I.J. Intelligent Systems and Applications, 2012, 12, 75-85
Published Online November 2012 in MECS (http://www.mecs-press.org/)
DOI: 10.5815/ijisa.2012.12.10

Distance Protection Settings Based Artificial Neural Network in Presence of TCSR on Electrical Transmission Line

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Abstract— This research paper study the performance of distance relays setting based analytic (AM) and artificial neural network (ANN) method for a 400 kV high voltage transmission line in Eastern Algerian transmission networks at Sonelgaz Group compensated by series Flexible AC Transmission System (FACTS) i.e. Thyristor Controlled Series Reactor (TCSR) connected at midpoint of the electrical transmission line. The facts are used for controlling transmission voltage, power flow, reactive power, and damping of power system oscillations in high power transfer levels. This paper studies the effects of TCSR insertion on the total impedance of a transmission line protected by distance relay and the modified setting zone protection in capacitive and inductive boost mode for three zones. Two different techniques have been investigated in order to prevent circuit breaker nuisance tripping to improve the performances of the distance relay protection.

Index Terms— Distance Protection, TCSR, Injected Reactance, Artificial Neural Network

I. Introduction

In recent years, power demand has increased substantially while the expansion of power generation and transmission has been severely limited due to limited resources and environmental restrictions. As a consequence, some transmission lines are heavily loaded and the system stability becomes a power transfer-limiting factor. Flexible AC transmission systems (FACTS) controllers have been mainly used for solving various power system steady state control problems [1].

There are two generations for realization of power electronics based FACTS controllers: the first generation employs conventional thyristor-switched capacitors and reactors, and quadrature tap-changing transformers while the second generation employs gate turn-off (GTO) thyristor-switched converters as voltage source converters (VSCs). The first generation has resulted in the Static Var Compensator (SVC), the Thyristor Controlled Series Capacitor (TCSC), and the Thyristor Controlled Phase Shifter (TCPS) [2-3]. The second generation has produced the Static Synchronous Compensator (STATCOM), the Static Synchronous Series Compensator (SSSC), the Unified Power Flow Controller (UPFC), and the Interline Power Flow Controller (IPFC) [4]. The two groups of FACTS controllers have distinctly different operating and performance characteristics. In the presence of series FACTS devices, the conventional distance relay characteristics such as MHO and Quadrilateral are greatly subjected to mal-operation in the form of overreaching or under-reaching the fault point [5,6]. Therefore, the conventional relay characteristics may not work properly in the presence of FACTS device.

Artificial neural network (ANN) based technology, which is inspired by biological neural networks, has developed rapidly in the previous decade and has been applied in power system protection applications. Specific applications include direction discrimination for protecting transmission lines [7-8], fault classification for faults on double circuit lines [9], ANN based distance relays [10], differential protection of three phase power transformers [11] and faults on generator windings [12], the ANN based designs of generic protection systems proposed so far work well only for ideal fault conditions but do not maintain the integrity of the boundaries of the relay characteristics. Some of the published results related to the application of ANNs in distance protective relaying improvements are stated in the survey given by [13-14]. Reference [15] demonstrates the use of neural networks as a pattern classifier for the distance relaying algorithm and shows that the proposed scheme improves protection system selectivity. In [16] the use of a multilayer feed forward network to reduce the influence of DC offset on fault distance computation is reported. Saturation of current transformers during a heavy fault could cause incorrect distance measurement by the relay.

Performance evaluation of distance protection scheme in presence of FACTS controllers, which affect the apparent impedance calculations at relay point, has been carried out in [17]. The apparent impedance calculations are generally carried out using power frequency components of voltage and current measured at relay point. Some of the published articles dealing with the impact on presence TCSC on distance relay and measured impedance have been reported in references [18-20].

In this paper, the three protection zones setting for a MHO distance relay using two different algorithms i.e. analytic and ANN method are investigated. The investigation concern a 400 kV single transmission line installed at eastern Algerian electrical network. The line is equipped with TCSR series FACTS devices, in capacitive and inductive modes. The performances of the distance relay protection are investigated for different values of firing angle (α) with series compensation located in midline electrical transmission.

II. Apparent Reactance Injected by Thyristor Controlled Series Reactor (TCSR)

The compensator TCSR mounted on figure 1 consists of variable inductance (L_1) connected in series with the transmission line controlled by thyristors mounted in anti-parallel and controlled by an firing angle (α) which varies between 90° and 180°, and a fixed value inductance (L_2) connected in shunt [1-2].

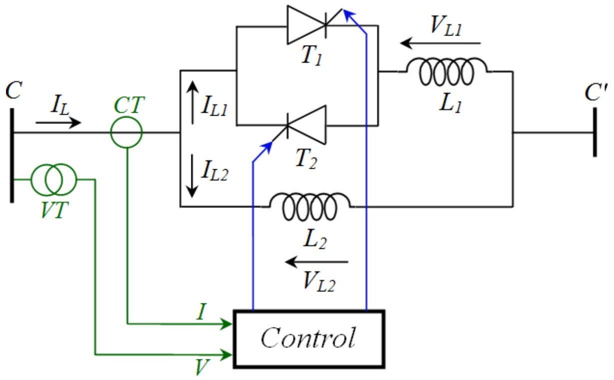


Fig. 1: Principal operation of TCSR

This compensator can be modeled as a variable reactance (X_{TCSR}) as shows in figure 2.

