} \\ \frac{\partial Q_i}{\partial e_i} & \frac{\partial Q_i}{\partial f_i} \end{bmatrix} \begin{bmatrix} \Delta e_i \\ \Delta f_i \end{bmatrix}, \tag{15}$$

where

$$\Delta P_i = P_{i,sch} - P_{i,cal}, \quad \Delta Q_i = Q_{i,sch} - Q_{i,cal}$$

$P_{i,sch} = P_{wind,i} - P_{di}$, which is the net real power at the i-th bus, includes the real power demand (P_{di}) and the WT's power generation ($P_{wind,i}$). $P_{i,cal}$ is the real power, which is calculated by load flow analysis. $Q_{i,sch} = Q_{wind,i} - Q_{di}$, which is the net reactive power at the i-th bus, includes the reactive power demand (Q_{di}) and the WT's reactive power generation ($Q_{wind,i}$). $Q_{i,cal}$ is the reactive power, which is calculated by load flow analysis. The reactive power generation of WTs is calculated based on the pre-specified power factor.

The Jacobian matrix in Eq. (16) can be given by:

$$J = \begin{bmatrix} \frac{\partial P_i}{\partial e_i} & \frac{\partial P_i}{\partial f_i} \\ \frac{\partial Q_i}{\partial e_i} & \frac{\partial Q_i}{\partial f_i} \end{bmatrix} \tag{16}$$

The ECI-based load flow uses current instead of power. The mismatch function can be re-written by:

$$\begin{bmatrix} \Delta I^r \\ \Delta I^i \end{bmatrix} = \begin{bmatrix} \frac{\partial I^r}{\partial e} & \frac{\partial I^r}{\partial f} \\ \frac{\partial I^i}{\partial e} & \frac{\partial I^i}{\partial f} \end{bmatrix} \begin{bmatrix} \Delta e \\ \Delta f \end{bmatrix} \tag{17}$$

$\Delta I = I^{eqv} - I^{cal} = \Delta I^r + j\Delta I^i$ and $\Delta V = \Delta e + j\Delta f$ are the real and imaginary components of mismatch currents and mismatch voltages, respectively. I^{cal} is obtained from load flow analysis. I^{eqv} is given by:

$$I^{eqv} = \left(\frac{P + jQ}{V}\right)^* = \mathrm{Re}(I^{eqv}) + j\mathrm{Im}(I^{eqv}) \tag{18}$$

where P, Q, and V are the constant real power, imaginary power, and voltage at a specified bus, respectively. P and Q are also the net power at a specified bus, which include the WT's power generations and load demands.

From Eq. (17), a constant Jacobian matrix can be obtained, which has the same matrix dimension as the traditional power-based Newton–Raphson (NR) algorithm. The constant Jacobian matrix can be written by:

$$J = \begin{bmatrix} G & -B \\ B & G \end{bmatrix}, \tag{19}$$

where G and B are the conductance and the susceptance matrix, respectively.

The Jacobian matrix is insensitive to the line parameters, and the memory requirement is less than the traditional load flow program. This formula can be used for ECI-based NR algorithm. NR algorithm is a gradient minimization problem in solving the nonlinear equations, where the Jacobian matrix provides the optimal direction to find the root. Due to the use of the constant Jacobian matrix approximations in ECI-NR algorithm, the computation is compensated for improving the overall performance. Whether the ECI-NR algorithm is used in power flow analysis, the final solution should remain unchanged. The ECI-NR algorithm is also superior to the other methods developed [22].

3.2. Particle Swarm Optimization

Particle Swarm Optimization (PSO) was proposed by Dr. Eberhart and Dr. Kennedy in 1995 [21]. By observing the foraging behaviors of birds and fish, PSO can apply the activity characteristics of biotic populations to optimization problems. When birds or fish forage, they not only refer to their own experiences, but also learn from the most efficient individual in the group. They learn and exchange their experiences, and pass this experience on until the whole population reaches the optimum condition. The advantage of PSO algorithm is that individuals can converge the optimal solution rapidly within permissible range through a small number of evolution iterations, and it also has a faster convergence rate. PSO has been successfully applied to many engineering problems [28,31–33].

