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Optimal economic-environmental dispatch in MT-HVDC systems via sine-cosine algorithm

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ABSTRACT

This paper addresses the problem of optimal economic-environmental dispatch in Multi-Terminal High-Voltage Direct Current (MT-HVDC) networks using the Sine-Cosine Algorithm (SCA). This optimization methodology allows working with nonlinear non-convex large-scale optimization problems via sequential programming. The SCA works with an initial population and rules of advance based on the best current solution and sine and cosine functions that define the direction of the next solution. Three variants of the SCA are evaluated in a standard six-node MT-HVDC system considering a linear combination of the objective functions (i.e., greenhouse emissions and energy production costs). The main advantage of the proposed evolutionary approach lies in its pure algorithmic structure. Thus, it can be easily adapted to any continuous optimization problem. All numerical calculations are performed using MATLAB software.

1. Introduction

Global warming is caused by greenhouse gas emissions, which are mainly generated by transport systems and energy systems based on thermal plants. These systems work with fossil combustion fuels such as diesel or gasoline (typical in transport systems) and coal or natural gas in power systems [1,2]. In addition, cattle breeding is the third most important factor in greenhouse emissions, which are composed of carbon, dioxide, and methane [3]. In order to address this significant problem, this study focuses on the analysis and operation of thermal plants that work with fossil fuels to produce higher amounts of power in high-voltage networks [4]. Furthermore, we assume that thermal power plants are interconnected to MT-HVDC grids, allowing power to be supplied at long distances from thermal plants to loads [5].

The analysis of thermal plants in MT-HVDC systems should consider two optimization objectives related to greenhouse emissions and the costs of the energy produced. In addition, if the topology of the network, its voltages, and its currents are also included in the optimization model, it becomes from a convex quadratic model to a nonlinear non-convex one [6]. The main challenge with the Economic-Environmental Dispatch Problem (EEDP) is its nonconvexity. Hence, it is not possible to guarantee the EEDP optimal solution or uniqueness [7]. Studies have proposed convex reformulations based on sequential quadratic programming models focusing on linearizations of the power balance equations. Nevertheless, these Taylor-based methods introduce estimation errors in the final solution to the problem. Other common approaches to similar problems (such as optimal power flow problems) consist of using semidefinite [8] or second-order cone relaxations [9] to address nonlinearities in the power balance equations. However, these approaches increase the number of variables in a quadratic form with the number of nodes implying a significant processing time to reach the optimal solution [10].

In the case of Alternating Currents (AC), the EEDP has been solved with metaheuristic optimization approaches such as Particle Swarm Optimization (PSO) [11], Genetic Algorithms (GA) [7], Bat Algorithms (BA) [12], and Grey Wolf Optimizer (GWO) [13], i.e., in general, evolutionary algorithms [14,15]. Nevertheless, the common denominator in these approaches is the fact that in AC models, the grid topology, voltages, and angles are not considered. This fact generates simplified versions of the EEDP. When this optimization problem is analyzed in Direct Current (DC) networks, only one approach was found based on sequential quadratic programming, as recently reported in

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Ref. [6]. Nonetheless, in the case of EEDP for MV-HVDC systems, no combinatorial optimization methods have been presented to address its solution, which represents a research opportunity for this work.

In order to deal with the problem of the EEDP in MT-HVDC systems, this research proposes the application of an evolutionary optimization algorithm known as the SCA. This optimization method has been applied for multiple combinatorial optimization problems, such as optimal power flow solution in AC and DC grids [16], and [17]; parametric estimation in single-phase transformers [18], optimal design of a pressure vessel problem [19], and multiple engineering optimization problems [20,21]. We, as researchers, select this optimization algorithm to solve the EEDP as the main contribution of this research since the SCA have reported excellent numerical results in similar optimization problems [22].

The SCA works with trigonometric functions to evolve the initial population. So, this study proposes three alternatives of using sine and cosine functions: *i)* roulette, *ii)* additive, and *iii)* product approaches. Validation of the SCA is made into a six-node test system with a voltage operation of about 400 kV, with three thermal plants and three loads that absorb 3700 MW. Simulations are carried out in the MATLAB programming environment, which identifies that all three evolution alternatives reach the optimal solution with minimal errors and lower processing times.

