Artificial bee colony algorithm applied to optimal power flow solution incorporating stochastic wind power

Vian H. Ahgajan¹, Yasir G. Rashid², Firas M. Tuaimah³

¹²Department of Electronic Engineering, College of Engineering, University of Diyala, 32001 Diyala, Iraq
³Department of Electrical Engineering, College of Engineering, University of Baghdad, Baghdad, Iraq

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ABSTRACT

This paper focuses on the artificial bee colony (ABC) algorithm, which is a nonlinear optimization problem, is proposed to find the optimal power flow (OPF). To solve this problem, we will apply the ABC algorithm to a power system incorporating wind power. The proposed approach is applied on a standard IEEE-30 system with wind farms located on different buses and with different penetration levels to show the impact of wind farms on the system in order to obtain the optimal settings of control variables of the OPF problem. Based on technical results obtained, the ABC algorithm is shown to achieve a lower cost and losses than the other methods applied, while incorporating wind power into the system, high performance would be gained.

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Corresponding Author:

Yasir G. Rashid
Department of Electronic Engineering
College of Engineering, University of Diyala
Baqubah, Diyala, Iraq
Email: yasserghazee_enge@uodiya.edu.iq

1. INTRODUCTION

The majority of the world's fossil-fuel power generation operations use coal and natural gas to generate electricity, which is one of the most expensive commodities used to generate electric power. Polluting emissions from electricity generation based on the combustion of fossil fuels account for a sizable portion of global greenhouse gas emissions [1], [2]. As a result of economic and environmental reasons, workers in the field of electric energy were encouraged to increase and develop renewable energy. The electrical power control are experiencing noteworthy changes due to an increase in wind energy penetration level, causing unused challenges to system operation and planning [3], [4]. Therefore, the operators of power systems both in the planning and operating stage are very interested in optimal power flow (OPF) [5]. The main objective of an optimal power flow methodology is to find the ideal working of a power system by optimizing a specific objective whereas fulfilling certain indicated physical and security limitations [6], [7].

In recent years, the rapid development of computational intelligence have motivated researchers in the field of optimization algorithms to resolve various complex optimization cases such as particle swarm optimization algorithm (PSO) [8], [9], improved colliding bodies optimization method [10], imperialist competitive method [11], black-hole-based optimization technique [12], differential evolutionary technique [13], hybrid algorithm of PSO and GSA algorithms [14], gravitational search method (GSM) [15], [16], improved PSO algorithm [17], biogeography-based optimization technique [18], chaotic self-adaptive differential harmony search method [19], grey wolf optimizer [20], fuzzy-based hybrid PSO algorithm [21], differential search technique [22], multiphase search optimization technique [23], harmony search technique
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2. OPF PROBLEM FORMULATION

The solution to the OPF problem involves the optimization of objective function and obtaining the optimal settings of the power system control variables. The formal OPF problem can be written as [31]:

\[ \text{Min. } F(x, u) \]  \hspace{1cm} (1)

Subject to

\[ g(x, u) = 0 \]  \hspace{1cm} (2)

\[ h(x, u) \leq 0 \]  \hspace{1cm} (3)

Where \( F \) refers to the target (objective) function to be minimized, \( x \) and \( u \) are state and control variables respectively. The state vector \( x \) including:

- i) \( P_{G1} \), generating power at swing (slack) bus,
- ii) \( Q_{G} \), reactive generating power outputs,
- iii) \( V_{L} \), load bus voltage.

\( x \) can be written as:

\[ x^T = \left[ P_{G1}, Q_{G}, \ldots, Q_{G_{N_G}}, S1, \ldots, S_{N_{TL}}, V_{L1}, \ldots, V_{L_{NL}} \right] \]  \hspace{1cm} (4)

Where \( N_G \), \( N_L \), \( N_{TL} \) and \( N_{NL} \) are the number of generator buses, number of load buses, transmission lines and number of transmission line loading, respectively.

The control vector \( u \) including:

- i) \( P_{G} \), generator active power outputs,
- ii) \( V_{G} \), generator voltages,
- iii) \( Q_{C} \), shunt VAR compensations,
- iv) \( T \), transformer tap settings.

