2017 7th International Conference on Power Systems (ICPS)
College of Engineering Pune, India. Dec 21-23, 2017

Localization of Partial Discharge Source in Power Transformer using Bat Algorithm

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***Abstract*—Partial discharge (PD) source location in power transformer by measured acoustic signals using bat algorithm is presented. The available literature data considered for this case study is five sensors but for identification of PD source location needs not more than four sensors. Thus, five combinations results are analyzed using bat algorithm. This algorithm is tested on the measured acoustic TDOA signals which were reported in the literature. The results shows that bat algorithm enhances the search operation and there by PD location accuracy is better with other population based methods existing in the literature.**

Keywords— partial discharge; PD location;

I. INTRODUCTION

Partial discharges have significant effect on the continuous degradation of the insulation system in any high voltage power apparatus like power transformers and it may results in catastrophic failure. Hence, the partial discharges diagnosis is more essential at early stage there by the further losses and unexpected failures can be decreased [1-3]. PD initiates acoustic waves which propagate within transformer tank surface. Acoustic sensors are placed on outside of the transformer tank wall to capture these acoustic waves that propagates from the PD source [4-5]. This acoustic method has several merits over direct electrical method because they are non-contact, non-interference prone and ease of installation. The Time Difference of Arrival (TDOA) method is popularly gained for accurate localization of PD source. In the present work, the above method make use of arrival time differences of AE signals with respect to reference sensor to other sensors there by PD source is determined.

However, several conventional PD localization methods have been found in literature [5-7]. Lu et al proposed pattern recognition method to acoustic PD source localization in an oil filled transformer and in the simulation, the transformer tank is partitioned into a number of sub -modules, the PD site is located by finding the small spatial distance between the two pattern vectors of each sub-module's i.e. standard pattern vector and its undetermined pattern vector, and the location error is also more. Hence, this methodology is inappropriate for the on-line checking [5]. Global Position System (GPS) algorithm which utilizes pseudo time analysis is also applied for acoustic PD source localization and the demerit is sometimes it may produces complex solution [6]. Veloso.et.al used the genetic algorithm for PD source localization and the source is accurately located after 618 iterations with the population size of 120 [7].The iterative least square method is always depends upon the initial guess value, it takes more number of iterations and there is no guarantee of attaining a, feasible PD location result [1, 9, 10]. Hence, it also suffers from local premature problem. Kundu et al reported a non-iterative algorithm for acoustic PD source localization, it also gives two sets of solutions like GPS algorithm but only one solution is within boundary, the location error is also more even though it has no convergence problem [9].

The metaheuristic methods are random search methods that can search both local and global solution based on the type of the problem and time constraint. The commonly applied metaheuristic methods to the PD source localization till date are genetic algorithm, sequential quadratic programming (SQP-GA), quadratic genetic algorithm (QGA), Tabu search, PSO, Linear PSO, simulated annealing and self-adaptive algorithms. These are population based searching methods derived from mimetic of natural system. These algorithms have ease of exploring the search region. The fundamental hindrance is the deciding parameters values and sometimes they may produce imprecise solution.

II. PD SOURCE LOCALIZATION PROBLEM

The positions of sensors and the PD source placed on the transformer tank are as shown in Fig. 1. In Fig.1, the PD source is estimated at P(x, y, z), τ_n is the time difference of arrival of AE signals between reference sensor and n^{th} sensor. The 's' sensors positions are S_1 (x_1,y_1,z_1), S_2 (x_2,y_2,z_2),S_3 (x_3,y_3,z_3) and so on S_n (x_n ,y_n ,z_n). The sensor $S_1$is selected as the reference sensor for triggering the other sensors.

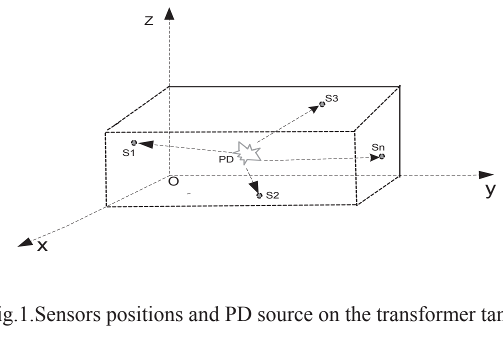

Fig.1.Sensors positions and PD source on the transformer tank.

