Optimal Planning of Ground Grid Based on Particle Swam Algorithm

Chun-Yao Lee and Yi-Xing Shen

Abstract—This paper presents an application of particle swarm optimization (PSO) to the grounding grid planning which compares to the application of genetic algorithm (GA). Firstly, based on IEEE Std.80, the cost function of the grounding grid and the constraints of ground potential rise, step voltage and touch voltage are constructed for formulating the optimization problem of grounding grid planning. Secondly, GA and PSO algorithms for obtaining optimal solution of grounding grid are developed. Finally, a case of grounding grid planning is shown the superiority and availability of the PSO algorithm and proposal planning results of grounding grid in cost and computational time.

Keywords—Genetic algorithm, particle swarm optimization, grounding grid.

I. INTRODUCTION

THE power systems occurs ground faults, the short-time large fault currents will make the power systems unstable and meantime be danger to persons. Hence, the grounding planning should consider the constraints of the step voltage, touch voltage, ground potential rise (GPR), and ground resistance for the sake of safety. Many studies related to grounding grid have been planned on the trail-and-error approaches [1-3]. These approaches make the mesh dimension of the grounding grid satisfy with constraints of the touch voltage, step voltage, GPR and grounding resistance from standards. Many standards published for grounding systems of power substations. ANSI/IEEE Std.80 has been widely revised for more than ten years and is generally followed as a standard for the grounding systems. This paper will calculate the step voltage, touch voltage, ground potential rise (GPR), and grounding resistance, based on ANSI/IEEE Std.80. We will apply the genetic algorithm (GA) and the particle swarm optimization (PSO) to plan the optimal grounding grid, which includes number of unilateral mesh, diameter of conductor cross-section, and depth of the grounding grid..

II. FORMULATION OF GROUNDING GRID

The purpose of the grounding grid planning is to determine

C.-Y. Lee is with the Department of Electrical Engineering, Chung Yuan Christian University, Taoyuan County, Taiwan, 32023. (Phone: +886-3-265-4827; e-mail:CYL@cycu.edu.tw).
Y.-X. Shen is with the Department of Electrical Engineering, Chung Yuan Christian University, Taoyuan County, Taiwan, 32023 (E-mail: g9778003@cycu.edu.tw).

material cost, excavation cost, and weld cost considering factors of safety and economic cost. Thus, the paper will develop the grounding grid cost model including material, excavation, and welding effects. The method is to model the formula from the total volume of the grounding grid conductors, total length of the grounding grid conductors, and total area of weld. Then, the cost of grounding grid could be estimated, based on ANSI/IEEE Std. 80, the constraints of grounding grid [4].

A. Grounding Grid in EHV Substation

The purpose of the objective function is to optimize the cost of the grounding grid, which is composed of material cost, excavation cost, and weld cost [2], shown as (1),

$$Ob(N,d,h) = k_1 \cdot \frac{\pi d^2}{4} \cdot \frac{L_p}{2}(N+1)$$
$$+ k_2 \cdot h \cdot \frac{L_p}{2}(N+1) + k_3 \cdot \frac{\pi d^2}{4}(N+1)^2 \tag{1}$$

Subject to

$$GPR \leq GPR_s \tag{2}$$

$$R_g \leq R_{gs} \tag{3}$$

$$E_s \leq E_{step70} \tag{4}$$

$$E_t \leq E_{touch70} \tag{5}$$

Where

N number of unilateral mesh

d diameter of grounding grid conductor cross-section (m)

h depth of the grounding grid (m)

L_p peripheral length of the grid (m)

k_1 coefficient of material cost

k_2 coefficient of excavation cost

k_3 coefficient of welding cost

R_g ground resistance of the grounding grid

E_s step voltage between a point above the outer corner of the grid and a point 1 m diagonally outside the grid (V)

E_t mesh voltage at the center of the corner mesh (V)

R_{gs} ground resistance

E_{step70} tolerable step voltage for human with 70kg body weight (V)

$E_{touch70}$ tolerable touch voltage for human with 70kg body weight (V)

GPR_s constraint of the ground potential rise

GPR ground potential rise of the grid,

B. Constraints

We consider the constraints of ground potential rise (GPR_s), ground resistance (R_{gs}), step voltage (E_{step70}) and touch voltage ($E_{touch70}$), based on ANSI/IEEE Std.80 [4], to be the constraints of the optimization problem.

