GUJARAT TECHNOLOGICAL UNIVERSITY

Ph.D. Synopsis

COMPARISION OF VARIOUS MACHINE LEARNING ALGORITHMS FOR PROTECTION OF SERIES COMPENSATED TRANSMISSION LINES

Submitted by:
PRANAV DHIRENDRABHAI RAVAL
Enrollment No.: 149997109009
Batch: 2014
Branch: Electrical Engineering

Supervisor Name: DR. ASHIT SURESHCHANDRA PANDYA

1 Abstract:

The transmission lines work as a backbone of the power system and play a critical role while transmitting power from generating stations to different areas in a utility grid. This requires carrying huge quantity of power to load center using transmission lines. For increasing the transmission line capacity further more to cater increasing power demands Series capacitors are installed. The use of Series compensation in transmission lines offers several advantages such as – increase in the stability limit, enhanced power transfer capability, reduced power loss while transmitting power, etc. There have been many different configurations that has come in to existence with fixed and variable capacitors used to provide compensation in extra high voltage transmission lines. Nevertheless, introduction of Series Compensation in high voltage transmission lines poses several challenges in protecting the transmission line. The challenges in the protection schemes are principally due to the non-linear behavior presented by group of devices used along with Series Compensation used for protecting transmission line.

2 State of the art of the research topic:

The use of series compensation in transmission lines employs a capacitor bank which is protected further by metal oxide varistor (MOV) along with an air gap in parallel. Having used this arrangement results in to transmission line the impedance seen by relay is severely affected. The impedance of the line undergoes a variation that gives rise to problems posed to relay in identifying faults occurring before and after the capacitor bank used for protection of line. In addition to this challenge the degree of compensation affects the transient as well as steady state parameters of the system considerably. It has been shown by many researchers that MOV protecting the capacitor as well as the air gap poses great difficulty in the decision making process of protective relaying.

It has been reported in literature survey the use of different protective arrangements done for protection of extra high voltage transmission line. The methods discussed in literature includes techniques using adaptive Kalman filtering [1], travelling waves scheme [2,3,4] discrete wavelet transforms [4,5], fuzzy logic [6,7], Artificial Neural Networks (ANN) [8-11], Wavelet [12-13] to list a some of them.

Two major challenges in developing the protection unit in recent years for EHV transmission lines include fault classification and fault location while dealing with series compensation. Several researchers have tried to solve the problem using methods which involve digital signal processing having Discrete Fourier Transform [14-16], to estimate the fundamental frequency component in the fault signal. To further investigate the occurrence of events following a fault scenario use of joint time frequency analysis at different frequency bands is attempted with Wavelet Transforms [17]. The use of Artificial Neural Network has been done by some researchers so as to perform pattern recognition of different faults occurring in transmission lines [18].

The insertion of series compensating device in transmission line creates numerous difficulties including under reaching and over reaching of traditional distance relays used for protection. Many researchers have attempted using measurement of power signals for further processing to arrive at the fault location that includes algorithms based on single end measurement, algorithms based on use of two end measurement and algorithms which are based on multiple end measurement. The single end measurement based fault location methods require less computational burden as compared to dual end or multiple end measurement based techniques. The two end/multiple end measurement algorithm based methods require communication channels which involve more cost. The use of Phasor estimation based methods are used to calculate the fundamental frequency component of voltage and current but it gets severely affected by different fault conditions arising in the system [20]. The literature survey shows attempts which use signal's time domain information while modeling MOV operation with compensation to derive the fault location [19,20,21]. The adaptation of smart discrete Fourier transform to estimate correctly the phasor magnitude and frequency is shown in [22] to improve the performance of digital protection algorithm employed. Researchers have also tried to use impedance estimation along with modeling of compensation device impedance. The combined impedance of Series compensated device along with MOV operation is modeled while doing curve fitting using Kalman filter [23,24]. The usage of synchronized samples of voltage from either ends of transmission lines have been reported in [25]. The usage of Phasor Measurement Unit on both sides of transmission line have been shown with compensating device by [26,27]. In recent times researchers have great interest in the use of Digital Signal Processing (DSP) and Neural nets. The use of wavelet packet based decomposition along with support vector regression has been reported in [28,29,30] for fault location estimation in series compensated transmission lines. There is a use of travelling wave approach shown by some researchers to approximate the distance of fault using the high frequency content of the signal's reflection during occurrence of fault [31,32]

3 Definition of the Problem:

The problem statement for the aforementioned problem for protection of EHV line with Series compensation involves development of a fast and accurate fault classification algorithm using computationally intelligent method.

