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Optimal active and reactive power dispatch in the presence of wind farms using voltage indicators and metaheuristic methods

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Abstract. Wind power plants penetration into power grids has grown considerably due to the fact of being cheap and clean. As a result, many countries require that the wind turbines must be capable of offering ancillary services such as reactive power control and voltage regulation. Furthermore, some voltage stability indices rely on both reactive and active power; consequently, it is useful to take also into account the active power during the planning stage so as to fulfil the load requirement and to enhance the voltage stability. The present study intends to present an optimization algorithm permitting to diminish the electrical losses and enhance the voltage profile by getting the fittest allocation of active power production of traditional generators and wind power plants. Besides, wind farms reactive power injection is determined. To verify the proposed algorithm, a 40 MW wind farm (WF) made up of doubly fed induction generator (DFIG) and the 14 IEEE bus system are used. In the case study, three different metaheuristic methods are used to resolve the objective function. Finally, the simulation results are reported.

1 Introduction

The wind power plants (WPP) integration into electrical networks has known a significant increase in the recent years. In fact, in 2022, the total installed wind capacity has reached 906 GW, which represents a growth of 9% in comparison to 2021 [1]. Besides, in various countries, wind farms (WF) are expected to engage in ancillary services, as an example the voltage regulation and the control of reactive power. In this regard, the wind turbines (WT) must possess the capability to keep the voltage in the tolerable limits by being involved in voltage regulation.

Reactive power optimization seeks to improve the voltage profile and minimize system real power losses [2]. Numerous studies have been conducted so that to analyse several optimal reactive power dispatch (ORPD) strategies in order to get the ideal solution of the control variables which are the voltage at generator buses, the VAR compensating devices,

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and tap changing transformer settings aiming to ensure the voltage stability and decrease the power losses by using metaheuristic methods [3-4]. In addition, in [5], the whale optimization method is employed to resolve an optimal power flow (OPF) issue so as to determine for different three cases the optimal values of real power output by generators, the voltage magnitude at generator buses, the reactive power of shunt var compensation, and the tap settings of the transformers. An objective is studied in each case from among the generation fuel expenses reduction, the real power losses reduction, and reactive power losses reduction.

However, wind farms (WF) can also participate to ensure voltage stability by producing or absorbing reactive power if some specific technologies of wind turbines are installed. As a result, it is useful to take also the WPP into consideration in the ORPD. For this regard, the authors in [6], propose an optimization strategy to get the reactive power contribution of the WPP and SVC devices so as to reduce the active power losses and to maintain the voltage profile within the allowable range by using the voltage indices. Nevertheless, some voltage indices depend on both active and reactive power. Thus, at the time of planning, it is practical to consider both the reactive and active power so as to handle the load requirements, and to ensure the voltage stability.

This paper aims to introduce an objective function allowing to get the fittest values of active power to produce by conventional generators and the WFs. Also, the objective function permits determining the fittest value of the wind farms reactive power injection targeting power losses reduction and voltage stability enhancement.

The following is the organization of this work: firstly, the line voltage stability indicators used in this study are presented. Secondly, the metaheuristic methods employed are outlined. Thirdly, the purpose of the function is defined. Lastly, the case evaluations are described and the simulation analysis is conducted.

2 Line voltage stability indicators

The line voltage stability indicators are established using a system's two bus representation by neglecting the shunt admittances, as shown in Fig. 1. The line voltage indices used to formulate the objective function are L_{QP}, L_{mn}, and $FVSI$. Stable, the system is viewed to be when the value of these indices is inferior than 1. However, the system becomes unstable when the value of these indices go beyond 1 [7]. The equations bellow are used to get these indices:

$$FVSI = \frac{4Z^2 Q_j}{V_i^2 X} \tag{1}$$

$$L_{mn} = \frac{4X\,Q_j}{\left(V_i \sin(\theta - \delta)\right)^2} \tag{2}$$

$$L_{QP} = 4\left(\frac{X}{V_i^2}\right)\left(Q_j + \frac{P_i^2 X}{V_i^2}\right) \tag{3}$$

Where

X, Z : line reactance and impedance amplitude between bus i and j (respectively the sending and receiving bus)

Q_j : reactive power flow at bus j

P_i : active power flow at bus i

V_i : voltage magnitude at bus i

θ : angle of the line impedance
δ : voltage angle difference between bus i and j

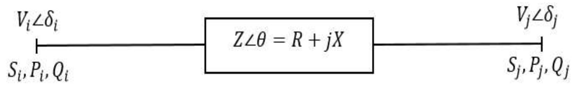

Fig. 1. Two bus model of a power system [6]

