Optimal Tuning of OLTC to Improve Power Transformer Voltage Stability based on Artificial Neural Network (Case Study in PT. YTL East Java)

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Abstract: ***This paper proposed an artificial neural network (ANN) based on Levenberg-Marquardt algorithm which attempts to improve the voltage stability of the power transformer with respect to minimum real power loss and proper voltages profile. This algorithm uses optimum settings of On-Line Tap Changer (OLTC) transformer and a minimum number of Reactive Power Compensation Equipment (RPCE). The proposed algorithm is programmed on MATLAB and examine on power transformer 500 kV in PT YTL East Java to demonstrate the validity and the convenience of back propagation (BP) approach with promising results. The results show that the proposed BP algorithm is reducing the position changes as much as 36 times to 14 times in hours comparing using controlled by the automatic voltage control (AVC). Also, the secondary voltage of power transformers is more stable.***

Keywords: on-load-tap changer (OLTC), ANN, voltage stability, reactive power

1. Introduction

The quality of electrical energy is influenced by the instability of voltage that will also affect the stability of the electrical power system. One of the factors causing voltage instability is the change of on load tap changers (OLTC) position on the transformer which is not optimal yet. The change of the OLTC position causes the secondary voltage to alter. The OLTCs are motorized mechanical switching arrangements that adjust the transformer turns ratio, typically in steps of 1.25% or 1.43%, whilst the transformers are in use and carrying a load [1]. Each OLTC transformer is linked to an automatic voltage control (AVC) relay in order to increase or decrease the voltage by changing the tap position of transformer [2] These different voltage levels are kept within acceptable limits by including an OLTC transformer where the substation secondary bus voltage is kept stable by adjusting the tap position [3]. The change in existing OLTC position is controlled by AVC with the concept of tap displacement in stages. This results to OLTC which frequently works, so OLTC becomes hotter and increases the risk of major mechanical damage.

Reference [4 - 5] shows an attempt to design an AVC relay based on the application of artificial neural network (ANN). The model developed the AVC relay based ANN is capable of operating similar to other types of AVC relay. The ANN based AVC relay a sends signal to change the tap-changer of OLTC transformer to retain the voltage within the allowable limits when the calculated AVC voltage exceeds the limits of ± 2% of the reference voltage.

The electromechanical OLTC enable the automatic tap commutation and consequent voltage regulation [6]. The concept has been adopted in high power systems and their high implementation costs. In addition, the commutation of taps in these devices results in arcing and carbonization of the contacts and degradation of the insulation oil, requiring regular maintenance [7]–[10].

Optimization of the right OLTC setting is expected to reduce OLTC position changes in order to reduce the risk of mechanical damage and the voltage stability can be achieved. The ANN method is used to determine the proper tap position. ANN is a control method that has the ability to solve nonlinear system problems which are difficult to solve such as finding isolation failure in the transformer coil and partial discharge in the transmission line [11].

In this paper, the voltage stability in a power transformer is improved by using the ANN based on Levenberg-Marquardt algorithm optimization technique. The power transformer 500 kV in PT YTL East Java to demonstrate the validity and the convenience of ANN optimization technique approach with promising results.

2. Materials and Methods

The back propagation (BP) algorithm has become efficient with the establishment of its mathematical formula as the standard process in adjusting weights and biases for training an ANN in many domains [12 - 15]. The formulation of the BP algorithm can be defined as follows. By given a set of testing data that was propagated to the Multi Layer Perceptron (MLP) then its start to calculate the output as follows:

$$h_i = f \sum x_i w_{ij} \tag{1}$$

$$y_i = f \sum h_i w_{jk} \tag{2}$$

where ***h*** is the hidden node, ***x*** is the input need, ***w*** is the weight, and ***y*** is the output node. The BP training algorithm is to minimize the mean square error between the actual output of a multilayer feed-forward perceptron with iterative gradient algorithm designed and the desired output. In this case, once the output is calculated then the network will start to compute the error, which will be the difference of the expected value ***t*** and the actual value, and compute the error information term ***δ*** for both the output and hidden nodes.

$$\delta h_i = h_i(1-h_i).\delta y_i.w_{ij} \quad (3)$$

$$\delta h_i = h_i(1-h_i).\delta y_i.w_{jk} \quad (4)$$

where ***δj*** representing the information error of the nodes.