4 Objective and Scope:

The major objectives of the thesis are as under

- To develop AI based Protective relaying algorithm using Single end three phase current for fixed and variable compensation.
- To do analysis of Multiresolution Wavelet transform in order to perform the joint time-frequency analysis of different fault signals.
- To develop Statistical Feature Extraction Module to extract critical statistical features which are representatives of the fault patterns from MRA.
- To develop a Classification system to classify different fault patterns using Machine learning techniques.
- To develop a Fault Location Algorithm using Machine learning techniques.
- To study Comparison of different Machine Learning techniques.

5 Original contribution by the thesis

The fault classification and fault location algorithms are developed and tested on two different systems. The two systems are having different configurations, the first having fixed compensation and second having variable compensation (with TCSC). The system analysis is done using single end current signal derived from the CT's placed in the line section to be protected. A Discrete Wavelet Transform with multiresolution analysis framework is used to provide joint time and frequency information. A statistical feature extraction module is developed to characterize different faults viz. Line to Ground fault (LG), Double line fault (LL), Double line to ground fault (LLG), triple line fault (LLL) and triple line to ground fault (LLLG). Different machine learning algorithms are applied for two different systems separately for two tasks: Fault Classification and Fault Location within the system.

The fault classification module is developed using Machine learning techniques like:

- Multi-Layer Perceptron (MLP)
- PSO based Neural Network Optimization with Feature Selection (PSO-NN-FS)
- Support Vector Machines (SVM)
- Probabilistic Neural Network (PNN)

- K-Nearest Neighbour (KNN)
- Ensemble Classifier (EC)
- Online Sequential Extreme Learning Machine (OS-ELM)

The Fault Location Algorithms uses ML techniques given below

- Least Square SVM (LS-SVM)
- Random Forest (RF)

6 Methodology of Research, Results / Comparisons

The first system under consideration consists of a multi terminal network with fixed compensation in each section. The transmission line voltage is 735 KV. The compensation level is set to 40% of the transmission line reactance. The second system has a Thyristor controlled series capacitor (TCSC) in the line section to be protected. The operating voltage of the transmission line is 400 KV. The TCSC module provided is protected by a circuit which includes Metal oxide Varistor (MOV) along with circuit breaker, air gap and Inductor provided to further protect the MOV in cases of excessively large voltage stress developed during faults with large magnitude of currents.

For both the systems different fault scenarios are considered based upon the system conditions which affect the nature of fault pattern to be later used by the protective relay. The fault patterns which comprises of prefault and one cycle post fault currents extracted from the single end of the system are used for the further processing.

Digital Signal Processing module is used to interpret the significant events of fault patterns using joint time-frequency analysis. A Multiresolution Wavelet Transform with different mother wavelet transforms were tested and finally *daubechies* (db4) mother wavelet transform was selected for capturing the critical events during occurrence of fault.

The feature extraction module is further constructed to extract critical features describing different fault patterns.

7 Wavelet Analysis

The wavelet transform is a useful tool for analyzing signals which are discontinuous and time varying in nature. The wavelet transform has attained a lot of attention in recent years for researchers in studying behavior of signals in joint time-frequency domain. It provides good time as well as frequency resolution. Wavelet transform can be effectively used to capture the transient behavior of power systems such as fault scenarios in time and frequency domains. This helps in providing information about high frequency components for small durations and low frequency components existing for long duration of time. The Discrete Wavelet Transform (DWT) utilizes two filter banks successively, namely low pass filter and high pass filter.

$$y_{low}[n] = \sum_{-\infty}^{+\infty} s[n] * u[2n-k] \qquad (1)$$

$$y_{high}[n] = \sum_{-\infty}^{+\infty} s[n] * v[2n-k] \qquad (2)$$

The power system signal is made to pass through two filter banks a low pass and high pass filter placed successively. It is illustrated by equations 1 and 2 how a signal is operated by a dyadic function by mother wavelet transform. The signal is firstly divided in to two halves in frequency band and subsequently applied to low pass and high pass filters. The output of the low pass filter is further divided in to two halves and applied to a second stage of low pass and high pass filters. The multiple level of filter banks employed here extracts the detailed information on the applied signal at every stage of decomposition.