A. *Objective function*

The objective of the PD source localization problem is the minimization of the location error and is given in Eqn. (1).

$$\min\{D_f(x, y, z, v_a)\} = \sum_{n=2}^{s} \{[(x - x_n)^2 + (y - y_n)^2 + (z - z_n)^2]^{1/2}$$
$$-[(x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2]^{1/2}$$
$$- v_a(t - \tau_n)\}^2 \quad (1)$$

where V_a is the acoustic velocity of the oil in the transformer tank. For a single PD source, the length, width, height and acoustic velocity are considered as constraints and taking care of sensor positions within the maximum limit of tank dimensions. In the present study there are two case studies. In the first case study, total number of sensors used is five, in that one sensor acts as a reference sensor, and with respect to other four sensors, the time difference of arrival is calculated. In the second case study, which is similar to first but only four sensors (each sensor has time of arrival information) will be considered out of five and therefore the total number of such combinations will be five and those are analyzed.

III. BAT ALGORITHM

The three basic steps involved for a single objective optimization bat algorithm are:

1. All bats avail echolocation to direct their search.
2. Bats release sound waves with some given frequencies and pulse rate emissions.
3. If Bats found their food, then its pulse rate emission increases and the loudness decreases.

A. Bat motion

Bat position x_i and velocity u_i in a dimensional search space at a time step't' are upgraded using Eqns (2)–(4).

$$Q_i = Q_{min} + (Q_{max} - Q_{min})\beta \quad (2)$$
$$u_i^t = u_i^{t-1} + (x_i^{t-1} - x^*)Q_i \quad (3)$$
$$x_i^t = x_i^{t-1} + u_i^t \quad (4)$$

where $\beta \in [0, 1]$ is a random vector drawn from a uniform distribution. Here 'x' is the current global best location (solution) which is located after comparing all the solutions among all the bats [12]. As the product w_iQ_i is velocity increment, Q_i (or w_i) is used to adjust the velocity change while fixing the other factor w_i (or Q_i), based on the interest of problem type. In this paper the value of Q_{min} and Q_{max} is set as 0 and 1.5. At first, each bat is randomly set a frequency which is drawn equally from $[Q_{min}, Q_{max}]$. Owing to this logic, bat algorithm can be observed as a frequency-tuning algorithm to impart a balanced combination of exploration and exploitation. The loudness and pulse emission rates essentially provide a mechanism for automatic control and auto zooming into the region with promising solutions.

For the local search part, once a solution is chosen from among the current best solutions, a new solution for each bat is produced locally by random walk using Eqn.(5)

$$x_i^t = x^* + (0.01 \times rand) \quad (5)$$

The velocities and positions of bats upgradation have some similarity to the procedure of the standard particle swarm optimization, as Q_i necessarily checks the pace and range of the movement of the swarming particles. To a degree, BA can be considered as a balanced combination of the standard particle swarm optimization and the rigorous local search checked by the loudness and pulse emission rate.

B. Loudness and pulse emission

Moreover, the loudness L_i and the pulse emission rate r_i have to be upgraded accordingly and the iterations begin as given in Eqn. (6). When bat has found its food, the pulse emission rate increases, while the loudness reduces. If $L_{min} = 0$ means that a bat has just found the food and temporarily stop emitting any sound and is given in Eqn. (7).

$$L_i^{t+1} = \alpha L_i^t, \quad r_i^t = r_i^0[1 - \exp(-\gamma t)] \quad (6)$$

Where α and γ are constants.

$$L_i^t \to 0, \quad r_i^t \to r_i^0, as\ t \to \infty \quad (7)$$

In this paper, the values of α and γ is chosen as 0.9 for both case studies. If we replace the variations of frequency 'Q_i 'by a random parameter and $L_i = 0$, $r_i = 1$, then bat algorithm becomes standard PSO. Similarly, if we do not use the velocities, and for fixed loudness and rate values, the bat algorithm reduces to a simple harmony search algorithm. Therefore, Bat algorithm is very promising for solving nonlinear global optimization problems.

C. Bat Algorithm Mechanism

Step 1 Initialize bats randomly into the search space.
Step 2 Move the bats by predefined rules and generate a random number.
Step 3 If that random number is higher than the fixed pulse emission rate, move the bat by the random walk process.
Step 4 Evaluate the every bat fitness values and update the global near best solution.

Step 5 Check the termination condition to decide whether to go back to step 3 or to stop the program and output the near best result.

IV. Results and Discussions

The simulations are done on the same data published in [10]. The transformer tank size considered is 5000mm x 3000mm x 4000mm, and the actual PD source is at P (4500,2600,3700); the sensors positions are S_1(2500,0,2000), S_2(2500,1500,4000), S_3(5000,1500,2000),S_4(2500,3000,2000) ,S_5(0,1500,2000);the t= 2600µs is the reference time for the first sensor, the time difference of arrival of other four sensors are [1600, 1500, 1900, 3524.69](µs) - t. The calculated best PD location results obtained from 20 runs.