\( u \) can be written as:

\[ u^T = \left[ P_{G2}, \ldots, P_{G_{N_C}}, V_{G1}, \ldots, V_{G_{N_G}}, Q_{C1}, \ldots, Q_{C_{N_C}}, T_1, \ldots, T_{N_T} \right] \]  \hspace{1cm} (5)

Where \( N_C \) and \( N_T \) are the shunt VAR compensators output and the transformers regulated number, respectively [31].

2.1. OPF objective functions

Two different objective functions are chosen in the current paper. The 1\textsuperscript{st} is the economic objective whereas the 2\textsuperscript{nd} is the technical objective.

2.1.1. Economic objective

The main objective of the optimization problem is minimizing the operating costs in the wind-thermal power system.

a. Cost model of thermal power generators

Consider \( f_i \) as a generator fuel cost, given as in (6) [25, 32]:

\[ f_1 = \sum_{i=1}^{N_G} \left( a_i + b_i P_i + c_i P_i^2 \right) \text{ ($/hr)} \]  \hspace{1cm} (6)

Where \( a_i \), \( b_i \), \( c_i \) cost coefficients of fuel generators \( i\textsuperscript{th} \), \( N \) number of generation units, \( P_i \) active power generation of generators \( i\textsuperscript{th} \).

b. Cost model of wind power turbines

The goal of the current paper's optimization problem is to minimize the overestimated and underestimated costs of wind energy caused by wind speed uncertainty. According to:

\[ f_2 = \sum_{j=1}^{m} WPCost_{ue,j} + WPCost_{dir,j} + WPCost_{oe,j} \]  \hspace{1cm} (7)
Where $WP_{Cost_{ue,j}}$ is underestimation scaled average cost for wind power in $$/MW h$, $WP_{Cost_{dir,j}}$ is directly cost output wind power and $WP_{Cost_{oe,j}}$ is overestimation scaled average cost for wind power in MW. $WP_{Cost_{dir}}$ be written as:

$$WP_{Cost_{dir}} = \sum_{j=1}^{m}(w_j \times q_j)$$

Where $w_j$ is active power generated by $j_{th}$ wind turbine and $q_i$ is direct cost coefficient.

$$WP_{Cost_{oe, j}} = \sum_{j=1}^{m}(qC_{rwj} \times E(Y_{oe,j}))$$

Where $w_j$ is active power generated by $j_{th}$ wind turbine and $q_j$ is direct cost coefficient.

$$E(Y_{(oe, j)})$$

$$E(Y_{(ue, j)})$$

Where $C_{pwj}$ and $C_{rwj}$ are the overestimation and underestimation cost coefficient of $j_{th}$ wind generator in $$/MW h respectively. $E(Y_{oe, j})$ and $E(Y_{ue, j})$ are the overestimation and underestimation anticipated value of wind power for $j_{th}$ wind turbine. $k_j$ and $c_j$ are a shape factor and a scale of the $j_{th}$ wind generator respectively estimating of wind speed in the Weibull probability density function (pdf). $v_{in}, v_{out}, v_{r}$ are cut-in, cut-out and rated wind speed respectively. $v_1 = v_{in} + (v_{r} - v_{in}) \frac{w_1}{w_r}$ is an intermediary parameter in [6]. Minimize the total production cost in wind-thermal power system can be expressed as [33]:

$$\text{Minimize } C = f_1 + f_2$$

2.1.2. Technical objective

In this paper, two objective functions are considered for the technical category. First, minimize the total active power losses which can be expressed as:

$$\text{PL} = \sum_{k=1}^{n} G_k \left( V_i^2 + V_j^2 \sin(\delta_i - \delta_j) \right)$$