PSO is similar to random search methods, but it does not contain complicated mechanisms, such as crossover or mutation. PSO generates a set of initial solutions, known as particles, through the initialization mechanism, and then searches for the optimal value through iteration evolution. More importantly, every particle has a memory capacity, and can provide a one-way message to the population. Thus, the search process of PSO is the process of following the current optimal solution. For example, if the distance to a food source is known to a population of birds, but its location is unknown, the simplest way to find the food is to search the peripheral regions of the birds that are closest to the food.

In a PSO system, Birds' (particles) flocking optimizes a certain objective function. Each particle knows its current optimal position (*pbest*), which is an analogy of personal experiences of each particle. Each particle also knows the current global optimal position (*gbest*) among all particles in the population. PSO can have several solutions at the same time, and particles have a cooperative relationship for sharing messages. Through specific equations, each particle adjusts its position and determines the search direction according to its search memory and those of others. In other words, it tries to reach compatibility between local search and global search. The search memory of a particle is the objective function and the optimum position found by the particle.

In this paper, Particle Swarm Optimization with Constriction Factor (PSO-CF) [34] is used to trace the *pbest* value and the *gbest* value. Using the PSO-CF, the velocity can be represented under Eq. (21) in the PSO algorithm. Using Eq. (20), a certain velocity

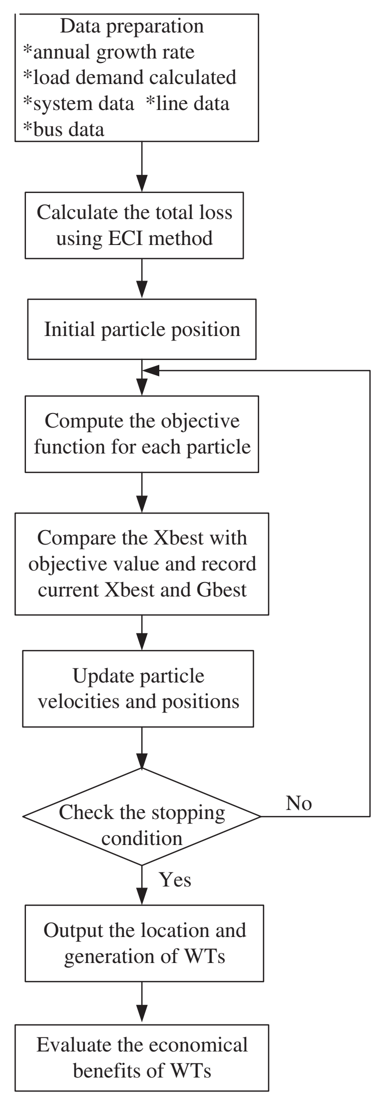

Fig. 3. Flowchart of the proposed methodology.

