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Fault Classification in Double-circuit Transmission Lines Based on the Hierarchical Temporal Memory

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ABSTRACT: *In this paper a novel machine intelligence framework called the Hierarchical Temporal Memory is used for fault classification in double transmission lines. Fault location data estimation including associated transmission line parameter values are obtained via computer simulations. The fault location data generation problem is then reformulated into a multi-class state using a unique data transformation technique. The proposed technique is compared with two very popular state-of-the art machine learning algorithms – the Online Sequential Extreme Learning Machine (OS-ELM) and the Support Vector Machine (SVM). The results show that the proposed HTM model clearly outperformed the OS-ELM and SVM technique.*

Keywords *-Double-circuit Power Transmission Lines; Fault Classification; Hierarchical Temporal Memory; Machine Intelligence*

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I. INTRODUCTION

Electrical energy demand has continuously been on the rise and it has led to the increasing number of generators, transmission lines, distribution networks alongside the required protective and controlling circuits making electrical power system an ever vast complex system. Electrical energy when produced mostly in suburb is conveyed to the load centres and electricity users in cities through transmission line held by transmission towers. The environmental and cost implications in power transmission are compelling power utilities to install more than one transmission line on a transmission tower thereby increasing their power transmitting abilities [1]. In the transmission of power by the use of double transmission lines, mutual impedance is a common phenomenon. The mutual impedance is responsible for the constant alterations of the voltage and also the current profiles measured by the protective relays protecting individual line. The proximity of the transmission lines increases the chances of fault occurring on the lines and this modifies the outputs of the protective relays attached to the line.

In power system networks a fault is any action or inaction which hinders the normal operation of the system. A fault can be very destructive to power system, especially in terms of cost. Faults occur mostly on transmission lines because they are the part of power systems that are open to the influence of external elements.

In considering the diverse forms of fault analysis, one unique problematic situation encountered is to obtain solutions for the networks that incur two or more faults occurring at the same time. Such simultaneous faults may involve sustaining more than one type of series and shunt faults on different phases, on a particular line or both lines, at a given location or at different locations in the electrical parallel transmission network.

Another problem with great challenge is the solution to the problem of inter-circuit faults on double-circuit lines which may be involving/not-involving ground or neutral. These inter-circuit faults could give rise to unusual current distributions amid the conducts of the double transmission lines. In addition to these requirements, there is also the utmost and desirable need to reliably predict the likelihood of a sustained or intermittent fault occurring in these transmission line systems.

Fault location approaches on transmission lines could be broadly classified into two, namely: two-terminal method and one-terminal method. For fault location process using one-terminal method, information of the fault data are referred simply to one terminal and this makes it very difficult to outweigh the aftermaths of the changes that the fault resistance and the impedance of the remote-terminal have on location accuracy. Whereas in two-terminal method of fault location, the information is not swayed by these factors and it is more accurate in theory [2]. In addition, transmission line fault location approaches could also be categorized into impedance base technique and travelling-wave technique. The impedance based technique utilizes the fundamental components of the voltage phasors and the current phasors measured by the connected transducers such as fault recorders, microcomputer and numerical relays [3]. While in the travelling wave technique, it is considered that in the event of a fault, an electrical pulse emanates at the fault point and travels through the line in directions away from the fault point. Time taken for the pulse to return to the point where fault occurred is used to estimate the fault distance [4]. Impedance-based techniques were found to be easier and more widely used compared to the traveling-wave techniques. In this research, the two-terminal method of fault location with impedance-based technique will be considered [5]. This paper also present experiments on using two AI neural online (continual learning) techniques for the prediction of fault location in a double circuit power transmission line system.

II. Related Works

Manyresearchers have investigated the potentials of AI techniques/tools for fault classification, estimation and monitoring. ANN with backpropagation learning have been proposed in [6], ANN based on Rough Membership Neural Network and a Generalized Regression ANN (GRNN) proposed in [7 and 8], Single-ended ANNs proposed in [9] and ANN using SVM including Support Vector Regressors (SVR) have also been proposed in [10].

Sharma &Saxena [11] investigated the potentials of supervised ANNs as possible candidates for fault detection and classification in AC transmission line systems. They found the Radial Basic Exact-Fit (RBEF) ANN and the Haar Mother wavelet to be the most suitable transmission line fault classifier and wavelet transform function particularly for noisy environments.

