Published in Lecture Notes in Computer Science, Volume 3801/2005, P 163-169

Distance Protection of Compensated Transmission Line Using Computational Intelligence

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Abstract. A new approach for protection of transmission line including TCSC is presented in this paper. The proposed method includes application of Fuzzy Neural Network for distance relaying of a transmission line operating with a thyristor controlled series capacitor (TCSC) protected by MOVs. Here the fuzzy neural network (FNN) is used for calculating fault location on the TCSC line. The FNN structure is seen as a neural network for training and the fuzzy view-point is utilized to gain insight into the system and to simplify the model. The number of rules is determined by the data itself and therefore, a smaller number of rules are produced. The network parameters are updated by Extended Kalman Filter (EKF) algorithm. with a pruning strategy to eliminate the redundant rules and fuzzification neurons resulting in a compact network structure . The input to the FNN are fundamental currents and voltages at the relay end, sequence components of current, system frequency and the firing angle with different operating conditions and the corresponding output is the location of the fault from the relaying point The location tasks of the relay are accomplished using different FNNs for different types of fault (L-G,LL-G,LL, LLL).

1 Introduction

The series inductive reactance of ac transmission lines is one of the factors which governs the maximum amount of power that can stably be transferred by these lines under steady-state conditions. One method of increasing the steady-state maximum power transfer capability of an ac line is to reduce its net series inductive reactance, and in practice this has traditionally been achieved by connecting a fixed capacitive compensating reactance in series with the line using static capacitor banks. However, it has long been recognized that if the capacitive reactance provided by such a series compensator can be dynamically controlled it is possible not only to increase the steady-state power transfer capability of a transmission system, but also to improve dramatically the ability of the system to retain stability during the transient conditions which follow system disturbances [1,2]. Subsequent studies have shown that the improvement in transient stability that results from the use of a dynamically-controllable series compensator allows for a significant potential improvement in the utilization of high-power transmission lines [3].

The TCSC [7] is one of the main FACTS devices, which has the ability to improve the utilization of the existing transmission system. However, the implementation of this technology changes the apparent line impedance, which is controlled by the firing angle of thyristors, and is accentuated by other factors including the metal oxide varistor (MOV). The presence of the TCSC in fault loop not only affects the steady state components but also the transient components. The controllable reactance, the MOVs protecting the capacitors and the air-gaps operation make the protection decision more complex and therefore conventional relaying scheme based on fixed settings has its limitation. Kalman filtering and artificial neural network techniques are applied for adaptive protection of transmission line possessing a TCSC.

Neural Network has the shortcoming of implicit knowledge representation, whereas, FLS is subjective and heuristic. The major limitations of FLS are the lack of a general systematic procedure for rule learning and tuning, and determining the best shape of membership functions. As NN and FLS have different advantages and drawbacks, it is quite reasonable to consider the possibility of integrating the two paradigms into the same system in order to benefit from both of them. One such approach is integrating the learning capabilities of neural network to the robustness of fuzzy logic systems in the sense that fuzzy logic concepts are embedded in the network structure. It also provides a natural framework for combining both numerical information in the form of input/output pairs and linguistic information in the form of IF-THEN rules in a uniform fashion. However, in the FNN, the training is carried out using the information from both designer's experiences and sample data sets. The other drawback of the approach is that the number of fuzzy rules increases exponentially with respect to inputs and as a consequence 17 rules are framed for 3 inputs only [8].

In this paper a simple neural network is used to implement a fuzzy-rule-based locator of a power system from input/output data for a transmission line operating with a TCSC. The MOVs, air-gaps and thyristor firing arrangement are designed and simulated using the EMTDC subroutines. In this approach, the FNN model can be viewed either as a fuzzy system, a neural network or a fuzzy-neural system. The structure is seen in neural viewpoint for training and fuzzy viewpoint is utilized to gain inside into the system and to simplify the model. Unlike earlier approach, in this strategy the number of rules needed is determined by the data itself and consequently a smaller number of rules are produced. The network is trained using EKF algorithm. To have a compact structure, a pruning strategy eliminates the redundant rules and fuzzification neurons. The location task is accomplished by using different FNNs.

