Journal of King Saud University – Computer and Information Sciences (2012) **24**, 17–26

King Saud University

Journal of King Saud University – Computer and Information Sciences

www.ksu.edu.sa
www.sciencedirect.com

ORIGINAL ARTICLE

Using the Bees Algorithm to select the optimal speed parameters for wind turbine generators

A.A. Fahmy *

Cardiff University, School of Engineering, Manufacturing Engineering Centre, Queen's Buildings, The Parade, Cardiff CF24 3AA, UK

Received 23 May 2011; accepted 9 July 2011
Available online 7 November 2011

KEYWORDS

Optimization;
Wind turbine generator;
Capacity factor;
Bees Algorithm;
PSO;
Swarm intelligence

Abstract The Bees Algorithm is a recently developed optimization technique that mimics the foraging behavior of honey bees in nature. This study investigates the use of the Bees Algorithm for the selection of the optimal operating speed parameters for wind power units. Three speed parameters need to be optimized, namely, the rated, cut-in, and cut-off (furling) speed of the turbine. The aim of the optimization process is to maximize the yearly power yield and turbine usage time. The choice of the best parameters depends from the wind frequency distribution at the site of installation. Eleven locations on the coastal areas of Egypt were chosen as case studies. The well-known Particle Swarm Optimization was used as a control optimization algorithm. A popular classical approach based on the manual optimization of the sole rated speed was used as baseline for the comparison of results. The optimization of all the three speed parameters and the use of intelligent optimization techniques represent the novelties of this paper. The study showed that the Bees Algorithm outperformed the other two optimization methods. The proposed algorithm was able to find speed parameters that greatly enhanced the power yield, without compromising the usage time or significantly increasing the capital costs. The comparison between the standard manual optimization method and the two intelligent optimization techniques proved the superiority of the latter ones.

1. Introduction

Wind represents a clean, free, and renewable source of energy for the generation of electric power at utility-scale and stand-alone distributed level. Due to environmental concerns and economic costs associated to the production of energy from fossil and nuclear fuels, the use of wind-powered electric generators has grown rapidly in recent years.

Two main factors affect the economic profitability and competitively of wind turbines, namely, the capital cost, and capability to exploit the available wind resources.

The production of wind-generated electric power at a given site depends on different variables such as the mean wind speed

* Corresponding author. Tel.: +44 02920874173.
E-mail address: fahmyaa@cf.ac.uk.

Peer review under responsibility of King Saud University.
doi:10.1016/j.jksuci.2011.07.001

Production and hosting by Elsevier

at the site, and the speed characteristics of the wind turbine. The speed characteristics of a turbine are defined by three parameters, namely the cut-in (V_c), rated (V_r), and furling (V_f) wind speeds at the hub height. These speed parameters determine largely the cost, maximum yearly generated power, and capacity factor of the unit. The capacity factor measures the usage time of a generator, and is defined as the ratio between the average generated power over one year and the nominal (rated) power (Huang and Wan, 2009, 2008; Raju et al., 2004).

There are many different models of wind power units with the same kW ratings, each characterized by different speed parameters. Solutions that aim to maximize the power yield require turbines of high rated power (i.e. a high rated speed), and hence imply a high capital cost. Solutions that aim to maximize the capacity factor are much cheaper, but require the use of low rated power units which have limited capability to exploit the wind resources.

Since it is not possible to maximize simultaneously the power output and capacity factor of a turbine, a tradeoff between the two conflicting goals is necessary. The selection of the optimal speed parameters for a turbine generator represents a three-variable (V_c, V_r, V_f) multi-objective optimization problem. Jansamshetti and Rau (2001a,b, 1999a,b) focused on the maximization of the arithmetic product between the power output and the capacity factor, reducing thus the problem to a single-objective optimization task. They also set V_c and V_f to a fixed fraction of the value of V_r, and manually tuned V_r to solve the maximization problem. As the speed parameters are not linearly correlated, this method could find only sub-optimal solutions.

Due to the complex and non-linear relationship between the speed parameters and the product between the power output and capacity factor, the optimization task cannot be solved using a standard gradient-based search approach.

This paper investigates the use of the Bees Algorithm (Pham and Castellani, 2009) for the selection of the optimal turbine speed parameters for eleven case study sites. The Bees Algorithm is a recently developed intelligent search technique inspired by the foraging behavior of honey bees in nature. Various versions of the Bees Algorithm have been applied to different optimization problems, such as pattern classifier training (Pham et al., 2006), manufacturing cell formation (Pham et al., 2007a), mechanical design (Pham et al., 2007b), machine shop scheduling (Phamet al., 2007c), inverse kinematics modeling (Pham et al., 2008), and control system tuning (Pham et al., 2009). In this study, the performance of the Bees Algorithm will be compared to that of other two optimization techniques: the popular intelligent optimization method Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995), and the classical Turbine Selection Index method (Abdel-Hamid et al., 2009) based on the approach of Jansamshetti and Rau (2001a,b, 1999a,b).

The proposed approach is novel since it focuses on the independent optimization of all the three speed parameters. The use of automatic intelligent optimization techniques is also new in this field.

Section 2 illustrates the problem domain and the analytical models that relate the wind turbine parameters to the maximum power yield and capacity factor. Section 3 outlines the Bees Algorithm and PSO. Section 4 presents the experimental results. Eleven locations on the Egyptian coasts of the Red Sea and the Mediterranean were chosen as application case studies. The monthly mean-wind speeds of these eleven sites were taken from records collected by the Egyptian Meteorological Authority. Section 5 concludes the paper.

2. Mathematical model

Given a geographical site, the goal of this study is to identify a set of turbine speed parameters that guarantees high energy production at a high capacity factor. The wind speed yearly variation at a site is usually expressed via its hourly frequency distribution curve. This curve is built from in situ observations over the year.

There are several statistical probability density functions which can be used to describe the wind speed frequency distribution curve. The Weibull distribution (Gary, 2006) usually fits well observed meteorological patterns, and for this reason it is often used. The Weibull probability distribution function is specified by two parameters, the shape parameter k (dimensionless), and scale parameter c (m/s). Four methods for the estimation of k and c were reported in literature (Gary, 2006).

