Insulation condition assessment of high-voltage rotating machines using hybrid techniques.

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Abstract: The enduring life span of the machine insulation will be decided based on degradation level in motor and generator stator windings. The non-destructive diagnostic tools like dielectric loss and capacitance test and partial discharge (PD) analysis, recognized to access the deterioration in the insulation system of rotating machines. The experiments reveal various characteristic parameters such as leakage current, dielectric dissipation factor, the capacitance value, and PD magnitude. The integrity of the rotating machine can be find out by analyzing these parameters. This research study shows the hybrid method for prediction of insulation condition in the stator winding by utilizing the artificial neural network (ANN) with gravitational search algorithm in comparison with ANN and ANN–genetic algorithm. The advent of expert systems ensures the quality assurance and service life assessment of the high-voltage assets. It offers a predictive maintenance solution to personnel dealt with power utilities thereby increasing the uptime, reliability, and productivity, which in turn reducing the operating costs, downtime and unplanned outages. For testing and predicting the insulation status, several 11 kV machines are considered. The predicted results using hybrid techniques extend a close agreement with reference to the data obtained from the experiments performed. The proposed method indicate the competent and trustworthy, by the presented test results.

1 Introduction

Electrical insulation plays a vital part in the normal operation of high-voltage (HV) power equipment. The insulation system forms an integral part of the electrical machine in which failure causes an adverse effect and carries huge interruption forfeitures [1]. When stronger electric field strength is influenced to insulation, the occurrence of partial discharge (PD) in HV power apparatus takes place due to gaseous ionisation process [2]. PD is a localised dielectric discharge in the solid insulation system that partially bridges the two conductors when it is subjected to HV stress. PDs may occur within or on the surface of the dielectric medium. Normally the nature of PD is in pulse form whose duration is <1 µs [3, 4]. The measurement of PD has been extensively adapted to detect the quality of the insulation system.

The quality of the stator winding insulation emphasises the reliability of the HV apparatus to a greater extent. The amount of degradation occurs in the stator winding insulation are mainly due to different stresses acting on it. The four main factors which influence the lifetime of winding insulations are Thermal, Electrical, Ambient and Mechanical stresses, the so called TEAM stresses. TEAM stresses progressively worsen the strength of the insulation system to a point that it loses the dielectric strength which leads to insulation failure during the normal operating condition [5–7]. Reliability surveys have been carried out on motors and generators over the years by the Electric Power Research Institute (EPRI) and Institute of Electrical and Electronic Engineers (IEEE). Studies reveal that percentages of motor failures are 41% (IEEE) and 50% (EPRI). The most important fact of both the studies shows that HV stator winding shares a significant failure rate around 37%. This statistical study is a warning sign that the insulation condition of the stator windings should be monitored periodically and effectively. On the other hand, various electrical machinery and power cable failures at their operating voltage are ensured due to the existence of PDs [8]. There are different types of non-destructive and non-invasive tests can be performed in evaluating the degree of insulation degradation in HV rotating machines. These tests permit the power utilities to ensure the reliability of the machine insulation under test and produce accurate results [9]. Due to a large number of failure mechanisms involved, it becomes a difficult task for non-experts to do a condition assessment precisely. There are certain circumstances under which periodic test is insufficient to perform. In such circumstances, the soft computing tool is highly suited to help the users handling motors and generators.

The role of the expert system can act as a tool for constructing the system with various phases of the selection process, testing, analysing test results and inspections to guide the maintenance workforce's in line with the requirement of the machine concerned. The objective of the condition assessment is to suggest the less number of diagnostic tests and reviews necessary to precisely predict the insulation status. Expert systems are highly adapted to stay away from the uncertainty on the defect identification. The necessity of computational intelligent system is mainly due to the complicated patterns involved. Different researchers have used various computational intelligent techniques for diagnosing the status of the insulation system. There are a number of diagnostic methods, such as statistical, neural networks, signal processing algorithms, and fractals are reported [10]. Research trends show that artificial intelligence techniques will have a greater role in a motor diagnose system with advanced practicability, sensitivity, reliability, and automation.

The review of the research shows that the PD is the significant reason for insulation failure. This phenomenon can bring about the dynamic deterioration of the insulation and eventually lead to catastrophic failure of the equipment. In the improvement of digital systems and signal processing methods, several artificial intelligence (AI) techniques such as artificial neural networks (ANNs), genetic algorithms (GAs), knowledge based system, fractal models, wavelet transformation, and support vector machines are considered for the classification of PD. In every case, there are still significant difficulties staying for effectively applying

Table 1 Experimental data of 11 kV in stable condition

Phase	Winding to ground	TestVoltage, V	Leakage current, mA	Capacitance, nF	Tanδ value, %	PD magnitude, pC
R	Y&B	2200	81.06	112.7	1.04	700
		4400	157.4	112.8	1.12	1000
		6600	238.7	113.2	1.433	1200
		8800	316.9	113.7	1.756	1750
		11,000	359.4	114	1.898	2150
Y	B&R	2200	80.47	112.2	1.025	750
		4400	158.9	112.3	1.108	900
		6600	234.6	112.7	1.417	1150
		8800	314.3	113.2	1.778	1700
		11,000	357.2	113.5	1.911	2250
B	R&Y	2200	78.37	112.3	1.044	800
		4400	157.9	112.4	1.122	1100
		6600	235.8	112.9	1.474	1300
		8800	314.6	113.4	1.806	1800
		11,000	357.9	113.7	1.95	2300

AI strategies to PD source. The three major problems associated are (i) extracting appropriate features from raw data acquired from PD measurement; (ii) using right pattern recognition approaches to classify it; and (iii) identifying multiple PD sources occurring in the HV apparatus at the same time. However, some methods based on AI suffer from low generality and high calculation needs [11, 12].

It has been learned that various types of ANNs are applied due to various capabilities like self-learning and self-organisation and so on [13, 14]. Hence the hybridisation of ANNs with several optimisation algorithms was proposed. The combination of ANNs with GAs rule out the constraints present in ANNs when used for optimisation problems. A GA is a technique used to compute or to find an exact solution or approximate answers to constrained and unconstrained optimisation problems. GA is influenced by the property of exploration and exploitation and resolves the drawbacks in the gradient-based method. However, it suffers from the mutation problem that leads to premature convergence and it requires more time to provide an optimum solution [15]. Due to the complexity of genetic operators, the convergence time of GA is high. GA assisted neural systems will also be widely used in the near future. Utilisation of particle swarm optimisation (PSO) provides better results for the power system. But in the PSO algorithm, the velocity equation consists of stochastic variables so the global best value goes on varying uncertainty. The ANN is operated based on the training dataset, but the training dataset generation is complicated. In the literature, very few works are presented to solve this problem and the presented works are ineffective. These problems and drawbacks have motivated to find a suitable alternative to do this research work. In recent times, the heuristic algorithms (HAs) imitate biological or physical processes that are in practice. gravitational search algorithm (GSA) based on Newtonian laws of gravity and motion is one of the new HAs used to achieve the optimum solution for the set of agents termed as masses [16, 17].