2 System Studied

A 400kV, 50Hz power system is illustrated in Fig.1. In this system a TCSC is located on a transmission line is used for the distance protection study. The power system consists of two sources, TCSC and associated components and a 300 km transmission line. The transmission line has zero sequence parameter Z(0)=96.45+j335.26 ohm and positive sequence impedance Z(1)=9.78+j110.23 ohm. $E_S = 400$ and $E_R = 400\angle\delta$ .The TCSC is designed to provide compensation varied form 30%(minimum) to 40%(maximum). All the components are modeled using the EMTDC subroutines .The sampling frequency is 1.0 kHz at 50 Hz base frequency. The metal oxide varistor (MOV) consists of a number of zinc oxide disks electrically connected in series and parallel. The purpose of the MOV is to prevent the voltage across the capacitor from rising to levels which will damage the capacitor. This is most likely to happen when a fault occurs at a point on the compensated line which minimizes the impedance of the fault loop. When instantaneous voltage across the capacitor approaches a dangerous level the MOV begins to draw a significant proportion of the line current thereby limiting the voltage across the capacitor at that level. Further, a bypass switch in parallel with the gap automatically closes for abnormal system conditions that cause prolonged current flow through the gap. The small inductance in the arrangement limits the current through the air-gap or switch circuit.

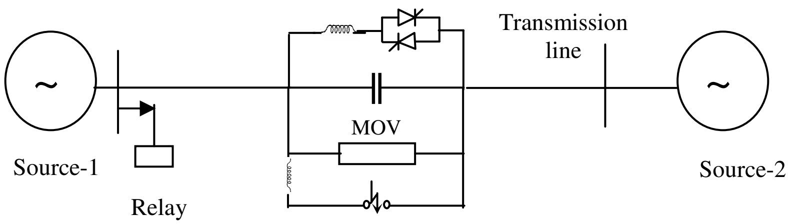

Fig. 1. The TCSE based line

3 Fuzzy Neural Network

The fuzzy neural network, comprising by input, fuzzification, inference and defuzzification layers. Further the network can be visualized as consisting of N inputs, with N neurons in the input layer and R rules, with R neurons in the inference layer. There are NxR neurons in the fuzzification layer and K neurons for output layer. The signal propagation and basic function in each layer of the FNN is introduced in the following. The input layer consists of x_i , i = 1,2, …N, along with unity. Each neuron in the fuzzification layer represents a fuzzy membership function for one of the input variables. The activation function used in this layer is $f(\mathrm{net}_{ij}) = \exp(-|net_{ij}|^{l_{ij}})$ and the input to these neurons $\mathrm{net}_{ij} = w_{ij1} x_i + w_{ij0}$, with w_{ij1} and w_{ij0} being the connecting weights between input layer and fuzzification layer. Thus, the output of the fuzzification layer becomes

$$\mu_{ij}(x_i) = \exp(-|w_{ij1}x_i + w_{ij0}|^{l_{ij}}) \tag{1}$$

where μ_{ij} is the value of fuzzy membership function of the i^{th} input variable corresponding to the j^{th} rule. The connections between fuzzification and inference layers have unity weights (shown in the figure as I).Each node j in the inference layer is denoted by Π, which multiplies the input signals and the output of the node becomes the result of product. Therefore, the output of the layer becomes

$$\rho_j(x_1, x_2....x_N) = \prod_i^N \mu_{ij}(x_i) \tag{2}$$

With v_{jk} being the output action strength of the kth output associated with the jth rule and utilizing weighted sum defuzzification, the network output becomes

$$\begin{aligned} o_k(x_1, x_2, ... \; x_N) &= \sum_j^R v_{jk} \rho_j(x_1, x_2, ... \; x_N) \\ &= \sum_j^R v_{jk} \prod_i^N \exp\left(-\left|w_{ij1}x_i + w_{ij0}\right|^{l_{ij}}\right) \end{aligned} \tag{3}$$

Inputs to the fuzzification layer are the variables used to define fuzzy operating regions each of these variables is transformed into several fuzzy sets in the fuzzyfication layer. appropriately shaped membership function at different positions can be obtained by changing the weights and parameters of the fuzzy neural network. Each neuron in rule layer corresponds to a fuzzy operating region of the particular classification objective. Its inputs are obtained from the fuzzification layer and its output is the product of its inputs and is the membership function of the corresponding fuzzy operating region. there are no weights to be estimated in this layer.