1). GPR_s and R_{gs} : based on ANSI/IEEE Std.80, we suppose the two constraints Ground potential rise GPR_s and ground resistance R_{gs} corresponds to 4,500 V and 5 Ω respectively. The formulas of ground potential rise and ground resistance are shown as (6) and (7) respectively.

$$GPR = R_g \cdot I_G \tag{6}$$

$$R_g = \rho\left[\frac{1}{L_T} + \frac{1}{\sqrt{20A}}\left(1 + \frac{1}{1+h\sqrt{20/A}}\right)\right] \tag{7}$$

Where

ρ soil resistivity ($\Omega \cdot m$)

L_T total length of grounding conductor (m)

A total area enclosed by the grounding grid (m^2)

I_G maximum grid current (A)

2). Step Voltage E_{step70} and Touch Voltage $E_{touch70}$: We calculate the two constraints, Step Voltage and Touch Voltage, shown as (8) and (9) respectively [4], based on IEEE Std.80.

$$E_{step70} = (1000 + 6 \cdot C_s \cdot \rho_s)\frac{0.157}{\sqrt{t_s}} \tag{8}$$

$$E_{touch70} = (1000 + 1.5 \cdot C_s \cdot \rho_s)\frac{0.157}{\sqrt{t_s}} \tag{9}$$

$$E_{touch70} = (1000 + 1.5 \cdot C_s \cdot \rho_s)\frac{0.157}{\sqrt{t_s}} \tag{9}$$

$$C_s = 1 - 0.09\left(1 - \frac{\rho}{\rho_s}\right)\Big/(2h_s - 0.09) \tag{11}$$

Where

C_s surface layer derating factor

ρ_s layer resistivity surface ($\Omega \cdot m$)

h_s surface layer thickness (m)

t_s duration of fault current (sec)

Moreover, from ANSI/IEEE Std.80, the formulas of maximum step voltage and maximum touch voltage are shown as (11) and (12) respectively [4].

$$E_s = \frac{\rho \cdot I_G \cdot K_i \cdot K_s}{L_T} \tag{11}$$

$$E_t = \frac{\rho \cdot I_G \cdot K_i \cdot K_m}{L_T} \tag{12}$$

Where

$K_i = 0.644 + 0.148n$

$n = 2L_c/L_p$

$K_s = \frac{1}{\pi}\left[\frac{1}{2h} + \frac{1}{D+h} + \frac{1}{D}(1 - 0.5^{n-2})\right]$

$K_m = \frac{1}{2\pi}\left[\ln\left(\frac{D^2}{16 \cdot h \cdot d} + \frac{D+2+h}{8 \cdot D \cdot h} - \frac{h}{4d}\right)\right.$
$\left. + \frac{K_{ii}}{K_h}\ln\left(\frac{8}{\pi(2n-1)}\right)\right]$

$K_{ii} = \frac{1}{(2n)^{2/n}}$

$K_h = \sqrt{1 + \frac{h}{h_0}}$

K_i correction factor for the grid geometry

K_s spacing factor for the step voltage

K_m spacing factor for the mesh voltage

K_{ii} corrective weighting factor that adjusts for the effects of inner conductors on the corner mesh

K_h corrective weighting factor that emphasizes the effects of the grid depth

n geometric factor composed of the grid

L_c total length of the conductor in the horizontal (m)

D spacing between parallel conductors (m)

h_0 grid reference depth, $h_0 = 1$ m

C. Diameter of Grid Conductor Cross-section

According to ANSI/IEEE Std.80, the minimum size of the ground conductor is expressed as a formula of the current duration, shown as (13). Therefore, the minimum diameter of grid conductor cross-section is calculated by (14). Practically, we would select an area which is larger than A_{mm^2} the cross-section of ground conductor.

$$A_{mm^2} = \frac{I}{\sqrt{\left(\frac{TCAP \cdot 10^{-4}}{t_c \alpha_r \rho_r}\right) \ln\left(\frac{K_0 + T_m}{K_0 + T_a}\right)}} \tag{13}$$

$$d_{min} = 2 \cdot 10^{-3} \sqrt{\frac{A_{mm^2}}{\pi}} \tag{14}$$

Where

I fault current of the grid conductor (kV)