Once the information errors for each node were calculated, then, the network will back-propagate this error through the network by adjusting all of the weights; starts from the weights to the output layer and ends at the weights to the input layer.

$$\Delta w_{jk} = \eta \delta y_i.h_i \quad (5)$$

$$\Delta w_{ij} = \eta \delta h_i.x_i \quad (6)$$

$$w_{new} = \Delta w + w_{old} \quad (7)$$

where ***η*** is the learning rate.

This research was conducted at PT. YTL, East Java. The transformer used in this research is a 500 kV power transformer as shown in Fig. 1. The transformer specifications are obtained based on the name plate as shown in Table 1.

Figure 1: Power transformers of 500 kV in PT. YTL

Table 1: Specifications transformer

Items	*Specification*
Type Transformer	TFSM 8957
Make	SIEMENS
Rated Power	765 MVA
Rated Voltage Ratio	512 500 V
Number of Phases	3
Rated frequency	50 Hz

The OLTC on the power transformer on the HV side (high voltage) has 29 taps in which tap 15 is used as the initial choice in determining the next tap options according to the value of the primary voltage per hour. The OLTC specification shown in Table II. More detail information about power transformer could read in Reference [16].

Table 2: Specifications OLTC

Items	*Specification*
TypeOLTC	MRR III 1200 - 72.5 / C - 16 313 W
Make	Reinhausen
Position Range	± 12.5%
Number of Step	± 14 steps
Number of Positions	29
Rated Current	1200 A

The design of ANN structure utilizes 2 *inputs layer* (Vp and Vs_1) with 1 *bias* (b_1), 20 *hidden layers*, and 1 output layer (z). The z value represents the position of the OLTC tap as shown in Fig. 2.

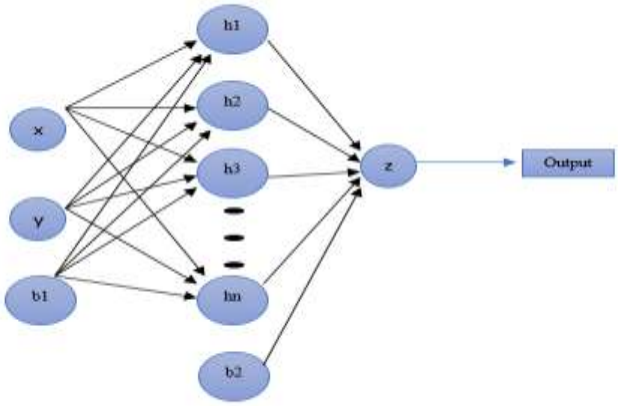

Figure 2: Neural network structure

Data were trained using the Lavenberg-Marquadrt Backpropagation algorithm. The data are consistent and the number of forming neurons on the *hidden layer* is sufficient, then the mapping will be easy to do using the algorithm. Hence, the resulted *output* will be in accordance with the expected target. After the *training* process is completed, then the next step is building *Simulink diagram* as shown in Fig. 3.

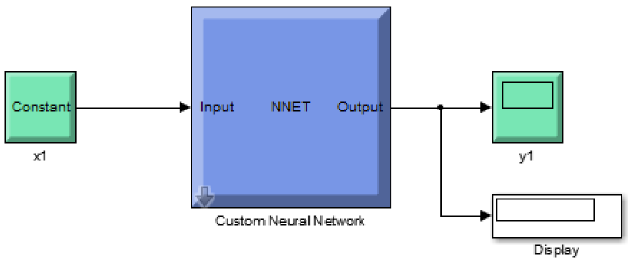

Figure 3:. Simulink diagram

Simulink diagram is used to perform testing in order to determine the suitability of the *output* results and target as well as the right tap position with Vp and Vs1 that have been determined. Voltage Vp is the actual data obtained from a 500 kV transformer (taken over 24 hours). While, the voltage Vs1 in this case is a new secondary voltage which is more stable and is resulted from calculation based on the comparison of primary and secondary windings (according to the *name plate*) which can be formulated as follows:

$$\frac{N_p}{N_s} = \frac{V_p}{V_s} \quad (8)$$

where $\boldsymbol{N_p}$ is the number of primary windings, $\boldsymbol{N_s}$**:** is the number of secondary windings, $\boldsymbol{V_p}$ is the primary voltage and $\boldsymbol{V_s}$ is the secondary voltage.

The tap position of the transformer is calculated using the following equation:

$$\frac{V_s^1}{V_{s\ ref}} \tag{9}$$

where V_s^1 is the new secondary voltage and $V_{s\ ref}$ is the reference voltage (*name plate*).

3. Results and Discussion

The tap setting system using the AVR method is done by comparing the actual data with the data obtained through the calculation (working on the basis of ΔV (voltage deviation)). If ΔV occurs at a primary voltage exceeding the tolerance limit of ± 1.5%, then OLTC will move 1 time to raise or lower the tap of OLTC. If ΔV> 1.5%, then OLTC will move again 1 time, and so on until ΔV <1.5%.

Optimization of the OLTC tap setting is conducted to increase the stability of the secondary voltage in the 500 kV transfomer. The aim of optimization is to reduce the number of OLTC tap position changes performed gradually. Thus, the tap setting system uses ANN method.

Testing of OLTC tap position setting using ANN method utilizes 36 data. The data are obtained every time when there is a tap change within 24 hours. The data obtained are used for the *training* process on ANN. The *training* process is performed to get the *regression* value close to 1. The *regression* value itself determines the correlation between the *output* and the target. If the *regression* value is close to 1, then there is a correlation between the *output* and the target.

In Fig. 4 shows the process of training based on the structure of the neural network has been designed.

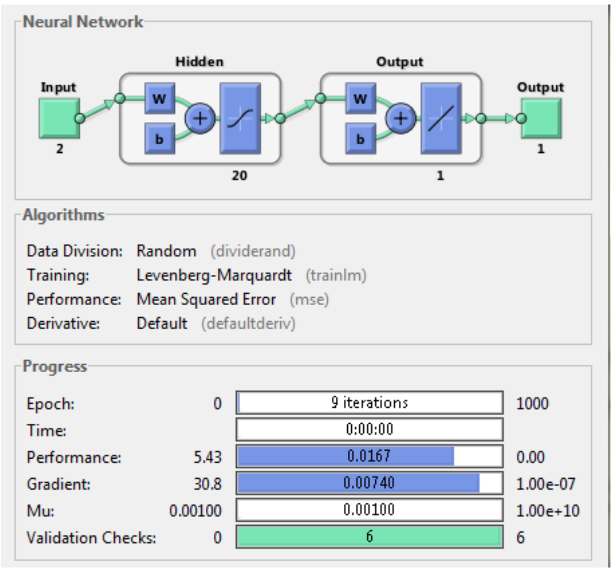

Figure 4:. Neural network structure

It can be noted that the *transfer function* is the *function tansig* (Tan-Sigmoid) on *layer* 1 and *function purelin* (Pure-Linear) at *layer* 2. Epoch 9 iterations of 1000 with a performance of Mean Square Error (MSE) 0.013129 as shown in Fig. 5.