In this study, the most common analytical model describing the generation of electrical power P_e from wind energy is used (Gary, 2006; Powell, 1981). This is a very general model that describes any wind-powered electrical generator. The power P_e is assumed to vary according to the wind speed v and the Weibull parameter k as follows:

$$P_e = 0 \quad (v < V_c) \tag{1}$$

$$P_e = a + bv^k \quad (V_c \leqslant v \leqslant V_r) \tag{2}$$

$$P_e = P_{er} \quad (V_r < v \leqslant V_f) \tag{3}$$

$$P_e = 0 \quad (v > V_f) \tag{4}$$

$$a = \frac{P_{er} V_c^k}{(V_c^k - V_r^k)} \tag{5}$$

$$b = \frac{P_{er}}{(V_r^k - V_c^k)} \tag{6}$$

$$P_{e,av} = \int_0^\infty P_e f(v)\, dv \tag{7}$$

where V_c, V_r, V_f are respectively the cut-in, rated, and furling speed, P_{er} is the rated electrical power, $P_{e,av}$ is the average electrical power generated per hour, and $f(v)$ is the Weibull probability density function of the wind speed,

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} * e^{-\left(\frac{v}{c}\right)^k} \tag{8}$$

If the mean (μ_v) and variance (σ_v) of the wind speed frequency distribution are known, the Weibull parameters c and k can be calculated (Gary, 2006) as,

$$k = \left(\frac{\sigma_v}{v}\right)^{-1.086} \tag{9}$$

$$c = \frac{\mu_v}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{10}$$

where Γ is the gamma function. Substituting Eqs. (2) and (3) into Eq. (7):

$$P_{e,av} = \int_{V_c}^{V_r} (a + bv^k) f(v)\, dv + \int_{V_r}^{V_f} P_{er} f(v)\, dv \tag{11}$$

Eq. (11) requires the calculation of two integral terms, and can be solved best by making the change in variable:

$$x = \left(\frac{v}{c}\right)^k \tag{12}$$

hence:

$$dx = k \cdot \left(\frac{v}{c}\right)^{k-1} \cdot d\left(\frac{v}{c}\right) \tag{13}$$

$$f(v) = \left(\frac{k}{c}\right) \cdot \left(\frac{v}{c}\right)^{-1} \cdot x \cdot e^{-x} \tag{14}$$

The first integral term on the right-hand of Eq. (11) can now be re-written as follows:

$$\int f(v)\,dv = \int e^{-x}\,dx = -e^{-x},$$
$$\int v^k f(v)\,dv = \int c^k \left(\frac{v^k}{c^k}\right) f(v)\,dv = c^k \int xe^{-x}\,dx = -c^k(x+1)e^{-x} \tag{15}$$

After substituting Eqs. (12) and (15) into Eq. (11) and integrating, the average electrical power $P_{e,av}$ corresponds to:

$$P_{e,av} = P_{er}\left\{\frac{e^{-\left(\frac{V_c}{c}\right)^k} - e^{-\left(\frac{V_r}{c}\right)^k}}{\left(\frac{V_r}{c}\right)^k - \left(\frac{V_c}{c}\right)^k} - e^{-\left(\frac{V_f}{c}\right)^k}\right\} \tag{16}$$

$$P_{e,av} = 0.5\eta_o \rho A V_r^3 \left\{\frac{e^{-\left(\frac{V_c}{c}\right)^k} - e^{-\left(\frac{V_r}{c}\right)^k}}{\left(\frac{V_r}{c}\right)^k - \left(\frac{V_c}{c}\right)^k} - e^{-\left(\frac{V_f}{c}\right)^k}\right\} \tag{17}$$

Once the turbine parameters are determined, the rated power for a turbine can be calculated given the turbine blades area, tower elevation, average air density, and overall efficiency. The yearly (8760 h) energy production of a turbine generator is:

$$\text{Energy(KWH)} = P_{e,av} * \text{time} = (\text{CF}) * P_{er} * (8760) \tag{18}$$

The average electrical power $P_{e,av}$ is customarily normalized in order to express it as a function of the dimensionless variable V_r/C, and eliminate constant factors such as the air density ρ, over-all turbine efficiency η_o, and turbine blades area A (Jansamshetti and Rau, 2001a).

$$P_N = \frac{P_{e,av}}{0.5\eta_o \rho A c^3} = \left(\frac{V_r}{c}\right)^3 * CF \tag{19}$$

$$CF = \left\{\frac{e^{-\left(\frac{V_c}{c}\right)^k} - e^{-\left(\frac{V_r}{c}\right)^k}}{\left(\frac{V_r}{c}\right)^k - \left(\frac{V_c}{c}\right)^k} - e^{-\left(\frac{V_f}{c}\right)^k}\right\} \tag{20}$$

where CF is the capacity factor (Albadi and El-Saadany, 2009). Fig. 1 shows the variation of the normalized power P_N and capacity factor CF versus V_r/C, for arbitrarily fixed values of V_c and V_f.

If the rated speed Vr is chosen to maximize the output power from the site ($Pmax$ in the figure) (Huang and Wan, 2009, 2008; Raju et al., 2004; Jansamshetti and Rau, 2001a,b, 1999a,b), turbines of large rated power P_{er} (i.e. large V_r) will be required. At the same time, the capacity factor CF will be low. This choice implies high costs for the generator, transformer, switches, circuit breakers and distribution lines. At the same time, the associated low CF means that the equipment will not be used for long times over the year.

If V_r is chosen to maximize the maximum capacity factor ($CFmax$ in the figure), the equipment costs will be reduced whilst the time usage of the equipment is maximized. This method is considered ideal in terms of capital cost. However, a low rated speed leads to a low rated power, and this reduces the actual benefit from the wind power available.