3 Optimization algorithms

3.1 Grey wolf optimizer (GWO)

The GWO is a metaheuristic algorithm invented by Seyedali et. al. in 2014 [8]. Its inspiration comes from the leadership structures and hunting tactics of gray wolves. As illustrated in fig. 2, the leadership hierarchy includes four kinds of grey wolves. Indeed, the leaders gray wolves pack are a male and a female named alpha. In the hierarchy, the beta wolves occupy the second position. Their role is to help the alpha to take decisions and other functions. In third position of the hierarchy, the delta wolves are placed. These wolves dominate the omega wolves, however; they must always respond to the directives of alpha and beta. The fourth level is where the omega wolves are found. These wolves must act according to the commands of all of the other dominant wolves.

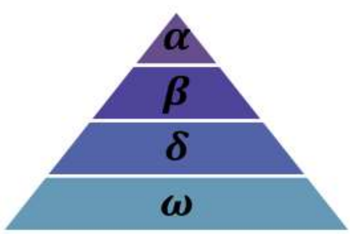

Fig. 2. Hierarchy of grey wolf

The grey wolves follow three main steps in order to hunt: first, to find, to pursue, and to move towards the prey. Second, to encircle and to harass the prey. Finally, to proceed attacking the prey.

In this method, α is perceived as the best solution. Consequently, β and δ are as the second and third optimal solutions, respectively, while ω wolves come after all the other wolves.

Equations (4) and (5) provide a mathematical model for the act of surrounding the prey:

$$\vec{D} = \left| \vec{C} \cdot \vec{x}_p(n) - \vec{x}(n) \right| \tag{4}$$

$$\vec{x}(n+1) = \vec{x}_p(n) - \vec{A} \cdot \vec{D} \tag{5}$$

$\vec{A}$ and $\vec{C}$ designate coefficient vectors, n indicates the ongoing iteration, $\vec{x}_p$ and $\vec{x}$ denote respectively the position vector of the prey and the grey wolf.

The equations bellow are employed to calculate $\vec{A}$ and $\vec{C}$:

$$\vec{A} = 2\vec{a} \cdot \vec{r}^{\,1} - \vec{a} \tag{6}$$

$$\vec{C} = 2\,\vec{r}^{2} \tag{7}$$

$\vec{r}^{1}$ and $\vec{r}^{2}$ express random vectors over the interval [0,1]

The components of $\vec{a}$ decrease linearly from 2 to 0 throughout the iterations.

In this technique, the initialization of a group of agents is performed randomly within the search domain. Then, at each iteration, the algorithm continues to search for the fittest solution by adjusting the position of each agent, considering α, β and δ positions. Finally, the position of α is regarded as the optimal solution. To adjust the grey wolves' positions, the equations outlined below are employed:

$$\vec{D}_{\alpha} = \left|\vec{C}^{1} \cdot \vec{x}_{\alpha} - \vec{x}\right|,\ \vec{D}_{\beta} = \left|\vec{C}^{2} \cdot \vec{x}_{\beta} - \vec{x}\right|,\ \vec{D}_{\delta} = \left|\vec{C}^{3} \cdot \vec{x}_{\delta} - \vec{x}\right| \tag{8}$$

$$\vec{x}_{1} = \vec{x}_{\alpha} - \vec{A}^{1} \cdot \vec{D}_{\alpha}\ ,\ \vec{x}_{2} = \vec{x}_{\beta} - \vec{A}^{2} \cdot \vec{D}_{\beta}\ ,\ \vec{x}_{3} = \vec{x}_{\delta} - \vec{A}^{3} \cdot \vec{D}_{\delta} \tag{9}$$

$$\vec{x}(n+1) = \frac{\vec{x}_{1} + \vec{x}_{2} + \vec{x}_{3}}{3} \tag{10}$$

3.2 Particle Swarm Optimization (PSO)

The PSO represents a metaheuristic technique developed in 1995 by Kennedy and Eberhart [9-10]. It seeks to identify the optimal solution permitting to minimize (or maximize) an objective function.

