Multi-objective optimization of 400 kV Composite Insulator Corona Ring Design

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ABSTRACT The electric field distribution is one of the main factors governing the long-term reliability of high voltage composite insulators. However, under severe pollution conditions, electric field stresses, when exceeding thresholds and applying for long periods, could lead to degradation and deterioration of the housing materials and, therefore, to failures of the composite insulators. This paper is intended to improve the electric field and potential distributions by minimizing the corona discharge on a 400 kV AC transmission line composite insulator. The performances of three powerful multi-objective meta-heuristic algorithms, namely Ant Lion Optimizer (MOALO), Particle Swarm Optimizer (MOPSO), and non-dominated sorting genetic algorithm (NSGA-II) are established to achieve this goal. First, variations of electrical fields on the critical parts of the string are obtained using three-dimensional finite element method (FEM) software. Then, three objective functions are developed to establish the relationships between the electric field and the guard ring parameters. Finally, the optimization parameters consist of diameter, tube diameter, and installation height of the corona ring. The obtained results confirm the effectiveness of the three algorithms; the MOLAO is the better in terms of computing time and solution quality.

INDEX TERMS Composite insulator, Corona ring, Electric field distribution, Finite element method (FEM), Multi-objective, MOALO, MOPSO, NSGA-II.

I. INTRODUCTION

In front of the expansion of national grids and the connection reasons with the Maghrebian and European networks, the Algerian Electricity and Gas Company (SONELGAZ) needed to develop 400 kV grids [1]. However, such transition of the electrical network to a higher voltage engenders high electric field. This latter should be enhanced to mitigate or even avoid hazardous consequences, whose the most harmful is the “insulators flashover” [2-7]. Nowadays, composite insulators are widely used in electrical networks because of their lower price, lighter weight, greater design flexibility, higher mechanical strength, better antipollution performance, and lower maintenance requirements [7-10]. However, since they are made up of organic materials, they are subject to probable chemical changes, erosion, and tracking, leading to the failure of such insulators [10-12]. To improve reliability and extend the life of composite insulators, several researchers have focused on the optimal distribution of the electric field along the non-ceramic insulator string to reduce corona degradation using, among others, conventional corona rings [7, 12-15]. The various studies carried out for the reduction of the electric field around the insulators string using the corona ring relate to the optimization of the design (based particularly on the diameter and the tube radius of the ring geometry) and the position of the ring setting [4,13, 15-18]. In real-life, many problems have more than one goal to be optimized. However, these goals, or objectives, could conflict with each other; i.e. an improvement in one objective could lead to the deterioration of at least one of the other objectives. Therefore, there exists a set of optimal compromise solutions called non-dominant or Pareto optimum solutions (Pareto front solutions) for which there is no alternative, in which all the parameters (factors) would be in a better position [19]. Optimization problems could be difficult to solve through conventional methods, especially when, in the presence of multiple constraints, these problems are complex,
multimodal, discrete or discontinuous [15]. In addition, they sometimes require considerable computing time. To overcome such difficulties, several meta-heuristic algorithms have been established to different kinds of real-life optimization problems [19-28]. The robustness of such algorithms overcomes the deficiencies of the conventional methods and allows finding the global optimum in shorter computation times. Furthermore, due to the simplicity of their mathematical models, these algorithms are easy to implement and among the most efficiently used approaches [19-22, 25, 26]. Some of the most common evolutionary algorithms consist in Genetic Algorithm (GA) [20], Ant Colony Optimization (ACO) [21], and Particle Swarm Optimization (PSO) [22]. Some other techniques are also developed and proposed in the literature such as Cuckoo search algorithm (CSA) [23], whale optimization algorithm (WOA) [24], grey wolf optimizer (GWO) [25], ant lion optimizer (ALO) [26], virus colony search (VCS) [27], and dolphin echolocation (DE) [28]. These algorithms have been successfully applied in a wide range of practical engineering problems. Otherwise, numerical techniques have been developed to optimize HV insulators design by improving the electric field performance [1, 29]. For instance, the Finite Element Method (FEM) has emerged as appropriate for low-frequency applications. FEM has been widely used by researchers in high-voltage engineering [1, 29]. In the present investigation, multi-objective versions of GA, PSO, and ALO are proposed to minimize the electric field at the high voltage composite insulator surface. A three-dimensional finite element model of 400 kV AC transmission lines composite insulator including the tower and corona ring is established to determine the electric field distribution. The influence of the corona ring parameters, namely the diameter, the tube radius, and the position (height) of the ring, are analyzed. The electric field at the triple point (HV side) is computed for a set of values of corona ring parameters by changing only one parameter and keeping the other constants. A mathematical model composed of three objective functions is developed based on the obtained results to establish the relationships between the electric field and the corona ring parameters. Optimizing such relationships allows obtaining the ring parameters leading to the lowest electrical field level on the composite insulator surface. For this purpose, the performances of three powerful multi-objective meta-heuristic algorithms, namely, Ant Lion Optimizer (MOALO), Particle Swarm Optimizer (MOPSO), and non-dominated sorting genetic algorithm (NSGA-II) are developed. The optimization results are discussed according to the quality of the solution and the computation time. It is worth noting that multi-objective optimization techniques have never been used in this area so far. In fact, such techniques generate a multitude of solutions, generally very different. The most representative solutions are kept and the other are rejected. Among the representative solution, the best one is selected by the decision marker. The greater the difference between the representative solutions, the more difficult the choice is [19, 30, 31]. Such drawbacks are not encountered in this study since the solutions we have obtained are very close and the choice of the best solution is too easy.