A trade-off between the P_{er} and CF requirements is to consider the maximization of their product that yields the best compromise solution, while the search algorithm sweep the whole multiplication domain results. As the visual example of Fig. 1 suggests, the speed parameters that maximize the product $P_N \cdot CF$ fall between the two values that maximize P_N and CF (Jansamshetti and Rau, 2001a; Albadi and El-Saadany, 2009). Often, the cut-in and cut-off speeds are fixed to a fraction of the rated speed, that is, $V_c = \delta V_r$ and

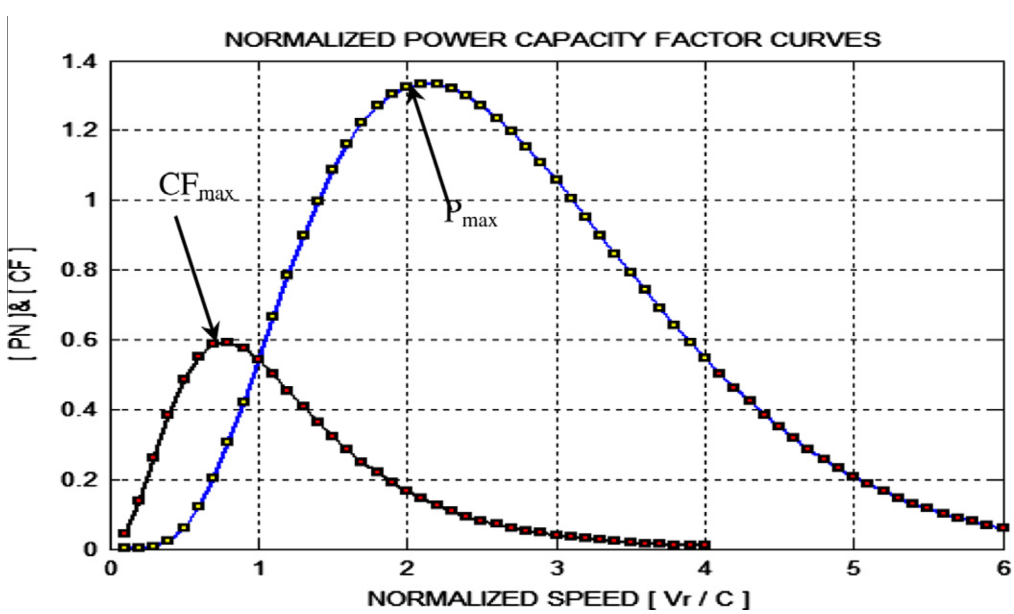

Figure 1 Normalized power and capacity factor curves at constant V_c and V_f.

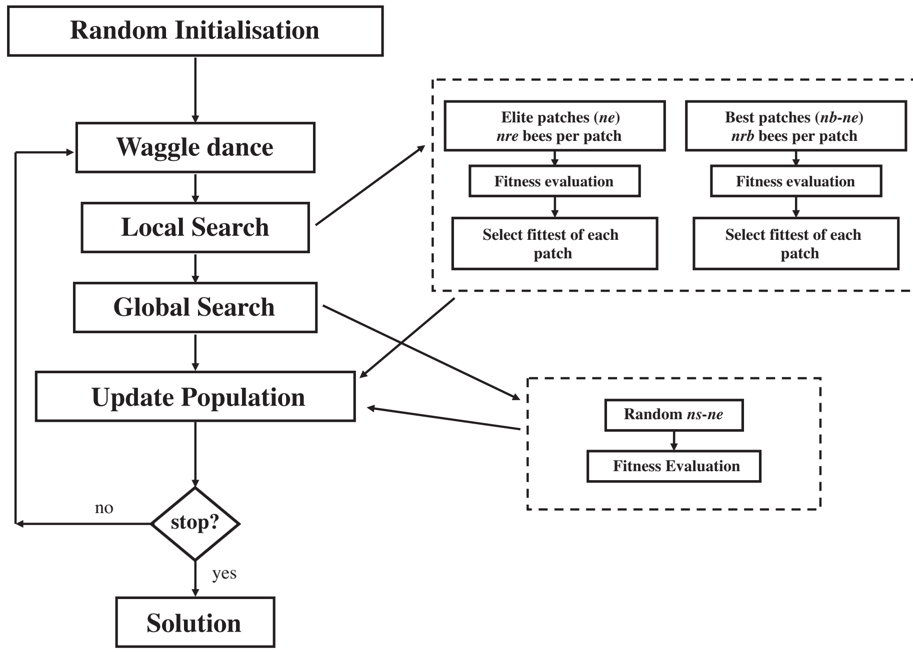

Figure 2 Flowchart of the Bees Algorithm.

$V_f = \gamma V_r$, where $\delta < 1$ and $\gamma > 1$ (Jansamshetti and Rau, 2001a). The optimal trade-off between P_N and CF is then obtained tuning manually V_r. This technique is not optimal, since changes in V_c and V_f result often in significant changes of the average generated power $P_{e,av}$ (Billinton and Chen, 1999). In this work, given an arbitrary site described by the Weibull parameters c and k, the whole search space of the three speed parameters V_c, V_r, V_f will be searched in order to maximize the product $PN \cdot CF$. This task entails the solution of the function optimization problem described by the following equation:

$$P_N * CF = \left(\frac{V_r}{c}\right)^3 * (CF)^2$$

$$= \left(\frac{V_r}{c}\right)^3 * \left\{ \frac{e^{-\left(\frac{V_c}{c}\right)^k} - e^{-\left(\frac{V_r}{c}\right)^k}}{\left(\frac{V_r}{c}\right)^k - \left(\frac{V_c}{c}\right)^k} - e^{-\left(\frac{V_f}{c}\right)^k} \right\}^2 \tag{21}$$

3. Intelligent optimization techniques

Swarm intelligence (SI) (Bonabeau et al., 1999) is a fast-growing multi-disciplinary field which encompasses several iterative optimization procedures based on the collective search capabilities of large ensembles of simple interacting agents. Thanks to their global population-based optimization approach, SI algorithms are particularly suitable to search complex and multimodal surfaces such as the one generated by Eq. (21). This study investigates the application of the Bees Algorithm (Pham and Castellani, 2009) to the wind turbine generator optimization problem. The state-of-the-art Particle Swarm Optimization (PSO) Kennedy and J., Eberhart, 1995) procedure is used as a control algorithm. In both cases, the candidate solutions are encoded via the three-dimensional vector $x = \{x_1, x_2, x_3\}$ representing the three operating speeds V_c, V_r, and V_f.

Table 1 Weibull parameters for selected sites.

Sites	Parameter c	Parameter k
Sallum	4.88	1.46
Sidi Barrani	4.27	1.47
Dekhaila	4.53	1.4
Alexandria	4.36	1.49
Balteam	3.62	2.46
Damiett	3.12	2.49
Port Said	4.77	1.71
El Arish	4.56	2.39
Zafarana	8.23	2.7
Abu Darag	8.23	3.0
Hurghada	6.6	2.03

Table 2 Parameters of Bees Algorithm.

Parameter	Value
No. of scout bees (n)	20
No. of selected bees (m)	5
No. of elite bees (e)	1
Size of neighborhood (ngh)	6.0
No of sites around selected bees (nsp)	10
No of sites around eleite bees (nep)	30

Table 3 Parameters of PSO Algorithm.

