The Study on Power Transformer Design Optimization Using Neural Network System

Kavita Rani[1]* Dr. Prerna Nagpal[2]

[1] Research Scholar, Sunrise University, Alwar, Rajasthan

[2] Associate Professor, Sunrise University, Alwar, Rajasthan

Abstract – The primary goal of this article to develop software based on AI techniques that could be utilized for the optimal design of distribution transformer. Artificial Intelligence approaches have been widely used to tackle the dynamic task of improving the architecture of the transformer. ANN were used to anticipate the attractive transformer center attributes and center misfortune, which for the most part focused on decreasing iron misfortunes of collected transformers, while cost estimation of transformer was proposed in the plan stage using NN. Developmental programming coupled with neural networks has been studied to improve the nature of wound core transformer conveyance.

Key Words – Transformer Design Optimization, Artificial Neural Networks, Adaptive-Network-Based Fuzzy Inference System

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INTRODUCTION

Distribution transformers are most important components in a power system network, where in any distribution network a huge number of distribution transformers are used. A transformer is a device with one or two magnetically coupled electric circuits by a common magnetic field that is used to transform voltage from one level to another. Distribution transformers are also the most varied types of transformers where in the Kingdom of Saudi Arabia a huge number of transformers are installed in the public electricity supply system ranging in size from 50 kVA to 1000 kVA.

Manufacturing companies have introduced computer aided transformer design that help reduce the man hour needed, but mainly to reduce and optimize the amount of material needed and to reduce the delivery cycle time to the customer. Computer design techniques will ensure that the user's requirements in addition to the standard design constraints such as efficiency, loaded and non-loaded losses, temperature rise and other constraints are all achieved. In the end this will give us a number of different designs which all guarantee the desired characteristics of the transformer. Even though all the designs meet the requirements, the transformers will have different parameters such as core radius, number of lamination layers, winding type and number of turns, and so on. This in turn indicates that the total cost for every transformer design will differ as the two main factors affecting the costs are; the amount of material used, and the total losses of the transformer.

TRANSFORMER DESIGN OPTIMIZATION

TDO is a mixed-integer non-linear programming problem with a dynamic & discontinuous objective feature & constraints, with the goal of comprehensive computation of the characteristics of the transformer centered on national & foreign specifications & the specifications of the transformer customer, utilizing available materials & manufacturing techniques, to reduce manufacturing. There are some various types of accurate functions defined in the TDO literature, however the most frequently used ones are the minimization of the cost of manufacturing the transformer & minimization of the TOC that was characterized as the cost of the life- associated with the purchase and operation of the transformer. Minimization of key material costs, manufacturing costs, & TOC are the three goal feature options available in the program prepared for this report. Although the governing bodies are implementing regulations requiring the utilize of high-efficiency transformers, transforming consumers are encouraged to continue utilizing TOC since the regulations are intended solely to raise the minimum standard of transforming efficiency (Global Industry Analysts 2014.).

ARTIFICIAL NEURAL NETWORKS ARCHITECTURE

Artificial Neural Networks (ANN) Architecture implies how neurons are arranged in the form of layers and the type of interactions between the neurons. Architectures of neural networks are closely related to the training/learning algorithm applied on these networks. There are three broad categories of neural network architectures.

(a) Single Layer Feed forward ANN

(b) Multilayer Feed forward ANN

(c) Recurrent Networks

Single Layer Feed forward ANN have a single layer in the whole network. It consists of input layer which is called the zeroth layer and the other layer is the output layer which is the single layer. The signals are passed from input layer to output layer and not in the reverse direction and there are no closed paths. Therefore these networks are called as Feed forward networks. Figure 1(a) depicts the Single Layer Feed forward Artificial Neural Networks. Multilayer Feed forward Artificial Neural Networks have more than one layer. The layers between the input & output layers are known as the hidden layers. Due to these hidden layers, the artificial neural networks are also known as Multi-Layer Artificial Neural Networks. The signals from the input layer are transmitted to hidden layer which are further passed to another hidden layer till the last layer known as the output layer. The signals are not passed in the reverse direction from output layer towards the input. Due to this property of a network, these networks are termed as Multi-Layer Feed forward Artificial Neural Networks. Figures 1 (b to e) show various types of Multilayer Feed forward Artificial Neural Networks. The Multilayer Feed forward ANN which use sigmoid ac tivation functions at the hidden layer nodes are termed as Sigmoidal Feed forward Artificial Neural Networks.