Attempts have been made to assess the status of the insulation condition in three different comparative studies viz (i) ANN-based prediction (ii) ANN with GA-based prediction and (iii) ANN with GSA-based prediction. This research paper presents a hybrid technique which is the combination of neural network and GSAs (HNNGSAs). The integration of two complementary approaches together results in an innovative methodology to construct an intelligent system. The remaining part of the paper is structured as follows. The methodology and detailed description of diagnostic tests for rotating machines are discussed in Section 2. A brief review of ANN with GSA is conveyed in Section 3. Section 4 details the experimental and simulated results along with the discussions. Finally, conclusions are presented in Section 5.

2 Methodology

In this paper, the hybrid technique is used to analyse the 11 kV machines for predicting the insulation status. The hybrid technique is the combination of the ANN and GSA. Here, GSA is used to train the ANN for improving their performance. Utilising the proposed hybrid method, the insulation quality of the rotating machines is evaluated from tanδ test and PD test. The performance analysis is made on experimental data obtained from eight machines of 11 kV stator voltage capacity. From the eight machines, five machines are healthy and remaining three machines are unhealthy which means that any one of the phase winding or multiple phase windings is suffering from insulation failure. The test data of *R* phase winding is obtained by short circuiting (grounding), the *Y* and *B* phases. The experimentation is done by applying a voltage magnitude equal to 20% of its rated value in steps. The parameters like leakage current, capacitance, tanδ, and PD magnitude are observed and tabulated. Similarly, the parameters are also noted in 40, 60, 80 and 100% of the rated voltage. Next, the test data of *Y* phase and *B* phase windings are obtained by adopting the similar approach used for *R* phase winding. Totally 15 numerical experiments are carried out in all the three phases to measure the four characteristic parameters. The values of leakage current, capacitance, tanδ and PD magnitude obtained from a healthy machine at each experimental run are furnished in Table 1. The test data for the remaining four healthy machines and three unhealthy machines are measured using the same procedure as explained.

2.1 Diagnostic tests for rotating machines

In the past few years, the condition monitoring of rotating machines was done effectively by the diagnostic tests, namely (i) dielectric factor and capacitance test and (ii) PD test. These non-destructive tests possibly access the progressive degradation of the insulation of the stator winding. Based upon the non-destructive characteristic parameters, the state, and quality of insulation will be ascertained using hybrid techniques.

2.1.1 Dielectric loss angle test: The insulation quality in an HV winding may be estimated by treating it like the dielectric in a capacitor. Dissipation factor (DF), also termed as tanδ is used to measure electrical losses occur in the insulation. The state of the insulation system can be ascertained with an aid of tanδ values. The capacitance and DF of all parts of a winding will be performed using a transformer ratio arm bridge. Measurements will be performed in increments that will not exceed 0.2 VL. During the test, the stator winding should be detached from the links on both impartial sides. While testing one phase section of the stator winding, the remaining phase sections are shorted and grounded to its frame. The DF is normally expressed as a percentage. In perfect insulation, the DF will not increase as the applied voltage increases. This test concentrates towards the applied voltage, capacitance value and tanδ which shall remain constant with an

Fig. 1 *Tanδ and capacitance measuring unit*

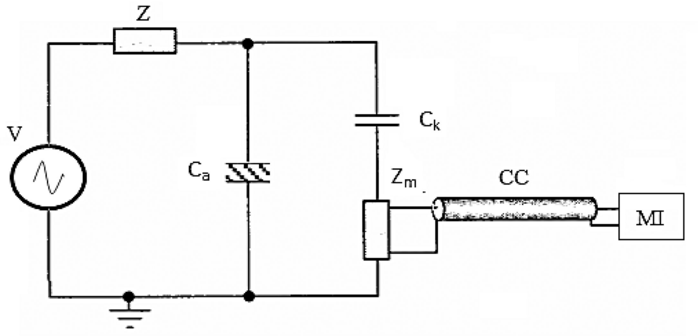

Fig. 2 *PD offline detection circuit*

increase in voltage. The insulation of the electrical machines shall be considered as linear systems and any 'tip-up' of the tanδ with voltage level, called 'ionisation knee', is a primary sign of PDs. The measured tanδ value is proportional to the volume of voids present within the insulation system, which in turn increases with ageing of the apparatus. The detailed procedure for performing power factor testing on individual coils and bars are in the present version of IEEE 286. Fig. 1 shows the test system for measuring the tanδ and capacitance values in the HV stator windings.

2.1.2 Partial discharge test: It has been a well-known fact that failures in motor and generator stator windings are mainly due to PDs. By assessing the PD levels of the machine winding, the deterioration can be effectively monitored [18]. PDs occur in the weaker regions like voids, cracks, delamination, and imperfections present inside the insulation. There is a direct relation between chemical deterioration on the insulation surface and ageing process due to the occurrence of PD event [19]. The PD is generally accepted as the predominant cause of long term degradation and failure of electrical insulation. The causes of PD in the material medium and its dependence on the life of the insulation system are deliberated. The rate of degradation due to PD will be decided by its severity [20]. The reason for the occurrence of PDs is mainly due to the delamination of insulation and looseness in the slot. Wide assistance on offline PD test systems is specified in IEEE 1434 and IEC 60034-27. Fig. 2 shows the test system for measuring the PD intensity in picocoulombs (pC) in compliance with IEC60270.

The PD measuring system consists of a measuring instrument, resonant filter, measuring impedance and coaxial cable. A resonant filter (*Z*) is used to avoid any pulses emerging from the capacitance offered by the windings and bushings in the transformer. The coupling capacitor (Ck) which offers low inductance value is connected to the power leads of the generator for detecting the PD pulses. The detected PDs in the test object results in a transfer of charge and cause changes in the phase value of the voltage on measuring impedance (Zm) which in turn carried out to the measuring instrument (MI) via coaxial cable (CC). The measured severity levels at different voltage levels are utilised to ascertain the quality of insulation.