The remainder of this paper is organized as follows: Section 2 presents the mathematical formulation of the EEDP in MT-HVDC as well as its main characteristic related to the solution space form. Section 3 shows the proposed solution methodology based on the SCA with three modifications in its evolutionary process. Section 4 defines the main characteristics of the six-node test system, including the topology, i.e., location of thermal generators and constant power consumption, and the objective function parameterization. Section 5 presents the numerical implementation of the proposed master-slave approach composed of the SCA in the master stage and the classical matricial successive approximation power flow in the slave stage. In addition, discussion and comments about the numerical results are included. Section 6 presents the main concluding remarks derived from this investigation.

2. Mathematical formulation

The economic-environmental dispatch problem corresponds to a nonlinear non-convex optimization problem composed of a linear combination of two objective functions that conflict. These functions are the minimization of greenhouse emissions and energy production costs. The mathematical model is described from Equation (1) to Equation (9).

2.1. Objective function

Equation (1) denotes the linear combination of the two objective functions.

$$\min z = \omega_1 z_1 + \omega_2 z_2 \tag{1}$$

Where z is the value of the objective function, and ω_1 and ω_2 are weighting factors that multiply the cost of energy production and greenhouse emissions, i.e., z_1 and z_2. Equation (2), the first objective function, corresponds to the energy production costs. Equation (3), the second objective function, corresponds to the kilograms of greenhouse emissions.

$$z_1 = \sum_{i=1}^{n} a_i p_{gi}^2 + b_i p_{gi} + c_i \tag{2}$$

$$z_2 = \sum_{i=1}^{n} \alpha_i p_{gi}^2 + \beta_i p_{gi} + \gamma_i \tag{3}$$

Where p_{gi} is the total power generated by the thermal plant connected at node i; in addition, a_i, b_i, and c_i are the coefficients of costs associated with fossil fuels, while α_i, β_i, and γ_i correspond to the coefficients related to the kilograms of greenhouse gas emissions released into the atmosphere.

2.2. Set of constraints

From Equation (4) to Equation (9) is denoted the set of constraints. Equation (4) represents the set of power balance equations, which are non-affine non-convex constraints owing to the product between voltage variables. Equation (5) limits the voltage profile between the maximum and minimum values. In Equation (6), the power generation capabilities in thermal plants are constrained. In Equation (7), the thermal capacities of the transporting current at each branch of the network are limited. Equation (8) and Equation (9) are related to the weighting factors and their bounds regarding the linear combination of the objective functions.

$$p_{gi} - p_{di} = v_i \sum\nolimits_{j=1}^{n} G_{ij} v_j, \forall i \in \mathcal{N} \tag{4}$$

$$v_i^{\min} \leq v_i \leq v_i^{\max}, \forall i \in \mathcal{N} \tag{5}$$

$$p_{gi}^{\min} \leq p_{gi} \leq p_{gi}^{\max}, \forall i \in \mathcal{N} \tag{6}$$

$$|v_k - v_m| \leq r_{km} i_{km}^{\max}, \forall k, m \in \mathcal{L} \tag{7}$$

$$\omega_1 + \omega_2 = 1 \tag{8}$$

$$0 \leq \omega_1, \omega_2 \leq 1, \tag{9}$$

Where v_i is the value of the voltage profile at node i, which is upper and lower bounded by $v_i^{\min}$ and $v_i^{\max}$, respectively, p_{gi} is the generation in thermal plant i, which is limited by $p_{gi}^{\min}$ and $p_{gi}^{\max}$. The capability of flowing current in the transmission line between nodes k and m is bounded by $i_{km}^{\max}$ r_{km}, the resistance value of the conductor in this line. Note that $\mathcal{L}$ and $\mathcal{N}$ are sets that contain all branches and nodes of the MT-HVDC system.

To solve the economic-environmental dispatch problem, which is non-convex owing to the power balance constraints, we propose in the next section an optimization algorithm based on sine and cosine functions that solves optimization problems via population searches.