II. COMPUTATION MODEL
For this investigation, a typical 400 kV polymer insulator is used. The insulator is 3368 mm long with 40 large sheds and 40 small sheds. The diameter of large shed is 114 mm while the small’s is 97 mm. The insulator is made of silicon rubber weather sheds with a relative permittivity of 4.3, a fiberglass rod with a relative permittivity of 7.2 and metallic fittings. The technical characteristics of the composite insulator are presented in Table 1. figure1 shows the non-ceramic insulator used in a 400 kV transmission system and the simplified model employed for the simulation. The insulator is vertically suspended. The top metallic end fitting is connected to the tower (the ground electrode), and the bottom one is connected to the line (the high voltage electrode) whose voltage is 231 kV (=400 kV/√3). A corona ring, which is essentially a toroidal shaped metal ring, is placed at the energized end side of the insulator, where a high electric field is normally produced. The optimal corona ring parameters (corona ring diameter, ring tube diameter and vertical position of the ring along the insulator string) will later be determined. Simulations have been conducted in clean and dry conditions.

| TABLE I TECHNICAL INFORMATION OF COMPOSITE INSULATOR |
|-----------------------------------------------|
| Line Voltage [kV]                            | 400            |
| Leakage distance [mm]                        | 7770           |
| Dry arcing distance [mm]                     | 3105           |
| Insulator length [mm]                        | 3368           |
| Number of Sheds (N/n)                        | 40/40          |
| Sheds diameter D/d [mm]                      | 114/97         |
The electric field control is important, especially in three main zones: the polymer weather-shed surface, the interior of the fiberglass rod and the surfaces of the metal fittings and corona rings. In addition, the electric field stress is more important at the triple point junction of three media consisting in HV end fitting, polymer, and air [4, 8, 9]. Such a situation may strongly reduce the insulation performance of the insulator.

The corona ring is used to reduce the electric field on the surface of the composite insulators below the threshold values for corona inception in both dry and wet conditions [15, 18]. As well known, the electric field distribution on the insulator surface does not depend only on the applied voltage level, but also on the insulator profile and the corona ring parameters consisting in the diameter D, the tube inner radius r and the mounting height H.

In this study, the electric field value is evaluated for different values of corona ring parameters since no standards exist for the design and placement of corona rings [15, 18]. Indeed, generic corona ring configurations have been considered with outer diameters ranging from 250 to 550 mm, tube diameter from 30 to 90 mm, and mounting height from 0 to 650 mm. Furthermore, the parameters D, r, and H are varied by steps of 50 mm, 5 mm, and 50 mm, respectively [15].

III. EFFECTS OF CORONA RING PARAMETERS

The corona rings are installed to reduce and improve the distribution of the electric field and consequently reduce the failures appearing in the transmission systems and extend the lifetime of the insulators [14, 15]. Manufacturers suggest the application of corona rings on the active end of the insulators used for more than 230 kV and on both ends for those employed for more than 500 kV. Since, there are no standards for the design and placement of rings, the latter’s dimensions vary from one manufacturer to another [14, 15].

The electric field should not exceed 450 kV/m on the sheath for the dry uncontaminated composite insulator and 350 kV/m on the end-fitting seal [4, 10, 14]. Otherwise, the parameters of the corona rings, namely the ring diameter, D, the inner radius of tube, r and the mounting height, H, are taken as decision variables since these parameters considerably affect the electric field on the insulator surface [4, 10, 15, 16].