In a PD test, the magnitude of the highest PD pulses at various voltages was measured. The PD intensity is measured in pC. The most commonly utilised index of PD intensity is the apparent charge. The apparent charge is normally used to access the level of PD activity in the insulation system [21]. One pC is equivalent to 10^7 electrons and thus represents the apparent number of electrons concerned in a particular PD event. The highest PD pulse is the point of interest and it contains the major number of electrons in the discharge. This is an indicator for the probability of damage to be happening in the insulation. The insulation failure will be happening very quickly when there is an existence of a larger number of electrons in the PD pulse [22, 23]. The insulation in stator windings is usually form wound coils made of Epoxy Vacuum Pressure Impregnation and Resin Rich Technology [24]. Such organic materials are degraded by PD due to voids present in the high stress regions. PD is a symptom of poor manufacturing and aging process to be the main cause of deterioration. Larger voids will lead to larger PD pulses and faster the failure. PD magnitudes are highly related to how quick a winding will damage. In [7] certain PD magnitudes that range from 2000 to 5000 pC and even some research findings show above 10,000 pC. The PD magnitude causes danger to the lifespan of insulation system of HV rotating machinery [24]. These measurements have advantages to categorise the winding insulation condition of the stator used for testing. Such conditional testing provides appropriate direction to carry out suitable maintenance and renovation methods to be planned and organised well in advance. The effects of PD in the stator winding can be found out based upon the effective monitoring of its severity levels [7]. PD measurement is the most important method for diagnosing the insulation of HV assets [25, 26]. These imperfections being small was not revealed in capacitance measurements but were revealed as power loss components in contributing to an increase in the DF. PD can be

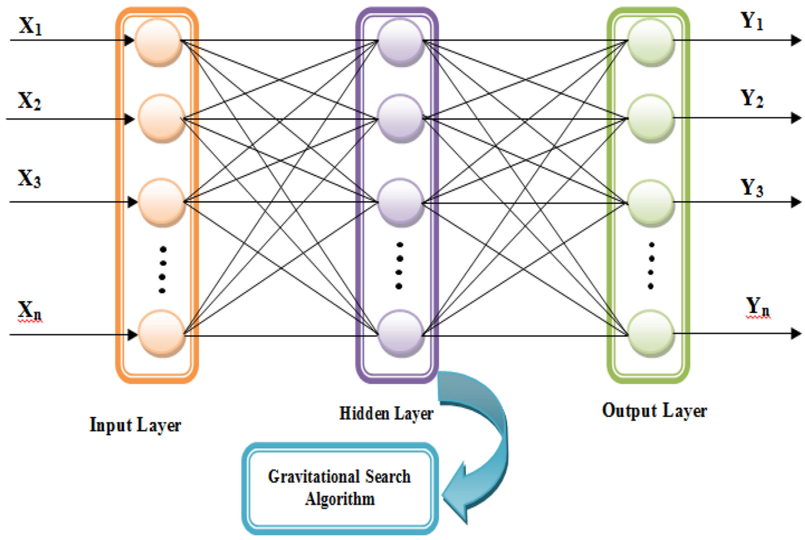

Fig. 3 *Proposed ANN first stage structure*

classified as surface discharge, slot discharge and so on, which is measured using PD test.

3 ANN with an aid of GSA for predicting the insulation quality

ANNs is a computational model between inputs and outputs based on the arrangement and tasks of biological neural networks. There are three interconnected layers in the ANN which have the capability to learn and acquire information from the training process. The training and testing are the two stages in the ANN. In the training stage, the feature vectors are applied as an input to the neural network. The input layer consists of two neurons, which are based on the parameters that are measured during the test data acquisition process [27]. The hidden layer contains 50 neurons and the output layer contains 3 neurons to predict the values of capacitance, dielectric loss factor, and PD magnitude. Once trained, the ANN develops a correlation between all inputs and outputs through its hidden layers [28, 29]. Fig. 3 represents the training structure of the proposed ANN.

3.1 Training algorithm

Process 1: Here, the weight of each neuron is assigned randomly for learning the network. The minimum and maximum weights are specified in the interval range (0, 1).

Process 2: In the section, the back propagation (BP) error is determined. Here, the BP error is evaluated using the GSA. In GSA, the optimised parameter of ANN is achieved while minimising the BP error function.

3.1.1 BP error minimisation using GSA technique: GSA is a newly developed heuristic optimisation algorithm that works based on the law of gravity and mass interactions. The search agents in GSA are defined as a collection of masses that interact with each other based on Newton's law of gravity and the laws of motion. It is entirely different from other renowned optimisation methods inspired by swarm intelligence [30, 31]. GSA is based on the concept of Newton theory which states that every particle in the universe experiences a gravitational force on every other particle.

GSA is considered as the collection of agents whose masses are proportional to the value of the fitness function. All masses will attract each other due to gravitational forces acting between them during generations [32]. Therefore, the heaviest masses in the search space which are probably near to the global minimum attract the other masses in proportion to their distances. In this section, GSA is used to improve the performance of ANN and to reduce the BP error of the network. From the network study, the inputs, weights, and corresponding outputs of the system are observed. Based on the network output, the BP error is evaluated. The GSA is fed with the applied voltage, leakage current, network output, and weights. Here, the inputs are considered as the agents [33]. The minimised BP error can be evaluated from the inputs.

The procedure of the proposed algorithm is briefly explained as follows.

3.1.2 Procedure of proposed algorithm:

Step 1: In this section, weights to all the neurons are initiated randomly. The weight initiation is exempted for the neurons in the input layer. The position of agents is defined by the following equation:

$$S = (s_i^1, \ldots, s_i^d, \ldots, s_i^n) \tag{1}$$

where n denotes the search space dimension of the problem, s_i^d is the position of the ith agent in the dth dimension.

Step 2: The fitness function of agents is evaluated as for their minimum range of BP error. The fitness function of the agent is calculated using the following equation:

$$F_i = \min\,(\mathrm{BP_{error}}) \tag{2}$$

where

$$\mathrm{BP_{error}} = \sum_{i=1}^{n} \left(Y_{\mathrm{target}}^i - Y_{\mathrm{output}}^i\right)^2 \tag{3}$$

From the above equation, the Y_{target} is the network target and Y_{out} is the current output of the network.

Step 3: The mass of agents is defined randomly and the force of each agent is determined. Here, the force between the mass i and mass j can be computed using the expression stated below:

$$f_{ij}^d(k) = g(t)\left(\frac{M_i(k) * M_j(k)}{r_{ij}(k) + \in}\right)\left(s_j^d(k) - s_i^d(k)\right) \tag{4}$$

where $M_i(k)$ and $M_j(k)$ represent the masses of the ith and jth agents, $g(k)$ be the gravitational constant, $\in$ is the small constant, $r_{ij}(k)$ denotes the Euclidian distance between the agents i and j. The gravitational constant is calculated using the following equation:

$$g(k) = g_0 * \mathrm{e}^{((-\alpha k)/t_r)} \tag{5}$$

From the above equation, t_r provides the number of iterations in the algorithm, g_0 will be the initial value and α is defined as user specified constant.