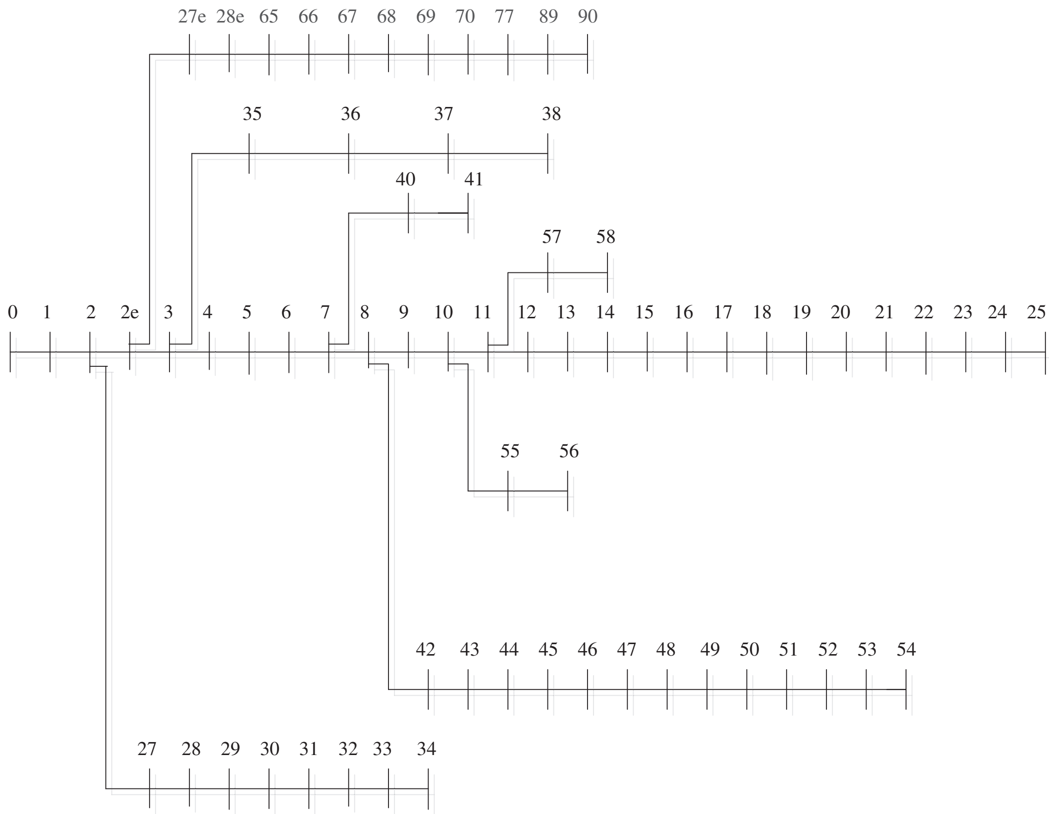

Fig. 4. Single diagram of the studied 69-bus power distribution system.

Table 1
Summary of the simulated results.

Horizon year	5	10	15	20
Total real load demand (kW)	4408.476	5110.632	5924.623	6868.262
Total reactive load demand (KVAR)	3123.803	3621.344	4198.130	4866.783
The total power output of WTs (kW)	430.5	1148	2009	3013.5
The worst system loss (kW)	92.37	123.78	154	193.2
The average system loss (kW)	88.69	117.3	144.8	184.1
The best system loss (kW)	84.811	107.63	131	170.1
The worst percentage of loss reduction (%)	12	22.1	29	34.91
The average percentage of loss reduction (%)	15.15	26.4	33.24	37.9
The best percentage of loss reduction (%)	19.23	32.7	39.6	42.7
The number of WTs installed	3	8	14	21
The location of WT (no. of bus)	62, 64, 65	9, 14, 24, 59, 60, 61, 62, 65	19, 26, 40, 49, 50, 55, 57, 59, 61, 62, 63, 64, 65, 67	5, 6, 7, 11, 12, 14, 16, 17, 19, 53, 57, 58, 59, 61, 62, 63, 64, 65, 67, 68, 69

Table 2
Counts of convergence and loss range for each trial test at the 10-th horizon year.

10-th horizon year	Range of loss (kW)									
	124–122	122–120	120–118	118–116	116–114	114–112	112–110	110–108	108–106	106–104
Counts of convergence	3	2	4	6	5	11	10	7	2	0

can be calculated as the position of individuals gradually moves closer to *pbest* and *gbest*. The current position can be modified by:

$$V_{i,d}^{j+1} = K \times \left[V_{i,d}^{j} + c_1 \times rand(0,1) \times \left(Xbest_{i,d}^{j} - X_{i,d}^{j}\right) + c_2 \times rand(0,1)\left(Gbest^{j} - X_{i,d}^{j}\right)\right] \quad (20)$$

$$X_{i,d}^{j+1} = X_{i,d}^{j} + V_{i,d}^{j} \quad (21)$$

where

$$K = \frac{2}{|2 - c - \sqrt{c^2 - 4c}|}, \quad c = c_1 + c_2, c > 4$$

c_1, c_2 is the acceleration constant, in this paper, $c_1 = c_2 = 2.05$, $rand(0,1)$ the uniform random value with a range of [0,1], $X_{i,d}^{j}$ the dimension d of the position of particle i at iteration j, $V_{i,d}^{j}$ the dimension d of the velocity of particle i at iteration j, $Xbest_{i,d}^{j}$ the dimension

