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Neuro Fuzzy Systems and Haar Wavelet-Based Location of Shunt Faults in Thyristor-Controlled Series Compensator Transmission Line

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ABSTRACT

The modern power system network is structurally problematic and is prone to undesirable situations like shunt faults in power transmission lines. In the event of shunt faults, precise fault location improves the restoration procedure, accordingly enhancing the whole power system network reliability. To resolve this critical issue, this paper proposes neuro fuzzy system (NFS) based fault distance location in the thyristor-controlled series compensator transmission line (TCSCTL). To locate distance of the fault position, the scheme uses current and voltage details from the source terminal with measures, however the scheme doesn't need current and voltage measurements from receiving terminals. The training samples are extracted with Haar wavelets and gathered, and then NFS is trained to locate the faults. A large number of experiments are conducted and simulation results show the good efficiency of scheme, even in case of changing fault parameters. The NFS outperforms other schemes suggested in the recent literature works in terms of many performance metrics. The validation reflects the NFS effectiveness in providing prompt fault protection against diverse faults in practical settings by adjusting relaying mechanism. The fault location error (FLE) does not exceed 0.08 % for all simulated fault cases and NFS performs superior compared to other schemes.

1. INTRODUCTION

In recent days, electricity demand has increased gradually while electricity generation and transmission expansion have been limited owing to inadequate resources and environmental restrictions. The flexible alternating current transmission system (FACTS) plays a significant role in enhancing the power grid's performance. The thyristor-controlled series compensator (TCSC) is an imperative member of the FACTS family. Nowadays, more and more thyristor-controlled series compensator transmission lines (TCSCTL) are being suggested to be buried in developed countries in order to enable enhanced load carrying capability of existing high power transmission lines. The TCSCTL is actively in use in different countries due to the enhancement of power flow control, improving transmission system transfer capability, mitigating sub-synchronous resonance, and increasing transient stability. Due to the better reliability of power transmission and the benefits of consequence, overhead lines comprising TCSCTL are becoming progressively widespread. Nevertheless, TCSCTL faults may result in power outages and quite large-scale. Hence, an accurate and rapid fault location method is crucial to the supporting staff in rapidly detecting and fixed problems, cutting down on cost and restoration time, and increasing the power supply dependability.

For past years, several studies are proposed by many researchers for TCSCTL [1-3]. A number of TCSCTL works [4, 5] have been made on the location of shunt faults. By prevailing literature study, recent fault location schemes for TCSCTL are based on currents and voltages [6-8]. The researchers [9, 10] introduced location methods with TCSCTL based on one terminal measures. The schemes for fault type classification in TCSCTL have been intensively implemented over the previous years. Some notable research works investigated extensive machine learning based fault classification methods on TCSCTL in the studies [11-13]. Several methodologies have been provided for finding the faults occurring on TCSCTL [14-19]. The enhanced version of Haar has been focused in the present literature owing to prominent practice in fault detection. In study [20], authors used Haar wavelets for high-frequency information extraction in shunt fault detection. Authors in study [21] adopted Haar wavelets for feature extraction for fault detection. The Haar wavelets were penetrated in a series capacitor-compensated line for detecting the shunts [22]. Another finding is addressed in the literature [23] based on the artificial intelligence techniques for TCSCTL with wavelet currents. Authors have recommended fault location algorithm in the TCSCTL for the multi-location faults and transforming faults [24].

Numerous neuro fuzzy systems (NFS) design works briefly reported in the literature study [25-27]. Rohani and Koochaki. [28] successfully developed NFS for the fault location.

Authors in study [29] used current and voltage as inputs to NFS. In study [30], researchers selected NFS for shunt faults diagnosis with one terminal measure. In study [31], the NFS for faults detection in transmission lines was applied by researchers. Hitherto, literature examination has focused that NFS has never been employed in shunt fault location in TCSCTL. Nonetheless, these studies motivation to design NFS schemes in several software and did not give a complete understanding of fault location in TCSCTL. This motivates us to propose briefly NFS and the implementation of NFS location scheme in the TCSCTL. While previously published studies have given NFS to fault study in TCSCTL, the suggested study differs in the following significant aspects:

1. The scheme was especially developed for fault location in TCSCTL rather than normal fault detection and classification.
2. The distinct input features and preprocessing strategy have been selected, enhancing fault location error (FLE) under changing parameters.
3. The proposed scheme integrates improving training approach, which is not implemented in the published papers.
4. The scheme has been tested under diverse faults, signifying enhanced robustness.