The electric field norm is computed along the central axis of the composite insulator core from the energized end to the ground one to determine the effect of corona rings parameters on the electric field distribution over the insulator. As explained in previous work [15], the electric field norm at first increases promptly to reach the maximum value, obtained at the axis point located at the same triple point height, and decreases rapidly than after.

The effects of the corona ring parameters on the maximum value of the electric field (computed at the triple point) are shown in Figures 2 to 4. Note that the electric field at the triple point is calculated by changing one parameter while the two others are kept constant. The maximum electric field norm strength was importantly decreased when using the corona ring.

Figure 2 depicts the synchronous effect of the ring diameter and the ring tube diameter on the maximum electric field at the triple point. A simultaneous decrease of the ring diameter and increase of the ring tube diameter leads to a significant decrease in the electric field norm. Note that, to avoid any contact between the ring and the large shed, the inferior limit of the corona ring rayon has been chosen, in our investigation, equal to 130 mm.

Figure 3 illustrates the simultaneous effect of the ring tube diameter and the installation height on the maximum electric field at the triple point. The electric field norm of the insulator decreases slightly with increasing the ring tube diameter when the mounting height is in the range of 150 mm to 300 mm, elsewhere there is no effect and the electric field is practically constant. On the other hand, the electric field norm first decreases significantly when increasing the corona ring mounting height. It reaches a minimum then after before increasing again. The minimum value, corresponding to more than 40% of maximum electric field norm reduction, is obtained approximately for 225 mm mounting height and 60 mm ring tube diameter.

As shown in Figure 4, the maximum electric field at the triple point of the insulator is almost constant for corona ring radius greater than 400 mm. However, the electric field norm at the triple point decreases significantly when the radius of the corona ring decreases when the mounting height is about 250 mm. For the other corona ring mounting height values, the decrease of the corona ring radius leads to the electric field increase.
IV. CORONA RING OPTIMIZATION PROBLEM FORMULATION

A. MULTI-OBJECTIVE OPTIMIZATION BASIC CONCEPT

In mono-objective optimization, there is only one global optimum solution that is relatively easy to find. However, in multi-objective problems, solutions must be compared to more than one objective (criterion). The general problem of multi-objective optimization involves minimizing or maximizing multiple objective functions subject to a set of constraints and can be mathematically expressed as follows [19]:

Minimize \( F(x) = [f_1(x), f_2(x), \ldots, f_n(x)] \) \hspace{2cm} (4.1)
Subject to \( g_k(x) \leq 0, k = 1, \ldots, m, \)
\( x_i(L) \leq x_i \leq x_i(U), i = 1, 2, \ldots \)

where
- \( x \) is a vector of \( d \) decision variables \( x = [x_1, x_2, \ldots, x_d]^T \).
- \( f_i(x), i = 1, \ldots, n \) are the objective functions.
- \( g_k(x), k = 1, \ldots, m \) are the constraint functions of the problem.
- \( x_i(L) \) and \( x_i(U) \) lower and upper bounds respectively.

The optimal solutions family of a multi-objective problem is composed of all those potential solutions so that no component of the corresponding objective vectors cannot be improved without the deterioration of other components. This is known as the concept of Pareto optimality. For example, in a minimization problem, Pareto dominance and Pareto optimality are defined as follows:

Pareto dominance: A given vector \( x = [x_1, x_2, \ldots, x_d] \) is said to dominate \( y = [y_1, y_2, \ldots, y_d] \) if and only if \( \forall i \in \{1, 2, \ldots, n\}, x_i \leq y_i \) and \( \exists i \in \{1, 2, \ldots, d\}, x_i < y_i \).

Pareto optimality: For a general MOP, a given solution \( x^* \in F \) (where \( F \) is the feasible solution space) is Pareto optimal if and only if there is no \( x \in F \) that dominates \( x^* \).

B. FORMULATION OF THE OPTIMIZATION PROBLEM (OBJECTIVE FUNCTION)

Based on the above results, the corona ring on the conductor side should have the optimum corona ring configuration to maintain the electrical field intensity, on the composite insulator, lower than the threshold value of 450 kV/m to prohibit the discharges activities in particular near the energized end fitting. The optimal configuration is achieved by minimizing the electric field via the multi-objective functions.