A_{mm^2} conductor cross-section (mm^2)

T_m maximum allowable temperature ($^\circ$C)

T_r ambient temperature ($^\circ$C)

α_0 thermal coefficient of the resistivity at 0 $^\circ$C ($1/\,^\circ$C)

α_r thermal coefficient of the resistivity at reference temperature T_r ($1/\,^\circ$C)

ρ_r resistivity of the ground conductor at reference temperature T_r ($\mu\Omega \cdot$m)

t_c duration of current (sec)

d_{min} minimum diameter of grid conductor cross-section (m)

TCAP thermal capacity per unit volume ($J/(cm^2 \cdot\,^\circ C)$)

III. GENETIC ALGORITHM

Genetic Algorithm (GA) is firstly introduced by John Holland in 1975 [5]. GA is a class of stochastic algorithm based on the biological evolution in the natural world. The technological process employs three operators: 1) selection and reproduction, 2) crossover and 3) mutation. GA would eliminate lowly fit individuals from the current population and retain highly fit individuals in new population. The process is continually implemented until the diversity of individuals restrains. Thus, we expect to find one or more highly fit individuals [5]-[8]. The optimal individual is the optimum solution of the problem. Fig. 1 presented a flowchart of genetic algorithm.

The steps of genetic algorithms (GA) are presented as the following description; see Fig. 1 [5].

Step 1) Generate n_{popu} the population size of individuals.

Step 2) Calculate each of the fitness value of individuals.

Step 3) If stopping criterion is satisfied (e.g., maximum iteration number), then the procedure would go to the end; otherwise, proceed to step (4).

Step 4) reproduce individuals by using the method of roulette wheel selection.

Step 5) If the random number is smaller than P_c, individuals will proceed crossover operator; otherwise, proceed step (6).

Step 6) If the random number is smaller than P_m, individuals will implement mutation operator otherwise, proceed step (7).

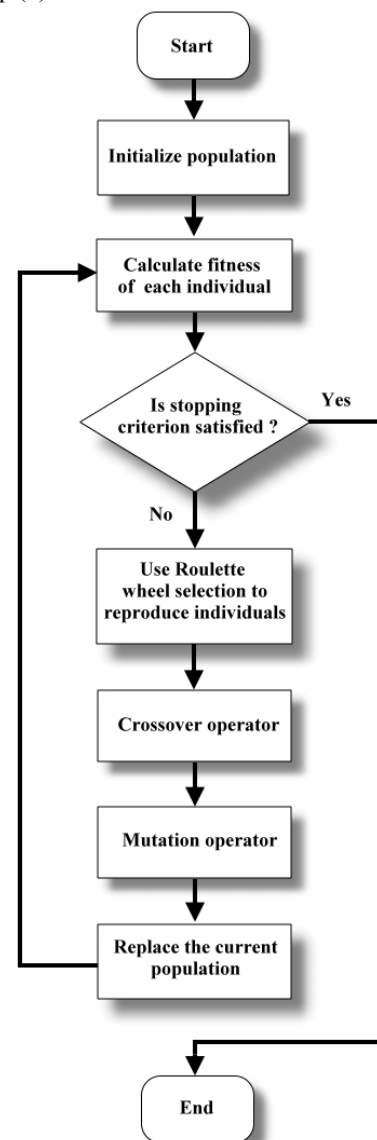Step 7) Replace current population, then implement back to step (2).

Fig. 1. Flowchart of genetic algorithm.

A. Population Initialization

GA randomly produces n_{popu} strings within the range from 0 to 1. These numbers are rounded to make up an individual, that is, a binary string. Every binary string respectively represents an individual. Each chromosome consists of several genes, and each gene is represented by 0 or 1, shown as Fig. 2. Moreover, the decoded individuals express the solutions of optimization problem [6].
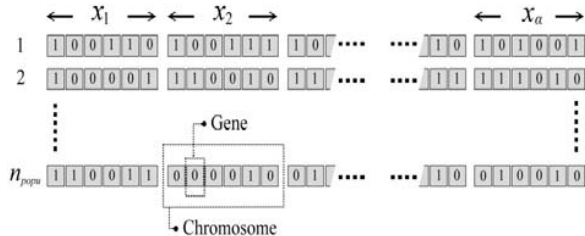

Fig. 2. Initial Population of GA for α variables.