Parameter	Value
No. of particles (m)	20
Max. velocity (u)	0.01
Social neighborhood of an agent (k)	10
c_1	2.0
c_2	2.0
$w_{\max}$	0.9
$w_{\min}$	0.4

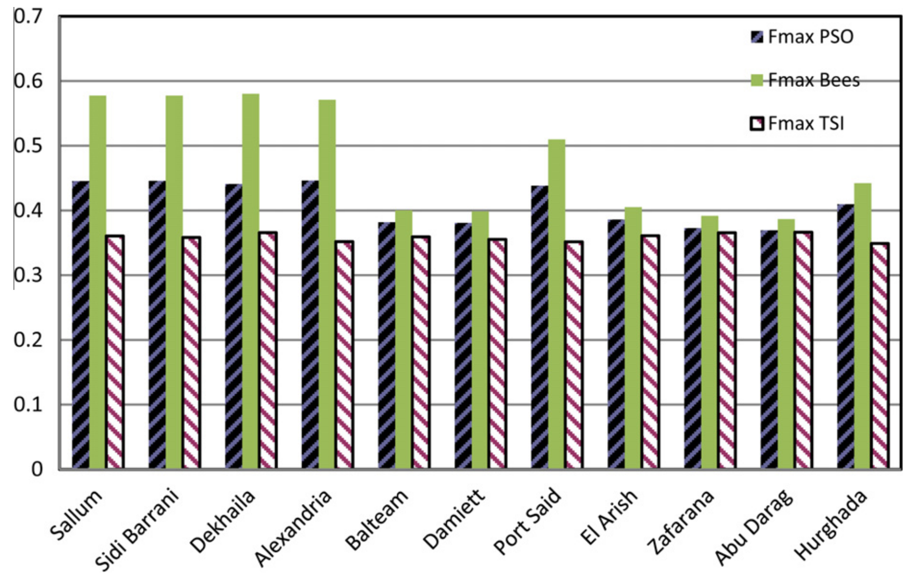

Figure 3 Results for the objective function.

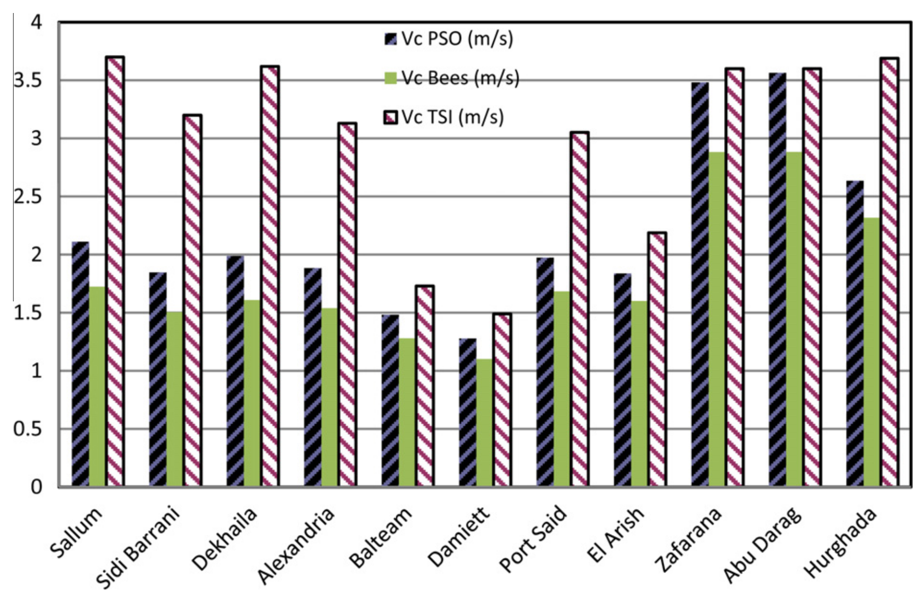

Figure 4 Results for the cut-in speed.

3.1. The Bees Algorithm

The Bees Algorithm (Pham and Castellani, 2009) is a recently developed optimization method that mimics the foraging behavior of honey bees in nature. The flowchart of the Bees Algorithm is shown in Fig. 2.

At the beginning, n solutions are randomly scattered on the search space. This phase mimics the exploration process carried out by scout bees in the fields surrounding the hive. The algorithm enters then the main loop.

In the main loop, the fitness of the solutions is assessed and the population is ranked according to the evaluation result. Local search is performed in the proximity of the best (i.e. fittest) $m \leqslant n$ solutions, sampling more thoroughly the area around the $e \leqslant m$ top performers. That is, *nep* solutions are generated in the neighborhood of the elite e individuals, and $nsp \leqslant nep$ solutions are generated in the neighborhood of the remaining m–e solutions. This differential allocation of local sampling opportunities simulates the recruitment of forager bees by those scouts that found rich food sources. Via a complex ritual known as the ''waggle dance'' (Seeley, 1996), the scout bees recruit a number of foragers that is proportional to the richness of the visited food source.

In the local search procedure, new solutions are randomly generated with uniform probability within a neighborhood of the selected solution. The size of the neighborhood is a system parameter. For each neighborhood, the best solution is kept.

The remaining n–m individuals of the population are randomly generated. This process mimics the ongoing scouting carried out by biological bees for new food sources. The main

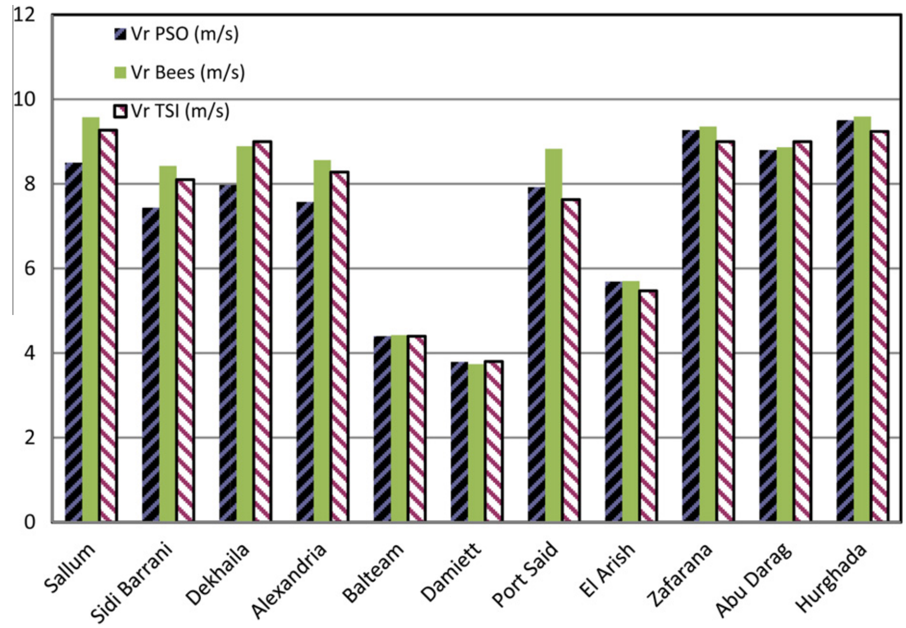

Figure 5 Results for the rated speed.

