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Artificial Neural-Network Architecture for Enhancing Power Transformers Security

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Abstract: As Artificial Intelligence (AI) advances, it promises to transform power transformer security. Machine learning, neural networks, and predictive analytics are driving this change. AI can help with predictive maintenance, fault diagnosis, real-time monitoring, and adaptive control systems. The goal is to make power grids more reliable and resilient. The use of AI in transformer security is increasing. The evolution of power system protection has been remarkable, shifting from fuses and electromechanical devices to advanced computer-based systems. These modern, expert-based solutions have proven to be the most effective and often necessary approach to addressing emerging protection challenges. This work explores the potential of AI in power transformer security by means of various architectures using different Artificial Neural Networks (ANN) architectures and its impact on power infrastructure.

Keywords: *Artificial Neural Networks, Differential protection, Power Transformers, Particle-Swarm-Optimization, Wavelet Neural Networks*

1. Introduction

In an age of swift technological progress, the integration of Artificial Intelligence stands out as a game-changing influence in strengthening the protective measures surrounding the power transformers. This vital element of electrical infrastructure requires robust safeguards and dependability to ensure continuous energy transmission and distribution in the network. Artificial Intelligence, equipped with its capacity to analyze extensive datasets, comprehend intricate patterns, and make instantaneous decisions, provides a promising opportunity for improving the security of power transformers. The implementation of AI technologies in this field has the potential to transform traditional approaches to predictive maintenance, fault detection, and real-time monitoring. This introduction aims to delve into the various implications, challenges, and potential advancements associated with employing AI to enhance power transformer security, recognizing the opportunities and complexities introduced by this integration in the electrical infrastructure domain. With the expanding role of AI in power systems, gaining an understanding of its consequences becomes essential for effectively harnessing its capabilities, while also addressing the potential challenges along with the ethical considerations taken into account.

The operational and maintenance phase constitutes the predominant portion, ranging from 70%-80%, of total costing associated with a resources asset throughout its life cycle [[1], [2], [3]]. A study conducted in 2018 by the NIST-National Institute of Standards and Technology highlighting the overall expenditure on operations and maintenance in the United States of America amounted to $50 billion every year [4].

2. Literature Review

In the field of Artificial Intelligence (AI), a network of neurons is employed to transform a set of inputs into an output. Each neuron operates similarly to a processor, generating a single power based on its input [5]. The arrangement and connectivity patterns of these neurons can be harnessed to construct computers addressing the real-world problems in the model recognition as well as pattern categorization, mimicking the process of human brain. The input signals undergoes mathematical operations by means of artificial neurons, replicating the cognitive processes of the human brain. The neural-network NN are structured with neurons organized in different layers and interconnected to facilitate the flow of information from input to output[6]. An activation function is utilized in each neuron of layer 'i', connecting it to the 'i+1' layer of neurons. The input signals to a particular neuron is derived from all the neurons in the preceding layer, and their excitation power is adjusted to controlling the extent of the signal reaching each neuron[7]. Artificial Neural Networks (ANNs) find different applications in scientific disciplines such as medical diagnostics, voice-recognition, and pattern recognition. ANNs are computing systems inspired by biological neural networks, featuring interconnected nodes(artificial neurons) organized in layers akin to human

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or animal brains. The signal—typically the real values—is sent by these artificial neurons through their connections, or synapses, and the result constitutes an output which is computed using the original input and taking into account the weights provided by each neuron [8]. ANNs, which are widely used as data-mining tools, are particularly good at modeling independent features with dependent functions that have non-linear forms. ANNs mimic the process of learning of the human brain by training with a comparable sample to predict future values of dependent variables [9]. The activation of neurons and the way in which signals are transmitted to other neurons are affected by variations in signal strength, as Fig. 1 shows. The neural-network architecture comprises three main layers:

1. Input layer—distributes input units without processing the data.

2. Hidden layer(s)—providing the capabilities mapping the non-linear problems.

3. Output layer—output units encoding the values assigning to the specific instance.

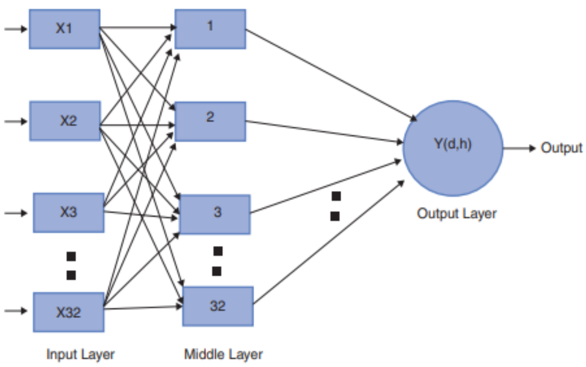

Fig-1.1: Artificial Neural-network

1.1 Power Transformer Security Challenges

Securing power transformers is critical due to their pivotal role in electrical infrastructure, serving as the backbone for power transmission and distribution networks. Despite their importance, power transformers face various security challenges that can jeopardize their reliability, performance, and the overall stability of the electrical grid. A comprehensive understanding of these challenges is essential for implementing effective protective measures. Security concerns for power transformers encompass a diverse range of issues, including physical vulnerabilities, cyber threats, aging infrastructure, operational risks, and environmental factors. Physical security risks involve the susceptibility of transformers to vandalism, natural disasters, or accidents, leading to potential physical damage and subsequent power disruptions. In the digital era, cyber threats have become significant, posing risks such as cyber attacks on control systems, remote access, and communication networks of power transformers, potentially resulting in data breaches, system manipulations, or sabotage[10].

Aging infrastructure introduces its own challenges, as older transformers are more prone to failures due to wear and tear, necessitating rigorous maintenance and modernization efforts. Operational risks involve issues like overloading, overheating, or insulation failures, which can cause performance degradation or catastrophic failures. Environmental factors, including temperature variations, humidity, and contaminants, also impact transformer performance, underscoring the need for enhanced protection measures [11].

Addressing these multifaceted challenges requires a comprehensive understanding of potential vulnerabilities and the adoption of proactive security measures for ensuring the reliability as well as resilience of power transformers within the broader electrical grid. This introduction aims to explore the intricate landscape of power transformer security challenges, delving into each aspect in detail to highlight the significance and complexity of fortifying these essential elements of the power grid.

1.2. Revolutionary Approach for Transformer Security

Artificial Intelligence (AI) emerges as a revolutionary force poised to revolutionize transformer security in the power sector. By simulating intelligent behavior and learning from data, AI introduces a new and innovative paradigms enhancing protection mechanisms for power transformers. Detection and fault isolation on time, rapidly and efficiently ensuring the stable power flow in the grid[12]. These components, crucial in electrical grids, efficiently transmit and distribute electricity. However, traditional approaches to ensuring their reliability and security often lack adaptability and agility. The advent of Artificial Intelligence, machine learning, neural networks, predictive analytics, marks a profound shift in fortifying these essential assets. The integration of AI technologies into transformer security holds the promise of elevating the field by enabling predictive maintenance, fault diagnosis, real-time monitoring, and adaptive control systems. This introduction seeks to explore the transformative potential of AI in this domain, analyzing its applications, benefits, challenges, and the broader impact on the reliability and resilience of electrical infrastructures. As the power sector increasingly adopts AI-powered solutions, understanding its capabilities in revolutionizing transformer security is fundamental for comprehending the implications and opportunities presented by this groundbreaking technological advancement.

1.3. AI in Predictive Maintenance for Power Transformers

The rise of AI signifies a new era in the realm of predictive maintenance for power transformers, reshaping traditional approaches and providing a paradigm shift in guaranteeing the reliability, durability, and efficiency of vital electrical infrastructure. Power transformers take part in a crucial role in electrical networks, enabling the transmission, distribution of electricity. Despite their significance, these assets are susceptible to failures that can lead to significant financial losses, power outages, and safety hazards. Predictive maintenance, focused on identifying potential issues before they escalate, is essential in mitigating these risks.