3. Solution methodology

The solution to the economic-environmental problem formulated from Equation (1) to Equation (9) is accomplished by creating a master-slave solution methodology. This study employs the SCA in the master stage and a classical power flow method in the slave stage. Next, the main characteristics of the proposed optimization approach are presented.

3.1. Slave stage: power flow solution

The main challenge of the economic-environmental dispatch problem is related to the solution of the power balance equations, because they are quadratic non-convex equalities and cannot be solved with exact methods. This challenge implies that numerical methods such as Gauss-Seidel [23], Newton-Raphson [24], Taylor-based methods [25] among others. So, it was selected a recently developed method called the matricial successive approximation method reported in Ref. [26]. This method allows rewriting Equation (4) in a matricial form by separating the slack nodes (i.e., voltage-controlled ones) from demands or constant power-load consumption.

In order to solve the power flow equations, the matricial successive approximation method uses the recursive Equation (10).

$$v_d^{t+1} = G_{dd}^{-1}\left[\mathbf{diag}^{-1}\left(v_d^t\right)\left[p_g - p_d\right] - G_{ds} v_s\right] \tag{10}$$

Where v_d is a vector that contains the values of the voltages in all demand nodes, G_{dd} is a square invertible matrix that contains all conductance effects among the demand nodes, G_{ds} is a rectangular matrix with the conductive effects among slacks and demand nodes, v_s is a vector with the slack voltages, p_g and p_d represent vectors that contain power generations in the thermal plants and constant power consumptions at the demand nodes, respectively. Note that $\mathbf{diag}(v_d)$ generates a square matrix with the components of the vector at its diagonal. It is relevant to mention that t is the iterative counter in the recursive Equation (10), which finishes its iterative procedure when $\max\left\{\left|v_d^{t+1} - v_d^t\right|\right\} \leq \varepsilon$ ε the tolerance parameter typically selected in the specialized literature as 1×10^{-10}.

3.2. Master stage: SCA

This stage defines all variables that enter into the power flow problem (i.e., the slack voltages) and the power generation in the remainder of the thermal plants, i.e., p_g. For this purpose, an iterative process named SCA is presented in this section. This optimization approach is based on a population and advancing rules defined by trigonometric functions. All of these aspects are discussed below.

3.2.1. Generation of initial population

The initial population consists of a set of individuals that are possible solutions to the optimization problem (Equation (11)). Let us define n_s as the number of slack nodes, t_p the number of thermal generators, and n_i the number of individuals. Then, the initial population is a matrix with dimensions $(n_s + t_p) \times n_i$, with the structure $x^0 = \left[x_1^0\ x_2^0 \dots x_{n_i}^0\right]^T$.

$$x^0 = \begin{bmatrix} v_{1,1} & \cdots & v_{1,n_s} & p_{1,n_s+1} & \cdots & p_{1,t_p+n_s} \\ v_{2,1} & \cdots & v_{2,n_s} & p_{2,n_s+1} & \cdots & p_{2,t_p+n_s} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ v_{n_i,1} & \cdots & v_{n_i,n_s} & p_{n_i,n_s+1} & \cdots & p_{n_i,t_p+n_s} \end{bmatrix} \tag{11}$$

Observe that to facilitate the evolution of the SCA, all individuals in the population are created in a feasible space, i.e., $x_j^{\min} \leq x_j \leq x_j^{\max}$, $\forall j = 1, 2, \dots, n_i$.

3.2.2. Fitness function

A metaheuristic optimization that deals with all inequality constraints includes the maximum and minimum lower bounds and uses fitness functions instead of an objective function. So, the fitness function described in Equation (12) is proposed.

$$\begin{aligned} f_f = \ & z - \theta_1 \min\{0, v_{\max} - v\} + \theta_2 \max\{0, v_{\min} - v\} - \theta_3 min\left\{0, p_g^{max} - p_g\right\} \\ & + \theta_4 max\left\{0, p_g^{min} - p_g\right\} - \theta_5 min_{k,m}\left\{0, r_{km} i_{km}^{max} - v_k - v_m\right\} \end{aligned} \tag{12}$$

Where θ_1 to θ_5 are penalization factors (positive values) that work when one of the, defined by Equation (5) to Equation (7), is not fulfilled; the power balance constraint solved through the matricial successive approach of Equation (10) allows evaluating the fitness function f_f defined by Equation (12). In addition, constraints related to weighting factors are not included in the fitness functions since the iterative procedure of the SCA controls them.

