OPTIMAL REACTIVE POWER DISPATCH IN ACTIVE DISTRIBUTION POWER SYSTEMS USING GREY WOLF OPTIMIZER

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The aim of the article is to implement and test the Grey Wolf Optimizer (GWO) for identifying the optimal reactive power dispatch (ORPD) in an active distribution network. The optimization problem is a multi-objective one consisting in keeping minimum power losses, while maintaining bus voltages close to their rated value. The performances of the GWO are evaluated through a comparative study between three meta heuristic algorithms – GWO, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The study is conducted on the test network IEEE 33, modified by integrating some distributed generation (DG) and capacitor banks (CBs).

Keywords: optimal reactive power dispatch, active distribution systems, distributed generation, meta heuristic algorithms

1. Introduction

In the context of continuously increasing penetration of distributed generation (DG), the active distribution power systems are transitioning from a theoretical concept towards a real-life application. Due to increasing power flow through network elements, DGs bring new operational challenges in terms of keeping minimum power losses and stability conditions. Thus, for successful economic and technic dispatch, it is a requirement to detect the optimal reactive power flow, considering operating constraints and keeping the power balance, especially considering the DG's uncertainty and intermittency, as stated in [1].

The optimal reactive power dispatch (ORPD) problem is a subsection of the optimal power flow and can be solved using both classical methods and meta heuristic algorithms, as described in [2-5]. The main advantages of using meta heuristic solvers include the high level of accuracy in identifying the global optimum, reduced computational time and robustness. This paper proposes a comparative study for solving the ORPD problem in active distribution systems,

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based on three meta heuristic algorithms: Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). The devices capable of providing reactive power flow control are the on-load tap changer (OLTC), that has a direct impact on all bus voltages, capacitor banks (CBs), capable of injecting reactive power and DGs, that can be set to inject or absorb a specific amount of reactive power within an admissible range, dependent on their technical capabilities.

In this article, the optimal reactive power dispatch is determined for the IEEE 33 test network, equipped with control means as presented in [4]. The optimal control strategy consists in determining the control variables for reactive power control devices to assure economic and safe operation [5].

The algorithm used to study the ORPD problem for the considered test network is implemented by the authors in the Matlab R2021b environment. The load flow computation is performed within the objective function, using a Newton-Raphson algorithm based on current mismatches developed by the authors. Within this algorithm, the high voltage bus of the high voltage/medium voltage substation (HV/MV Ss), which supplies the distribution network, is considered the slack bus for the distribution system. The GWO open-source solver proposed by the authors of [6] and the Matlab toolboxes for the GA and PSO solvers are also applied in this paper.

2. Mathematical model of the optimization problem

The purpose of an optimization problem is to identify the set of independent parameters, that optimize a certain quantity, in the presence of constraints. The quantity is modelled as an objective function that can be either minimized or maximized, the parameters are control variables, while the constraints are described as both equality and inequality functions. The general mathematical model of a constrained optimizing problem is, [7]:

$$\begin{cases} \min F(\boldsymbol{X}) \\ g(\boldsymbol{X}) = 0 \\ h(\boldsymbol{X}) \le 0 \end{cases} \tag{1}$$

where:

F – the objective function.

X – the vector of control variables.

g – equality constraint function.

h – inequality constraint function.

The selection of control variables has a significant contribution on the formulation of the objective function and its influence on the optimum solution. Consequently, the lower and upper limits of the control variables define the search space and a clear definition of it can simplify and accelerate the convergence of the solving algorithm. Problem formulation for the case of optimum reactive power dispatch results from the general case of optimal power flow (OPF) in terms of economic and safe operation, [8]. The objective function can consist of a single or multiple goal, depending on what is to be optimized. The main objective of the ORPD problem is minimising the power losses, but the problem can be formulated considering other goals such as improving the voltage profile, maintaining the stability conditions, increasing the transfer capacity of the network elements, [3].

In this paper, two objective functions are chosen for the ORPD problem, namely the active power losses minimization and the total bus voltage deviation minimization, to simultaneously assure safe and economical operation conditions. The importance of each objective is decided depending on the needs identified by the distribution dispatch centre. As a result, the objective function used in the general model (1) includes the goals of minimizing the total active power losses in the considered system (ΔP_{sys}) and the total bus voltage deviation (*TVD*).

$$F(\mathbf{X}) = \alpha \cdot Obj_1 + (1-\alpha) Obj_2 = \alpha \cdot \Delta P_{sys} + (1-\alpha) TVD \tag{2}$$

In order to study the influence of both objectives on the distribution system operation, a weighting coefficient α is introduced in the expression of the objective function (2), establishing the importance of each goal in the objective function. When α = 1, a single-objective problem is obtained with the goal of minimising power losses, while for α = 0, the only purpose of the resulting ORPD problem is to maintain the bus voltage profile close to the rated voltage value.

