Prediction of Tap Changing Transformer Losses Minimization using Artificial Neural Network.

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Abstract
This research proposes a stable and efficient approach to estimating real power losses in tap-changing transformers using the Artificial Neural Network (ANN) technique. Power losses can have a substantial impact on the stability of the electrical supply to customers, especially when increased power demands cause uneven voltage profiles. Tap-changing transformers are crucial for adjusting output voltages to the desired levels. The suggested ANN algorithm was tested on an IEEE 30-bus system, and the findings show a high correlation between the training and testing outputs, with the correlation coefficient (R) approaching unity. This indicates the reliability and accuracy of the ANN model in determining the optimal tap setting for minimizing losses. The paper also underscores the significance of transmission loss and the associated costs.

Keywords: Power system, transmission loss, IEEE 30-bus system, Artificial Neural Network (ANN).

1.0 Introduction
The power system faces many challenges that affect its operational efficiency and related costs. The power system needs to sustain stability and provide a reliable supply of electricity to users (Alhelou et al., 2019) It is critical that the power system remain stable and deliver a consistent supply of electricity to consumers. However, defects such as symmetrical three-phase faults, symmetrical components, and unsymmetrical faults are found in power systems, and these faults greatly contribute to the system's power quality issues. As a result, sagging voltage becomes a common problem, especially due to the widespread use of sensitive and complex control systems at the residential and industrial levels.

In power systems, tap-changing transformers are essential for controlling voltage. The tapping meter and connection point situated alongside the transformer winding comprise the actual structure of the transformer tap-changer. The desired output can be achieved through stepped voltage regulation by varying the turn ratio by selecting different turns. In order to maintain consistent voltage levels for end users, the transformer tap-changer plays a critical role in controlling voltage variances throughout the transmission and distribution system. On the other hand, changing the transformer's tap setting may lead to higher losses, which would lower the power system's overall efficiency. To prevent potential risks, alertness must also be applied when switching taps. Inadequate isolation of taps can lead to arc flashes (Si et al., 2019). It is essential to follow the correct safety protocols when changing the taps on transformers.

The following paper proposes the utilization of MATLAB - Artificial Neural Network (ANN) for minimizing the losses that are caused by transformer tap changing. ANNs are capable of being trained through raw data bus systems. Once the ANN model has been trained, it can be used to predict the most optimal setting for transformers, which will result in minimal losses and maximum efficiency during operation.

2.0 Literature Review

Power transmission commonly utilizes tap-changing transformers to adjust voltage levels. Nevertheless, altering the tap setting could lead to elevated transformer losses. To deal with this issue, a predictive model was developed using an Artificial Neural Network (ANN) in MATLAB. Compared to other learning algorithms, ANNs have shown superior performance on larger datasets (Qi et al., 2019). The ANN learns to identify patterns and relationships between input and output data using a set of input-output pairs. With a wide range of applications in science and technology, ANN is a powerful tool for data analysis and prediction (Goel et al., 2022). The allocation of transmission losses in the power system was verified using the AC load flow method of the IEEE 30-bus system, a well-known benchmark system in power system analysis and optimization.

Generator set points, reactive power compensation, and transformer tap changers are commonly used to maintain voltage profile stability and control transmission loss. Structural and operational constraints have to be inside acceptable boundaries and limitations. The single-line diagram for an IEEE 30-bus system, illustrated in Figure 1, was evaluated during this research, and depicts the transmission loss behavior in a distribution system. Bus numbers 4, 12, 11, 9, 10, and 6 serve as chosen bus and line flow parameters, with ANN being provided to achieve the required goal.

