

Aging Assessment of Power Transformer Insulation Oil using Hybrid Meta-Heuristic Trained Artificial Neural Network



Harkamal Deep Singh, Jashandeep Singh

Abstract: In today's economic state, power transformer remains as the most expensive equipment in electrical system, in which insulation oil has been taken a significant role for performing a prominent operation. Since the insulation oil happens to degrade soon due to aging, high temperature and chemical reactions such as the oxidation, the periodic checking of oil followed by its replacement is necessary to stop the unexpected failure of the transformer. Moreover, it will be very advantageous if it happens to implement an automated model for predicting the age of transformer oil from time to time. The main intent of this paper is to develop an age assessment framework of transformer insulation oil using intelligent approaches. Here, diverse parameters associated with the transformer such as Breakdown Voltage (BDV), moisture, resistivity, tan delta, interfacial tension, and flash point is given as input for predicting the age of the insulation oil. These data have been already collected using 20 working power transformers operated at various substations in Punjab, India. In the proposed model, the collected parameters are subjected to a well-performing machine learning algorithm termed as Artificial Neural Network (ANN) in order to predict the age of the insulation oil. As a main contribution, the existing training algorithm in ANN so called as Levenberg–Marquardt (LM) is replaced by a hybrid meta-heuristics algorithm. The newly developed hybrid algorithm merges the idea of Crow Search Algorithm (CSA), and Particle Swarm Optimization (PSO), and the new algorithm is termed as Particle Swarm-based Crow Search Algorithm (PS-CSA). The new training algorithm optimizes the weight of ANN using the hybrid CS-PSO updating procedure, in such a way that the difference between the predicted and actual outcome is minimum. Hence, this age prediction of transformer insulation oil will be beneficial for the environs to avoid the drastic condition.

Keywords: Power Transformer insulation oil; Aging Assessment; Artificial Neural Network; Training algorithm; Particle Swarm-based Crow Search Algorithm

Nomenclature

Abbreviations	Descriptions
BDV	Breakdown Voltage
CSA	Crow Search Algorithm
PSO	Particle Swarm Optimization
PS-CSA	Particle Swarm based Crow Search Algorithm
GTL	Gas-To-Liquid
DP	Degree of Polymerization
TS	Tensile Strength
FDS	Frequency Domain Spectroscopy
PDC	Polarization and Depolarization Currents
NFS	Neuro-Fuzzy Scheme
WIP	Winding Insulation Paper
PSEB	Punjab State Electricity Board
IS	Indian standard
SMAPE	Symmetric Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
IFT	Inter Facial Tensions
ANN	Artificial Neural Network
LM	Levenberg–Marquardt

I. INTRODUCTION

The transformer insulation scheme basically consists of mineral oil, paper, and other cellulosic materials, which has a narrow life even if the transformers function under ideal conditions [10] [14]. Oil and / or paper insulation aging is one of the major significant reasons for the breakdown of transformers [9]. The aging process of transformer oil, which typically takes place during the service of a transformer, could be another cause of the change of electric properties of the oil that might collapse the insulation scheme. In order to predict the trustworthiness and stability of these models, the upcoming features of transformer oil have been established and proved the compatibility with experimentally calculated results. Transformer oil is an individual oil, which has outstanding electrical insulating properties and is constant at elevated temperatures. Transformer oil is utilized in oil-filled electrical power transformers to insulate, discontinue arcing and corona discharge, and to dissolve the heat of the transformer. It is also employed to protect the transformer's core and windings, fully immersed in the oil. An additional significant property of insulating oil is its capacity to avert oxidation of the cellulose-made paper insulation. The dielectric strength of the transformer oil is BDV, which is vital and accepted test of transformer oil, as it is a crucial indicator of the strength of oil [19] [23]. Insulating oil in service is subjected to heat, oxygen and electrical discharge, which may lead to its degradation [11].

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This severely limits the oil to carry out its primary functions of insulating and heat transfer as aging products reduce electrical properties and cooling efficiency. Acids and sludge are the oxidation products, which are harmful to the solid insulation [22]. Therefore, monitoring and maintaining oil quality is essential in ensuring the reliable operation of oil-filled electrical equipment. Even in ideal conditions, oil will degrade, as its useful service life is finite. The rate of aging is normally a function of temperature and moisture [17] [18]. Oil will age rapidly at high temperatures and moisture acts as a catalyst for its aging [24]. There are also other catalysts present in a transformer that is responsible for oil degradation. These include copper, paint, varnish and oxygen.

It is critical to assess the condition of transformer oil, especially that, it reflects the age of the transformer itself [15] [16]. Age assessment of transformer oil will not only assist in satisfying the consistent delivery of power but also in shunning the unnecessary oil substitution with substantial costs [12]. Age assessment of transformer oil will help for assuring reliable power delivery, and avoiding unnecessary oil replacement with substantial costs [21] [25]. Age assessment of transformer oil can be accomplished by investigating the variation in the different properties of insulating oil, such as BDV, dielectric dissipation factor, water content, acidity and interfacial tension [13]. However, these traditional methods require expertise, expensive equipment, and various tests to achieve accurate age assessment of insulating oil [20].

The significant contributions of this paper are depicted hereunder.

- To extract the data like BDV, moisture, resistivity, tan delta, interfacial tension and flash point from different 20 transformers, which are located at various locations in Punjab, India to predict the age of transformer insulation oil.
- To develop a novel machine learning algorithm called PS-CSA trained neural network for automatic prediction of aging of transformer insulation oil with the objective of minimizing the error difference between actual and predicted outcome. The efficiency of the implemented model is certified by some relevant error measures.

The whole paper is demonstrated in the following manner: Section II describes the literature review and features and challenges of aging assessment of power transformer insulation oil. Experimental data of aging assessment of power transformer insulation oil: parameter description is mentioned in Section III. Analytical representation of aging assessment of power transformer insulation oil is discussed in Section IV. Experimental Results and discussions are shown in Section V. At last, the conclusions of the entire paper are given in Section VI.

II. LITERATURE REVIEW

A. Related Works

In 2019, Gouda and Dein [1] has proposed a new diagnostic and screening approach via Polynomial regression modelling for predicting the aged transformer oil and paper insulation. The experiment was performed on ten power

transformers, which were in process in the Egyptian networks. The transformers oils were screened in the revision phase up to 10years. By using Polynomial regression modelling approach, the outcome has confirmed the first-quality conformity by the experimental oil feature. In this critique, the left-over examination of the transformer was calculated approximately with the DP of paper insulation.

In 2016, Matharage *et al.* [2] have focused on the applicability of new paper aging gauges in the narration, GTL knowledge based transformer oil through a step up laboratory aging experiment. The testing was carried out at 120 °C for up to 280 days. Along with that, conventional mineral oil was also tested as a reference. Kraft paper aged in both types of oils has shown same decrements in DP, and TS. The amount of methanol present in the oil was more than that of 2-FAL when DP was above 375, so that, usage of methanol as an early paper aging indicator was confirmed. 2-FAL was valid for GTL oil in both new paper aging indicators without any changes. Further, the oil aging tests have shown that the oil generates methanol, which was insignificant.

In 2017, Singhe *et al.* [3] have found an association between dielectric properties, and the state of aging of transformer pressboard samples. This was used to suggest new approaches to consider the state of aging by measuring dielectric at the elevated frequencies. Dielectric dimensions were finished with a microstrip ring resonator. The state of aging was resolute by calculating the tensile index. Experiments were done on dry and wet oil-impregnated pressboard samples thermally aged at lab situations for up to 45days. Finally, the results were contrasted with field aged samples were taken from 33kV sealed type distribution transformer of 18 years in examination. It was found that the permittivity values had a good association with particular tensile index values when compared to dry and wet samples. Hence, the permittivity of pressboard samples from the ring resonator was utilized efficiently in order to calculate the state of aging transformer insulation.

In 2019, Yang *et al.* [4] have suggested a new technique exploiting FDS and the water balance qualities of oil-paper insulation, to calculate the aging state of oil-paper insulation. To estimate the moisture content of the insulating paper, FDS curves were utilized, and oil samples were used to measure the moisture substance of the oil. In addition, the ratio among the moisture substance of the oil and paper were considered as the aging attribute parameter to calculate the aging position of oil-paper insulation. The possibility of the suggested approach has been certified by oil-paper insulation samples at various aging states and with distinct moisture levels.

In 2016, Gao *et al.* [5] have interpreted the oil-paper insulation state of the power transformer with the help of dielectric response approach. PDC, and FDS, were the measurements of dielectric response, accomplished on pressboard samples at peculiar temperatures. By using the master curve method, the effect of the temperature on FDS

was efficiently removed where the results shown that the dielectric responses of oil impregnated pressboards were extremely sensitive to aging, water, and temperature. In the mean time, dielectric characteristic parameters were collected to form a fingerprint database in order to signify the different states of the oil impregnated pressboard. Initially, a grey correlation diagnosis model was established to measure the aging state and water content of the oil-paper insulation. At last, FDS measurements were executed on field transformer to authenticate the efficiency of proposed method for condition estimation of the transformer oil-paper insulation.

In 2019, Liu *et al.* [6] have analysed the aging condition of cellulosic insulation using average activation energy procedure. Initially, the test procedure was discussed and later, the second-order dynamic equation created by Arrhenius equation and Ekenstam equation was firmly examined to evaluate the DP value of transformer cellulosic insulation in a precise manner. Finally, the test result shown that the average activation energy was efficient.

In 2019, Serrano *et al.* [7] had utilized two contours of photopyroelectric approaches for optical absorption coefficient and thermal diffusivity dimensions of mineral oils aged up to 2300h below controlled situations. Then, it was observed that, partially up to particular period of time, thermal diffusivity doesn't demonstrate major distinctions, and further shown large variations at 1000h. As a result, the respective optical parameter was beneficially adopted for diagnostic purposes.