Where $m$ is the total number of lines in the system, $G_k$ is the conductance of the $k_{th}$ line, $V_i$ and $V_j$ are the voltage magnitude at bus $j$ and bus $i$ respectively, $\delta_i$ and $\delta_j$ are the voltage phase angle at bus $j$ and $i$ respectively [34]. Second, minimize the voltage deviation (VD) of all load buses to improve the voltage profile on load buses. The voltage deviation given by (15) [35]:

$$\Delta V = \sum_{k=1}^{Npq} |V_K - V_{K^{des}}|$$

3. OVERVIEW ON ARTIFICIAL BEE COLONY ALGORITHM

In 2005, Dervis Karaboga proposed a new optimization technique that is the artificial bee colony (ABC) algorithm. The ABC algorithm has been shaped by closely watching the exercises and actions of genuine bees while they were looking for nectar assets and sharing the sum of the assets with other colony
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The colony of artificial bees consists of three main groups, which are the employed bees, onlooker bees and scout bees. This breed of bee features a distinctive part within the optimization preparation. The employed bee can remember the location of the extra nectar as well as it chooses the best of the others to drink from, while the onlooker bees use what the employed bees have collected to come up with a solution for what nectar they can't remember. For an optimization problem, an algorithm consists of three steps is as follows: In the first step, the employed bees are dispatched to find all the resources needed, and then the nectar amount is calculated. Step two, the onlooker bees choose an asset that matches the information from the already-discovered honeydew assets. The employed bumblebee was sent out to the fields to select new locations in order to identify potential food sources. "Looking" bees would be further broken into two categories: the "used" bees and the "observing" bees. The algorithm works on the basis that the number of employable bees equals the number of available sources of nectar. When we understand where the issues likely lie, we'll be better equipped to deal with them [36].

ABC algorithm:

a) Initialization phase
In the first step, variables \( x_i \) \((i = 1, 2, 3, \ldots S)\) that have not been measured yet are selected at random, using some sort of random methodology.

b) Employed bee phase
The new sources are identified by each employed bee whose amounts are equal to the half of the total sources. a new source can be found by:

\[
V_{ij} = X_{ij} + \varphi_{ij} (X_{ij} - X_{kj})
\]  

(16)

Where \( j \) is a randomly selected parameter index, \( k \) is a random number between \([0, 1]\) and it has to be different from \( i \). \( \varphi_{ij} \) is a random number within the range \([-1, 1]\), \( X_{ij} \) is the current position of food source which comparing two food position visually by bee from this parameter the production of the neighbor food source can be controlled. The new food source position \( V_{ij} \) is produced and evaluated by the artificial bee, by comparing the current food source with previous source taking its consideration in the consider. From the information that obtained if the new source has equal or better amount of food or nectar than the old source, it used to replace the old source in the memory. Otherwise, the old source would be retained in memory.

c) Onlooker bee phase
In this phase, the onlooker bees are work on the principle of probability by selecting the food source with probability can be written as:

\[
p_i = \frac{f_{i}}{\sum_{i=1}^{n} f_{i}}
\]  

(17)

Where \( f_{i} \) and \( p_i \) are the fitness value and probability associated with solution \( i \) respectively. In each colony, great responsibility for random research is scout bees’ bear.

d) Scout bee phase
In this stage, the scout bee randomly investigates food sources without direction from the queen. Every scout in the swarm thinks that he or she is an explorer. If the supply of food decreases below the gainful level or as a result of applying a given level of the food application of the nectar, the bees associated with it cease feeding. When you have new information, a new understanding, or a new insight, the limit on the number of bees tells you how many from the source and how many to the destination.

\[
X_{ij} = X_{\text{min},j} + \text{rand} (0, 1) \times (X_{\text{max},j} - X_{\text{min},j})
\]  

(18)

Where \( X_{\text{max},j} \) and \( X_{\text{min},j} \) are the maximum and minimum limits for optimization parameter, \( \text{rand} (0, 1) \) is a random number within the range \([0, 1]\). The number of iterations in ABC algorithm considered as the important criterion for stopping an ABC algorithm.