This introduction delves into the transformative impact of AI on predictive maintenance for power transformers. AI, particularly through machine learning, neural networks, and data analytics, empowers predictive maintenance systems to process vast amounts of historical and real-time data, recognize patterns, and predict potential faults or performance degradation. AI-based systems utilize algorithms that learn from data trends and patterns, enhancing their ability to accurately predict potential issues in power transformers and enabling proactive maintenance actions. Moreover, AI facilitates a departure from traditional calendar-based or usage-based maintenance to a more precise and efficient condition-based approach. This AI-driven approach assists in prioritizing maintenance tasks, reducing downtime, optimizing operational costs, and ensuring the longevity of power transformers. The application of AI in predictive maintenance for power transformers signifies a fundamental shift towards a more proactive, precise, and cost-effective strategy in ensuring the reliability and efficiency of critical electrical assets, a complete inspection of the advancements, challenges, real-world implementations, and future prospects of AI in predictive maintenance for power transformers will be explored, shedding light on its transformative potential within the domain of electrical infrastructure maintenance and reliability[13].

1.4 Applications of Neural-network Approaches for Transformer Current Differential Protection

The following transformer operating situations are the primary causes of mal-operation for transformer differential relays:

- Magnetizing in-rush current
- Over-excitation of the core
- Current Transformer CT-saturation

Recent advancements in power systems, such as their increased scale and complexity, have resulted in a rise in the second harmonic component of fault current. As a result, a special plan must be developed to avoid relay blockage when a transformer really has an internal defect and to prevent relay malfunction when a transformer is in another operational condition that necessitates the relay not working [14–16]. This works deals with new neural network-based techniques. When wavelet transforms and neural networks are integrated, the signal is effectively characterized by wavelets, that divide the time domain into longer duration intervals at lower frequencies and shorter periods of time at higher frequencies.

1.5 Problem Formulation and Objectives

A power transformer protection relay's functions include stopping tripping whilst the power transformer is in a normal operational state and swiftly starting tripping when it is malfunctioning. In today's power systems, distinguishing between magnetizing inrush-current and Internal-fault becomes quite challenging[17]. This is because of the fact that inrush-current magnetization-induced unexpected excursions are frequently avoided by a second harmonic component in power transformers by blocking differential relays. However, internal defects also result in the production of the second harmonic element. Developing a precise system to distinguish between various conditions of operation is also essential, particularly between Internal-fault and magnetizing inrush current. This part so provides novel neural network-based methods for categorizing transient events in power transformers such as digital transformer differential protection.

1.6 Stage 1:

This is the point, when internal current and inrush are separated. The required current signals are acquired by means of the mathematical model. This technology, depending on the residual flux values selected and the angle at which the voltage is switched on, develops and simulates a range of simulated alternate inrush as well as internal current waveforms for diverse power transformers. After that, an analysis and display of the simulated results for the same scheme using ANN and WNN are produced.

1.7 Stage 2:

This is where the discrimination between different operating circumstances is done. The required current signals are generated using the SIMULINK-model. Using the Back-Propagation approach, multilayered feed-forward-neural-networks (ANN) are first trained to distinguish between various operating conditions. Next, the Particle-Swarm-Optimization(PSO) method is deployed for training the same multilayered feed-forward-neural-networks to distinguish between the different operating conditions.

1.8 Stage 3:

During this phase, the simulated signals are generated for discrimination using the SIMULINK-model are carried over from the previous step. To accomplish distinguishing, a NN and the wavelet-transform were combined along with Back-Propagation technique. Finally, the same architectures were trained using the PSO approach, which combined neural networks (WNNs) with wavelet transformations.

The wavelet-transform is used in the WNN approach to first divide the power transformer system's Differential-Current Signals over the number of wavelet-components, each of it covering a certain frequency range. Consequently, the temporal domain as well as frequency-domain properties of the transitory signals are recovered. Next, Internal-faults are distinguished from all other power transformer operating-conditions using a neural network. Wavelet transformations provided the properties that were given into these artificial neural-network designs (ANNs).

The intended system has been implemented using the two different ANN-Architectures. The first is employed as an Internal-fault-Detector(IFD), and another is CM detecting and differentiates between different working circumstances including normal condition, inrush current, over-excitation condition, and CT-Saturation induced by external faults. These two ANNs are first trained using the BPN and PSO methodologies, and the obtained results are then compared(Stage of Parents). The PSO and Back-Propagation algorithms are then used to develop and assess a novel approach based on combining neural networks and WNN-transformations (Third Stage).The simulation's results are shown and compared to previous cases.

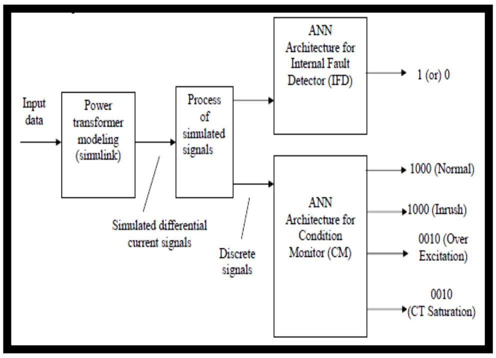

Fig 1.2. Block Diagram of the suggested plan

The wavelet-transform is used in the WNN approach to first divide the power transformer system's, Differential-Current Signals into a number of wavelet-components, everyone covering a range of certain frequencies. Consequently, the temporal-domain and frequency-domain properties of the transitory signals are recovered. Next, Internal-faults are distinguished from all other power transformer operating-conditions using a neural network. Wavelet transformations provided the properties that were given into these artificial neural-network designs (ANNs). Figure depicts the essential architectural element of the recommended design

1.9 Stage-1: Development of Protection scheme using Mathematical model

Discrimination among inrush and Internal-fault current signals is accomplished using this recommended protection mechanism using equation-1 and equation-2 [16, 23].

Inrush current

$$I\,(t) = 4.949 * \sin\,(314 + (\alpha - \Phi)) - 0.954\exp(-18.85(t)) * \sin(\alpha - \Phi - 0.189)$$ **Equation-(1)**

Internal-fault

$$I(t) = \left(\frac{1}{Z}\right) e\left(-\frac{R}{L}\right) * t\,\{\sin(314 + \alpha - \Phi)\} - e\big((-314t + \alpha_s) * R\big) * \sin\,(\alpha_s + \alpha - \Phi)$$ **Equation-(2)**

Where α- switching angle at which the transformer input voltage is switched on.

α_s represents saturation angle

Φ represents $\tan^{-1}$ (X/R)

X represents Reactance of transformer primary winding

R represents Resistance of transformer primary winding

By adjusting the impedance of the transformer's main winding, the residual flux of the core, and the point during which the transformer is switched ON, one can generate many sets of internal and inrush simulated current signals using equations (1) and (2). The simulated current signals—both the inrush and internal fault—are transformed into a set of wavelet coefficients using wavelet-transformations. The DB2 filter and resolution level 2 are used with the Dabuchies Wavelet to provide an approximation and detailed coefficients for decomposition.

Table 1.1. Parameters of ANN structural design

Parameters	Number of Neurons		
	ANN-1	ANN-2	ANN-3
Inputs to the ANN	6	6	9
Output to the ANN	2	2	2

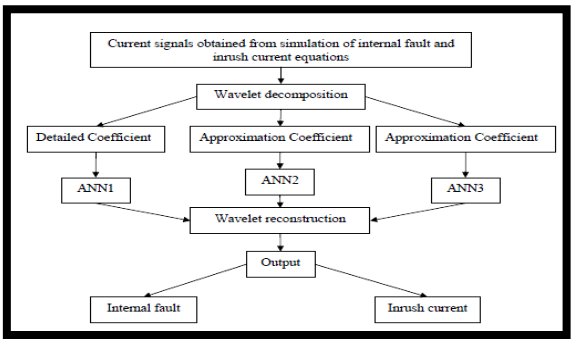

Fig 1.3. Flow diagram for the designed neural-network and wavelet-transform integrated power transformer protection scheme

1.10 ANN Architectural Design

Selecting the appropriate number of neurons for each hidden layer and determining the overall number of hidden layers is a critical decision in the development of an artificial neural network (NN). In this study, a multi-layered feed-forward Back-Propagation Neural Network (BPNN) was employed to distinguish between internal faults and inrush currents using approximations and detailed coefficients. The input data consisted of 16 samples, representing four transformers with eight sets of inrush and internal-fault current signals. The NN output was designed to assign a value of 0 for inrush currents and 1 for internal faults. The experiment utilized 6 and 21 wavelet coefficients for the target and simulated output current signals, respectively, resulting in 21 inputs and 6 targets. Three NN topologies were created, varying the number of neurons in a single hidden layer from 4 to 32 through numerous tests. After thorough testing, it was concluded that a single hidden layer with 32 neurons produced the best results. Training the NN architecture involved using data from eight different transformers and implementing the Back-Propagation approach with a sigmoid activation function. The momentum factor employed during training was set at 0.85.