In 2013, Malik *et al.* [8] have been attempted to inspect the efficiency of NFS, to recognize the weakening of the WIP in an oil-immersed power transformer, and contrast its performance over conventional approaches (IEEE/IEC). The suggested approach spoke a practical statement to the power components for successful understanding of electrical health of oil-immersed power transformer below contemplation. Here, the testing analysis was done on 25 transformer samples, which has been taken to exhibit the strength of the examined four status circumstances for large transformation in operating state and loading state disruption.

B. Review

Even though aging assessment of power transformer insulation oil has been still under development, there is

more new technology to be focussed, and determined in the upcoming researches. Table 1 reveals some of the advantages and disadvantages of aging estimation of power transformer insulation oil. Among them, Polynomial regression [1] offers best estimation of the association between the dependent and independent variable, and a wide range of function can be easily fit. But, it is having some disadvantages like very sensitive, and the occurrence of one or two outliers affect the results. DP [2] was utilized at low temperatures, and the resultant solution might be directly usable. Though, it is having defect like it will restrict to high reactive systems. Ring Resonator Method [3] is approximately free of loss of radiation, and it can be used to measure the state of aging of power transformer insulation. Yet, it is having a challenge i.e., the areas are concentrated in dielectric, and in wave frequencies, the substrate loss might become inadequately high. FDS [4] calculates the contents of unknown data accurately using mathematical analysis algorithm, and provides consistent data. Nevertheless, there are some objections like the extent of aging of oil-paper insulation couldn't be calculated. Dielectric Response Method [5] is a thin band measurement method, which makes it easy to filter noise especially for higher frequencies, and Grey Correlation Model [5] can handle both incomplete data and uncertain problems accurately. But, it is highly sensitive to the water and aging state of insulation. Average Activation Energy Method [6] provides high accuracy and reliability, still, it is directly used in evaluation without any modification, it provides great evaluation error. Photopyroelectric [7] is small in size, as well as less cost, and it has low noise equivalent power and can operate without window. But, there are few conflicts like lower detectivity, and Spectral need to be improved. NFS [8] has better performance compared to individual method, and gives a mathematical robustness to confine the uncertainties linked with human cognitive process. Yet, it depends on the existence of an expert to establish the inference logical rules. Hence, the above depicted challenges are greatly forced to implement a new prediction model in the forthcoming researches.

Table 1. Features and Challenges of Aging Assessment of Power Transformer Insulation Oil

Authors [Citations]	Methodology	Features	Challenges
Gouda <i>et al.</i> [1]	Polynomial Regression	<ul style="list-style-type: none"> It offers best estimation of the association between the dependent and independent variable. A wide range of function can be easily fit. 	<ul style="list-style-type: none"> These are very sensitive. The occurrence of one or two outliers affect the results.
Matharage <i>et al.</i> [2]	DP	<ul style="list-style-type: none"> Relatively low temperatures are utilized. The resultant solution might be directly usable. 	<ul style="list-style-type: none"> Restricted to highly reactive systems.

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singhe <i>et al.</i> [3]	Ring Resonator Method	<ul style="list-style-type: none"> It is approximately free of loss of radiation. It can be used to measure the state of aging of a power transformer insulation. 	<ul style="list-style-type: none"> The areas are concentrated in dielectric, and in wave frequencies, the substrate loss might become inadequately high.
Yang <i>et al.</i> [4]	Frequency Domain Dielectric Spectroscopy	<ul style="list-style-type: none"> Calculates the contents of unknown data accurately using mathematical analysis algorithm. It provides consistent data. 	<ul style="list-style-type: none"> The extent of aging of oil-paper insulation couldn't be calculated.
Gao <i>et al.</i> [5]	Dielectric Response Method and Grey Correlation Model	<ul style="list-style-type: none"> Grey Correlation Model can handle both incomplete data and uncertain problems accurately. Dielectric Response Method is a thin band measurement method, which makes it easy to filter noise specially for higher frequencies. 	<ul style="list-style-type: none"> Highly sensitive to the water and aging state of insulation.
Liu <i>et al.</i> [6]	Average Activation Energy Method	<ul style="list-style-type: none"> The method provides high accuracy and reliability. 	<ul style="list-style-type: none"> If it is directly used in evaluation without any modification, it provides great evaluation error.
Serrano <i>et al.</i> [7]	Photopyroelectric	<ul style="list-style-type: none"> It is small in size, as well as less cost. It has low noise equivalent power and can operate without window. 	<ul style="list-style-type: none"> It has lower detectivity. Spectral need to be improved.
Malik <i>et al.</i> [8]	NFS	<ul style="list-style-type: none"> It has better performance compared to individual method. Gives a mathematical robustness to confine the uncertainties linked with human cognitive process. 	<ul style="list-style-type: none"> Depends on the existence of an expert to establish the inference logical rules.

III. EXPERIMENTAL DATA OF AGING ASSESSMENT OF POWER TRANSFORMER INSULATION OIL: PARAMETER DESCRIPTION

A. Details of Power Transformers

In order to analyse the aging of power transformer insulation oil, this paper performs an experiment on 20 different power transformers from PSEB located at various places in Punjab. The detail of the power transformers from which the experiment is carried out is clearly mentioned in Table II and Table III, respectively for 10 transformers each. The information like constructed authorities, locations, serial no., MVA rating, HV/LV in KV, phases, year of manufacturing, date of installation, and aging have been given in the tabulation. Moreover based on IS: 335-1993 (2005), the mineral oil was selected. The above mentioned parameters were computed using numerous National and International standards [26].

Table 2. Details of Power Transformers No. 1,2,3,4,5,6,7,8,9, and 10

Transformer No.	1	2	3	4	5	6	7	8	9	10
Constructed By	BBL	NUCON	BBL	BBL	NUCON	ECE	TAL	NUCON	IMP	BBL
Location	Nathana Dist. Bathinda	Balianwali Dist. Bathinda	Phul Dist. Bathinda	Phase 7 Mohali	Bhuc ho Kalan Dist. Bathinda	Nathana Dist. Bathinda	Dhan Singh Khana Dist. Bathinda	Rampura Dist. Bathinda	Kurali	Kurali
Serial No.	5317/	64503	5425/	4656	64505	84799	S00000	6480	PT.7	5390/

	12		17	/2			258		004	10
MVA Rating	20	20	20	20	20	20	20	20	20	20
HV/LV in KV	66/11	66/11	66/11	66/11	66/11	66/11	66/11	66/11	66/11	66/11
Phases	3	3	3	3	3	3	3	3	3	3
Year of Manufacturing	2012	2015	2014	2004	2015	2003	2014	2016	2012	2014
Date of Installation	13-08-2015	24-08-2015	21-11-2014	23-04-2004	08-12-2015	14-11-2003	26-03-2014	24-11-2016	27-10-2012	24-05-2014
Aging (Days)	1474	1369	1657	5471	1270	5764	1940	919	2394	1820

Table 3. Details of Power Transformers No. 11,12,13,14,15,16,17,18,19, And 20

Transformer No.	11	12	13	14	15	16	17	18	19	20
Constructed By	T.A.	ECE	ECE	ECE	CTR	T.A.	TA	ECE	ECE	ECE
Location	Rampura Dist. Bathinda	Rampura Dist. Bathinda	Phul Dist. Bathinda	Balianwali Dist. Bathinda	Kurali	Ropar	Ropar	Phase-8b Mohali	Phase-8b Mohali	Phase 7 Mohali
Serial No.	2000030	85950	8536	86274	1220642	TA2000093	TA2000025	84807	86370	86424
MVA Rating	20	20	20	20	20	20	20	20	20	20
HV/LV in KV	66/11	66/11	66/11	66/11	66/11	132/11	132/11	66/11	66/11	66/11



Phases	3	3	3	3	3	3	3	3	3	3
Year of Manufacturing	2009	2006	2004	2009	2012	2010	2009	2004	2012	2011
Date of Installation	26-03-2010	24-07-2007	11-03-2004	25-05-2010	27-10-2012	26-06-2011	07-04-2010	26-04-2004	20-03-2012	10-08-2011
Aging (Days)	3354	4330	5564	3360	2394	2638	3083	5376	2491	2806

B. Break Down Voltage

BDV [26], a most significant parameter helps to precisely estimate the oil condition. The moisture content and soil constituents present in the oil is determined by BDV measure. If the BDV is high, then it indicates dry and clean oil. Electro-convection, fluid viscosity, density, pressure, and temperature are the features, which makes complex in modelling and evaluating the breakdown and conduction approaches. To measure the dielectric strength of the oil, an oil breakdown experiment set was utilized. After every breakdown, the oil is stirred for avoiding the electrodes from the carbon particles and for keeping away from the production of air bubbles. The graphical representation of BDV showing the effect of aging is shown in Fig. 1. It represents that BDV of insulation oil slowly reduces and tolerates the non-linear relationship with aging. Along with that, it also decreases the content of moisture, accomplish the impurities as an outcome on oxidising the oil, and it might improve the size and density of free particles created.