A detailed study of Fault Analysis is done by using Multi resolution Wavelet transform in discrete form. Daubachies-4 mother wavelet transform is selected with a study of 8th level of decomposition of fault signals during various scenarios. The output of the Multiresolution wavelet transform is followed up with the statistical feature extraction which describe the fault patterns belonging to each type.

8 Machine Learning Algorithms based Classification

8.1 Multi-layer Perceptron

Here a feed forward neural network is designed with multilayer perceptron (MLP) structure. Here in the presented work the information flow is feed forward along with back propagation of error used as learning technique. Each neuron in the input layer is further connected to the hidden layer neurons. The inputs applied to the MLP are processed through these connection weights between input and hidden layer. In addition to this a threshold value called 'bias' is associated to produce an output. The sum of the weighted output is made to pass through a non-linear function called as '*activation function*' or '*transfer function'*. Different learning algorithms are used for training the neural network. Table 1 shows the learning algorithms applied for fault classification.

The ANN structure comprises of 11 input layer neurons, 11 hidden layer neurons and 5 output neurons. The hidden layer utilizes a '*tansig*' transfer function and the output layer utilizes a ‘*softmax*’ transfer function. The inputs provided to the MLP are the statistical features extracted from the signal decomposition using multi resolution wavelet transform.

The MLP structure is trained and tested with various learning algorithms to verify the accuracy of the classifier and finally “*Levenberg-Marquardt*” is selected as training algorithm for the final Classification task. The 5 outputs class labels of the MLP structure are coded as 1 correct class and 0 for in-correct class. The table 2 highlights the various parameters used for training, testing and validating of the fault patterns. The MLP structure target output classes are verified against the generated outputs for the unseen patterns. The performance of the MLP classifier in classifying the fault patterns is checked through the “*Cross-Entropy*” measure of the network. The results with Levenberg Marquardt learning algorithm is shown in fig. 1 and fig. 2 with overall classification accuracy and ROC curve.

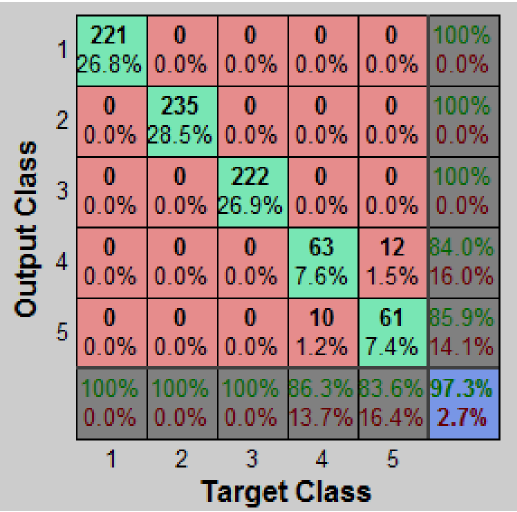

Fig 1. Classification Accuracy

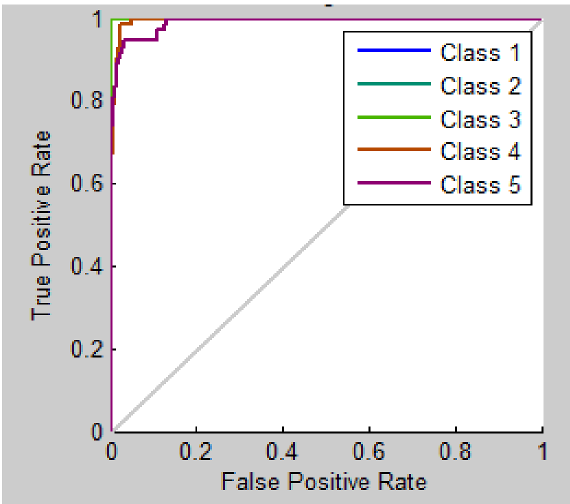

Fig 2. ROC

Table 1: Learning Algorithms for MLP

Sr.No.	Training Algorithm
1	Levenberg-Marquardt
2	BFGS Quasi-Newton
3	Resilient Back propagation
4	Scaled Conjugate Gradient
5	Conjugate Gradient with Powell/Beale Restarts
6	Fletcher-Powell Conjugate Gradient
7	Polak-Ribiére Conjugate Gradient
8	One Step Secant
9	Variable Learning Rate Back propagation

