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Optimal Power Flow Solution of Hybrid AC–DC Network Using Particle Swarm Method

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Abstract

In this article, we have tackled the multi-objective optimization problem of hybrid AC–DC networks using a metaheuristic method called particle swarm optimization (PSO). The approach of our work answers the following questions: how to model and integrate a direct current (DC) system, including VSC lines and converter stations, into the power optimization computation (OPF) process. To do this, the entire DC system (lines and VSC stations) is converted into a notional AC equivalent system using appropriate modeling, enabling the application of traditional AC OPF methods. Within the framework of multi-objective optimization, the Pareto technique is used to select the optimal solution from among those satisfying the defined objectives. The algorithm developed was implemented in the Matlab environment and tested on a modified IEEE-30 bus test network. The results obtained were compared with those of similar work published previously. The contribution of our research in the field of AC-DC hybrid power system optimization lies in the modeling of VSC stations integrated in an AC network, aiming to perform multi-objective optimization using tools developed for AC networks.

Keywords

optimal power flow, particul swarm, modeling AC–DC network

1 Introduction

Power optimization in modern power grids is an essential pillar in meeting today's energy supply challenges. It not only maximizes the operational and energy efficiency of power infrastructures, but also enables the harmonious integration of variable renewable energies such as solar and wind power [1]. By minimizing losses during long-distance electricity transmission, this optimization contributes to a more sustainable use of available energy resources, thus reducing the overall carbon footprint [2]. In addition, improved power flow management enhances the resilience and stability of networks in the face of demand fluctuations and unforeseen events, ensuring a reliable and continuous power supply [3]. By integrating advanced network control and management technologies, such as energy storage systems and smart grids, power optimization paves the way for a more flexible energy infrastructure, adaptable to the evolving needs of electricity consumers and producers.

The move towards mixed AC-DC grids represents an innovative response to the growing challenges posed by the modernization of the world's energy infrastructures. This transition is driven by the need to efficiently integrate intermittent renewable energy sources into the existing power grid [4]. Direct current (DC) lines offer several key advantages over alternating current (AC) lines, including increased transmission efficiency over long distances and better management of power flows across national and regional borders [5]. In addition, AC-DC and DC-AC conversion technologies enable greater operational flexibility and cost optimization, facilitating the seamless integration of microgrids and energy storage systems into the overall grid [6].

The use of metaheuristic methods to solve the Optimal Power Flow (OPF) problem in power grids offers significant advantages in terms of the ability to handle the complexity and non-linearity inherent in modern power systems. These methods, such as genetic algorithms, particle swarms and ant colony algorithms, are well suited to efficiently exploring the vast and often complex search space of the OPF [7]. By enabling a thorough exploration of potential solutions, metaheuristics are able to find solutions close to optimality, even under conditions where

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traditional methods may fail due to the non-convexity of the problem [8]. Moreover, their flexibility enables them to adapt to the different physical and operational constraints of power networks, such as voltage limits and equipment capacities, while effectively integrating network cost and performance objectives [9]. This robust and fast approach makes metaheuristic methods a valuable tool for power system engineers and planners, contributing to optimal sustainable management of modern networks.

2 AC–DC OPF problem formulation

AC–DC or hybrid networks have a complex architecture Fig. 1 shows the integration of a DC network with two AC networks.

The solution of the economic and environmental operating problem is a power flow solution that provides optimal values of control variables for a particular load situation by optimizing specific objective functions while respecting the constraints of operational variables. In formulating the OPF problem, various objectives can be addressed, such as minimizing fuel costs, reducing environmental emissions from generating plants, reducing active power losses in AC and DC system lines, reducing active power losses in VSC stations, etc., while maintaining equality and inequality constraints. The selection of these multiple objectives to solve the proposed problem is very important as it offers several advantages.

Minimizing fuel costs represents an economic dimension, while reducing emissions from generating plants represents an environmental dimension, and reducing active power losses on AC, DC and VSC systems represents a technical dimension. On this basis, the proposed problem is considered a multi-objective optimization, as it involves the simultaneous optimization of several objective functions.

The general form of the PFEO problem can be obtained as follows:

$$\min \boldsymbol{F} = \left\{ \boldsymbol{F}_1(x,y),\ \boldsymbol{F}_2(x,y),\ \ldots,\ \boldsymbol{F}_N(x,y) \right\}, \tag{1}$$

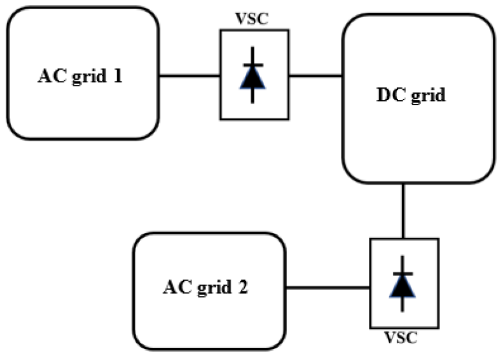

Fig. 1 Basic AC–DC grid configuration

where $\boldsymbol{F}$ is a vector of N objectives functions, with x and y representing the dependent variables. The solution of vector $\boldsymbol{F}$ is conditioned by equality constraints $g(x,y)$ and inequality constraints $h(x,y)$.

$$\begin{cases} g_1(x,y) = 0 \\ g_2(x,y) = 0 \\ \quad \vdots \\ g_N(x,y) = 0 \end{cases} \tag{2}$$

$$\begin{cases} h_1(x,y) \le 0 \\ h_2(x,y) \le 0 \\ \quad \vdots \\ h_N(x,y) \le 0 \end{cases} \tag{3}$$