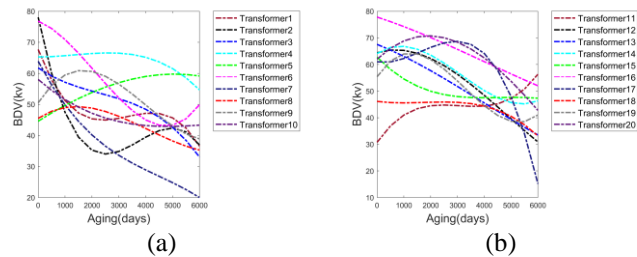


Fig. 1. Graphical representation showing the effect of aging on BDV of (a) power transformers no.1,2,3,4,5,6,7,8,9, and 10 (b) power transformers no.11,12,13,14,15,16,17,18,19, and 20

C. Moisture

The moisture [26] content existing in oil is mostly unwanted because it is impacting the dielectric properties of oil as well as solid insulation of transformer. If the transformer is full of oil then the paper sucks up the moisture from the oil influencing the insulating property and decreases its life time. In order to define the moisture content, Karl fischer instrument was utilized, which is flexible, modelled to find the moisture content in oil samples, and the results are computed in ppm. The Karl fischer instrument, model MA-101 B, spectra lab was used to determine the moisture content. This equipment is a versatile instrument; fully microprocessor based and designed to measure the moisture content of oil samples. The results were calculated automatically in ppm. Fig. 2 shows the influence of moisture on aging of transformers. In Fig. 2 (a), transformer 9 is having high moisture content and from Fig. 2 (b), transformer 17 is having more ppm level, it is because of merged stresses on insulation of power transformer moisture improves the aging constantly. As mentioned above, the

moisture content is life-shortening parameter, and it impacts on the insulation system like deteriorating the breakdown system, decreases the capacity of overload, accelerates insulating weakening process, and reduces the strength, etc.

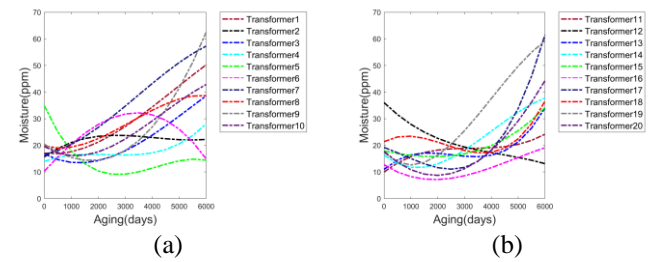


Fig. 2. Graphical representation showing the effect of aging on moisture of (a) power transformers no.1,2,3,4,5,6,7,8,9, and 10 (b) power transformers no.11,12,13,14,15,16,17,18,19, and 20

D. Resistivity

The resistivity of oil should be as high as possible for having the best performance. Fig. 3 shows the impact of aging on resistivity for real power transformers. From Fig. 3 (a), the resistivity of transformer 3 is high, and the resistivity of transformer 7 is less. Similarly from Fig. 3 (b), transformer 19 is having less resistivity while transformer 14 is having high resistivity. Having high resistivity replicates the free ions and ion-forming particles in less content and represents less concentration of conductive contaminants.

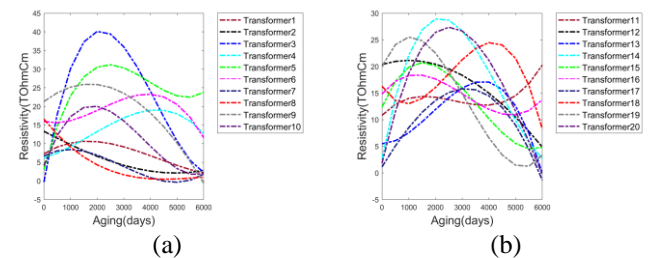


Fig. 3. Graphical representation showing the effect of aging on resistivity of (a) power transformers no.1,2,3,4,5,6,7,8,9, and 10 (b) power transformers no.11,12,13,14,15,16,17,18,19, and 20

E. Dielectric Dissipation Factor

It is also known as Tan delta, in which the value of 0.01 might have the super fine quality of insulating oil. The impact of aging on dielectric dissipation factor [26] is graphically represented in Fig. 4. Fig. 4 (a) shows the tan delta of transformer 9 is less, and transformer 10 is high. From Fig. 4 (b), the tan delta of transformer 19 is having less and transformer 20 is having more. If the value of tan delta is more, then it is denoted that there exists more number of contaminants. It has a relationship with the resistivity. If resistivity reduces, then tan delta increases. The power dissipation in dielectric losses in an alternating region as denoted in Eq. (1), where it specifies that the loss of power is directly proportional to loss of tan delta and it is called as loss factor.



$$Pow = \omega Vo^2 (\tan \delta) \tag{1}$$

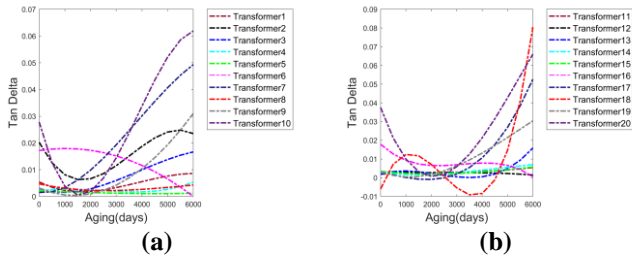


Fig. 4. Graphical representation showing the effect of aging on dielectric dissipation factor of (a) power transformers no.1,2,3,4,5,6,7,8,9, and 10 (b) power transformers no.11,12,13,14,15,16,17,18,19,, and 20

F. Interfacial Tensions

This parameter is necessary to split the oil surface present in the interface of oil-water, and it is utilized to calculate the degree of contamination and purifying the new oil. To define the existence of polar oil decay products and polar contaminants, IFT [26] is utilized. Moreover, it decreases with aging on impact of oil oxidation, merged stresses, etc. If there is improvement in oxidation, then there is a decrement in IFT because of more similarities existing between water and oil molecules. Fig. 5 shows the impact of aging on IFT. From Fig. 5 (a), transformer 2 is exhibiting low IFT, and transformer 9 is providing high IFT. Fig. 5 (b) shows low IFT for transformer 15 and high for transformer 12.

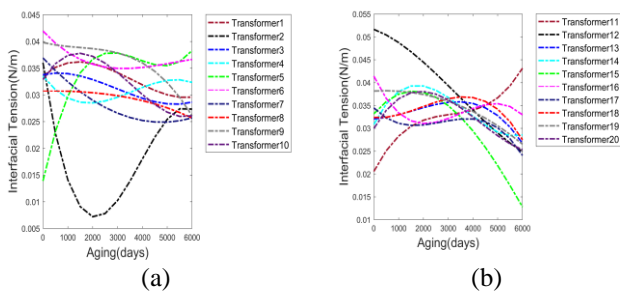


Fig. 5. Graphical representation showing the effect of aging on interfacial tensions of (a) power transformers no.1,2,3,4,5,6,7,8,9, and 10 (b) power transformers no.11,12,13,14,15,16,17,18,19,, and 20

G. Flashpoints

It is advisable that the oil must have extreme flash point [26]. Due to the impact of combined stresses, the flash point decreases with aging. The graphical representation of flash point is shown in Fig. 6. In Fig. 6 (a), transformer 10 is having low flash point. Transformer 12 is having low flash point from Fig. 6 (b). It is because of flexible explosive products exist in the oil and low molecular weight hydrocarbons, etc.

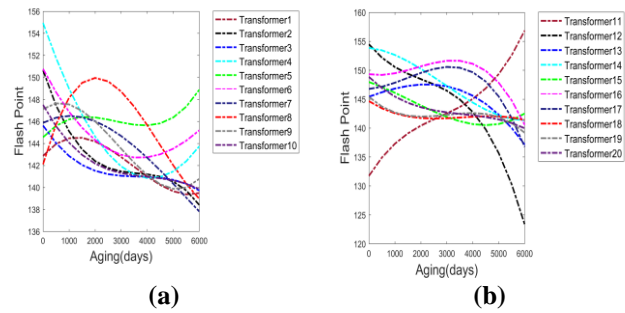


Fig. 6. Graphical representation showing the effect of aging on flashpoints of (a) power transformers no.1,2,3,4,5,6,7,8,9, and 10 (b) power transformers no.11,12,13,14,15,16,17,18,19,, and 20

IV. ANALYTICAL REPRESENTATION OF AGING ASSESSMENT OF POWER TRANSFORMER INSULATION OIL

A. Proposed Description

The intelligent age prediction model of transformer insulation oil is shown in Fig. 7. Initially, the experiment is carried out in different substations of Punjab for 20 power transformers. The data such as BDV, moisture, resistivity, tan delta, interfacial tension and flash point for each transformer is given as input for predicting the age of the insulation oil. The collected input parameters are subjected to a well performing machine learning algorithm called ANN. As an improvement to the existing ANN, the training algorithm LM is replaced by a hybrid meta-heuristic algorithm called PS-CSA in order to predict the better aging output. The proposed PS-CSA helps in updating the weight of ANN, which intends to minimize the error difference between the measured and predicted output. Hence, the newly implemented prediction model is effective, which is proved by the different error measures.

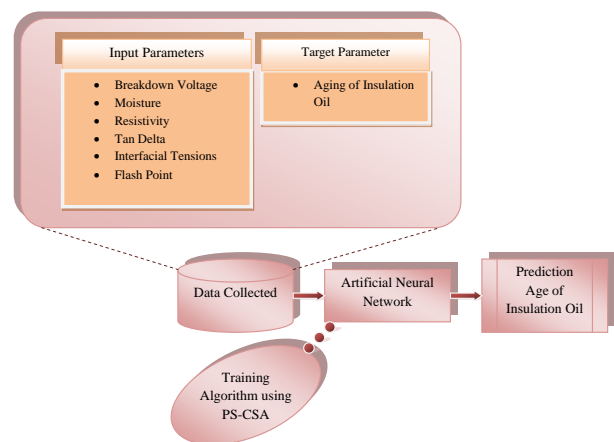


Fig. 7. Proposed block diagram of aging assessment of power transformer insulation oil

B. Artificial Neural Network-based Aging Assessment

In order to predict the aging of power transformer insulation oil, optimized ANN-based algorithm is used here. ANN [29] is called as well-known scheme for classification in many applications owing to its flexibility. ANN architecture takes features as input.