Also, more recently, ANN embedded in microcontroller for transmission line fault identification and classification was proposed in [12].

All these AI approaches have one thing in common, they are specifically hand-coded and require manual parameter tweaking; in addition most do not operate in a continual (online) learning manner where there is the huge requirement to process streaming information or data. Thus, better approaches are desired that can adapt to real-time processing of streaming data and also algorithms that are fault tolerant.

III. METHODOLOGY

The methodology employed in this research study is two-fold. First a description of the fault location estimation system model is made using a dynamic systems approach, and then an artificial intelligence (AI) technique called the Hierarchical Temporal Memory (HTM) technique is used for the performance evaluation. This technique is also compared with two other popular state-of-the-art algorithms.

3.1. Fault Location Estimation Model

A fault location model is developed to generate an artificial fault dataset for training the AI techniques described in sub-sections 3.2 under methodology. The fault location model is based on the one-end impedance technique proposed in [5]. The model is a sub-system of a double-circuit power transmission line system model developed in the MATLAB/SIMULINK which is dependent on certain fault dependent parameters. The fault location algorithm due to [5] is captured in a flowchart given in Figure 1 where the parameters for the fault location estimation are defined as follows:

I_{S6} = during -fault current measured at node S.
I_{S06} = pre-fault current measured at node S.
I_{Sp6} = the pure-fault (superimposed) current vector at node S.
I_F = 6-dimensional fault current vector.
D_m = the current distribution matrix.
$Z = 6 \times 6$ series impedance matrix of the line.
V_{S6} = 6-dimensional voltage vector of node S at (during) fault condition.
m = distance of the fault point from node S.

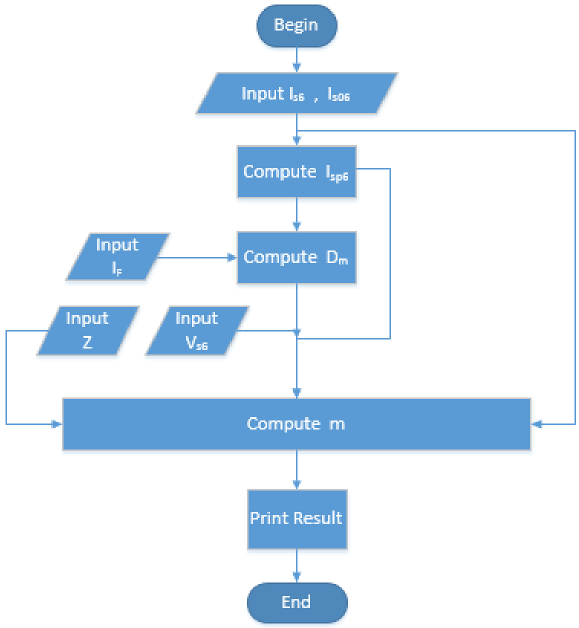

Figure 1- Flowchart of a Fault Location Estimation Process for a double (parallel) circuit TL model

3.2. AI Techniques

As mentioned earlier, the AI technique used is called the Hierarchical Temporal Memory (HTM). HTM is a biological machine intelligence algorithm, technology and tool for prediction type problems [13]. HTM is implemented as a suite of algorithms called the Cortical Learning Algorithm (CLA). HTM has been applied in different fields of domain including but not limited to anomaly detection [14, 15], sign language recognition [16], gaze gesture recognitions [17] and weld flaw detection [18]. The key feature of the HTM is in its unique ability to form highly sparse patterns that is robust to noise or neuron failure using a large number of competing columns.

The algorithm of the HTM is given in Algorithm 1 and the parameters given in Table 2 as shown in the Appendix. The HTM is fundamentally composed of two parts; a spatial pooler (SP) part for forming sparse distributed representations (SDR) and a temporal pooler (TP) part for slowly predicting the SDR patterns formed in the SP part.

For the comparative evaluations in this research study, two state-of-the-art AI technologies are considered for the estimation and classification analysis. The techniques include the HTM based on CLA and the Online Sequential Extreme Learning Machine (OS-ELM). The reason for this choice is that both algorithms seem to operate sequentially and in an online manner and hence it is better to compare these algorithms. Other popular algorithms such as the Support Vector Machines (SVMs) and conventional Artificial Neural Networks (ANN) do not have this inherent feature.