Table 2: Parameters used for MLP

ANN Parameters		
Sr.No.	Parameters	Values
1	Data Division	Random
2	Training data	50% of Complete Data
3	Testing data	25% of Complete Data
4	Validation data	25% of Complete Data
5	Performance	Cross-Entropy
6	Training method	Levenberg- Marquardt
7	Learning Rate	0.01
8	Momentum Constant	0.9
9	Maximum Epochs	1000

8.2 Neural Network Optimization (PSONNFS)

As a part of study the optimization of MLP structure along with selection of the number of features for classification is considered. The proposed algorithm comprises use of a hybrid structure using Particle Swarm Optimization (PSO) and Neural Network (NN) referred as PSONNFS algorithm. The use of PSONNFS based classifier in learning of fault patterns ensures an optimal performance of the NN Classifier. The training and testing of the NN structure is assisted with a PSO based algorithm with different parameters. The use of PSO helps in deriving NN structure with optimality for large range of fault patterns. The designed algorithm provides a good generalization capability avoiding over fitting. During the learning process of NN the Feature Selection (FS) criteria is incorporated in PSO to attain multi-objective functionality. Different experiments were conducted by changing the parameters within PSONNFS algorithm to see the effect on performance of fault classifier.

It is seen that with 8 features the performance of the classifier is optimal. The optimal number of features provides a classification accuracy of 99.75% on training patterns and 99.6% accuracy on testing patterns. Fig.3 shows the change in accuracy of classifier with number of selected features.

In third experiment the experimental results with different size of hidden layer neurons was done to check for the performance of the classifier using PSONNFS algorithm. The number of feature vectors selected were 8 in number to check for the performance of the classifier. It was observed that with a size of 11 hidden layer neurons the overall performance achieved for training and testing was the best with an accuracy of 100 % and 99.19% respectively with a feature size of 8.

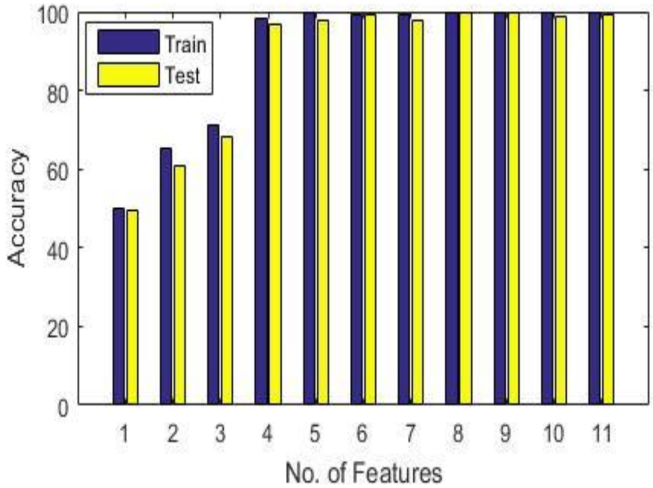

Fig. 3 Accuracy of PSONNFS for different Features

In fourth experiment results were obtained with different hidden layer size is done using PSONNFS. The feature length was set equal to 4. It was observed that the best results were obtained for 9 hidden layer neurons. The training-testing performance results with highest training accuracy of 97.66% and testing accuracy of 95.76% with feature size of 4.

To check the effect of selection of population size of the particles a separate test was conducted in fifth experiment. The numbers of feature vectors selected were four. It was see that with the increase in the number of population of swarm the probability of finding a better solution increased. The PSONNFS algorithm was run with a population size of 5, 10, 15, 20 and 25 resulted in to increment in training and testing classification accuracy with a best performance of 97.8% with training and 94.6% with testing patterns with a population size of 20.

The effect of selection of PSO parameters C1 and C2 on the performance of the PSONNFS was carried out in sixth experiment. The number of features used were 4 and the hidden layer size was kept equal to 11. The number of iteration for convergence was set equal to 50. It was observed from the results that the best result was achieved with C1=1 and C2=1. The training accuracy achieved was 99.22% and testing accuracy was 98.59%. It was concluded that with appropriate selection of personal and global learning coefficient a better overall accuracy can be guaranteed.

It was seen through successive runs of training and testing of ANN, the global minimum weight space using back propagation (BP) assisted with Levenberg-Marquardt (LM) optimization could not find global optimal solution. This is because LM algorithm relies on the gradient information of error and gets trapped in local minimum. The updating of weights in ANN using PSONNFS provides better results. As against to that PSO based heuristic search has superior capability to explore solution space and exploit the space with better solution to provide global optimal solution. The learning with hybrid structure (PSO+NN) with feature selection encompassed alongside provides meeting multiple objectives of selecting features having maximum relevance in the group of features alongside updating the weights to find global optimal solution. The PSONNFS has a slower rate of convergence comparison to BP algorithm. But with proper selection of feature size the convergence rate improved drastically.

