Partial discharge detection in transformer using adaptive grey wolf optimizer based acoustic emission technique

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Abstract: Partial discharge (PD) occurring in the insulation systems of the transformer is an important indicator of their deterioration. Insulation degradation is a well-known source of power transformer failure. Many methods have been realized for detection and localization of PD source in the transformer. In this paper sensor based acoustic emission technique has been implemented for PD detection. To repair site of PD after detection it is very important to find the exact location of PD sources in the equipment. This paper proposed adaptive grey wolf optimizer (AGWO) algorithm for localization of PD source using acoustic emission technique. A novel bio-inspired optimization algorithm based on the hunting process of wolves in nature called the grey wolf optimizer (GWO) Algorithm. In contrast to meta-heuristics; the main feature is randomization having a relevant role in both exploration and exploitation in the optimization problem. A novel randomization technique termed adaptive technique is integrated with GWO and exercised on unconstrained test benchmark function and optimum location of PD in the transformer. Integration of new randomization adaptive technique provides potential to AGWO algorithm to attain global optimal solution and faster convergence.
with less parameter dependency. AGWO solutions are evaluated and a result shows it's competitively better performance over other optimization algorithms.

Subjects: Acoustical Engineering; Electrical & Electronic Engineering; Power Engineering

Keywords: partial discharge; acoustic emission; grey wolf optimizer

1. Introduction

The term partial discharge (PD) is defined by International Electrotechnical Commission IEC-60270 as “A localized electrical discharge that only partially bridges the insulation between conductors and which may or may not occur adjacent to a conductor” (High-voltage test techniques. Partial discharge measurements, 2000). The transformer is key elements in power systems which represent the largest portion of the capital investment. Reliability of transformer affects the economical operation of the utility. In the majority of the cases reducing insulating properties leads to major faults in the transformer. Cumulative effects of the thermal, electrical and mechanical stresses are main factors which lead to dielectric breakdown (Zargari & Blackburn, 1996). Regular monitoring of PD activity is essential to avoid a sudden outage of the transformer. Electrical and chemical detection are conventional PD detection techniques while acoustic emission and UHF detection are modern and futuristic PD detection techniques.

Current streamer generates electrical pulses in the void. Electrical detection method captures these electrical pulses. Electrical PD detection techniques are more user-friendly, standardized, vulnerable, effortless implementation compared to other technique. Types of PD and its severity can be identified by the analyzing intensity of electrical discharge signals, shape of pulse and its relative phase location within AC cycle. The electrical PD detection methods are divided into intrusive and non-intrusive methods. To detect PD pulses by the intrusive method, the sensing element needs to be put inside the power equipment. However, this method is predominantly an offline method. It is also vulnerable to electrical disturbances and noise during on-site measurement.

In PD detection by a chemical method, current streamer across the void may lead to chemical decomposition. Dissolved gas analysis (DGA) and high-performance liquid chromatography (HPLC) are two acclaimed methods for further analysis of different chemical components. A fundamental part of DGA is periodic oil sampling. Primary diagnostic gasses have been identified as hydrogen (H₂), ethylene (C₂H₄), ethane (CH₄), methane (C₂H₆), acetylene (C₂H₂), carbon monoxide (CO) and carbon dioxide (CO₂). Gassing characteristic is greatly reliant on size and structure of transformer, loading of transformer and history of maintenance. DGA is thus considered as “art” instead of “science”. Most of the harmful PD occurs close to the paper insulation. Hence, CO₂ emitted from the cellulose is considered to be an indicator for the presence of PD.