To fully reflect the electric field distribution of composite insulator, mathematical relations (objectives functions) between the electric field magnitudes and corona ring parameters are established. These functions allow us to apply...
different optimization algorithms to find the optimal corona ring parameters minimizing the electric field. The polynomial regression approach models the relationship between the independent variables (corona ring parameters) and the dependent variable electric field. The polynomial regression deviations are evaluated based on optimum mean square error (RMSE) and coefficient of determination (R2) values.

The following equations represent the proposed model:

\[
E(H, R) = \sum_{i,k} a_{ik} H^i R^k \quad i, k = 0, \ldots, \beta
\]  
(4.1)

\[
E(H, r) = \sum_{i,j} a_{ij} H^i r^j \quad i, j = 0, \ldots, \beta
\]  
(4.2)

\[
E(r, R) = \sum_{j,k} a_{jk} r^j R^k \quad j, k = 0, \ldots, \beta
\]  
(4.3)

Where \(a_{ik}\), \(a_{ij}\) and \(a_{jk}\) are the polynomial coefficients. \(R\), \(H\) and \(r\) are the ring diameter, the installation height and the ring tube diameter respectively.

In order to avoid an impractical corona ring size, the objective function should be subjected to various constraints defining by the influence ranges of the ring parameters. Depending upon performed simulation tests presented in figures 2 to 4 (corona ring parameters effects) and geometric feasibility, the selected constraints are given as follows:

\[
\begin{align*}
0 \text{ mm} & \leq H \leq 650\text{ mm} \\
130 \text{ mm} & \leq R \leq 550\text{ mm} \\
15 \text{ mm} & \leq r \leq 60\text{ mm}
\end{align*}
\]

C. MULTI-OBJECTIVE OPTIMIZATION ALGORITHMS

The goal in a multi-objective problem solving is to find a representative set of Pareto optimal solutions, and/or quantify the trade-offs in satisfying the different objectives. In this study, three efficient meta-heuristic algorithms, MOALO (SeyedaliMirjalili et al. 2016) [19], NSGA-II (Deb et al. 2002) [30], and MOPSO (J. Moore et al. 1999) [31] are adopted to optimize the corona rings design parameters. The details of the recently proposed multi-objective Ant Lion Optimizer (MOALO) and a very brief description of the two others algorithms are presented in the following subsections.

1) MULTI-OBJECTIVE ANT LION OPTIMIZER (MOALO)

Like all multi-objective algorithms, the Multi-Objective Ant Lion Optimizer starts the optimization process with multiple candidate solutions. These latter are compared with each other using the Pareto dominance operator. In each iteration, the non-dominated solutions are selected and stored in a repository and the algorithm tries to improve them in the next iterations.

The Multi-objective ant lion optimizer (MOALO) is the multi-objective version of the Mono-objective ant lion optimizer (ALO). The ALO algorithm [26] mimics the interaction between Ant Lions and ants in the trap. The ALO approximates the optimal solutions employing a set of random solutions. This set is improved based on the principles inspired from the hunting mechanism of Ant Lions and the interaction of their favorites prey (ants) with them. The ants are supposed to move randomly over the search space, and the Ant Lions can use traps and are expected to hunt them to model such interactions.

In their search for food in nature, the ants first wander randomly. Their random walks can be modeled as follows:

\[
x(t) = [0, \text{cumsum}(2r(t_1) - 1), \text{cumsum}(2r(t_2) - 1), \ldots, \text{cumsum}(2r(t_n) - 1)]
\]  
(4.5)

where cumsum calculates the cumulative sum, \(n\) is the maximum number of iterations, \(t\) shows the step of random walk, and \(r(t)\) is a stochastic function defined as follows:

\[
r(t) = \begin{cases} 
1 & \text{if } \text{rand} > 0.5 \\
0 & \text{if } \text{rand} \leq 0.5 
\end{cases}
\]  
(4.6)

rand is a random number generated with uniform distribution in the interval of \([0,1]\). During optimization, the position of an ant refers the parameters for a particular solution and the position of all ants is saved in the \(M_{Ant}\) matrix and also each Ant Lion position is saved in the \(M_{Ant Lion}\) matrix:

\[
M_{Ant} = [A_{ij}]M_{Ant Lion} = [AL_{ij}]
\]  
(4.7)

where \(A_{ij}\) presents the value of \(i\)-th variable of \(j\)-th ant (Ant Lion).