3.2.3. Evolution of population

The evolution in the SCA is defined by trigonometric functions of sine and cosine types. To explain this, let us consider that the individual with the best fitness function (minimum value) is named x_{best}^m, with m the iterative counter of the SCA. To design the evolution of the population, we propose the three following alternatives:

3.2.3.1. Roulette approach. In this approach, the next potential individual y_j^m is generated through Equation (13).

$$y_j^m = \begin{cases} x_j^m + r_1 \sin(r_2)\left|r_3 x_{\text{best}}^m - x_j^m\right| & r_4 \geq \dfrac{1}{2} \\ x_j^m + r_1 \cos(r_2)\left|r_3 x_{\text{best}}^m - x_j^m\right| & r_4 < \dfrac{1}{2} \end{cases} \tag{13}$$

Where r_1 is defined as a decreasing factor associated with the number of iterations, i.e., $r_1 = 1 - \frac{m}{m_{\max}}$, where $m_{\max}$ is the maximum number of iterations carried out by the SCA. r_2 is a random vector between 0 and 2π with appropriate dimensions, r_3 is a random vector between 0 and 1 with appropriate dimensions, and r_4 is a random number contained in the interval [0, 1]. The calculation of the potential individual y_j^m by Equation (13) is named the roulette approach owing to the function of the r_4 number that allows for selecting a sine or cosine function at each time.

Once the potential individual is formed, its maximum and minimum values are guaranteed by comparing each component with its bounds. If one or more values violate the upper or lower bounds, then these are generated again inside their limits. This procedure guarantees the feasibility of all potential solutions.

To determine if the potential solution y_j^m will become x_j^{m+1}, the fitness function is evaluated (Equation (14)).

$$x_j^{m+1} = \begin{cases} y_j^m & f_f\left(y_j^m\right) < f_f\left(x_j^m\right) \\ x_j^m & f_f\left(y_j^m\right) \geq f_f\left(x_j^m\right) \end{cases} \tag{14}$$

3.2.3.2. Additive approach. The potential solution is reached by adding the sine and cosine functions (Equation (15)).

$$y_j^m = x_j^m + r_1(\sin(r_2) + \cos(r_2))r_3 x_{\text{best}}^m - x_j^m \tag{15}$$

For this potential solution, it is also verified that it is feasible before evaluating its fitness function. Through Equation (14) is selected the later individual in the population.

3.2.3.3. The product approach. The potential solution, in this approach, yields by multiplying the sine and cosine functions (Equation (16)).

$$y_j^m = x_j^m + r_1 \sin(r_2)\cos(r_2) r_3 x_{\text{best}}^m - x_j^m \tag{16}$$

In addition, its feasibility is verified. Then, when it is feasible, Equation (14) is employed to choose the later individual in the population. Each of the evolution approaches works with trigonometric functions that help with new solutions around the current individual x_j^m based on circular movements governed by the random angle r_2. This angle defines the direction of the movement as a function of the best solution located in the population. This is a form of exploring the solution space. In addition, with the decrement of the parameter r_1, this exploration becomes exploitation of the solution space, which allows for refining the best solution reached. The random value r_3 works as an important factor between the current solution and the best one, and it helps to explore the solution space by tracing a linear combination among them.

3.2.4. Stopping criteria

The SCA algorithm stops its search process in the solution space when each of the following conditions is reached:

- If all iterations have been made, i.e., $m = m_{\max}$.
- If during l consecutive iterations the best fitness function has not been modified, where $l_{\max}$ is the maximum number of consecutive iterations without improvement, i.e., $l = l_{\max}$.

3.2.5. Pseudocode of proposed SCA

Algorithm 1 presents the main steps of the proposed sine-cosine algorithm for the optimal economic-environmental dispatch of thermal plants for MT-HVDC systems and resumes the numerical implementation of this optimization approach.