UHF detection is an advanced technique for PD detection. Discharges are exceptionally fast and transient pulse. Pulse emission energy is in GigaHertz range. PD is detected by means of electromagnetic transient signals frequency range of 300–3,000 MHz. UHF detection is famous due to various reasons like online monitoring, less noise interference. The UHF detection technique was first implemented in Gas Insulated Switchgear and later on used to power transformers. The amplitude of UHF pulses and time interval between two pulses are a very important parameter for a detailed understanding of PD activity. Basically, UHF sensor (antenna) will capture PD signal, which is subsequently connected to a preamplifier, multiplexer, and a digital oscilloscope. Capacitive sensor and inductive sensor are two broad categories of UHF sensor. Capacitive sensor has higher sensitivity than inductive. Mainly four types of sensors are widely in use (i) Window sensor (ii) Internal disk sensor (iii) Barrier sensor and (iv) Oil valve sensor. Other than these waveguides sensor, hatch sensor, directional electromagnetic sensor, etc. are also in use. In transformer localization of PD is possible by installing more number of sensors. For this purpose provision for sensor has to make at the time of transformer manufacturing.

Hot current streamer in void vaporized surrounding materials which cause a sudden increase of mechanical energy in terms of acoustic waves. External system and internal system are two
categories of acoustic detection techniques based on sensor location in the transformer. The external system is widely accepted as sensors are mounted outside of the transformer. In external system typically Lead Zirconium Titanate types of sensors are used.

PD generates acoustic signals in 20 kHz to 1 MHz frequency range. Acoustic emission signals are being captured by sensors mounted at transformer walls. Localization of PD source can be implemented based on time difference of arrival (TDOA) between different sensors. Different optimization techniques can be implemented to find optimum PD source location. In this work adaptive grey wolf optimization (AGWO) algorithm has been implemented for localization of PD source. AGWO algorithm has a quality feature that it uses the simple mathematical equation to update the position of grey wolf towards targeted prey or towards optimal solution over the end of maximum iteration limit.

Nature inspired grey wolf optimizer (GWO) algorithm (Mirjalili, Mirjalili, & Lewis, 2014) based on the hunting mechanism. Wolves are a member of a troop in which a number of the grey wolves is the population size of wolves that takes part in hunting. Wolves in a troop are separated according to their leadership quality. Troop consists of four types of wolves identified as alpha (α), beta (β), delta (δ) and omega (ω). α wolves have higher dominance and decision maker in the troop and rest of wolves have their dominance decreasing sequentially as the name above written. In the meta-heuristic algorithms, randomization plays a very important role in both exploration and exploitation where more strengthen randomization techniques are Markov chains, Levy flights, and Gaussian or normal distribution and a new technique are adaptive technique. So meta-heuristic algorithms on integrated with adaptive technique results in less computational time to reach an optimum solution, local minima avoidance, and faster convergence.

GWO is meta-heuristic population-based optimization algorithm. GWO optimizer can solve different optimization problems without structural modification. This algorithm can be applied to non-differentiable, stochastic, and discontinuous functions (Gupta & Saxena, 2016). GWO integrated with adaptive technique reduces the computational time for highly complex problems.

The recent trend of optimization is to improve the performance of meta-heuristic algorithms (Gandomi, Yang, Talatahari, & Alavi, 2013) by integrating with chaos theory, Levy flights strategy, Adaptive randomization technique, Evolutionary boundary handling scheme, and genetic operators like as crossover and mutation. Popular genetic operators can accelerate its global convergence speed (Gandomi & Alavi, 2012). Evolutionary constraint handling scheme is used in interior search algorithm (Gandomi, 2014) that avoid upper and lower limits of variables.

This paper highlights the application of AGWO technique in transformer for PD source localization.

2. Grey wolf optimizer

GWO (Mirjalili et al., 2014) based on natural hunting process of grey wolves. Hunting process and dominance of wolves in troops showed in Figure 1.

In hunting process, first grey wolves discover the location of prey and enclose them. α is the leader of the hunting process. However, in a theoretical hunt space, we have no clue about the area of the prey (optimum). α, β, and δ have better information about the potential area of prey for mathematical simulation of hunting action.

In the course of the chasing, the grey wolves enclose prey. The mathematical model of the enclosing action is introduced in the subsequent equations.

\[
\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right|
\]

\[
\vec{X}(t + 1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D}
\]
where \( t \) is the existing iteration, \( A \) and \( C \) are coefficient vectors, \( \mathbf{X}_p \) is the location vector of the prey, and \( \mathbf{X} \) indicates the location vector of a grey wolf. The vectors \( A \) and \( C \) are calculated as follows:

\[
\mathbf{A} = 2 \cdot \mathbf{\tilde{a}} \cdot \mathbf{r}_1 - \mathbf{\bar{a}} \quad (3)
\]

\[
\mathbf{C} = 2 \cdot \mathbf{\tilde{r}}_2 \quad (4)
\]

where components of \( a \) linearly decreased from 2 to 0 over the course of iterations and \( r_1, r_2 \) are random vectors in [0, 1].

