Training an Artificial Neural Network (ANN) to Control the Tap Changer of Parallel Transformers for a Closed Primary Bus

Alireza Sedaghati
Shahrood University of Technology
(Tel: +98-915-110-2201; email: ars@shahrood.ac.ir)

Abstract

Voltage control is an essential part of the electric energy transmission and distribution system to maintain proper voltage limit at the consumer's terminal. Besides the generating units that provide the basic voltage control, there are many additional voltage-controlling agents e.g., shunt capacitors, shunt reactors, static VAr compensators, regulating transformers mentioned in [1], [2]. The most popular one, among all those agents for controlling voltage levels at the distribution and transmission system, is the on-load tap changer transformer. It serves two functions-energy transformation in different voltage levels and the voltage control. Artificial Neural Network (ANN) has been realized as a convenient tool that can be used in controlling the on load tap changer in the distribution transformers. Usage of the ANN in this area needs suitable training and testing data for performance analysis before the practical application. This paper briefly describes a procedure of processing the data to train an Artificial Neural Network (ANN) to control the tap changer operating decision of parallel transformers for a closed primary bus. The data set are used to train a two layer ANN using three different neural net learning algorithms, namely, Standard Backpropagation [3], Bayesian Regularization [4] and Scaled Conjugate Gradient [5]. The experimental results are presented including performance analysis.

1. INTRODUCTION

A number of methods have been devised to automatically control the parallel operation of power transformers. These are the master/follower method, the power factor paralleling method, the negative reactance paralleling method, the circulating current paralleling method, the transformer auto paralleling scheme and the VAr balancing paralleling method [6-7]. Among these paralleling methods the two most commonly used are Master/Follower and Circulating Current methods. Both are applied without any change for more than 50 years [8]. The most recently developed one, VAr balancing method [7] is in the early stage of application. Other methods did not gain acceptance because of various limitations. The two widely used methods namely, Master/Follower and Circulating Current do not still operate up to the satisfactions for complex substation configuration.

A conceptual framework to apply Artificial Neural Network (ANN) for tap changer control of multiple transformers in parallel is described in [9]. In this method an ANN is trained with five different parameters, e.g. as loaded common bus bar voltage, coupling circuit breaker status, circulating current, individual transformer's output power factor and the network power factor. Once trained, the network can respond by changing to appropriate tap position if any change in load or system requires so. This method has the potential to be implemented locally or remotely using Supervisory Control and Data Acquisition (SCADA).

An important aspect of using ANN in this method is to prepare the data set in a way that can be trained by ANN. This data set is prepared from transformer details covering extreme variations of load condition. This paper describes the techniques to prepare data for ANN to control tap-changer of parallel transformers with closed primary bus connection. Using this technique, real world data from a substation of Australian Electric Company is used to train an ANN and its performance as parallel tap changer is presented in this paper. Simulated result shows very good performance except few false responses.

2. PREPARATION OF DATA TO FEED ANN

Data for training and testing the ANN are the vectors consisting four variables such as voltage, coupling circuit breaker status, circulating current, and power factor ratio of transformer load to total substation load. Calculation of these variations from transformer specification and substation load are given below.

2.1 Circulating Current

If the transformer secondary voltages at the paralleling point are not matched, a circulating current flows between the transformers. The circulating current can be measured from the following equation.

$$I_{circ} = \frac{\Delta V}{Z_{t1} + Z_{t2}} \tag{1}$$

where ΔV = difference of transformers voltages in pu,
Z_{t1} = Impedance of the transformer 1 in pu and
Z_{t2} = Impedance of the transformer 2 in pu.

When the primary sides of the parallel transformers are closed and transformers are identical as shown in the substations A and C of Fig. 1, the voltage difference ΔV is caused due to the tap positions only. Transformers in substation B and D are also operating in closed bus configuration as the primary side is closed at the upstream substation. In this case Z_{t1} and Z_{t2} will include the impedances of the respective supply lines. Z_{t1} and Z_{t2} also vary with tap positions.

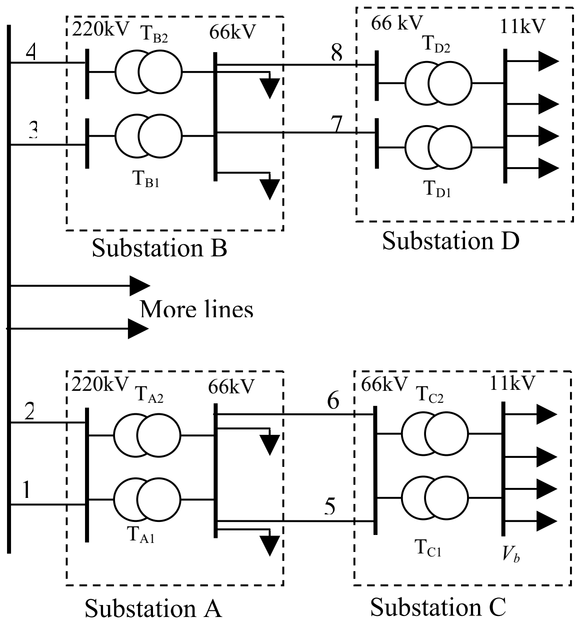

Fig. 1. A network showing parallel transformers in substations.