Here, the feature set is represented as FES_{in} , which includes the parameters BDV, moisture, resistivity, tan delta, interfacial tension and flash point. In the ANN architecture, the output of the hidden layer is computed based on Eq. (2), and the overall output of the network is represented in Eq. (3). Assume ip as the input neuron, hn as the hidden neuron, and op as the output neuron.

$$\bar{H}^{(H)} = Acf\left(\tilde{A}_{(whn)}^{(H)} + \sum_{ip=1}^{IP(Nu)} \tilde{A}_{(iphn)}^H FES_{in}\right) \quad (2)$$

$$\hat{O}_{op} = Acf\left(\tilde{A}_{(wop)}^{(O)} + \sum_{hn=1}^{OP(Nu)} \tilde{A}_{(hnop)} \bar{H}^{(H)}\right) \quad (3)$$

In Eq. (2), and Eq. (3), $IP(Nu)$ signifies the number of input neurons, $OP(Nu)$ specifies the number of hidden neurons, $\tilde{A}_{(whn)}^{(H)}$ describes the bias weight to hn^{th} hidden neuron, $\tilde{A}_{(wop)}^{(O)}$ denotes the bias weight to op^{th} output neuron, $\tilde{A}_{(iphn)}^{(H)}$ indicates the weight from ip^{th} input to hn^{th} hidden neuron, and $\tilde{A}_{(hnop)}^{(O)}$ indicates the weight from the hn^{th} hidden neuron to the op^{th} output neuron. The term Acf denotes the activation function, and the network output \hat{O}_{op} refers to the classified output. Moreover, the weight function $A_w = \{\tilde{A}_{(whn)}^{(H)}, \tilde{A}_{(wop)}^{(O)}, \tilde{A}_{(iphn)}^{(H)}, \tilde{A}_{(hnop)}^{(O)}\}$ needs to update using the proposed PS-CSA algorithm. The weight update pattern of ANN architecture using new training algorithm is shown in Fig. 8.

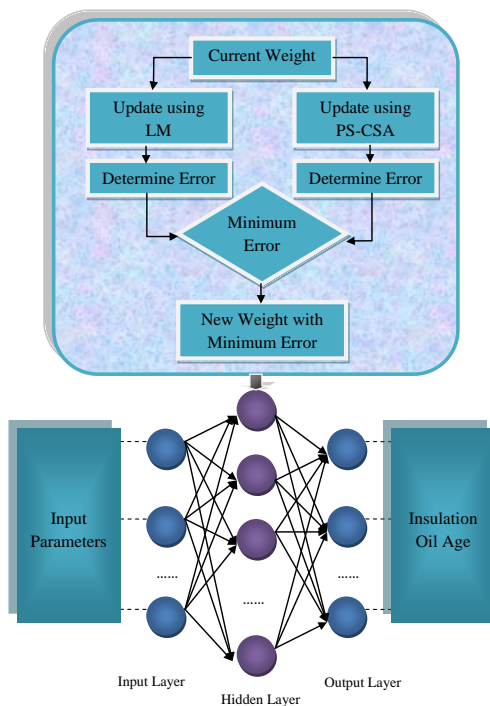


Fig. 8. Weight Update procedure in Artificial Neural Network using LM and proposed PS-CSA

To provide better training to the ANN, weight $A_w = \{\tilde{A}_{(whn)}^{(H)}, \tilde{A}_{(wop)}^{(O)}, \tilde{A}_{(iphn)}^{(H)}, \tilde{A}_{(hnop)}^{(O)}\}$ is optimally selected by

focusing on the objective function (minimum) as shown in Eq. (11), which is the measured error.

$$ME = \left\{ \tilde{A}_{(whn)}^{(H)}, \tilde{A}_{(wop)}^{(O)}, \tilde{A}_{(iphn)}^{(H)}, \tilde{A}_{(hnop)}^{(O)} \right\} \sum_{op=1}^{O(Nu)} |O_{op} - \hat{O}_{op}| \quad (4)$$

The error difference between the predicted \hat{O}_{op} and the actual O_{op} output is given in Eq. (4), which should be minimized by optimizing the weight A_w using proposed PS-CSA. Based on Fig. 8, the weight is initially updated by LM, and further updated by proposed PS-CSA. These both updated weight check the error difference, and minimum error provided weight is subjected to the corresponding neurons.

C. Objective Model

The main intention of this research work is to design a frame work for aging assessment in power transformer insulation oil. The proposed algorithm called PS-CSA trains the ANN architecture, which is adopted here for aging prediction model. When new training is performed in ANN architecture, the objective of the prediction model is to minimize the error difference between the predicted and actual outcome as given in Eq. (4). Therefore, Eq. (5) shows the objective model of the proposed aging assessment of power transformer insulation oil.

$$OBJ = \min (ME) \quad (5)$$

The solution to the proposed PS-CSA is the weight of different layers of ANN architecture.

D. Conventional Crow Search Algorithm

CSA [28] is inspired by the behaviour of crows in case of searching for food, which was stored by others in the concealed locations. This algorithm mainly concentrates on a collection of brilliant crows. The job of crows is seeing the remaining crows where they are hiding the food and theft it when the owner crow is not there in that location. The key points of CSA are as follows: Crows exists in the form of group, the hidden locations are remembered by the crows, for pilfering the food, crows follow one another, and crows protect their food from robbery. Assume ds dimensional space that contains the location of the crow a at time ti is determined by $C^{a,ti} (a = 1, 2, \dots, N; ti = 1, 2, \dots, ti_{max})$, in which $C^{a,ti} = [C_1^{a,ti}, C_2^{a,ti}, \dots, C_{ds}^{a,ti}]$, the total count of crows is N , and ti_{max} is the maximum count of iterations.

The position of hidden crow a at time ti is indicated by $hid^{a,ti}$ and that will be the best position of the crow. The crow b wishes to see the hidden location and that is given by $hid^{b,ti}$, while the crow a plans to follow the crow b i.e., going in the direction of the concealed place of crow b . At that point of view, two conditions might occur: one is the second crow doesn't know that the first crow is following it then the new location of crow a is obtained by Eq. (6), where $fl^{a,ti}$ indicates the length of the flight of crow a at ti iterations, and $rand$ be the random number ranging from $[0,1]$.

The other one is the second crow knows that the first crow is following it then the second crow fools the first crow by going to the false location of the search space. Finally, these two conditions are represented in Eq. (7), in which $PA^{b,ti}$ is the awareness probability of the crow b in ti iterations.

$$C^{a,ti} = C^{a,ti} + rand_a \times fl^{a,ti} \times (hid^{b,ti} - C^{a,ti}) \quad (6)$$

$$C^{a,ti} = \begin{cases} C^{a,ti} + rand_a \times fl^{a,ti} \times (hid^{b,ti} - C^{a,ti}) & \text{if } rand_b \geq PA^{b,ti} \\ a \text{ random position} & \text{otherwise} \end{cases} \quad (7)$$

The step by step procedure of CSA is mentioned below:

- (1) Decision variables and conditions are used to optimize the problem. Later, CSA parameters such as N, ti, fl, PA are validated.
- (2) N crows are randomly positioned in ds -dimensional search space. Every crow denotes a feasible solution using Eq. (8), where the number of decision variables is indicated by $d \text{ var}$. In addition, the initialization of memory is necessary for each crow and it is given in Eq. (9) as the crow doesn't have the knowledge previously.

$$Cr = \begin{bmatrix} C_1^1 & C_2^1 & \dots & C_{d \text{ var}}^1 \\ C_1^2 & C_2^2 & \dots & C_{d \text{ var}}^2 \\ \vdots & \vdots & \vdots & \vdots \\ C_1^N & C_2^N & \dots & C_{d \text{ var}}^N \end{bmatrix} \quad (8)$$

$$Mem = \begin{bmatrix} hid_1^1 & hid_2^1 & \dots & hid_{d \text{ var}}^1 \\ hid_1^2 & hid_2^2 & \dots & hid_{d \text{ var}}^2 \\ \vdots & \vdots & \vdots & \vdots \\ hid_1^N & hid_2^N & \dots & hid_{d \text{ var}}^N \end{bmatrix} \quad (9)$$

- (3) The efficiency of the position of each crow is determined by putting the values of the decision variables in the objective function.
- (4) Crows create the new search space position. The crow selects one from the cluster spontaneously and follows other crows to find the hidden foods. The crow's new position is obtained in Eq. (6).
- (5) The feasibility of the new place of the crow is assessed. If it is perfect, the crow will update its position or it will stay in the present location.
- (6) In order to find the new position of each crow, fitness function is determined.
- (7) Crow's memory is updated using Eq. (10), in which the value of objective function is denoted as $f(\cdot)$.

$$hid^{a,ti+1} = \begin{cases} C^{a,ti+1} & \text{if } f(C^{a,ti+1}) \text{ is better than } f(hid^{a,ti}) \\ hid^{a,ti} & \text{otherwise} \end{cases} \quad (10)$$

The best memory position associated with the value of objective function is called the optimal solution at the time of termination criterion.

E. Conventional Particle Swarm Optimization

PSO [27] is a population based approach that is utilized for optimizing the ANN. The PSO approach is actually intended for reproducing the behaviour of group of birds. Here, the particles are positioned randomly in the search space, and moving in random directions. The particle's direction is usually altered as it move towards the earlier best positions of itself and its peers, searching in the surrounding area and finding more best positions in terms of

fitness metric $fm: R^n \rightarrow R$. Assume $C \in R^n$ be the position of the particle, and ve be the velocity. Velocity and the position are selected randomly and updated.