B. Binary Code and Decoded Integer

Since GA represents an individual as a binary string, each individual needs to be decoded [6], [9] before evaluating. The models of the binary code and decoded integer are shown as (15) and (16) respectively.

$$X_{code,j} = \frac{2^{L_{binary}} - 1}{X_{max,j} - X_{min,j}} (X_j - X_{min,j}) \qquad (15)$$

$$X_j = X_{min,j} + \frac{X_{max,j} - X_{min,j}}{2^L - 1} X_{code,j} \qquad (16)$$

Where

L_{binary} number of genes in chromosome

X_j value of j-th variable function

$X_{max,j}$ maximum value of j-th variable

$X_{min,j}$ minimum value of j-th variable

$X_{code,j}$ coded value of j-th variable

C. Fitness Function

Each individual is evaluated with fitness function. Generally, GA takes an objective function as the fitness function for the optimization problem without any constraint. However, the optimization problem in this paper needs to consider the constraints of the grounding grids. When the individuals do not satisfy the safe limits, they need to be penalized for reducing their fitness. Considering the constraints of the grounding grids, the fitness function is shown as (17).

$$Fit(N,d,h) = \frac{1}{Ob(N,d,h) + \varepsilon + \sum_{p=1}^{m} \eta_p (\Delta\lambda_p)^2} \qquad (17)$$

Where

$Ob(\cdot)$ objective function of optimization problem,

ε constant, making the denominator of $Fit(\cdot)$ to be a positive value

η_p coefficient of p th constraint

$\Delta\lambda_p$ $\Delta\lambda_{1\sim4}$ are the violation degree of (2)-(5) respectively

D. Selection and Reproduction

Each individual is probably selected for mating. Highly fit individuals have a higher probability of being selected than less fit individuals [6]. There are normally two types of selection in GA, including the roulette wheel selection and the tournament selection. This paper uses the roulette wheel selection to choose a pair of individuals for reproduction. The number of the reproduced individuals is rounded R_i. It randomly selects two individuals from the individuals reproduced by roulette wheel selection for mating. To avoid losing superior genes, we retain the optimal individual to a new population. The type of retaining optimal individual is termed elitist strategy [6],[7]. The roulette wheel selection is shown as the following equation.

$$R_i = \left(Fit_i \bigg/ \sum_{i=1}^{n} Fit_i \right) \cdot n_{popu} \qquad (18)$$

Where

R_i the number of i-th reproduced individual,\

n_{popu} population size

Fit_i fitness value of i-th individual

E. Crossover

If the random number in [0,1] is smaller than P_c, the two randomly-selected individuals will exchange a part of their genes which is divided by crossover point [7]. The position of crossover point is randomly produced before crossover operator.
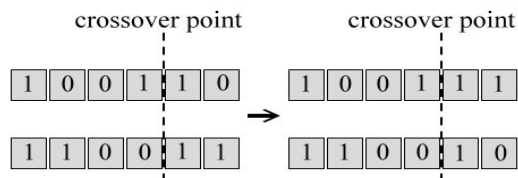

Fig. 3. Type of one-point crossover.

Conversely, the random number in [0,1] is bigger than the P_c, the two individuals will not exchange their genes. P_c is a predefined number in [0,1] as the threshold of crossover occurring. The type of one-point crossover is shown as Fig. 3.

F. Mutation

If the individuals are extremely similar, the solutions of the optimal problem would focus in the local search. If the situation comes too early, then it is harmful to the global optimum solution [6,7,8]. Therefore, it needs the mutation operator to increase the diversity of the individuals for expanding searching space. The type of mutation operator is that a few genes of the individual changes from 0 to 1 and from 1 to 0. If the random number in [0,1] is smaller than P_m, the mutation operator will occur. Conversely, the random number in [0,1] is bigger than P_m, the mutation operator will not occur. P_m is a predefine number in [0,1] as the threshold of mutation occurring.