2.1 Objective function

The OPF problem is a non-linear, non-convex, multi-objective optimization problem. The first objective considered is the fuel generation cost ($\boldsymbol{F}_1$). Since steam admission to generating units is always subject to continuous changes in the steam valves, known as the valve point load effect, this effect leads to fluctuations in the fuel cost [10]. Consequently, the fuel cost function in this paper is formulated by adding a therme rectifying the standard quadratic form of the cost [11]:

$$\boldsymbol{F}_1 = \sum_{i=1}^{N_g} \left\{ a_i + b_i P_{g_i} + c_i P_{g_i}^2 + \left| e_i \sin\left(f_i \left(P_{g_i}^{\min} - P_{g_i} \right) \right) \right| \right\}. \tag{4}$$

In Eq. (4) P_{g_i} representing the power injected by generator i, a_i, b_i and c_i are the associated cost coefficients, e_i and f_i are the valve point load coefficients.

Fossil fuel turbines are the main cause of air pollution in power systems, where SOX, NOX and CO_2 are emitted. Total emissions in tons per hour ($\boldsymbol{F}_2$) of pollutants are formulated as follows [12]:

$$\boldsymbol{F}_2 = \sum_{i=1}^{N_g} \left\{ \alpha_i + \beta_i P_{g_i} + \gamma_i P_{g_i}^2 + \delta_i e^{\left(\lambda_i P_{g_i}\right)} \right\}. \tag{5}$$

In Eq. (5), α_i, β_i, γ_i, δ_i and λ_i are the air pollution coefficients for production unit i.

Total power loss (TPL) ($\boldsymbol{F}_3$) in AC-DC networks is a combination of transmission losses in the AC network, transmission losses in the DC network, and losses in VSC stations, as shown in [13, 14]:

$$\boldsymbol{F}_3 = P_{Loss_{\mathrm{AC}}} + P_{Loss_{\mathrm{DC}}} + P_{Loss_{\mathrm{VSC}}}, \tag{6}$$

where $P_{Loss_{\mathrm{AC}}}$ is the total loss of active power in the AC network, $P_{Loss_{\mathrm{DC}}}$ is the total active power loss in the DC network, $P_{Loss_{\mathrm{VSC}}}$ is the total loss of active power in the network's VSC stations.

The power loss in the AC and DC network is given by:

$$P_{Loss_{\mathrm{AC}}} = \sum_{i,j} G_{ij} \left(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij} \right), \tag{7}$$

$$P_{Loss_{\mathrm{DC}}} = \sum_{i,j} R_{ij} I_{ij}^2. \tag{8}$$

where V_i and V_j represent the voltage at bus i, j respectively; G_{ij} is the conductance of the line between bus i and bus j, θ_{ij} is the angle between voltages V_i and V_j, R_{ij} is the resistance of the DC line connecting bus i with bus j and I_{ij} is the electric current in line ij.

Loss modeling in VSC converters can be treated in its general form as a quadratic function of the converter current [15, 16]:

$$P_{Loss_{\mathrm{VSC}}} = \sum_{i=1}^{N_{\mathrm{VSC}}} \left(\psi_{1_i} + \psi_{2_i} I_{Ci} + \psi_{3_i} I_{Ci}^2 \right), \tag{9}$$

where ψ_{1_i}, ψ_{2_i} and ψ_{3_i} represents the quadratic coefficients of active power loss in VSC stations.

2.2 Control variables

In AC-DC networks, the control devices for AC and DC power systems are interdependent. Traditionally, control variables for AC systems include generator output power, voltage, transformer tap settings and reactive power injection sources, as described in [17]:

$$x_{\mathrm{AC}} = \begin{bmatrix} P_{g_1}, \ldots, P_{g_N}, V_1, \ldots, V_{N_b}, \\ Tp_1, \ldots, Tp_{N_T}, Q_{1_{\mathrm{var}}}, \ldots, Q_{N_{\mathrm{var}}} \end{bmatrix}. \tag{10}$$

The power transmitted through VSC converters can be controlled according to the strategy imposed by the power grid operator, and this is achievable with advanced control of VSC stations. In this context, four types of control strategy can be distinguished [18]:

- V_{DC}–Q_C constant: this mode ensures constant voltage on the DC side with constant reactive power consumption on the AC side.
- V_{DC}–V_C constant: this mode ensures a constant voltage on both the DC and AC sides.
- Constant P_{DC}–Q_C: this mode ensures constant active power transferred to the DC line with constant reactive power consumption on the AC side.
- Constant P_{DC}–V_C: this mode ensures constant active power transferred to the DC line with constant AC voltage.

In this article, the control mode of VSCs will not be discussed, but a detailed modeling of VSC stations will be presented in Section 3. The aim, through proper modeling of VSC stations, is to be able to transform the DC network (DC-operated lines and VSC stations) into a notional AC network, and to use the standard formulas of the OPF problem.

2.3 Dependent variables

The dependent variables of AC networks are generally voltages at load nodes, reactive powers injected by generators, and transmission line loads [19]:

$$y_{\mathrm{AC}} = \left[V_{PQ_1}, \ldots, V_{PQ_{N_{PQ}}}, Q_{g_1}, \ldots, Q_{g_N}, S_1, \ldots, S_{NL} \right]. \tag{11}$$

2.4 Equality constraints

The active and reactive power injected into the AC network are formulated by [20]:

$$P_{g_i} - P_{load_i} - V_i \sum_{j=1}^{N_{\mathrm{AC}_b}} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) = 0, \tag{12}$$

with: $i = 0, 1, 2, \ldots, \left(N_{\mathrm{AC}_b} - \text{Slack bus} \right)$:

$$Q_{g_i} + Q_{C_i} - Q_{load_i} - V_i \sum_{j=1}^{N_{\mathrm{AC}_b}} V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij} \right) = 0. \tag{13}$$

where: $i = 0, 1, 2, \ldots, (N_{PQ})$.