Grey wolf hunting process is calculated as following equations:

\[
\mathbf{D}_\alpha = |\mathbf{C}_1 \cdot \mathbf{X}_\alpha - \mathbf{X}| \quad (5)
\]

\[
\mathbf{D}_\beta = |\mathbf{C}_2 \cdot \mathbf{X}_\beta - \mathbf{X}| \quad (6)
\]

\[
\mathbf{D}_\delta = |\mathbf{C}_3 \cdot \mathbf{X}_\delta - \mathbf{X}| \quad (7)
\]

\[
\mathbf{X}_1 = \mathbf{X}_\alpha - \mathbf{A}_1 \cdot \mathbf{D}_\alpha \quad (8)
\]

\[
\mathbf{X}_2 = \mathbf{X}_\beta - \mathbf{A}_2 \cdot \mathbf{D}_\beta \quad (9)
\]
3. Adaptive GWO Algorithm

In the meta-heuristic algorithms, randomization plays a very important role in both exploration and exploitation where more randomization techniques are Markov chains, Levy flights, and Gaussian or normal distribution and a new technique is adaptive technique. The adaptive technique used by Pauline Ong in Cuckoo search algorithm (CSA) (Ong, 2014) and shows improvement in results of CSA algorithms. The adaptive technique (Naik & Panda, 2016) includes best features like it consists of less parameter dependency, not required to define the initial parameter and step size or position towards an optimum solution is adaptively changes according to its functional fitness value over the course of the iteration. So meta-heuristic algorithms on integrated with adaptive technique results in less computational time to reach an optimum solution, local minima avoidance, and faster convergence.

\[
X_{t+1}^{i} = \left( \frac{1}{T} \right) \left[ \text{best}(f(t)−f(t_i))/\text{best}(f(t)−\text{worst}(f(t_i))) \right]
\]

where \(X_{t+1}^{i}\) step size of \(i\)-th dimension in \(t\)-th iteration \(f(t)\) is the fitness value.

All computational complexity of the developed AGWO algorithm depend on numbers of grey wolves, iteration size and sorting mechanism that find out best wolves. Quick sort mechanism has been implemented for sorting. Complexity for best case \(O(n \log n)\) and worst case \(O(n^2)\). Overall Computational complexity of the developed AGWO algorithm as follows:

\[O(AGWO) = O(I(n^2 + n \times d \times \log n))\]

where \(n\) are a number of grey wolves, \(I\) is the maximum number of iterations, and \(d\) is a number of objects.

Due to better convergence, high exploration, low computational complexity, faster local minima avoidance and less computational time required to solve real problems represent that proposed AGWO algorithm can use to solve large-scale optimization problems.

4. Results for unconstraint test benchmark function

Unconstraint test benchmark functions shown in Table 1 are simulated for comparison (Table 2).

Figure 2 shows the performance of AGWO in compare to GWO for different benchmark test functions. Result analysis of benchmark test functions is given in Table 3.

5. Acoustic PD detection and localization technique

Insulation breakdown in transformers is often initiated by PD activities. Regular monitoring of PD activity is essential to know deterioration in insulation. Otherwise, this process leads to sudden failure of the transformer. So it is possible to foretell developing fault condition by online monitoring and precautionary tests. It is very much essential to have information of PD level and location to plan maintenance of electrical equipment. A famous method of understanding the health of the transformer is by studying the PD signals. Monitoring of transformer can be either online or offline. An electrical current and radio frequency pulse has been measured in electrical PD detection system. Interference is the main challenge which required attention in a noisy surrounding.

