Grounding grid design in electrical power substation using optimization methods

V K Voon, K I Wong, T C Tiong, A Mansour and K H Law
Department of Electrical and Computer Engineering, Faculty of Engineering and Science, Curtin University, Malaysia, CDT 250, Miri 98009, Sarawak, Malaysia
E-mail : tiong.teck.chai@curtin.edu.my

Abstract. A good substation grounding grid is essential to ensure safety of personnel working in the substation, and also to protect the equipment to ensure continuous operation of the substation. The design of the substation grounding grid is often carried out to meet the IEEE Std 80-2000 requirements of grounding resistance, touch voltage and step voltage at an economical cost. However, the conventional grounding grid design is normally over calculated to meet these IEEE requirements without considering the total cost. The grounding grid is often costly to implement due to high number of grounding conductors and rods, and large area size of the interconnected bare conductors. In this study, Gravitational Search Algorithm (GSA) and Particle Swarm Algorithm (PSO) are proposed to achieve an effective grounding grid calculation. The reliability of these algorithms has been validated using a typical medium voltage substation grounding grid parameters. It was found both that GSA and PSO were capable to achieve a lower cost of grounding grid with 29% cost saving as compared to the conventional calculation technique, without compromising the safety requirements of grounding grid.

1. Introduction
The purpose of substation grounding system is to provide a safe neutral point for all the conductive part of the substation equipment, including transformer, capacitor and reactor, and switchboard. It also provides the discharge path for the lighting impulses, fault current, or any high voltage switching related surges into the earth via the protective conductors so that it can ensure the safety of the personnel by limiting the hazardous potential gradients that can exist anywhere within a substation. Besides that, workers always disconnect and ground live equipment in substation before they proceed with the maintenance works. This is to ensure any electrical current in the conductors is discharged into the ground. Thus a good grounding system is playing an essential role in terms of protection for personnel and equipment.

The grounding grid that is comprised of interconnected horizontal bare conductors and vertical bare conductor (or rod), is often buried under a substation to provide sufficient low resistance path to ground to minimize rise in ground potential with respect to remote ground [1]. It is necessary to ensure that the entire ground potential rise is as low as possible so that personnel are not exposed to the danger of hazardous electrical shock and equipment are protected from any circumstances of short circuit current or over voltage transient during an abnormal or fault incident. The calculated touch voltage and step voltage that are computed as defined in IEEE Std 80-2000 during the abnormal condition must be within the safe values [1]. Safe values are defined as the values that are not large
enough to induce a current that can cause ventricular fibrillation in human body [1]. Without the safe and effectively grounded system, the safety and fitness of the personnel and equipment will be at higher risk getting electric shock, due to the failure of protection relaying system and the high rise of the ground system potential that is unsafe for human contact.

Design of a proper substation grounding system based on ANSI/IEEE Std 80-2000 are related to how to achieve the thresholds of a number of variables, such as touch voltage, mesh voltage, step voltage, tolerable touch voltage, tolerable step voltage, ground potential rise and grid resistance. These safety aspects of variables have been widely revised over the past years for safety improvements. This paper describes about applying gravitational search algorithm (GSA) and particle swarm optimization (PSO) for modelling and analysis optimization for ground grid system.

The contribution of this paper is total grounding conductor length reduction which results in 29% cost saving compared to the existing un-optimized grounding grid.

2. Literature Review
The grounding grid design parameters, which are consists of step voltage, touch voltage as well as grounding resistance, are the most important criteria to ensure safety in a substation grounding. The method proposed by ANSI/IEEE Std 80-2000 is not enough to provide an accurate solution. Therefore, the related computer program and numerical computing methods have been developed since 1970. Dividing the grounding conductors and grounding rods using the numerical simulations and superposition was first proposed in [2]. In addition, the unbalance current distribution could be handled by multi step analysis of interconnected earthing electrodes.

Prior computing work on grounding resistance considering the effects of leakage current magnitude due to adjacent cross conductors, parallel conductor and end effect was done in [3]. This approach could also verified touch and step potentials. Several heuristic techniques have been developed over these years incorporated optimization process for the grounding grid system [3]. The system optimization objective was to minimize the cost function with optimized parameters for the grounding system [3]. These included conductor size, spacing between conductors, total excavation area, grid depth for the grounding grid. The optimized design should produce actual step and touch voltages below the tolerable limits.