The first objective, representing ΔP_{sys}, is determined as follows, [4]:

$$Obj_1 = \Delta P_{sys} = P_{sl} - \sum_{i=1}^{N} \left(P_{d,i} + P_{g,i} \right) \tag{3}$$

where:

P_{sl} – active power of the slack bus, considered the HV bus of the Ss.

$P_{d,i}$ – active power demanded at the i^{th} bus.

$P_{g,i}$ – active power injected at the i^{th} bus.

N – the total number of buses in the considered network.

The second objective, consisting in the *TVD* is determined as, [4]:

$$Obj_2 = TVD = \sum_{i=1}^{N} \left(V_i - V_{i,r} \right)^2 \tag{4}$$

where:

V_i – the voltage of the i^{th} bus.

$V_{i,r}$ – the rated voltage of the i^{th} bus.

Given the objective function expression, (2), the ORPD is a nonlinear problem, subject to both equality and inequality constraints, whose objective must be minimized.

For this case, the model presented in (1) consists in an objective function represented by minimum power losses and minimum total voltage deviation (2), equality constraints represented by the nodal current mismatch equations (5), inequality constraints represented by voltage admissible limits (6) and permissible branch current (7), and the limits of the control variables represented by the capabilities of the control devices (8)-(10).

The equality constraints, consist in the nodal current balance equations which assure that the load flow calculation is correctly determined. The active ($\Delta I_{x,i}$) and reactive ($\Delta I_{y,i}$) nodal current mismatches expressions of the i^{th} bus, in rectangular coordinates, are presented below:

$$\begin{aligned} g_{\Delta I_{x,i}}\left(\boldsymbol{X}\right) &= \Delta I_{x,i} = \frac{P_i V_{x,i} + Q_i V_{y,i}}{V_{x,i}^2 + V_{y,i}^2} - \sum_{k=1}^{n}\left(G_{ik}V_{x,k} - B_{ik}V_{y,k}\right) = 0 \\ g_{\Delta I_{y,i}}\left(\boldsymbol{X}\right) &= \Delta I_{y,i} = \frac{P_i V_{y,i} - Q_i V_{x,i}}{V_{x,i}^2 + V_{y,i}^2} - \sum_{k=1}^{n}\left(G_{ik}V_{y,k} + B_{ik}V_{x,k}\right) = 0 \end{aligned} \tag{5}$$

where:

P_i, Q_i – the active and reactive power of the i^{th} bus.

$V_{x,i}$, $V_{y,i}$ – the active and reactive voltage of the i^{th} bus.

$V_{x,k}$, $V_{y,k}$ – the active and reactive voltage of the k^{th} bus.

G_{ik} – the conductance between buses i and k.

B_{ik} – the susceptance between buses i and k.

As the ORPD problem is solved, in this paper, using metaheuristic solvers, the load flow calculation is performed within the objective function by applying a Newton-Rapshon algorithm developed by the authors in Matlab. The algorithm is adapted for the distribution systems' particularity consisting of relatively large values of the R/X ratio. As no other voltage-controlled buses, excepting the slack bus, are modelled, the considered algorithm, is suitable for distribution systems load flow computation providing high-accuracy and reduced computational times.

The first inequality constraint is derived from the performance standard imposed for the distribution systems of Romania, [9], which requires the bus voltage values to be maintained within a band of ±10% of the rated value:

$$0.9 \cdot V_{i,r} \le V_i \le 1.1 \cdot V_{i,r}, (\forall) i \in N \tag{6}$$

The second inequality constraint is based on the maximum current that can be transferred through each branch. This value results from the maximum admissible current in normal operating conditions:

$$\left|I_i\right| \le I_i^{\max}, (\forall) i \in N_{branch} \tag{7}$$

The inequality constraints also include the control variables limits, which result from the technical restrictions and the voltage control method of each considered device. In distribution power systems, the voltage drop depends on both active and reactive power. Even if the DG operation is dependent on a P-Q capability curve, in terms of voltage control, only the reactive power is considered a control variable. As a result, the control variable of each DG is the reactive power output $Q_{DG,i}$ characterized by a continuous variation between the lower $Q_{DG,i}^{\min}$ and upper $Q_{DG,i}^{\max}$ limits, which correspond to the lagging and leading power factor limits:

$$Q_{DG,i}^{\min} \le Q_{DG,i} \le Q_{DG,i}^{\max}, (\forall) i \in N_{DG} \tag{8}$$