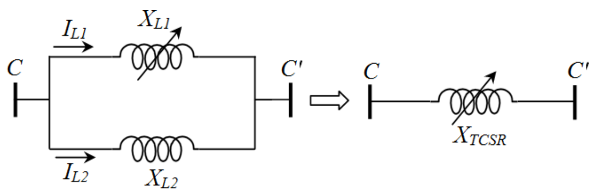


Fig. 2: Apparent reactance injected by TCSR

From figure 2, the total reactance of the TCSR is defined by the following formula [1-4]:

$$X_{TCSR}(\alpha) = X_{L1}(\alpha)//X_{L2} = \frac{X_{L1}(\alpha).X_{L2}}{X_L(\alpha)+X_{L2}} \quad (1)$$

The reactance of the first inductance X_{L1} (α) controlled by thyristors is defined by formula:

$$X_{L1}(\alpha) = X_{L1-\max}\left[\frac{\pi}{\pi-2\alpha-\sin(2\alpha)}\right] \quad (2)$$

Where,

$$X_{L1-\max} = L_1.\omega \quad (3)$$

And the second reactance of inductance (X_{L2}) is defined by formula:

$$X_{L2} = L_2.\omega \quad (4)$$

From formula (2) and (4), the final formula (1) becomes:

$$X_{TCSR}(\alpha) = \frac{L_2 L_1 \omega^2\left(\frac{\pi}{\pi-2\alpha-\sin(2\alpha)}\right)}{\omega\left(L_2+L_1\left(\frac{\pi}{\pi-2\alpha-\sin(2\alpha)}\right)\right)} \quad (5)$$

III. Distance Protection in Electrical Transmission Line

Distance protection is so called because it is based on an electrical measure of distance along a transmission line to a fault. The distance along the transmission line is directly proportional to the series electrical impedance of the transmission line (Z_L). Impedance is defined as the ratio of voltage to current [21-23]. The philosophy of setting relay at Sonelgaz Group [24] is three zones forward (Z_1, Z_2 and Z_3) for protection the transmission line HV between busbar A and B with total impedance Z_{AB} as shown in figure 3.

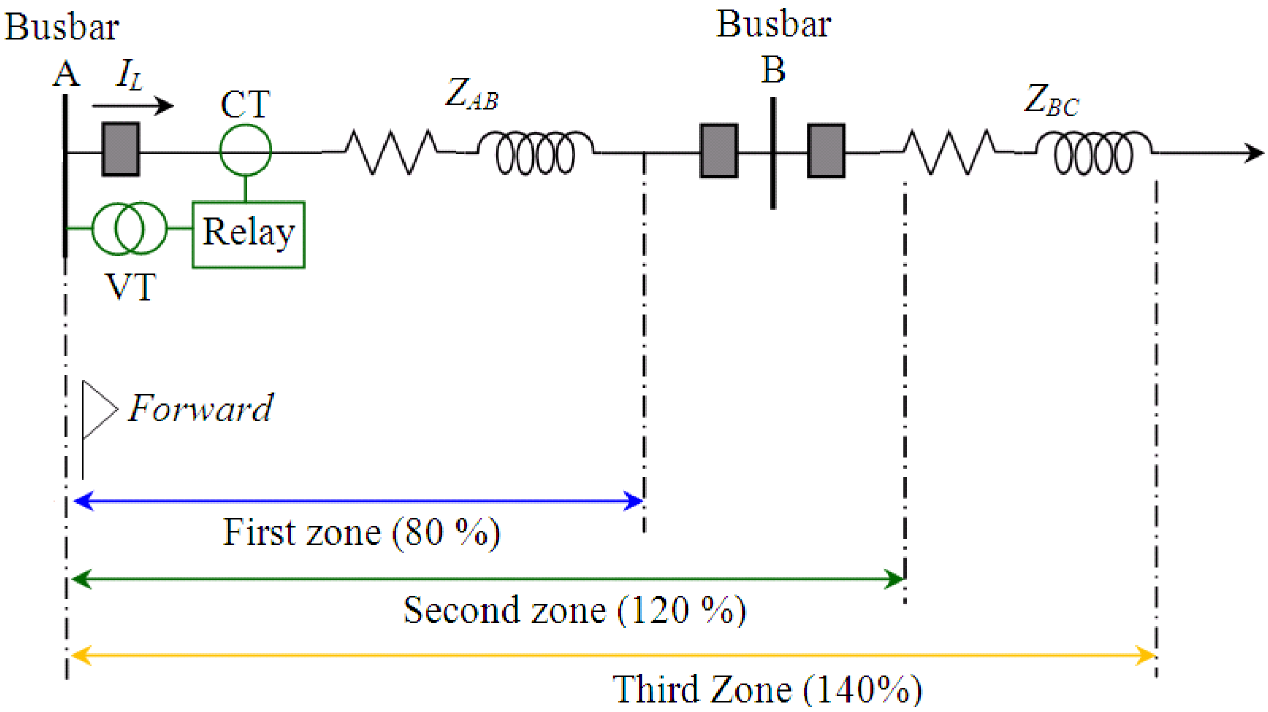


Fig. 3: Setting zones for distance protection

The setting zones for protected transmission line without TCSR systemare expressed by [22-23]:

$$Z_1 = R_1 + jX_1 = 80\% Z_{AB} = 0,8.(R_{AB} + jX_{AB}) \quad (6)$$

$$Z_2 = R_2 + jX_2 = R_{AB} + jX_{AB} + 0,2.(R_{BC} + jX_{BC}) \quad (7)$$

$$Z_3 = R_3 + jX_3 = R_{AB} + jX_{AB} + 0,4.(R_{BC} + jX_{BC}) \quad (8)$$

The total impedance of electrical transmission line AB measured by distance relay is:

$$Z_{AB} = K_Z.Z_L = \left(K_{VT} / K_{CT} \right).Z_L \quad (9)$$

Where,

$$K_{VT} = V_{prim} / V_{sec} \quad (10)$$

And,

$$K_{CT} = I_{prim} / I_{sec} \quad (11)$$

The impedance Z_{AB} is real total impedance of transmission line AB, and K_{VT} and K_{CT} is ratio of voltage to current respectively. The presence of TCSR compensator (X_{TCSR}) has a direct influence on the total impedance of the protected line (Z_{AB}). This effect especially on the reactance X_{AB} and no influence on the resistance R_{AB}, it is represented in figure 4.

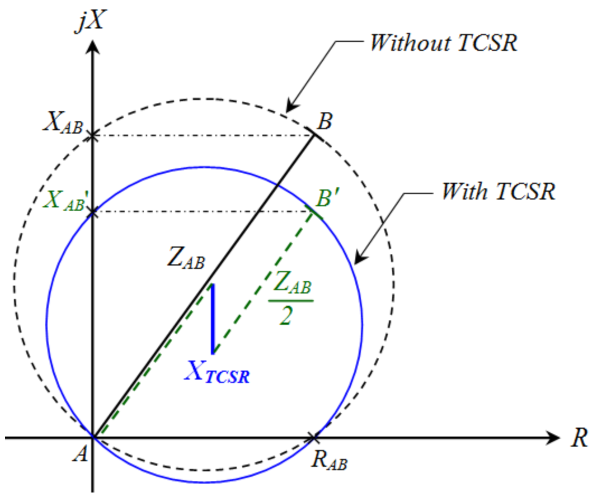


Fig. 4: Impact of presence TCSR on total impedance Z_{AB} for distance protection

From figure 4, the setting zones for protected transmission line with TCSR connected at midline are:

$$Z_1 = 0,8\left[\left(Z_{AB}/2 \right) \pm X_{TCSR}(\alpha) + Z_{AB}/2 \right] \quad (12)$$

$$Z_2 = \left(Z_{AB}/2 \right) \pm X_{TCSR}(\alpha) + Z_{AB}/2 + 0,2.Z_{BC} \quad (13)$$

$$Z_3 = \left(Z_{AB}/2 \right) \pm X_{TCSR}(\alpha) + Z_{AB}/2 + 0,4.Z_{BC} \quad (14)$$

IV. Application ANN on Power Systems

The multilayer perception neural network is built up of simple components. We will begin with a single-input neuron, which we will then extend to multiple inputs. We will next stack these neurons together to produce layers.

Finally, we will cascade the layers together to form the network. A single-input neuron is shown in figure 5. The scalar input (p) is multiplied by the scalar weight (w) to form (wp), one of the term that is sent to the summer. The other input 1 is multiplied by a bias (b) and then passed to the summer. The summer output (n), often referred to as the net input goes into a transfer function (f), which produces the scalar neuron output (a) [25-26].

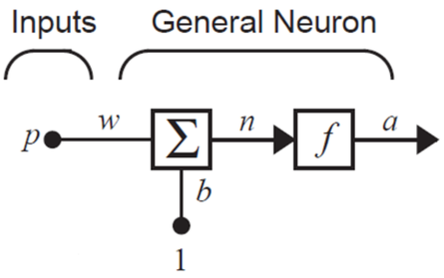


Fig. 5: Single input neuron

Note that and are both adjustable scalar parameters of the neuron. Typically the transfer function is chosen by the designer, and then the parameters w and b are adjusted by some learning rule so that the neuron input/output relationship meets some specific goal.

The transfer function may be a linear or a nonlinear function of n. One of the most commonly used functions is the log-sigmoid transfer function, which is shown in figure 6.

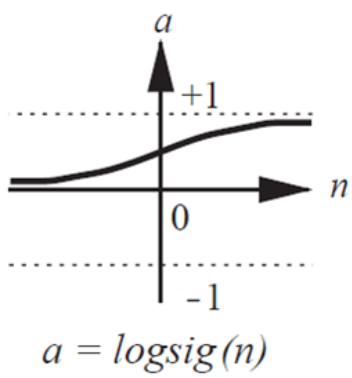


Fig. 6: Log-Sigmoid transfer function

This transfer function takes the input (which may have any value between plus and minus infinity) and squashes the output into the range 0 to 1, according to the formula:

$$a = \frac{1}{1+e^{-n}} \tag{15}$$

The log-sigmoid transfer function is commonly used in multilayer networks that are trained using the back propagation algorithm, in part because this function is differentiable.