8.3 Support Vector Machines

Support Vector Machines (SVM) uses the idea of producing decision planes that decide decision boundaries between data set containing different class values. The linear discriminant function used here can be represented by the following equation:

$$f(x) = w^T x + w_0 \tag{4}$$

w_0 is the bias term, vector w is weight vector, which is the space of respective hyper planes creating support vectors from the origin. The SVM then can be used for classification purpose. The resulting equation is of the form linear discriminant.

$$y = w^T \varphi(x) + w_0 \tag{5}$$

Where φ is the function which translate the non-linear feature space to linear space.

Support vector machines have the capability of producing a hyperplane by appropriate selection of kernel function. Here different type of SVM kernel functions were selected along with different feature vector groups to verify the performance of the SVM. This method provides a better selection of feature vectors for final classification.

The SVM Classifier is used here with different feature vector groups and tested for the classification performance under different fault scenarios. The SVM classifier with different types of kernel functions were tested in order to understand a better learning capability of the different SVM's with a given feature space. A classification accuracy of 92.4% was achieved with the use of quadratic kernel function with 9 features. The average accuracy of 98.45% was obtained with cubic kernel function with experiments done for fault classification in fixed compensation lines.

8.4 Probabilistic Neural Networks(PNN)

A PNN based classifier was constructed for classifying faults. A typical PNN structure consists of four layers namely: Input layer, Pattern layer, Summation layer and Decision layer. The PNN structure associates the input pattern to the output layer by learning the multivariate probability density estimates. A set of three PNN's are used for deciding the resultant class of the fault type. A classification accuracy of 99.58% is achieved with group of classifiers during training. The testing accuracy is achieved 95.63%. The training and testing accuracy greatly depends on the spread factor.

8.5 K-Nearest Neighborhood (KNN)

The K-Nearest Neighborhood (KNN) classification is a non-parametric algorithm which can be used for finding the belongingness of a feature vector nearest to a particular class. It is one of the simplest algorithms in machine learning as it can be trained for any data quickly. The decision rules for classification be formulated based on the nearest point of neighborhood in a given data set.

A KNN based classifier is trained and tested with three different distance measures. The KNN classifier performances with 3 cases were considered for both the systems.

Case 1: Distance metric: Euclidean, Distance Weight: Equal, Standardize Data: Yes
Case 2: Distance metric: City Block, Distance Weight: Equal, Standardize Data: Yes
Case 3: Distance metric: Minkowski (cubic), Distance Weight: Equal, Standardize Data: Yes

The KNN performance is tested using different values of K. It was observed that the classification accuracy for all the three cases were quite high for K=1 and decreases with the increase of number of K values. The average classification accuracy obtained for 10-NN is 96.3% for fixed compensation and 78 % for TCSC based protection.

8.6 Ensemble Classifier

Many classifier systems are recently investigated with class imbalance using techniques like Bagging, Boosting and Hybrid approaches [33]. With combination of pattern classifiers for decision making for a given classification task helps in solving problems quite difficult as shown in [34,35]. Genetic programming based heterogeneous ensemble is recommended to form a classification system [36]. In order to shrink the problem of over fitting negative correlation based learning mechanism with Ensemble of Neural nets is proposed in [37]. The prominent methods noted in the literature for solving multiclass problems using binary classifiers include one against all, one against one and ECOC (Error Correcting Output Code) [38]. Here in the research work conducted the multi class classification problem is solved using group of binary classifiers. The results obtained have an overall classification accuracy of 99.5%.

8.7 Online Sequential Extreme Learning Machines (OS-ELM)

An Extreme learning machine with fully connected structure has been used with single hidden layer. The weights between input and hidden layer are randomly assigned. The weights between hidden and output layer are evaluated using a single step process analytically [39].

The online sequential learning Extreme learning machine provides an advance learning procedure for data streaming in online mode [40]. In the work a recursive least square method is adopted to update the weights between the hidden layer and the output layer. It provides a batch learning of the features presented to the structure in a chunk after chunk of the data. The size of the chunk of the data presented can be varied over the period of learning. Different chunk sizes were tested in the learning phase of OS-ELM. Results were derived using different kernel functions used such as: RBF, Sin and Sigmoid.