\[
X_3 = X_d - A \cdot D
\]

\[
\bar{X}(t + 1) = \frac{X_1 + X_2 + X_3}{3}
\]
Table 1. Benchmark test functions

| No. | Name                        | Function                                                                 | Dim | Range                     | Fmin  |
|-----|-----------------------------|--------------------------------------------------------------------------|-----|---------------------------|-------|
| F_1 | Sphere                      | $f(x) = \sum_{i=1}^{n} x_i^2 \times R(x)$                               | 10  | $[-100, 100)$             | 0     |
| F_2 | Schwefel 2.22               | $f(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i| \times R(x)$          | 10  | $[-10, 10)$               | 0     |
| F_3 | Schwefel 1.2                | $f(x) = \sum_{i=1}^{n} \left( \frac{1}{x_i} \right)^2 \times R(x)$     | 10  | $[-100, 100)$             | 0     |
| F_4 | Schwefel 2.21               | $f(x) = \max \left\{ |x_i|, 1 \leq i \leq n \right\}$                  | 10  | $[-100, 100)$             | 0     |
| F_5 | Rosenbrock’s function       | $f(x) = \sum_{i=1}^{n-1} \left[ 100(x_{i+1} - x_i^2) + (x_i - 1)^2 \right] \times R(x)$ | 10  | $[-30, 30]$               | 0     |
| F_6 | Step function               | $f(x) = \sum_{i=1}^{n} \left( |x_i| + 0.5 \right)^2 \times R(x)$       | 10  | $[-100, 100)$             | 0     |
| F_7 | Quartic function            | $f(x) = \sum_{i=1}^{n} k_i^4 + \text{random}(0, 1) \times R(x)$         | 10  | $[-1.28, 1.28)$           | 0     |
| F_8 | Schwefel 2.26               | $f(x) = \sum_{i=1}^{n} -x_i \sin\left( \sqrt{|x_i|} \right) \times R(x)$ | 10  | $[-500, 500]$             | $(-418.9829 \times 5)$ |
| F_9 | Rastrigin                   | $f(x) = \sum_{i=1}^{n} \left( x_i^2 - 10 \cos(2\pi x_i) + 10 \right) \times R(x)$ | 10  | $[-5.12, 5.12]$           | 0     |
| F_{10}| Ackley’s function          | $f(x) = -20 \exp\left( -0.2 \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2} \right) - \exp\left( \frac{1}{n} \sum_{i=1}^{n} \cos(2\pi x_i) \right) + 20 + e \times R(x)$ | 10  | $[-32, 32]$               | 0     |
| F_{11}| Griewank function          | $f(x) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left( \frac{x_i}{\sqrt{n}} \right) + 1 \times R(x)$ | 10  | $[-600, 600]$             | 0     |
| F_{12}| Penalty 1                  | $F(x) = \frac{1}{n} \left\{ 10 \sin\left( \pi y_1 \right) + \sum_{i=1}^{n} \left( y_i - 1 \right)^2 \right\} \left\{ 1 + 10 \sin^2\left( \pi y_{i+1} \right) \right\} \left( y_i - 1 \right)^2 \left\{ x_i > \alpha \right\}$ | 10  | $[-50, 50]$               | 0     |