A group of particles in the PSO method are initialized randomly within the search field. Assigned to each *i*th particle are its position x_i , velocity v_i , and the best position $Pbest_i$. For every iteration, the algorithm seeks for the suitable solution by adjusting the velocity and position of each *i*th particle by employing the equations provided below:

$$v_i^{n+1} = w^{n} \cdot v_i^{n} + c^{1} \cdot R^{1}.(Pbest_i^{n} - x_i^{n}) + c^{2} \cdot R^{2}.(Gbest^{n} - x_i^{n}) \tag{11}$$

$$x_i^{n+1} = x_i^{n} + v_i^{n+1} \tag{12}$$

Where R^1 and R^2 are random numbers uniformly distributed over the interval [0, 1], c^1 and c^2 indicate the acceleration coefficients, w designates the inertia weight, and $Gbest$ represents the global best.

To determine the inertia weight, the equation that follow is implemented:

$$w^{n} = w_{\max} - \frac{w_{\max} - w_{\min}}{n_{\max}} n \tag{13}$$

Where n represents the ongoing iteration, $n_{\max}$ is the iteration limit, $w_{\min}$ and $w_{\max}$ indicate the lower and upper values of the inertia weight parameters, in that order.

3.3 Hybrid Particle Swarm Optimization with Grey Wolf Optimizer (PSOGWO)

The PSOGWO is obtained by hybridizing the PSO with the GWO algorithm employing low level coevolutionary mixed hybrid approach [11]. This modification permits to enhance the exploitation capacity of PSO while providing exploration features for GWO in order to get the advantages of both variants.

In this method, equations (14), (15) and (16) are used to adjust the position of the first three agents. The inertia constant controlled the exploitation and the exploration of the gray wolf in the search domain.

$$\vec{D}_\alpha = \left|\vec{C}^1 \cdot \vec{x}_\alpha - w \cdot \vec{x}\right| \tag{14}$$

$$\vec{D}_\beta = \left|\vec{C}^2 . \vec{x}_\beta - w \cdot \vec{x}\right| \tag{15}$$

$$\vec{D}_\delta = \left|\vec{C}^3 \cdot \vec{x}_\delta - w \cdot \vec{x}\right| \tag{16}$$

So as to mix the GWO and PSO, the following equations are used to adjust for each agent the velocity as well as position:

$$v_i^{n+1} = w.(v_i^n + C^1.r^1.(x_1 - x_i^n) + C^2.r^2.(x_2 - x_i^n) + C^3.r^3.(x_3 - x_i^n)) \tag{17}$$

$$x_i^{n+1} = x_i^n + v_i^{n+1} \tag{18}$$

With

$$w = 0{,}5 + rand()/2 \tag{19}$$

4 Problem formulation

The outlined objective function, in the present study, seeks to determine the perfect distribution of real power production of a mix of wind farms based DFIG technology and traditional generators, as well as the reactive power contribution of these renewable energy sources, with the purpose of enhancing voltage stability and diminishing electrical losses.

The following equation describes the objective function to minimize

$$F(x) = l_1.P_L + l_2.\sum_{i=1}^{N} \frac{L_{mn}(i) + L_{QP}(i) + FVSI(i)}{3} \tag{20}$$

Where

l_1, l_2 : weight coefficients

P_L : electrical grid losses

N : grid lines number

The following equations define the constraints to which the objective function is exposed:

- Equations of power flow

$$P_i = V_i \sum_{j=1}^{N_b} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \tag{21}$$

$$Q_i = V_i \sum_{j=1}^{N_b} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) \tag{22}$$

Where

V_i and V_j : represent the voltage magnitude at buses i and j, in that order

$\theta_{ij} = \theta_i - \theta_j$: indicates the voltage angle difference between bus i and j

B_{ij} : is the susceptance of transmission branch ij

G_{ij} : is the conductance of transmission branch ij

- Active power limits of conventional generators

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{23}$$

- Active power limits of WFs

$$0 \le P_{WF} \le P_{WF}^{\max} \tag{24}$$

Where $P_{WF}^{\max} = \sum_i P_{r_i}$

With P_{r_i} represents the rated output of the wind turbine i

- Reactive power limits of WFs

$$Q_{WF}^{\min} \le Q_{WF} \le Q_{WF}^{\max} \tag{25}$$

5 Case study

For the purpose of validation of the proposed optimization algorithm, two diverse cases are simulated by applying the IEEE 14 bus test network and a WPP with a capacity of 40 MW. The test grid is made up of five conventional generators and a WF. The WPP is made up of twenty 2 MW DFIG technology.