1.11 Results and analysis

The simulation results generated using just neural networks (ANNs) are shown in An ideal result with a 99% accuracy rate is found after 1129 iterations. Pre-specified as 0.01 is the mistake. provides the simulated results of the recommended protection system utilizing a neural-network (WNN) and linked wavelet transform. The results indicate that an optimal solution with a 99% accuracy rate is reached after 36 repetitions. The error has been assigned a preset value of 0.01.

The performance comparison of the recommended protection strategy using ANN and WNN methods is shown in It is clear from that a protection strategy based on WNNs outperforms one that just employs ANNs.

Table 1.2. Simulation results using Neural Network(ANN) alone

Transformer ratings with parameters	Condition	ANN architecture	Output				Error %	Accuracy %
			Train		Test			
			T	A	T	A		
63 KVA, 11KV/433V R=4.0783 L=0.01298	Inrush	16-32-1	0	0.0069	0	0.0069	0.0069	99.31
	Internal	16-32-1	1	0.9901	1	0.9876	0.0099	99.01
800KVA 11KV/433V R=4.194 L=0.01335	Inrush	16-32-1	0	0.0070	0	0.0036	0.0070	99.3
	Internal	16-32-1	1	0.9905	1	0.9876	0.0095	99.05
100KVA 11KV/433V R=4.698 L=0.01495	Inrush	16-32-1	0	0.0077	0	0.0045	0.0077	99.23
	Internal	16-32-1	1	0.9901	1	0.9905	0.0099	99.01
1250KVA, 11KV/433V R=5.563 L=0.0177	Inrush	16-32-1	0	0.0159	0	0.0012	0.0159	98.41
	Internal	16-32-1	1	0.9901	1	0.9923	0.0099	99.01

Table 1.3. Simulation results using the combined wavelet transforms & Neural Network(WNN)

Transformer ratings with parameters	Condition	ANN architecture	Output				Error %	Accuracy %
			Train		Test			
			T	A	T	A		
63 KVA, 11KV/433V R=4.0783 L=0.01298	Inrush	16-32-1	0	0.0162	0	0.0134	0.0162	98.38
	Internal	16-32-1	1	1.0012	1	1.0002	0.0012	99.88
800KVA 11KV/433V R=4.194 L=0.01335	Inrush	16-32-1	0	0.0161	0	0.0003	0.0161	98.39
	Internal	16-32-1	1	1.0001	1	0.9976	0.0001	99.99
100KVA 11KV/433V R=4.698 L=0.01495	Inrush	16-32-1	0	0.0150	0	0.0005	0.0150	98.52
	Internal	16-32-1	1	1.0006	1	1.0005	0.0006	99.94
1250KVA, 11KV/433V R=5.563 L=0.0177	Inrush	16-32-1	0	0.0107	0	0.0002	0.0107	98.93
	Internal	16-32-1	1	0.9999	1	0.9983	0.0001	99.99

A-Actual, T-Target

Table 1. 4. Performance Comparison of WNN and ANN

Parameters	Wavelets & neural network	Neural Network
Error	0.01(Pre specified)	0.01(Pre specified)
No of Iterations	36	1129
Time taken for convergence	1.5Sec	30Sec
Accuracy	99%	99%

1.12 SIMULINK-model for power transformer modeling in stages two and three.

An appropriate transformer representation is necessary to explain the diverse power transformers operating-conditions often known as a functional approximator, which describes the terminal behavior of the power transformers in different conditions. This sort of transformers are simulated by means of SIMULINK. This representation makes it possible to simulate mistakes and other disturbing factors that can directs to a breakdown in power protection system.

1.13 Operating-conditions taken into account are:

1) Normal Condition.

2) Magnetizing inrush-current, As a result of transformer energy.

3) Over-excitation condition.

4) CT-Saturation, Due to the external faults.

5) Internal-fault

For 20-power transformers with different ratings running under the aforesaid operating conditions, the simulated waveforms were obtained and used for the suggested procedure. The obtained simulated waveform for a 16-MVA, 110/33-KV power transformers operating-conditions as discussed under various circumstances, for instance, as in Figure (a), (b), (c), (d) and (e).

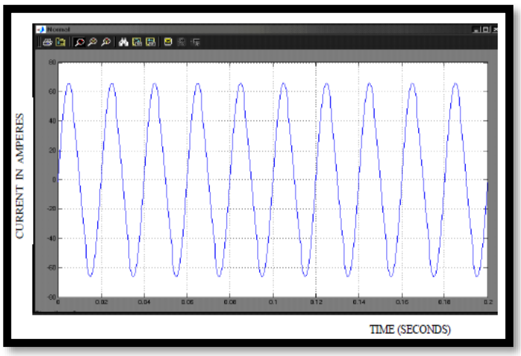

Fig 1.3. (a). Operating under Normal Condition

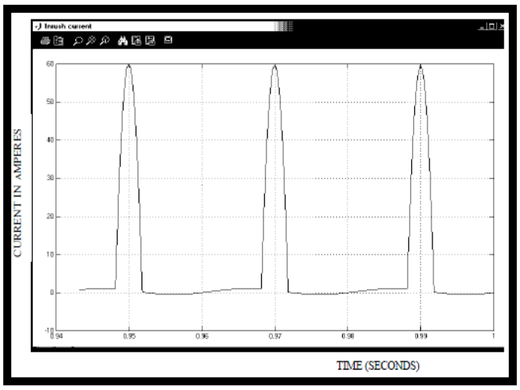

Fig 1.4. (b) Operating under Inrush Current

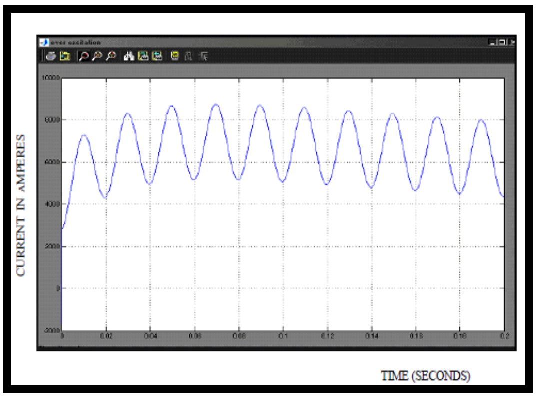

Fig 1.5 (c) Operating under Over-excitation condition

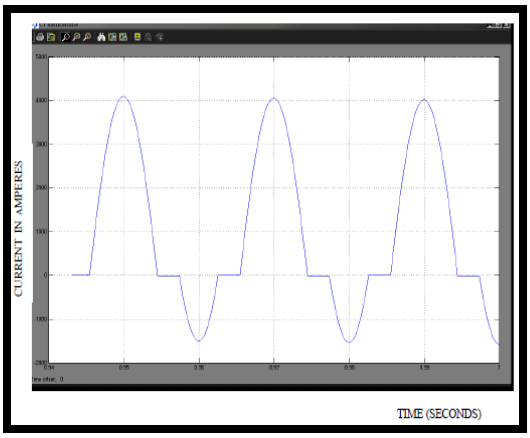

Fig 1.6 (d) Operating under CT-Saturation

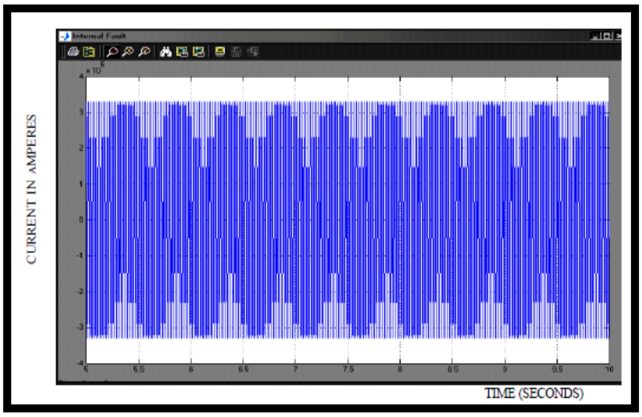

Fig 1.7. (e) Internal-Fault Condition

1.14 Second stage: ANN development of Models for a Protection Strategy

This suggested approach employs MLFFNN. This sort of learning process is supervised. PSO methodology and the Back-Propagation method are the learning paradigms that are employed. Bounded and differentiable activation functions are necessary for both PSO and BP training procedures. Consequently, sigmoid function has been used.