To address this issue, an artificial intelligence technique is presented to make move towards NFS. The fault locator is the article extension in study [32] that illustrates the fuzzy application to locate faults in a TCSCTL considering numerous challenging works. Imperative highlight points of NFS are:

1) NFS gives low TCSCTL location error percentage.

2) NFS is computationally efficient to develop, and by using fuzzy rules.

3) NFS facilitates a rapid fault location.

4) NFS uses only currents and voltages.

5) NFS doesn't require any type of communication network from the receiving terminal of TCSCTL.

The rest of this paper is organized as follows: Section II studies the TCSCTL description and explains the current and voltage waveforms processing. Section III introduces NFS by employing prepossessed waveforms and a fault location procedure. Section IV depicts the simulation results and compression analysis. Section V describes the conclusions at the end.

2. THYRISTOR-CONTROLLED SERIES COMPENSATOR TRANSMISSION LINES STUDIED

The TCSCTL consists of a 500 km, 50Hz, three-phase, 440 kV model connected with two generating stations on either side. This system is operated with 200 MW and 300 MW loads. The TCSC is equipped with an innovative series compensator at the middle as depicted in Figure 1. The aim of series capacitor compensation is to change the complete series transmission system reactance between the receiving and sending terminals. It gives adjustable series capacitor compensation employing firing angle control of thyristor. It can be used for dynamic stability, transient stability, power flow control, damping oscillations and voltage stability. Here, series capacitor gives static series capacitor compensation and cannot be suitable for variations in transmission line outage. It can also be used to change the compensation level based on the transmission configuration. The static series capacitor compensation provides oscillations at instability and sub-synchronous frequencies. It gives an improved response in damped oscillations and produces stability.

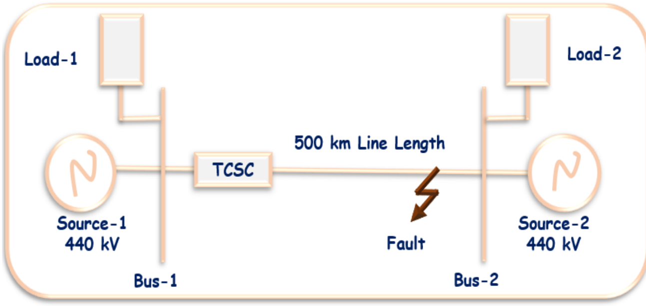

Figure 1. The thyristor-controlled series compensator transmission line (TCSCTL) diagram

The TCSCTL with NFS is developed and implemented in the MATLAB Simulink environment. The voltage and current signals are generated from the TCSCTL are sent to the preprocessing module of NFS via current transformers and potential transformers. The current and voltage details are exemplified with Haar wavelets. Based on TCSCTL signals NFS will locate faults in the proposed system. Haar wavelet study was independently initiated by Haar 30 years back. Nowadays, Haar wavelets have been employed in diverse engineering, science, and technology fields such as edge extraction, binary logic, and image coding. The wavelets are very simple compared to other type of wavelets. Haar wavelets are compact, simple, orthogonal wavelet transforms and piecewise step functions. Haar wavelet is the rescaled "square-shape" function sequence which combined form wavelets family in mathematics. This wavelet study is similar to a Fourier study in that it permits an output function over the interval to be indicated in terms of the orthonormal family. The Haar wavelet sequence is now identified as the primary known wavelet family. The decomposition level 4 is used in the mother wavelet transforms. The processed Haar wavelet current and voltages are prepared in matrix format for NFS training as reported in Table 1. The proposed workflow chart is shown in Figure 2.