3.3 Proposed Model

In this section, the proposed system is described. The system is described in terms of a power transmission line systems model. Both models are developed in MATLAB/SIMULINK and are used for generation of fault data.

3.3.1. Double Transmission Line Power System Model

The double power transmission the model is as shown in Fig. 2. It represents the main power transmission line. The model also includes the fault location estimation model as a subsystem component of a main transmission line system model. The main transmission line model include the following other components. A power source block for specifying a fixed power source, frequency and other associated generation parameters as provided. The fault location estimation model as described previously is represented as a subsystem. It is modelled as shown in Fig. 3.

3.3.2. Experimental details and data

Experiments have been performed using a synthetic dataset generated using the model described in Sub-section 3.3.1. The model is developed into systems application software in MATLAB version 7.5, R2007b. The generated data is first transformed to a multi-class set using a modification of the Support Vector Machine (SVM) toolbox in MATLAB and then fed to the HTM network using the toolbox application developed in [21, 22]. The same (transformed) data is also used to train an OS-ELM application developed in [23]. Online Sequential Extreme Learning Machine (OS-ELM) is a variant of the popular Extreme Learning Machine (ELM) techniques developed in [19]. It was developed in [20] and has been shown to be extremely fast. The algorithm of the OS-ELM allows a chunk-chunk sequential learning of data. SVM was developed by Vapnik [24] and represents the state-of-the-art in supervised learning systems. The used parameters for the HTM, OS-ELM and SVM are given in Tables 3-5 respectively as shown in the Appendix.

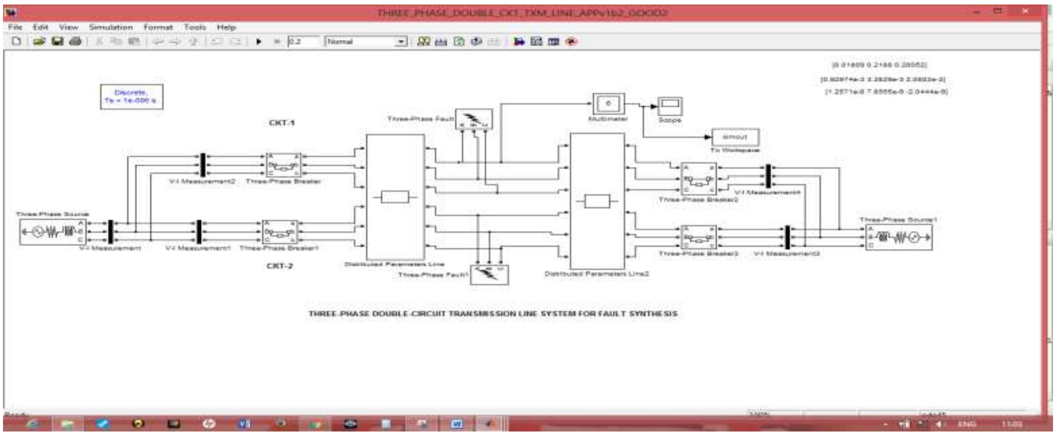

Figure 2- SIMULINK Model of Three Phase Double Circuit Transmission Line System for Fault Analysis