1.15 Data which is used for the Training and Testing.

Matlab-based training programme was developed to identify the power transformer's various operational conditions. The SIMULINK-model generates a 100-sets of samples, 80-set to be trained and 20-set for testing and evaluation, of the simulated differential output current signals with five distinct operating states of 20-different power transformers. We gather a total of 20-sets of samples for every working situation. The simulated differential output current signals are discretized to yield 100- training sets of samples using the FFT block. By reducing the number of neural-network processing units, this signal processing reduces the amount of time needed for neural-network testing and training. Achieving high performance discrimination is aided by it. A total of sixteen samples are taken of these signals every cycle, a tabulation of the aforementioned discrete sample data that were collected using various power transformer ratings in various operational situations. For every operational stage, the sixteen numbers of sampled data are sent into the ANN designs. The network is trained to provide a binary output indicating whether the observed differential-current is normal condition, inrush, over-excitation condition, CT-Saturation condition, or an internal-fault conditions as a result of constructing of the learned matrices.

1.16 Designing and developing Condition Monitor (CM-ANN) and Internal Fault Detector IFD architectures.

Power transformers may be identified and categorized by ANN architecture, which allows for using supply as a trip-signal upon issue detection. The proposed solution takes into account two different designs. To find internal power transformer problems and keep an eye on other operating-conditions that might cause a differential relay to malfunction, two alternative designs are used.

16-samples of the power transformer's output current signals corresponded to the set of inputs which were used. The total number of neurons in a single hidden layer may range starting 4 to 32; 32-neurons provides the greatest outcomes. Gradually, the number of neurons in the hidden-layer rises to 64. However, as the number of neurons in the hidden-layer increases, the system obtains more complex, which does not significantly improve the outcomes. To obtain the highest level of accuracy, several alternative architectures are tried before settling on the final design, for example, the outcomes of training and testing three distinct CM structures (16-8-4, 16-16-4, and 16-32-4) and three distinct IFD designs (16-8-1, 16-16-1, and 16-32-1). The configuration with one output and one hidden-layer of 32-neurons is found to be delivering the best results for IFD after extensive testing. Moreover, the hidden-layer architecture with four outputs and 32-neurons yields the best outcome for CM state. At the last stage, the architecture with 1-output layer (16-32-1) and a single output, 1-hidden-layer (32-neurons), and 1-input layer (16-neurons) is selected for IFD in the model. Four output layers (16-32-4), 1-hidden-layer amid 32-neurons, and 1-input layer amid 16-neurons make up the architecture utilized for CM. Each architecture is trained over five thousand iterations. The momentum factor stays at 0.8 for the during this period of work. The NN is trained by means of BP, and PSO algorithms, giving simulated outcomes as shown. There is just one output in the internal failure detection (IFD) architecture, and it may be either '1' or '0'. In this case, a value of '0' denotes an external fault, while a value of '1' denotes anyone of mentioned non-internal-fault states (i.e., normal condition, inrush condition, over-excitation condition, and CT-Saturation condition). Four outputs make up the architecture (CM) that is used to keep an eye on the various power transformers operating characteristics. The network produces a distinct set of outputs, as seen below.

'1000'-Under Normal Condition.

0100'-During Inrush.

'0010'-Over-excitation condition.

'0001'-CT-Saturation Condition.

1.17 Utilizing PSO and BP algorithms for training and testing.

In order to simply, adjust the error during the iteration phases, the Back-Propagation Algorithm (BP algorithm) basically leverages the sensitivity (gradient) of the error with regard to the weights. By connecting the input training patterns to the output training patterns through successive solutions to a linear set of equations, the paradigm generates an ideal non-linear mapping. The least squares method served as the foundation for the development of this algorithm. The error function E at the nth iteration of an output layer with "k" perceptrons is K.

$$\mathbf{E(n)} = \left(\frac{\mathbf{1}}{\mathbf{2}}\right) * \sum_{\mathbf{i=1}}^{\mathbf{k}} \quad \{\mathbf{Ti - O * i(n)}\} \qquad \mathbf{(3)}$$

where 'T' and 'O' are target, and the actual pattern respectively.

The BP methodology is first used to train the ANN structures that have been built using this method. Stated differently, the weights of neurons are changed using the error Back-Propagation technique.

1.18 PSO algorithm

PSO begins through the collection of random-particles, and iterate to explores through generations in search of optimal solution. Each iteration updates apiece particle with the two "best" values, 'pbest' and 'gbest'. The particle updates its locations as well as velocity using the relevant equations [(3) and (4)] after determining the two optimum values. The chosen inertia weight value in this method is 0.9. Both 'c1' and 'c2' values be assumed to be 1.8. The objective function (i.e. fitness function) is

$$\mathbf{f = \sum\sqrt{\ } \{[target]–[actual\ output]\}^2} \qquad \mathbf{(4)}$$

Equation-4 is used to determine the Mean Squared Error achieved during ANN training in order to estimate each particle's fitness function. The ANN weights are then updated in accordance with the particle's variables. The fitness functions of every particle in the population are defined in a similar way. The particle with the lowest fitness function is the best one, and a predefined accuracy level is used to compare its fitness function. After the required accuracy is obtained, the training comes to a conclusion. If not, the new location and velocity of the particles are updated using equations (3) and (4). The process is continued until the required precision is reached.

In this study, the set of weights is modified using the PSO approach because the weight modification of neurons is dynamic and non-linear. The location and velocity of the particles are varied to get the optimal weight value that will meet a predefined mean squared error. The initial population extent of 20-particles are selected. Each particles in the population are slowly brought closer to the global minimum as the system iterates. When the pre-specified error condition is satisfied, the iterations come to a conclusion, and the collection of these optimized weights are done and employed as suggested in design. The flowcharts represents the PSO and BP algorithm implementations that are employed to train as well as evaluate the proposed ANN architectures. Thus, an artificial neural-network (ANN) trained with the BP and PSO algorithms distinguishes between different power transformer operating-conditions by means of the waveforms received for real power transformers, then the results are further analyzed.