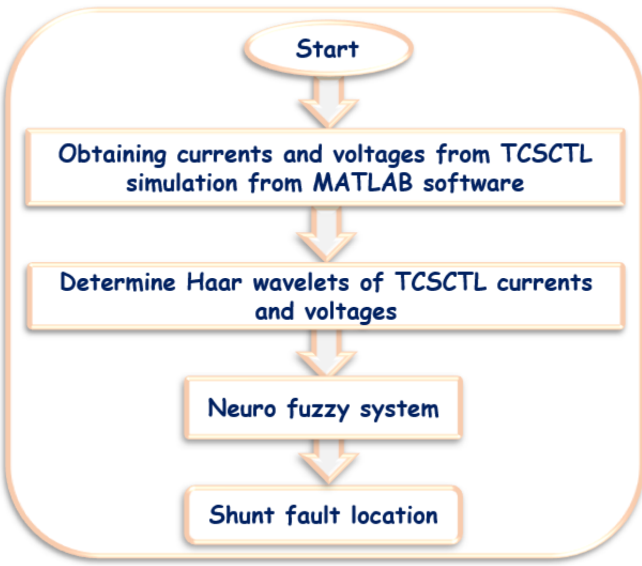

Figure 2. The flowchart of neuro fuzzy system (NFS)

Table 1. Training data samples collection for neuro fuzzy system (NFS) matrix

Parameter Considered	Value	Types
Shunt faults	11	AB, BC, CA, ABC, ABC-G, A-G, B-G, C-G, AB-G, BC-G, CA-G
Inception angles	11	0°, 30°, 45°, 90°, 135°, 180°, 225°, 270°, 315°, 330°, 360°
Resistances	11	0 Ω, 15 Ω, 30 Ω, 45 Ω, 60 Ω, 75 Ω, 90 Ω, 105 Ω, 120 Ω, 135 Ω, 150 Ω
Locations	11	1 km, 50 km, 100 km, 150 km, 200 km, 250 km, 300 km, 350 km, 400 km, 450 km, 499 km
Total cases	14,641	11*11*11*11
Inputs	6	IA, IB, IC, VA, VB, VC
Output	1	Location

3. PROPOSED MODELLING

The main parts of soft computing, such as artificial neural network and fuzzy systems, have exposed great capability in the complex nonlinear system recognition and control system problems solving. The NFS is hybrid predictive system that integrates the learning abilities of neural network with the reasoning abilities of fuzzy systems. The NFS has processed input-output training dataset and fuzzy rules. The NFS is specifically effective in several complex engineering applications, when dataset is nonlinear or inconsistence, where traditional schemes are too complex to apply and fail to employ. A representative NFS architecture having total five layers in which each layer is structured by the variety of nodes. The first is input layer (fuzzy layer), second is database layer (product layer), third is rule base layer (normalised layer), fourth is decision making layer (consequence layer) and last is defuzzification layer. Here, previous layer output is applied as current layer input. The first order Takagi-Sugeno NFS with two inputs (x and y), single output (f), membership functions (A1, B1, A2 and B2), consequence parameters (p1, q1, r1, p2, q2 and r2) and two rules are shown in Figure 3.

For training of the NFS implementation, TCSCTL faults are simulated in MATLAB with variation in possible faults, inception time angles, location points and resistances. The current and voltage measures are collected from the starting terminal for all faults. It can be noted that the total number of faults for NFS training is 14,641. After TCSCTL simulating many faults by altering fault parameters, the current and voltage measures at the starting terminal are processed with Haar wavelets. The NFS has been created in MATLAB environment with the TCSCTL simulation information. A NFS has been established to find shunt fault location under TCSCTL working conditions. Six inputs and only one output is selected for establishing NFS. The processed Haar voltage and current measures are applied to NFS for the TCSCTL faults. The NFS inputs signify IA, IB, IC, VA, VB and VC. Its output signifies L. The matrix size for NFS is 14,641×7. All inputs are divided as fuzzified with I1 to I8 for (IA, IB and IC) and V1 to V8 for (VA, VB and VC) and output L is divided as L1 to L8. These are divided based on Gaussian fuzzy membership function. The Eight IF-Then rules are made for NFS. The number of inputs (6), output (1) each input membership functions (8) and types (Gaussian) and total number of If-Then rules (8) created in this study. The Takagi Sugeno model computation is used in fuzzy inference process. The error tolerance value of NFS is signified to 0.0001. The fuzzy inference network and training samples are processed to the NFS. The neural network is trained by the back-propagation approach. The outstanding performance is reached by the back-propagation approach with 90 epochs, 8 Gaussian type membership fuzzy functions in inputs and outputs with 8 rules has been made. The proposed NFS fuzzy rules and NFS structure is depicted in Figure 4 and Figure 5, respectively.