Step 4: The total force exerts on the agent in the kth dimension is computed as follows:

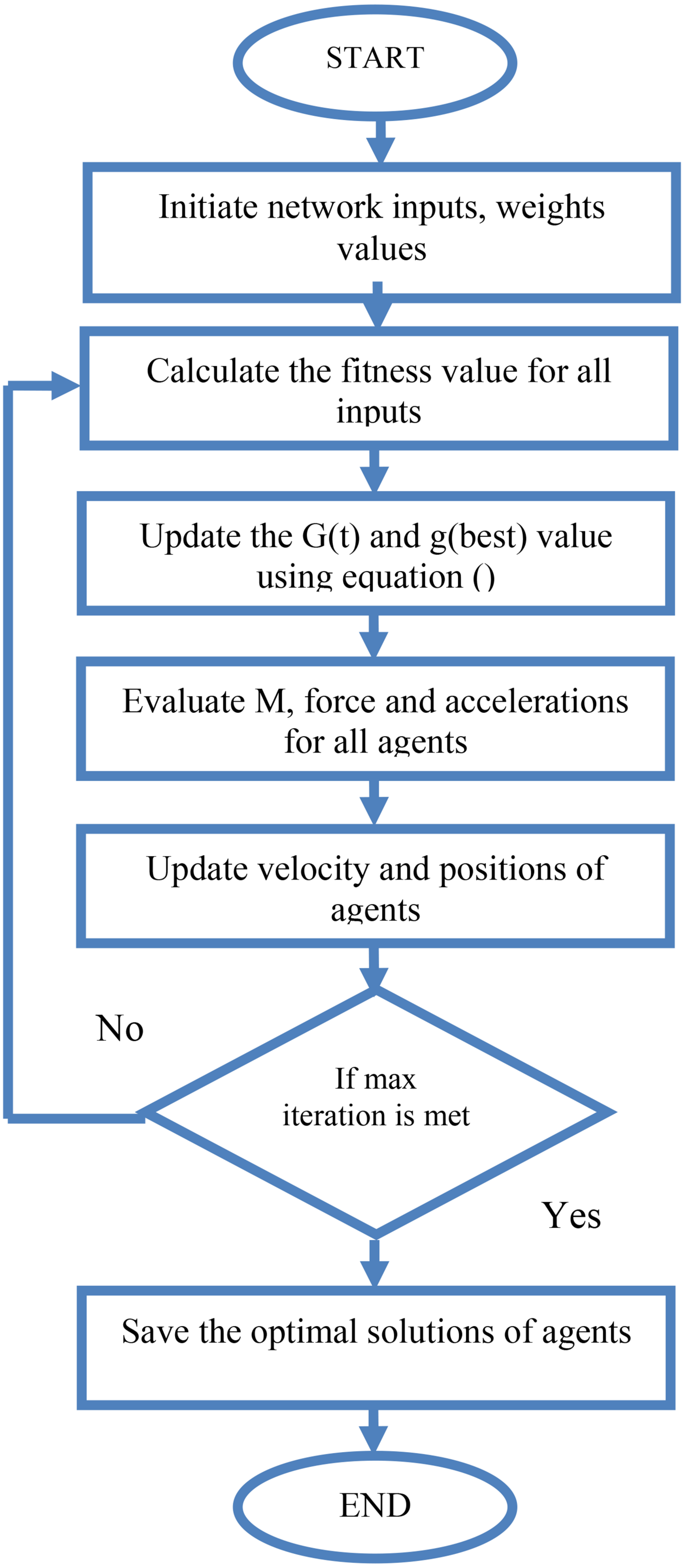

Fig. 4 *Flowchart of the proposed ANN–GSA technique*

$$f_i^d(kt) = \sum_{i=1 j \neq i}^{N} \text{rand}_i f_{ij}^d(k) \quad (6)$$

where rand_j is a random number lies between the intervals 0 and 1.

Step 5: Acceleration of mass is calculated using the formula

$$\alpha_i^d(k) = \frac{f_i^d(k)}{M_i(k)} \quad (7)$$

Step 6: The new position of the agents and its inertia masses are updated using the following equations:

$$m_i(k) = \frac{\text{fit}_i(k) - \text{worst}(k)}{\text{best}(k) - \text{worst}(k)} \quad (8)$$

$$M_i(k) = \frac{m_i(k)}{\sum_{j=1}^{N} m_j(k)} \quad (9)$$

Table 2 Test result of 11 kV in stable condition using ANN technique

Phase	Winding to ground	TestVoltage, V	Leakage current, mA	Capacitance, nF	Tanδ value, %	PD magnitude, pC
R	Y&B	2200	81.06	113.278	1.291	702.24
		4400	157.4	113.457	1.317	1002.927
		6600	238.7	114.127	1.85	1202.647
		8800	316.9	114.425	2.124	1753.789
		11,000	359.4	114.624	2.468	2152.752
Y	B&R	2200	80.47	113.124	1.222	753.745
		4400	158.9	112.896	1.622	902.467
		6600	234.6	113.198	1.936	1154.295
		8800	314.3	114.162	2.105	1702.528
		11,000	357.2	114.223	2.208	2252.139
B	R&Y	2200	78.37	112.924	1.191	801.988
		4400	157.9	113.253	1.389	1104.127
		6600	235.8	113.389	1.821	1302.785
		8800	314.6	114.357	2.223	1803.16
		11,000	357.9	114.298	2.407	2302.07

Table 3 Test result of 11 kV in stable condition using ANN–GA technique

Phase	Winding to ground	TestVoltage, V	Leakage current, mA	Capacitance, nF	Tanδ value, %	PD magnitude, pC
R	Y&B	2200	81.06	113.021	1.124	701.58
		4400	157.4	113.097	1.186	1001.589
		6600	238.7	113.618	1.572	1201.247
		8800	316.9	114.097	1.879	1752.327
		11,000	359.4	114.411	2.088	2151.324
Y	B&R	2200	80.47	112.521	1.091	752.574
		4400	158.9	112.589	1.279	901.217
		6600	234.6	112.889	1.590	1152.216
		8800	314.3	113.456	1.887	1701.267
		11,000	357.2	113.857	2.010	2252.017
B	R&Y	2200	78.37	112.459	1.093	801.507
		4400	157.9	112.749	1.211	1103.017
		6600	235.8	113.578	1.590	1301.284
		8800	314.6	113.911	1.945	1802.347
		11,000	357.9	114.129	2.102	2301.687

Table 4 Test result of 11 kV in stable condition using proposed technique

Phase	Winding to ground	TestVoltage, V	Leakage current, mA	Capacitance, nF	Tanδ value, %	PD magnitude, pC
R	Y&B	2200	81.06	112.797	1.057	699.241
		4400	157.4	112.879	1.133	1000.271
		6600	238.7	113.295	1.461	1200.875
		8800	316.9	113.978	1.781	1750.654
		11,000	359.4	114.158	1.936	2151.124
Y	B&R	2200	80.47	112.285	1.038	749.894
		4400	158.9	112.498	1.142	900.674
		6600	234.6	112.766	1.452	1150.274
		8800	314.3	113.230	1.800	1700.197
		11,000	357.2	113.693	1.931	2250.182
B	R&Y	2200	78.37	112.360	1.054	799.982
		4400	157.9	112.445	1.140	1100.267
		6600	235.8	112.919	1.497	1300.678
		8800	314.6	113.428	1.834	1801.047
		11,000	357.9	113.702	1.980	2300.015

where $\mathrm{fit}_i(k)$ denotes the fitness value of the ith agent in the kth iteration.