Since the primary side is closed the transformers in each substation are receiving equal voltage at the primary side. The transformer having higher tap position will have higher output voltage and vice versa. The industrial and domestic consumptions of electric energy show that the load current I_L is mostly inductive and lags the source voltage. If the transformer1 (T_{C1}) is in higher tap position than the transformer2 (T_{C2}) and the transformers are identical, transformer1 current (I_{t1}) will lag the load current (I_L) and transformer2 current (I_{t2}) will lead the load current. Such a circulating current vector diagram with the load currents is shown in Fig 2.

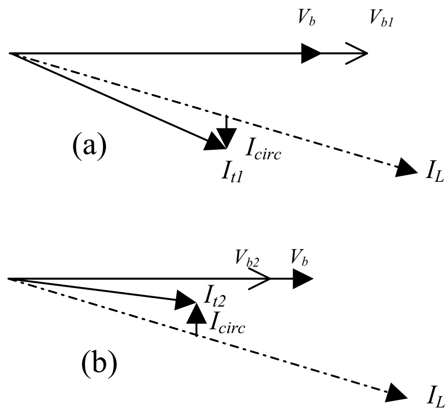

Fig. 2. Vector diagram of currents when two transformers operating in parallel (a) for transformer 1 and (b) for transformer 2.

Flow of this circulating current between transformers causes voltage drops across their impedances. The two transformers will have output voltages different in magnitude (V_{b1}, V_{b2}) due to operation in different tap positions. Secondary bus voltage V_b is the result after regulation of the voltage drops due to circulating current as shown in Fig. 3.

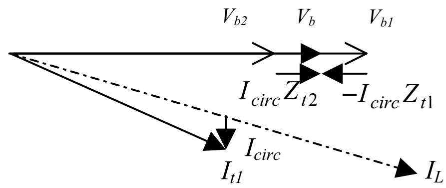

Fig. 3. Vector diagram showing the voltage adjustment at the secondary bus bar.

Load current shared by the transformers are inversely proportional to the impedances of the transformers for closed primary bus. Sharing of this load current by transformer1 (I_{Lt1}) and transforemer2 (I_{Lt2}) can be expressed by the equations (2) and (3) respectively.

$$I_{Lt1} = \frac{I_L * Z_{t2}}{Z_{t1} + Z_{t2}} \tag{2}$$

$$I_{Lt2} = \frac{I_L * Z_{t1}}{Z_{t1} + Z_{t2}} \tag{3}$$

From the fact that the circulating current lags or leads with reference to load current as shown in Fig. 3, it can be stated that the transformer current lags the load current if its output voltage is higher than the secondary bus voltage and leads the load current if its output voltage is lower. The following equations can then be established for calculating the total transformer1 currents I_{t1} for different tap position referring the secondary bus voltage.

$$I_{t1} = I_{Lt1} + I_{circ} \qquad \text{for } V_{b1} > V_b \qquad (4)$$

$$I_{t1} = I_{Lt1} - I_{circ} \qquad \text{for } V_{b1} < V_b \qquad (5)$$

Similarly other transformer individual current I_{t2} for different tap positions producing its output voltage higher or lower than the secondary bus voltage have been calculated. From this transformer currents power factor variations are determined. If two parallel transformers are not identical that means voltage ratings are slightly different (for example, one has rating 11kV and another 11.5kV on the secondary), they can be used in parallel after adjusting on-load taps, if available to obtain identical turn ratio or recognizing that the transformers will find optimum operating load taps which will not be the same on the two units [10]. From the rated voltages and impedances at different tap positions of such transformers the circulating and individual transformer currents can be measured from the equations (1) ~ (5).

In the calculation of circulating current, the magnitude of the voltage differences (ΔV) is considered as the adjustable step voltage ranges ($\pm$ 10% of the rated voltage) of the OLTC transformers used in the distribution system. The purpose is to train an ANN to achieve a good generalization over all possible difference in tap positions and rated voltage that might occur in practice. Circulating current is used as a supervisory status using a threshold value and fed to ANN as an input. This threshold value will be less than the circulating current caused by the ΔV when two parallel transformers operate with one tap position apart.

$$I_{circ} = \begin{cases} 0 & \text{circulating current is within the threshold value} \\ 1 & \text{circulating current exceeds the threshold value} \end{cases}$$

2.2 Voltage Band

The main purpose of the on-load tap changer is to keep the secondary bus voltage to a desired level. For control purpose the rated voltage of power transformers are reduced to 120V using instrument voltage transformer called voltage transformer (VT). This voltage level is always referred as the desired level as this is the exact reproduction of the actual voltage.