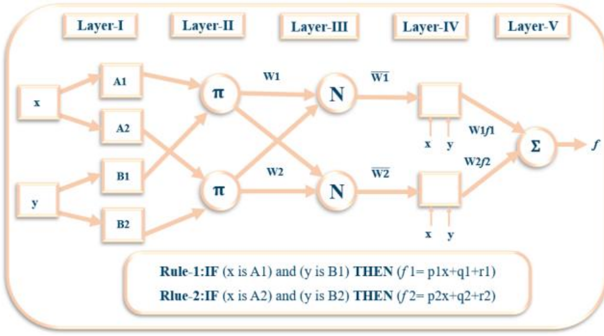

Figure 3. The first order Takagi-Sugeno neuro fuzzy system (NFS)

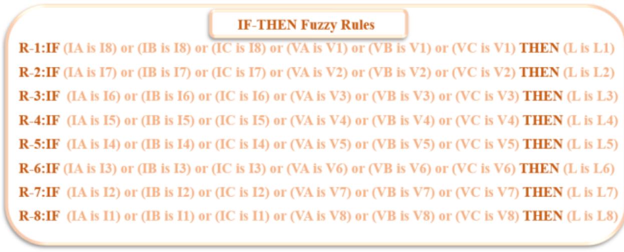

Figure 4. The fuzzy rules

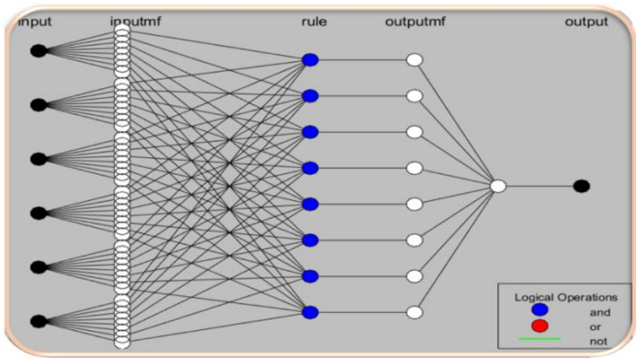

Figure 5. The neuro fuzzy system (NFS) structure

4. RESULTS AND DISCUSSIONS

To estimate the proposed NFS scheme efficiency, TCSCTL introduced in the aforementioned section is simulated for numerous faults. Similar faults are considered for other transmission lines all for comparison purposes. The diverse faults create district transient signatures. Its impact may change in fault location error (FLE) value of TCSCTL. The suggested fault location scheme for TCSCTL has been evaluated in this study using 30000 fault patterns, which are different from the training samples. The NFS based scheme significantly enhances the performance in terms of error for the complicated work of TCSCTL fault location. The validated results are reported in Table 2. According to the testing results, phase-to-phase ground FLE is very low for most of fault locations, phase-to-phase FLE is almost zero for all fault locations, and single-phase to ground and double phase to ground FLE have acceptable values. The FLE in all selected samples is below 0.08% from Eq. (1). The fault location change has no significant effect on fault location scheme accuracy.