For DC transmission, the active power transmitted between bus i and bus j is determined by Eq. (14) [21]:

$$P_{\mathrm{DC}_i} = V_{\mathrm{DC}_i} \sum_{\substack{j=1 \\ i \neq j}}^{N_{\mathrm{VSC}}} G_{\mathrm{DC}_{ij}} \left(V_{\mathrm{DC}_i} - V_{\mathrm{DC}_j} \right). \tag{14}$$

2.5 Inequality constraints

Eqs. (15)–(21) represent inequality constraints for the AC network only, while Eqs. (22) and (23) define inequality constraints for VSC stations:

$$p_{g_i}^{\min} \le P_{g_i} \le p_{g_i}^{\max};\ i = 1, 2, \ldots, N_g, \tag{15}$$

$$Q_{g_i}^{\min} \le Q_{g_i} \le Q_{g_i}^{\max};\ i = 1, 2, \ldots, N_g, \tag{16}$$

$$V_{g_i}^{\min} \le V_{g_i} \le V_{g_i}^{\max};\ i = 1, 2, \ldots, N_g, \tag{17}$$

$$Tp_{g_i}^{\min} \le Tp_{g_i} \le Tp_{g_i}^{\max};\ i = 1, 2, \ldots, N_T, \tag{18}$$

$$Q_{\mathrm{var}_i}^{\min} \le Q_{\mathrm{var}_i} \le Q_{\mathrm{var}_i}^{\max};\ i = 1, 2, \ldots, N_{\mathrm{var}}, \tag{19}$$

$$V_{PQ_i}^{\min} \le V_{PQ_i} \le V_{PQ_i}^{\max};\ i = 1, 2, \ldots, N_g, \tag{20}$$

$$S_i \le S_i^{\max};\ i = 1,2,\ldots,N_{ligne}, \tag{21}$$

$$P_{\mathrm{DC}_i}^{\min} \le P_{\mathrm{DC}_i} \le P_{\mathrm{DC}_i}^{\max};\ i = 1,2,\ldots,N_{\mathrm{VSC}}, \tag{22}$$

$$V_{\mathrm{DC}_i}^{\min} \le V_{\mathrm{DC}_i} \le V_{\mathrm{DC}_i}^{\max};\ i = 1,2,\ldots,N_{\mathrm{VSC}}. \tag{23}$$

3 AC–DC hybrid network modeling

To model a hybrid network, we consider a VSC$_i$ station linking an AC network with a DC network (see Fig. 2). The impedance $Z_{S_i} = R_{S_i} + jX_{S_i}$ represents the line and the coupling transformer of the VSC station. The approach used to model the hybrid AC–DC network is based on the transformation of the OPF AC–DC problem into an OPF AC–AC problem. The computational algorithm proposed in this article will enable us to simultaneously process the AC and DC networks by converting the DC network into a notional AC network [22–24].

The exchange of active power between the AC and DC network is determined by:

$$P_{\mathrm{AC}_i} + P_{\mathrm{DC}_i} + P_{Loss_{\mathrm{VSC}_i}} = 0. \tag{24}$$

The active power loss $P_{Loss_{\mathrm{VSC}_i}}$ in the VSC$_i$ can be calculated using Eq. (9), the voltages at the VSC$_i$ terminals are linked by the modulation index m_i Eq. (25):

$$V_{\mathrm{AC}_i} = m_i V_{\mathrm{DC}_i},\ 0 \le m_i \le m_i^{\max}. \tag{25}$$

The max value of the modulation index in the per unit system [25, 26] is given by:

$$m_i^{\max} = \sqrt{\frac{3}{2}}\frac{V_{Base_{\mathrm{DC}}}}{V_{Base_{\mathrm{AC}}}}, \tag{26}$$

where $V_{Base_{\mathrm{DC}}}$ and $V_{Base_{\mathrm{AC}}}$ are the base voltages for the DC and AC systems.

The VSC$_i$ station is modeled as a complex tap-changing transformer and the DC network is represented as a notional AC network (i.e., with resistive AC lines), as shown in Fig. 3. The power loss in each VSC$_i$ station is represented by a bypass conductance G_{SW_i} [27].

$$P_{Loss_{\mathrm{VSC}_i}} = G_{SW_i} V_{\mathrm{DC}_i}^2 \tag{27}$$

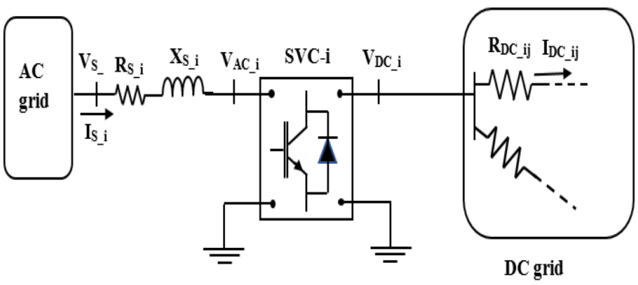

Fig. 2 VSC$_i$ station

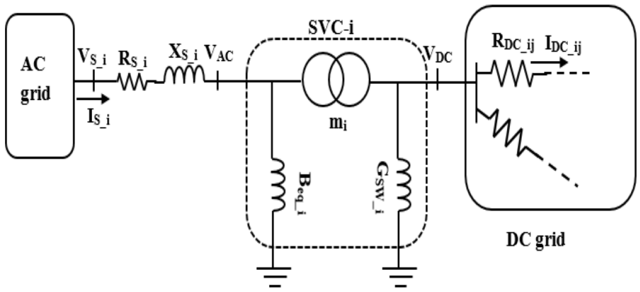

Fig. 3 Modeling VSC$_i$ station

An additional susceptance B_{eq_i} is used to guarantee zero reactive power injection into the DC network. The constraint ensuring that $Q_{\mathrm{DC}_i} = 0$ for each VSC$_i$ is given by [27]:

$$Im\left\{\begin{matrix} G_{SW_i}V_{\mathrm{DC}_i}^2 + \left(Y_{m_i}^* + jB_{eq_i}\right)m_i^2 V_{\mathrm{DC}_i}^2 \\ -m_i e^{j\phi_i} Y_{m_i}^* V_{\mathrm{DC}_i} V_{s_i}^* \end{matrix}\right\} = 0, \tag{28}$$

with: $Y_{m_i} = \dfrac{R_{s_i} + jX_{s_i}}{R_{s_i}^2 + X_{s_i}^2}$.

The power transmitted by a line in a DC system is a special case of transmission in an AC system. This is true if the reactive power is zero. Consequently, the following similarity can be established (see Fig. 4).

Then we can write:

$$V_i = V_{\mathrm{DC}_i},\ V_i = V_{\mathrm{DC}_i},\ \theta_i = \theta_j = 0, \tag{29}$$

$$Z_{\mathrm{AC}_{ij}} = R_{\mathrm{DC}_{ij}} + j_0,\ B_{\mathrm{AC}_{ij}} = 0, \tag{30}$$

$$P_{\mathrm{AC}_{ij}} = V_i V_j\left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) - G_{ij}V_i^2 = P_{\mathrm{DC}_{ij}}, \tag{31}$$

$$Q_{\mathrm{AC}_{ij}} = V_i V_j\left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) + \frac{B_{ij}}{2}V_i^2 = Q_{\mathrm{DC}_{ij}} = 0. \tag{32}$$

And so, the solution of the OPF AC–DC problem is transformed into an OPF AC–AC problem, and the basic equations from Eq. (1) to Eq. (9) can be used. Now it's time to choose the optimization tool. In this article, the choice is made for a metaheuristic method called

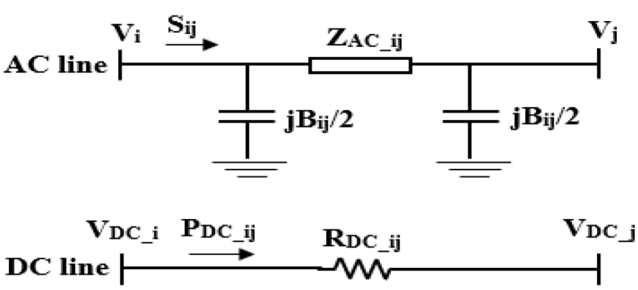

Fig. 4 Transmission line

"Particle Swarm". Section 4 presents the principle and algorithm of the AC–DC OPF.

4 Basic concepts of PSO

The PSO method is an innovative optimization method developed by Kennedy and Eberhart [28, 29]. Inspired by behavioral processes observed in the societies of flying birds, it is an integral part of evolutionary computation techniques. The method involves a set of particles forming a swarm, each exploring the search space in search of the global minimum (or maximum).

In a PSO system, particles navigate through a multi-dimensional search space. Each particle adjusts its position according to its own experience ($pbest$) and that of its neighbors ($gbest$). The swarm, or group of particles, is guided by these historical optimal positions. Specific formulas for calculating the velocity and new position of each particle are established according to [25, 26]:

$$v_j^{(i+1)} = k\begin{pmatrix} \omega v_j^{(i)} + c_1 rand(\ )\left(pbest_j - x_i^{(i)}\right) \\ +c_2 rand(\ )\left(gbest_j - x_i^{(i)}\right) \end{pmatrix}, \tag{33}$$

$$x_j^{(i+1)} = x_i^{(i)} + v_j^{(i+1)},\ \ \forall j = 1,2,\ldots,n_S. \tag{34}$$

where x_j and v_j represent respectively the current position and velocity of the particle at j-th generation, ω is the inertia weight factor, c_1 and c_2 are acceleration constants, rand( ) represents a random number between 0 and 1, *pbest* is the best previous experience of the i-th particle that is recorded, *gbest* is the best particle among the whole population, n_S is the number of swarms (or groups), k is a contraction factor derived from the stability analysis of Eq. (33) to ensure that the system converges without precipitation, and can be represented by a function [26] of c_1 and c_2 in Eq. (35):

$$k = \frac{2}{\sqrt{2-\varphi-\sqrt{\varphi^2-4\varphi}}}, \tag{35}$$

with: $\varphi = c_1 + c_2$.

PSO uses *pbest* and *gbest* to adjust the current search point, preventing the particles from moving uniformly, but rather converging gradually towards *pbest* and *gbest*. The right choice of inertia weight ω balances global and local exploration. Usually, ω can be dynamically adjusted using the following equation [29–31]:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{i_{\max}} i, \tag{36}$$

where $i_{\max}$ is the maximum number of iterations, $i_{\min}$ is the minimum number of iterations, i is the current iteration, $\omega_{\max}$ and $\omega_{\min}$ are the upper and lower limits of the inertia weight.

Particle velocity is limited by a maximum value $V_{\max}$. The $V_{\max}$ parameter determines the quality of problem solving, with which the regions between the current position and the target position are explored. This limit reinforces local exploration of the problem space and realistically simulates the incremental changes of human learning.