| F_{13}| Penalty 2                  | $F(x) = 0.1 \left\{ \sin^2\left( 3\pi x_1 \right) + \sum_{i=1}^{n} \left( x_i - 1 \right)^2 \right\} \left\{ 1 + \sin^2\left( 3\pi x_i \right) \right\} \left( x_i - 1 \right)^2 \left\{ 1 + \sin^2\left( 2\pi x_i \right) \right\} \left\{ 0 \leq x_i < 1 \right\}$ | 10  | $[-50, 50]$               | 0     |
| F_{14}| De Jong (Shekel’s Foxholes)| $F(x) = \left( \frac{1}{100} + \sum_{i=1}^{25} \frac{1}{1 + \left( x_i - 0.05 \right)^2} \right)^{-1}$ | 2   | $[-65.536, 65.536]$       | 1     |
| F_{15}| Kowalik’s function         | $f(x) = \sum_{i=1}^{n} \left( \frac{\left( x_i^4 + 5 \right)^{1/3}}{10} \right)^2 \left( x_i^4 + 5 \right)$ | 4   | $[-5, 5]$                 | 0.00030 |
| F_{16}| Shekel                     | $f(x) = -\sum_{i=1}^{10} \left[ (X - a_i)^2 + c_i \right]^{-1}$         | 4   | $[0, 10]$                 | $-10.5363$ |
| F_{17}| Cube function              | $f(x) = 100(x_2 - x_1^2)^2 + (1 - x_1)^2$                                | 30  | $[-100, 100)$             | 0     |
| F_{18}| Matyas function            | $f(x) = 0.26(x_1^2 + x_2^2) - 0.48x_1x_2$                               | 30  | $[-30, 30)$               | 0     |
| F_{19}| Powell function            | $f(x) = \sum_{i=1}^{D-2} \left\{ (x_{i+1} + 10x_i)^2 + 5(x_{i+1} - x_{i+2})^2 \right\}$ | 4   | $[-30, 30)$               | 0     |
| F_{20}| Beale function             | $f(x) = \sum_{i=1}^{n} \left\{ (1.5 - x_i + x_i^2)^2 + (2.25 - x_i + x_i^2)^2 \right\}$ | 30  | $[-100, 100)$             | 0     |
| F_{21}| Levy13 function            | $f(x) = \frac{\sin^2\left( 3\pi x_1 \right) + (x_1 - 1)^2 \left( 1 + \sin^2\left( 3\pi x_1 \right) \right) + (x_2 - 1)^2 \left( 1 + \sin^2\left( 2\pi x_2 \right) \right)}{ \left( x_1 - 1 \right)^2 \left( 1 + \sin^2\left( 2\pi x_2 \right) \right)}$ | 30  | $[-10, 10]$               | 0     |
Figure 2. Performance of AGWO over GWO algorithm on benchmark test function.
Figure 2. (Continued).
It is well known that the occurrence of discharge results in discharge current or voltage pulse, electromagnetic impulse radiation, ultrasonic impulse radiation and visible or ultraviolet light emission. Accordingly, there are several detection methods that have been developed to measure those phenomena respectively. Acoustic detection is one of them which is very famous nowadays.