Distribution lines experience a drop of voltage due to the current flow. This causes a change of voltages at the consumer ends. In order to keep the standard voltage at the consumer ends, line drop compensation is used where the bus voltage is maintained in the range of 5% higher or lower from the desired level depending on the load demand. The transformer is capable of operating continuously in this range of voltage at maximum rated KVA for any tap without exceeding the limits of temperature rise [11]. This capability of transformer operation at 5% above the rated voltage is made standard to overcome the 5% regulation of voltage drop in the line [12]. Therefore a voltage band of 114V to 126V can be safely considered as the desired voltage level of transformer operation.

There is a risk of core damage if the transformer is excited more than 110% of rated voltage [12]. However, transformer operation needs to be prohibited beyond the desire voltage band. ANN control has to be trained to recognize the voltage level beyond the desired voltage level. Hence two more voltage bands are prepared for training and testing the ANN so that it can direct tap changer to connect proper tap to match with the desired voltage level. These two are named as undesired higher voltage level and undesired lower voltage level. The undesired higher voltage level covers the voltage range 5% to 10% above the rated voltage. The undesired lower voltage level covers the voltage range 5% to 10% below the rated voltage.

2.3 The Status of Coupling Circuit Breakers

The status of coupling circuit breakers (CCB) determines the paralleling of the transformers. It includes the breakers connecting the transformers to the buses and also the breakers connecting bus sections. If any of these beakers is switched off the associated transformer goes out of service or change the status of parallel operation. The breaker auxiliary switches can be used to signal the transformer paralleling status as follows.

$$\text{CCB} = \begin{cases} 1 & \text{when transformer is parallel} \\ 0 & \text{when transformer is not parallel} \end{cases}$$

2.4 Power Factor Ratio

Load power factor is taken from the statistical record of electric power supply from a substation in Victoria, Australia. The power factors of the transformer loads at the substation for different tap position were determined from the reactive and real components of the load. The power factor ratio which is a component of the input vector is then determined as

$$\text{Power factor ratio} = \frac{\text{Power factor of transformer current}}{\text{Power factor of total load}} \qquad (6)$$

3. INPUT VECTOR AND TARGET ASSOCIATION TO TRAIN ANN

The four variables, e.g., voltage level (x_1), circulating current (x_2), coupling circuit breaker status (x_3), and the ratio of the transformer load power factor to total load power factor (x_4) are grouped into an input vector $\mathbf{x} = (x_1, x_2, x_3, x_4)$. Each of the four variables has essential features in determining tap changer control. Input vectors are assigned target levels that are required for supervised training of the ANN architecture. There are three operational decisions for the transformer tap-changer to be made by the ANN. So, it is a three class problem such as tap lower (C_1), tap hold (C_2) and tap rise (C_3). Each input vector is associated with a target level as follows.

$t^n = -1$ if $\mathbf{x}^n$ is from class C_1

$t^n = 0$ if $\mathbf{x}^n$ is from class C_2

$t^n = 1$ if $\mathbf{x}^n$ is from class C_3

The first variable x_1 will allow the tap-changers to hold when voltage level is in desired voltage band; raise or lower the tap-position when voltage senses is in lower band or higher band respectively. It will be the dominating factor in all the operating conditions. Control will sense transformer in radial operation when second and third variables both have '0' values. It will sense parallel operation when the third variable is '1'. In radial operation the fourth variable does not have significant concern since the transformer takes independent load instead of sharing from the total load with others. Therefore, the input vectors, for radial operation of transformers, are grouped into classes according to the voltage band irrespective of the third variable's deviations.

In parallel operation the safe operating condition will be when x_1 is in desired voltage band, x_2 is '0', x_3 is '1' and x_4 is '1'. x_4 equals '1' signifies proportionate sharing of real and reactive load between transformers. This condition ensures that transformers do not have any circulating current flow and $\Delta V = 0$. Therefore for the numerical data determined under this condition are grouped into class C_2. Since the aim is to limit the transformer voltage within the desire voltage band, the input vectors containing x_1 component in higher voltage band are grouped into class C_1 to reduce the voltage. Similarly the input vectors that has x_1 component lower than the desired voltage band are grouped into class C_3 for raising the voltage. Within the desired voltage band, input data containing the fourth variable higher than 1 are grouped into class C_3 and those lower than 1 are grouped into class C_1.

4. EXPERIMENTS

The neural network architecture used in the experiment has four inputs for input vector described in section 3, one hidden layer of 5 units and one output unit for changing decision. The network was trained using three different learning algorithms namely standard backpropagation (SBP) [3], Bayesian regularization (BR) [4] and scaled conjugate gradient (SCG) [5]. These are the three algorithms chosen as they are found to have good performance in a wide range of application [13]. There are two data sets created from different parallel transformers as below.