If $V_{\max}$ is too high, particles may exceed good solutions. On the other hand, if $V_{\max}$ is too low, particles may not explore sufficiently beyond local solutions. Based on experience with PSO methods, $V_{\max}$ is often adjusted between 10% and 20% of the dynamic range of the variable on each dimension. In this paper, a $V_{\max}$ limit equivalent to 15% of the dynamic range of the variable is adopted [31].

In conclusion, this work addresses a constrained multi-objective optimization problem for hybrid AC–DC networks, solved using the particle swarm method (PSO). The algorithm used in this paper was developed in the MATLAB environment, based on the following steps:

1. Step 1: Initialization:
   - Enter AC–AC network data.
   - Convert the OPF AC–DC problem into OPF AC–AC (Eqs. (25) to (30)).
   - Initialize a population of N particles. For each particle i, assign random values to position x_i and velocity V_i:

     $$x_i = \left[P_{g_{1i}},\ldots,P_{g_{N_i}},Tp_{1_i},\ldots,Tp_{NT_i},Q_{1_{\text{var}_i}},\ldots,Q_{N_{\text{var}_i}}\right],$$

     $$y_i = \begin{bmatrix} VP_{g_{1i}},\ldots,VP_{g_{N_i}},VTp_{1_i},\ldots,VTp_{NT_i}, \\ VQ_{1_{\text{var}_i}},\ldots,VQ_{N_{\text{var}_i}} \end{bmatrix}.$$

   - Assign the best position $pbest_i$ of each particle i by its initial position.

     $$pbest_i = x_i$$

   - Initialize the archive of best non-dominated positions to empty.
2. Step 2 : Evaluation:
   - For each particle i, evaluate the values of the objective functions ($\boldsymbol{F}_1$, $\boldsymbol{F}_2$, $\boldsymbol{F}_3$): Eqs. (4)–(6). For Eq. (6), Eqs. (7)–(9) are used.

- Calculation of AC power flow using the Newton-Raphson method.

3. Step 3: Stress verification: Eq. (12) to Eqs. (23), (31) and (32)
   - If all constraints are met, proceed to Step 4.
   - If not, adjust the particles. In this article, we've used a correction method that adjusts the particles to the limit values imposed by the constraints.
4. Step 4: Updating the archive by Pareto front:
   - Add the new valid particle positions to archive A if they are not dominated by other solutions in the archive.
   - Eliminate dominated solutions from archive A.
5. Step 5: Finding the best overall solution:
   - Identify the best particle among the elements in archive A.
6. Step 6: Update speeds and positions:
   - For each particle i, update the velocity V_i and position x_i (Eqs. (33) and (34)).
7. Step 7: Update some personal best positions:
   - For each particle i, if particle xi is better than:

$$pbest_i = x_i.$$

- If not, $pbest_i$ keeps its value.

8. Step 8: End:
   - Repeat steps 2 to 7 until the stopping criterion is reached (in this article, the stopping criterion is a max number of iterations, $ite_{max} = 95$).

5 Simulation and results

In Section 5, the algorithm proposed in this article is programmed in the MATLAB environment and applied to the modified IEEE 30-bus network to solve the multi-objective optimization problem of the AC–DC hybrid power system. The standard IEEE 30-bus system consists of 30 buses, 41 lines, 6 generators, 4 tap-changing transformers and 9 capacitive sources in parallel. Fig. 5 shows the modified network with two DC systems [32]. The VSC stations are characterized by a maximum power of 100 MW, with voltage limits ranging from 0.9 to 1.1 pu.

Reactive power compensators can inject a maximum of 5 M_{var} of reactive power into the grid. VSC stations operate as follows:

- VSC 1 and 4 have a V_{DC}–Q_C control mode;
- VSC 2, 3, 5 and 6 have constant P_{DC}–V_C control.

Generator and load bus voltages must be in the range [1.1–0.95] pu. Cost and emission coefficients are taken from [33].

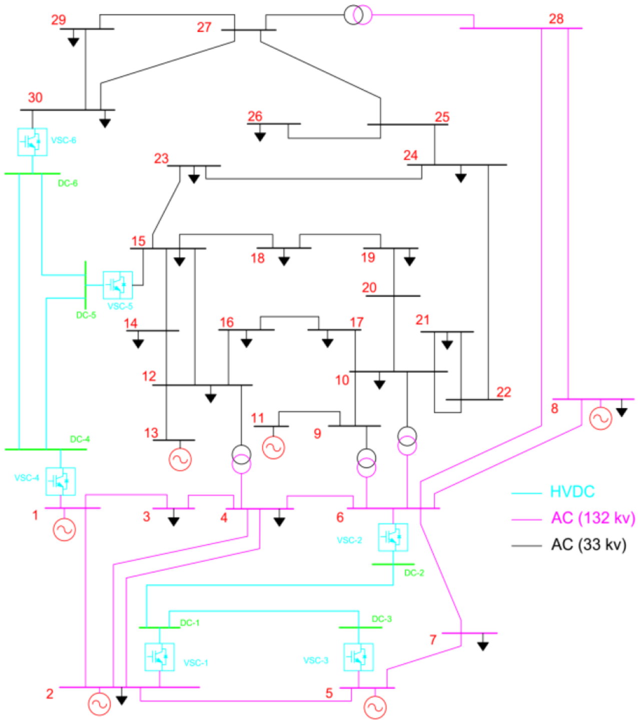

Fig. 5 Modified IEEE 30-bus system

To validate our approach (PSO-OPF AC-DC), we proceeded as follows:

- First: cost optimization (function F1). In Section 5, a Matlab program is developed to optimize the total cost of production for the AC-DC hybrid system. The results obtained are then compared with those of other similar studies.
- Second: a multi-objective approach aims to minimize total production cost ($\boldsymbol{F}_1$), CO_2 emissions ($\boldsymbol{F}_2$) and total active power losses ($\boldsymbol{F}_3$) in AC, DC and VSC stations. The results obtained are compared with those of other work and then discussed.
- Case 1: Table 1 shows all the optimized parameters, and the numerical values of the results obtained do not differ from those in [17, 34]. The cost optimized by our approach is equal to 837.0018 \$/h, whereas in [34] it is equal to 840.08 \$/h and in [17] it is equal to 840.3 \$/h.