The mathematical equation for updating the particle's velocity is given in Eq. (11), in which $\hat{C}(ti)$ denotes the best solution of individual particle, $C_g(ti)$ denotes the global best solution from all iterations, $\omega \in R$ is the weight of inertia, which manages the quantity of recurrence present in the velocity of the particle. The variables r_c, r_d are the random variables between 0 and 1, and ϕ_c, ϕ_d are the user defined behavioural parameters. In order to move the particle to the other location in the search space, the particle's present position is added with the velocity as shown in Eq. (12).

$$ve(ti+1) = \omega ve(ti) + \phi_c r_c (\hat{C}(ti) - C(ti)) + \phi_d r_d (C_g(ti) - C(ti)) \quad (11)$$

$$C(ti+1) = C(ti) + ve(ti+1) \quad (12)$$

F. Hybrid PS-CSA

Using the benefits of various optimization algorithms, a novel algorithm can be implemented, which could perform well with the advantage of other algorithm. Even though CSA performs well in most of engineering applications, it suffers from some basis drawbacks. One of the significant drawbacks is that it does not consider the best solution so far. In order to enhance the efficiency of CSA, the beneficial concept of PSO is included, which considers the global best and local best solutions as well. Hence, the proposed particle swam-based CSA is termed as PS-CSA.

In the proposed PS-CSA, the CSA update in Eq. (6) is used if the random number is greater than awareness probability and PSO update in Eq. (11) is used in other case. The algorithmic representation of proposed PS-CSA is shown in Algorithm 1.

<p>Algorithm 1: Pseudo code of state-of-the-art CSA [28]</p> <p>The position of N crows is initialized Calculate the fitness Perform the memory initialization While $ti < ti_{\max}$ For $1: N$ Randomly choose a crow Awareness probability is set to 0.1 If $rand_b \geq PA^{b,ti}$ The position of each crow is updated based on CSA using Eq. (6) else Compute velocity of crows based on PSO using Eq. (11) The position of each crow is updated based on PSO using Eq. (12) End if End for The probability of novel locations is evaluated Do fitness validation Perform memory update by Eq. (10) End while</p>
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V. RESULTS AND DISCUSSIONS

A. Experimental Setup

The proposed aging assessment model of power transformer insulation oil was implemented in MATLAB 2018a, and the analysis was carried out. Here, the experimental work as well as analytical work was done, in which the proposed novel analytical work have attained improved performance for predicting the age of insulation oil. Here, the experimental work was done in different substations in Punjab using 20 transformers. After the implementation of proposed age assessment of power transformer insulation oil using PS-CSA-based ANN, the efficiency of the proposed model was compared over conventional algorithms like LM-ANN [29], PSO-ANN [27], FF-ANN [30], and CSA-ANN [28] by analysing various error metrics like SMAPE, MASE, MAE, RMSE, L1-Norm, L2-Norm, and L-Infinity Norm.

B. Error Measures

Here, seven error measures are considered for experimental analysis. The description of seven error measures is as follows:

(a) **SMAPE**: “SMAPE is an accuracy measure based on percentage errors”. The formula for SMAPE is given in Eq. (13), where F_t is the forecasted value, A_t is the actual value, n is the number of fitted points, and the value of computation is added for each fitted point is denoted by t .

$$SMAPE = \frac{100\%}{n} \sum_{t=1}^n \frac{|F_t - A_t|}{\frac{(|A_t| + |F_t|)}{2}} \quad (13)$$

(b) **MASE**: “It is the mean absolute error of the forecast values, divided by the mean absolute error of the in-sample one-step naive forecast”. The equation is shown in Eq. (14)

$$MASE = mean \left(\frac{|F_t|}{\frac{1}{n-1} \sum_{t=1}^n |A_t - A_{t-1}|} \right) \quad (14)$$

(c) **MAE**: “It is a measure of difference between two continuous variables”. The numerical equation for MAE is denoted in Eq. (15)

$$MAE = \frac{\sum_{t=1}^n |F_t - A_t|}{n} \quad (15)$$

(d) **RMSE**: RMSE “is a frequently used measure of the differences between values predicted by a model or an estimator and the values observed”. The mathematical formula for RMSE is given in Eq. (16)

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (F_{t_2} - F_{t_1})^2}{n}} \quad (16)$$

(e) **L1-Norm**: “L1 Norm is the sum of the magnitudes of the vectors in a space”. The equation for this norm is denoted in Eq. (17), where L is a matrix, and $t = 1, 2, \dots, n$, and n is the size of the matrix.

$$L_1 = \sum_t |L_t| \quad (17)$$

(f) **L2-Norm**: “It is the shortest distance to go from one point to another”. It is also known as Euclidean norm. The equation is represented in Eq. (18).

$$L2 = \left(\sum_{t=1}^n L_t^2 \right)^{\frac{1}{2}} \quad (18)$$

(g) **L-Infinity Norm**: “The length of a vector can be calculated using the maximum norm”. It is also called as Max norm and the formula is given in Eq. (19)

$$L_{\infty} = \max_{1 \leq t \leq n} |L_t| \quad (19)$$

C. Error Analysis at Learning Percentage 25

The error measures considered for the proposed age assessment model are SMAPE, MASE, MAE, RMSE, L1-Norm, L2-Norm, and L-infinity Norm. The error analysis of the proposed prediction at learning percentage 25 is shown in Table IV. From Table IV, the SMAPE for the developed PS-CSA is determined exactly for all transformers. It is 4.79% better than LM, 66.2% better than FF, and 48.6% better than CSA for transformer 1. Moreover for transformer 2, the SMAPE of the presented PS-CSA is 59.3% superior to LM, 81.7% superior to FF, and 79.6% superior to CSA-based ANN. Similarly, the other transformers are also providing the best performance for the proposed PS-CSA-ANN. Moreover, MASE for the transformer 3 by the offered PS-CSA is 73.4% improved than LM, 87.7% improved than FF, and 31% improved than CSA. The next measure, MAE of the developed PS-CSA is defined absolutely for all the transformers. Here, the MAE of the suggested PS-CSA is 41.4% enhanced than LM, 62.1% enhanced than FF, and 66.7% enhanced than CSA, when considered transformer 4. On considering the transformer 5, the RMSE of the presented PS-CSA is 9.7% superior to LM, 15.6% superior to FF, and 64.6% superior to CSA. Consequently, all other measures are also providing better results for the developed PS-CSA. For transformer 6, the L1-norm of the suggested PS-CSA is 65.2% better than LM, 67.9% better than FF, and 47.3% better than CSA. Now, considering the transformer 7 then the L2 norm of the implemented PS-CSA is 80.9% enhanced than LM, 8.6% enhanced than FF, and 83.3% enhanced than CSA-based training. Finally, L-infinity norm of the developed PS-CSA is 25.5% improved than LM, 3.4% improved than FF, and 65.1% improved than CSA-based ANN. Hence, it is concluded that the implemented approach is efficient in aging estimation of power transformer insulation.

Table 4. Error analysis of proposed and conventional age assessment model of power transformer insulation oil at learning percentage 25

Transformer No.	SMAPE				
	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	0.35306	0.33613	0.99691	0.22607	0.33613
2	0.12937	0.31791	1.7366	0.17656	0.31791
3	0.19062	0.085853	0.26697	0.25232	0.085853
4	0.24514	0.12094	0.078643	0.27166	0.12094
5	0.27882	0.16751	0.29323	0.2781	0.16751



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6	0.060241	0.10518	0.054424	0.23339	0.10518
7	0.084577	0.29522	0.41398	0.072353	0.29522
8	0.1081	0.37265	0.13408	0.11921	0.37265
9	0.31635	0.33682	0.31315	0.52155	0.33682
10	0.20812	0.18162	0.2076	0.22792	0.18162
11	0.34776	0.11041	0.28129	0.11539	0.11041
12	0.046878	0.081762	0.053953	0.064067	0.081762
13	0.15781	0.11478	0.098618	0.25022	0.11478
14	0.050939	0.061169	0.05786	0.078698	0.061169
15	0.25282	0.13309	0.21775	0.20477	0.13309
16	0.22855	0.17053	0.057052	0.10419	0.17053
17	0.18697	0.14821	0.11043	0.067215	0.14821
18	0.11509	0.064137	0.81732	0.074734	0.064137
19	0.11576	0.24005	0.25232	0.16207	0.24005
20	0.17726	0.20187	0.19283	0.29088	0.20187
MASE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	3.2431	2.7505	7.7359	2.5451	2.7505
2	0.70398	1.7989	11.398	1.2051	1.7989
3	1.59	0.42214	3.4326	0.61241	0.42214
4	2.5475	1.1536	0.79612	1.6057	1.1536
5	2.3205	0.8378	2.6226	1.3686	0.8378
6	0.5337	0.95283	0.4443	2.6347	0.95283
7	0.26695	3.1489	0.95839	0.22275	3.1489
8	0.5093	1.779	0.44068	0.4498	1.779
9	3.0336	1.5605	0.83448	2.916	1.5605
10	0.85807	1.1985	0.91882	0.79714	1.1985
11	1.8125	0.66986	1.7338	0.80011	0.66986
12	0.1745	0.59421	0.31149	0.49482	0.59421
13	1.6792	1.3275	0.9872	2.2386	1.3275
14	0.1508	0.45119	0.31273	0.35465	0.45119
15	1.3822	0.97396	1.3255	0.8418	0.97396
16	1.7454	1.9785	0.27024	0.58904	1.9785
17	2.0201	0.91379	0.76764	0.66601	0.91379
18	0.68365	0.47004	8.2072	0.74435	0.47004
19	0.68914	2.0316	0.54933	1.4369	2.0316
20	1.7569	1.2489	1.4159	3.6163	1.2489
MAE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	699.95	567	2321.6	452.49	567
2	178.72	379.44	3316.8	252.08	379.44
3	242.32	59.601	626.73	88.823	59.601
4	553.85	324.04	199.87	975.98	324.04
5	401.07	193.75	550.62	642.69	193.75
6	72.576	208.61	66.855	396.6	208.61
7	38.674	430.51	214.99	31.772	430.51
8	86.169	289.5	63.489	64.299	289.5
9	506.94	355.51	227.94	895.85	355.51
10	166.83	219.11	199.25	164.55	219.11
11	458.02	84.329	353.74	118.87	84.329
12	22.013	106.04	41.8	76.422	106.04
13	236.15	302.37	227.48	410.7	302.37
14	19.816	61.795	41.017	48.933	61.795
15	300.51	151.33	223.83	193.1	151.33
16	269.5	282.74	35.242	100.01	282.74
17	356.74	112.03	90.419	88.525	112.03
18	278.69	104.75	2434	209.76	104.75
19	102	277.68	73.135	191.76	277.68
20	279.39	287.5	279.73	442.68	287.5
RMSE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	950.77	767.32	2519.1	1037.3	767.32
2	678.96	524.74	3675.5	784.99	524.74
3	327.78	130.28	767.25	207.07	130.28
4	692.48	694.97	614.94	2671.8	694.97
5	586.28	643.58	762.7	1820.7	643.58
6	155.93	581.76	152.64	595.9	581.76
7	108.92	570.58	525.01	94.855	570.58
8	214.24	508.17	155.21	144.4	508.17
9	818.61	481.22	495.04	1364.4	481.22