The value for the fitness function of each ant is saved in the matrix MOA and analogously, the values of Ant Lions fitness function are saved in the matrix MOAL:

\[
M_{OA} = \begin{bmatrix}
[f(A_{1,1}, \ldots, A_{1,d})] \\
\vdots \\
[f(A_{n,1}, \ldots, A_{n,d})]
\end{bmatrix} \\
M_{Ant Lion} = \begin{bmatrix}
[f(AL_{1,1}, \ldots, AL_{1,d})] \\
\vdots \\
[f(AL_{n,1}, \ldots, AL_{n,d})]
\end{bmatrix}
\]  
(4.8)

\(n\) and \(d\) are the number of ants and the number of variables. Considering that the ants update their positions with a random walk at each stage of optimization. So, to keep them inside the search space, they are normalized using the following expression:

\[
X_i^t = (X_i^t - a_i) \ast (d_i^t - c_i^t)/(b_i - a_i) - c_i^t
\]  
(4.9)

where \(a_i\) and \(b_i\) are the minimum and the maximum of random walk in \(i\)-th variable. Also, \(c_i^t\) and \(d_i^t\) are the minimum and the maximum of \(i\)-th variable at \(t\)-th iteration.

The equations describe mathematical modeling of ants trapping in Ant Lion's pits:
\[ c_i^t = Antlion_j^t + c^t \]
\[ d_i^t = Antlion_j^t + d^t \]  

(4.10)

where \( c \) and \( d \) are respectively the minima, and the maximum of all variables at \( t \)-th iteration, of all variables at \( t \)-th iteration, and \( Ant Lion \) is the position of the selected \( j \)-th Ant Lion at \( t \)-th iteration.

Ant Lion’s hunting capability is modeled by fitness proportional roulette wheel selection. The roulette wheel assists fitter Ant Lions to attract more ants. In other way, it consists in adaptively reducing the radius (the boundaries) of the random walking hyper-sphere of the ants. The mathematical model that describes the way how the trapped ant slides down towards Ant Lion is set as follows:

\[ c^t = c^t / l \]
\[ d^t = d^t / l \]  

(4.11)

where \( l \) is a ratio \( (l = 1 + 10^9 t / T) \), \( T \) is the maximum number of iterations, and \( w \) is a constant defined based on the current iteration \( (w = 2 \) when \( t > 0.1T, w = 3 \) when \( t > 0.5T, w = 4 \) when \( t > 0.75T, w = 5 \) when \( t > 0.9T, \) and \( w = 6 \) when \( t > 0.95T) \). Basically, the constant \( w \) can adjust the accuracy level of exploitation.

The final stage of hunt in ALO is catching the ant and reconstructing the pit to catch new prey. The formulation of this mechanism is as follows:

\[ Antlion_j^t = Ant_j^t \quad if \quad f(Ant_j^t) < f(Antlion_j^t) \]  

(4.12)

where \( Antlion_j^t \) and \( Ant_j^t \) show the position of selected \( j \)-th Ant Lion and \( i \)-th ant at \( t \)-th iteration.

Finally, elitism is applied in the following way, the best Ant Lion in each iteration is considered to be elite. It means that every ant randomly walks around selected Ant Lion and has position according to:

\[ Ant_j^t = (R_i^t + R_L^t) / 2 \]  

(4.13)

\( R_i^t \) is the random walk around the Ant Lion selected by the roulette wheel at \( t \)-th iteration, and \( R_E^t \) is the random walk around the elite Ant Lion at \( t \)-th iteration.

For finding and storing Pareto optimal solutions, MOALO algorithm uses an archive to store Pareto optimal solutions. However, finding the Pareto optimal solutions set with a high diversity is challenging. Therefore, MOALO utilizes the leader selection and archives maintenance to overcome this challenge, which is inspired by the MOPSO algorithm.

The Ant Lions are selected from the solutions with the least populated locality to improve the solutions’ distribution in the archive. Therefore, the probability of choosing a solution in the archive is:

\[ P_i = c / N_i \]  

(4.14)

When the archive is full, the solutions with the most populated locality are removed to accommodate new solutions. The probability of removing a solution from the archive is defined by:

\[ P_i = N_i / c \]  

(4.15)

where \( c \) is a constant and should be greater than 1 and \( N_i \) is the number of solutions in the vicinity of the i-th solution. The basic steps of the MOALO are illustrated in the pseudo-code in Algorithm 1 [19] and the flowchart of figure 5.