For both the CBs and the OLTC, the control variables, namely the operating step ($Step_i$) and operating tap (n_p), are discrete. The lower and upper bound of the capacitor banks depend on the number of steps that can be connected (9), while the limits of the tap changer depend on its construction (10):

$$Step_i^{\min} \le Step_i \le Step_i^{\max}, (\forall) i \in N_{CB} \tag{9}$$

$$n_p^{\min} \le n_p \le n_p^{\max} \tag{10}$$

By solving the mathematical model (1) with an optimizer algorithm, the set of values that respect the limits presented in (8)-(10), represent the control variables of the available voltage control devices that assure both an economic and safe dispatch, for normal operating conditions.

3. Metaheuristic solvers used for ORPD problem

Generally, two major categories are available for solving optimization problems: deterministic algorithms or metaheuristic solvers, which are increasingly popular in the research community as they usually provide high-accuracy results on all types of optimization problems, including the ORPD problem given that it comprises non-linear functions and mixed variables.

Among the first methods resulted from natural evolution is the Genetic Algorithm (GA), which identifies the optimum as the fittest solution resulted from selection, crossover, and mutation principles, [10]. The convergence time is reduced due to the selection and crossover mechanisms which assure that the best features of the evolving individuals are transmitted to their offspring, while the search space is randomly investigated due to the stochastic nature of mutation, which is a major component of evolutionism.

The second category of metaheuristic algorithms are based on swarm intelligence, as investigated firstly in [11]. These take in consideration the decentralised conduct of a group of agents, that are capable of collaboration and self-organization in the solution space, with the aim of identifying the location of the optimum. One of the widely known method is the Particle Swarm Optimization (PSO), proposed in [12]. The principle of the algorithm is to update the position of each member of the swarm, according to its best personal position and the best location of the entire population. The PSO algorithm applies mechanisms for guiding the swarm towards the areas with the highest probability of finding the global optimum, while keeping some random movements to avoid local optimums.

The metaheuristic solver applied in this paper is the Grey Wolf Optimizer (GWO), proposed in [6], a swarm intelligence-based algorithm, inspired by the hierarchic organisation and the hunting mechanism of grey wolves.

In the mathematical model the optimum is associated with the prey while the search space is investigated by agents, whose movement is coordinated by the top ranked members (α, β and δ members). The hunting strategy includes promoting the best members from a randomly generated population, who are guiding the exploration and exploitation processes to determine the location of the global optimum within the search spare. Changing position, from the current location $X(t)$, to another, $X(t+1)$ is described by expression (11), [6]:

$$X\left(t+1\right)=X_p\left(t\right)-A\cdot D \tag{11}$$

The tactic of encircling the prey, associated with the solution, takes in consideration the current wolf's location $X(t)$, the prey's location $X_p(t)$, the distance between $X(t)$ and $X_p(t)$, denoted D and two random vectors, A and C:

$$\begin{aligned} &A=2a\cdot r_1-a \\ &D=\left|C\cdot X_p\left(t\right)-X\left(t\right)\right| \\ &C=2r_2 \end{aligned} \tag{12}$$

The r_1 and r_2 parameters are random numbers assuring the stochastic nature of the GWO algorithm. Parameter a, in (12), plays a major role in the hunting mechanism, by deciding the balance between exploration and exploitation as it decreases its value from 2 towards 0 during the iterative process. In this manner A, adjusts its value from $|A|\geq 1$ in the beginning of the process where the exploration of the search space is essential, to $|A|<1$, to focus on the exploitation in the final iterations. Vector C is random throughout the process to avoid local optimums.

The position update mechanism is expressed in (13), depending on the location of the hierarchically superior wolves, X_1 for α member, X_2 for β member and X_3 for δ member, expressed in (14):

$$X\left(t+1\right)=\frac{\sum_{i=1}^{3}X_i\left(t+1\right)}{3} \tag{13}$$

$$\begin{aligned} &X_i=X_k-A_i\cdot D_k,\ i=1,2,3 \\ &D_k=\left|C_i\cdot X_k-X\right|,\ k=\alpha,\beta,\delta \end{aligned} \tag{14}$$

The GWO algorithm is suitable for the ORPD problem, owing to its simplified mathematical model which assures fast convergence, high-accuracy results and local minimum avoidance.