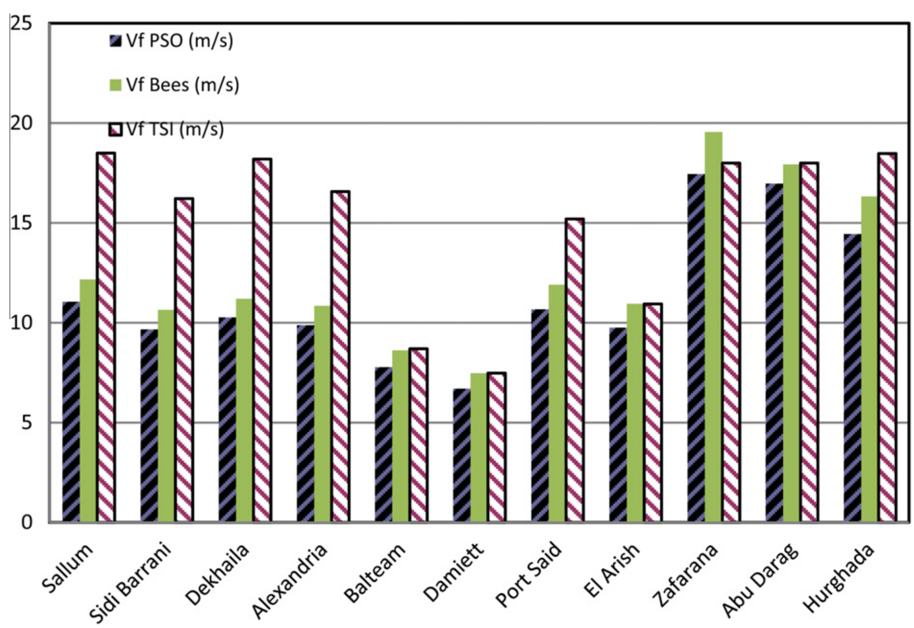

Figure 6 Results for the cut-off speed.

cycle is repeated until the stopping condition is met. An in-depth description and experimental analysis of the Bees Algorithm can be found in Pham and Castellani (2009).

3.2. Particle Swarm Optimization

Particle Swarm Optimization (Kennedy and Eberhart, 1995) is one of the first and best known SI algorithms. In this paper, the standard procedure formulated by Kennedy and Eberhart (1995) is used.

The position x (i.e. the encoding) of each agent is updated as follows:

$$\Delta x_i(t) = v_i(t+1) \tag{22}$$

where t is the tth PSO cycle and $v = \{v_1, v_2, v_3\}$ is the velocity of the agent. The velocity is updated according to the following formula:

$$\begin{aligned} &p_i(t) = random_1 \cdot [pbest(t)_i - x(t)_i] \\ &s_i(t) = random_2 \cdot [gbest(t)_i - x(t)_i] \\ &v_i(t+1) = w(t) \cdot v(t)_i + c_1 \cdot p_i(t) + c_2 \cdot s_i(t) \\ &i = 1, 2, 3 \end{aligned} \tag{23}$$

where c_1 and c_2 are system parameters, and $random_1$ and $random_2$ are random numbers drawn with uniform probability in

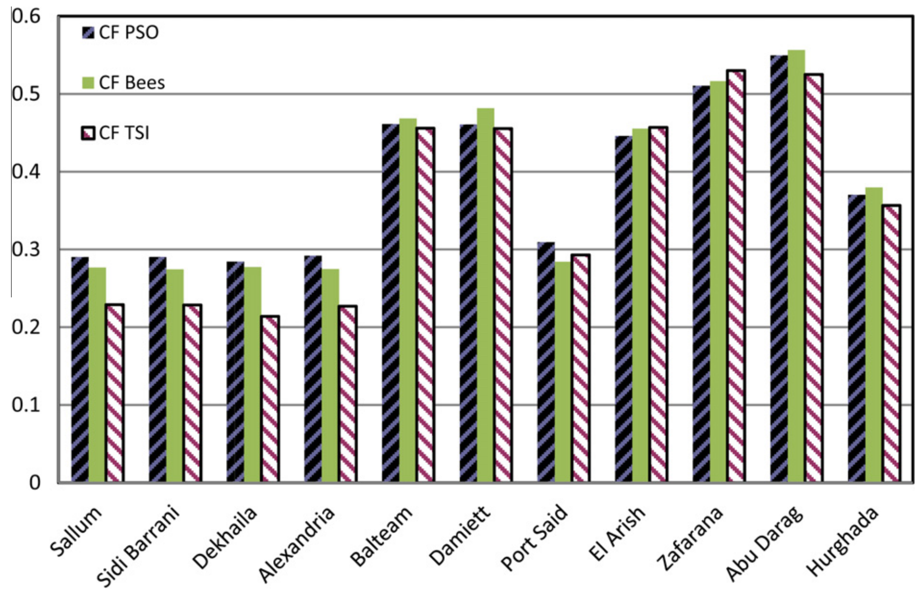

Figure 7 Results for the capacity factor.