4.1. Multiple Inputs and Output

Typically, a neuron has more than one input. A neuron with R inputs is shown in figure 7. The individual inputs p_1 , p_2 ... p_R are each weighted by corresponding elements w_1 , w_2 ... w_R of the weight matrix (W).

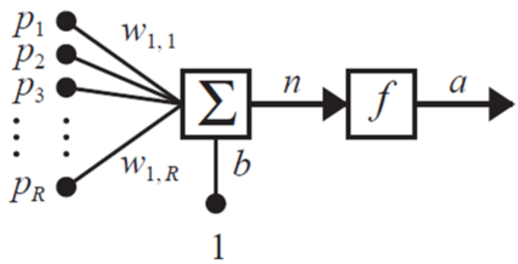


Fig. 7: Multiple Input Neurons

The neuron has a bias b, which is summed with the weighted inputs to form the net input n:

$$n = w_{1,1}.p_1 + w_{1,2}.p_2 + ... + w_{1,R}.p_R + b \tag{16}$$

Where the matrix W for the single neuron case has only one row. Now the neuron output can be written as:

$$a = f(W.p + b) \tag{17}$$

Figure 8 represents the neuron in matrix form.

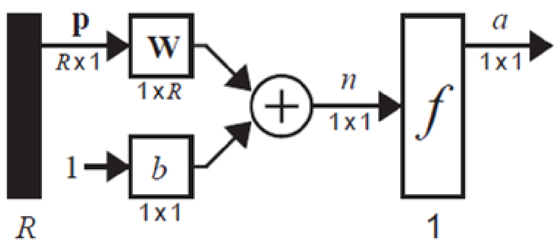


Fig. 8: ANN structure with R inputs

Commonly one neuron, even with many inputs S, is not sufficient. We might need five or ten, operating in parallel, in what is called a layer. A single-layer network of neurons is shown in figure 9. Note that each of the R inputs is connected to each of the neurons and that the weight matrix now has S rows.

The layer includes the weight matrix W, the summers, the bias vector a, the transfer function boxes and the output vector b. Some authors refer to the inputs as another layer, but we will not do that here. It is common for the number of inputs to a layer to be different from the number of neurons (i.e., $R \neq S$) [26].

The S neuron, R input, one-layer network also can be drawn in matrix notation, as shown in figure 9.

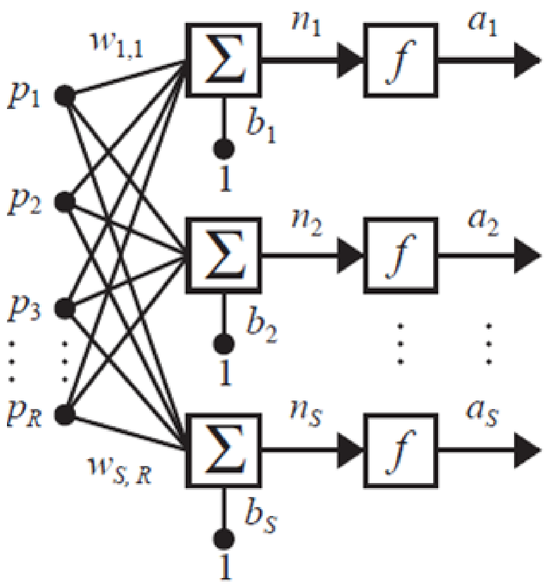


Fig. 9: ANN structure with Layer of S neurons

4.2. Multiple Layers of Neurons

Now consider a network with several layers. Each layer has its own weight matrix W, its own bias vector b, a net input vector n and an output vector a.

We need to introduce some additional notation to distinguish between these layers. We will use superscripts to identify the layers. Thus, the weight matrix for the first layer is written as W^1, and the weight matrix for the second layer is written as W^2. This notation is used in the three-layer network shown in figure 8. As shown, there are R inputs, S^1 neurons in the first layer, S^2 neurons in the second layer, etc. As noted, different layers can have different numbers of neurons.

The outputs of layers one and two are the inputs for layers two and three. Thus layer 2 can be viewed as a one-layer network with $R = S^1$ inputs $S^2 = S^1$ neurons, and an $S^2 \times S^1$ weight matrix W^2.

The input to layer 2 is a^1, and the output is a^2. A layer whose output is the network output is called an *output layer*. The other layers are called *hidden layers*. The network shown in figure 10 has an output layer (layer 3) and two hidden layers (layers 1 and 2).