  Fig. 6 illustrates the evolution of the cost as a function of iteration. Convergence to the optimal solution is reached as early as 57th iterations, which testifies to the rapid convergence of the PSO approach.

  Fig. 7 shows the initial voltages of the problem, the voltages taken from [17, 34] and the voltages obtained by our optimized network bus approach. The voltage constraints V_{min} and V_{max} are respected.

  The results obtained, compared with those of references [17, 34], validate our optimization approach for

Table 1 Results of Case 1

Variables	Initial	Propoced PSO	Ref. [34]	Ref [17]
V_{g1}	1.05	1.0952	1.1	1.079
V_{g2}	1.04	1.0803	1.079	1.061
V_{g5}	1.01	1.0401	1.063	1.040
V_{g8}	1.01	1.0719	1.068	1.045
V_{g11}	1.05	1.0740	1.075	1.007
V_{g13}	1.05	1.0481	1.03	1.054
Tp_{6-9}	1.078	1.0962	1.1	1.024
Tp_{6-10}	1.069	1.0010	0.9688	1.071
Tp_{4-12}	1.032	1.0080	1.014	1.038
Tp_{27-28}	1.068	1.0344	1.064	1.026
Q_{var10}	19	7.7601	0	13.996
Q_{var12}	0	3.7695	2.438	1.765
Q_{var15}	0	15.0163	21.93	6.480
Q_{var17}	0	3.0032	1.403	5.723
Q_{var20}	0	2.1600	4.149	2.670
Q_{var21}	0	8.4965	2.479	12.793
Q_{var23}	0	5.3101	6.296	3.047
Q_{var24}	4.3	5.2276	11.09	6.527
Q_{var29}	0	0.8724	5.549	1.198
P_{g1}	105.3237	197.871	200.0135	200
P_{g2}	80	44.9700	45.97	44.835
P_{g5}	50	18.6667	18.03	18.601
P_{g8}	20	11.7401	10.24	10.323
P_{g11}	20	11.5912	10.03	10.660
P_{g13}	20	11.5651	12.16	12.007
Q_{S1}	17.31	−15.0076	−32.33	0.431
Q_{S4}	−17.45	7.2609	29.05	−19.485
V_{C2}	1	1.0810	1.072	1.051
V_{C3}	1	1.0381	1.025	0.999
V_{C5}	1	1.0510	1.039	1.041
V_{C6}	1	1.0340	1.025	1.041
P_{S2}	25.74	15.8732	16.53	14.067
P_{S3}	52.53	26.9987	33.67	31.285
P_{S5}	40.44	35.6301	36.57	36.818
P_{S6}	18.45	17.9041	16.03	18.374
V_{DC1}	1.06	1.0917	1.1	1.083
V_{DC4}	1.06	1.0965	1.1	1.072
F_1 [$/h]	975.64	837.0018	840.08	840.3
PAC_{Loss}	1.8956	5.0012	4.58	–
PDC_{Loss}	2.4972	1.0167	1.2287	–
$PVSC_{Loss}$	7.5309	6.0001	7.2348	–

a single-objective problem in hybrid AC-DC networks and pave the way for multi-objective optimization.

- Case 2: in this case, our objectives is to simultaneously minimize total production cost, CO_2 emissions

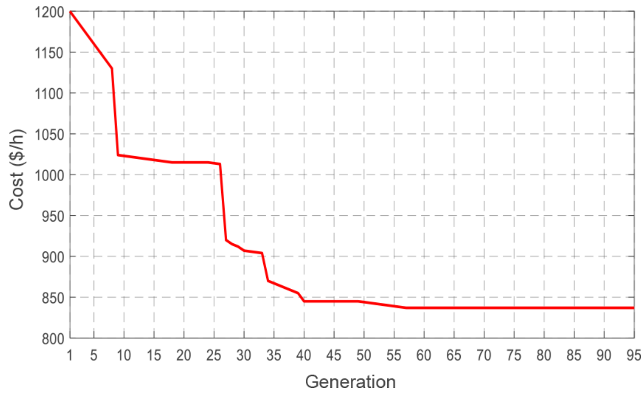

Fig. 6 Cost over iteration Case 1

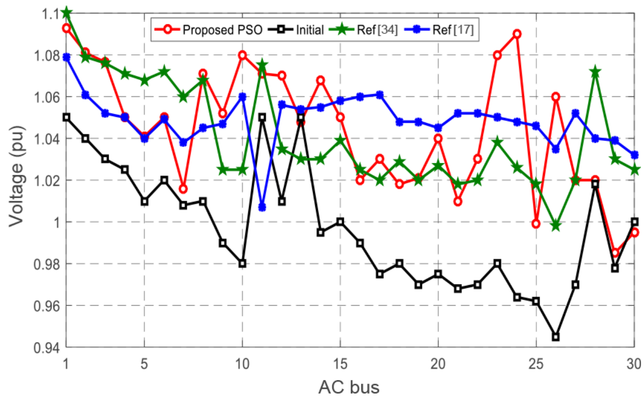

Fig. 7 Voltage in AC system, Case 1

and active power losses in AC transmission lines, DC transmission lines and VSC converters, while respecting the equalities and inequalities constraints described in Section 2. The results obtained are presented in Table 2.