The losses of reactive power in the WF are not considered in this study. The equations (26) and (27) express the WF's reactive power capability:

$$Q_{wpp}^{\max} = \sum Q_{wt}^{\max} \tag{26}$$

$$Q_{wpp}^{\min} = \sum Q_{wt}^{\min} \tag{27}$$

Where $Q_{wt}^{\max}$ and $Q_{wt}^{\min}$ are the reactive power limits of the WT employing the parameters cited in [12] and the method proposed in [13]. More details can be found in [14].

Table 1 illustrates the power output range limits of each traditional generator and the WF as well as their location.

Table 1. Thermal generators and wind farm data

Unit	Bus	Real power upper limit (MW)	Real power lower limit (MW)
1	2	80	20
2	3	50	15
3	6	35	10
4	8	30	10
5	14	40	0

In both cases, it is considered that the real power loads at buses 12 and 14 are elevated to 97,1 MW and 114,9 MW, in that order. As a result, the voltage magnitude decreases in these busbars. Also, busbar 1 is identified as the slack bus.

- Case 1: without the injection of reactive power by the WF
  Where $x=(x^1,x^2,x^3,x^4,x^5)$
  $x^i = P_{Gi}$ for i = $\{1,2,3,4\}$, P_{Gi} :is the active power set for the conventional generators at buses 2, 3, 6 and 8.
  $x^5 = P_{WF}$: is the active power set for the WF
  $l_1 = l_2 = 0{,}5$

- Case 2: with the injection of reactive power by the WF.
  Where $x=(x^1,x^2,x^3,x^4,x^5,x^6)$
  $x^i = P_{Gi}$ for i = $\{1,2,3,4\}$, $x^5 = P_{WF}$, $x^6 = Q_{WF}$: is the reactive power set for the WF.
  $l_1 = l_2 = 0{,}5$

In the purpose of comparison, in each case three metaheuristic optimization methods are used: GWO, PSO and PSOGWO.

Table 2 illustrates the results obtained with the three metaheuristic methods in each case. As it can be noticed, the same results are obtained with GWO, PSO and PSOGWO. Consequently, the losses and the voltage profile are the same for the three optimization techniques.

Table 2. Simulation results

	Case 1	**Case 2**
P_{G1} (MW)	80	80
P_{G2} (MW)	50	50
P_{G3} (MW)	35	35
P_{G4} (MW)	30	30
P_{WF} (MW)	40	40
Q_{WF} (MVAR)	-	12,5558
Objective function	17,3829	17,0229

The significant drop of the voltage magnitude is obtained at buses 12 and 14 which is due to the increase of active power loads in these buses. As shown in fig. 3 and 4, the voltage amplitudes at buses 12 and 14 rises respectively from 0,949 per unit and 0,954 per unit in the first case to 0,953 per unit and 0,983 per unit in the second case. Moreover, as illustrated in fig. 5, the power losses recorded a reduction in case 2 compared to case 1.

In fact, in case 2, the amelioration of the voltage profile and the reduction of the electrical losses compared to case 1 is resulting from the WF reactive power injection.

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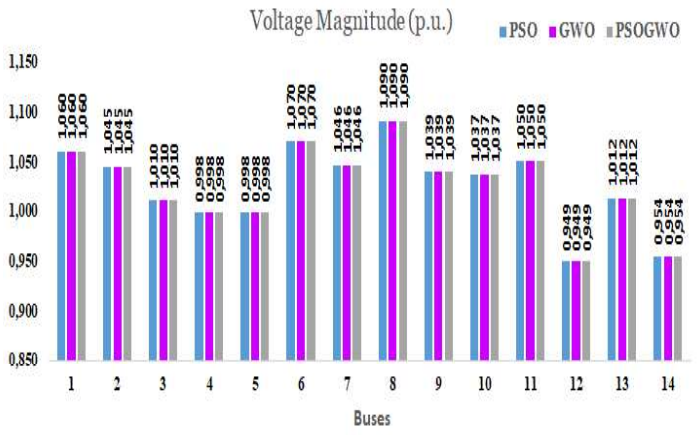