Algorithm 1
Pseudocode of the SCA for economic-environmental dispatch problems in MT-HVDC systems.

Data: Select the test system and the parameters SCA: $t_{\max}$, $m_{\max}$, n_i, $l_{\max}$,ϵ, v_0 = **1** PU. Generate the initial population x^0 with Equation (11)
for $j = 1 : n_i$ **do**
    Solve the power flow problem in the slave stage by using Equation (10) for x_j^0.
    Evaluate the fitness function by employing the Equation (12) for $f_f\left(x_j^0\right)$
end
for $m = 1 : m_{max}$ **do**
    Select the best current solution: x_{best}^m.
    for $j = 1 : n_i$ **do**
        Select the evolution alternative: **A1**, **A2** or **A3**.
        Solve the power flow problem in the slave stage by using Equation (10) for y_j^m.
        Evaluate the fitness function by employing the Equation (12), i.e., $f_f\left(y_j^m\right)$
        Select x_j^{m+1} with Equation (12) and Equation (14).
    end
    if $l == l_{\max}$ *or* $m == m_{\max}$ **then**
        Result: Return x_{best}^m.
    end
end

Algorithm 1: Pseudocode of the SCA for economic-environmental dispatch problems in MT-HVDC systems.

4. Test system

To validate the proposed SCA and its evolution variants, we adapt the CIGRE test system originally presented in Ref. [5] and recently proposed in Ref. [6]. This system includes three thermal plants at nodes 1 to 3 and three constant power loads at nodes 4 to 6 (Fig. 1). For this system, the voltage design is 400 kV, and the slack node is located at node 2.

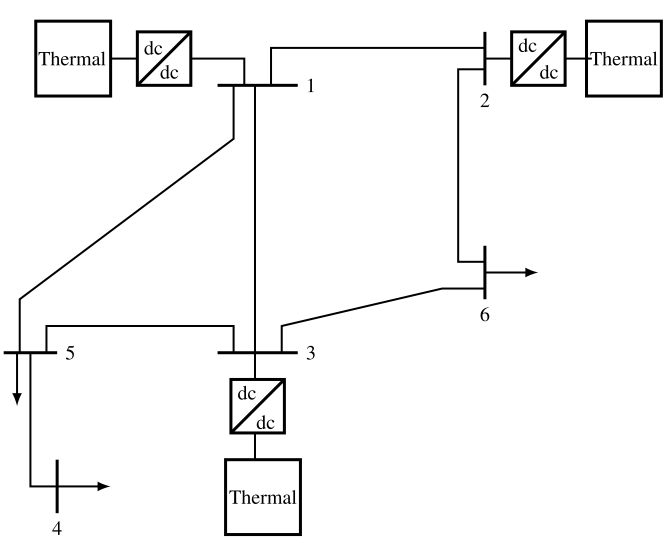

Fig. 1. Six-node MT-HVDC system.

All information related to the line parameters and power consumption is listed in Table 1, while the parameters associated with the environmental and economic functions are listed in Table 2. These coefficients were selected to provide similar solutions in terms of cost and gas emissions of thermal plants in the United States.

5. Computational validation

This section presents the software and computer characteristics for solving the economic-environmental dispatch problem with SCA and its three variants. These computational validations are carried out using a desktop computer with an Intel(R) Core(TM) *i*5 − 3550 processor at 3.50 GHz with 8 GB of RAM running a 64-bit Windows 10 Professional operating system using the MATLAB programming environment 2021a.

To examine the efficiency of the proposed SCA and its three evolutionary alternatives, three simulation scenarios based on the values of the weighting factors ω_1 and ω_2 are created. **Scenario 1 (S1):** the solution of EEDP considering $\omega_1 = 1$ and $\omega_2 = 0$, which implies that the main interest is to minimize the total cost of energy production; **Scenario 2 (S2):** the solution of EEDP considering $\omega_1 = 0.5$ and $\omega_2 = 0.5$, which implies that both objective functions have the same numerical importance; and **Scenario 3 (S3):** the solution to EEDP considering $\omega_1 = 0$ and $\omega_2 = 1$, which corresponds to the minimization of the total greenhouse gas emissions.