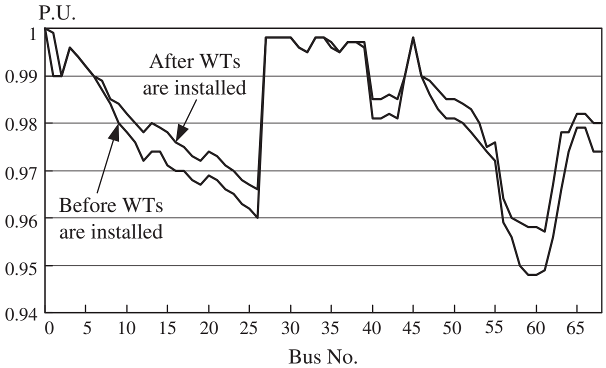

Fig. 5. Voltage profiles before and after the WTs are installed.

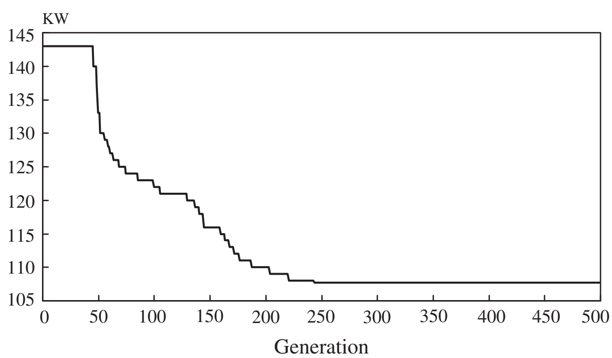

Fig. 6. The convergent characteristics of the proposed method.

Table 3
The conditions of three scenarios in this study.

	Electricity price (NT$/kW h)	Carbon price (NT$/ton)	Power generation (kW/unit)
Case-1	1.4–5	924	143.5
Case-2	2.6	0–2000	143.5
Case-3	2.6	924	100–200

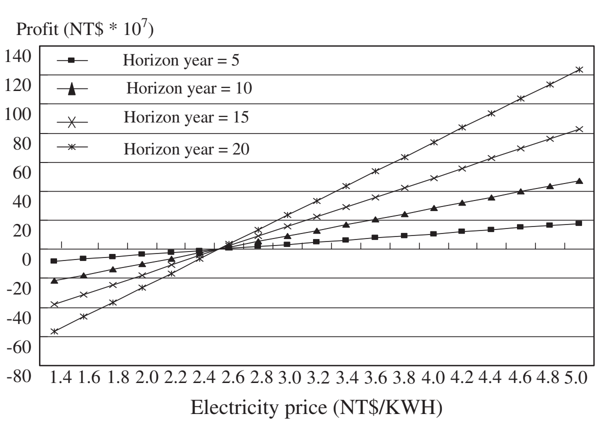

Fig. 7. The benefits of WTs installed in Case-1.

d of the own best position of particle i at iteration j, and $Gbest^j$ is the dimension d of the best particle in the swarm at iteration j.

3.3. Implementing the proposed algorithm

The proposed algorithm can be summarized in the following steps.

(a) Set the horizon year and calculate the load demand.

$$P_{di}^n = P_{di}(1+a)^n \tag{22}$$

$$Q_{di}^n = P_{di}^n \times \tan(\cos^{-1} PF) \tag{23}$$

P_{di}^n and Q_{di}^n are the real and reactive demand for the n-th horizon year. P_{di} is the real load demand for the current year. a is the load growth rate. PF is the power factor.

(b) Input system data, the line data, and bus data by considering the load growth.

(c) Calculate the total line losses using a load flow program with ECI.