Step 7: The velocity and position of the agents are updated by considering the new position of the masses using the following equations:

$$V_i^d(k+1) = \mathrm{rand} \times v_i^d(k) + \alpha_i^d(k) \quad (10)$$

$$s_i^d(k+1) = s_i^d(k) + v_i^d(k+1) \quad (11)$$

where $V_i^d(k)$ is the velocity of the agent, $s_i^d(k)$ is the position of an agent, rand_i is the random number at the interval at [0, 1].

Step 8: Once the BP error is minimised, then terminate the otherwise steps 3–8 have to be repeated. For the minimised BP error values the corresponding outputs are noted. The flowchart of GSA is illustrated in Fig. 4.

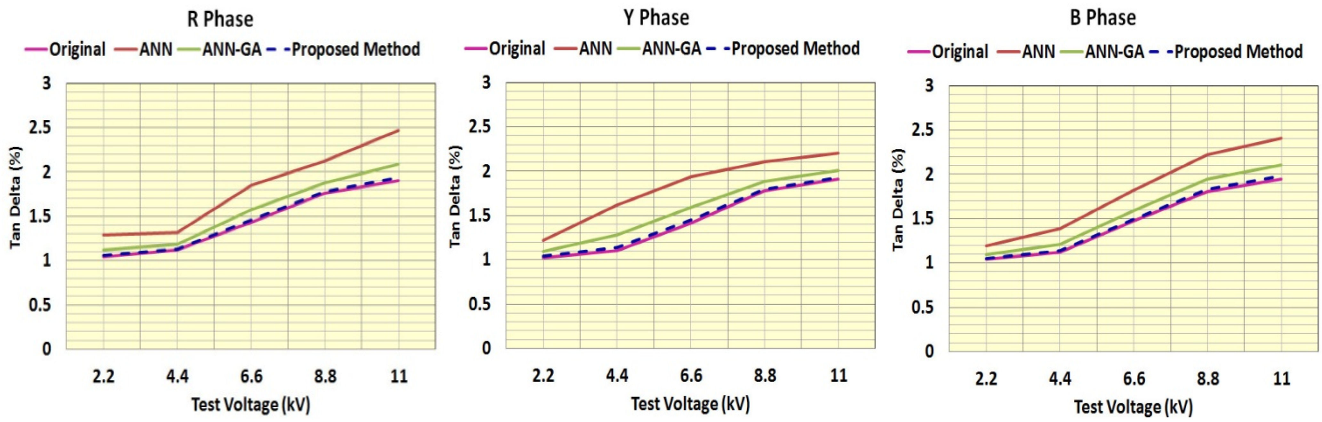

Fig. 5 *Comparison of measured and predicted tanδ values of 11 kV healthy machine*
(a) R-phase (left), ***(b)*** Y-phase (middle), ***(c)*** B-phase (right)

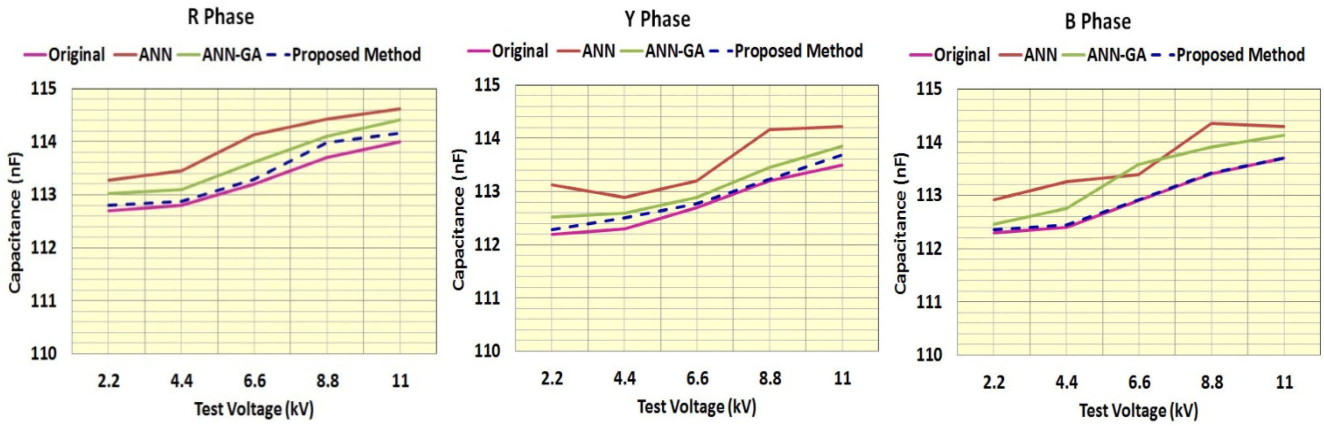

Fig. 6 *Comparison of measured and predicted capacitance values of 11 kV healthy machine*
(a) R-phase (left), ***(b)*** Y-phase (middle), ***(c)*** B-phase (right)

Table 5 Experimental data of 11 kV machine in unstable condition

Phase	Winding to ground	TestVoltage, V	Leakage current, mA	Capacitance, nF	Tanδ value, %
R	Y&B	2200	67.12	90.98	0.799
		4400	131.41	91.26	0.836
		6600	197.41	92.15	1.028
		8800	265.71	93.36	1.275
		11,000	303.51	93.96	1.325
Y	B&R	2200	68.64	91.47	1.537
		4400	132.21	91.72	2.014
		6600	197.61	92.53	3.126
		8800	267.11	93.64	4.319
		11,000	304.71	94.21	4.976
B	R&Y	2200	67.06	90.67	1.627
		4400	131.11	90.96	2.132
		6600	196.91	91.83	3.302
		8800	266.21	93.07	4.586
		11,000	303.21	93.69	5.256

Process 3: By neural network, the present output is determined by the following expression:

$$Y_{\text{out}} = \beta + \sum_{n=1}^{N} w_{2n} Y_i(n) \qquad (12)$$

Here w_{ij} is the weight of the $i - j$ link of the network. Then, y_i is the output of the ith hidden neuron. Also, find out the change in weights based on the obtained BP error.