Recurrent Neural Networks (RNN) have feedback loops, that is, the computation flow is bi-directional. For example, Hopfield Networks have feedback loops from every node to every node, and is a completely connected network. Elman and Jordan Networks (which are used for temporal analysis) have feedback loops from higher layers to lower layers, while competitive networks have lateral connections. See Figure 2 for RNN architectures. Feedback loops means that outputs of the network are fed back to the inputs in a single layer network and in networks which also have hidden layers feedbacks can be from outputs of the hidden layers to previous hidden layers or/and input nodes or the feedbacks can be from outputs of the network to hidden layers and/or input nodes. Recurrent Neural Networks also allow interconnections between the nodes of the same layer. Recurrent Neural Networks have several variants depending upon the problems these networks solve like function approximation, forecasting and control, pattern association and optimization.

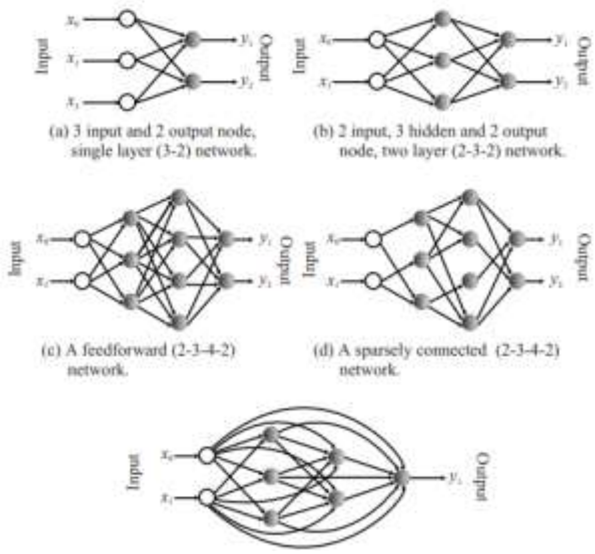

Figure 1: Architecture of Artificial Neural Networks.

POWER TRANSFORMER PROTECTION SCHEMES

Power Transformer is the nerve center of any distribution system. Generally speaking, the ability of power transformers is determined from the charge survey data. The electricity transformers are the substation's primary machinery, while other machinery is concerned with the transformers' practical aspects. Any transformer fault will have Buchholz relay and differential relay operated. The transformer will not be paid with working on such relays. It must be isolated, & tests should be carried out. The unit should only be put into service if the healthiness is confirmed by tests. The potential faults in power transformers are usually the following:

- Within the transformer tank faults
- On heat treatment
- Outside transformer region errors (due to fault)
- Initial faults
- Internal faults (For fixing these faults Differential safety schemes shall be provided)

- Over excitation (It is given to resolve this type of fault over the flux relay)

- Switch to fault, Arcs inside the Oil(Sudden stress relay schemes are given to resolve such kinds of faults)

For addition, transformer faults can be separated into two major groups for review purposes. They are: I by faults, i.e. by overloads and by external short circuits. (ii) External defects, i.e., transformer winding & contact failures. External faults may be sub-divided into starting faults & severe faults.

Recent Advancements in Learning and Training of ANN

While BP can provide a very concise distributed analysis of various data sets, it does have its drawbacks such as slow learning, broad training sets, simple sticking to local minima and weak robustness. A variety of approaches have been suggested to strengthen the BP norm in this way. Genetic algorithms, wavelet transforms and neural networks based on particle swarm intelligence are becoming promising alternatives amongst them. This has been a topic of active research in the recent past and the open literature contains many good methods.

Since ANNs can provide outstanding pattern recognition, several researchers recommend them for power transformer relaying implementation. Neural network research must be treated with special caution. The multilayer perceptron with controlled back-propagation learning algorithms is often utilized in developing new security strategies. For power transformer security systems, however, a hybrid wavelet transforms & neural network (WNN) approach and PSO-trained ANN method is being used in the research work.