![Convergence curve (F_{31})](image)

**Table 2. Internal parameters**

| Parameter name | Number of search agents | Number of maximum iteration | Number of evolution |
|----------------|-------------------------|-----------------------------|---------------------|
| F₁₋F₂₁        | 30                      | 500                         | 20–30               |

**Table 3. Result for benchmark function**

| Function | Grey wolf optimizer (GWO) | Adaptive grey wolf optimizer (AGWO) |
|----------|---------------------------|-------------------------------------|
|          | Average | Best | SD    | Average | Best | SD    |
| F₁       | 1.181E-27 | 8.4259E-28 | 4.785E-28 | 1.6974E-28 | 1.8058E-29 | 2.1451E-28 |
| F₂       | 1.6891E-16 | 1.576E-16 | 1.5994E-17 | 8.0155E-17 | 5.8067E-17 | 3.1236E-17 |
| F₃       | 9.3408E-06 | 2.9251E-06 | 9.0731E-06 | 3.581E-05 | 7.5664E-07 | 4.9574E-05 |
| F₄       | 1.1029E-06 | 6.3635E-07 | 1.1013E-06 | 3.1456E-07 | 1.1126E-06 |
| F₅       | 27.1668 | 27.1574 | 0.013245 | 27.1064 | 26.2695 | 1.1836 |
| F₆       | 0.98986 | 0.71907 | 0.38295 | 0.73301 | 0.44929 | 0.40123 |
| F₇       | 0.0024822 | 0.0018047 | 0.00095814 | 0.0011139 | 0.0010094 | 0.00014787 |
| F₈       | -6000.4501 | -6063.1864 | 88.7226 | -6112.1627 | -6603.6221 | 695.0286 |
| F₉       | 1.7569 | 4.8885E-12 | 2.4847 | 1.0923 | 1.0232E-12 | 1.5448 |
| F₁₀      | 1.0214E-13 | 9.6811E-14 | 7.3664E-15 | 8.9706E-14 | 7.9048E-14 | 1.5073E-14 |
| F₁₁      | 0.0509 | 0.021061 | 0.0422 | 0.015748 | 0.013732 | 0.0028504 |
| F₁₂      | 0.0701 | 0.043894 | 0.037062 | 0.044573 | 0.039188 | 0.0071656 |
| F₁₃      | 1.0382 | 0.92549 | 0.15943 | 0.73517 | 0.40537 | 0.46641 |
| F₁₄      | 6.8726 | 2.9821 | 5.5021 | 0.998 | 0.998 | 1.4588E-10 |
| F₁₅      | 0.010344 | 0.00032534 | 0.014169 | 0.00038262 | 0.00030822 | 0.000010522 |
| F₁₆      | -10.5345 | -10.5351 | 0.00092324 | -10.535 | -10.5357 | 0.00093196 |
| F₁₇      | 1.361E-06 | 1.0252E-06 | 4.7483E-07 | 6.972E-07 | 6.4705E-07 | 7.0913E-08 |
| F₁₈      | 8.6499E-104 | 6.808E-114 | 1.2233E-103 | 2.0827E-104 | 3.5435E-120 | 2.9453E-10 |
| F₁₉      | 3.8146E-08 | 1.1174E-08 | 3.8145E-08 | 6.199E-09 | 4.2344E-09 | 2.7783E-09 |
| F₂₀      | 6.0394E-07 | 2.8958E-07 | 4.4458E-07 | 2.0745E-07 | 1.9532E-07 | 1.716E-08 |
| F₂₁      | 5.6947E-07 | 3.726E-07 | 2.7842E-07 | 6.5165E-07 | 1.0084E-07 | 7.7896E-07 |
PD generates acoustic waves in the range of 20 kHz to 1 MHz. External system and internal system are two categories of acoustic detection techniques based on sensor location in the transformer. The external system is widely accepted as sensors are mounted outside of the transformer. An obvious advantage of the acoustic method is that it can locate the site of a PD by TDOA algorithm.

An acoustic wave travels from PD source to sensors either directly through transformer oil or indirectly through transformer tank. In indirect path acoustic waves hitting the nearby tank wall create an alternate propagation path via the tank walls to the sensor. As the acoustic wave hits the tank wall, its frequency characteristics remain the same, but its mode of propagation and propagation speed changes. The indirect path comprises the structure-borne path as well as the path travelled in the oil. In the majority of the cases, the structure-borne path is larger than the oil-borne path. The speed of the waves travelling through transformer oil is 150,000 cm/s and in transformer tank surface (steel) is 600,000 cm/s (Ramu & Nagamani, 2010). Wave travelling through transformer walls (indirect path) will hit sensor earlier than oil path (direct path) as velocity of acoustic wave in metal path is higher than oil path.

It is also important to note that the attenuation of the AE signals in the metal is higher than in transformer oil and therefore the intensity of the wave travelling along the indirect path is lesser than the waves travelling along the direct path. Thus, it is evident that the contribution of the indirect path AE signals in the output signature obtained is a small proportion (Dhole, Sinha, & Nayak, 2008).

The main objective is to determine the position of the PD source based on signals captured by sensor array inside the transformer tank as shown in Figure 3. Each sensor will capture acoustic signals at a different time as shown in Figure 4. TDOA algorithm has been implemented to find the location of PD source.

Partial differential equations in homogeneous medium for propagation of acoustic wave:

\[
\frac{\partial^2 P}{\partial t^2} = \nu^2 \nabla^2 P = \nu^2 \left( \frac{\partial^2 P}{\partial x^2} + \frac{\partial^2 P}{\partial y^2} + \frac{\partial^2 P}{\partial z^2} \right)
\]

where \( P(x, y, z, t) \) pressure wavefield; the function of space and time; \( x, y, z \) Cartesian coordinates (mm) and \( \nu \) is acoustic wave velocity (m/s).