To combine both objective functions are normalized with $z_1^{\max}\ \$\ 456\,269.8969$ and $z_2^{\max} = 253\,864.6205$ kg, which are taken from Ref. [6] by solving the problems for **S1** and **S3**, respectively.

In all simulations, we consider 1000 iterations for the SCA, 20 individuals in the population, and 100 consecutive iterations without improvement.

5.1. Results for Scenario 1

This scenario optimizes the total cost of energy production by assuming that $\omega_1 = 1$ and $\omega_2 = 0$. Table 3 lists the main results for this simulation case.

Results in Table 3 evidence that the maximum, minimum, and mean values for the roulette, additive, and product evolution approaches are the same. This result implies that all of them reach the optimal global solution of the EEDP in MT-HVDC systems when the objective function is the minimization of the total energy production cost. Note that the maximum reduction yield in this cost is about 7.73% for its maximum value. One of the main characteristics of these numerical results is that it is confirmed that when the energy production cost is at a minimum, the greenhouse emissions are at a maximum.

Regarding the standard deviation, we can say that exponents of about 1×10^{-10} for z_1 and 1×10^{-06} for z_2 show that after multiple iterations of the SCA, its results are close to the mean value. This outcome confirms the efficiency of the proposed master-slave optimization approach. Concerning processing times, from the last column of Table 3, we conclude for scenario 1 that the roulette method is the

Table 1
Parameters of six MT-HVDC system proposed by CIGRE-B4 working group.

Line parameters					
From	To	$R_{ij}[\Omega]$	From	To	$R_{ij}[\Omega]$
1	5	5.70	3	6	4.75
5	3	2.28	1	2	1.90
5	4	1.71	2	6	1.90
1	3	2.28	–	–	–
Load consumptions					
Node	P [MW]	Node	P [MW]	Node	P [MW]
4	1500	5	1250	6	950

Table 2
Generation coefficients of thermal plants.

Generation	c [$]	b [$/MWh]	a [$/MW^{2}h]	γ [kg]	β [kg/MWh]	$\varLambda$ [kg/MW^{2}h]	p_{gi}^{min} [MW]	p_{gi}^{max} [MW]
p_{g1}	100	20	0.10	4.091	−5.543	0.0649	50	1500
p_{g2}	100	15	0.12	2.543	−6.047	0.05638	100	2000
p_{g3}	200	18	0.04	4.258	−5.094	0.04586	140	1800

Table 3
Simulation results for **S1** applying three evolutionary alternatives.

Alt.		max	min	Mean	Stand. Dev.	Time [s]
A1	z_1	0.9227	0.9227	0.9227	9.8892×10^{-10}	3.3193
	z_2	1.0000	1.0000	1.0000	3.9469×10^{-06}	
A2	z_1	0.9227	0.9227	0.9227	1.6825×10^{-09}	3.4951
	z_2	1.0000	1.000 0	1.0000	5.8072×10^{-06}	
A3	z_1	0.9227	0.9227	0.9227	1.3825×10^{-10}	3.6818
	z_2	1.0000	1.0000	1.0000	1.6535×10^{-06}	

Table 5
Simulation results for **S3** applying three evolutionary alternatives.

Alt.		max	min	Mean	Stand. Dev.	Time [s]
A1	z_1	1.0005	0.9997	1.0000	1.2304×10^{-04}	3.5001
	z_2	0.9663	0.9663	0.9663	1.1258×10^{-07}	
A2	z_1	1.0004	0.9995	1.0000	1.8320×10^{-04}	3.5060
	z_2	0.9663	0.9663	0.9663	2.4522×10^{-07}	
A3	z_1	1.0002	0.9998	0.9255	6.3697×10^{-05}	3.5071
	z_2	0.9663	0.9663	0.9663	4.2240×10^{-08}	

quickest evolutionary approach, taking approximately 0.175 8 s ($time_{A2} - time_{A1}$) and 0.362 5 s ($time_{A3} - time_{A1}$) for the additive and product approaches, respectively.