Adaptive-Network-Based Fuzzy Inference System (ANFIS)

An ANFIS in which each node executes an incoming signal unique operation (node function) & series of parameters relating to that node. Conceptually, there are virtually no limitations on an adaptive network's node functions beyond differentiability piecewise. Structurally, the only disadvantage in network setup is that the form in feed forward will be this. Because of these minimal restrictions, the applications of the adaptive network in various fields are immediate & immense. The current framework is referred to as ANFIS, which stands for Fuzzy Inference Scheme based on the Adaptive-Network. Throughout this case, a hybrid learning rule is suggested that combines the gradient method & estimation of the least squares (LSE) to define parameters. The variable set method of decomposition is defined to implement the hybrid learning law (Jang. J.R 1995).

Wavelet Transforms

Wavelet transforms is an useful tool for simultaneously extracting information from the current signals in the time & frequency domains. This is simply a flexible windowing strategy. Such flexible window duration requires long time periods to be utilized when desiring more precise low frequency information & quick time intervals while desiring high frequency information. Figure shows a time series signal for Wavelet transformation. Analysis Wavelet adopts the concept of scale & connections between scale & frequency. Discrete Wavelet Transform (DWT) is commonly used with the analysis of non-static signals.

Figure Wavelet transform of a Time Series Signal

Discrete Wavelet Transform (DWT)

Discrete wavelet transformations (DWT) allow for the use of dyadic scales and positions, inferring scales and positions based on a two-probable power. The DWT will establish fine-scale coefficients to capture data of high recurrence and the coarse-scale coefficient to capture data of low recurrence. Typically, the DWT technique is used to capture the signal distress. The intent behind prominence was its ability to set an immense magnitude of the coefficients to zero without substantial data malfortune. In addition, if more properties are required than fixed properties of a signal, DWT will also most likely be a good alternative to conventional Fourier transform (FT) strategy.

LITERATURE REVIEW

Eleftherios I et al. (2006) Transformer architecture is basically calculated by reducing general production costs, including commodity costs and labor costs. In every event, this minimization has to rely on the limitations set by external determinations and the wishes of clients. In this article, an groundbreaking theory similar to the Decision Tree approach is proposed that power transformers can be constructed using just ten simple input parameters. The method is modified by programming. The resulting kit is appropriate for consumers who are not experts in the field of transformers and, however, for transformer manufacturers who want a robust and favorable solution to come similar to the optimal structure. In fact, the total expense of the power transformer configuration is continuously calculated, in accordance with various approaches that are impossible to succeed in a potential solution in the initial run. In fact, the production meetings of the transformer are integrated into this particular system, which allows only the novice to create the perfect configuration of the transformer. The suggested method and programming consists of a simple unit that is currently widely used in the manufacturing of transformers.

ELEFTHERIOS I. AMOIRALIS et al. (2008) In this article, a robust enhancement approach is introduced with the goal of reducing the complex component expense of wound center allocation transformers, taking into consideration the limitations faced by both external data and company requirements. In order to be carried out in these lines, Mixed Integer Programming relevant to Branch and Bound Strategy is used. There is a comparison between the current approach and the heuristic development program of the industrial transformer sector, and the findings demonstrate the power and predominance of this modern methodology.

Ali Soldoozy et. al. (2018) Numerous improvement equations and methods have been suggested during the last decades, most of which are in some form or another influenced by design and by regular circumstances, in particular those that can be essentially investigated and formulated. The goal of this work is to propose another streamlining strategy, inspired by the growth and fertility of plants, that enables them to prune a few sections of the plant or tree, i.e., horrible sections of the pursuit space that do not meet the constraints of the issue and quickly scan the whole research space. Through partnership, we will prune the shooting area of the improvement problem, cut and forget its awful pieces, pieces that definitely do not follow the requirements of the question, with the goal that the speed and consistency of the inquiry will be significantly enhanced. Through enhancing the standard of shooting, we hope to fully dispose of getting shot at the very minimum. There are subtle comparisons with pruning a tree to increase its diversity and pruning a shooting field for an development problem to boost the efficiency of the measurement of enhancement. JMAG-Designer technology is used for the study of finite components.