10	357.28	534.83	463.62	421.23	534.83
11	748.08	123.8	456.03	177.6	123.8
12	63.224	302.8	90.384	206.35	302.8
13	359.36	755.35	543.33	499.98	755.35
14	39.807	180.47	112.11	146.28	180.47
15	607.66	283.39	415.83	404.25	283.39
16	347.7	453.98	62.225	218.51	453.98
17	494.56	149.95	126.49	198.83	149.95
18	1066.3	347.86	3331.6	661.76	347.86
19	259.54	382.98	162.24	252.01	382.98
20	371.73	694.2	532.18	516.08	694.2
L1-Norm					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	34297	27783	1.14×10 ⁵	22172	27783
2	8757.4	18593	1.63×10 ⁵	12352	18593
3	11873	2920.4	30710	4352.3	2920.4
4	27139	15878	9793.4	47823	15878
5	19653	9493.5	26980	31492	9493.5
6	3556.2	10222	3275.9	19433	10222
7	1895	21095	10534	1556.8	21095
8	4222.3	14185	3110.9	3150.6	14185
9	24840	17420	11169	43897	17420
10	8174.8	10736	9763.3	8063.1	10736
11	22443	4132.1	17333	5824.5	4132.1
12	1078.6	5196	2048.2	3744.7	5196
13	11571	14816	11146	20124	14816
14	970.96	3028	2009.8	2397.7	3028
15	14725	7414.9	10967	9462.1	7414.9
16	13205	13854	1726.8	4900.6	13854
17	17480	5489.4	4430.5	4337.7	5489.4
18	13656	5132.6	1.19×10 ⁵	10278	5132.6
19	4998.1	13607	3583.6	9396.1	13607
20	13690	14087	13707	21691	14087
L2-Norm					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	6655.4	5371.2	1.76×10 ⁴	7261.1	5371.2
2	4752.7	3673.2	2.57×10 ⁴	5494.9	3673.2
3	2294.5	911.97	5370.7	1449.5	911.97
4	4847.4	4864.8	4304.6	18702	4864.8
5	4104	4505.1	5338.9	12745	4505.1
6	1091.5	4072.3	1068.5	4171.3	4072.3
7	762.45	3994	3675.1	663.99	3994
8	1499.7	3557.2	1086.5	1010.8	3557.2
9	5730.3	3368.5	3465.3	9550.8	3368.5
10	2501	3743.8	3245.3	2948.6	3743.8
11	5236.6	866.61	3192.2	1243.2	866.61
12	442.57	2119.6	632.69	1444.5	2119.6
13	2515.5	5287.5	3803.3	3499.8	5287.5
14	278.65	1263.3	784.74	1023.9	1263.3
15	4253.6	1983.7	2910.8	2829.7	1983.7
16	2433.9	3177.9	435.58	1529.5	3177.9
17	3461.9	1049.6	885.4	1391.8	1049.6
18	7464.2	2435	2.33×10 ⁴	4632.3	2435
19	1816.8	2680.9	1135.7	1764.1	2680.9
20	2602.1	4859.4	3725.3	3612.6	4859.4
L-infinity Norm					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	2278.6	2409.3	4.33×10 ³	4653.6	2409.3
2	4133.6	2250.6	6.47×10 ³	3327.2	2250.6
3	1031.4	620.6	1297.4	823.46	620.6
4	1777.7	2531	2954.7	12250	2531
5	1562.2	2727.5	2630.2	7056.2	2727.5
6	513.7	2827.4	611.85	2297.2	2827.4
7	546.95	1530.9	2003.2	506.45	1530.9
8	1288.5	1613.4	633.17	658.19	1613.4
9	1946.6	1355	2066.7	3885.5	1355



10	1347	2358	2117.2	2014.9	2358
11	2669.2	395.44	1379.8	676.42	395.44
12	280.45	1498.7	304.38	957.83	1498.7
13	1240.3	2966.7	2561.6	1098	2966.7
14	205.64	837.58	532.58	672.01	837.58
15	2385.3	1158.6	1238.4	1649.2	1158.6
16	907.77	1527.3	204.9	1144.4	1527.3
17	1573.3	274.41	363.81	819.65	274.41
18	6236.6	1848.8	9.04×10 ³	3371.8	1848.8
19	1068.8	876.16	569.91	817.87	876.16
20	1088.2	3024.6	1619.5	1047.6	3024.6

D. Error Analysis at Learning Percentage 50

Here, the error analysis at learning percentage 25 is discussed in Table V. From Table IV, the SMAPE for the developed PS-CSA is 7.3% better than LM, 20.3% better than FF, and 30.1% better than CSA for transformer 9. Moreover for transformer 10, the SMAPE of the presented PS-CSA is 17.8% superior to LM, 6.4% superior to FF, and 22.9% superior to CSA. The MASE for the transformer 11 by the offered PS-CSA is 66% improved than LM, 66.1% improved than FF, and 20.3% improved than CSA-based ANN. Moreover, the MAE of the suggested PS-CSA is 84.5% enhanced than LM, 60.1% enhanced than FF, and 43.3% enhanced than CSA, when considering transformer 12. Similarly, RMSE of the proposed PS-CSA, the RMSE of the presented PS-CSA is 51.9% superior to LM, 27.6% superior to FF, and 45.5% superior to CSA-based ANN for transformer 13. In addition, L1-norm by the offered PS-CSA for transformer 14 is 68% better than LM, 53.8% better than FF, and 25.2% better than CSA. Now, considering the transformer 15, L2 norm of the implemented PS-CSA is 51.9% enhanced than LM, 29.3% enhanced than FF, and 26.4% enhanced than CSA-based ANN. Finally, L-infinity norm of the developed PS-CSA is 68.2% improved than LM, 87.5% improved than FF, and 33.4% improved than CSA. For the other transformers also the proposed PS-CSA is showing the best results. Therefore, from the above results it has been confirmed that the presented PS-CSA-ANN is effective when compared over conventional meta-heuristic-based ANN.

Table 5. Error Analysis of Proposed and Conventional Age Assessment Model of Power Transformer Insulation Oil At Learning Percentage 50

SMAPE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	0.35356	0.35125	1.01×10 ⁴	0.2376	0.35125
2	0.12318	0.33026	1.74×10 ⁴	0.17993	0.33026
3	0.20533	0.11924	0.2816	0.26893	0.11924
4	0.26949	0.15166	0.11193	0.30241	0.15166
5	0.29554	0.17408	0.31384	0.23781	0.17408
6	0.098378	0.13654	0.090866	0.25532	0.13654
7	0.12159	0.31692	0.40386	0.10655	0.31692
8	0.15677	0.37383	0.13543	0.13636	0.37383
9	0.32816	0.35241	0.28287	0.50458	0.35241
10	0.23386	0.19219	0.20542	0.24948	0.19219
11	0.35821	0.1401	0.30222	0.15218	0.1401
12	0.084097	0.11494	0.091226	0.099358	0.11494
13	0.18249	0.15379	0.13391	0.27261	0.15379
14	0.088348	0.097748	0.094199	0.10529	0.097748
15	0.28124	0.16608	0.24137	0.20597	0.16608
16	0.25103	0.20286	0.094244	0.12837	0.20286
17	0.21221	0.17401	0.13409	0.10557	0.17401
18	0.16598	0.097828	8.44×10 ⁻¹	0.10796	0.097828
19	0.14964	0.26311	0.26854	0.19821	0.26311