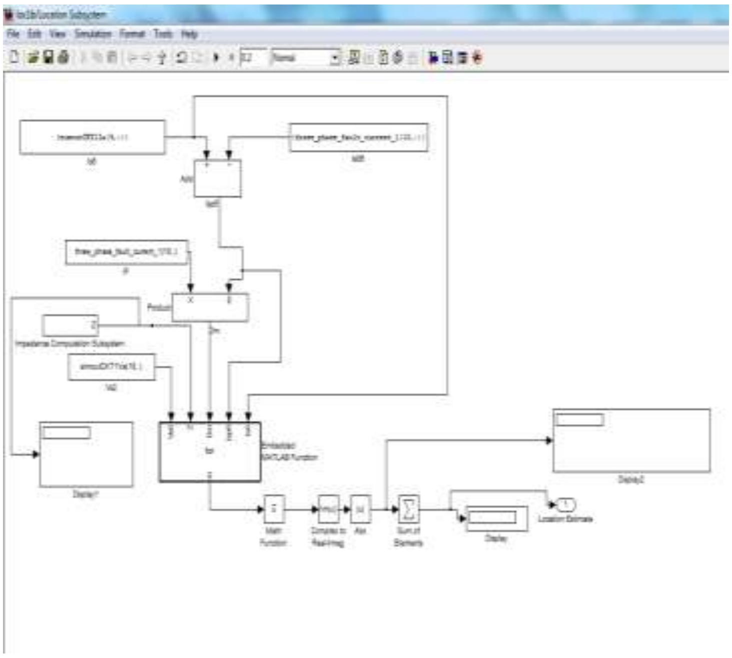

Figure 3- Fault location subsystem

The data is divided into two sets – a training set for training the other two algorithms in both techniques and a test set for evaluation purposes. For validation purposes, the training sets also serve as the test set.

IV. RESULTS AND DISCUSSIONS

Table 1 shows the classification accuracies of HTM when compared to a variant of the OS-ELM and a multi-class SVM on the train/test data for the first 10 samples. Similarly, Table 2 gives the results using an extended dataset (20 samples). Sub-sampling training iterations was set to 10 for all algorithms.

From both results (Tables 1 and 2) the HTM algorithm clearly outperformed both the OS-ELM and SVM networks. It can also be seen that for the extended data set, the performance of HTM appreciated while that of OS-ELM and the SVM reduced drastically.

Table 1: Comparative fault location predictions for 10 trial runs for the first 10 samples

Dataset	*HTM-CLA*	*OS-ELMsig* [1]	*SVM* [2]
Class accuracy (%)	*85*	*40*	*50*

[1]*OS -ELMrbf – OS-ELM using sigmoid activation function*

[2]*SVM – SVM using radial basis function*

Table 2: Comparative fault location predictions for 10 trial runs for the next 20 samples

Dataset	*HTM-CLA*	*OS-ELMsig* [1]	*SVM* [2]
Class accuracy (%)	*94*	*20*	*35*

[1]*OS -ELMrbf – OS-ELM using sigmoid activation function*

[2]*SVM – SVM using radial basis function*

V. CONCLUSION

A novel approach to the power transmission fault estimation and classification has been described in this research paper. We have proposed and used the Hierarchical Temporal Memory (HTM) as primary AI tool for online estimation and classification of power data obtain from a doubly fed transmission line. We have developed a simulation system in the MATLAB/SIMULINK language for implementing the transmission line and for assisting with simulation data gathering. The proposed technique is also compared with another similar classical online capable AI technique called Online Sequential Extreme Learning Machine (OS-ELM). From the results, it is obvious that the proposed HTM AI technique can outperform the OS-ELM and SVM techniques.

APPENDIX

Appendix 1: HTM Algorithm

Present data inputs, Si as sequences per time change: Si(t), … S(t)

Initialize parameters: Co, perms, min_overlap, iteration counter (iters) …

- Encode data, Si: Se = Encode(Si)
- Form a sparse distributed representation (SDR) $\forall$ Columns, Co = Sparse_act(Se)
  - ○ Spatial Pool the SDRs
    - ▪ Compute Overlap : $\sum S_{SDR\ (ro,\forall Co)}$
    - ▪ Boost: Boost.* S_{SDR}
    - ▪ Perform Inhibition: S_{SDR} >= min_overlap
    - ▪ Learning by Hebbian updates:
      - • perms = perms + 0.1
      - • perms = perms – 0.1
  - ○ Temporal Pool the SDRs
    - ▪ Repeat Spatial Pooler steps using spatial pool output as input
    - ▪ Compute Union of SDR,s

Until number of iters is reached

End

Appendix 2:Parameter Tables

Table 3: HTM KEY PARAMETERS

HTM-MAT parameter/symbol	Default Values
No. of Monte Carlo Iterations (iters)	5
Minimum overlap (min_overlap)	2
Desired Local Activity (desired_localActivity)	2
Sequence Size (seq_size)	200
Percent Adjust (per_adjust)	90

Table 4: OS-ELM PARAMETERS

Parameter	Block size	Activation Function	Number of Hidden Neurons	Number of initial training data*
Values	500	Radial basis Function (rbf)	250	10

Table 5: SVM PARAMETERS

Parameter	Kernel Function	Kernel Function Value	Optimization Method
Values	Radial basis Function (rbf)	0.1	Quadratic Programming

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