IV. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is firstly introduced by Kennedy and Eberhart [9] in 1995. PSO is a population-based searching algorithm that uses social behavior of birds within a swarm. Every bird recalls its flying experience which is the shortest distance between food and itself. Birds communicate their flying experience with each other, and then these behaviors lead all birds into the location of food, so called *Swarm Intelligence* [9],[10]. Numerous experts assume some simple rules for modeling this kind of social behavior and employ three kinds of vector to simulate this complex social behavior [11]. The basic flowchart of particle swarm optimization is presented in Fig. 4.

Given the description of social behavior above, the simulation step of the particle swarm optimization (PSO) is shown as follows.

Step 1) Generate equivalent n_{popu} quantity of position and velocity randomly, and record $Pbest_i$, $pbest_i$, $gbest$ and $Gbest$.

Step 2) Calculate each fitness value of particles.

Step 3) If stopping criterion is satisfied (e.g., maximum iteration number), then the procedure would go to the end; otherwise, proceed to step (4).

Step 4) Update $Pbest_i$ and $pbest_i$.

Step 5) Update $gbest$ and $Gbest$.

Step 6) Update particles position and velocity by employing equation (21) and (22), then go back to step (2).

A. Population Initialization

The process of population initialization of the PSO is introduced as follows. PSO randomly produces n_{popu} particles, population size, in the k-dimensional searching space, and each particle includes position X_i and velocity V_i, where X_i is the position of i-th particle in the search space, $X_i = (X_{i1},...,X_{ij},...,X_{ik})$, and V_i is the velocity of i-th particle in the search space, $V_i = (V_{i1},...,V_{ij},...,V_{ik})$. Both of position X_i and velocity V_i are matrixes in the paper. The

dimension of the searching space expresses the number of variables in the objective function [11]. The position X_i of each particle represents a solution of the problem and the velocity V_i of each particle represents its displacement in the searching space.
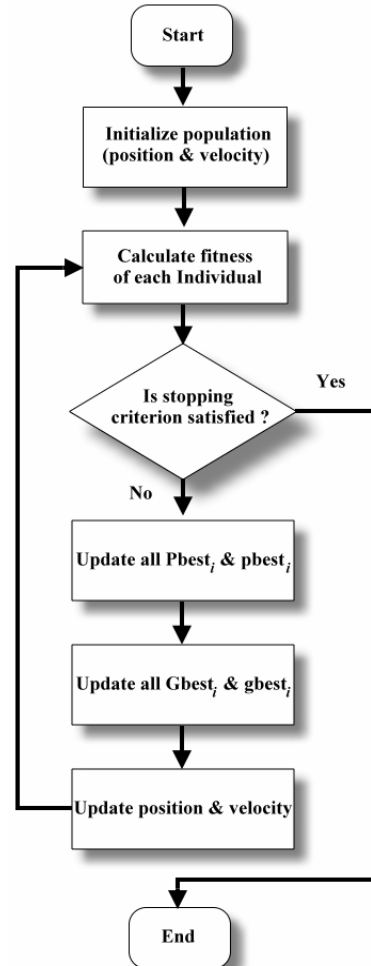

Fig. 4. Algorithm of particle swarm optimization.

B. Fitness Function

Each particle is estimated by the fitness function. If the fitness value of the particle is higher, the particle is better fit. On the contrary, if the fitness of the particle is lower, the particle is less fit. To satisfy the constraints of the grounding grid, mentioned on page 1 and 2, the fitness function is shown as the following equation.

$$Fit(N,d,h) = \frac{1}{Ob(N,d,h) + \varepsilon + \sum_{p=1}^{m} \eta_p (\Delta\lambda_p)^2} \quad (19)$$

Where

$Ob(\cdot)$ objective function of optimization problem.

ε a constant that lets the denominator of $Fit(\cdot)$ be a positive.

η_p coefficient of p-th constrain.

$\Delta\lambda_p$ $\Delta\lambda_{1\sim4}$ are respectively the violations of (2)-(5).