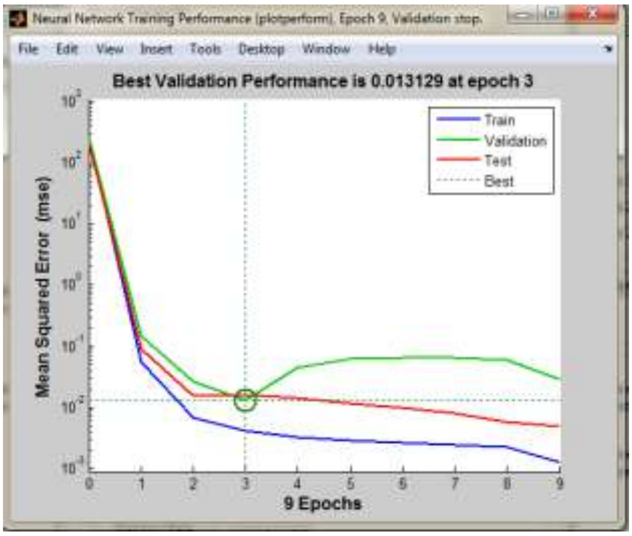

Figure 5: Mean squared error

The *regression* and *validation* values of the *training* process are 0.99654 (close to 1) and 0.99998, respectively as shown in Fig. 6.

The next test is done with voltage Vp = 20670 V and Vs1 = 504446 V, with target tap position is 2. The results of *Simulink diagram* show that the resulted tap positions are as much 2,009. This value is 2 using the *round* function contained in the *Interpreted MATLAB* block *function* as shown in Fig. 7.

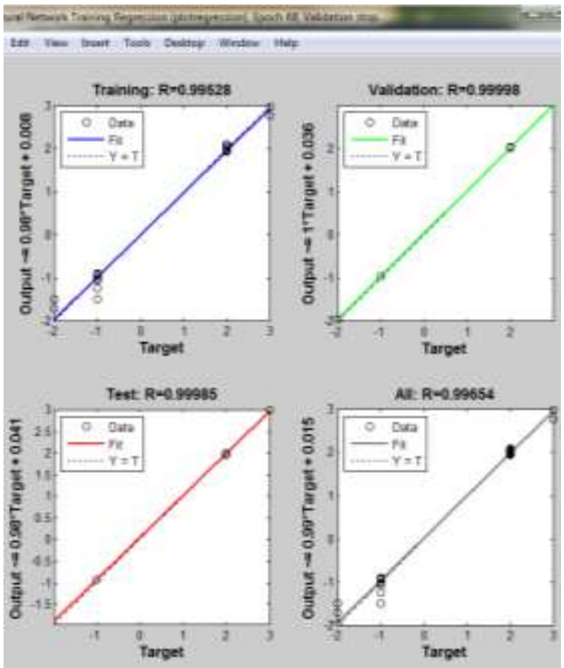

Figure 6: Regression plot

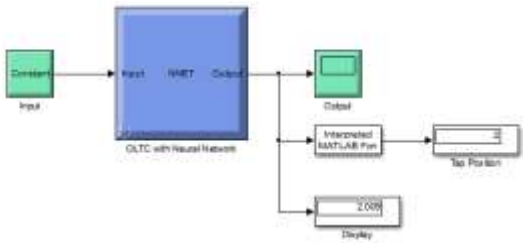

Figure 7: Results of the Simulink Diagram

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The comparison of OLTC tap settings using AVR and ANN controlled is shown in table 3. The value of V_s^1 is more stable than V_s. It is considered stable because the resulted secondary voltage is closer to the reference voltage (Vnp), so the problem of voltage instability can be solved by the ANN method. For more details, it can be seen in Fig. 8.

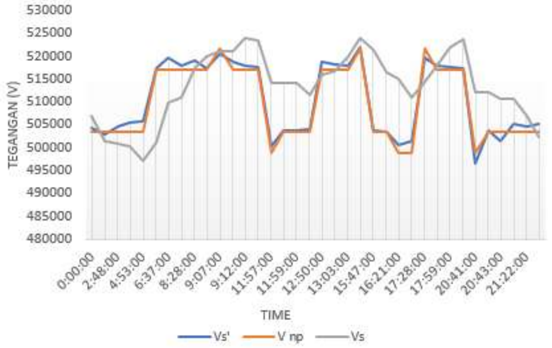

Figure 8: Chart of comparison secondary voltage with AVR dan ANN controlled

The presence of voltage stability is also influenced by the change of OLTC tap position on the transformer/the change of OLTC tap position with ANN method is only 14 times; while with the AVR method, it is changed 36 times. The comparison of OLTC tap position changes between the two methods is shown in Fig. 9.