An optimization algorithm might therefore determine that the stopping criteria to be:
1. Number of maximum iterations
2. Maximum error between two consecutive iterations

Figure 1 shown the flowchart of the ABC algorithm based OPF problem.
CASE STUDY

In this paper, two wind farms connecting to bus 10 and bus 24 are suggested. Figure 2 shown the standard IEEE 30 system with two wind farms. The wind power penetration level is defined as the ratio of the installed wind power capacity to the total-installed system generation capacity of 10%. The total power generation of six thermal generating in system are around 400MW, therefore the installed wind power capacity is 40 MW. Two wind farms included 10 wind turbines each one has rating 2 MW (Vestas V90, 2 MW) and connected at bus 10 and bus 24 (20 MW in each bus) is used to analyse the impact of incorporating wind farm on different performance analysis of system. Several scenarios with dispersed wind penetration levels from 0% to 100% have been investigated.

Figure 2. Single-line diagram of the IEEE 30-bus system including two wind farms at bus10 & bus 24
4.1. OPF without incorporating wind power

In this case, they used the artificial bee colony (ABC) algorithm to find a solution for OPF that did not include a wind farm. The power generation in thermal generator, active power loss and total production cost obtained by ABC algorithm is compared with other methods obtained in the [34]. Table 1 shows the results of this comparison. An 800.638 $/hr total production cost has been obtained by ABC, which is better than linear programming (LP) in [34].

| Variable          | ABC          | LP [33]       |
|-------------------|--------------|---------------|
| Pg1(MW)           | 177.05       | 195.6439      |
| Pg2(MW)           | 49.76        | 43.8668       |
| Pg5(MW)           | 21.38        | 21.4574       |
| Pg8(MW)           | 20.76        | 10.5771       |
| Pg11(MW)          | 11.63        | 10.0866       |
| Pg13(MW)          | 12           | 12.0000       |
| Power Loss (MW)   | 8.9246       | 10.31         |
| Production cost ($/hr) | 800.6380     | 803.26        |

4.2. OPF incorporating single wind farm site

In this case, the wind farm is incorporated on bus 10 and bus 24 separately (20 MW in each bus), for penetration levels from 25% to 100% with an interval of 25. The comparison results between ABC and the results obtained in the [34] for slack bus generation, total production cost, active power losses and voltage deviation are shown in Table 2. Figure 3 shows the load bus voltage profiles and Figure 4 shows the convergence characteristic of total production cost for this case when the wind farm is incorporated at bus 10.

| Wind penetration | Bus no. | ABC slack bus | ABC Cost($/hr) | ABC Losses (MW) | ABC VD (p.u.) | LP slack bus | LP Cost($/hr) | LP Losses (MW) | LP VD (p.u.) |
|------------------|---------|---------------|----------------|-----------------|---------------|--------------|---------------|----------------|---------------|
| 0%               | 10      | 177.05        | 800.638        | 8.9246          | 0.8977        | 176          | 802.46        | 10.31          | 0.8513        |
| 25%              | 25      | 171.38        | 783.142        | 8.522           | 0.920         | 171          | 778.20        | 9.05           | 0.900         |
| 50%              | 50      | 166.01        | 765.221        | 8.072           | 0.931         | 166          | 764.63        | 8.79           | 0.912         |
| 75%              | 75      | 155.31        | 730.943        | 7.550           | 0.941         | 160          | 753.42        | 8.27           | 0.930         |
| 100%             | 100     | 155.09        | 730.234        | 7.326           | 0.993         | 163          | 753.42        | 7.96           | 0.984         |

Figure 3. Load bus voltage profile 30-bus IEEE system
Figure 4. Convergence characteristics of the ABC for penetration levels of wind power at bus 10 only

4.3. **OPF incorporating multiple wind farm**

This case shows the impact of incorporating a wind farm connected to bus 10 and bus 24 together (20 MW in each bus). For penetration levels from 25% to 100% with an interval of 25%. Table 3 shows the slack bus generation, the total production cost, active power losses and voltage deviation. Figure 5 shows the load bus voltage profiles and Figure 6 shows the convergence characteristic of total production cost for this case.