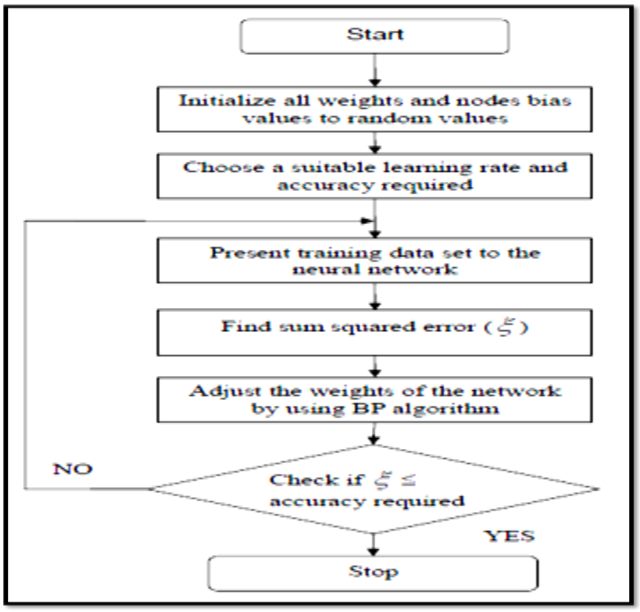

Fig 1.8. ANN Training and Testing Flow Chart using the BP Algorithm

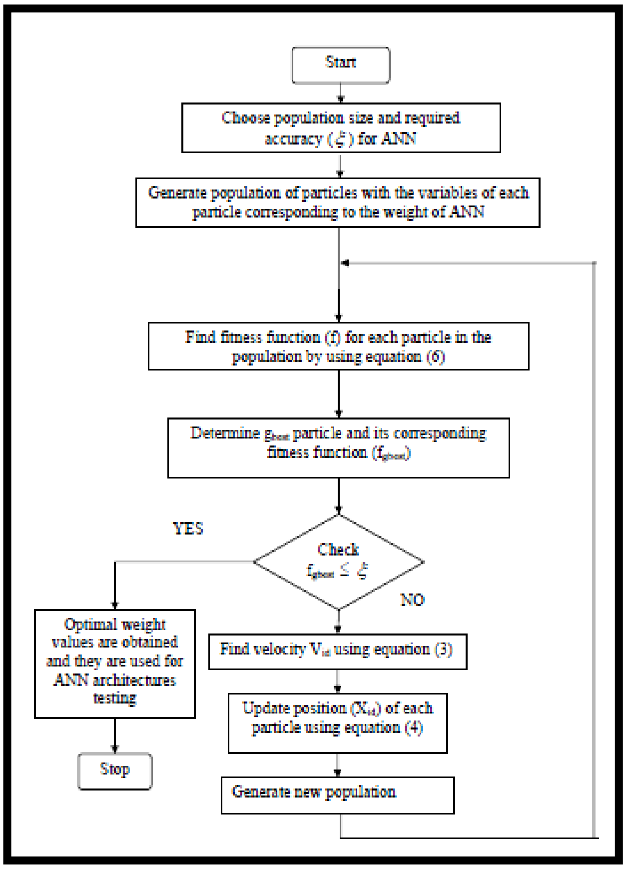

Fig 1.9- ANN training and testing flow chart using the PSO algorithm

1.19. Results and Analysis

The results obtained provides the comprehensive simulated outcome for BPN training of IFD and CM designs. It also gives the comprehensive simulated results for PSO training of IFD and CM designs. Following sufficient training, the ANN model was evaluated by means of BP-algorithm and PSO-algorithms on every conceivable data set for various power transformer operating circumstances. To see whether the matching indication was provided, the network was examined. In the event of an internal problem, IFD sends out a trip signal. A 4-output network is used to monitor the condition of the power transformer in case of internal problem does not arise.

The Mean-Average-Error during BP algorithm training is 0.009225 for IFD and 0.036575 for CM. It demonstrates that the Mean-Average-Error is lesser in IFD for similar number of repetitions because the ANN design of IFD is structurally simpler than CM. Nevertheless, the error obtained decreases to the order of 10–15 in both the IFD structure and CM structures when the same architectures are trained using the PSO algorithm method. This suggests that the weight modifications are improved utilizing optimum values when the ANN is trained using the PSO technique. The PSO-trained NN therefore presents an 100% of accuracy.

The findings of the performance comparisons between the training of the PSO algorithm and BP algorithms demonstrate that PSO training yields better results, when compared to the two scenarios. The BP approach turned out to take about 90-seconds to simulate the IFD and 120-seconds to simulate the CM. The mean average values of testing and training error for the IFD and CM designs were, respectively, 0.001623 and 0.00325 following the networks' training via the BP approach. On the other hand, training the same designs with the PSO technique improved the accuracy, i.e., decreased error to 10-15. Furthermore, 100% accuracy was reached in just 520-epochs. Furthermore, the PSO training simulation period was reduced to 4-seconds.

Table 1.5. BP Algorithm-Based Internal-Fault Detector

Operating Conditions	ANN Architecture	Output for the training of developed ANN Architectures			Output for the testing of developed ANN Architectures		
		A	T	Error	A	T	Error
Normal	16-8-1	0.0000	0	0	0.0000	0	0
	16-16-1	0.0000	0	0	0.0000	0	0
	16-32-1	0.0000	0	0	0.0002	0	-.0002
Inrush	16-8-1	0.0038	0	-.0038	0.0022	0	-.0022
	16-16-1	0.0036	0	-.0036	0.0031	0	-.0031
	16-32-1	0.0038	0	-0.0038	0.0034	0	-.0034
Over Excitation	16-8-1	0.0003	0	-0.0003	0.0001	0	-.0001
	16-16-1	0.0002	0	-0.0002	0.0016	0	-.0016
	16-32-1	0.0002	0	-0.0002	0.0013	0	-.0013
CT Saturation	16-8-1	0.0183	0	-0.0183	0.0176	0	-.0176
	16-16-1	0.0157	0	-0.0157	0.0144	0	-.0157
	16-32-1	0.0154	0	-0.0154	0.0123	0	-.0154
Internal Fault	16-8-1	0.9813	1	-0.0187	0.9811	1	-.0189
	16-16-1	0.9842	1	-0.0158	0.9841	1	-.0159
	16-32-1	0.9843	1	-0.0157	0.9847	1	-0.0153

Table 1.6. Condition Monitor using BP Algorithm

Operating Conditions	ANN Architecture	Output during training and testing of ANN architectures								
		* 1		** 2		*** 3		**** 4		Error
		A	T	A	T	A	T	A	T	
Normal	16-8-4	0.9681	1	0.0071	0	0.0183	0	0.0262	0	0.0457
	16-16-4	0.9884	1	0.0109	0	0.0077	0	0.0000	0	0.0238
	16-32-4	0.9914	1	0.0069	0	0.0039	0	0.0022	0	0.0111
Inrush	16-8-4	0.0046	0	0.9647	1	0.0042	0	0.0251	0	0.0931
	16-16-4	0.0122	0	0.9652	1	0.0018	0	0.0188	0	0.0414
	16-32-4	0.0094	0	0.9782	1	0.0044	0	0.0180	0	0.0301
Over Excitation	16-8-4	0.0137	0	0.0012	0	0.9752	1	0.0226	0	0.0362
	16-16-4	0.0049	0	0.0020	0	0.9876	1	0.0012	0	0.0135
	16-32-4	0.0043	0	0.0037	0	0.9910	1	0.0014	0	0.0107
CT Saturation	16-8-4	0.0301	0	0.0352	0	0.0143	0	0.9519	1	0.0682
	16-16-4	0.0012	0	0.0210	0	0.0018	0	0.9707	1	0.0361
	16-32-4	0.0022	0	0.0190	0	0.0043	0	0.9781	1	0.0290

1*, 2**, 3***, 4****-- The corresponding outputs of the 1st, 2nd, 3rd, and 4th outputted neurons are in the following sequence, '1000' for the normal Condition, '0100' for inrush, '0010'-for over-excitation condition, and '0001' for CT-saturation condition.

Table 1.7. Detector of Internal-Faults Using PSO Algorithm

Operating Conditions	ANN Architecture	Output for the training of developed ANN Architectures			Output for the testing of developed ANN Architectures		
		A	T	Error	A	T	Error
Normal	16-8-1	0.0000	0	0	0.0000	0	0
	16-16-1	0.0000	0	0	0.0000	0	0
	16-32-1	0.0000	0	0	0.0000	0	0
Inrush	16-8-1	0.0000	0	0	0.0000	0	0
	16-16-1	0.0000	0	0	0.0000	0	0
	16-32-1	0.0000	0	0	0.0000	0	0
Over Excitation	16-8-1	0.0000	0	0	0.0000	0	0
	16-16-1	0.0000	0	0	0.0000	0	0
	16-32-1	0.0000	0	0	0.0000	0	0
CT Saturation	16-8-1	0.0000	0	0	0.0000	0	0
	16-16-1	0.0000	0	0	0.0000	0	0
	16-32-1	0.0000	0	0	0.0000	0	0
Internal Fault	16-8-1	1.0000	1	0	1.0000	1	0
	16-16-1	1.0000	1	0	1.0000	1	0
	16-32-1	1.0000	1	0	.0000	1	0

Table 1.8. Condition Monitor using PSO Algorithm

Operating Conditions	ANN Architecture	Output during training and testing of ANN architectures * ** ****								
		1		2		*** 3		4		Error
		A	T	A	T	A	T	A	T	
Normal	16-8-4	1	1	0	0	0	0	0	0	0
	16-16-4	1	1	0	0	0	0	0	0	0
	16-32-4	1	1	0	0	0	0	0	0	0
Inrush	16-8-4	0	0	1	1	0	0	0	0	0
	16-16-4	0	0	1	1	0	0	0	0	0
	16-32-4	0	0	1	1	0	0	0	0	0
Over Excitation	16-8-4	0	0	0	0	1	1	0	0	0
	16-16-4	0	0	0	0	1	1	0	0	0
	16-32-4	0	0	0	0	1	1	0	0	0
CT Saturation	16-8-4	0	0	0	0	0	0	1	1	0
	16-16-4	0	0	0	0	0	0	1	1	0
	16-32-4	0	0	0	0	0	0	1	1	0

1*, 2**, 3***, 4****-- The corresponding outputs of the 1st, 2nd, 3rd, and 4th outputted neurons are in the following sequence, '1000' for the normal Condition, '0100' for inrush, '0010'-for over-excitation condition, and '0001' for CT-saturation condition.