**Algorithm1:** Multi-Objective Ant Lion pseudo-code

```
Initialize the first population of ants and antlions randomly while the end condition is not met
for every ant
    Select a random antlion from the archive
    Select the elite using Roulette wheel from the archive
    Update c and d using equations Eq. (4.11)
    Create a random walk and normalize it using Eq. (4.12)
    Update the position of ant using (3.8)
end for
Calculate the objective values of all ants
Update the archive
if the archive is full
    Delete some solutions using Roulette wheel and Eq. (3.10) from the archive
    to accommodate new solutions.
end
end while
return archive
```

![Flowchart of MOALO](image-url)
2) MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION (MOPSO)

MOPSO is the multi-objective version of the PSO. It is one of the most popular algorithms in the multi-objective optimization area. The basic principle of the MOPSO algorithm is the initialization and the evaluation of the population and then repetition of the search by combining PSO operators with Pareto-dominance criteria. In this process, the non-dominated solutions (particles) are archived in repository, and are used to guide the particles search. If the number of solutions exceeds the directory size, they are reduced by using a crowding operation, which is used to crowd the best global solutions known as leaders. An effective elitist-mutation strategy was also used to maintain the population's diversity and explore the research space more intensively. The basic steps of the MOPSO are summarized within the pseudo-code in Algorithm 2 [32] and in the flowchart of figure 6.

Algorithm 2: Multi-Objective Particle Swarm Optimization pseudo-code

Initialize swarm
Initialize Leaders Archive
Determine Leaders Quality
Start iterations
While iter < maxit do
    For j = 1: popesize do
        Select Leader
        Update Position
        Mutation
        Evaluation
        Update Pbest
    End for
    Update Leaders Archive
    Determine Leaders Quality
    iter = iter + 1
End while
Return Archive

3) NON-DOMINATED SORTING GENETICALGORITHM (NSGA-II)

Non-Dominated Sorting Genetic Algorithm (NSGA-II) is a multi-objective version of the genetic algorithm [20]. In 2002, Deb et al. proposed the NSGA-II. They introduced the elitism to enhance the convergence properties and subsequently improve the efficiency and robustness of the algorithm searches [30]. NSGA-II uses elitism method for sorting and classifying all individuals and employs a crowding operation to crowd the best global solutions that are known as leaders for keeping the diversity among the obtained Pareto optimal solutions [30]. The NSGA-II basic steps pseudo-code is summarized in Algorithm 3 and flowchart of figure 7.

Algorithm 3: Non-dominated Sorting Genetic Algorithm (NSGA-II)

Initialize Population; Generate random population
Evaluate objective values
Assign rank (level) based on Pareto dominance—“sort”
Generate child population
Binary tournament selection and crossover
Recombination and mutation
While i ≤ the number of generations do
    For parent and child population do
        Assign rank (level) based on Pareto—“sort”
        Generate sets on non-dominated fronts
        Loop (inside) by adding solutions to next generation starting from the “first” front until M individuals found
        Determine crowding distances between points on each front
    End for
    Select points (elitist) on the lower front (with lower rank) and are outside a crowding distance
    Create next generation
    Binary tournament selection
    Recombination and mutation
End while
V. SIMULATION RESULTS AND DISCUSSION

In the remainder of this article, the three proposed meta-heuristic algorithms (MOALO, MOPSO and NSGA-II) are used to optimize corona ring settings based on the previous mathematical model to reduce the maximum electrical field located at the triple point junction (of three media consisting in HV end fitting, polymer, and air) of the composite insulator, to acceptable levels.

To measure the three algorithms performance, the multi-objective functions best values obtained and the iterations number required to converge are used as main criteria. The same initial starting values, obtained from ten randomly selected populations, are used for the three algorithms.

Due to the random factor included in the three algorithms, these latter are run five times and the statistical results are reported. It is noted that all along the five different executions, the three algorithms converge towards the same solution (optimal solution of multi-objective functions). This explains their great stability and robustness in the search for global solutions. Note that for the three algorithms, the common parameters were set at 250 iterations, 100 search agents and an archive size of 100 in the optimization trials. Basing on Design of Experiments (DOE), a sensitive analysis of the MOPSO and the NSGA-II is performed for each algorithm with different combinations of each parameter. During this analysis, the parameter values resulting in better quality solutions are adopted. The corresponding parameters are shown in Table 2. Note that there are no parameters of MOALO to be adjusted.

The Pareto optimal fronts obtained by the three algorithms are presented in Table 4, the electric field optimal minimization considered as the optimum (the best) solution for each multi-objective function as well as the number of iterations, the computational time for convergence, and the total computational one.