20	0.19758	0.21872	0.19875	0.30865	0.21872
MASE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	1.6312	1.3401	3.99×10 ⁰	1.3859	1.3401
2	0.44612	0.92499	5.95×10 ⁰	0.64861	0.92499
3	0.82554	0.20216	1.7376	0.31879	0.20216
4	1.4611	0.53803	0.38926	0.81412	0.53803
5	1.1241	0.32517	1.7406	0.71566	0.32517
6	0.25451	0.48197	0.18414	1.4017	0.48197
7	0.12979	1.6189	0.42588	0.097378	1.6189
8	0.30876	0.89165	0.22814	0.19518	0.89165
9	1.653	0.7564	0.37805	1.4534	0.7564
10	0.39213	0.62056	0.40315	0.40828	0.62056
11	0.94574	0.32109	0.94839	0.40288	0.32109
12	0.058	0.27245	0.14213	0.21259	0.27245
13	0.86277	0.65121	0.52769	1.2633	0.65121
14	0.0708	0.21599	0.13606	0.15891	0.21599
15	0.67045	0.50576	0.65692	0.37605	0.50576
16	0.97205	0.98773	0.13613	0.2966	0.98773
17	1.032	0.48482	0.38597	0.33553	0.48482
18	0.36104	0.2272	4.28×10 ⁰	0.32045	0.2272
19	0.33764	1.0218	0.25859	0.74845	1.0218
20	0.91145	0.61196	0.69932	1.792	0.61196

MAE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	685.59	552.53	2.39×10 ³	489.32	552.53
2	226.52	390.21	3.41×10 ³	271.35	390.21
3	251.63	56.391	622.67	90.104	56.391
4	568.09	292.75	184.56	989.69	292.75
5	387.53	150.4	564.03	665.65	150.4
6	69.219	211.04	52.925	419.85	211.04
7	37.607	442.66	187.3	24.345	442.66
8	104.48	290.21	61.457	55.803	290.21
9	518.85	344.64	206.53	865.22	344.64
10	150.87	223.13	171.42	165.05	223.13
11	463.02	80.273	339.07	114.25	80.273
12	14.589	94.126	37.49	65.666	94.126
13	242.67	296.65	243.19	440.08	296.65
14	17.538	54.904	35.692	43.85	54.904
15	283.22	157.16	215.39	167.29	157.16
16	283.01	281.96	34.599	100.72	281.96
17	361.67	115.75	90.924	89.195	115.75
18	279.62	79.477	2.52×10 ³	179.91	79.477
19	99.951	279.32	68.172	199.24	279.32
20	288.52	281.75	276	438.73	281.75

RMSE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	948.81	774.33	2.59×10 ³	1138.2	774.33
2	880.02	567.75	3.77×10 ³	844.15	567.75
3	362.73	133.26	769.54	212.93	133.26
4	703.57	700.47	632.66	2845.3	700.47
5	578.64	567.3	779.74	1954.4	567.3
6	159.7	629.51	144.16	657.8	629.51
7	117.59	590.09	499.88	68.963	590.09
8	279.61	520.67	149.15	136.81	520.67
9	847.7	474.61	510.25	1345.6	474.61
10	354.29	556.19	458.7	459.38	556.19
11	775.51	129.3	455.33	178.8	129.3
12	54.404	305.03	87.437	205.19	305.03
13	371.51	773.02	605.35	531.04	773.02
14	32.238	162.68	100.66	138.59	162.68
15	617.17	296.67	420.13	403.17	296.67
16	370.84	460.6	63.394	247.14	460.6
17	520.14	152.52	132.3	207.68	152.52
18	1252.9	290.29	3.45×10 ³	693.43	290.29
19	267.72	382.89	160.47	265.64	382.89
20	391.75	713.37	559.38	513.14	713.37

L1-Norm



Aging Assessment of Power Transformer Insulation Oil using Hybrid Meta-Heuristic Trained Artificial Neural Network

Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	17140	13813	5.96×10 ⁴	12233	13813
2	5662.9	9755.3	8.52×10 ⁴	6783.7	9755.3
3	6290.6	1409.8	15567	2252.6	1409.8
4	14202	7318.7	4614	24742	7318.7
5	9688.2	3759.9	14101	16641	3759.9
6	1730.5	5276	1323.1	10496	5276
7	940.19	11067	4682.4	608.62	11067
8	2612	7255.1	1536.4	1395.1	7255.1
9	12971	8616	5163.3	21631	8616
10	3771.8	5578.2	4285.5	4126.2	5578.2
11	11575	2006.8	8476.7	2856.3	2006.8
12	364.72	2353.2	937.25	1641.6	2353.2
13	6066.7	7416.2	6079.7	11002	7416.2
14	438.45	1372.6	892.29	1096.2	1372.6
15	7080.6	3929	5384.8	4182.4	3929
16	7075.2	7049	864.97	2518	7049
17	9041.8	2893.7	2273.1	2229.9	2893.7
18	6990.5	1986.9	6.29×10 ⁴	4497.8	1986.9
19	2498.8	6983.1	1704.3	4980.9	6983.1
20	7213.1	7043.7	6900.1	10968	7043.7

L2-Norm					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	4744.1	3871.7	1.30×10 ⁴	5691.1	3871.7
2	4400.1	2838.7	1.89×10 ⁴	4220.8	2838.7
3	1813.6	666.3	3847.7	1064.6	666.3
4	3517.8	3502.3	3163.3	14227	3502.3
5	2893.2	2836.5	3898.7	9772.1	2836.5
6	798.52	3147.5	720.82	3289	3147.5
7	587.94	2950.4	2499.4	344.81	2950.4
8	1398	2603.3	745.77	684.03	2603.3
9	4238.5	2373	2551.3	6728	2373
10	1771.4	2780.9	2293.5	2296.9	2780.9
11	3877.5	646.49	2276.7	894.02	646.49
12	272.02	1525.2	437.19	1026	1525.2
13	1857.5	3865.1	3026.7	2655.2	3865.1
14	161.19	813.38	503.3	692.93	813.38
15	3085.9	1483.3	2100.6	2015.9	1483.3
16	1854.2	2303	316.97	1235.7	2303
17	2600.7	762.58	661.51	1038.4	762.58
18	6264.5	1451.4	1.72×10 ⁴	3467.1	1451.4
19	1338.6	1914.4	802.33	1328.2	1914.4
20	1958.7	3566.9	2796.9	2565.7	3566.9

L-infinity Norm					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	2270.9	2409.3	4.33×10 ³	4653.6	2409.3
2	4133.6	2250.6	6.47×10 ³	3327.2	2250.6
3	1031.4	620.6	1297.4	823.46	620.6
4	1758.4	2531	2954.7	12250	2531
5	1562.2	2727.5	2630.2	7056.2	2727.5
6	513.7	2827.4	611.85	2297.2	2827.4
7	546.95	1530.9	2003.2	283.15	1530.9
8	1288.5	1613.4	597.91	658.19	1613.4
9	1946.6	1299.5	2066.7	3813.4	1299.5
10	1347	2358	2117.2	2014.9	2358
11	2669.2	395.44	1379.8	676.42	395.44
12	268.38	1498.7	283.89	957.83	1498.7
13	1240.3	2966.7	2561.6	1098	2966.7
14	100.48	625.46	477.62	664.1	625.46
15	2385.3	1158.6	1238.4	1649.2	1158.6
16	907.77	1527.3	190.66	1144.4	1527.3
17	1573.3	274.41	363.81	819.65	274.41
18	6236.6	1398.1	9.04×10 ³	3371.8	1398.1
19	1068.8	863.13	569.91	817.87	863.13
20	1088.2	3024.6	1619.5	1030.8	3024.6

E. Error Analysis at learning percentage 75

The comparative analysis of the proposed and the conventional algorithms in terms of different error measures for the aging assessment of power transformer insulation oil is represented in Table VI. In Table VI, the SMAPE of the

implemented PS-CSA is 17.4% better than LM, 23.5% better than FF, and 36.3% better than CSA for the transformer 17. The MASE of the suggested PS-CSA is 9.3% superior to LM, 92.6% superior to FF, and 17.1% superior to CSA for the transformer 18. Now, considering the transformer 19 then the RMSE of the offered PS-CSA is 59.4% enhanced than LM, 58.1% enhanced than FF, and 38.2% enhanced than CSA. In addition, the L2-Norm of the recommended PS-CSA is 66.6% improved than LM, 7% improved than FF, and 23.8% improved than CSA for the transformer 20. Hence, it is concluded that the proposed PS-CSA is efficient in aging estimation of power transformer insulation oil.

Table 6. Error Analysis of Proposed And Conventional Age Assessment Model Of Power Transformer Insulation Oil At Learning Percentage 75

SMAPE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	0.41246	0.3808	1.02×10 ⁰	0.27142	0.3808
2	0.1779	0.32805	1.76×10 ⁰	0.23858	0.32805
3	0.21203	0.16505	0.312	0.26638	0.16505
4	0.28598	0.19082	0.1453	0.37725	0.19082
5	0.31005	0.19733	0.29958	0.32113	0.19733
6	0.13586	0.16169	0.12963	0.2823	0.16169
7	0.15044	0.33058	0.47524	0.13994	0.33058
8	0.16016	0.38769	0.16255	0.17138	0.38769
9	0.3413	0.34365	0.3226	0.62685	0.34365
10	0.28154	0.22545	0.27094	0.31161	0.22545
11	0.37115	0.17307	0.32323	0.18476	0.17307
12	0.1237	0.16216	0.13027	0.14147	0.16216
13	0.20623	0.18315	0.17078	0.28679	0.18315
14	0.12623	0.14524	0.1296	0.13459	0.14524
15	0.31443	0.19805	0.26834	0.27397	0.19805
16	0.2661	0.23304	0.13244	0.15475	0.23304
17	0.24061	0.19857	0.16077	0.1456	0.19857
18	0.14256	0.14969	8.72×10 ⁻¹	0.14733	0.14969
19	0.17929	0.28608	0.27584	0.23051	0.28608
20	0.21696	0.24063	0.22541	0.32839	0.24063