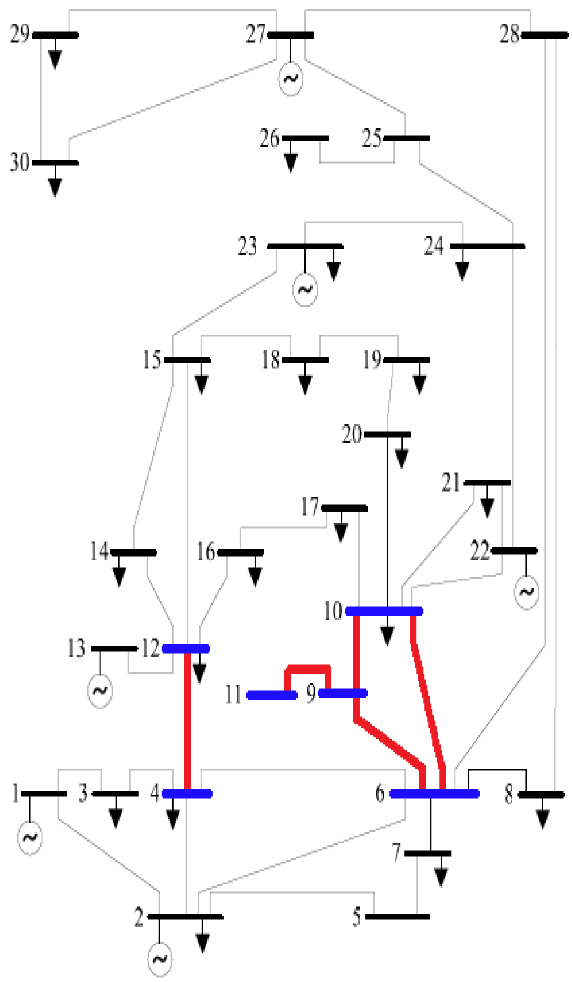

Figure 1: Single Line Diagram IEEE 30-Bus System

The power system scope was divided into three primary components: generation, transmission, and distribution. This project uses an electrical component known as a power transformer. Power transformers play an important role in ensuring transmission system reliability (Ma et al., 2021). Tap changers are commonly used on power transformers to control the output voltage to the required values. Typically, this is performed by varying the ratios of the system's transformers by changing the number of turns in each winding of the relevant transformers.

Power systems are experiencing overloading transmission lines, voltage instability, and real power loss (Gaur et al., 2019). These issues are affecting power system performance, either directly or indirectly (Gaur et al., 2019). This dilemma would result in a loss of economic and system efficiency. As a result, the approaches that may be adopted will benefit the system while avoiding economic problems.

Furthermore, injecting a reactive load (loading condition) at a specific load bus will cause the system to approach a reduction technique that can lower the number of features necessary, as well as the number of system quantities that must be measured and conveyed. Regarding the issue chosen, tap changing transformer has provided a lot of strategies and ways with plenty of study to improve and increase the operation of the device, resulting in the lowest possible cost. Several approach strategies have been introduced in a journal or technical article. One technique discovered is the solid-state on-load tap changing transformer.

The tap-changing system consists of solid-state devices (SCRs) and several transformer taps. These approaches were able to transport mechanical tap changers from one tap to another without using any intermediate taps (Torrey et al., 1997). In terms of economic analysis, it will be 20-50% less expensive than past efforts to approach solid-state tap changers. Aside from that, determining the minimum adjustments in transformer taps to manage voltage levels is an attractive topic for a lot of researchers (Salem and Talat, n.d.). The methods are minimization algorithms that form the Lagrangian and were developed and solved using the Newton-Raphson method (Salem & Talat, n.d.). Furthermore, the fundamental purpose of the Optimal Reactive Power Dispatch (ORPD) is to reduce true power loss while improving voltage stability (Etappan et al., 2020).

3.0 Methodology

Artificial Neural Networks (ANN) is a technique that aims to mimic the functionality of the human brain. Researchers widely use this approach, especially in solving power system issues. ANN comprises interconnected neurons that act as summing junctions to process multiple inputs and generate a single output. An ANN typically consists of input layers, one output layer, and multiple hidden layers. In this project, we develop an ANN to conduct load flow studies utilizing information obtained from the IEEE bus system. The dataset contains various sets of data, which was divided into training sets and testing sets, making it easier to perform regression analysis.