The parameters of the BA for PD source location are as follows:

Bat Population=20
Maximum number of Iterations=100
Loudness=0.2; Pulse Emission Rate=0.6

The Location Error can be determined by using Eqn. (8)

$$\sqrt{(x_{actual} - x_{calculated})^2 + (y_{actual} - y_{calculated})^2 + (z_{actual} - z_{calculated})^2} \tag{8}$$

Maximum deviation $Deviation_{max}$ of coordinates can be estimated by using Eqn. (9)

$$Deviation_{max} = \max \left\{ \begin{array}{l} \left| x_{actual} - x_{calulated} \right| \\ \left| y_{actual} - y_{calculated} \right| \\ \left| z_{actual} - z_{calculated} \right| \end{array} \right\} \tag{9}$$

Where x_{actual}, y_{actual}, z_{actual} is actual PD location and $x_{calulated}$, $y_{calculated}$, $z_{calculated}$ is calculated PD location.

The PD Source location results using proposed BA method and available literature results are shown in Table I and Table II shows that proposed method BA locates the PD Source within location error of 101.26 mm. From the Table II, it is noted that the PD location error decreases for proposed algorithm and increases for GA and QGA algorithms of available literature.

Table I Comparison of PD Location results in first case study among available literature with proposed method

Coordinates (mm)	Actual PD source	PD Location results of GA [10]	PD Location results of QGA [10]	PD Location results of BA
X	4500	4223.76	4394.77	4402
Y	2600	2391.71	2475.98	2577
Z	3700	3503.04	3656.17	3689

Table II Comparison of Error analysis in first case study among available literature with proposed method

Error	GA [10]	QGA [10]	BA
Location error (mm)	398.10	168.45	101.26
Maximum Deviation (mm)	276.24	124.02	88
Relative Error (%E)	6.24	2.64	1.58

Table II shows that proposed method BA locates the PD Source within maximum deviation of 88mm, which can be allowed negligible for distances of practical interest. From the Table II, it is noted that the maximum deviation of PD source decreases for proposed algorithm and increases for GA and QGA algorithms of available literature. The proposed BA method has less relative error that is obtained with reference to the tank diagonal (D_{tank} =6379.66 mm) when compared with other methods.

Table III Comparison of PD Location results of second case study with proposed method

Combinations number	Coordinates (mm)		
	X	*Y*	*Z*
1	4490.5	2544.4	3601
2	4449.1	2558.8	3744.8
3	4356.5	2394.5	3541.2
4	4375.2	2452.3	3510.2
5	4421	2510	3756

Table III shows the PD location results of the second case study using bat algorithm. The second combination outperforms among other combinations.

Table IV Comparison of second case study Error analysis with proposed method

Combinations number	Error		
	Location Error (mm)	*Maximum Deviation (mm)*	*Relative Error (%E)*
1	113.94	99	1.786
2	79.34	50.9	1.244
3	296.71	205.5	4.651
4	270.95	189.8	4.247
5	132.20	90	2.072

The second case study error analysis is analysed using bat algorithm is shown in the Table IV. The second combination locates the PD source within 79.34 mm location error, 50.9 mm maximum deviation error and 1.244% relative error. After that first locates the PD source within 113.94 mm location error, 99 mm maximum deviation error and 1.786% relative error, fifth locates the PD source within 132.20 mm location error, 90 mm maximum deviation error and 2.072% relative error, fourth locates the PD source within 270.95 mm location error, 189.8 mm maximum deviation error and 4.247% relative error and third combination locates the PD source within 296.71 mm location error, 205.5 mm maximum deviation error and 4.651% relative error.

It is observed that the proposed method locates the PD source much better for the reported data in the literature when compared with the existing population based optimization methods. It is also noticed that in the second case study, the bat algorithm locates PD source with relatively less error as compared to first case study. Therefore, the proposed method possesses its ability to locate the source with relatively high accuracy in single step of calculation. The Proposed BA gives small location error and maximum deviation error with less execution time when compared to other methods.

V. CONCLUSION

The proposed bat algorithm for PD source location using measured TDOA signals is tested on the existing literature data. It is observed that the proposed BA method converges to global optimum solution in comparison to QGA and GA of the considered first case study. Also in the second case study relatively less error is observed. Finally, this proposed method has proven appropriate for PD source localization problem and the output results of this proposed method attained better desired results compared to other methods existing in the literature. This accurate PD source location method can be benefitted for many manufacturers and utilities.

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