C. Update Velocity and Position

Corresponding to the behavior of flying birds, every particle retains its optimal fitness value and position according to its accumulated flying experiences, referring to $pbest_i$ and $Pbest_i$ respectively. At the same time, each particle acquires the optimal fitness value and position by sharing the experiences of others. By comparing with the experiences of others, the fittest value and position will be selected, referring to $gbest$ and $Gbest$ respectively. Therefore, each particle is guided to its previous velocity, $Pbest_i$, and $Gbest$. The inertia weight method, shown as the following equation, is applied to update velocity and position of the particles [11], [12].

$$V_{ij}^{new} = w \cdot V_{ij} + c_1 \cdot rand1 \cdot (Pbest_{ij} - X_{ij})$$
$$+ c_2 \cdot rand2 \cdot (Gbest_j - X_{ij}) \tag{20}$$

$$X_{ij}^{new} = X_{ij} + V_{ij} \tag{21}$$

Where

$w = w_{max} - iter \cdot (w_{max} - w_{min})/iter_{max}$

$Pbest_i = (Pbest_{i1},...,Pbest_{ij},....,Pbest_{ik})$

$Gbest = (Gbest_1,...,Gbest_j,....,Gbest_k)$

$Pbest_i$ the optimal position of the i-th particle

$Gbest$ the optimal position of entire particles

c_1, c_2 acceleration coefficient

w coefficient of the inertia weight

w_{min} minimum coefficient of the inertia weight

w_{max} maximum coefficient of the inertia weight

$iter$ current iteration number

$iter_{max}$ maximum iteration number

D. Bound of Velocity and Position

The positions of particles exceed the searching space after updating should be limited to the bounds of the k-dimensional search space, presented in (22). In order to control excessive roaming of particles outside the searching space, each velocity of particle should have the bounds of velocity [11], [12]. The corrected velocities are shown as (23).

$$\begin{cases} X_{ij} = X_{max,j} & \text{for } X_{ij} = X_{max,j} \\ X_{ij} = X_{min,j} & \text{for } X_{ij} = X_{min,j} \end{cases} \tag{22}$$

$$\begin{cases} V_{ij} = V_{max\,j} & \text{for } V_{ij} = V_{max\,j} \\ V_{ij} = V_{min\,j} & \text{for } V_{ij} = -V_{max\,j} \end{cases} \tag{23}$$

Where

$V_{max\,j} = (X_{max,j} - X_{min,j})/2$

$X_{max,j}$ maximum value of j-th variable

$X_{min,j}$ minimum value of j-th variable

$V_{max,j}$ maximum velocity of j-th dimension

V. Simulation of Grounding Planning

The data of the substation 115/13 kV obtained from ANSI/IEEE Std.80-2000 is a case study of 70m×70m square grid of equal space without ground rods [4]. Moreover, the constraints such as $GPR \le GPR_s$, $R_g \le R_{gs}$, $E_s \le E_{step70}$, and $E_t \le E_{touch70}$ are considered. The related data of the substation are as Table 1.

TABLE I Data of the 115/13 kV substation

Z = 9% at 15MVA, 115/13 kV	
Fault duration, t_f	0.5 s
Positive sequence equivalent system impedance, Z_1 (115kV side)	4.0+j10.0Ω
Zero sequence equivalent system impedance, Z_0 (115kV side)	10.0+j40.0Ω
Current division factor, S_f	0.6
Soil resistivity, ρ	300.0 Ω-m
Crushed rock resistivity (wet), ρ_s	2,500.0 Ω-m
Thickness of crushed rock surfacing, h_s	0.102 m
Transformer impedance, Z_1 (13kV side)	0.034+j1.014Ω
Transformer impedance, Z_0 (13kV side)	0.034+j1.014Ω

Based on the formula of ANSI/IEEE Std.80, we calculated the maximum grid current $I_G = 1.908$ A. Suppose the ground conductor material is the cooper-clad steel wire. We employ (13) and (14) to calculate the minimum diameter of ground conductor cross-section $d_{min} = 0.0065$ m. Practically, $d_{min} = 0.01$ m will be selected for steady state of the ground conductor. We suppose that GPR_s and R_{gs} are 4,500 and 5 Ω respectively, based on ANSI/IEEE Std.80. Moreover, formulas (8) and (9) are employed to calculate the tolerable step voltage and touch voltage, $E_{touch70}$, and then $E_{step70} = 830.3$ V and $E_{touch70} = 2655.3$ V is obtained. In this study, we suppose that three variables of the objective function are N, d and h respectively, where $N \in [1,32]$, $d \in [0.1,0.01]$, and $h \in [0.25,2.5]$.