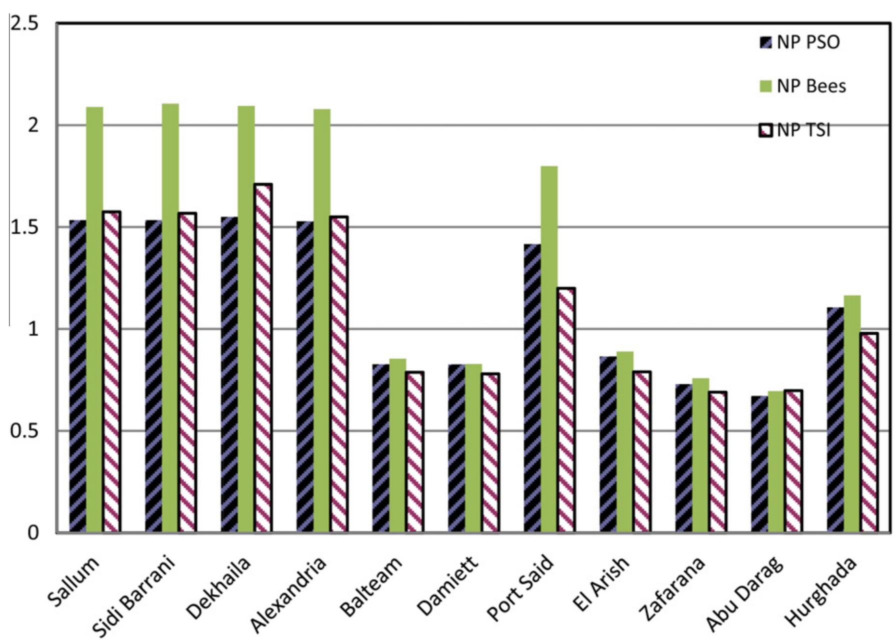

Figure 8 Results for the normalized power.

the interval $(0,1)$. $pbest(t)$ is the best position (maximum fitness) visited so far by the particle and represent the memory of the agent of its past actions. $gbest(t)$ is the best position visited so far by the neighbors of the particle, and represents the social interaction amongst agents. The third component $v(t)_i$ represents the momentum of the particle, that is, the persistence of each agent in following a direction. The weight $w(t)$ is decayed according to the following formula:

$$w(t) = w_{\max} - \frac{w_{\max} - w_{\min}}{T} \cdot t \tag{24}$$

where $w_{\max}$ and $w_{\min}$ are system parameters, and T is the duration of the PSO search.

In this study, the components of the velocity vector were bounded within the interval $[-v_i^{\max}, v_i^{\max}]$, where

$$v_i^{\max} = u \cdot \frac{\max_i - \min_i}{2} \tag{25}$$

u is a system parameter, and $\max_i$ and $\min_i$ are the constraints on the variable x_i.

4. Case study of wind energy in Egypt

Egypt started investing on wind farms since the late seventies. Following detailed surveys of wind patterns, the most

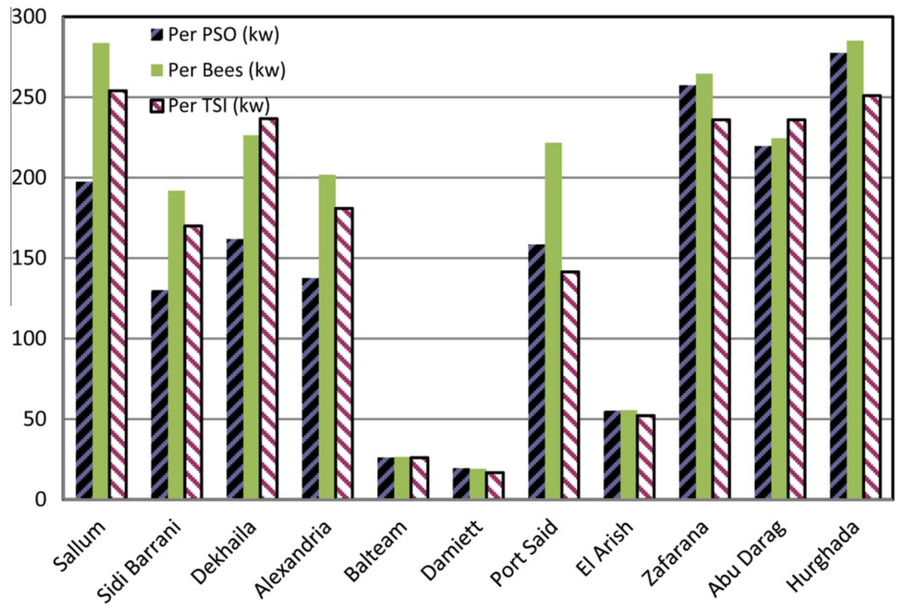

Figure 9 Results for the rated electrical power.

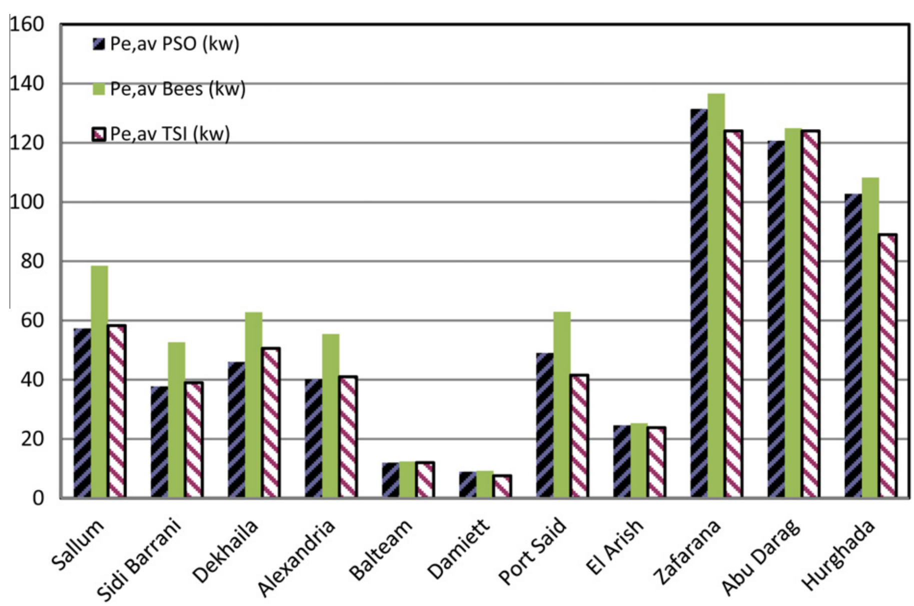

Figure 10 Results for the average electrical power ($P_{e,av}$).

promising regions for eolic power generation were located along the Mediterranean and Red Sea coasts. In these regions, wind speed data were collected in many sites (Shata and Hanitsch, 2006a). The measurements were taken in open areas where the sensors were located at a height of 10m above ground level. The data used in this study were provided by the Egyptian Meteorological Authority, and concern eleven locations monitored for a period of more than 10 years (Shata and Hanitsch, 2006b). In order to identify the Weibull parameters, the Wind Atlas Analysis Application Program (WASP) was used to predict the annual mean frequency distribution for the sites (Shata and Hanitsch, 2006b). Table 1 lists the Weibull parameters calculated for the 11 sites considered in this study (Shata and Hanitsch, 2006a,b).