N Aishwarya et al. (2019) Established social orders currently require an ever-increasing supply of electrical power, and the requirement has risen last year. Complex systems are developed to satisfy this increasing demand. The efficient functioning of such a complex system typically relies on the ability of that structure to include a strong and continuous inventory of loads. Throughout the dream universe, all loads will be taken care of at steady voltage and recurrence. Throughout this case, satisfying the need for electricity is not the key requirement but, throughout addition, it is the responsibility of the power system engineers to provide the buyers with steady and reliable control. Such problems require the need to examine the soundness of the control system. Throughout this article, a consistent state security investigation is carried out using swing conditions and the knowledge gathered from the investigative methodology is used to train the Artificial Neural Network(ANN) such that a reliable state stability status structure is established.

Sudhaet al. (2019) Scenario preparation is one of the most important activities faced by large-scale strategy and operation engineers. Power grid engineers use a contingency model to analyze the design of the network and to determine the need for additional transmission extensions due to the change in load or age. The various approaches used to evaluate such contingencies rely on the complete AC load flow analysis or the reduced load flow or responsiveness variables. In any scenario, such techniques need an immense amount of computing resources and are not appropriate for on-line applications in broad power frameworks. It is difficult to make up-to-date on-line contingency research using traditional methods in the context of the disagreement between the quicker method and the consistency of the arrangement. Accordingly, this paper suggests a computationally efficient technique for contingency research utilizing a synthetic neural system.

Mahesh Yanagimath et. al. (2019) Power transformers are the central components of electrical power transfer and control systems. They are continually under the control of physical, hydraulic, warm and normal anxieties. It is the most important and expensive parts of the control system. Owing to the expense of the power transformer, the monitoring and maintenance of the state of the transformer is becoming important. There are various predictive approaches necessary for the transition of the well-being situation. One technique named ANN is used to evaluate and differentiate blames for oil-filled power transformers that are based on Dissolved Gas in Oil Analysis (DGA). By using the ANN feed forward, the most severe precision can be obtained with the aid of the back spread algorithm. This paper presents the problem description structure for the ANN power transformer.

METHODOLOGY

Throughout this research, Genetic Algorithms (GA), Particle Swarm Optimization (PSO) & Teaching Learning Based Optimization (TLBO) have been utilized to solve the Transformer Design Optimization (TDO) problem. The No-Free Lunch

Theorem notes that there is no particular metaheuristic that is ideally equipped to solve all optimization problems. In several other words, it may be assumed that a certain meta-heuristic might have very good results on a certain set of problems, yet the same algorithm may have bad results on a specific set of problems. Thus, in this segment, the success of three separate artificial intelligence strategies (i.e. GA, PSO and TLBO) will be evaluated to solve TDO problems.

Implementation of GA **for unconstrained optimal transformer design**

This section explains the methods utilizing GA for optimum design of 100 kVA, 11/0.433 kV, propagation transformer. The key benefit of GA is that a minimal change in the software multiple target functions may be streamlined. The set of decision variables chosen for 100 kVA, 11/0.433 kV, Dyn-11 delivery transformer as seen in Table 1.1 after consultation with a local transformer supplier.

Table 1.1 Limits on Transformer Design Variables

Sr. No.	Design Variables	Limits
1	Volt per turn	3.2-4.7
2	Maximum flux density (T)	1.2-1.7
3	Current density in LV (A/mm²)	1.5-1.54
4	Current density in HV (A/mm²)	1.5-1.54

The MATLAB software built incorporates unconstrained GA methodology to reduce of four targets, including (1) active component cost (2) total loses (3) percentage impedance (4) volume of transformer tanks. As per necessity, the user may select either of the above-mentioned objectives.