The grounding results obtained by applying the PSO method and GA method are shown as Tables 2, 3, 4 and 5. In Table 2 and 3, all the constraints of grounding grid satisfy the IEEE Std. 80, including step voltage, touch voltage, ground potential rise (GPR), and grounding resistance. In Table 4 and Table 5, the three parameters and cost of grounding grid, and computational time of GA and PSO methods are demonstrated. The three parameters of grounding grid do not show significant difference and the cost of GA method is only slightly higher than PSO method. Nevertheless, it is noted that the computational time of GA method is considerably more than PSO method.

TABLE II CHARACTERISTIC OF GROUNDING GRID (SIZE = 25)

Iteration number = 800 and population size = 25				
Constraints (IEEE Std.80)	GPR (V)	R_g (Ω)	E_s (V)	E_t (V)
	4,500	5	2,655	830.3
GA	4,052	2.12	99.12	830.3
PSO	4,042	2.11	96.75	830.3

TABLE III CHARACTERISTIC OF GROUNDING GRID (SIZE = 100)

Iteration number = 800 and population size = 100				
Constraints (IEEE Std.80)	GPR (V)	R_g (Ω)	E_s (V)	E_t (V)
	4,500	5	2,655	830.3
GA	4,049	2.12	98.38	829.7
PSO	4,042	2.11	96.75	830.3

TABLE IV OPTIMAL RESULTS OF GROUNDING GRID DESIGN (SIZE = 25)

Iteration number = 800 and population size = 25		
Algorithms	GA	PSO
Number of unilateral mesh	5	5
Depth of the grounding grid (m)	2.90	3.02
Diameter of conductor cross-section (m)	0.034	0.033
Cost of the grounding grid (USD)	178,005	177,726
CPU time (ms)	2,114	1,013

The cost and computational time of Table 2 is presented in Table 4 in which we can observe that the cost utilized the PSO method, USD 178,005, is lower than the utilized GA method, USD 177,726, 0.16%. On the other hand, the cost and computational time of Table 3 is demonstrated in Table 5 in which we can examine that the cost utilized the PSO method, USD 177,783, is lower than the utilized GA method, USD 177,726, 0.03%. However, by comparing to the methods of PSO and GA, as shown in Table 4 and 5, population size 25 reveals the computational time of GA method, 2,114ms, is two times greater than that of PSO method, 1,013ms. Correspondingly, the computational time of population size 100 by applying methods of GA, 8109ms, and PSO, 3981ms, also demonstrates the same situation. That is, the computational time of GA method is two times greater than that of PSO method in both 25 and 100 population size.

TABLE V OPTIMAL RESULTS OF GROUNDING GRID DESIGN (SIZE = 100)

Iteration number = 800 and population size = 100		
Algorithms	GA	PSO
Number of unilateral mesh	5	5
Depth of the grounding grid (m)	2.94	3.02
Diameter of conductor cross-section (m)	0.034	0.033
Cost of the grounding grid (USD)	177,783	177,726
CPU time (ms)	8,109	3,981

Furthermore, Table 6 presents the methods of GA and PSO based on different iteration and population size and demonstrates the results of 100 trails. The grounding cost utilized the GA and PSO methods by *worst cost*, *optimal cost*, *mean cost* and *mean time* in variable population sizes, 25, 50, 75, and 100 are shown in Table 6, in which the cost with PSO method is lower (177,726 USD), in population size being 25 and 200 iterations, than that with GA method (177,783 USD), in population size being 50 and 200 iterations. And the computational time with the PSO method is only 50% of that with the GA method under the identical conditions of iteration and population size. In addition, the iteration number 200, 400, 600, and 800 is dependent on the results when the PSO method is applied. The *mean cost* of GA method is larger than that of PSO method under identical conditions. We can say that the PSO method is superior to the GA method in the cost and computational time.

Table 6 Cost and computational time of GA and PSO

In Figs. 5 and 6, the convergent rate with the GA method is slower than that with the PSO method. The curve utilized the GA method is presented as ladder-like shape and the PSO method is demonstrated a steeper shape, regardless of the population size. The convergent speed with the PSO method is faster and steadier than that with the GA method.