Process 4: Determine the bias (or) activation function of the network

$$Y_i(n) = \frac{1}{1 + \exp(-w_{1n} * Y_i(n))} \qquad (13)$$

Process 5: The weight updating of each neuron is done using the following equation:

$$w_{\text{new}} = w_{\text{prev}} + \Delta w \qquad (14)$$

Here w_{new} denotes the new weight, w_{prev} represents the previous weight and Δw is the change in weight of each output neuron.

Process 6: Using the following equation, change of weight of the network is evaluated:

Table 6 Test result of 11 kV machine in unstable condition using ANN technique

Phase	Winding to ground	TestVoltage, V	Leakage current, mA	Capacitance, nF	Tanδ value, %
R	Y&B	2200	67.12	91.558	1.05
		4400	131.41	91.917	1.033
		6600	197.41	93.077	1.445
		8800	265.71	94.085	1.643
		11,000	303.51	94.584	1.895
Y	B&R	2200	68.64	92.394	1.734
		4400	132.21	92.316	2.528
		6600	197.61	93.028	3.645
		8800	267.11	94.602	4.646
		11,000	304.71	94.933	5.273
B	R&Y	2200	67.06	91.294	1.774
		4400	131.11	91.813	2.399
		6600	196.91	92.319	3.649
		8800	266.21	94.027	5.003
		11,000	303.21	94.288	5.713

Table 7 Test result of 11 kV in machine unstable condition using ANN–GA technique

Phase	Winding to ground	TestVoltage, V	Leakage current, mA	Capacitance, nF	Tan δ value, %
R	Y&B	2200	67.12	91.301	0.883
		4400	131.41	91.557	0.902
		6600	197.41	92.568	1.167
		8800	265.71	93.757	1.398
		11,000	303.51	94.371	1.515
Y	B&R	2200	68.64	91.791	1.603
		4400	132.21	92.009	2.185
		6600	197.61	92.719	3.299
		8800	267.11	93.896	4.428
		11,000	304.71	94.567	5.075
B	R&Y	2200	67.06	90.829	1.676
		4400	131.11	91.309	2.221
		6600	196.91	92.508	3.418
		8800	266.21	93.581	4.725
		11,000	303.21	94.119	5.408

Table 8 Test result of 11 kV machine in unstable condition using proposed technique

Phase	Winding to ground	TestVoltage, V	Leakage current, mA	Capacitance, nF	Tanδ value, %
R	Y&B	2200	67.12	91.077	0.816
		4400	131.41	91.339	0.849
		6600	197.41	92.245	1.056
		8800	265.71	93.638	1.300
		11,000	303.51	94.118	1.363
Y	B&R	2200	68.64	91.555	1.550
		4400	132.21	91.918	2.048
		6600	197.61	92.596	3.161
		8800	267.11	93.670	4.341
		11,000	304.71	94.403	4.996
B	R&Y	2200	67.06	90.730	1.637
		4400	131.11	91.005	2.150
		6600	196.91	91.849	3.325
		8800	266.21	93.098	4.614
		11,000	303.21	93.692	5.286

$$\Delta w = \delta \cdot Y_{\text{out}} \cdot \text{BP}_{\text{error}} \tag{15}$$

In (15), δ is the learning rate. Repeat the above steps till the BP_{error} gets minimised. Once the neural network training process is completed, the network is trained well for predicting the insulation condition of the machine. The output of the network is presented with the testing data, the capacitance; tanδ and PD values are predicted.

4 Results and discussion

This section aims at demonstrating the performance of the newly proposed fault diagnosis technique for 11 kV rotating machines. The proposed hybrid technique is utilised to determine the condition of the machine insulation system based on four parameters, namely leakage current, capacitance, tanδ value and partial discharge magnitude measured from the machine. The relationship between the voltage applied and the change in

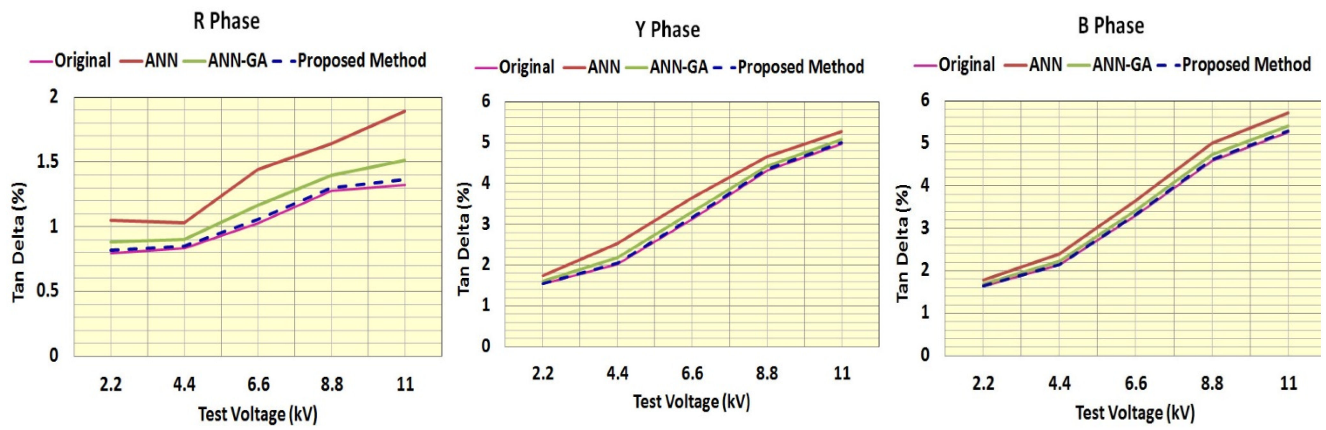

Fig. 7 *Comparison of measured and predicted tanδ values of 11 kV unhealthy machine*