Evolutionary algorithm was used to optimize the design of 115/13kV substation with a size of 70x70m grounding grid (without the rod). The computed earth surface was compared with the corresponding formulae of ANSI/IEEE Standard 80-2000 and the results were in good agreement.

PSO was used to optimize the grounding grid design [5]. The authors proposed an cost minimization objective with constraints including material, installation, and excavation cost. PSO was applied in [6] to optimize the substation grounding grid with 200 x 150m size and fault current 21kA. The author proposed a cost function which included the diameter of the rod, length of the rod, depth of grid, excavation by taking into account the safety tolerance of ground potential rise (GPR), step potential and touch potential as defined in ANSI/IEEE Standard 80-2000.

3. Methodology

3.1. Gravitational Search Algorithm
GSA is an algorithm which is based on Newton’s law gravitation and is proposed by an Iranian professor, Esmat Rashedi, in 2009 [7]. Based on this algorithm, it stated that any two particles in the universe will be attracted to each other by a force that in the direction of the centre line. From the algorithm, agents are normally the objects which its performance is determined by means of masses. The whole agents will be attracted to each other by the gravitational force and subsequently the movement for all agents are induced by the force globally move towards the agents with heavier masses. In GSA, there are 4 variables which are inertial mass, position, active gravitational mass and passive gravitational mass. Based on the algorithm, every population will have two capabilities which are exploitation and exploration. From the exploration capability, it prevents local optimum issue at
the beginning. Other particles are attracted by a time function which called as \( K_{best} \) particle agent. Nevertheless, the performance of GSA is essentially enhanced by controlling the exploration and exploitation will decrease linearly according to the time and there left only the agent with the heavy mass which represents the final solution. The complete steps of the GSA are described below:

a) Identification of search space
b) Produce the Initial population
c) Assess the fitness function for each particle of the population
d) Update the gravitational constant value accordingly

GSA can be concluded as the following steps:

Step 1: Initialization of Agents – Within the given search interval, initialize the position of \( N \) number of agents randomly by using (1)

\[
x_i = (x_i^1, x_i^2, ..., x_i^d) \quad \text{for} \quad i = 1, 2, 3, ..., N
\]

where \( x_i^d \) is the position of \( i^{th} \) mass in \( d^{th} \) dimension.

Step 2: Compute best fitness and fitness evolution for each required agent at each iteration \((t)\). From each iteration, it should locate the best and worst fitness.

\[
best(t) = \min_{j=1 \ldots N_{max}} \text{fit}_j(t) \quad (2)
\]

\[
worst(t) = \max_{j=1 \ldots N_{max}} \text{fit}_j(t) \quad (3)
\]

where \( \text{fit} \) \((t)\) is defined as the fitness value of particle of each iteration, \( best(t) \) and \( worst(t) \) are best which is minimum and worst which is maximum fitness of all agent.

Step 3: Compute gravitational \( G \) at iteration \( t \) as (4)

\[
G(t) = G_0 e^{(-\alpha \frac{t}{T})} \quad (4)
\]

where \( G_0 \) : initial gravitational constant
\( \alpha \) : constant
\( T \) : total number of iteration of algorithm

Step 4: Calculate the mass of agents at each iteration \((t)\) from (5) to (7)

\[
M_{ai} = M_{pi} = M_{ii} = M_i \quad (5)
\]

\[
m_i(t) = \frac{\text{fit}_i(t) - worst(t)}{best(t) - worst(t)} \quad (6)
\]

where \( m_i \) is the inertial mass of particle \( i \)

\[
M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N_{max}} m_j(t)} \quad (7)
\]

Step 5: Calculate each agent’s acceleration at each iteration

\[
a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \quad (8)
\]
where

\[
F_i^d(t) = \sum_{j \in k_{best}} F_j^d(t)
\]

\(k_{best}\) : set of first \(K\) agents with the best fitness value and biggest mass.