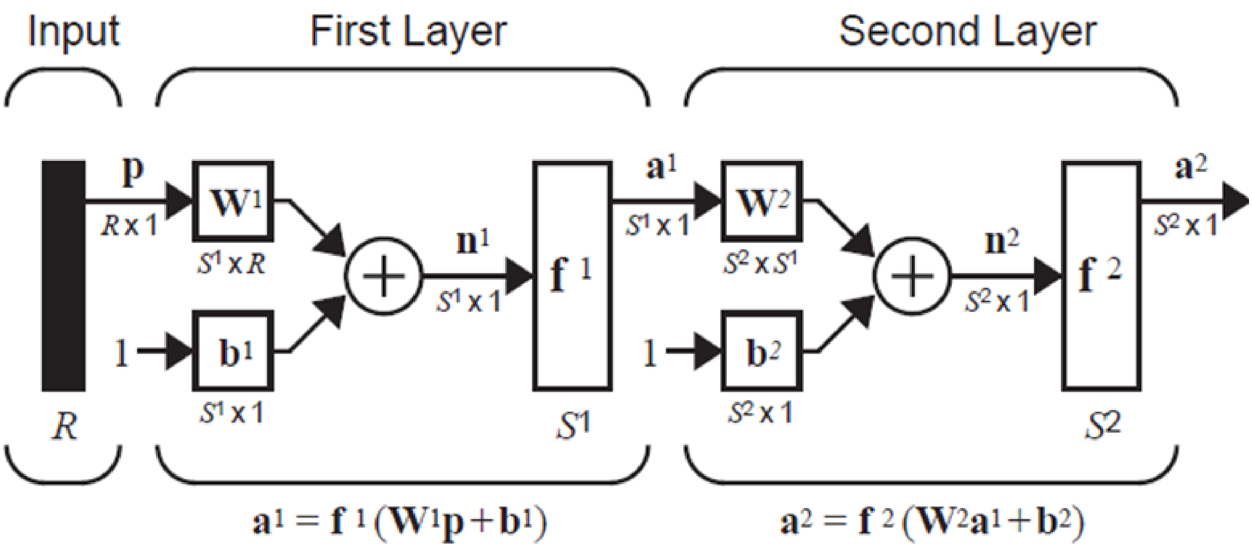


Fig. 10: ANN structure with two layer

4.3. Application on Power System

The electric power industry is currently undergoing an unprecedented reform. One of the most exciting and potentially profitable recent developments is increasing usage of ANN techniques. A major advantage of ANN approach is that the domain knowledge is distributed in the neurons and information processing is carried out in parallel-distributed manner [26].

Being adaptive units, they are able to learn these complex relationships even when no functional model exists. This provides the capability to do 'Black Box Modeling' with little or no prior knowledge of the function itself. ANNs have the ability to properly classify a highly non-linear relationship and once trained, they can classify new data much faster than it would be possible by solving the model analytically.

The rising interest in ANNs is largely due to the emergence of powerful new methods as well as to the availability of computational power suitable for simulation. The field is particularly exciting today because ANN algorithms and architectures can be implemented in VLSI technology for real-time applications. The application of ANNs in many areas under electrical power systems has lead to acceptable results.

V. Case Study and Simulation Results

The figure below represents the 400 kV, 50 Hz power system eastern Algerian electrical transmission networks at Sonelgaz group (Algerian Company of Electricity and Gas) studied in this paper [24]. The distance relay is located in the busbar *A* at Ain M'lila substation to protect transmission line between busbar *A* and busbar *B* at Batna substation, the bus bar *C* is located at Biskra substation.

The series FACTS study type TCSR is installed in the midpoint of the electrical line protected by a distance relay. The parameters of line and TCSR installed are summarized in the appendix.