Figs. 8, 9 and 10 show the evolution of total cost, CO_2 emissions and total active power losses as a function of calculation iterations. The algorithm proposed in this article converges on an optimal solution as early as 73^{th} iterations, with values of $\boldsymbol{F}_1$ = 874.7523 $/h, $\boldsymbol{F}_2$ = 0.2432 ton/h and $\boldsymbol{F}_3$ = 10.0543 MW.

Fig. 11 compares the voltages obtained by our algorithm with those taken from references [17, 34] for the AC system. It can be seen that the voltage constraints are well respected.

Fig. 12 shows the DC system voltages obtained by our OPF AC–DC approach using PSO, comparing them with the IEEE-30 bus reference network voltages and those taken from references [17, 34].

Fig. 13 shows well-distributed Pareto alternatives solutions, the best compromise as the overall optimum solution, with $\boldsymbol{F}_1$ = 874;7523 $/h, $\boldsymbol{F}_2$ = 0.2432 ton/h and $\boldsymbol{F}_3$ = 10.0543 M_w.

Table 2 Results of Case 2

Variables	Initial	Propoced PSO	Ref. [34]	Ref. [17]
V_{g1}	1.05	1.0967	1.0313	1.0955
V_{g2}	1.04	1.0943	1.0263	1.0729
V_{g5}	1.01	1.0121	1.0057	1.0517
V_{g8}	1.01	1.0451	1.0196	1.062
V_{g11}	1.05	1.0298	0.9953	1.0529
V_{g13}	1.05	1.0784	1.009	1.081
Tp_{6-9}	1.078	1.0086	1.0079	1.0585
Tp_{6-10}	1.069	1.0056	1.0011	1.0314
Tp_{4-12}	1.032	1.0043	1.0057	1.0126
Tp_{27-28}	1.068	1.0021	1.0025	1.0198
Q_{var10}	19	15.7634	18.3016	6.7464
Q_{var12}	0	16.2343	12.5042	19.0608
Q_{var15}	0	13.7602	19.062	15.0916
Q_{var17}	0	10.5423	4.3011	20.0593
Q_{var20}	0	3.2131	7.8544	5.2101
Q_{var21}	0	6.0053	4.5984	5.3426
Q_{var23}	0	7.3472	6.0811	4.3013
Q_{var24}	4.3	6.8274	7.2819	5.316
Q_{var29}	0	6.9062	6.0811	8.8216
P_{g1}	105.3237	132.5621	125.845	129.3655
P_{g2}	80	66.7688	64.0449	66.2022
P_{g5}	50	21.5456	29.3297	22.6008
P_{g8}	20	26.0097	24.7692	32.8303
P_{g11}	20	24.5501	23.4756	22.9121
P_{g13}	20	22.6753	26.5573	20.3413
Q_{S1}	17.31	−30.7648	8.9691	−43.7106
Q_{S4}	−17.45	−10.7623	−7.0387	3.0458
V_{C2}	1	1.0308	1.0178	1.0688
V_{C3}	1	1.0781	1.0153	1.0457
V_{C5}	1	1.0098	1.01	1.0785
V_{C6}	1	1.0654	1.0154	1.0821
P_{S2}	25.74	12.0675	10.3418	16.1855
P_{S3}	52.53	22.0021	21.8713	21.0756
P_{S5}	40.44	21.9043	19.7401	26.2714
P_{S6}	18.45	13.7659	15.337	12.7149
V_{DC1}	1.06	1.0687	1.0579	1.078
V_{DC4}	1.06	1.0206	0.9927	1.0156
$\boldsymbol{F}_1$ (\$/h)	975.64	874.7523	896.55	882.5743
$\boldsymbol{F}_2$ (ton/h)	0.2417	0.2532	0.25698	0.264915
$\boldsymbol{F}_3$ (Mw)	11.9237	10.0543	10.622	10.85332

6 Conclusion

The integration of high-voltage direct current (HVDC) networks into alternating current (HVAC) networks represents a major challenge for power system operators. Indeed, this integration modifies the voltage profile and the