**Step 6:** Update velocity and position of the agents at the next iteration \((t + 1)\)

\[
v_i^d(t + 1) = rand_i \times v_i^d(t) + a_i^d(t)
\]

\[
Mass_i^d(t + 1) = Mass_i^d(t) + v_i^d(t + 1)
\]

where \(rand\) : random number from [0, 1]

\(v_i^d\) : speed of particle \(i\) at dimension \(d\) at time \(t\).

\(Mass_i^d\) : position of particle \(i\) at dimension \(d\) at time \(t\).

**Step 7:** Repeat the steps from step 2 to step 6 until the iteration reach the criteria. The algorithm will return the value of positions of the corresponding agents at specified dimension at final iteration.

### 3.2. Particle Swarm Optimization

PSO was introduced by Kennedy and Eberhart that adopted the idea of swarm behaviour of birds in 1995 [6]. The basic ideas of PSO are:

- a. Each particle is searching for optimum and at the same time each particle is moving and hence has a velocity.
- b. Along the moving progress, each particle will remember the position it was which develops the best result.
- c. By cooperation among the particles in the swarm, they exchange information of the locations they have visited.
- d. To exchange information, it depends on the neighbourhood associated. Then the particles will know the fitness among these neighbourhood, and use the position which has the best fitness. Positions are then used to update their velocities accordingly.

**Step 1: Population Initialization**

Initialize the population of the PSO with randomly generated \(n_{popu}\) particles, population size, in the \(k\)-dimensional searching space, and each particle include position \(X_i\) and velocity \(V_i\) where \(X_i\) represent the position of \(i\)th particle, \(X_i = (X_{i1}, X_{i2}, \ldots, X_{ik})\) whereas \(V_i\) represent the velocity of \(i\)th particle, \(V_i = (V_{i1}, V_{i2}, \ldots, V_{ik})\). The parameter of the search space represents the number of variable in the application [6]. Position \(X_i\) and velocity \(V_i\) represent the solution of the problem and its displacement in the searching space respectively.

**Step 2: Fitness Function**

Fitness function is determined for each particle. The higher the value of the particle, the better fit of the particle. Otherwise the particle is considered less fit. The fitness function’s equation is shown below.

\[
Fit(N, d, h) = \frac{1}{Ob(N, d, h) + \mathcal{E} + \sum_{p=1}^{m} n_p (\Delta p)^2}
\]

where

\(Ob(.)\) : Objective function of optimization problem

\(\mathcal{E}\) : constant that lets the denominator of \(Fit(.)\) be a positive
\( \eta_p \): Coefficient of p-th constraint
\( \Delta \lambda_p - \Delta \lambda_{1-4} \) are respectively the violations of step 2 to 5

Step 3: Update Velocity and Position

Every particle keep hold of its optimal position value based on the characteristic of flying birds which they accumulated the flying experience. Subsequently, the particle best local position, \( P_{best} \), can be selected respectively. The particles share their optimal values as well as their best local position subsequently the global best, \( G_{best} \) can be selected according to the fitness value and position. Therefore, the velocity of each particle will be guided by previous particle velocity (\( P_{best} \) and \( G_{best} \)) [6].

\[
V_{ij}^{new} = w \cdot V_{ij} + c_1 \cdot \text{rand1} \cdot (P_{best,j} - X_{ij}) + c_2 \cdot \text{rand2} \cdot (G_{best,j} - X_{ij}) \quad (13)
\]

\[
X_{ij}^{new} = X_{ij} + V_{ij} \quad (14)
\]

Where
\[
W = w_{\max} - \text{iter}(w_{\max} - w_{\min})/\text{iter}_{\max}
\]
\[
P_{best} = (P_{best,1}, \ldots, P_{best,j}, \ldots, P_{best,k})
\]
\[
G_{best} = (G_{best,1}, \ldots, G_{best,j}, \ldots, G_{best,k})
\]

\( P_{best} \) is the optimal position of the ith particle
\( G_{best} \) is 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
\( \text{iter} \) – current iteration number
\( \text{iter}_{\max} \) – maximum iteration number