Table 1.2 Control Parameters for GA

Sr. No.	Parameter	Value
1	Population size	40
2	Crossover probability	0.8
3	Mutation probability	0.02
4	String length	20 bits
5	Number of dimensions	4
6	Chromosome length	80 bits
7	Elite count	1

Table 1.3 Performance of Various GA Selection Operators for TDO Problem

Sr. No.	Selection Operator	Objective Function	Best value	Worst value	Mean	Standard Deviation
1	RWS	Active part cost (INR)	45662	47554	46516	499.82
		Total losses (W)	1608.79	1722.79	1649.40	29.50
		Percentage Impedance	3.192	3.330	3.259	0.037
		Tank Volume (cm³)	228358	244905	231970	3978
		Active part cost (INR)	45545	46841	45977	327.18
		Total losses (W)	1605.25	1638.94	1618.98	10.08
2	SRWS	Percentage Impedance	3.191	3.270	3.211	0.027
		Tank Volume (cm³)	227354	230958	226139	917.45
		Active part cost (INR)	45165	45207	45174	12.08
		Total losses(W)	1594.16	1620.02	1599.72	10.04
3	TS	Percentage Impedance	3.176	3.181	3.178	0.002
		Tank Volume (cm³)	226098	227210	226289	403.96

CONSTRAINED OPTIMIZATION RESULTS

This section explores the findings obtained by GA, PSO and TLBO in the optimisation of transformer architecture. Table 1.1 describes the restrictions on judgment factors, whereas the constraints are just like those mentioned in Table 1.1. For statistical inferences, each optimization routine was run 20 times to track the optimum global out of many local minima.

Optimization Results with GA

Every decision variable in this study is coded as a 20 bit binary string in GA. Optimum size measurements & efficiency parameters are extracted from the analysis as objective function of a collection of GA parameters & penalty factor with active component rate. To find the global optimum, 3 distinct RWSBGA techniques, SRWSBGA & TSBGA were used.

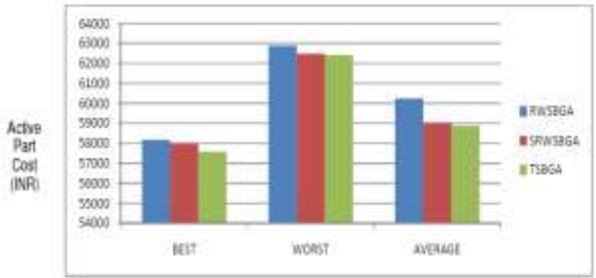

Figure 1.1 Comparative Performance Analyses of RWSBGA, SRWSBGA and TSBGA for 2-Star Rated Transformer

Comparison of results obtained from GA, PSO and TLBO

In this article, each optimization algorithm was run for 500 generations. However, no improvement in objective function was observed when the numbers of iterations were increased beyond 100. Table 1.4 and Table 1.5 indicate the value of optimal design variables of a 100 kVA, 11/0.433 kV distribution transformer obtained by RWSBGA, SRWSBGA, TSBGA, PSO and TLBO after performing 20 trial runs. Results indicate that PSO and TLBO were able to find a better value of the objective function as compared to GA . After conducting 20 trial runs with different initial random values, TLBO was found to be more robust as the solutions generated by TLBO showed small range of variations of cost objective function, yielding a smaller value of standard deviation.

Table 1.4 Optimal Design Variables & Objective Function for 1-Star Rated Transformer

Parameter	Units					
Active Part Cost	45924	45395	45320	45304	45304	INR
Max. Flux density	1.679	1.690	1.693	1.693	1.693	T
Volt per turn	3.227	3.225	3.226	3.225	3.225	--------
Current density in HV	1.529	1.537	1.539	1.54	1.54	A/mm²
Current density in LV	1.538	1.539	1.535	1.538	1.536	A/mm²
Gross core area	89.25	88.63	88.47	88.44	88.44	cm²
Core diameter	110.24	109.86	109.76	109.74	109.74	mm
Core weight	167.30	165.07	164.79	164.72	164.72	kg
Conductor weight	60.96	60.61	60.53	60.52	60.52	kg
Avg deviation from best value	624.32	618.46	605.96	585.47	105.76	-----
Avg deviation from global best value	1244.32	709.46	621.96	585.47	105.76	-----

Table 1.5 Optimal Design Variables and Objective Function for 2-Star Rated Transformer