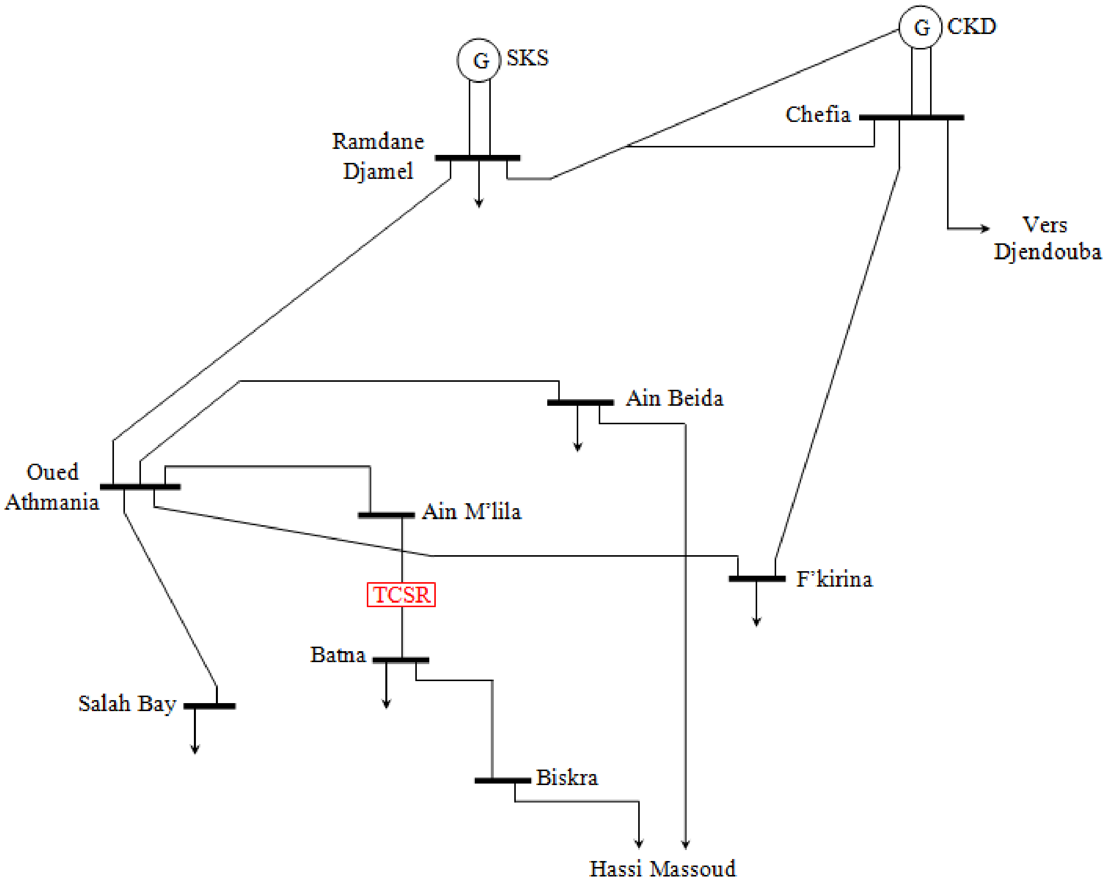


Fig. 11: Electrical networks 400 kV study in presence TCSR

The characteristic curve $X_{TCSR}(\alpha)$ of the TCSR used in this case study is shown in figure 12.

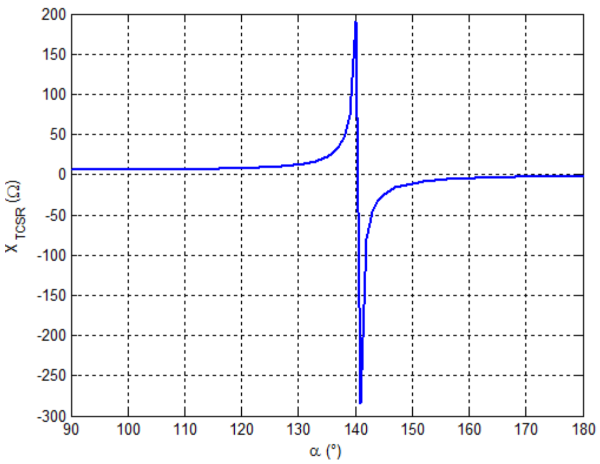


Fig. 12: Characteristic curve of TCSR installed

5.1. Setting relay without TCSR

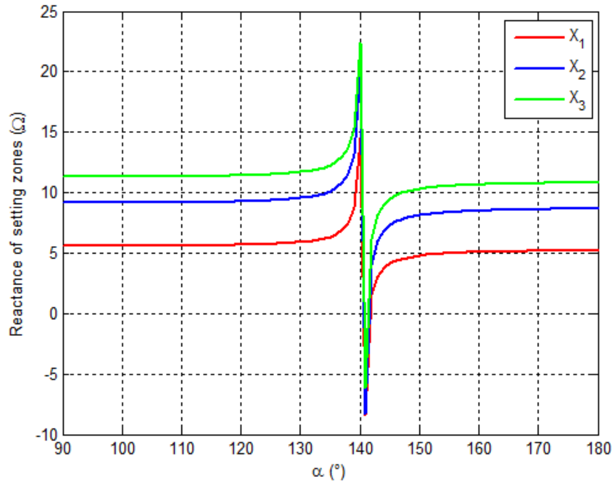
The total impedance measured by the distance relay without series FACTS is: Z_L = 2.4039 + *j* 23. 2432 Ω. The settings zones are summered in table 1.

Table 1: Setting distance protection without TCSR

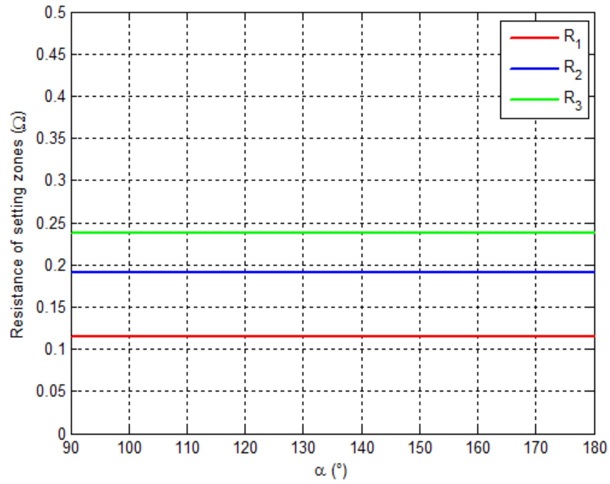
Setting zones	Values	
	X_1 (Ω)	R_1 (Ω)
Z_1	1,1157	0,1154
Z_2	1,8493	0,1913
Z_3	2,3039	0,2383

5.2. Setting relay on presence TCSR based AM method

Figures 13.a and 13.b represented the impact of the angle variation α on the settings zones reactance and resistance respectively for transmission line based analytical method.



(a)



(b)

Fig. 13: Parameters of setting zones in variation angle α (a). Reactance, (b). Resistance.

5.3. Topology of ANN Proposed

One of the keys to the success of any ANN application is the choice of input signals. In this case measured impedance (i.e.: R_{AB} and X_{AB}) and change rate of reactance X_{TCSR} and firing angle α are taken as input signals as shown in figure 14.