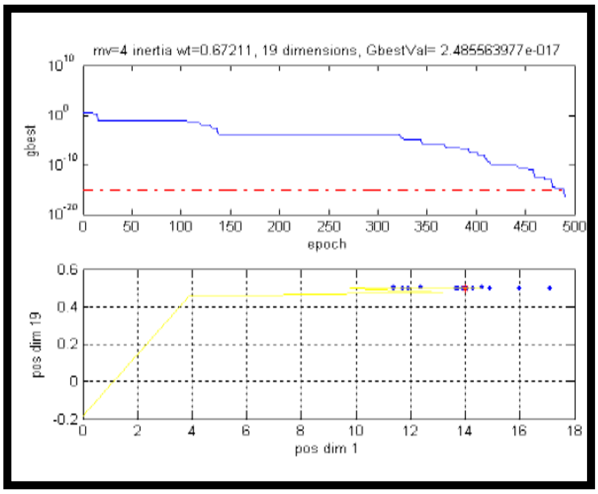

Fig 1.10. Results obtained from PSO algorithm based Training

Table 1.9. Comparison of BP and PSO training's performance

Used Parameters	**BP-Algorithm**	**PSO- Algorithm**
Convergence-Parameter	5000-iterations	520-iterations
Time taken for simulation	122-seconds	4.21-seconds
Mean-Average-Error-MAE	0.013	0.0001
Accuracy in Percentage	99%	100%

The proposed approach has 100% accuracy in differentiating between four different scenarios using the PSO algorithm. This is because the PSO technique's precise weight alteration optimization was used. The PSO scenario requires a lot fewer iterations to reach convergence than the BP instance.

The PSO trained neural-network design yields results that are both faster and more accurate in-terms of the no. of iterations necessary to attain a pre-specified error criteria as well as the simulation times, as can be seen when comparing the simulation results of the two situations. As a result, the power transformer's recommended ANN-based differential relaying provides encouraging operational speed, dependability, and security.

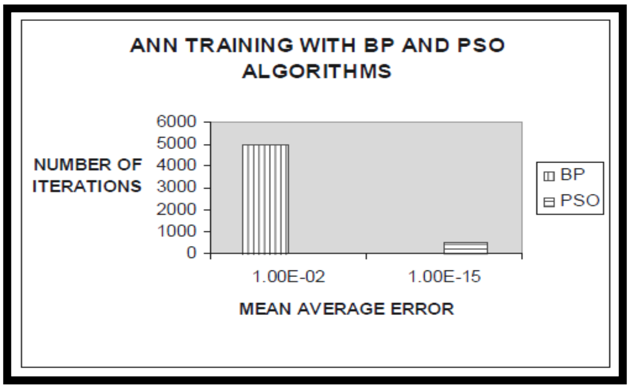

Fig 1.11 Results of ANN training using BP and PSO algorithms**.**

1.20 Third Stage: Creating a protection plan with the WNN model

Neural networks and wavelet transforms are used in the proposed approach to classify transient occurrences in power transformers. Different attributes might be extracted from differential-current waveforms utilizing the wavelet transform. To distinguish the power transformer's intrinsic problem from other operational circumstances, a neural-network may be employed. Figure 4 depicts the flow chart of the suggested procedure, which may be summed up as follows:

- Differential-Current Signals are broken down to a set of wavelet-coefficients (i.e., detailed, approximation coefficients) using the wavelet transform. The Differential-Current Signals are produced via power transformer modeling in the Simulink environment under various operating-conditions (Normal conditions, Inrush current condition, Over-excitation condition, CT-Saturation condition, and Internal-fault condition).
- The failure state is distinguished from other operational circumstances by the ANN architecture. Thus far, two different ANN-architectures have been formed.
- First design has a single output and functions as an internal-fault detector (IFD). One of the non-internal fault situations is indicated by a value of 0, but an internal fault scenario is indicated by a value of 1.
- An additional design with four outputs is called a Condition Monitor (CM).To determine if a given transient is an internal problem or represents another operational state, the output from the artificial neural-network (ANN) is reconstructed back to the original output.

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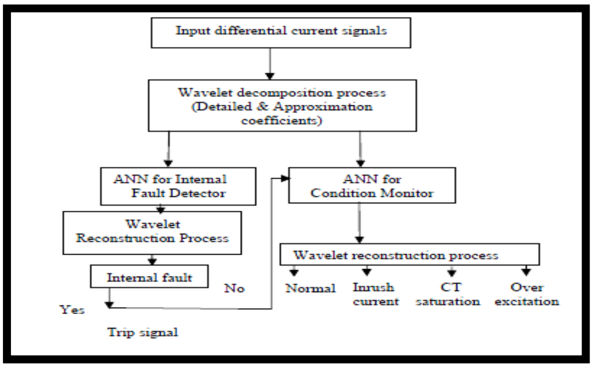

Fig 1.12. Diagram showing the planned WNN scheme's flow.

1.21 Use of Wavelet Transforms for processing of differential- current signals.

By means of Simulink, an appropriate power transformers modeling is done to account for the power transformer's various operating circumstances (Such as Normal conditions, Inrush condition, Over-excitations, CT-Saturations, and Internal-fault), as well as the simulated differential- waveforms of current that were recorded in Stage-1. The WNN model also makes advantage of these signals.

Figure 1.13. illustrates the three main stages of the suggested WNN using IFD and CM model for power transformers safety to

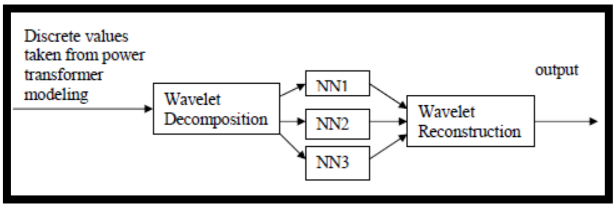

Fig 1.13 Three stages of the proposed protection model (WNN)

illustrates how wavelet approaches are used in the first and last stages. First, we break down the real discrete data from modeling power transformers under diverse operating environment into a collection of wavelet-coefficients. In order to predict the future patterns of each signal's output, the decomposed coefficients are fed into neural networks (NNs) in the second phase. The intended final output pattern is created in the last step by merging the anticipated signals once again.

1.22 Step-1-Pre-Signal Processing

Depending on the resolution level selected, the associated inputs (discrete data) are broken down into a range of wavelet-coefficients by the model's pre-signal processor, i.e., DWT. Then the decomposed coefficients are forwarded to signal predictor-NNs as training data after normalization. The decomposition technique used for this investigation is the Daubichies Wavelet as it can detect current signals with high frequency, low amplitude, brief duration, and fast fading.

For the wavelet decomposition process, the Daubichies wavelet family provides a large range of wavelet filters (DB2 to DB44). Make sure the wavelet decomposition and reconstruction stages can both eliminate aliasing effects and reconstruct the original signal after reconstruction when selecting the filters and resolution settings. It also depends on the amount of smoothness of the approximated signal at that level (i.e., after eliminating all higher frequencies). A higher resolution level would provide an approximation signal that is smoother.

1.23. Step-2-Signal-Prediction

This proposed defensive tactic uses neural networks to predict signals. The amount of wavelet-coefficient signals at the pre-processor's output dictates how many neural networks are required for the model. One NN is needed to produce the accurate forecast for each wavelet- coefficient signal, including the approximated one.

1.24. Step-3: Post Signal-Processing

The resolution level and wavelet technique (DWT) employed in step-1 are selected for the wavelet-reconstruction in post-processing yielding final anticipated output is created at this stage by combining different outputs of the signal predictors-NNs. In order to do this, the outputs are joined back together. In order to sample the simulated Differential-Current Signals into discrete values under various operating situations, this work uses power transformer modeling. 16-samples are selected for each cycle as the sampling rate. After being converted into wavelet coefficients, these discrete data are fed into neural networks as input variables. For the decomposition procedure, the Daubichies family with DB2 filter is selected after testing and verification that the DB2 to DB44 filters can replicate the original signal following reconstruction. In this instance, 16-samples of Differential-Current Signals yield 21-wavelet-coefficients (6 for approximation and 6 and 9 for detail-1 and detail-2, respectively). In order to help the neural-network distinguish between internal faults and other operating situations, these coefficients are used during the training phase.