For each of the eleven sites of Table 1, the Bees Algorithm and PSO were used to find those speed parameters V_c, V_r, and V_f that maximize Eq. (21), given the constraint $V_c < V_r < V_f$. The three variables are defined within the intervals:

$$0.2c \leqslant V_c < c \tag{26}$$

$$0.8c \leqslant V_r \leqslant 3.0c \tag{27}$$

$$2.5c < V_f < 5.0c \tag{28}$$

These intervals represent the variation domain of the parameters. The settings of the learning parameters of the Bees Algorithm and PSO are listed in Tables 2 and 3 respectively. The two optimization methods were run using Visula C++ for

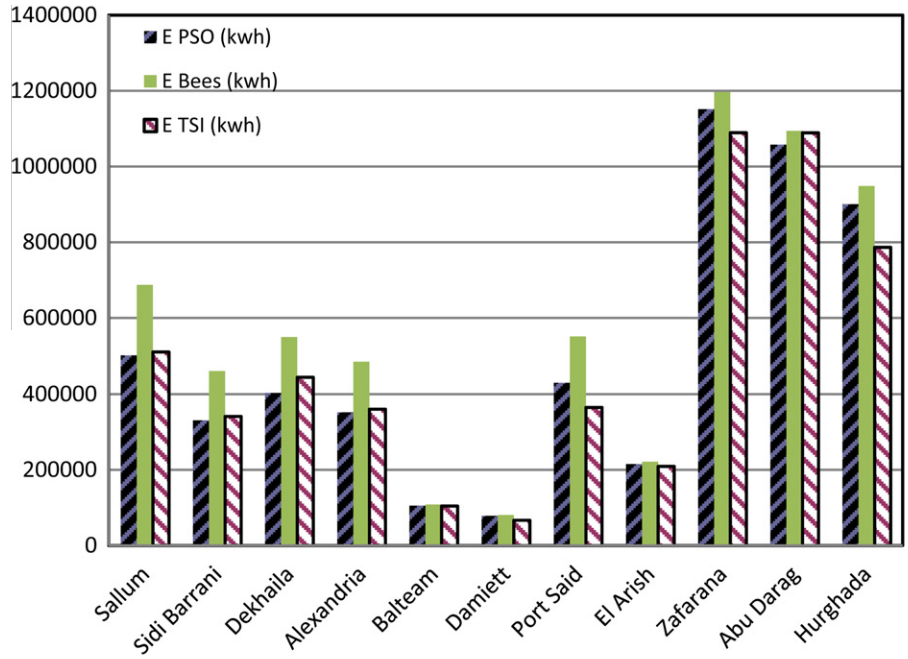

Figure 11 Results for the total energy generated in one year.

at least 100 learning cycles. The stopping criterion was either the stagnation of the evolution process, or the completion of 200,000 objective function evaluations. The search was considered to stagnate if the difference between the fitness of the best solutions of two consecutive learning cycles was less than 0.01, meaning that the algorithm succeeded in reaching the best compromise global maximum and no further improvement is possible.

The results obtained by Abdel-Hamid et al. (2009) using the single-input–single-output model of Jansamshetti and Rau (2001a,b, 1999a,b) were used as a baseline to assess the success of the proposed intelligent search approach. Abdel-Hamid and his colleagues used the Turbine Selection Index method (TSI) to determine the optimal V_r, while V_c and V_f were calculated as a percentage of V_r.

Figs. 3–6 show respectively the $P_N \cdot CF$ optima and corresponding V_c, V_r, and V_f settings found by the three algorithms under comparison for the eleven sites listed in Table 1. In the case of the two stochastic techniques, the plots report the average of 50 independent optimization trials. The separate values of CF and P_N are presented respectively in Figs. 7–11 show the corresponding rated electrical power, average electrical power ($P_{e,av}$), and yearly generated electrical energy (Eq. (20)) obtained.

Concerning the maximization of the objective function, the Bees Algorithm clearly outperformed the other methods. PSO also performed well, although in many cases inferior to the Bees Algorithm. As Figs. 7 and 8 show, the differences in $P_N \cdot CF$ results seem to be determined mainly by the normalized power yields P_N obtained by the three algorithms. The results concerning the capacity factor CF are less consistent, even though also in this case the two intelligent techniques gave often better or comparable results.

In most cases, the Bees Algorithm and PSO obtained much higher power yields than TSI without significantly increasing the rated speed (Fig. 5) of the turbine, and hence its rated power (Fig. 9). This is a very important result, since the capital cost associated to the installation of a wind power unit is directly related to its rated power. Taking for example the locality of Sidi Barrani, there are only small differences in the V_r and P_{er} values obtained using the Bees Algorithm and TSI, while PSO selected a significantly lower P_{er}. However, by selecting much smaller V_c and V_f values, the Bees Algorithm and PSO obtained much higher power yields than the TSI method.

In general, the results proved that fixing V_c and V_f to a constant ratio of V_r can only lead to sub-optimal solutions. Being free to search the space of all the three parameters independently, the Bees Algorithm and PSO obtained consistently better solutions than the TSI method. The results proved also the ability of the two swarm optimization methods, and in particular of the Bees Algorithm, to search effectively the complex three-dimensional space of the speed parameters, and produce highly effective solutions.

5. Conclusion

To optimize the speed parameters of the turbines for the wind characteristics of a site is an important problem in the design of wind farms. If the rated speed is chosen too low, the units have only a limited capability of exploiting the available energy during periods of high wind activity. If the generator rated speed is chosen too high, the turbines will seldom operate at low wind speeds, and the capital cost will be high. The cut-in and cut-off speeds have a less straightforward influence on the power yield and capacity factor of the units.

This paper presents a novel approach for the selection of the optimal speed operating parameters for wind turbines. The proposed technique employs the recently developed Bees Algorithm to maximize the product between the normalized hourly power yield and the capacity factor for a given site. The proposed approach aims to optimize simultaneously all the three speed parameters. Eleven locations on coastal areas of Egypt were used as case studies.