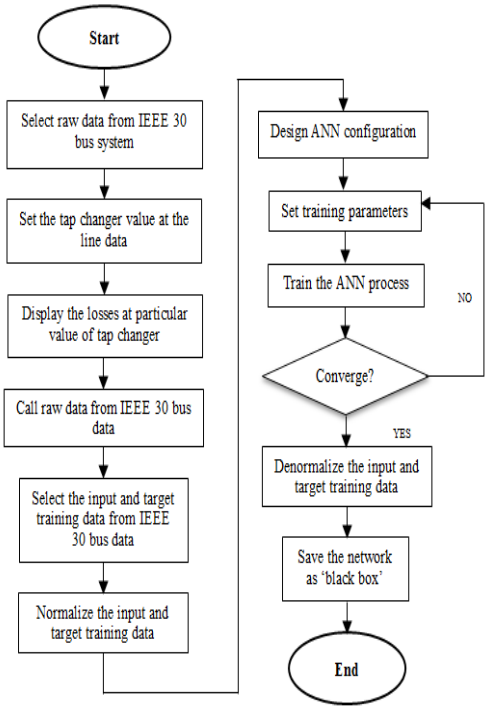

Figure 2: Flowchart Generating Data & Training Process

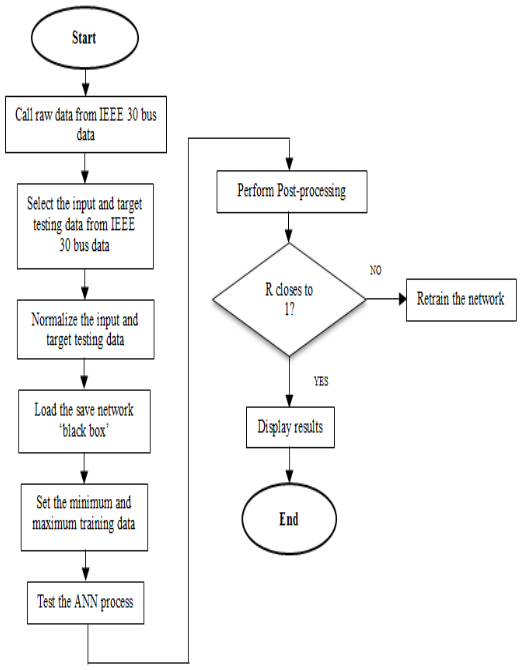

Figure 3: Flowchart Testing Process

The research utilizes an Artificial Neural Network (ANN) approach involving a multilayer feedforward network and the backpropagation learning algorithm. Figure 2 illustrates the data generation process from the IEEE 30-bus system, followed by the training process. The data is generated by executing the load flow process on the bus system while modifying the tap changer value to capture the system's losses. The tap changing transformer value is varied systematically from 0.75 to 1.75, incremented by 0.01 in each cycle, and incorporated into the line data to obtain the corresponding losses. The training process begins by organizing the input and target data obtained from the previous step using the ANN toolbox. 250 training patterns are used, and careful consideration is given to the selection of several data points. The ANN training involves specifying the structure of the hidden layer, setting the momentum rate value, determining the learning rate value, and selecting the number of stopping criteria. The training process continues until convergence is achieved, and the fully trained network is saved as a "black box" for subsequent testing purposes in the following stages.

During the testing phase, the trained network is used to process 250 testing pattern data as shown in Figure 3. The minimum and maximum loss values obtained during the training process are then tested with varying data values in relation to the trained network. To assess the reliability and effectiveness of the network, regression analysis is employed. The performance of the constructed network can be assessed by calculating the absolute error for each testing pattern. The correlation coefficient's results are shown by the number of root mean square (RMS) errors produced during the post-processing stage, which indicate whether the network achieves or approaches unity.

4.0 Results & Discussion

It was clear that the ANN method successfully forecasts the transformer ratio for tap changing, which in turn determines the accurate power losses in power system. The technique proposed was tested using the commonly used IEEE 30-bus system, which is often applied thein the utility companies' distribution systems. The ANN is trained and tested utilizing appropriate data from the bus system. The data includes several alterations to the tap changer value, which works as a controlled variable set to specific values.

Table 1: Training Network Parameter

Neural network	[8, 4, 1] 'logsig','logsig','purelin'
Training algorithm	Levenberg-Marquardt
Epoch	13
Performance	0.00047561
Learning rate	0.9
Momentum rate	0.95
Halting criterion	1e-1
Gradient	0.061733

The ANN model was built in three layers using the 'logsig', 'logsig', and 'purelin' configurations. The number of layers was chosen after several testing in order to obtain the fewest faults with optimum efficiency throughout testing. Table 1 summarizes the parameters used in this research, includes learning rate, momentum rate, halting criterion, and the training algorithm. The learning rate determines the step size during weight updates in the training process. It affects the rate of convergence and the stability of the learning process. The momentum rate helps to keep the model from being stuck in local minimums through the training process. It includes a momentum term to the weight updates, helping the model to better navigate the parameter space. The halting criterion specifies the conditions under which the training process terminates. It could be based on a set number of epochs, a given error threshold, or another criterion. An acceptable halting criterion is essential for avoiding overfitting or underfitting the model. The addition of three layers allows the model to incorporate more complicated correlations in the data, potentially increasing prediction accuracy. The training algorithm defines how the ANN learns from the training data to modify its weights and biases. The training algorithm used in this study is Levenberg-Marquardt, as shown in Figure 4.