(d) Randomly initialize 30 particles (WTs) with feasible positions in the system buses. The position vector for each particle is formed as follows:

$$X_i = \left[(P_{wind,1} \underset{WT_1}{Bus\_No.}), (P_{wind,2} \underset{WT_2}{Bus\_No.}), \ldots, (P_{wind,30} \underset{WT_{30}}{Bus\_No.}) \right] \tag{24}$$

(e) Calculate the value of the objective function for each particle.

(f) Compare each particle's objective value with the *Xbest*. If the objective value is smaller than *Xbest*, set the value as the current *Xbest*.

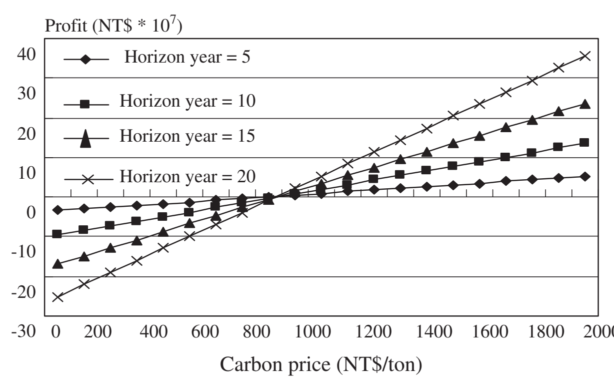

Fig. 8. The benefits of WTs installed in Case-2.

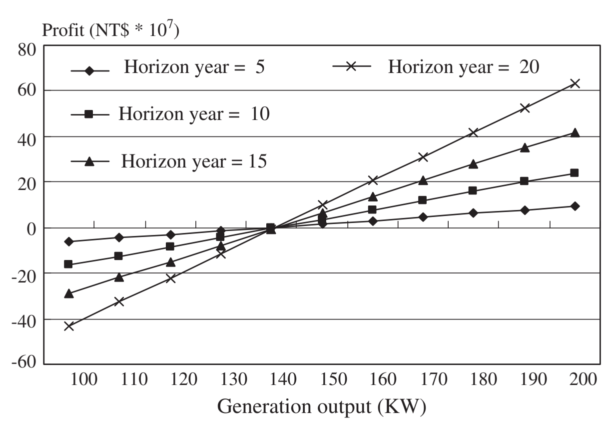

Fig. 9. The benefits of WTs installed in Case-3.

(g) Determine the best particle associated with the minimal *Xbest* of all particles, and set the value of this *Xbest* as the current *Gbest*.
(h) Update velocity and position vectors according to Eqs. (20) and (21) for each particle.
(i) The terminating condition is the maximal number of iterations. If the preset target is not yet attained, then go back to step (d) and repeat the step. In this paper, 500 generations is the set stop condition.
(j) Calculate the benefits with the different electricity prices, power generation, and carbon prices in the lifetime of WTs.

Fig. 3 shows the flowchart of the proposed methodology.

4. Case study

The proposed algorithm was applied to solve the 69-bus distribution system problem, as shown in Fig. 4 [23]. The total real and reactive power demand of the 69-bus system were 4408 kW and 3033 KVAR, respectively. The maximal power generation of WTs is set to 200 kW. The numerical computations were performed using Matlab on a PIV-2.6 GHz computer with 512 Mb RAM.