4. Case study

The purpose of the case study is to identify the optimal control variables values by solving the ORPD problem for an active distribution system. The first part of this section presents a comparison between the GWO, GA and PSO metaheuristic algorithms, while in the second part the results obtained with GWO, for three different load scenarios are presented and discussed.

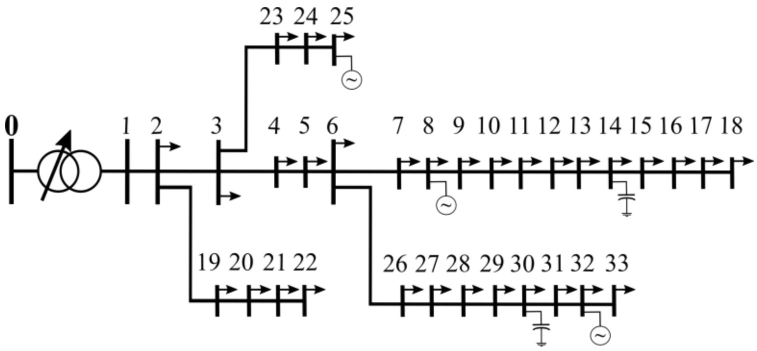

Fig. 1. The modified single line diagram of IEEE 33-bus test network

The active distribution network under study, based on the original IEEE 33 distribution system, proposed in [13] and modified according to [4] is presented in Fig. 1. Firstly, a new slack bus, represented by the HV bus “0”, and the OLTC transformer, that supplies the distribution network, are introduced. The adaptation of the network, according to [4], also includes the characteristics of three DGs and two CBs. The DGs are connected at buses 8, 25 and 32 and are injecting 500 kW, 650 kW and 350 kW respectively, while the two CBs with the rated reactive power per each step of 50 kVAr, are connected at buses 14 and 30. The control variables limits of voltage control devices are given in Table 1.

Table 1

Limits of the voltage control devices

Type	Control variable	Bus	Lower bound	Upper bound
OLTC	Tap	0	–9	9
DG	Q_g (kVAr)	8	–164	164
		25	–214	214
		32	–115	115
CB	Step	14	0	8
		30	0	20

It should be mentioned that the DGs are modelled as constant power sources, being capable of controlling the reactive power in a range determined by the power factor (PF) of 0.95 leading and lagging, as imposed in [14].

4.1. Performance study between considered meta heuristic algorithms

This section presents a comparative study between the performances obtained by the GWO, GA and PSO methods in solving the ORPD problem, for ten consecutive trials, using $\alpha = 1$ in (2). In order to assure a fair comparison, the number of agents in each population is considered 100, while the maximum number of iterations is 100 for all three methods.

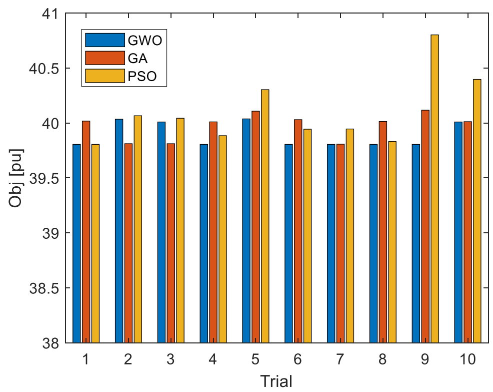

Fig. 2. The GWO, GA, PSO objective functions

Fig. 2 presents the minimum values of the objective function (2), obtained by the three considered metaheuristic solvers, at each trial. It should be noted that, because of the stochastic nature of the meta heuristic algorithms, the optimums have variations at each run. Nonetheless, in 60% of the trials, the best solution is provided by the GWO method, while the AG algorithm identifies the most performant solution in 30% of the cases, and PSO only in 10% of the trials.

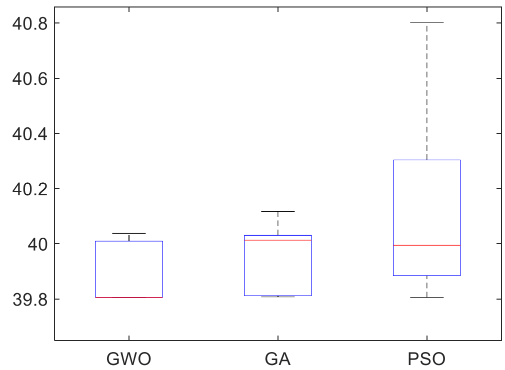

Fig. 3. The distribution of optimal solutions obtained by GWO, GA and PSO

The boxplot representation of the minimum values of the objective function identified by the considered methods is presented in Fig. 3 and it highlights the superior performance of the GWO algorithm. Even if the median values for all three meta heuristic algorithms are relatively close, the GWO obtained the lowest value of 39.8055, followed by the PSO with 39.9947, and the AG with 40.0132. In addition, the median obtained by the GWO is closer to its minimum, while for GA the median value is close to the 75% quartile, and the PSO shows a wider spread of the solutions. Consequently, the GWO demonstrated superior performances in solving the ORPD problem and will be further used in this case study.