It can be noticed that NFS achieves reasonable FLE at nearby sending end, middle and nearby receiving end of TCSCTL. The overall results are explained in Figure 6. Recently, few fault study schemes for TCSCTL have been addressed in the literature survey. Table 3 reports suggested scheme performance comparison with some superior previous works. For effective study, the fuzzy [22, 32], support vector machines [8, 12], decision tree [16], neural networks algorithms [14, 23, 24] and NFS [29] are considered, as explained earlier in the literature work, along with NFS approach. In fact, one can compare NFS in Table 2 to other approaches of TCSCTL in Table 3. From this wen observed that NFS outperforms the other schemes with less FLE. The algorithm and [6, 8] require the measurement samples at both TCSCTL ends, while the NFS involves the voltages and currents samples at single bus records. The NFS approach does not required the communication platform.

$$\text{FLE (\%)} = \left| \frac{\text{Location (km) of Actual Fault} - \text{Location (km) of Estimated Fault}}{\text{TCSCTL length}} \right| \times 100 \qquad (1)$$

Table 2. Neuro fuzzy system (NFS) location results

Parameter Variations	Faults	Inception Angle (°) of Fault	Resistance (Ω) of Fault	Location (km) of Actual Fault	Location (km) of Estimated Fault	FLE (%)
Changing Faults, Inception angle Fixed, Resistance Fixed, Location Fixed	A-G Fault	110	85	346	345.844	0.031
	B-G Fault	110	85	346	346.121	0.024
	C-G Fault	110	85	346	346.252	0.050
	AB-G Fault	110	85	346	346.218	0.043
	AC-G Fault	110	85	346	346.291	0.058
	AC-G Fault	110	85	346	345.947	0.010
	AB Fault	110	85	346	345.898	0.020
	AC Fault	110	85	346	345.787	0.042
	AC Fault	110	85	346	346.095	0.019
	ABC Fault	110	85	346	346.121	0.024
	ABC-G Fault	110	85	346	345.895	0.021
Changing Inception angle, Fault is Fixed, Resistance Fixed, Location Fixed	C-G Fault	0	53	189	189.023	0.004
	C-G Fault	20	53	189	189.204	0.040
	C-G Fault	40	53	189	189.192	0.038
	C-G Fault	80	53	189	189.341	0.068
	C-G Fault	120	53	189	188.856	0.028
	C-G Fault	160	53	189	189.137	0.027
	C-G Fault	200	53	189	188.902	0.019
	C-G Fault	240	53	189	188.891	0.021
	C-G Fault	280	53	189	189.194	0.038
	C-G Fault	320	53	189	188.827	0.034
	C-G Fault	360	53	189	189.189	0.037
Changing Resistance, Fault is Fixed, Inception Angle Fixed, Location Fixed	AC Fault	220	7	94	93.735	0.053
	AC Fault	220	17	94	94.123	0.024
	AC Fault	220	27	94	94.328	0.065

	AC Fault	220	37	94	94.127	0.025
	AC Fault	220	47	94	94.098	0.019
	AC Fault	220	57	94	93.759	0.048
	AC Fault	220	67	94	94.291	0.058
	AC Fault	220	77	94	94.087	0.017
	AC Fault	220	87	94	94.142	0.028
	AC Fault	220	97	94	93.849	0.030
	AC Fault	220	117	94	94.208	0.041
	ABC-G Fault	330	18	79	79.321	0.064
	ABC-G Fault	330	18	116	115.890	0.022
	ABC-G Fault	330	18	193	192.874	0.025
	ABC-G Fault	330	18	238	237.793	0.041
	ABC-G Fault	330	18	271	270.908	0.018
Location of Fault, Fault is Fixed, Inception Angle Fixed, Resistance Fixed	ABC-G Fault	330	18	303	303.345	0.069
	ABC-G Fault	330	18	342	342.012	0.002
	ABC-G Fault	330	18	394	393.868	0.026
	ABC-G Fault	330	18	421	421.107	0.021
	ABC-G Fault	330	18	473	473.320	0.064
	ABC-G Fault	330	18	498	498.382	0.076