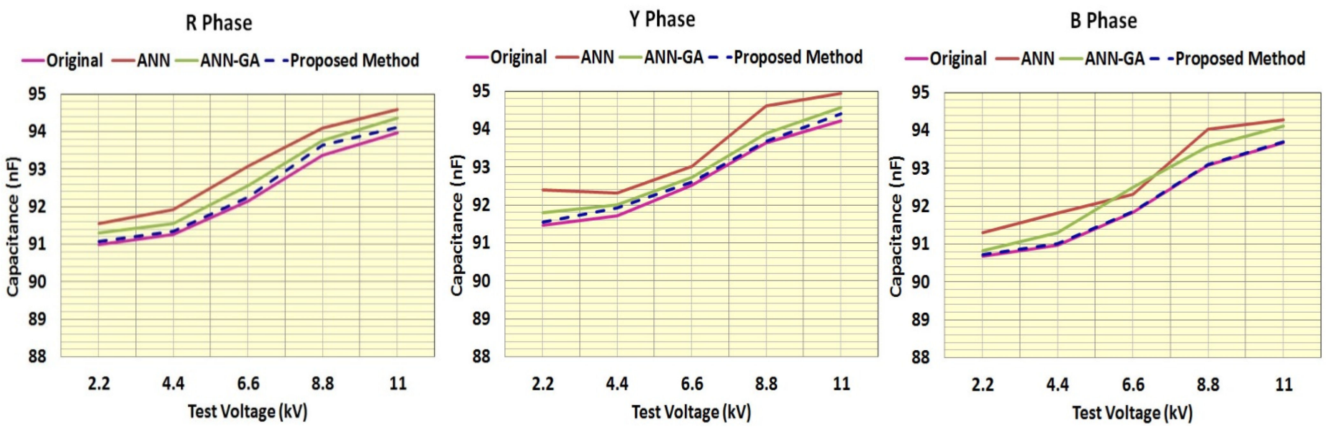

Fig. 8 *Comparison of measured and predicted capacitance values of 11 kV unhealthy machine*

Table 9 Performance comparison of percentage error

Description	ANN	ANN–GA	ANN–GSA
tan*δ*	0.173	0.067	0.014

capacitance, tan*δ,* and PD magnitude are used to classify the faulty machines from healthy machines. The applied voltage and leakage currents of eight 11 kV machines are fed into the neural network as input for the training process. The machine data such as capacitance, tan*δ*, and PD values are predicted using ANN, ANN–GA, and proposed method, which are furnished in Tables 2–4, respectively. It is clearly evident that the capacitance, tan values and PD values of the proposed method are having the close agreement with the testing data presented in Table 1 than the other methods.

The comparison of experimental result with the predicted values of ANN, ANN-GA, and proposed method is depicted in Figs. 5 and 6 for the healthy machine. Figs. 5*a–c* show the comparison of tan*δ* behaviour with the applied voltage of *R*, *Y* and *B* phases for all three methods. Figs. 6*a–c* show the comparison of capacitance behaviour with the applied voltage of *R*, *Y* and *B* phases, respectively. From the literature studies, it has been specified that worsening of the insulation condition exhibits a variation in the DF value. There is a slight variation is DF at the initial level, have a tendency to increase when the insulation life is headed towards the ending level. Deterioration in insulation excites increase in capacitance, which in turn leads to an increase in electrical stress and added deterioration. It is inferred that the deviation in predicting the machine parameters in comparison with experimental data is lower for the proposed technique. This reveals the effectiveness of the proposed method which in turn greatly helps to determine the condition of the machine insulation system.

The investigation is further continued for the 11 kV machines suffering from insulation defects in one or multiple phase windings. The experimental data obtained by applying the voltage in steps is furnished in Table 5. The machine data such as capacitance and tan*δ* values are predicted using ANN, ANN–GA, and proposed method for unstable condition and their values are presented in Tables 6–8, respectively. The changes in the capacitance and tan*δ* values are highly useful to identify the defects in the insulation of rotating machines. From the numerical values furnished in Tables 5–8, the proposed method is capable of producing tan*δ* and capacitance value very close to the experimental data of unhealthy machine. This shows that the hybrid technique holds a superior assessment profile than ANN and ANN–GA. Further investigation is continued by plotting the characteristic behaviour of tan*δ* and capacitance values with respect to test voltage as illustrated in Figs. 7 and 8. On examining the results, the proposed scheme is found to be significant since a considerable difference is observed in the predicted values of ANN and ANN–GA relates to the test data.

Subsequently, the performance analysis of the proposed technique is assessed by computing the percentage error for the three methods. In order to show cause the effectiveness of the proposed method for prediction, the error calculation was carried out on tan*δ* results. The tan*δ* results obtained for eight machines are taken into account for error calculation and the percentage error values are accordingly presented in Table 9. It is noticeably evident that the percentage error of the proposed method is infinitesimal in comparison with other methods. The same trend was experienced with the capacitance and PD values too. It is inferred that the neural network with gravity search concept gives reduced error compared with ANN and ANN–GA based diagnosis tool. This system serves as a diagnostic tool that helps the power utilities to make an objective and quantitative analysis of condition assessment of machine winding insulation. In general, the proposed system based on ANN with an aid of GSA is found to be highly efficient and deserves to be a reliable system for evaluating the integrity of the rotating machines.

5 Conclusion

In this paper, an ANN and GSA based hybrid technique are utilised for assessing the condition of the insulation failures of the HV rotating machine. The proposed hybrid technique is used for analysing the rotating machine with the help of the parameters, such as leakage current, capacitance, dissipation loss factor, and PD magnitude. Based on the characteristic parameters, the 11 kV machines winding conditions are predicted to assess the whether it is healthy or unhealthy. The predicted results of the proposed method are found to be very close to the experimental values when compared with the ANN–GA and ANN. From the results analysis, the hybrid method based fault diagnosis system results in low percentage error. Hence the proposed hybrid technique is the effective method for fault condition prediction.

6 References

[1] Grubic, S., Aller, J.M., Lu, B.*, et al.*: 'A survey on testing and monitoring methods for stator insulation systems of low-voltage induction machines focusing on turn insulation problems', *IEEE Trans. Ind. Electron.*, 2008, **55**, (12), pp. 4127–4136

[2] Macedo, E.C.T., Araujo, D.B., da Costa, E.G.*, et al.*: 'Wavelet transform processing applied to partial discharge evaluation', 25th International Conference on Condition Monitoring and Diagnostic Engineering, *J. Phy., Conf. Ser.*, 2012, **364**, pp. 1–16

[3] IEC Standard 60270: 'High voltage testing techniques: partial discharge measurement', 2000

[4] Mayoux, C., Laurent, C.: 'Contribution of partial discharges to electrical breakdown of solid insulating materials', *IEEE Trans. Dielectr. Electr. Insul.*, 1995, **2**, (4), pp. 641–652

[5] IEEE 1043: 'IEEE recommended practice for voltage endurance testing of form wound bars and coils', 1996

[6] Sathiyasekar, K., Thyagarajah, K., Krishnan, A.: 'Neuro fuzzy based predict the insulation quality of high voltage rotating machine', *Expert Syst. Appl.*, 2011, **38**, pp. 1066–1072