Step 4: Bound of velocity and Position

The particle will be updated accordingly with the bounds of the k-dimensional search space as shown below

\[
X_{ij} = X_{\max,j} \quad \text{for} \quad X_{ij} = X_{\max,j}
\]
\[
\text{and} \quad X_{ij} = X_{\min,j} \quad \text{for} \quad X_{ij} = X_{\min,j}
\]

\[
V_{ij} = V_{\max,j} \quad \text{for} \quad V_{ij} = V_{\max,j} \quad , \quad V_{ij} = V_{\min,j} \quad \text{for} \quad V_{ij} = -V_{\min,j}
\]

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

\( V_{\max,j} \) – maximum velocity of j-th dimension
\( X_{\min,j} \) – minimum value of j-th dimension
\( X_{\max,j} \) – maximum value of j-th dimension

4. Simulation of grounding planning

The design is initiated for a substation rectangular grounding grid 132/11kV case study for a small general industry with the transmission circuit and the step down delta-wye transformer. The grounding grid size is given as 90m (length) and 50m (width). The average soil resistivity is 300 Ωm. Table 1 shows the substation parameters.
Table 1. Input parameters for substation.

| Parameter                                | Value      |
|------------------------------------------|------------|
| Average Soil resistivity                 | 300Ωm      |
| Fault Current                            | 3100A      |
| Resistivity of crushed Rock layer        | 3000Ωm     |
| Soil location type                       | uniform    |
| Switch Yard operator                     | >50kg      |
| Soil location Type                       | Uniform    |
| Projection Factor                        | 20%        |
| Shock Duration                           | 0.15s      |
| Fault duration                           | 0.15s      |
| Surface layer derating factor            | 1.2        |
| Crushed rock layer inside sub            | 0.10m      |
| X/R ratio at the fault                   | 15         |
| Current Division Factor Sf               | 0.8        |
| Length in X direction                    | 90 m       |
| Length in Y direction                    | 50 m       |
| Ambient Temperature                      | 30°C       |
| Grid Shape                               | Rectangular|

The objective function is to optimize 4 parameters for the grounding grid conductors, i.e. number of horizontal rows, number of horizontal columns, vertical rod length and number of vertical rods. The population size is set as 10n with n as the number of parameters to be optimized, thus 10 x 4 = 40. The attempt of searching the optimized design is taken by 20 iterations to be completed during simulation. The upper and lower bound of these 4 defined parameters are 10 and 3 respectively. The gravitational time constant G0 is set at 150 and the value of α is at 12. GSA input parameters are shown in Table 2.

Table 2. Input parameter setting for GSA.

| Parameter | Value |
|-----------|-------|
| Population size | 40    |
| Max iteration  | 20    |
| Upper bound    | 10    |
| Lower bound    | 3     |
| A             | 12    |
| G0            | 150   |

The maximum tolerable voltages for step and touch scenarios can be calculated empirically from IEEE Std Section 8.3 for operator body weights of 50 kg and 70 kg: $E_{step,70} = 5664V$, $E_{step,50} = 4184V$ and touch voltage, $E_{touch,70} = 1720V$, $E_{touch,50} = 1270V$ are obtained.

For setting up the optimization of GSA, there are methods used in objective function that will minimize the cost of the construction for the rectangular grounding grid system. This could be achieved through an optimization process which can find a minimal cost needed to construct a grounding grid.

Based on the formula of ANSI/IEEE Std.80, the calculated maximum grid current IG = 1860A by assuming that the ground conductor material are the copper-clad steel wire at ambient temperature ($T_a$) of 300°C. The ground potential rise (GPR) and grounding grid resistance with respect to remote earth ($R_g$) are 5829V and 2.275 Ω respectively based on ANSI/IEEE Std.80[1].

GSA parameters have been initialized (such as x – number of horizontal rows, y – number of horizontal columns, z – number of vertical rods, w – number of vertical rod length), with each agent randomly selected while satisfying different equality and inequality constraints, upper bound and lower bound as 10 & 3 respectively. There are 40 agents generated. Therefore each set in the agent matrix X presents a solution for the 4 parameters. Then the grounding function program could determine the different dependent variables such as tolerable touch and step voltages, GPR, grid
resistance and total length of conductor. The $G(t)$, $best(t)$, $worst(t)$ and $mi(t)$ are updated for each set of agents. The fitness function or objective is calculated by using (9). The velocity and position of each agent are also calculated by using (10) and (11) accordingly.