Fig. 3. The profile of voltage in the first case

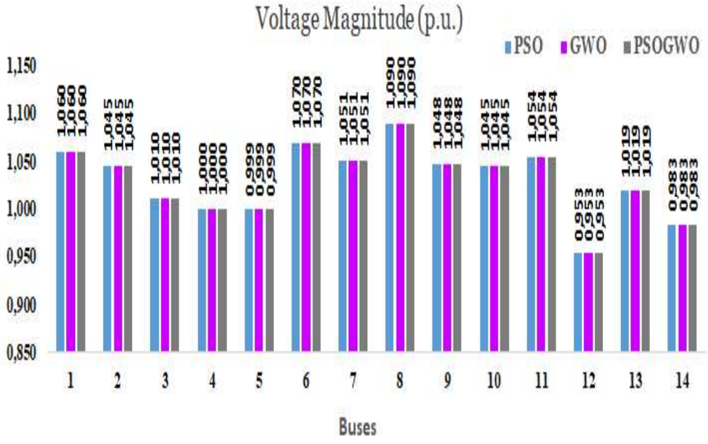

Fig. 4. The profile of voltage in the second case

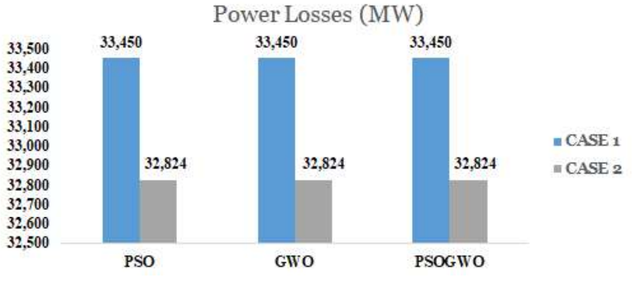

Fig. 5. Power losses in case 1 and 2

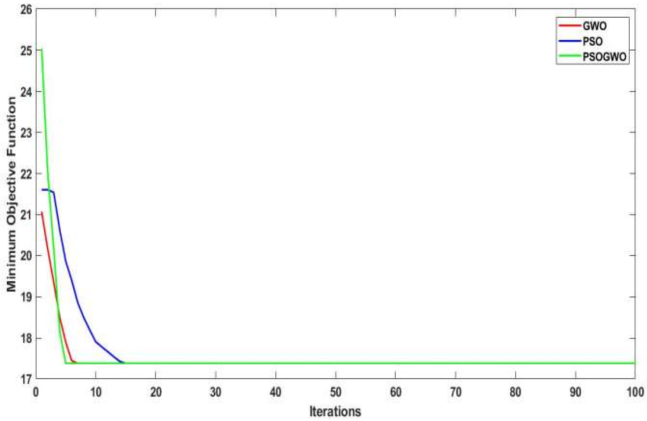

Fig. 6. Minimum objective function in case 1

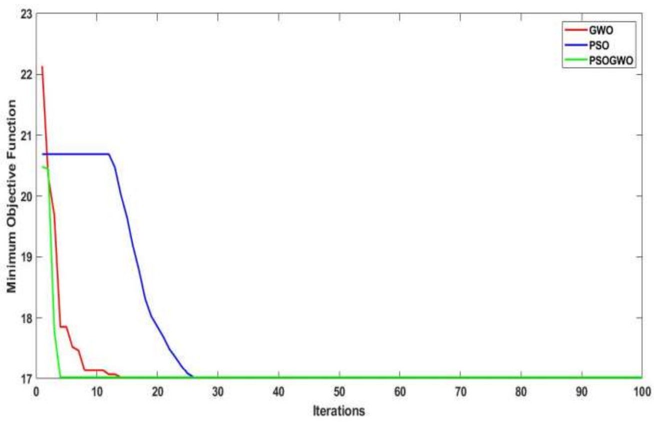

Fig. 7. Minimum objective function in case 2

The method which has the best convergence is the one that gets its best solution in earlier iterations. As shown in fig. 6 and 7, PSOGWO shows faster convergence at early iterations comparing to PSO and GWO in case 1 and 2.

As it can be noticed, the three metaheuristic methods permits getting the same results. In fact, PSO, GWO and PSOGWO allow decreasing the electrical losses and improving the profile of the voltage equally. However, with regard to convergence speed, PSOGWO can reach the best results more quickly compared to PSO and GWO.

6 Conclusion

This study aims to present an optimization approach allowing to determine the fittest distribution of active power generation of traditional generators and wind power plants, along with the reactive power injection from these renewable sources. The goal of this approach is power losses reduction and voltage profile enhancement. Two different cases utilizing PSO, GWO and PSOGWO are examined and compared. As revealed in the simulation findings, the three metaheuristic methods allow power losses reduction as well as voltage profile improvement equally. However, PSOGWO permits faster convergence to the best result in comparison to GWO and PSO.

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