4.1. Optimal locations of WTs

The PSO parameter used in this paper was 30 particles, and 500 generations was set as the stopping criterion. The power output for each WT ranged from 100 kW to 200 kW, while all network bus voltage magnitudes remained within 0.95–1.05/unit. The power factor for each WT was 0.82. The load growth rate was 3% in the distribution system, and the horizon years were set at 5, 10, 15 and 20 years. Table 1 shows the summary of the simulation results. Due to the load growth, the number of WTs installed was 3, 8, 14 and 21 at 5, 10, 15 and 20 horizon years in order to meet the load growth and operational constraints. The total power output of WTs was 430.5 kW, 1148 kW, 2009 kW and 3013.5 kW at the different horizon years. The results suggested that the WTs installed significantly improved on the system losses. Because the executed characteristics of PSO might converge at different solutions for each test, the problem was solved 50 times by the proposed method. The best and worst system losses were found from the 50 trial tests. The counts of convergence and loss range at the 10-th horizon year are shown in Table 2. The best percentage of loss reduction ranged from 19.23% to 42.7% at the various horizon years. Fig. 5 shows the voltage profiles before and after the WTs were installed at the 10-th horizon year. As shown in Fig. 5, the voltage profile was clearly improved after the WTs were installed, almost satisfying the voltage limits along the feeder. Fig. 6 shows the convergent characteristics of the proposed method at the 10-th horizon year. The convergent generation was about the 260-th generation.

4.2. Benefits sensitivity analysis of WTs

The benefits sensitivity analysis of WTs contained three scenarios which varied with the electricity price, carbon price, and power generation after the WTs were installed. Table 3 shows the conditions of three scenarios in this study. In Case-1, the electricity price varied from NT$1.4/kW h to NT$5/kW h, if the carbon price and power generation of WTs were maintained at 924 NT$/ton and 143 kW/unit, respectively. Similarly, Case-2 and Case-3 varied with the carbon price and power generation of WTs. A lifetime of 20 years was assumed for the WTs installed.

Fig. 7 shows the benefits of WTs installed in Case-1. In this study, the return time of WTs was 20 years. Based on different horizon years, the benefits of WTs installed were evaluated based on different electricity prices. In Fig. 7, when the electricity price was about NT$2.6/kW h, the investment of WTs arrived at economical equilibrium. The benefits of the WT investment were directly proportional to the electricity price.

Fig. 8 shows the benefits analysis of WTs installed in Case-2. The largest positive contribution to the WTs' benefit was from the reduction in CO_2 charges. The investment in WTs arrived at economical equilibrium when the carbon prices were sold at NT$1000/ton in this case. When the carbon price was high, the benefits of the WT investment would increase.

Fig. 9 shows the benefits of WTs installed in Case-3. As seen, when the power generation for each WT was about 145 kW, the investment in WTs could arrive at economical equilibrium. When the power generation of WTs increased, the benefits of the WT investment were also higher.

5. Conclusion

This study successfully solved the WT allocation problem in distribution systems by combining load flow and PSO. To enhance the performance of the proposed algorithm, a load flow model with Equivalent Current Injection (ECI) was used to analyze the power flow of distribution systems. By considering electricity price and carbon price, the economical benefits of the installation of WTs were evaluated in three different scenarios. The effectiveness of the proposed algorithm was demonstrated and tested on the IEEE 69-bus distribution system. This study found that electricity price or carbon price is a key parameter in the development of WTs. Simulation results also showed that incorporating the WTs in the distribution system can reduce system losses, as well as improve the voltage profiles. It is noted that the tradeoff between investment cost and environmental policy can be clearly shown for future electricity and carbon markets.

The wind power generator and its production are still in the stages of rapid growth and development. It has been proved that the optimal location of WTs can improve system reliability, reduce losses, and improve voltage profiles [35]. Some government strategies, such as financial incentives, feed-in tariffs, export credit subsides, and purchasing rates, have been proposed to promote wind power technology in different countries. New WT installations seem to be a political compromise between consumer interest in lower electricity prices and producer interest in making profits. In a deregulated power system, each IPP may wish to decide the costs and benefits of WTs from different points of view [36]. There are unprecedented volatility and risk in the deregulated markets [37]. It is difficult to forecast the energy and emissions over a long-term horizon to satisfy all IPPs [38]. This study took the benefits and costs of WT allocation into account, and attempted to find a compromise between an IPP's investments and government policies. Any variations including electricity price, carbon price, and generation output of WTs will affect the long-term benefits for IPPs. The results of this study can provide risk management in future WT investment, and intensify competition among IPPs.

Acknowledgment

Financial support for this work by the National Science Council of ROC under contract number NSC101-2221-E-230-021 is gratefully appreciated.

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