The dependent variables like total length, GPR etc will be iteratively calculated for the agents in the matrix. In the end of process, the fitness value for each newly generated set of agent matrix $X$ are determined. This process is updating $G(t)$, $best(t)$, $worst(t)$ and $mi(t)$ to optimize the fitness value until maximum iterations i.e. 20 is reached.

Figure 1 shows a screenshot for GSA simulation (one trial sample) with Matlab.

For setting up the optimization of PSO, there are also 4 parameters to be optimized which are number of horizontal rows ($x$), number of horizontal columns ($y$), number of vertical rods ($z$), and vertical rod length ($w$). For PSO optimization, the input parameters listed in Table 3. The population size is set as 10n with n as the number of parameters to be optimized, thus $10 \times 4 = 40$. Maximum iteration is set it as 20. The upper bound and lower bound limits are set at 10 and 3 respectively, similar to the parameter settings for GSA. An initial population is generated with randomly generated particles. Then from each particle, the fitness value which is the total length of conductors will be determined for number of horizontal rows, number of horizontal columns, number of vertical rods and each vertical rod length. If the fitness value is better (lower) than its personal best, the current value of total length will set as the new $Pbest_i$. Therefore the particle with the best or lowest fitness value will be chosen as $Gbest$. For each particle, its position will be calculated according to (15). Subsequently the particle velocity will be updated according to (16). Anyway, it is applicable to use the inertia weight which is decreasing over time, typically from 0.9 to 0.4 as it has the effect of narrowing the search according to the analysis. So the process will keep running until the maximum iteration which is 20 in this case.

Table 3. Input parameter setting for PSO.

| Population size | Max iteration | Upper bound | Lower bound | wmax | wmin | C1  | C2  |
|-----------------|--------------|-------------|-------------|------|------|-----|-----|
| 40              | 20           | 10          | 3           | 0.9  | 0.4  | 0.7 | 0.7 |
Figure 2 shows a screenshot of PSO simulation (one trial sample) with Matlab.

![Screenshot for PSO simulation](image)

**Figure 2.** Screenshot for PSO simulation.

5. Simulation results

Table 4 shows that increase in soil resistivity from 300 Ωm to 600 Ωm does not introduce a remarkable change in tolerable step and touch voltage but it affects the grid resistance, $R_g$. When soil resistivity increases from 300 Ωm to 600 Ωm, $R_g$ increases from 2.297 Ω to 4.410 Ω. Increase in $R_g$ will increase GPR, which in turn require more earthing rods. Hence it is desirable to keep soil resistivity and GPR low.

| Soil resistivity & crush rock resistivity (Ωm) | Safety Factor | GSA | PSO |
|---------------------------------------------|---------------|-----|-----|
| 300, 3000                                   | Estep70 (V) 5664 | 5664 |     |
|                                             | Etouch70 (V) 1720 |     | 1720 |
|                                             | Estep50 (V) 4186 | 4186 |     |
|                                             | Etouch50 (V) 1271 | 1271 |     |
|                                             | GPR (V) 6428.4 | 6154 |     |
|                                             | $R_g$ (Ω) 2.297 |     | 2.407 |
| 600, 3000                                   | Estep70 (V) 5890.5 | 5890.5 | |
|                                             | Etouch70 (V) 1776.6 | 1776.6 | |
|                                             | Estep50 (V) 4353 | 4353 |     |
|                                             | Etouch50 (V) 1313 | 1313 |     |
|                                             | GPR (V) 11229 | 11941 |     |
|                                             | $R_g$ (Ω) 4.410 |     | 4.339 |

Table 5 shows that increase in crush rock resistivity from 3000 Ωm to 10000 Ωm increase the tolerable step and touch voltage i.e. Estep70 increases from 5664 V to 17406 V and Etouch70 increases from 1720 V to 4656 V. Increase in tolerable step and touch voltage lower the safety requirement.
### Table 5. Safety limit with different crush rock resistivity.