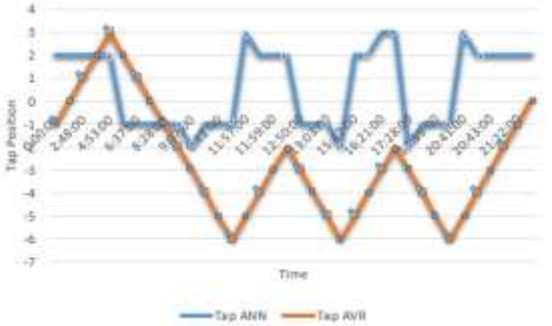

Figure 9: Chart of comparison position of the OLTC tap with AVR dan ANN controlled

It can be seen clearly that the changes of OLTC tap position with AVR method is changeable. The tap position changes from tap +3 position to tap -6 position. The change of OLTC tap position with ANN method is more stable than AVR method. This happens because the way AVR works is still step by step, so that OLTC tap does not match with the tap that it should. In addition, the step-by-step movement will cause OLTC mechanics frequently work and take a long time to be stable.

The OLTC tap setting using ANN can reduce the occurrence of OLTC tap position changes. OLTC tap changes only occur in the +3 to -2 tap position range. This indicates that OLTC tap position changes are reduced compared to the AVR method.

Table 3: Comparison of results of OLTC tap Settings using the AVR controlled and ANN controlled

No.	Tegangan (V)			Posisi Tap	
	AVR (Vs)	ANN (Vs^1)	Referensi (Vnp)	AVR	ANN
1	507006	504446	503350	-1	2
2	501409	502982	503350	0	2
3	500917	504739	503350	1	2
4	500364	505593	503350	2	2
5	496981	505667	503350	3	2
6	501163	517381	517080	2	-1
7	509712	519577	517080	1	-1
8	511126	518040	517080	0	-1
9	517338	519211	517080	-1	-1
10	519859	517308	517080	-2	-1
11	521089	520432	521650	-3	-2
12	521089	518894	517080	-4	-1
13	524103	517991	517080	-5	-1
14	523549	517552	517080	-6	-1
15	514201	500346	498770	-5	3
16	514078	503714	503350	-4	2
17	514078	503714	503350	-3	2
18	511680	504080	503350	-2	2
19	515800	518772	517080	-3	-1
20	516723	518113	517080	-4	-1
21	519859	517869	517080	-5	-1
22	524103	522018	521650	-6	-2
23	521520	503714	503350	-5	2
24	516354	503519	503350	-4	2
25	515062	500590	498770	-3	3
26	511065	501323	498770	-2	3
27	514447	519748	521650	-3	-2
28	518076	517991	517080	-4	-1
29	521950	517552	517080	-5	-1
30	523857	517308	517080	-6	-1
31	512110	496393	498770	-5	3
32	512049	503836	503350	-4	2
33	510757	501445	503350	-3	2
34	510696	505227	503350	-2	2
35	507006	504568	503350	-1	2
36	502209	505301	503350	0	2

4. Conclusion

This paper presents the ANN based on Levenberg-Marquardt algorithm optimization technique for determining the tap change of an OLTC in order to improve voltage stability in a power transformer. The proposed technique was tested on the power transformer 500 kV in PT YTL East Java with real data and the result obtained indicates that the network is capable to perform its task with accuracy. The application of optimization technique to power transformer 500 kV in PT YTL East Java is reducing the position changes as much as 36 times to 14 times in hours comparing using controlled by the AVC.

The optimal OLTC tap setting produces a more stable secondary voltage and the changes in OLTC tap position are reduced/rarely occurring. This can be done by ANN method because ANN can know the tap position which should be regardless of the primary and secondary voltage value. This condition will be very advantageous since the primary voltage changes often occur. The *training* process on ANN is influenced by the number of *hidden layers*, activation function, and network type used. Furthermore, the more *training* data it has, the ANN will be "smarter" in recognizing a pattern.

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