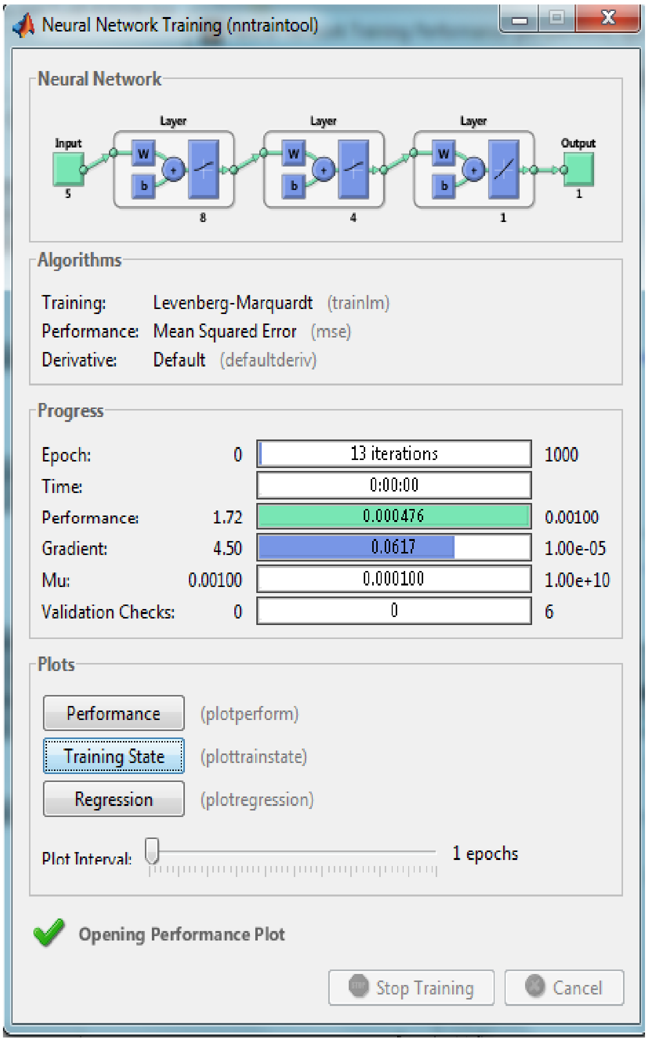

Figure 4: Neural Network Training Tools

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%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%% ANN Training Process %%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
p=input
t=output

% This is to normalise the input and target training data
[pn,minp,maxp,tn,mint,maxt] = premnmx(p,t)

% Default codes for training process
% Minmax(pn) = minimum & maximum value for normalised input p. i.e: pn.
net = newff(minmax(pn),[5,5,1],{'logsig','logsig','purelin'},'trainlm');
net = init(net);                  % To initialise

% Training parameters
net.trainParam.show = 1;
net.trainParam.lr = 0.9;         % Learning rate used in some gradient schemes
net.trainParam.mc = 0.95;        % Momentum is used for slight tolerence on the learning rate
net.trainParam.epochs =1000;     % Max number of iterations
net.trainParam.goal =1e-1;       % Error tolerance; stopping criterion

% Training network
net = train(net, pn, tn);        % Train the network based on the normalised p and t
an = sim(net, pn)

% Denormalised the data
[p,t] = postmnmx(pn,minp,maxp,tn,mint,maxt)
```

Figure 5: Training - Value of minimum and maximum losses

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%% ANN Testing Process %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%


load FYP_ANN30busdata.mat % This is the black box created during training process

% Setting the minimum and maximum training target
mint = [17.5176];
maxt = [26.4678];

an = sim(net, pn)    % output
[p] = postmnmx(an,mint,maxt)
[m,b,r] = postreg(p,t);
```

Figure 6: Testing - Value of minimum and maximum losses

Figures 5 and 6 show the losses analyzed after data generation. The results examine the values of losses incurred during the operation of the tap changing transformer. These losses are evaluated and analyzed based on the data that has already been generated in the process of creating the dataset for the ANN model. Both the bus system used in the research and the value of the tap-changing transformer significantly affect the losses experienced by the transformer. The ANN model trained on the data considers these modifiable factors and their influence on losses during the prediction process.