Although the three algorithms converge towards practically the same result, Table 4 shows that the execution time of the MOALO algorithm is less than the other two algorithms MOPSO and NSGA-II ones, therefore the MOALO converges more quickly. The average time to run only one iteration is 0.0463s for the MOALO against 0.1218s, and 0.568s for the MOPSO and the NSGA-II. Note that for MOPSO, the run time of an iteration increases during the second half of the total iterations number, while this time is almost the same for all iterations for the other algorithms. Compared to the computation time found by the MOPSO (respectively the NSGA-II), a reduction of about 55% (respectively 75%) has been obtained when using the MOALO.

The Pareto optimal fronts obtained by the three algorithms are presented in figures 8 and 9. Figure 8 illustrates the plane (f1, f2) of the three-objective optimization Pareto fronts. This figure shows that the three algorithms spread the solutions differently over the non-dominated front. MOPSO can find a much better distribution than the MOALO algorithm; the NSGA-II is the worst in spreading the solutions over the non-dominated front. Multiple runs of the three algorithms (MOALO, MOPSO and NSGA-II) for the corona ring settings design optimization generate very stable Pareto frontiers for each algorithm as shown in figure 8.

From optimal solutions presented by the Pareto fronts in figures 5 and 6, we present in Table 4 the electric field optimal minimization considered as the optimum (best) solution for each multi-objective function as well as the number of iterations, the computational time for convergence, and the total computational one.

Although the three algorithms converge towards practically the same result, Table 4 shows that the execution time of the MOALO algorithm is less than the other two algorithms MOPSO and NSGA-II ones, therefore the MOALO converges more quickly. The average time to run only one iteration is 0.0463s for the MOALO against 0.1218s, and 0.568s for the MOPSO and the NSGA-II. Note that for MOPSO, the run time of an iteration increases during the second half of the total iterations number, while this time is almost the same for all iterations for the other algorithms. Compared to the computation time found by the MOPSO (respectively the NSGA-II), a reduction of about 55% (respectively 75%) has been obtained when using the MOALO.

The Pareto optimal fronts obtained by the three algorithms are presented in figures 8 and 9. Figure 8 illustrates the plane (f1, f2) of the three-objective optimization Pareto fronts. This figure shows that the three algorithms spread the solutions differently over the non-dominated front. MOPSO can find a much better distribution than the MOALO algorithm; the NSGA-II is the worst in spreading the solutions over the non-dominated front. Multiple runs of the three algorithms (MOALO, MOPSO and NSGA-II) for the corona ring settings design optimization generate very stable Pareto frontiers for each algorithm as shown in figure 8.

\[ IGD = \frac{\sum_{i=1}^{n} d_i^2}{n} \]  \hspace{1cm} (5.1)

where n is the number of the optimal Pareto front and \(d_i\) is the Euclidean distance between each point of the front and the nearest member of the approximation.

The algorithms are run 10 times and the statistical results are presented in Table 3. Since the IDG are very small, the solutions are very close to the optimal Pareto front.

TABLE II
ALGORITHMS PARAMETERS

| Algorithm | Mutation Rate | Inertia Weight | Personal and Global Learning Coefficient |
|-----------|---------------|----------------|-----------------------------------------|
| MOALO     | 0.1           | 0.5            | c1=1, c2=2                              |
| MOPSO     | 0.1           | 0.5            |                                         |
| NSGA-II   | 0.02          | 0.4            | 0.7                                     |

To evaluate the approximation performance of the algorithms, we used the Inverted Generational Distance (IGD) formulating as follows:

\[ IGD = \frac{\sum_{i=1}^{n} d_i^2}{n} \]  \hspace{1cm} (5.1)

where n is the number of the optimal Pareto front and \(d_i\) is the Euclidean distance between each point of the front and the nearest member of the approximation.

The algorithms are run 10 times and the statistical results are presented in Table 3. Since the IDG are very small, the solutions are very close to the optimal Pareto front.

TABLE III
STATISTICAL RESULTS OF IGD

| Algorithm | IGD  | MOALO | MOPSO | NSGA-II |
|-----------|------|-------|-------|---------|
| Average   | 0.03732 | 0.03810 | 0.04644 |
| Standard deviation | 0.001069 | 0.006231 | 0.008772 |

The Pareto optimal fronts obtained by the three algorithms are presented in figures 8 and 9. Figure 8 illustrates the plane (f1, f2) of the three-objective optimization Pareto fronts. This figure shows that the three algorithms spread the solutions differently over the non-dominated front. MOPSO can find a much better distribution than the MOALO algorithm; the NSGA-II is the worst in spreading the solutions over the non-dominated front. Multiple runs of the three algorithms (MOALO, MOPSO and NSGA-II) for the corona ring settings design optimization generate very stable Pareto frontiers for each algorithm as shown in figure 8.
FIGURE 8. Best Pareto optimal solution set of the electric field objective functions 1 and 2 according to the multi-objective algorithms MOALO, MOPSO and NSGA-II.