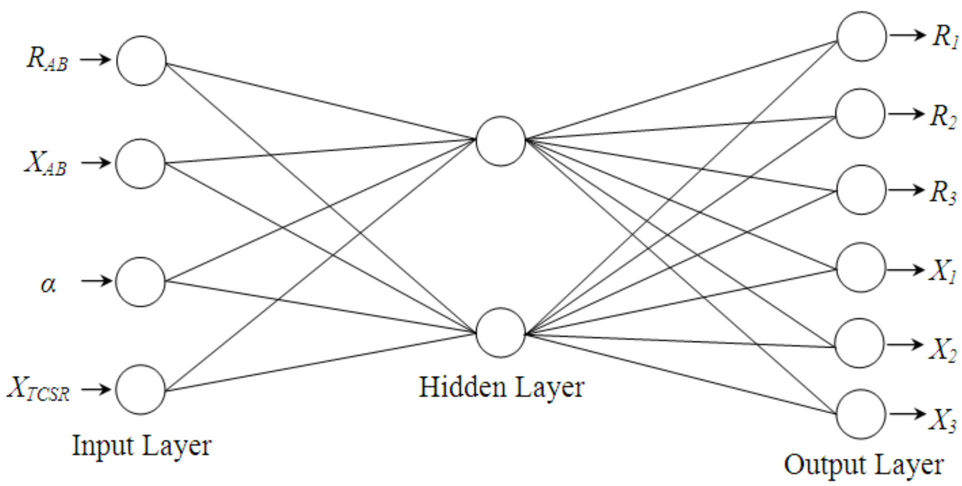


Fig. 14: Structure ANN proposed for setting zones

In block pre-processing is calculate the inputs parameters for ANN by this relations:

$$X_{GCSC} = {V_F(t)}\Big/{I_F(t)} \tag{18}$$

$$Z_{AB} = R_{AB} + j.X_{AB} = {V_L(t)}\Big/{I_L(t)} \tag{19}$$

We will use the networks of neurons with training supervised especially of the multi-layer networks, pulled by the algorithm of back propagation which remains more used.

The algorithm of Levenberg-Marquardt has a good robustness for the diagnosis by networks of neurons and seems to be most effective according to the researchers in this field. The architecture of the ANN is a significant factor deciding on the quality of the training more than the parameters of training.

The block diagram of the proposed ANN based setting protection for three zones (R_1, R_2, R_3, X_1, X_2 and X_3) at outputs for MHO distance relay scheme as indicated in figure 15.

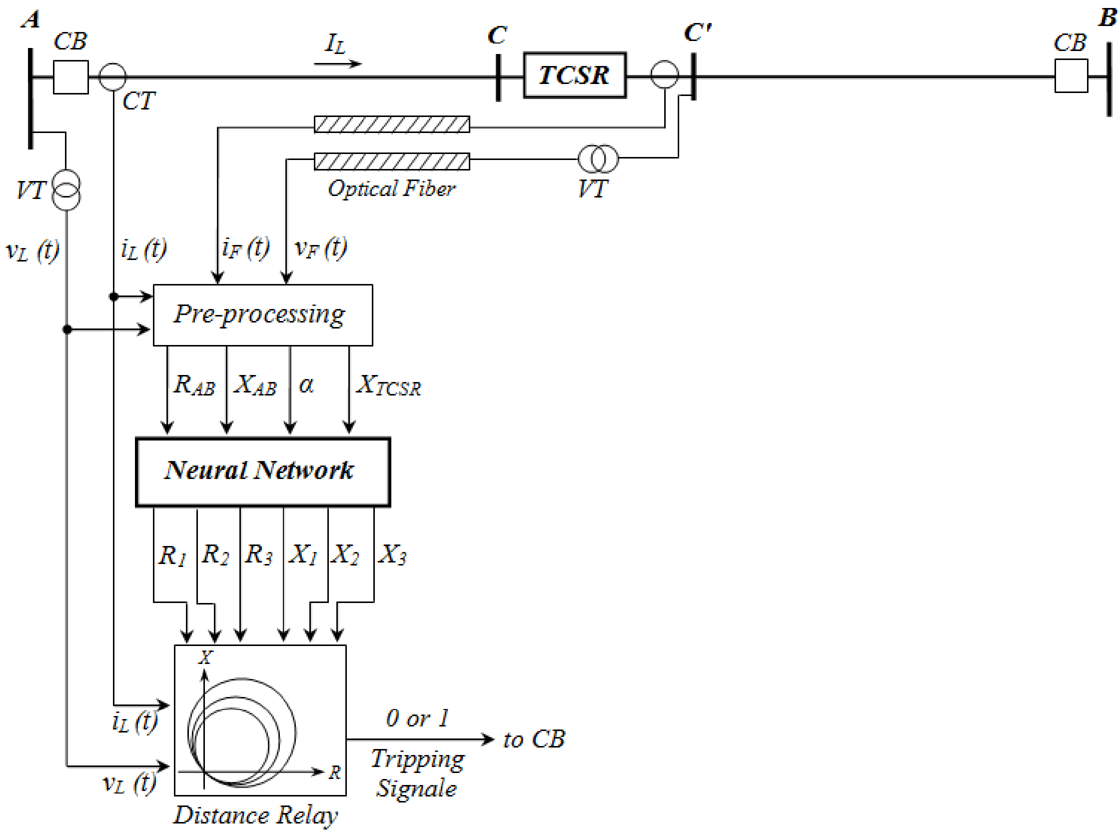


Fig. 15: Topology of MHO distance relay based ANN

The parameters for ANN are summered in table 2.