4.2. ORPD analysis with GWO algorithm

This section analyses the operating conditions of the active distribution system, obtained by solving the ORPD problem using the GWO algorithm. Firstly, an analysis regarding the influence of the weight α is conducted by generating the ORPD solutions for α between 0 and 1 with a 0.1 increment. The variation of the objective function presented in (2) is depicted in Fig. 4, where the active power losses are expressed in percentage relative to the value obtained in the no-reactive power control case. For α = 0, one can notice that the *TVD* has a minimum registered value of 0.0036 pu., while the power losses are reduced to 64.88%. In the opposite case, for α = 1, the power losses are further reduced to 39.81%, while the *TVD* increases to the maximum value of 0.1841 pu.

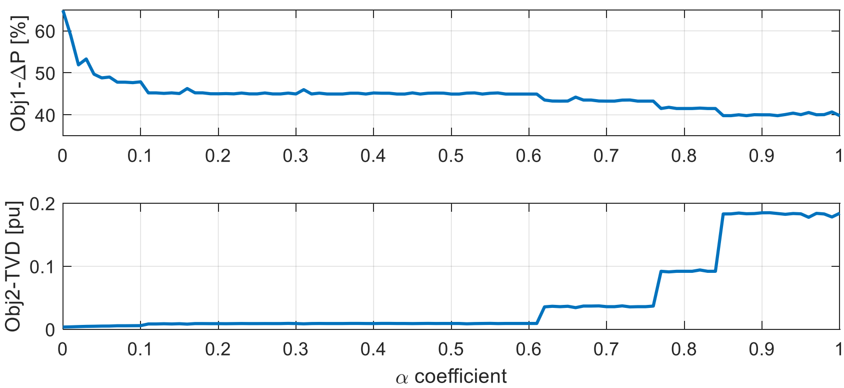

Fig. 4. The α dependent variation of the two objectives

As voltage profile has a major impact on the operation of the considered power system, Fig. 5 presents the impact of the control devices on the bus voltages of the IEEE 33 grid, for the considered α values. For the initial scenario, in which no additional equipment is active, the voltage profile shows an important variation from buses close to the HV/MV substation to the end buses of each branch. For α = 0, the objective is to minimise voltage deviation from the rated value represented by 1 pu, hence the variation is smoother along branches. As the α values are increasing, bus voltage values are increasing, as the emphasis is shifting towards minimizing power losses. Finally, when α = 1, the voltage profile is close to the upper limit of admissible values, given by (6), and the active power losses are minimum.

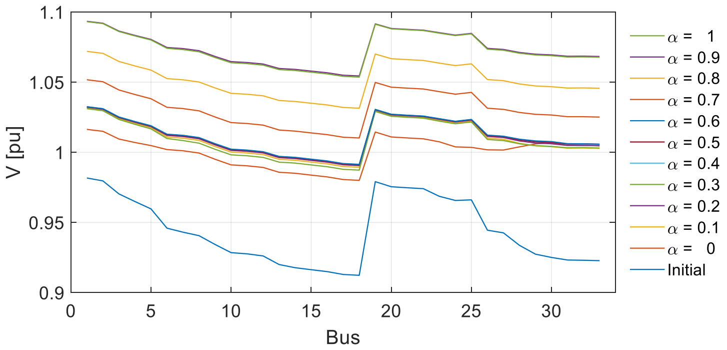

Fig. 5. The α dependent voltage profile variation

The voltage profiles, shown in Fig. 5, are grouped in steps, dependent on the α values. The explanation is provided by the optimal values obtained for the control variables, presented in Fig. 6, as a function of the α coefficient. For α values between 0.1 and 0.7, the corresponding voltage profiles are grouped as the operating tap is fixed at n_p = –2. For these cases, there are no switches at the OLTC level, and the objective function is minimised by the control variables of the DGs and CBs. For α ≥ 0.7, the bus voltage values are increasing in steps as the operating tap is decreasing to n_p = –5, where the bus voltage are close to the maximum limit.