Parameter	Units					
Active Part Cost	58168	57972	57577	57554	57554	INR
Max. Flux density	1.426	1.425	1.433	1.434	1.434	T
Volt per turn	3.649	3.652	3.649	3.649	3.649	---------
Current density in HV	1.502	1.514	1.513	1.513	1.513	A/mm²
Current density in LV	1.505	1.507	1.508	1.500	1.500	A/mm²
Gross core area	118.79	118.98	118.20	118.15	118.15	cm²
Core diameter	127.18	127.29	126.87	126.84	126.84	mm
Core weight	219.84	219.14	217.35	217.25	217.25	kg
Conductor weight	67.79	67.52	67.41	67.40	67.40	kg
Avg. deviation from best value	1869.04	906.17	981.24	232.16	2.60	-----
Avg. deviation from global best value	2483.04	1324.172	1004.24	232.16	2.60	-----

The final design dimensions & performance parameters of 1-star & 2- star rated transformers found out by PSO & TLBO and their comparison with the Exhaustive Search Method is depicted in Table 1.6, while the dynamic performance characteristics of transformers designed by TLBO is shown in Table 1.7.

Table 1.6 Main Design Dimensions & Important Technical Parameters of 1-Star and 2-Star Rated Transformers by ESM & TLBO

Parameter	Design of 1-star rated transformer by	Design of 1-star rated transformer by	Design of 2-star rated transformer by	Design of 2-star rated transformer by	Units
Active part cost	46579	45304	58702	57554	INR
No load losses	219.43	219.99	195.11	199.47	W
Loan losses	1797.05	1799.04	1658.62	1642.11	W
Total losses	2016.48	2019.04	1853.73	1841.58	W
Total half load losses	668.70	669.76	609.74	609.99	W
Volt per turn	3.20	3.225	3.60	3.649	-------
HV turns	3604	3557	3188	3142	-------
LV turns	78	77	69	68	-------
Gross core area	88.98	88.44	118.56	118.15	cm²
Core limb centre	252	251	277	276	mm
Total yoke length	1108	1104	1108	1104	mm
Total limb length	1554	1506	1410	1374	mm
Core weight	169.16	164.72	221.53	217.25	Kg
Conductor weight	62.45	60.52	68.81	67.40	Kg
Percentage impedance	4.376	4.340	4.458	4.447	%
Tank length	79.3	79.0	86.8	86.5	Cm
Tank breadth	31.9	31.8	34.4	34.3	Cm
Tank height	91.7	90.1	90.1	88.9	Cm
Tank volume	231970	226349	269031	263761	cm³
Efficiency (full load, upf)	98.02	98.02	98.18	98.19	%
Execution time	85.04	7.91	82.65	7.20	Sec

Table 1.7 Dynamic Performance Characteristics of Transformers designed by TLBO under short circuit conditions

Parameter	1-star rating	2-star rating	Units
Asymmetrical SC current on HV side	125.68	126.26	A
Asymmetrical SC current on LV side	5530.11	5555.71	A
Asymmetrical SC Ampere turns in LV	431349	383344	AT
Asymmetrical SC Ampere turns in HV	452953	402525	AT
Hoop stress in LV	29.67	27.31	kg/cm²
Hoop stress in HV	47.56	52.34	kg/cm²
Radial bursting force experienced by LV	16429	15308	kg
Radial bursting force experienced by HV	17207	15978	kg
Axial compressive force in both windings	1883.19	2058.51	kg
Temperature of LV for SC of 2 sec	113.27	111.97	⁰C
Temperature of HV for SC of 2 sec	113.48	112.43	0c
Magnetizing current inrush in HV	52.40	38.99	A

CONCLUSION

Transformers carry on a crucial job of connecting power systems at different voltage levels. It would actually not be possible, without the transformer; to use electric power from different perspectives is used today. Genetic algorithms were used to develop transformers and minimize work costs, just as they were used to prepare the neural network for power misfortune prediction in transformers. The transformer structure optimization problem depends on minimizing or amplifying a target function that is exposed to a couple of imperatives. Between various target functions, the target functions normally used include minimizing absolute mass, minimizing complex component costs, minimizing specific material costs, minimizing assembly costs, minimizing all out reporting costs or boosting transformer rated power.

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Corresponding Author

Kavita Rani*

Research Scholar, Sunrise University, Alwar, Rajasthan