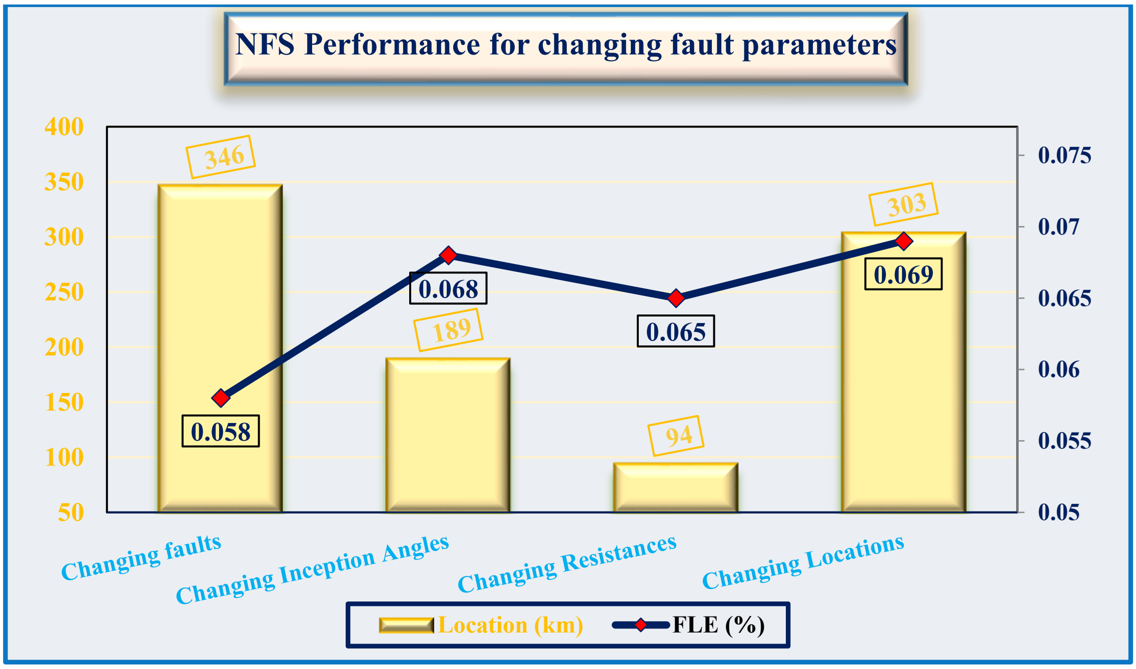

Figure 6. The overall results of neuro fuzzy system (NFS)

Table 3. Comparison study

Ref.	Inputs	Approaches	FLE (%)
[6]	Two end voltages and currents	Distributed parameter line model	-
[8]	Two end voltages and currents	Support vector machines	-
[16]	Local end currents	Decision Tree	-
[22]	Single bus currents	Fuzzy system	0.232
[23]	Single bus voltages and currents	Neural Networks	1
[24]	Single bus voltages and currents	Neural Networks	1
[29]	Single bus voltages and currents in double circuit line	NFS	0.261
[32]	Single bus currents	Fuzzy system	0.25
Proposed method	Source end current and voltage samples	NFS	0.08

5. CONCLUSION REMARKS

Faults create detailed technical challenges for transmission line protection and ensure reliability in the power system. The FLE accuracy in TCSCTL can make many features such as time searching, cost reduction, maintenance, breakdown time, and line restoration acceleration. A new NFS based shunt fault location in TCSCTL is presented in this paper. In fact, the study is based on the data recorded after the occurrence of a fault at the starting terminal of TCSCTL, applied by the NFS. This study employs NFS in MATLAB for implementing this work. The proposed NFS scheme is composed of five layers to locate the faults. Haar wavelets are used for fault characteristic extraction from currents to train NFS. Hence, the training sample should be chosen so that similar challenges are characterized so that the NFS does not encounter problematic conditions in its fault diagnosis. The performance of NFS is largely based on training data diversity and quality, which can restrict its overview to unseen fault cases. Finally, the suggested NFS has been tested on TCSCTL at numerous distances. And testing results specify that the suggested NFS can estimate fault distances dependent on fault type in numerous parameters. In the future, we can design a direction-relaying scheme using NFS.

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