1.25 IFD and CM-ANN architectures

Back-Propagation approach by supervised multilayered FFNN (feed-forward-neural-network) which is one of the popular choice used for classification jobs. Thus, in relation to the proposed protective paradigm. In this work, two different ANN designs have been analyzed. One of the two outputs from a single Internal issue Detector(IFD) design is either 1(indicating an internal issue) or 0 (representing a non-Internal-fault conditions). An alternative design such as the CM having 4-outputs: '0100'-over-excitation condition, '0010'-inrush current, and '000'- normal condition. Six samples—two for detailed and two for approximation—are used to estimate the data, and the input—simulated differential-current signals—is divided into wavelet-coefficients. Three ANN architectural modules are built utilizing these coefficients, as shown in Table 1.10, and having the Internal-fault detector-IFD and condition monitor-CM structures listed below.

Table 1.10. Structure of Neural-network Architecture

Parameters	Number of Neurons		
	ANN- 1	ANN- 2	ANN- 3
Inputs to ANN	6	6	9
Outputs to ANN	2	2	2

The quantity of neurons in a neural network's hidden-layer determines how well it can learn new things. It's challenging to figure out how many neurons are concealed. The nearly all appropriate no. of neurons for this NN is explored and examined in order to determine the precise number of hidden-neurons needed, with enough time for testing. A large number of tests were conducted in this work using a single hidden-layer and a range of 4 to 32-neurons. After sufficient testing, it was determined that a single hidden-layer with 16-neurons produced the best outcomes for both CM and IFD.

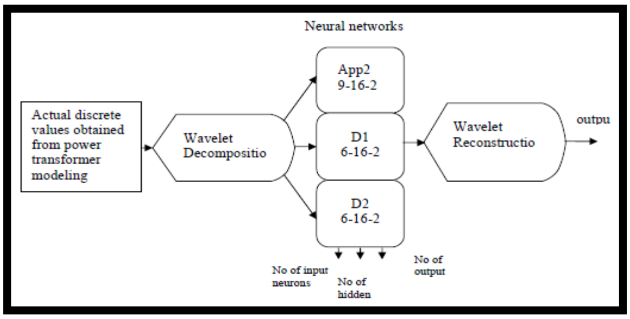

Fig 1.14 Protection Model based on Final WNN

After taking into consideration every element of design, the final joint wavelet-transform and neural-network based-WNN model for the power transformers safety is constructed. It has been observed that, the discrete values obtained by modeling power transformers were broken down into neural-network training data i.e., IFD and CM to construct wavelet-coefficients. To determine, if the observed differential-current was an internal defect, over-excitation condition, inrush current, or normal, neural-network outputs were recreated to get the original output.

1.26 Training and Learning

For the suggested protection model, the Back-Propagation method with sigmoid-activation- function will be used. The benefit of rapid calculation time for any big neural-network size is the cause of this. The selected momentum factor is 0.85. Two different ANN architectures such as IFD, and CM have been created and designed for this method. When an internal defect is found, an Internal-fault detector (IFD) triggers a trip signal. The Condition Monitor (CM) keeps an eye on the various operating states, including over-excitation condition, inrush current, and normal. Initially, the BP method is used to train both the IFD and CM ANN structures, followed by the PSO algorithm. Then, using the BP technique, the same structures are trained using a wavelet-transform and neural-network (WNN) combination. Lastly, a combined wavelet-transform and neural-network-WNN using PSO-algorithm is used to train the same architectures. As a consequence, all four scenarios are used to train the ANN designs, and the resulting simulation results are examined below.

3. Results and Analysis

We collect 40-sets of samples from 10-distinct power transformers. The four distinct operating conditions—normal conditions, inrush current conditions, over-excitation condition, and internal fault conditions are represented by these 40-pieces of data. For training neural-network based architectures on IFD, CM for each of the 4-previously outlined scenarios, these data are broken down into wavelet-coefficients. Reconstructing the original output from neural-network outputs allows one to ascertain whether the observed differential-current in normal conditions, an inrush current conditions, an over-excitation conditions, or an internal problem conditions. For example, a detailed description of the WNN simulation results for a '25-MVA', '110/33-KV' power transformers is given. The Internal-fault Detector (IFD) condition and Condition-Monitor (CM) condition of the proposed approach, which solely employ neural networks (ANNs), are displayed in and, respectively. These show that after 5000-iterations, an optimal solution with 99% accuracy is produced for both the IFD, CM designs, with an error of 0.01 for an IFD and 0.0301 for CM.

Table 1.11. Internal-fault Detector using ANN alone

Operating conditions	ANN Architecture	Output					
		Training			Testing		
		A	T	error	A	T	Error
Normal	16-16-1	0.0000	0	0.0000	0.0002	0	0.0002
Inrush current	16-16-1	0.0006	0	0.0006	0.0006	0	0.0006
Over excitation	16-16-1	0.0000	0	0.0000	0.0012	0	0.0012
Internal fault	16-16-1	1.0000	1	0.0000	0.9818	1	0.0182

Table 1.12. Condition Monitor using ANN alone

Operating condition	ANN Architecture	Output								
		1*		2**		3***		4***		Error
		A	T	A	T	A	T	A	T	
Normal	16-16-4	0.0000	0	0.0042	0	0.0003	0	0.9957	1	0.0043
Inrush Current	16-16-4	0.0000	0	0.0000	0	1.0000	1	0.0040	0	0.0000
Over excitation	16-16-4	0.0000	0	0.9997	1	0	0	0.0094	0	0.0003

A-Actual T-Target

1*, 2**, 3***, 4****--The corresponding outputs of the 1st, 2nd, 3rd, and 4th outputted neurons are in the following sequence, '1000' for the normal Condition, '0100' for inrush, '0010'-for over-excitation condition, and '0001' for CT-saturation condition.

The simulated results for both IFD and CM are shown in These results were generated by employing the BP method in conjunction with coupled wavelet transformations and neural networks (WNN). After 1500 iterations, a 99% accurate optimum solution is identified based on the data, with a $6.6*10^{-7}$ error for IFD and 0.03 for CM.

The protection system that was developed using just ANN is then trained using the PSO approach (for both IFD and CM), and the outcomes are shown in

Subsequently, a neural-network (WNN) was trained using the Combined Wavelet-transform in order to generate the protection strategy utilizing the PSO approach. Additionally included are the simulation findings in Tables 1.17 and Table 1.18.

Table 1.13. WNN-based Internal-Fault Detector-IDF

Operating conditions	ANN Architecture	Output					
		Train			Test		
		A	T	error	A	T	error
Normal	16-16-1	0.0034	0	0.0034	0.0034	0	0.0034
Inrush current	16-16-1	0.0034	0	0.0034	0.0016	0	0.0036
Over excitation	16-16-1	0.0034	0	0.0034	0.0014	0	0.0014
Internal fault	16-16-1	1.0006	1	0.0006	1.0002	1	0.0002

Table 1.14. WNN based Condition-Monitor-CM

Operating condition	ANN Archite cture	Output								
		1*		2**		3***		4****		error
		A	T	A	T	A	T	A	T	
Normal	16-16-4	0.0000	0	0.0042	0	0.0003	0	0.9957	1	0.0043
Inrush Current	16-16-4	0.0000	0	0.0000	0	1.0000	1	0.0040	0	0.0000
Over excitation	16-16-4	0.0000	0	0.9997	1	0	0	0.0094	0	0.0003

Table 1.15. Using ANNs trained on PSO, an internal-fault detector

Operating conditions	ANN Architecture	Output					
		Train			Test		
		A	T	error	A	T	error
Normal	16-16-1	0.0000	0	0.0000	0.0000	0	0.0000
Inrush current	16-16-1	0.0000	0	0.0000	0.0000	0	0.0000
Over excitation	16-16-1	0.0000	0	0.0000	0.0000	0	0.0000
Internal fault	16-16-1	1.0000	1	0.0000	1.0000	1	0.0000

A-Actual T-Target

1*, 2**, 3***, 4****--The corresponding outputs of the 1st, 2nd, 3rd, and 4th outputted neurons are in the following sequence, '1000' for the normal Condition, '0100' for inrush, '0010'-for over-excitation condition, and '0001' for CT-saturation condition