| Soil resistivity & crush rock resistivity (Ωm) | Safety Factor | GSA       | PSO       |
|-----------------------------------------------|---------------|-----------|-----------|
| 300, 3000                                     | Estep70 (V)   | 5664      | 5664      |
|                                               | Etouch70 (V)  | 1720      | 1720      |
|                                               | Estep50 (V)   | 4186      | 4186      |
|                                               | Etouch50 (V)  | 1271      | 1271      |
|                                               | GPR (V)       | 6428.4    | 6154      |
|                                               | $R_g$ (Ω)     | 2.279     | 2.407     |
| 300, 10000                                    | Estep70 (V)   | 17406     | 17406     |
|                                               | Etouch70 (V)  | 4656      | 4656      |
|                                               | Estep50 (V)   | 12860     | 12860     |
|                                               | Etouch50 (V)  | 3440      | 3440      |
|                                               | GPR (V)       | 6768.7    | 6815.3    |
|                                               | $R_g$ (Ω)     | 2.324     | 2.660     |

Table 6 shows the GSA and PSO optimum parameters for earthing rods; number of horizontal rows, number or horizontal columns, number of vertical rods and each vertical rod length. The table shows that increase in soil resistivity from 300 Ωm to 600 Ωm increase the total length of rod conductors i.e. (GSA 672m to 1425m, PSO 673m to 1440m). GSA and PSO produce optimum results with negligible difference in total length of conductor (1.5%, 1.05%).

### Table 6. Optimized parameters with different soil resistivity.

| Soil resistivity & crush rock resistivity (Ωm) | Optimized Parameter | GSA   | PSO   | Difference (%) |
|------------------------------------------------|---------------------|-------|-------|----------------|
| 300, 3000                                      | Number of row       | 4     | 4     | N/A            |
|                                                | Number of column    | 6     | 6     | N/A            |
|                                                | Number of rod       | 5     | 4     | N/A            |
|                                                | Rod length (m)      | 3     | 3     | N/A            |
|                                                | Total Length of conductor | 672 | 673 | 1.5          |
|                                                | $R_g$ (Ω)           | 2.297 | 2.407 | 5.2           |
| 600, 3000                                      | Number of row       | 10    | 10    | N/A            |
|                                                | Number of column    | 10    | 9     | N/A            |
|                                                | Number of rod       | 5     | 10    | N/A            |
|                                                | Rod length (m)      | 5     | 9     | N/A            |
|                                                | Total Length of conductor | 1423 | 1440 | 1.05          |
|                                                | $R_g$ (Ω)           | 4.400 | 4.339 | 1.39          |

Table 7 shows the GSA and PSO optimum parameters when crush rock resistivity increases from 3000 Ωm to 10000 Ωm. Increase in rock resistivity decreases the total length of conductors (GSA 672m to 447m, PSO 673m to 429m).
Table 7. Optimized parameters with different crush rock resistivity.

| Soil resistivity & crush rock resistivity (Ωm) | Optimized Parameter | GSA | PSO | Difference (%) |
|-----------------------------------------------|---------------------|-----|-----|---------------|
| 300, 3000                                     | Number of row       | 4   | 4   | N/A           |
|                                               | Number of column    | 6   | 6   | N/A           |
|                                               | Number of rod       | 5   | 4   | N/A           |
|                                               | Rod length (m)      | 3   | 3   | N/A           |
|                                               | Total Length of conductor | 672 | 673 | 1.5          |
|                                               | Grid resistance $R_g$ (Ω) | 2.297 | 2.407 | 5.2          |
| 300, 10000                                    | Number of row       | 3   | 3   | N/A           |
|                                               | Number of column    | 3   | 3   | N/A           |
|                                               | Number of rod       | 9   | 3   | N/A           |
|                                               | Rod length (m)      | 3   | 3   | N/A           |
|                                               | Total Length of conductor | 447 | 429 | 4.02         |
|                                               | Grid resistance $R_g$ (Ω) | 2.324 | 2.660 | 12.8          |

Table 8 shows that total length of conductors required decrease from up-optimized 956m to GSA optimum 672m, saving 29.7% buried conductor length. This can be achieved at negligible increase (1.0%) in grid resistance that results in negligible increase in GPR.