![Figure 3. Illustration of PD source and sensor arrangement.](image-url)
6. Problem formulations and implementation

Acoustic PD detection techniques have been implemented in transformer like geometry and best PD source localization results obtained by implementation of AGWO algorithm. Tables 4 and 5 shows dimension of transformer and sensor location for simulation and parameters of the AGWO algorithm respectively.

\[ \tau_1 (\mu s) = 1,600, 1,500, 1,900, 3,524.69 - t_1, i = 2, 3, 4, 5. \] Assume \( S_1 \) as reference sensor (Yang & Wang, 2007).

Problem formulation:

\[ \tau_{21} = -1,000 \times 10^{-03}, \tau_{31} = -1,100 \times 10^{-03}, \tau_{41} = -700 \times 10^{-03}, \tau_{51} = -924.69 \times 10^{-03}, \] (14)

\[ P = \left( (x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2 \right)^{0.5} \] (15)

\[ a = \left( (x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2 \right)^{0.5} - P - v_e \tau_{21}; \] (16)

\[ b = \left( (x - x_3)^2 + (y - y_3)^2 + (z - z_3)^2 \right)^{0.5} - P - v_e \tau_{31}; \] (17)

Table 4. Transformer dimension and position of sensors

| Element                  | X-axis (mm) | Y-axis (mm) | Z-axis (mm) |
|--------------------------|-------------|-------------|-------------|
| Transformer dimension    | 5,000       | 3,000       | 4,000       |
| Actual PD source         | 4,500       | 2,600       | 3,700       |
| Sensor (S1)              | 2,500       | 0           | 2,000       |
| Sensor (S2)              | 2,500       | 1,500       | 4,000       |
| Sensor (S3)              | 5,000       | 1,500       | 2,000       |
| Sensor (S4)              | 2,500       | 3,000       | 2,000       |
| Sensor (S5)              | 0           | 1,500       | 2,000       |

\( t_1 = 2,600 \mu s \) (Reference)

Table 5. AGWO parameters

| Parameter                | Value  |
|--------------------------|--------|
| Number of iteration      | 200    |
| Number of search agents  | 40     |
Subjected to,

\[ 0 \leq x \leq x_{\text{max}} \]
\[ 0 \leq y \leq y_{\text{max}} \]
\[ 0 \leq z \leq z_{\text{max}} \]
\[ 1,200 \leq v_e \leq 1,500, \text{ (m/s)} \]

where \( x_{\text{max}}, y_{\text{max}}, z_{\text{max}} \) and \( v_e \) are transformer tank dimension and equality sound velocity. Calculated PD source is \( P_c(x_c, y_c, z_c) \) thorough separation error of it with real PD source \( P(x, y, z) \) is

\[ \Delta R = \left[ (x - x_c)^2 + (y - y_c)^2 + (z - z_c)^2 \right]^{0.5} \]

Error of each coordinates formulated by,

\[ \epsilon_r = \left| \frac{L_{\text{act}} - L_{\text{cal}}}{L_{\text{act}}} \right| \times 100\% \]

Maximum deviation \( D_{\text{max}} \),

\[ d = \left[ (x - x_s)^2 + (y - y_s)^2 + (z - z_s)^2 \right]^{0.5} - P - v_e \tau_{s1}; \]

\[ D_{\text{max}} = \max \left\{ \left| x_{\text{act}} - x_{\text{cal}} \right|, \left| y_{\text{act}} - y_{\text{cal}} \right|, \left| z_{\text{act}} - z_{\text{cal}} \right| \right\} \]

where \( L_{\text{act}}, x_{\text{act}}, y_{\text{act}}, z_{\text{act}} \) and \( L_{\text{cal}}, x_{\text{cal}}, y_{\text{cal}}, z_{\text{cal}} \) actual and calculated co-ordinates respectively.