Table 2: Neural networks specifications

Parameters	Values
Number of input neurons	4
Number of output neurons	6
Number of hidden layers	1
Number of neurons of hidden	8
Stimulating of hidden neurons	Hyperbolic Tangent
Stimulating of output neurons	Sigmoid
Training algorithm	Levenberg Marquardt

5.4. Setting relay on presence TCSR based ANN

The resultants of testing data of ANN algorithm proposed for calculation setting distance relay on two boost modes, inductive in Table3 and capacitive in Table 4, with the percentage error (ε) between the accurate value based AM and the estimated based ANN one where:

Table 3: Relay setting in the inductive boost mode

Setting zones		Firing angle (°)				
		90	100	120	130	140
X_{TCSR} (Ω)		6,0500	6,1048	7,8640	12,706 9	191,00 8
R_{AB} (Ω)		2,4039	2,4039	2,4039	2,4039	2,4039
X_{AB} (Ω)		116,46	116,52	118,28	123,12	301,42
Z_1	X_1 (Ω)	5,5141	5,4322	5,5441	5,8243	14,331
	R_1 (Ω)	0,1154	0,1154	0,1154	0,1154	0,1154
	ε_r (%)	1,361	2,871	2,346	1,445	0,942
Z_2	X_2 (Ω)	9,0822	9,112	9,1443	9,4355	20,100
	R_2 (Ω)	0,1913	0,1913	0,1913	0,1913	0,1913
	ε_r (%)	0,715	0,425	1,211	1,167	0,716
Z_3	X_3 (Ω)	11,115	11,146	11,290	11,623	22,130
	R_3 (Ω)	0,2383	0,2383	0,2383	0,2383	0,2383
	ε_r (%)	1,701	1,456	1,106	0,716	1,227

Table 4: Relay setting in the capacitive boost mode

Setting zones		Firing angle (°)				
		145	155	165	175	180
X_{TCSR} (Ω)		-24,396	-6,6227	-3,5657	-2,3663	-2,0167
R_{AB} (Ω)		2,4039	2,4039	2,4039	2,4039	2,4039
X_{AB} (Ω)		86,0164	103,79	106,85	108,05	108,40
Z_1	X_1 (Ω)	4,0525	4,7947	5,1132	5,1528	5,1121
	R_1 (Ω)	0,1154	0,1154	0,1154	0,1154	0,1154
	ε_r (%)	1,847	3,757	0,300	0,644	1,747
Z_2	X_2 (Ω)	7,2822	8,3575	8,5343	8,6102	8,6303
	R_2 (Ω)	0,1913	0,1913	0,1913	0,1913	0,1913
	ε_r (%)	0,527	0,354	0,424	0,374	0,384
Z_3	X_3 (Ω)	9,3211	10,1972	10,5611	10,7584	10,7701
	R_3 (Ω)	0,2383	0,2383	0,2383	0,2383	0,2383
	ε_r (%)	1,683	3,317	1,578	0,408	0,492

VI. Conclusion

Neural networks could be used as a part of a new generation of high speed advanced protection relays. It results in a more reliable distance scheme for transmission line protection. ANN as control technique was used to be implemented in distance relay. New setting zones for distance relay relaying technique based on ANN technique have been developed. The relay has been tested for different value of firing angle for different boost modes. In all these test cases, the maximum error was found to be less than 4%. The proposed relaying technique has the ability to provide accurate and vigorous estimation for the variation of TCSR installed on 400 kV electrical transmission line.

Acknowledgments

The authors would like to thank the anonymous reviewers for their careful reading of this paper and for their helpful comments.

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Annexes

1. Electrical Transmission Line

U_n = 400 kV,

f_n = 50 Hz,

$Z_L = 0{,}03293 + j\,0{,}3184$ Ω/km,

l_{AB} = 73 km,

l_{BC} = 119 km.

2. TCSR Study

L_1 = 0,0048 H,

$Q_{L1\text{-}max}$ = 20 MVar,

L_2 = 0,0193 H,

$Q_{L2\text{-}max}$ = 80 MVar.

3. Current Transformer

I_{pri} = 1200 A,

I_{sec} = 5 A,

K_{CT} = 240.

4. Voltage Transformer

V_{pri} = 400000 / √3 V,

V_{sec} = 100 / √3 V,

K_{CT} = 4000.

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How to cite this paper: Mohamed Zellagui, Abdelaziz Chaghi,"Distance Protection Settings Based Artificial Neural Network in Presence of TCSR on Electrical Transmission Line", International Journal of Intelligent Systems and Applications(IJISA), vol.4, no.12, pp.75-85, 2012. DOI: 10.5815/ijisa.2012.12.10