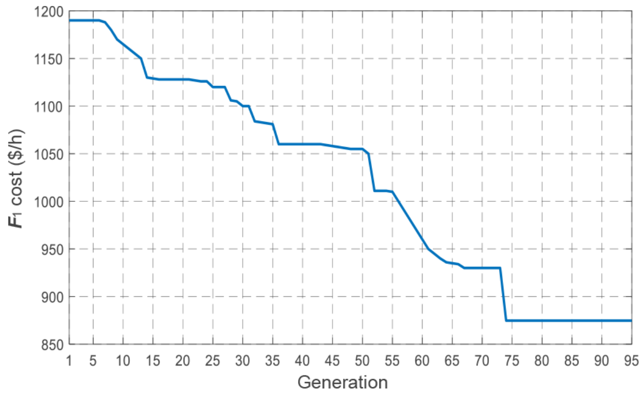

Fig. 8 Objectif $\boldsymbol{F}_1$ Cost over iterations, Case 2

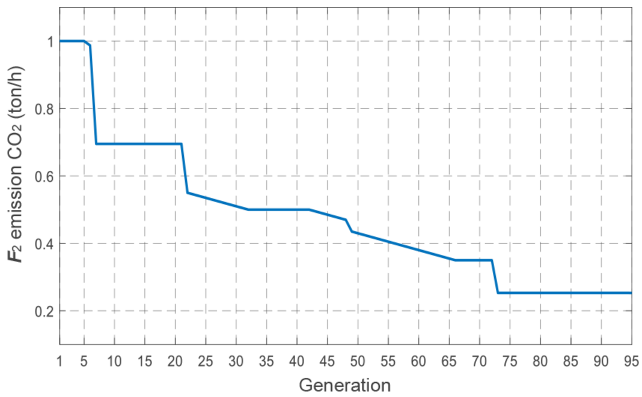

Fig. 9 Objectif $\boldsymbol{F}_2$ CO_2 emission over iterations, Case 2

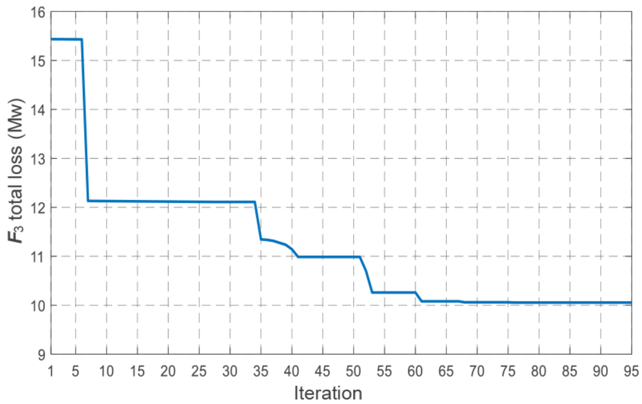

Fig. 10 Objectif $\boldsymbol{F}_3$ Total loss over iterations, Case 2

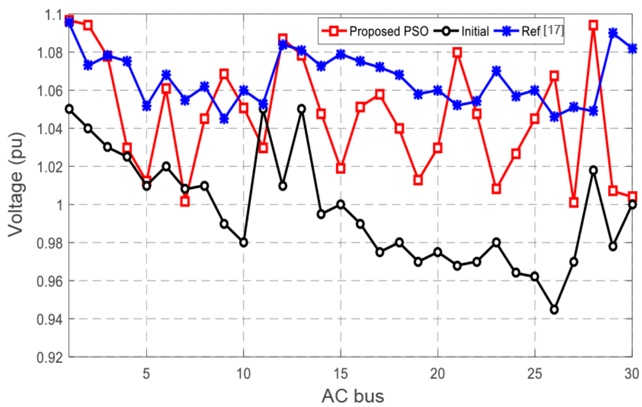

Fig. 11 Voltage in AC system, Case 2

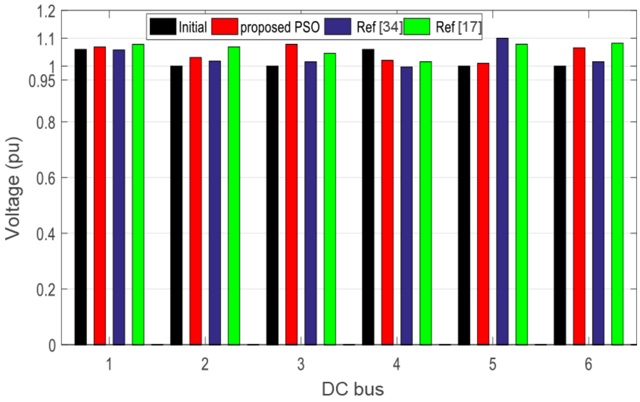

Fig. 12 Voltage in DC system, Case 2

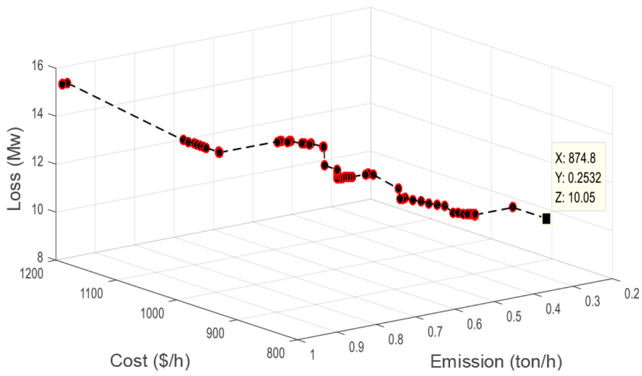

Fig. 13 Pareto solution for AC–DC grid, Case 2

transmitted power, calling into question conventional optimization methods due to their inability to account for the specificities of DC lines and VSC stations. Several studies are focusing on the global reformulation of the problem and the development of new AC-DC OPF calculation tools. This poses a significant technical challenge for network operators, equivalent to a radical transformation of current processes. The main idea is to find solutions for integrating DC operation into conventional OPF calculation tools.

We conducted hybrid AC–DC network modeling based on the operating principle of VSC stations, allowing us to convert the DC part of the network into a notional AC network. This conversion enabled us to use classical methods to solve the AC–DC OPF problem. Our AC–DC OPF approach, utilizing the PSO metaheuristic method, has been validated through two trials. The first trial involved a single-objective optimization applied to the overall cost of production, the results of which, compared with those of previous work, validate and confirm our approach. The second trial focused on multi-objective optimization, simultaneously addressing overall cost, CO_2 emissions, and total losses. The results obtained are particularly significant compared to other work carried out in the same context.

The contribution of our research in the field of optimization relies on a robust approach that provides more optimized results than those of previously presented works, with a very acceptable computation time. Furthermore, our approach can handle multi-objective optimization problems with equality and inequality constraints for hybrid AC–DC networks, without modifying the method of calculating power distribution in AC networks.

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