### Table 6. Optimized location of PD source

| Co-ordinate (mm) | Actual PD source | AGWO | GWO | GA (Liu, 2016) | QGA (Liu, 2016) | PSO (Ma & Tao, 2013) | Linear PSO (Ma & Tao, 2013) | SA (Ma & Tao, 2013) |
|------------------|------------------|------|-----|----------------|-----------------|----------------------|--------------------------|------------------|
| \( X \)          | 4,500            | 4,398.0613 | 4,394.21 | 4,223.76 | 4,394.77 | 4,383.32 | 4,382.14 | 4,387.78 |
| \( Y \)          | 2,600            | 2,479.4974 | 2,467.51 | 2,391.71 | 2,475.98 | 2,470.53 | 2,469.99 | 2,470.01 |
| \( Z \)          | 3,700            | 3,664.2644 | 3,641.66 | 3,503.04 | 3,656.17 | 3,649.16 | 3,648.11 | 3,666.64 |
7. Simulation result analysis

Adaptive grey wolf optimizer (AGWO) used to find the optimum location of PD source location. Simulation parameter is quoted from reference paper (Yang & Wang, 2007) as given in Table 4.

Simulation results of optimum PD source location by different algorithm and error analysis are given in Tables 6 and 7 respectively. Results of AGWO have been compared with results of genetic algorithm (GA), particle swarm optimization (PSO), linear PSO, simulated annealing (SA) and quantum genetic algorithm (QGA) (Liu, 2016). PD source localization coordinates obtained by AGWO algorithm are better than other algorithms as per results compared in Table 6. Coordinate wise percentage error analysis is given in Table 7. In AGWO, the Comprehensive error is approximately 164 which is less than QGA and other algorithms and a maximum deviation of coordinate components is approximately 124 which are very close to QGA and less than other algorithms compared in the table. Even AGWO is approximately 1.33 times faster than GWO algorithm as shown in Table 7.

Figure 5 shows a three-dimensional view of sensor and source location in transformer like geometry. Results obtained in AGWO algorithm are more accurate in compare to other algorithms.

This paper targets PD detection and localization using AGWO algorithm for single PD source in the transformer. In future AGWO algorithm can be used to solve PD detection and localization problem with multiple PD sources in the transformer. Looking to the strength of AGWO algorithm, it can be used to solve different engineering problems like complex automotive system control (Zhang, Karimi, Zhang, & Wang, 2014), active suspension control in vehicle (Wang, Jing, Yan, Karimi, & Chen, 2014), floating structural control (Si, Karimi, & Gao, 2014), non-linear process control (Bououden, Chadli, & Karimi, 2015) and vehicle crash test modelling problems (Andreas et al., 2014).

| Error          | AGWO  | GWO   | GA (Liu, 2016) | QGA (Liu, 2016) | PSO (Ma & Tao, 2013) | Linear PSO (Ma & Tao, 2013) | SA (Ma & Tao, 2013) |
|----------------|-------|-------|----------------|----------------|----------------------|-----------------------------|---------------------|
| Error of x%    | 2.265 | 2.795 | 6.14           | 2.34           | 2.59                 | 2.62                       | 2.49                |
| Error of y%    | 4.788 | 5.095 | 8.01           | 4.77           | 4.98                 | 5.00                       | 5.00                |
| Error of z%    | 0.965 | 1.576 | 5.32           | 1.18           | 1.37                 | 1.40                       | 0.90                |
| $D_{\text{max}}$/mm | 124.5026 | 132.4817 | 276.24         | 124.02         | 129.47               | 130.01                     | 129.99              |
| Comprehensive error ($\Delta R$/mm) | 164.8315 | 191.7737 | 398.10         | 168.45         | 181.55               | 182.99                     | 174.94              |
| Elapsed time (s) | 126.52 | 168.39 | -              | -              | -                   | -                          | -                   |
8. Conclusion
GWO has an ability to find out an optimum solution with constrained handling which includes both equality and inequality constraints. While obtaining optimum solution constraint limits should not be violated. Randomization plays an important role in both exploration and exploitation. The adaptive technique causes faster convergence, randomness, and stochastic behaviour for improving solutions. The adaptive technique also used for random walk in search space when no neighbouring solution exists to converse towards an optimal solution. Acoustic PD source localization method based on AGWO algorithm is feasible and easy to implement. PD localization by AGWO gives a better result than GWO algorithm and also accurate in compare to GA, PSO, QGA. The AGWO result of various unconstrained problems proves that it is also an effective method for solving challenging problems with unknown search space.

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