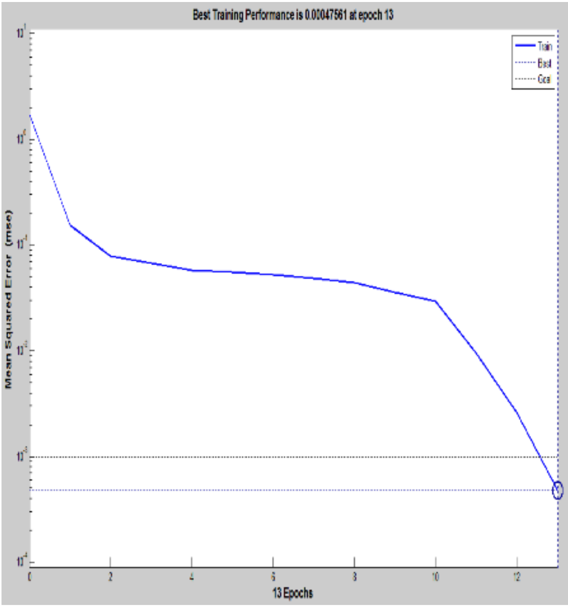

Figure 7: Training Performance

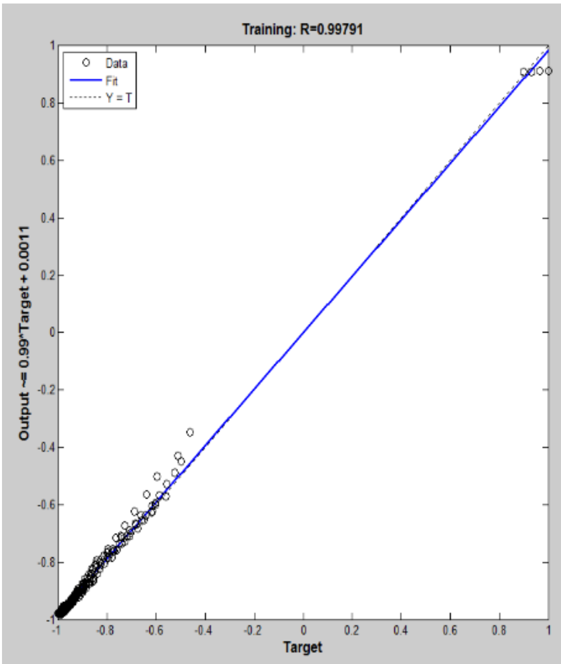

Figure 8: Training Regression

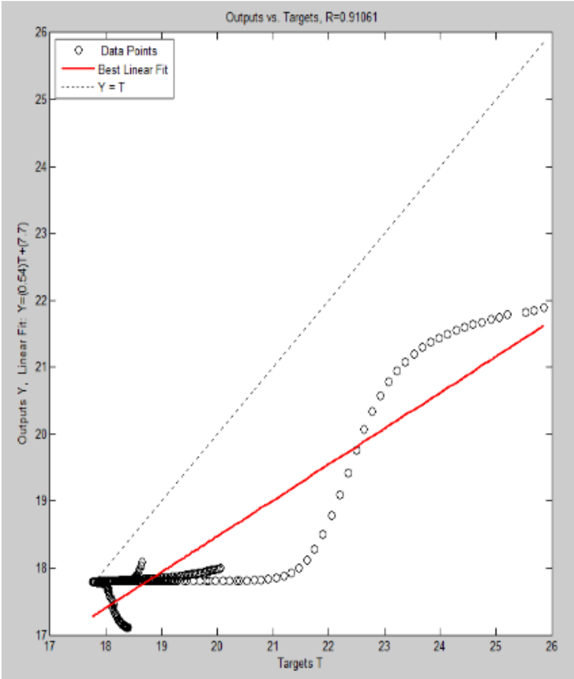

Figure 9: Testing Regression

Figures 7 and 8 showcase the results obtained from the training process. These figures show that training process has successfully converged, opening doors for further post-processing through the testing process. Table 1 details the parameters used in the training phases, which were identified by several tests using various values. The training performance graph indicates the training data's error tolerance and whether it satisfies the required goal limit. The graph shows that the training procedure functioned successfully, with small absolute error. As a result, great efficiency is obtained, demonstrating the trained network's "black box" ability to properly forecast unknown information in the testing phase. Figure 9 shows the correlation coefficient (R) produced by using the "black box" throughout training and implementing it to the specified testing dataset. Interestingly, the graph roughly matches with a linear trend towards unity., showing that the network is highly reliable and performs well. The relatively small root mean square (rms) error reflects an exact alignment of the real and intended outcomes.

5.0 Conclusion and Recommendations

The primary goal of this study is to apply the ANN approach to produce the most accurate tapping ratio prediction for tap changing transformers. To achieve the purpose, this study demonstrates how ANN may be employed to determine the losses in the IEEE 30-bus system, considering a number of tap changer variables that are changed. The project starts with a load flow test to create data for the bus system. This technique demonstrates that the network is reliable and efficient when tested. Furthermore, it is strongly advised to use artificial neural networks (ANN) to handle power system issues, particularly for activities involving monitoring and control. The study's findings suggest that the suggested approach is successful in achieving the goal while abiding by the limits of the system. To further enhance the strategy's flexibility and reliability, future studies should concentrate on exploring the applicability and efficacy of the proposed ANN technique on larger and more intricate bus networks. This will give us a better understanding of the suggested technique's potential and help us identify any constraints that may develop during implementation.

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