MASE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	1.5138	1.0954	3.49×10 ⁰	1.0687	1.0954
2	0.45723	0.69266	4.17×10 ⁰	0.67618	0.69266
3	0.59533	0.15862	1.379	0.20493	0.15862
4	0.91035	0.63516	0.26213	0.75774	0.63516
5	0.76389	0.23887	1.2346	0.65469	0.23887
6	0.18555	0.42777	0.15386	1.0405	0.42777
7	0.077001	1.4855	0.45139	0.052093	1.4855
8	0.14689	0.59448	0.16041	0.14986	0.59448
9	1.2431	0.56554	0.29879	1.2052	0.56554
10	0.3637	0.5787	0.35978	0.3381	0.5787
11	0.72655	0.22984	0.62001	0.2771	0.22984
12	0.060497	0.25615	0.11726	0.21022	0.25615
13	0.5868	0.44704	0.44692	1.0695	0.44704
14	0.050766	0.22582	0.09097	0.10658	0.22582
15	0.60692	0.3639	0.46317	0.42561	0.3639
16	0.66111	0.66251	0.099273	0.19256	0.66251
17	0.78336	0.31375	0.2659	0.25797	0.31375
18	0.22445	0.2454	3.33×10 ⁰	0.29636	0.2454
19	0.2279	0.70223	0.17882	0.49841	0.70223
20	0.7172	0.50034	0.59255	1.2139	0.50034

MAE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	2270.9	2409.3	4.33×10 ³	4653.6	2409.3
2	4133.6	2250.6	6.47×10 ³	3327.2	2250.6
3	1031.4	620.6	1297.4	823.46	620.6
4	1758.4	2531	2954.7	12250	2531
5	1562.2	2727.5	2630.2	7056.2	2727.5
6	513.7	2827.4	611.85	2297.2	2827.4
7	546.95	1530.9	2003.2	283.15	1530.9
8	1288.5	1613.4	597.91	658.19	1613.4
9	1946.6	1299.5	2066.7	3813.4	1299.5
10	1347	2358	2117.2	2014.9	2358
11	2669.2	395.44	1379.8	676.42	395.44
12	268.38	1498.7	283.89	957.83	1498.7
13	1240.3	2966.7	2561.6	1098	2966.7
14	100.48	625.46	477.62	664.1	625.46
15	2385.3	1158.6	1238.4	1649.2	1158.6
16	907.77	1527.3	190.66	1144.4	1527.3
17	1573.3	274.41	363.81	819.65	274.41
18	6236.6	1398.1	9.04×10 ³	3371.8	1398.1
19	1068.8	863.13	569.91	817.87	863.13
20	1088.2	3024.6	1619.5	1030.8	3024.6



1	729.04	543.14	2.42×10 ³	560.42	543.14
2	332.45	387.33	3.56×10 ³	327.92	387.33
3	236.7	62.595	629.63	87.422	62.595
4	530.93	311.21	142.82	881.17	311.21
5	360.86	150.52	573.54	658.46	150.52
6	73.105	192.76	58.607	467.51	192.76
7	29.271	452.71	228.06	19.535	452.71
8	55.071	278.36	68.032	60.301	278.36
9	511.42	323.04	181.27	886.03	323.04
10	170.44	228.56	186.62	195.01	228.56
11	404.4	86.191	325.9	103.36	86.191
12	22.687	129.12	45.239	88.773	129.12
13	237.36	273.17	262.93	415.99	273.17
14	18.863	85.353	33.3	38.522	85.353
15	285.53	148.65	214.32	198.22	148.65
16	281.48	278.29	37.847	88.13	278.29
17	372.18	111.48	93.961	99.977	111.48
18	118.65	145.11	2.58×10 ³	175.77	145.11
19	95.178	277.27	70.696	199.54	277.27
20	294.88	273.68	298.8	440.14	273.68
RMSE					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	977.04	739.27	2.60×10 ³	1250.3	739.27
2	1067.2	513.47	3.91×10 ³	894.29	513.47
3	336.5	138.8	764.92	213.21	138.8
4	683.66	676.24	420.2	2290.4	676.24
5	535.35	587.05	833.03	1858.1	587.05
6	158.24	486.65	128.94	721.55	486.65
7	80.208	603.05	567.62	48.912	603.05
8	91.036	474.47	171.88	131.4	474.47
9	823.81	451.9	403.19	1297.1	451.9
10	327.8	478.77	389.17	516.81	478.77
11	662.28	130.67	420.88	144.5	130.67
12	67.172	371.66	93.757	245	371.66
13	350.85	697.4	681.62	505.46	697.4
14	29.909	235.72	71.751	88.603	235.72
15	574.11	258.99	424.06	397.8	258.99
16	378.58	440.98	68.558	176.71	440.98
17	536.87	149.12	135.16	220.16	149.12
18	438.38	459.97	3.51×10 ³	529.28	459.97
19	240.5	383.51	160.31	277.41	383.51
20	377.87	629.6	588.15	508.5	629.6
L1-Norm					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	12394	9233.3	4.11×10 ⁴	9527.1	9233.3
2	5651.6	6584.7	6.05×10 ⁴	5574.7	6584.7
3	4024	1064.1	10704	1486.2	1064.1
4	9025.8	5290.6	2427.9	14980	5290.6
5	6134.6	2558.9	9750.2	11194	2558.9
6	1242.8	3276.9	996.31	7947.7	3276.9
7	497.6	7696	3877	332.1	7696
8	936.21	4732.1	1156.5	1025.1	4732.1
9	8694.1	5491.8	3081.6	15062	5491.8
10	2897.5	3885.6	3172.6	3315.1	3885.6
11	6874.8	1465.2	5540.4	1757.1	1465.2
12	385.67	2195	769.07	1509.1	2195
13	4035.1	4643.9	4469.9	7071.9	4643.9
14	320.67	1451	566.09	654.88	1451
15	4854.1	2527.1	3643.4	3369.7	2527.1
16	4785.1	4731	643.39	1498.2	4731
17	6327	1895.1	1597.3	1699.6	1895.1
18	2017.1	2466.8	4.38×10 ⁴	2988.2	2466.8
19	1618	4713.5	1201.8	3392.1	4713.5
20	5013	4652.5	5079.6	7482.3	4652.5
L2-Norm					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	4028.4	3048.1	1.07×10 ⁴	5155.1	3048.1
2	4400.1	2117.1	1.61×10 ⁴	3687.2	2117.1
3	1387.4	572.28	3153.8	879.08	572.28
4	2818.8	2788.2	1732.5	9443.6	2788.2

5	2207.3	2420.5	3434.7	7661.3	2420.5
6	652.46	2006.5	531.62	2975	2006.5
7	330.71	2486.4	2340.4	201.67	2486.4
8	375.35	1956.3	708.69	541.77	1956.3
9	3396.6	1863.2	1662.4	5347.9	1863.2
10	1351.5	1974	1604.6	2130.9	1974
11	2730.6	538.78	1735.4	595.77	538.78
12	276.96	1532.4	386.57	1010.2	1532.4
13	1446.6	2875.5	2810.4	2084	2875.5
14	123.32	971.9	295.84	365.32	971.9
15	2367.1	1067.8	1748.4	1640.2	1067.8
16	1560.9	1818.2	282.67	728.59	1818.2
17	2213.6	614.85	557.27	907.75	614.85
18	1807.5	1896.5	1.45×10 ⁴	2182.3	1896.5
19	991.63	1581.3	660.96	1143.8	1581.3
20	1558	2595.9	2425	2096.6	2595.9
L-infinity Norm					
Transformer No.	LM-ANN [29]	PSO-ANN [27]	FF-ANN [30]	CSA-ANN [28]	PS-CSA-ANN
1	1995.2	1853.7	4053.2	4653.6	1853.7
2	4133.6	1536.9	6.47×10 ³	3327.2	1536.9
3	1031.4	536.81	1.30×10 ³	787.68	536.81
4	1710.6	1890.7	1665.9	7126.6	1890.7
5	1501.4	2416.3	2630.2	7056.2	2416.3
6	513.7	1589.8	430.83	2297.2	1589.8
7	310.67	1530.9	1984.5	165.62	1530.9
8	298.03	1518.2	633.17	521.85	1518.2
9	1946.6	1355	1381.6	3813.4	1355
10	927.16	1388.5	1414.1	2014.9	1388.5
11	1838.1	395.44	1086.2	377.38	395.44
12	268.38	1498.7	273.02	957.83	1498.7
13	976.15	2263.9	2561.6	922.93	2263.9
14	88.829	837.58	256.92	314.77	837.58
15	1587.5	737.19	1231.6	1345	737.19
16	907.77	1218	190.66	605.83	1218
17	1573.3	272.31	363.81	819.65	272.31
18	1797	1848.8	9042.6	2059.8	1848.8
19	732.43	863.13	5.56×10 ²	817.87	863.13
20	771.34	2019.4	1619.5	1047.6	2019.4

VI. CONCLUSION

In this paper, the age evaluation framework of transformer insulation oil by a new intelligent method was introduced. For that, different parameters linked with BDV, moisture, resistivity, tan delta, IFT, and flash point was provided as an input to forecast the age of insulation oil. This information was gathered by 20 working power transformers operated under different substations in Punjab, India. The gathered parameters were given to machine learning algorithm named as ANN for age assessment using hybrid training algorithm called PS-CSA. The results have shown that the RMSE of the developed PS-CSA-ANN was 49.6% better than LM-ANN, 15.3% better than FF-ANN, and 26.9% better than CSA-ANN at learning percentage 25, 56.9% superior to LM-ANN, 21.2% superior to FF-ANN, and 21% superior to CSA-ANN at learning percentage 50, as well as 46% improved than LM-ANN, 23% improved than FF-ANN, and 7.3% improved than CSA-ANN at learning percentage 75. Finally, from the results, it has been proved that the implemented PS-CSO was effective training algorithm for ANN to reduce the error difference among the actual and the predicted aging output of power transformer insulation oil.



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