Compared to the classical TSI approach based on manual optimization of the sole rated speed, the proposed method achieved superior results in terms of power yield at often comparable capacity factors, rate speed, and rated power.

The effectiveness of the Bees Algorithm as an intelligent optimization method was proved testing the state-of-the-art PSO algorithm on the same optimization task. The Bees Algorithm outperformed PSO in nearly all the case studies.

The Bees Algorithm proved to be particularly capable of solving the complex non-linear relationship that links the three speed parameters to the objective function $P_N \cdot CF$. Given that all the three algorithms produced similar figures for the optimal V_r value, the reason for the superior results obtained by the Bees Algorithm was in the better choices of V_c and V_f. As a result, the Bees Algorithm increased the power yield of the wind turbines without significantly increasing their capital cost (V_r and P_{er}).

Further studies should investigate the opportunity to express the task as a multi-objective optimization problem that extend to include more information about the turbine loading profile, in order to produce the complete set of P_N and CF trade-offs from the Pareto set of solutions tasking in consideration the load profile as well.

Acknowledgments

The research described in this paper was supported by the EC FP6 Innovative Production Machines and Systems (I*PROMS) Network of Excellence. The author thanks A. Simonnet and A. Dubois from the Institute of Automotive and Transport Engineering (ISAT) in Nevers (France) for their help in the collection of the experimental data during their stay at the Cardiff School of Engineering on an Industrial Traineeship.

References

Abdel-Hamid, R.H., Adma, M.A.A., Fahmy, A.A., Samed, S.F.A., 2009. Optimization of wind farm power generation using new unit matching technique. In: 7th IEEE International Conference on Industrial Informatics. Cardiff, UK, June 24–26, INDIN.

Albadi, M.H., El-Saadany, E.F., 2009. Wind turbines capacity factor modeling – a novel approach. IEEE Transactions on Power Systems 24 (3).

Billinton, R., Chen, H., 1999. Determination of the optimum site-matching wind turbine using risk-based capacity benefit factors. IEEE Proceedings of Generation, Transmission, and Distribution 146, 96–100.

Bonabeau, E., Dorigo, M., Theraulaz, G., 1999. Swarm Intelligence: From Natural to Artificial Systems. Oxford University Press, New York.

Gary, L.J., 2006. Wind Energy Systems, Electronic Edition. Manhattan, KS.

Huang, S.J., Wan, H.H., 2008. A study on generator capacity for wind turbines under various tower heights and rated wind speeds using Weibull distribution. IEEE Transactions on Energy Conversion 23 (2).

Huang, S.J., Wan, H.H., 2009. Enhancement of matching turbine generators with regime using capacity factor curves strategy. IEEE Transactions on Energy Conversion 24 (2).

Jansamshetti, S.H., Rau, V.G., 1999a. Site matching of wind turbine generators: a case study. IEEE Transactions on Energy Conservation 14 (4).

Jansamshetti, S.H., Rau, V.G., 1999b. Height extrapolation of capacity factors for wind turbine generators. IEEE Power Engineering Review 19 (6).

Jansamshetti, S.H., Rau, V.G., 2001a. Normalized power curves as a tool for identification of optimum wind turbine generator parameters. IEEE Transactions on Energy Conservation 16 (3).

Jansamshetti, S.H., Rau, V.G., 2001b. Optimum siting of wind turbine generators. IEEE Transactions on Energy Conservation 16 (1).

Kennedy, J., Eberhart, R., 1995. Particle swarm optimization. In: Proceedings of 1995 IEEE International Conference on Neural Networks, vol. 4. Perth, Australia, pp. 1942–1948.

Pham, D.T., Castellani, M., 2009. The Bees Algorithm – modelling foraging behaviour to solve continuous optimization problems. Proc. ImechE, Part C 223 (12), 2919–2938.

Pham, D.T., Soroka, A.J., Ghanbarzadeh, A., Koc, E., Otri, S., Packianather, M., 2006. Optimising neural networks for identification of wood defects using the Bees Algorithm. In: Proceedings of the IEEE International Conference on Industrial Informatics. Singapore, pp. 1346–1351.

Pham, D.T., Afify, A.A., Koç, E., 2007a. Manufacturing cell formation using the Bees Algorithm. In: Proceedings of the Third Virtual International Conference on Innovative Production Machines and Systems, 2–13 July. Whittles (Dunbeath), pp. 523–528.

Pham, D.T., Castellani, M., Ghanbarzadeh, A., 2007b. Preliminary design using the Bees Algorithm. In: Proceedings of the 8th International Conference on Laser Metrology, CMM and Machine Tool Performance (LAMDAMAP) Cardiff. Euspen, UK, pp. 420–429.

Pham, D.T., Koc, E., Lee, J.Y., Phrueksanant, J., 2007c. Using the Bees Algorithm to schedule jobs for a machine. In: Proceedings of the 8th International Conference on Laser Metrology, CMM and Machine Tool Performance (LAMDAMAP) Cardiff. Euspen, UK, pp. 430–439.

Pham, D.T., Castellani, M., Fahmy, A.A., 2008; Learning the inverse kinematics of a robot manipulator using the Bees Algorithm. In: Proceedings of the 6th IEEE International Conference on Industrial Informatics (INDIN 2008). pp. 493–498.

Pham, D.T., Haj Darwish, A., Eldukhri, E.E., 2009. Optimization of a fuzzy logic controller using the Bees Algorithm. International Journal of Computer Aided Engineering and Technology 1, 250–264.

Powell, W.R., 1981. An analytical expression for the average output power of a wind machine. Solar Energy 26.

Raju, A.B., Fernandes, B.G., Chatterjee, K., 2004. Estimation of optimum wind turbine generator speed parameters. IEEE Power Engineering Society General Meeting 2.

Seeley, T.D., 1996. The Wisdom of the Hive: The Social Physiology of Honey Bee Colonies. Harvard University Press, Cambridge, Massachusetts.

Shata, A.S.A., Hanitsch, R., 2006a. Evaluation of wind energy potential and electricity generation on the coast of Mediterranean Sea in Egypt. Renewable Energy 31.

Shata, A.S.A., Hanitsch, R., 2006b. The potential of electricity generation on the east coast of Red Sea in Egypt. Renewable Energy 31 (13).