4 EKF Training Algorithm

The fuzzy neural network is trained using Extended Kalman Filter (EKF) algorithm.. Here the first step is to organize the weights as a state vector *w(t)*, where *t* counts for iterations. The desired output can be defined as

$$o(t) = f[w(t), x(t)] + \varepsilon(t) \tag{4}$$

where *o(t)* is the output, *x(t)* is the input and $\varepsilon(t)$ is discrepancy of the desired output from the estimated output. The state estimation is then to determine *w(t)* to minimize the cost function *J* defined as

$$J = \frac{1}{2}\sum_t \left\| o(t) - f[w(t), x(t)] \right\|^2 \tag{5}$$

The EKF formula can be found out by Taylor series expansion of *f [w(t), x(t)]*. The estimated output *o'(t)* is as:

$$o'(t) = f[w'(t), u(t) + H(t)(w(t) - w'(t)) + G(t)(x(t) - x'(t)) + HOT \tag{6}$$

where
$$H(t) = \left(\frac{\partial f[w(t), x(t)]}{\partial w(t)}\right)^T \tag{7}$$

and
$$G(t) = \left(\frac{\partial f[w(t), x(t)]}{\partial x(t)}\right)^T \tag{8}$$

HOT is the higher order terms and *x'(t)* is the unpredicted input in the next iteration. Neglecting the higher order terms the discrepancy between desired output and estimated output will be

$$o''(t) = o(t) - o'(t) = H(t)(w(t) - w'(t)) + G(t)(x(t) - x'(t)) \tag{9}$$

Now the update equations are

$$S(t+1) = H(t+1)P(t)H(t+1)^T + G(t+1)\sum_x (t+1)G(t+1)^T + R(t+1) \tag{10}$$

$$K(t+1) = P(t)H(t+1)^T S(t+1)^{-1} \tag{11}$$

$$P(t+1) = P(t) - K(t+1)H(t+1)P(t) \tag{12}$$

$$w(t+1) = w(t) + K(t+1)\{o(t) - o'(t)\} \tag{13}$$

Where *K(t)* is the Kalman gain and *P(t)* is the weight covariance matrix. The variance of the each output can be obtained from the diagonal elements of the innovation matrix *S(t+1)*. *R(t)* is the noise co-variance matrix. Initially *R(t)=I.* During training, the number of rules is increased from 1 till a satisfactory performance of the network is found. The initial weights are randomly selected in the interval [-1, +1]. The maximum number of iteration is set to 3000 in all cases. The training is continued till $\varepsilon(t) <$ $1*e^{-4}$ at all points for a window length of 100 or the number of iteration reaches its maximum during training. The initial value of covariance matrix is chosen as *P(t)* = 100 *I,* where *I* is unit matrix. As this rule does not contribute to the network performance, the rule should be pruned.

5 Training and Computational Result

For LG fault type the first two elements of the input vector are the faulty phase current and voltage, the seventh one for the zero sequence component, eighth is for system frequency and the ninth one for the firing angle of TCSC. The first four inputs of the LL or LLG locators are for the corresponding voltage and current of faulty phases, seventh is for the negative sequence component, eighth one represents for frequency and the ninth input element is the firing angle of the TCSC. However the LLL fault locator does not include sequence component as an input (total 8 inputs). The training data sets include fault situations for different prefault conditions, inception angles, system frequencies, fault resistances and fault distances. The total number such sets is 80 for all four FNNs. The networks are trained by EKF algorithm and pruning strategy is applied. The structure of FNN1 (L-G) locator becomes 9 inputs, 7 rules, 61 fuzzification neurons and 1 output. Similarly for FNN2 (LL-G) the number of rules and fuzzification neurons are 8 and 69, respectively and for FNN3 (LL) 8, 71 and FNN4 (LLL-8 inputs) 8, 64, respectively.