Finally, the values of the variables that produce the results in Table 3 are $v_2 = 400$ kV, $p_{g1} = 1093.5$ MW, $p_{g2} = 927.47$ MW, and $p_{g3} = 1800$ MW. These results coincide exactly with the numerical values reported in Ref. [6], where a sequential quadratic programming model was developed.

5.2. Results for Scenario 2

In this scenario is optimized is given the same importance for both objective functions $\omega_1 = 0.5$ and $\omega_2 = 0.5$. Table 4 lists the main results for this simulation case.

From the results in Table 4, we observe that the standard deviation is on the order of 1×10^{-6} to 9×10^{-6}, which is considered negligible for practical optimization purposes. This outcome implies that the maximum, mean, and minimum are numerically identical for the first six decimals. On the other hand, it is significant to note when factors ω_1 and ω_2 are different from 1. Both objective functions take values different from their maximums and minimums.

In **S2**, we observe that the improvement in the energy production costs is about 7.45%, and the greenhouse emissions decrease by about 0.84%. This behavior is maintained if ω_1 decreases and ω_2 increases. In addition, it is evident that in terms of processing times, the roulette approach is faster than the additive and product methods (see the last column in Table 4). In this scenario, the final values of the state variables are as follows: $v_2 = 400$ kV, $p_{g1} = 1018$ MW, $p_{g2} = 1003.4$ MW, and $p_{g3} = 1800$ MW.

5.3. Results for Scenario 3

This scenario optimizes the total amount of greenhouse emissions by assuming that $\omega_1 = 0$ and $\omega_2 = 1$. Table 5 lists the main results for this simulation case.

Table 5 shows the numerical performance of the objective functions when we try to minimize the total greenhouse emissions without considering the energy reduction costs. Observe that in each evolutionary alternatives, the objective function z_2 remains equal with standard deviations lower than 1×10^{-6}, which implies that these results are numerically equal in their first six decimals. In the case of the energy production costs, there are some variations concerning their maximums. These variations can be attributed to decimal variations in the values of the state variables. However, in all of these cases, the objective function z_1 is at a maximum when z_2 is at a minimum, which confirms the multiobjective nature of the EEDP in MT-HVDC systems.

Table 4
Simulation results for **S2** applying three evolutionary alternatives.

Alt.		max	min	Mean	Stand. Dev.	Time [s]
A1	z_1	0.9255	0.9255	0.9255	1.7912×10^{-06}	3.2057
	z_2	0.9916	0.9916	0.9916	1.7907×10^{-06}	
A2	z_1	0.9255	0.9255	0.9255	2.5364×10^{-06}	3.4015
	z_2	0.9916	0.9916	0.9916	2.5361×10^{-06}	
A3	z_1	0.9255	0.9255	0.9255	8.1896×10^{-07}	3.5804
	z_2	0.9916	0.9916	0.9916	8.1891×10^{-07}	

It is important to mention that the maximum reduction of greenhouse emissions is about 3.37%, which is about 8555.28 kg of greenhouse emissions per hour. In terms of processing times, the last column in Table 5 shows that the roulette approach is faster than the additive and product methods. Finally, for this simulation scenario, all state variables take the following values: $v_2 = 400$ kV, $p_{g1} = 1070.6$ MW, $p_{g2} = 1225.7$ MW, and $p_{g3} = 1529.9$ MW.

6. Conclusion and future work

This paper analyzes an application of the SCA for solving economic-environmental dispatch problems in MT-HVDC systems. This study also proposes three evolution alternatives for selecting the potential individuals based on sine and cosine functions. Each alternative allows reaching the optimal global solution in minimum processing times. The main advantage of the proposed evolutionary approach lies in its pure algorithmic structure. Thus, it can be easily adapted to any continuous optimization problem.

As future work, SCA and its evolution alternatives will be expanded into a multiobjective optimization approach for solving nonlinear non-convex optimization problems with objectives in conflict, as in the case of the EEDP in MT-HVDC systems. In addition, it is possible to propose a second-order cone programming formulation for the EEDP with a guarantee of global applicability and uniqueness in the optimal solution. Finally, considering several metaheuristic optimization strategies, future work consists of implementing other optimization methods to compare the efficiency and results of the strategy analyzed in this work.

Author statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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