The possible reason may be the different approaches which prevents individual/particles from stagnating. The GA method increases the diversity of population to prevent individuals from stagnating. If GA does not mutate for several generations, the result will lead individuals toward a local optimum prematurely. The PSO method employs inertia velocity and results in the positions of particles change consecutively to avoid particles from being trapped.

Comparing with the PSO and GA methods, we found that PSO method is more efficient when expending searching space. Although the increase of population size of the GA method reaches lower cost, the convergence is relatively worse. On the contrary, the population size of the PSO method barely affects the curve of convergence, shown as Figs. 5 and 6. Therefore, the effect on population size of GA method is significant.
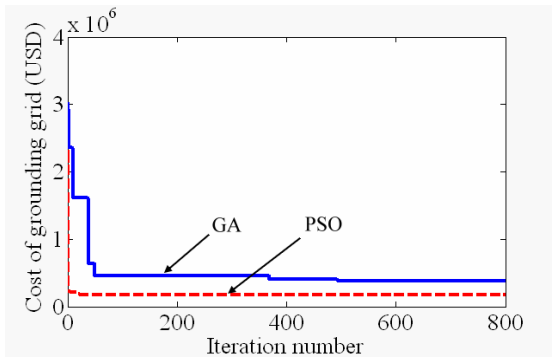
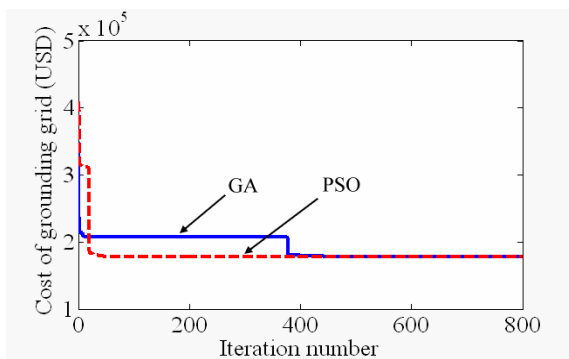Fig. 5. Cost curve of grounding grids for GA and PSO (Population size=25).

Fig. 6. Cost curve of grounding grids for GA and PSO (Population size=100).

VI. CONCLUSION

This paper mainly applies both theories of GA and PSO methods to discuss the research of optimal grounding grid. The result of the simulation reveals that the GA and PSO methods are practicable approaches of grounding optimization design. Different from the traditional grounding grid design, namely, trial-and-error approach, the PSO and GA methods are not only planed to meet the requirements of constraints but also save great amount of time.

Although the grounding grid cost of PSO method is only slightly smaller than the cost of GA method, there still exits some advantages and disadvantages between PSO method and GA method, e.g., 1) the complexity of algorithm, 2) computational time, 3) demand of population size, and 4) steady state of optimal solution. Different from the reproduction, crossover, and mutation of GA method for proceeding solution improvement based on biological evolution mechanism, PSO method describes behavior of particle movement based on simplified mathematical equation. The complexity of GA method is much greater compared to that of PSO method. As for computational time, each iteration of GA method is greater than that of PSO method. Under the identical conditions of iteration number and population size, PSO method requires only half computational time of GA. As for the population size, GA requires more population size compared to PSO to reach to the approximate grounding grid cost. As for the steady state of optimal solution, the difference between mean cost and optimal cost of grounding grid by employing PSO method is closer than employing that of GA method. The grounding grid planning of PSO is steadier than that of GA method.

Based on the advantages mentioned above, we expect the future application of the PSO method can be a more complex shape to conduct a speedy and accurate grounding grid design system.

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Chun-Yao Lee (S'05–M'08) received his Ph. D. in electrical engineering from Taiwan University of Science and Technology in 2007. During 2000-2007, he was a distribution system designer in the engineering division, Taipei Government. In August 2007, he joined Chung Yuan Christian University as a faculty member. He is presently an Assistant Professor. His major areas of research include power distribution and power filter design.

Yi-Xing Shen was born in Taiwan in 1986. He received his B.S. degree in electrical engineering from Chung Yuan Christian University in 2008. He is presently a graduate student toward his M.S. program in electrical engineering department of Chung Yuan Christian University in Taiwan.