These networks are tested at different situations of the power system by varying frequency, load angle, fault resistance, inception angle and source capacities. Further network performance is studied by adding noise to the input signals Table-1 through Table-4 show the location for LG, LL-G, LL and LLL faults respectively at a fault distance of 15%, 35%, 55%, 75% and 95 % of the line, respectively and fault resistance of 10 to 200 Ω. The above results are obtained for the input vectors at 10ms after the fault. The maximum error found for these networks is less than 4%.

Table 1. Fault Location for L-G faults (FNN-1)

Distance (%)	Fault Resistance (R_f)	Error (%)
15	10	2.01
	200	2.58
35	10	1.57
	200	1.23
55	10	2.04
	200	2.33
75	10	2.56
	200	1.44
95	10	2.47
	200	2.89

Table 2. Fault Location for LL-G faults (FNN-2)

Distance (%)	Fault Resistance (R_f)	Error (%)
15	10	1.58
	200	1.98
35	10	2.01
	200	2.55
55	10	2.53
	200	1.98
75	10	1.05
	200	1.26
95	10	1.88
	200	2.04

Table 3. Fault Location for LL faults (FNN-3)

Distance (%)	Fault Resistance (R_f)	Error (%)
15	10	1.27
	200	2.01
35	10	1.36
	200	2.11
55	10	2.65
	200	2.32
75	10	2.17
	200	3.12
95	10	2.49
	200	3.55

Table 4. Fault Location for LLL faults (FNN-4)

Distance (%)	Fault Resistance (R_f)	Error (%)
15	10	2.11
	200	2.54
35	10	1.98
	200	2.22
55	10	2.58
	200	1.98
75	10	1.23
	200	1.56
95	10	1.23
	200	2.03

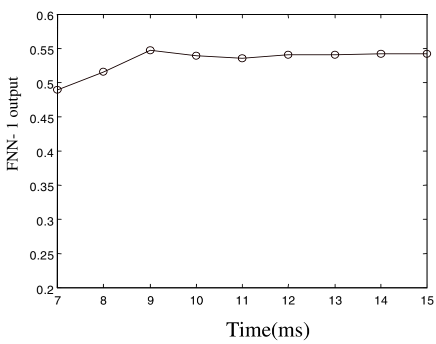

Fig. 2. Convergence loci of the FNN-1(L-G) for 'ag' fault at 55% of the line, 45^0 inception angle, Rf=100Ω

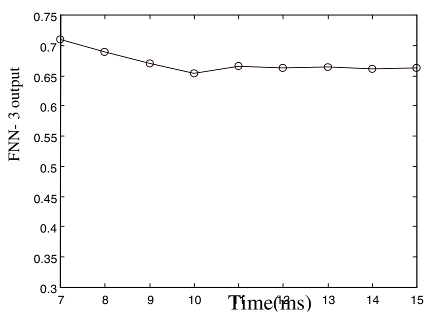

Fig. 3. Convergence loci of the FNN-3(LL) for 'ab' fault at 65% of the line, 30^0inception angle, R_f=100Ω

The convergence speed of the designed networks (FNNs) are tested to the corresponding input vector on sample to sample basis. Results are presented in Figs.2 shows the output of FNN-1(L-G) for 55% of line, 45^0 inception angle at a fault resistance of 100 Ω. Similarly Fig.3 shows the output of FNN-3(LL) for 65% of line, 30^0

inception angle at a fault resistance of 100 Ω. The test cases demonstrate the superior estimation accuracy and speed of the FNNs protection scheme. As seen from the figures the FNN converges within half cycle of fault inception. which depicts the fastness of the proposed algorithm.

6 Conclusions

The paper presents a novel approach for distance relaying of flexible ac transmission line using fuzzy neural network. The FNN is used to calculate the location of the fault from the relaying point. The FNN parameters are updated by EKF algorithm and a pruning strategy result in a compact network structure. The fault location networks for the transmission line employing a TCSC are tested under a variety of different system conditions and fault situations. The results from the FNN indicate the accuracy of the proposed system for protection. Also the convergence speed is very fast to the requisite values of the output variables under fault conditions of the power system. Hence the proposed method found to be very accurate and fast for protection of flexible ac transmission line including TCSC.

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