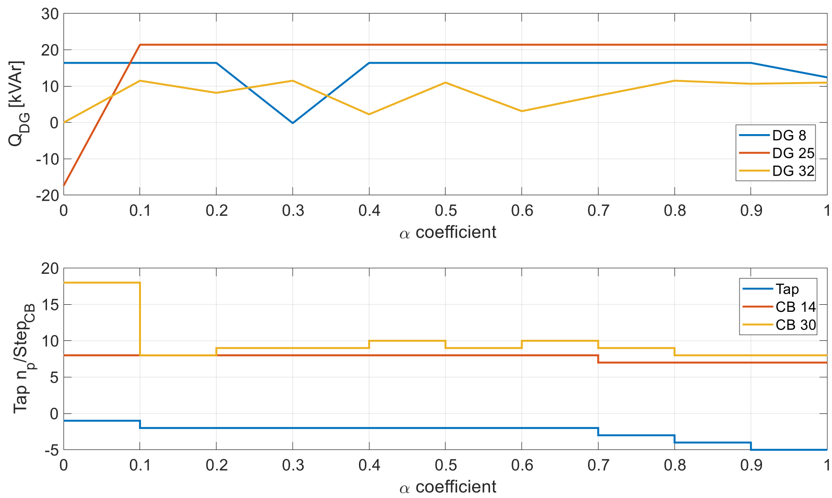

Fig. 6. The α dependent control variables variation

A balance between the two objectives is achieved for α = 0.5, therefore this value is considered hereinafter for the analysis of the system under various load conditions. In this purpose, three different load cases are considered:

a. Heavy Load case (C1) – the active and reactive power demanded by the loads is increased with 20%, compared to the base case.

b. Base case (C2) – the power demanded by the loads integrated in the studied network is equal to the values presented in [13].
c. Light Load case (C3) – the power demanded by the loads integrated in the studied network is decreased with 20%, compared to the base case.

The optimal values for control variables and for the two objectives, obtained in the three considered scenarios are presented in Table 2.

Table 2

The optimal objective function and set of control variables

	ΔP [%]	TVD [p.u]	Q_{DG} [kVAr]			$Step_{CB}$		Tap n_p
			Bus 8	Bus 25	Bus 32	Bus 14	Bus 30	
C1	76.87	0.0244	16.4	21.4	11.5	8	11	–3
C2	44.98	0.0091	16.39	21.4	9.11	8	9	–2
C3	22.19	0.0026	16.4	21.4	2.82	6	8	–1

The results presented in Table 2, reveal that, in the heavy load scenario, the operating tap is decreased from –2 (in the base case) to –3 and two additional steps are connected by the CB from bus 30, while the other control variables remain close to values resulted for the base case. On the other hand, in the light load scenario, the tap is increased to –1, the number of steps connected by the two CBs are reduced by two (CB at bus 14), and by one (for the CB at bus 30). Also, the reactive power outputs of the first two DGs are unmodified, while the DG at bus 32 supplies 2.82 kVAr instead of 9.11 kVAr in the base case.

5. Conclusion

The economic and secure operation of an active distribution power system is dependent on the bus voltage profile, upon which the reactive power control has a major influence. Considering the increasing penetration of distributed generation sources, distribution systems are provided with an important number of devices capable of assuring reactive power support, alongside the traditional devices that influence the voltage profile, which are the CBs and the OLTC from the HV/MV substation. In this context, the optimal reactive power dispatch problem is formulated in order to determine the optimal settings for the reactive power control devices with the purpose of minimizing active power losses and maintaining the bus voltage values close to the rated voltage. The mathematical model includes both objectives, and the α coefficient is introduced for deciding each objective's importance.

The ORPD optimization problem for an active distribution system is solved by applying a metaheuristic algorithm, namely the Grey Wolf Optimizer. A performance analysis between the GWO and two classical algorithms namely GA and PSO, demonstrated that the GWO provides superior performances in solving the ORPD problem. Consequently, the operating conditions obtained for the active distribution system by solving the ORPD problem using the GWO are analysed for the base load case and different values of the α coefficient and for the heavy and light load scenarios. The results demonstrated a significant reduction of active power losses and a considerable improvement of the voltage profile, when the optimal settings for the reactive power control devices were determined by solving the ORPD problem using the GWO. In conclusion, a safe and economic dispatch is obtained for all the considered scenarios.

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