Figure 9. Three-dimensional Pareto optimal solution set of the electric field objective functions 1, 2 and 3 according to the multi-objective algorithms MOALO, MOPSO and NSGA-II.
The minimum values reached for the three multi-objective functions on the five different executions of all algorithms are shown in the figures 10 and 11. The first figure shows the best solution for the fitness functions, while the second figure shows the best values for corona ring parameters.

For the three algorithms, the search begins with a high random value. This value obtained for the multi-objective functions, falls rapidly on the first iterations (up to 10) and then a regular decrease thereof before reaching the minimum value (optimal value). From figure 10, it is noticeable that both the two algorithms MOALO and the MOPSO converge promptly to the optimal solutions, whereas the NSGA-II cannot converge before the 68 iterations.

As stated above, corona may occur on composite insulator surface, especially at triple junctions where the electric field is more intense. The installation of a corona ring reduces the electric field stress near the HV end fitting. Some corona ring parameters must be considered during design for maximum field stress reduction. These parameters include the radius of the ring tube, the radius of the corona ring and the vertical position of the ring. The results presented in figure 11 and table 5, show that the minimum (optimal) value of the electric field (1.8489 kV/cm) on the insulator shed (the triple point) is achieved for 130 mm corona ring diameter, 60 mm corona ring tube radius and 223 mm corona ring tube height (corona ring position).

With this optimized configuration, the electric field magnitudes on the surface of insulator sheds and flange, given in table 6, are lower than the critical value [30].

### Table V
**Optimal Corona Ring Parameters**

| Parameters       | Corona Ring thickness [mm] | Corona Ring tube Radius [mm] | Corona Ring tube height [mm] | Electric field [kV/cm] |
|------------------|----------------------------|-----------------------------|-----------------------------|------------------------|
| MOALO            | 60                         | 130                         | 223.634                     | 1.84891                |
| MOPSO            | 60                         | 130                         | 222.745                     | 1.84893                |
| NSGA-II          | 57.9978                    | 137                         | 223.607                     | 2.1085                 |

### Table VI
**Electric Field**

| position          | Electric field [kV/cm] |
|-------------------|------------------------|
| Insulator sheds   | 1.3                    |
| Corona ring       | Outer radius 11.15     |
|                   | Inner radius 1         |

The electric field distribution on the composite insulator surface and on the corona ring is illustrated in figure 12 to show the improvement of the electrical field distribution on the surface of the composite insulation, due to the use of an optimal corona ring. It is visible that the electrical field is concentrated mainly on the cross-section of sheds close to the energized end and on metal parts. In addition, it should be noted that the electric field magnitude at the inner radius of corona ring is less than at the outer one (table 6). It is due to self-cancellation field created by the ring and one created on insulators’ surface.
The use of an optimized corona ring improves the distribution of the electric field (tangential) on the insulator surface. Its amplitude is reduced by almost 82%, especially on the VH side. In addition, the installation of a corona ring allows obtaining more uniform distribution of the voltage as illustrated in figure 13.

VI. CONCLUSION
In this paper, a multi-objective optimization problem giving the electric field norm as function of the corona ring parameters (consisting in its radius, the radius of its tube, and its vertical position concerning the HV terminal) over 400 kV composite type insulator string is established. Three powerful multi-objective algorithms MOALO, MOPSO and NSGA-II are developed to achieve this problem. The proposed algorithms successfully solved the problem, demonstrating their applicability and computational efficiency. The optimization study for three objectives optimization was carried out and the results showed that MOPSO gives much better distribution solutions over the non-dominated front. However, MOALO allows obtaining a reduction of about 55% and 75% in computational time, compared to those taken while executing the MOPSO and the NSGA-II, respectively.

With the optimized corona ring parameters configuration, the electric field magnitude in the triple point was decreased of about 95% compared to without corona ring, and even the electric field value along the surface of the insulator sheds and flange (1.3kV/cm on the insulator sheds), is well below the maximum recommended electric field. In addition, an improvement of about 38% in the voltage distribution is noted.

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