[7] Stone, G.C.: 'Partial discharge diagnostics and electrical equipment insulation condition assessment', *IEEE Trans. Dielectr. Electr. Insul.*, 2005, **12**, (5), pp. 891–904

[8] Cavallini, M., Conti, M., Contin, A.*, et al.*: 'Advanced PD inference in on-field measurements. Part 2: identification of defects in solid insulation systems', *IEEE Trans. Dielectr. Electr. Insul.*, 2003, **10**, (3), pp. 528–538

[9] Farahani, M., Borsi, H., Gockenbach, E.: 'Study of capacitance and dissipation factor tip-up to evaluate the condition of insulating systems for high voltage rotating machines', *Electr. Eng.*, 2007, **89**, pp. 263–270

[10] Markalous, S., Streh, T., Herold, C.*, et al.*: 'Enhanced signal processing for conventional and unconventional PD measuring methods: wavelet de-noising, automatic detection algorithms and averaging for arrival time based PD location in transformers and power cables'. Int. Conf. on Condition Monitoring and Diagnosis, Beijing, China, April 2008, pp. 1115–1118

[11] Abdel-Galil, T.K., Sharkawy, R.M., Salama, M.M.A.*, et al.*: 'Partial discharge pattern classification using the fuzzy decision tree approach', *IEEE Trans. Instrum. Meas.*, 2005, **54**, (6), pp. 2258–2263

[12] AlSaedi, M.A., Yaacob, M.M.: 'Partial discharge signal analysis using wavelet transform technique: review', *Int. J. Sci. Eng. Res.*, 2014, **5**, (2), pp. 553–555

[13] Chen, K., Huang, C., He, J.: 'Fault detection, classification and location for transmission lines and distribution systems: a review on the methods', *IET High Volt.*, 2016, **1**, (1), pp. 25–33

[14] Rigatos, G., Siano, P., Piccolo, A.: 'Neural network based approach for early detection of cascading events in electric power systems', *IET Gener. Transm. Distrib.*, 2009, **3**, (7), pp. 650–665

[15] Pham, D.T., Karaboga, D.: '*Intelligent optimization techniques, genetic algorithms, tabu search, simulated annealing and neural networks*' (Springer-Verlag, London, UK, 2000)

[16] Rashedi, E., Nezamabadi-Pour, H., Saryazdi, S.: 'GSA: a gravitational search algorithm', *Inf. Sci.*, 2009, **179**, (13), pp. 2232–2248

[17] Narimani, M.R., Vahed, A.A., Abarghooee, R.A.*, et al.*: 'Enhanced gravitational search algorithm for multi objective distribution feeder reconfiguration considering reliability, loss and operational cost', *IET Gener. Transm. Distrib.*, 2014, **8**, (1), pp. 55–69

[18] Stone, G.C., Sedding, H.G., Costello, M.J.: 'Application of partial discharge testing to motor and generator stator winding maintenance', *IEEE Trans. Ind. Appl.*, 1996, **32**, (2), pp. 459–464

[19] Bruning, A.M, Kasture, D.G., Campbell, F.J.*, et al.*: 'Effect of cavity sub-corona current on polymer insulation life', *IEEE Trans. Electr. Insul.*, 1991, **26**, (4), pp. 826–836

[20] Harlin, A., Danikas, M.G., Hyvönen, P.: 'Polyolefin insulation degradation in electrical field below critical inception voltages', *J. Elect. Eng.*, 2005, **56**, (5–6), pp. 135–140

[21] Illias, H.A., Chen, G, Lewin, P.L.: 'Partial discharge measurements for spherical cavities within solid dielectric materials under different stress and cavity conditions'. 2009 IEEE Conf. on Electrical Insulation and Dielectric Phenomena, Virginia Beach, VA, 2009, pp. 388–391

[22] Abdel-Galil, T.K., Hegazy, Y.G., Salama, M.M.A.*, et al.*: 'Fast match-based vector quantization partial discharge pulse pattern recognition', *IEEE Trans. Instrum. Meas.*, 2005, **54**, (1), pp. 3–9

[23] Kim, H.-D., Kim, C.-H.: 'Stator insulation quality assessment for high voltage motors based on probability distributions', *J. Electr. Eng. Technol.*, 2008, **3**, (4), pp. 571–575

[24] Danikas, M.G., Karlis, A.: 'Partial discharge diagnostics in wind turbine insulation', *J. Zhejiang Univ. Sci. C, Comput. Electr.*, 2011, **12**, (6), pp. 515–522

[25] Florkowski, M., Florkowska, B.: 'Distortion of partial discharge images caused by high voltage Harmonics', *IET Gener. Transm. Distrib.*, 2006, **153**, (2), pp. 171–180

[26] Kemp, I.J., Zhu, H., Sedding, H.G.*, et al.*: 'Towards a new partial discharge calibration strategy based on the transfer function of machine stator windings', *IEE Proc. Sci. Meas. Technol.*, 1996, **143**, (1), pp. 57–62

[27] Mohanty, A., Viswavandy, M.: 'A novel ANN based UPFC for voltage stability and reactive power management in a remote hybrid system'. Int. Conf. on Intelligent Computing, Communication & Convergence, Bhubaneswar, Odisha, India, 2015, pp. 555–560

[28] Verma, R., Pal, S., Sathans, S.: 'Intelligent automatic generation control of two-area hydrothermal power system using ANN and fuzzy logic'. Int. Conf. on Communication Systems and Network Technologies, Gwalior, India, April 2013, pp 552–556d

[29] Sabo, A., Wahab, N.I.A., Radzi, M.A.M.*, et al.*: 'A modified artificial neural network algorithm to control shunt active power filter (SAPF) for current harmonics reduction'. IEEE Conf. on Clean Energy and Technology, Lankgkawi, Malaysia, November 2013, pp. 348–352

[30] Anumeha, , Yadav, K.B., Agarwal, S.: 'Economic operation of Two area power system through gravitational search algorithm'. Int. Conf. on Recent Developments in Control, Automation and Power Engineering, Noida, India, March 2015, pp. 194–198

[31] Chen, G., Liu, L., Huang, S.: 'Enhanced GSA-based optimization for minimization of power losses in power system', *Math. Probl. Eng.*, 2015, **2015**, pp. 1–13

[32] Eslami, M., Shareef, H., Mohamed, A.*, et al.*: 'PSS and TCSC damping controller coordinated design using GSA', *Energy Procedia*, 2012, **14**, pp. 763–769

[33] Duman, S., Guvenc, U., Sonmez, Y.*, et al.*: 'Optimal power flow using gravitational search algorithm', *Energy Convers. Manage.*, 2012, **59**, pp. 86–95