I. For identical transformers with closed primary bus

II. For similar transformers with slight difference in voltage rating

The two data sets comprise incoming voltage magnitude variation in the range ±10% of the transformer rated voltage. For each of the two data sets separate investigations were carried out for each of the algorithms. There were 1500 data in each set. From this data set 1005 (67%of the total data in each set) were chosen randomly proportionate to different classes to use as training set. In the learning process the stopping criteria was set as either completion of 100,000 epochs or achievement of minimum average error at 0.002. The performance of the network depends on the final set of weights. The set of weights to which a neural network settles down depend on the initial weights chosen and learning parameters. In this study, we conducted 20 trials for each algorithm varying the initial weights and learning parameters.

Typical learning characteristic of each algorithm is shown in Fig. 4. The curves show that BR and SCG learning algorithms minimize the error much faster than SBP.

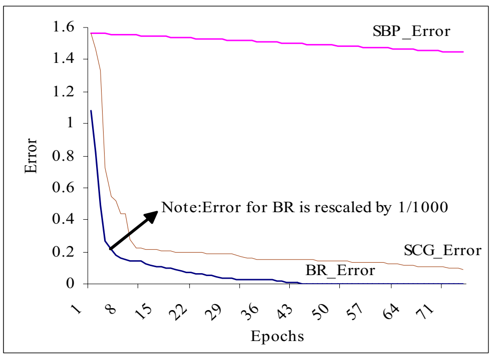

Fig. 4. Typical learning characteristic of each algorithm.

The ANN output with respect to target levels are shown in Fig. 5. The predicted values associated with target levels spread over highest for SBP and lowest for BR. In the case of SCG algorithm the ranges are reasonably short. In case of SBP the output ranges associated with three target levels are overlapped exhibiting more false responses.

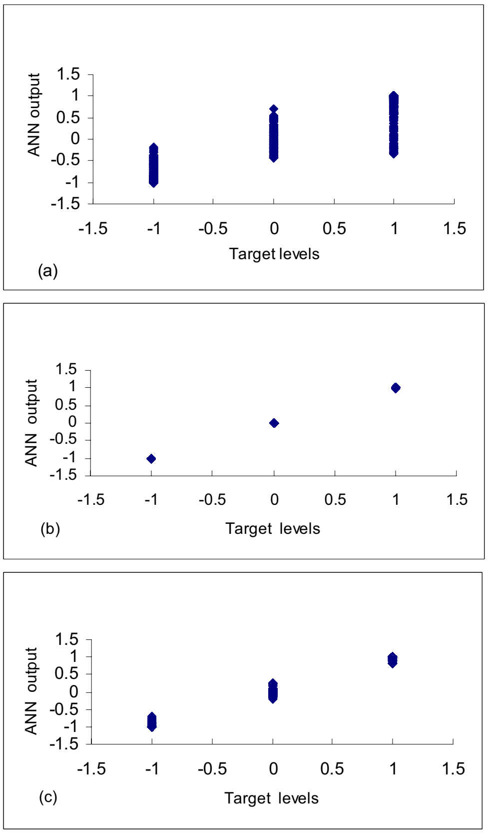

Fig.5. Scatter graph of the ANN output for (a) Standard backpropagation (b) Bayesian regularization (c) Scaled conjugate gradient.

The predicted values of the ANN output are interpreted as follows:

$$\text{ANN output} \begin{cases} > 0.5 & \text{tap rise} \\ < -0.5 & \text{tap lower} \\ \text{otherwise} & \text{tap hold} \end{cases}$$

The average false responses over 20 trials are summarized in Table 1.

Table 1: Average False Responses.

Algorithms	Data sets	False Responses$_{avrg}$		
		Training Data	Test Data	Total Data
SBP	I	85	41	126
	II	83	43	126
BR	I	0	2	2
	II	1	1	2
SCG	I	1	1	2
	II	0	2	2

The results show promising in the case of two data sets when the network is trained by Bayesian regularization and scaled conjugate gradient algorithms. There are some false responses in training data, which are significant in the case of SBP. The percentage of correct responses in BR and SCG are more than 99% which is acceptable for the practical application of ANN in transformer parallel tap-changing control in the case of closed primary bus connection.

5. CONCLUSION

This paper investigates the use of artificial neural network to control the tap changer operation of parallel transformer for primary close bus connection. It describes the preparation of suitable data to train ANN for application to the tap changer control. The response of an ANN trained with the data sets has been presented and analyzed. The results in the case of BR and SCG algorithm indicate the viability of practical application of ANN in parallel transformers tap-changing control for closed primary bus connection.

6. REFERENCES

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