| Wind penetration | Bus no. | ABC | LP [33] |
|------------------|--------|-----|---------|
|                  | slack bus | Cost($/h) | Losses (MW) | VD (p.u.) | slack bus | Cost($/h) | Losses (MW) | VD (p.u.) |
| 0%               | 10      | 177.05 | 808.6380 | 8.9246 | 0.8977 | 176 | 802.46 | 10.31 | 0.8513 |
| 25%              | & 165.90 | 764.670 | 8.614 | 0.639 | 170 | 758.89 | 9.03 | 0.602 |
| 50%              | 24 155.12 | 730.526 | 8.502 | 0.643 | 159 | 736.91 | 8.85 | 0.609 |
| 75%              | 144.44 | 694.795 | 7.599 | 0.905 | 148 | 701.78 | 8.34 | 0.885 |
| 100%             | 133.86 | 661.621 | 7.565 | 0.813 | 138 | 680.59 | 7.96 | 0.803 |
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**5. CONCLUSION**

This paper proposes the application of artificial bee colony (ABC) algorithm optimal power flow for a system that incorporates thermal units and wind farms during normal operation. The performance of the ABC was applied to standard IEEE-30 bus system with and without incorporating wind farm to show its impact on the the slack bus generation, the total production cost, active power losses and voltage deviation, and compared its simulation results with another method. Based on technical results obtained are it can be noticed that the ABC high performance than the rest methods, and concluded that an optimal integration and location of wind farms give significant to system, such as reducing in the total production cost, active power losses and improvement in the load bus voltage profile, while high performance can be noticed when a wind farm site on bus 24 rather than its site on bus 10. Finally, the results are exceptionally much promising.

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REFERENCES

[1] M. Čepin, “Evaluation of the power system reliability if a nuclear power plant is replaced with wind power plants,” Reliability Engineering & System Safety, vol. 185, pp. 455-464, 2019, doi: 10.1016/j.ress.2019.01.010.

[2] Y. G. Rashid, F. M. Tuaimah, and K. Mohammed, “Assessment of integrating wind energy system on iraqi power grid capability limit,” Journal of Engineering and Applied Sciences, vol. 14, no.17, pp. 5942-5954, 2019, doi: 10.36478/jeasci.2019.5942.5954.

[3] D. Wang et al., “Optimal scheduling strategy of district integrated heat and power system with wind power and multiple energy stations considering thermal inertia of buildings under different heating regulation modes,” Applied Energy, vol. 240, pp. 341-358, 2019, doi: 10.1016/j.apenergy.2019.01.199.

[4] J. Liu, Q. Yao, and Y. Hu, “Model predictive control for load frequency of hybrid power system with wind power and thermal power,” Energy, vol. 172, pp. 555-565, 2019, doi: 10.1016/j.energy.2019.01.071.

[5] P. P. Biswas, P. N. Suganthan, and G. A. J. Amaratunga, “Optimal power flow solutions incorporating stochastic wind and solar power,” Energy Conversion and Management, vol. 148, pp. 1194-1207, 2017, doi: 10.1016/j.enconman.2017.06.071.

[6] R. Roy, and H. T. Jadhav, “Optimal power flow solution of power system incorporating stochastic wind power using Gbest guided artificial bee colony algorithm,” International Journal of Electrical Power & Energy Systems, vol. 64, pp. 562-578, 2015, doi: 10.1016/j.ijepes.2014.07.010.

[7] J. Luo, L. Shi, and Y. Ni, “A solution of optimal power flow incorporating wind generation and power grid uncertainties,” IEEE Access, vol. 6, pp. 19681-19690, 2018, doi: 10.1109/ACCESS.2018.2823982.

[8] C. Shilaja, and T. Arunprasath, “Optimal power flow using moth swarm algorithm with gravitational search algorithm considering wind power,” Future Generation Computer Systems, vol. 98, pp. 708-715, 2019, doi: 10.1016/j.future.2018.12.046.

[9] Y. Merzoug, B. Abdelkrim, and B. Larbi, “Optimal placement of wind turbine in a radial distribution network using PSO method,” Journal of Power and Energy Drive Systems (JIPEDS), vol. 11, no. 2, pp. 1074-1081, 2020, doi: 10.11591/jipeds.v11.i2.pp1074-1081.

[10] H. R. E. H. Boucchkara, A. E. Chaib, M. A. Abido, and R. A. El-Sehiemy, “Optimal power flow using an improved colliding bodies optimization algorithm,” Applied Soft Computing, vol. 42, pp. 119-131, 2016, doi: 10.1016/j.asoc.2016.01.041.