Table 8. Comparison between un-optimized grid and optimized grid by using GSA.

| Parameter                                      | Un-optimized grid | Optimized with GSA | Difference (%) |
|-----------------------------------------------|-------------------|--------------------|---------------|
| Number of horizontal rows                     | 6                 | 4                  | N/A           |
| Number of horizontal columns                  | 7                 | 6                  | N/A           |
| No. of vertical rod                           | 22                | 5                  | N/A           |
| Vertical rod length (m)                       | 3                 | 3                  | N/A           |
| Grid resistance $R_g$ (Ω)                     | 2.275             | 2.297              | 1.0           |
| Total Length of conductor (m)                 | 956               | 672                | 29.7          |

Table 9 shows that total length of conductors required decrease from up-optimized 956m to PSO optimum 673m, saving 29.6% buried conductor length. This can be achieved at small increase (6%) in grid resistance that results in small increase in GPR.

Table 9. Comparison between un-optimized grid and optimized grid by using PSO.

| Parameter                                      | Un-optimized grid | Optimized with PSO | Difference (%) |
|-----------------------------------------------|-------------------|--------------------|---------------|
| Number of horizontal rows                     | 6                 | 4                  | N/A           |
| Number of horizontal columns                  | 7                 | 6                  | N/A           |
| No. of vertical rod                           | 22                | 4                  | N/A           |
| Vertical rod length (m)                       | 3                 | 3                  | N/A           |
| Grid resistance $R_g$ (Ω)                     | 2.275             | 2.407              | 6.0           |
| Total Length of conductor (m)                 | 956               | 673                | 29.6          |

6. Conclusion

Substation grounding grid design is an important part for substation design process. The design of the grounding grid must be developed for safety and reliability. There are several steps to produce a safe and effective grid design. Manual calculation will be a tedious and difficult process as it takes time and
the precision might be an issue. Hence, computer program is developed nowadays to greatly improve the process of grounding grid design in terms of time saving, reliability and preciseness.

In this research an overview of substation grounding grid design based on IEEE Std. 80-2000 was carried out. The grounding grid design equations, provided by the IEEE standard, were used to design a typical substation grounding grid. The substation grounding grid was then designed using optimization algorithms: GSA and PSO. For the optimization process, the necessary data including the population size and iteration number, are required to key into the templates provided by GSA and PSO respectively. These templates were further integrated with the preliminary grounding design code to work out the most optimized grid parameters. The results showed that both GSA and PSO were capable of optimizing the problem of grounding grid design and results in minimum total length of conductor rods. Both GSA & PSO produced consistent results and were able to produce a more cost effective grounding grid as compared to the equations provided by IEEE Std. 80-2000.

7. References
[1] IEEE Power Engineering Society Jan 2000 IEEE Guide for Safety in AC Substation Grounding IEEE-SA Standards
[2] F. Dawalibi F and Mukhedkar D Apr 1975 Optimum design of substation grounding in two layer earth structure analytical study IEEE Trans. Power Apparatus and Systems 94 no. 2 pp 252-261
[3] Heppe R J Dec 1979 Computation of potential at surface above an energized grid or other electrode allowing for non-uniform current distribution IEEE Trans. Power Apparatus and Systems 98 no. 6 pp 1978-89
[4] Ghoneim S, Hirsch H, Elmorshedy A and Amer R Optimum Jun. 24–28, 2007 Grounding grid design by using an evolutionary algorithm Proc. IEEE Power Eng. Soc. Gen. Meeting pp 1–7
[5] Lee C and Shen Y 2009 Optimal planning of ground grid based on particle swam algorithm Int. Journal of Electrical and Computer Engineering 3 no.12 pp 2235-42
[6] Nezhad N K, Fallahi M H and Dozein M G Jul 2013 An optimal design of substation grounding grid considering economic aspects using particle swarm optimization Research. J. Appl. Sci. Eng. Technol. 6 no. 12 pp 2159–65
[7] Tong C Mar 2014 Gravitational search algorithm based on simulated annealing J. Convergence Information Technol. (JCIT) pp 231–7