Table 1.16. Monitoring Condition with PSO-Trained ANN

Operating condition	ANN Architecture	Output								
		1*		2**		3***		4****		error
		A	T	A	T	A	T	A	T	
Normal	16-16-4	-0.0042	0	-0.0071	0	0.0196	0	0.9986	1	0.0014
Inrush Current	16-16-4	-0.0026	0	0.0054	0	0.9988	1	0.0048	0	0.0012
Over Excitation	16-16-4	-0.0036	0	0.9989	1	0.0148	0	-0.0055	0	0.0011

Table 1.17. Internal-fault Detector employing WNN trained by PSO

Operating conditions	ANN Architecture	Output					
		Train			Test		
		A	T	error	A	T	error
Normal	16-16-1	0.0000	0	0.0000	0.0000	0	0.0000
Inrush current	16-16-1	0.0000	0	0.0000	0.0000	0	0.0000
Over excitation	16-16-1	0.0000	0	0.0000	0.0000	0	0.0000
Internal fault	16-16-1	1.0000	1	0.0000	1.0000	1	0.0000

Table 1. 18. Condition Monitor using PSO-Trained WNN

Operating condition	ANN Architecture	Output								
		1*		2**		3***		4****		error
		A	T	A	T	A	T	A	T	
Normal	16-16-4	-0.0098	0	-0.0067	0	-0.0087	0	1.0088	1	0.0088
Inrush Current	16-16-4	0.0151	0	-0.0025	0	1.0026	1	-0.0192	0	0.0026
Over excitation	16-16-4	0.0055	0	0.9918	1	0.0038	0	0.0096	0	0.0082

A-Actual T-Target

1*, 2**, 3***, 4****--firstThe corresponding outputs of the 1st, 2nd, 3rd, and 4th outputted neurons are in the following sequence, '1000' for the normal Condition, '0100' for inrush, '0010'-for over-excitation condition, and '0001' for CT-saturation condition. When compared to the previously mentioned techniques, the PSO-trained WNN network produced more accuracy with fewer iterations and a significantly shorter simulation time. Figure displays the convergence curve for the PSO trained wavelets neural-network (WNN) for both IFD and CM.

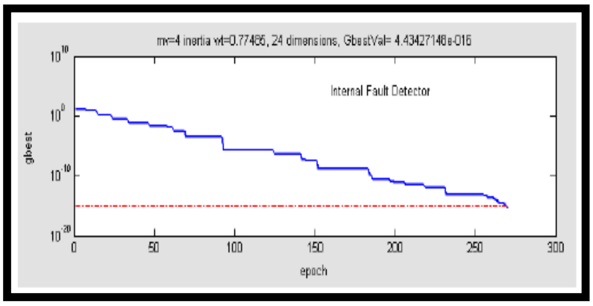

Fig 1.15 . The convergence curve for the WNN-scheme trained on PSO (IFD)

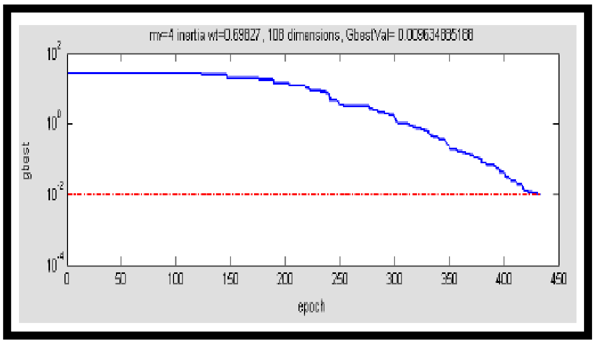

Fig 1.16 . Convergence curve for PSO trained WNN scheme (CM)

The performance evaluation of all the above four cases is shown in table 1.19.

Table 1.19. Performance comparison of results

Parameters	ANN	WNN	PSO trained ANN	PSO trained WNN
Convergence	5000	1500	625 (IFD) 900 (CM)	275 (IFD) 440 (CM)
Error	0.01 (IFD) 0.0026 (CM)	$7.83*10^{-7}$ (IFD) 0.025 (CM)	10^{-15} (IFD) 10^{-2} (CM)	10^{-15} (IFD) 10^{-2} (CM)
Accuracy	99%	99%	100%(IFD) 99.98(CM)	100%(IFD) 99.98%(CM)

shows that the wavelets neural-network that was trained using PSO yielded the best outcomes. In the case of the Internal-fault detector (IFD), 100% accuracy is reached in 275 repetitions with an error of 10-15. In contrast, after 440 trials, condition monitor (CM) attains 99.98% accuracy with an error of 10^{-2}. The PSO approach has thoroughly optimized the weight adjustments when the accuracy reaches 100%. As a consequence, our proposed PSO trained wavelets neural-network generates more accurate outputs. It is also faster to react and better at distinguishing low-level internal trouble signals from other operational situations. PSO trained wavelets neural networks (WNNs) are also shown to drastically reduce convergence times and the number of iterations required for simulation.

MATLAB 6.5 version is utilized for all simulation investigations in this study effort, and a Pentium IV, 2.4 GHz computing machine is utilized. This paper provides a novel method for differentiating between power transformer working modes using wavelet transformations and neural networks. The shortcomings of traditional transformer relays are addressed by this neural network-based digital transformer differential relay. The results show that neural networks do fairly well when it comes to solving classification challenges. Additionally, they suggest that a digital differential relay could be thought of as a classifier that determines the type of event that takes place in a transformer. The current differential relaying approach for power transformers has several important limitations. The differential relaying principle, for instance, is not able to distinguish clearly between internal faults and other power transformer operating conditions, such as inrush magnetizing currents, stationary over-excitation of the transformer core, and external faults combined with current transformer saturation, some of which have been identified as major causes of relay mal-operation. This particularly needless trip in the differential relay is caused by 'magnetizing inrush-current'. Power transformer differential relay blocking is frequently used to stop this by utilizing the second harmonic component. However, as power networks become more complex, different power transformer operations also result in the production of the second harmonic component. As such, the development of an accurate technique for distinguishing between the various working conditions of a power transformer is imperative [18]. Thus, ANN-based approaches were established in the previous chapter. The defensive method offered multiple potential for optimization through the use of ANN-based techniques. However, a variety of internal coefficients, functions, and thresholds need to be adjusted in order to fine-tune the relay for protection. Nonetheless, the fuzzy logic technique yields better internal relay settings[19,20]. It was selected for this investigation because of this. This chapter introduces a few new fuzzy logic techniques. This study combines wavelet transforms with fuzzy logic. By splitting the time domain into large time intervals at low frequencies and short time intervals at high frequencies, wavelets effectively capture the signal[21–23]. To differentiate between different power transformer working conditions, it is provided in three steps. This method can be used to transformer differential protection via digital relaying.

4. Conclusions

In conclusion, there is a chance that the application of artificial intelligence (AI) technologies—specifically, machine learning and neural networks—will greatly enhance the security of electrical transformers. Artificial intelligence (AI) has the potential to change conventional methods and meet new protection issues in predictive maintenance, fault detection, and real-time monitoring. Power transformers are subject to a range of security concerns, such as environmental conditions, operational hazards, ageing infrastructure, cyber attacks, and physical vulnerabilities. Incidents, natural catastrophes, and vandalism are examples of physical security threats that can cause power outages. Power transformers are vulnerable to cyber assaults that target communication networks and control systems. Performance deterioration and outages may result from outdated infrastructure and operating hazards. Transformer performance is also impacted by environmental variables including pollution and temperature swings. AI-driven solutions provide proactive, accurate, and economical ways to guarantee power transformer efficiency and dependability. Artificial intelligence (AI) solutions for predictive maintenance can minimize downtime, maximize operating expenses, and guarantee the lifespan of power transformers by analyzing the vast volumes of data and precisely forecasting probable malfunctions. When neural networks are used in conjunction with wavelet-transforms, for example, power transformers protection can effectively distinguish between various operating-conditions, such as normal-operation, inrush-current, over-excitation, the CT-Saturation, and internal faults. Wavelet Transformations and Artificial Neural Networks (ANNs) can be used to monitor and safeguard the power transformers. All things considered, to be ground-breaking method for power transformer safety. They could question established methods, take on fresh difficulties, and raise the dependability and effectiveness of transformers used in the electrical energy industry. Proactive and economical transformer safety solutions can result from combining AI with fault-detection, predictive maintenance, and real-time monitoring.

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