[11] A. J. Ghanizadeh, G. Mokhtari1, M. Abedi, and G. B. Gharehpetian, “Optimal power flow based on imperialist competitive algorithm,” International Review of Electrical Engineering, vol. 6, no. 4, pp. 1847-1852, 2011.

[12] H. R. E. H. Boucchkara, “Optimal power flow using black-hole-based optimization approach,” Applied Soft Computing, vol. 24, pp. 879-888, 2014, doi: 10.1016/j.asoc.2014.08.056.

[13] A. M. Shaheen, R. A. El-Sehiemy, and S. M. Farrag, “Solving multi-objective optimal power flow problem via forced initialised differential evolution algorithm,” IET Generation, Transmission & Distribution, vol. 10, no. 7, pp. 1634-1647, 2016, doi: 10.1049/iet-gtd.2015.0892.

[14] J. Radosavljević, D. Klimenta, M. Jevtić, and N. Arsić, “Optimal power flow using a hybrid optimization algorithm of particle swarm optimization and gravitational search algorithm,” Electric Power Components and Systems, vol. 43, no. 17, pp. 1958-1970, 2015, doi: 10.1080/15325008.2015.1061620.

[15] S. Duman, U. Güvenç, Y. Sönmez, and N. Yöürkeren, “Optimal power flow using gravitational search algorithm,” Energy conversion and management, vol. 59, pp. 86-95, 2012, doi: 10.1016/j.enconman.2012.02.024.

[16] M. S. Jahan, and N. Amjadi, “Solution of large-scale security constrained optimal power flow by a new bi-level optimisation approach based on enhanced gravitational search algorithm,” IET Generation, Transmission & Distribution, vol. 7, no. 12, pp. 1481-1491, 2013, doi: 10.1049/iet-gtd.2012.0697.

[17] Dieu Ngoc V, and Peter Schegner, “An improved particle swarm optimization for optimal power flow,” in Metaheuristics Optimization Algorithms in Engineering, Business, Economics, and Finance, IGI Global, 2013, pp. 1-40, doi: 10.4018/978-1-4666-2086-5.ch001.

[18] P. Pravina, M. R. Babu, and A. R. Kumar, “Solving optimal power flow problems using adaptive quasi-oppositional differential migrated biogeography-based optimization,” Journal of Electrical Engineering & Technology, vol. 16, pp. 1891-1903, 2021, doi: 10.1007/s42835-021-00739-z.

[19] R. Arul, G. Ravi, and S. Velusami, “Solving optimal power flow problems using chaotic self-adaptive differential harmony search algorithm,” Electric Power Components and Systems, vol. 41, no. 8, pp. 782-805, 2013, doi: 10.1080/15325008.2013.760933.

[20] A. Meng et al., “A high-performance crisscross search based grey wolf optimizer for solving optimal power flow problem,” Energy, vol. 225, p. 120211, 2021, doi: 10.1016/j.energy.2021.120211.

[21] R.-H. Liang, S.-R. Tsai, Y.-T. Chen, and W.-T. Tseng, “Optimal power flow by a fuzzy based hybrid particle swarm optimization algorithm,” Electric Power Systems Research, vol. 81, no. 7, pp. 1466-1474, 2011, doi: 10.1016/j.enersys.2011.02.011.

[22] H. R. E.-H. Boucchkara, and M. A. Abido, “Optimal power flow using differential search algorithm,” Electric Power Components and Systems, vol. 42, no. 15, pp. 1683-1699, 2014, doi: 10.1080/15325008.2014.9499912.

[23] H. Pulluri, R. Naresh, and V. Sharma, “A solution network based on stud krill herd algorithm for optimal power flow problems,” Soft Computing, vol. 22, no. 1, pp. 159-176, 2018, doi: 10.1007/s00500-016-2319-3.

[24] S. S. Reddy, “Optimal power flow using hybrid differential evolution and harmony search algorithm,” International Journal of Machine Learning and Cybernetics, vol. 10, no. 5, pp. 1077-1091, 2019, doi: 10.1007/s13042-018-0786-9.
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