The best performance found through several run of the algorithm resulted in to classification accuracy of 99.42% was achieved in training and 100% accuracy in testing phase of OS-ELM. The OS-ELM provides far better classification accuracy with a high degree of generalization.

In the next phase of the work the fault location algorithms were studied.

8.8 Comparison of Fault Classifiers

A comparison is done for different types of Fault Classifier discussed in the previous section based on ability to generalization and classification accuracy. The classifiers are also compared based on training and testing time for individual classifier.

9 Fault Location Algorithm

As a part of protective function locating fault on the transmission line also plays an important role. Fault location algorithm using the extracted statistical features is considered. The features belonging to particular fault zone are modeled using learning algorithms namely, Random Forest and LS-SVM.

The Random Forest approach uses a bag of Decision trees which are used to associate the faults features based on the filter coefficient values derived. The process of bagging which is referred as bootstrap aggregation is used which helps in dividing the data in to several parts thus reducing the variance in the approximations done.

The Random forest algorithm provided an overall fault distance estimation accuracy of 98.7%.

The use of Random forest algorithm additionally provides the feature relevance while deciding the fault zone of uncompensated and compensated transmission line. This method gives better accuracy and generalization compared to other method.

The Least Square-Support Vector Machine (LS-SVM) is an advancement of Support Vector Machine which is used for associating the fault zone features with respect to fault distance. The overall fault estimation accuracy achieved through this method is 97.39%.

9.1 Fault location Algorithm comparison

The overall accuracy of Fault location algorithm using Random Forest is 98.7 %. The fault location algorithm performs well in identifying fault distance near to compensating device whereas the fails to locate at the ends.

The overall accuracy of LS-SVM is 97.39%. The algorithm performs well near the compensating device and fails to perform well at the ends.

10 Conclusion

The EHV transmission line play a crucial role in power system which requires robust protective algorithms. Different fault classification algorithms were designed and tested on two different type of Systems with Series compensation. The MLP provides a good way for pattern classification with appropriate selection of the number of hidden layer neurons and training parameters. The MLP structure with different back propagation learning algorithms were tested on the different systems and the multiple run results provide considerably better results. The multiple run of the Neural Network with random selection of initial weights provides a considerably good performance but it was seen that optimal performance is not assured. PSONNFF Algorithm provides better results compared to the other backpropagation learning algorithms tested previously. PNN provides a good result in case of fixed compensation but underperforms for variable compensation. The performance depends upon the selection of radial basis function and spread factor used as smoothing parameter. The KNN is an unsupervised learning algorithm which provides good results on smaller values of K. But as K increases the performance of the KNN reduces drastically. The Ensemble Classifier algorithm provided much better results as opposed to other algorithms on different types of fault scenarios. Proper selection of combination method for classifiers in ensemble can ensure better accuracy. The OS-ELM Classifier algorithm gave the best performance for all different fault scenarios for both the systems. The training time of the algorithm is smaller compared to other algorithms. It optimality in terms of performance using the minimal structure as well as good generalization capability.

List of Papers Published

1. P.D.Raval, A.S.Pandya "A hybrid Wavelet-ANN Protection Scheme for Series compensated EHV Transmission Line", Journal of Intelligent & Fuzzy Systems, vol. 32, no. 4, pp. 3051-3058, March 2017
2. P.D.Raval, A.S.Pandya , "A Novel Fault Classification technique in Series Compensated Transmission Line using Ensemble method", International Journal of Pattern Recognition and Artificial Intelligence, June 2019
3. P.D.Raval, A.S.Pandya , "Accurate Fault Classification in Series Compensated Multi-Terminal Extra High Voltage Transmission Line using Probabilistic Neural Network", International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), 3-5 March 2016
4. P.D.Raval, A.S.Pandya ,"Improved Fault Classification in Series compensated EHV Transmission Line using Wavelet transform and Artificial Neural Network", IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), 4-6 July 2016
5. P.D.Raval, A.S.Pandya ,"Protection of Series Compensated Transmission Line using Wavelet-KNN", National Conference On "Emerging Trends in Computer Vision, Wireless Communication and Industrial Automation (ETCVWCIA-2016)"

11 References

[1] A. Girgis, A. A. Sallam and A. Karim, El-Din, "An adaptive protection scheme for advanced series compensated(ASC) transmission lines," IEEE Transaction on Power Delivery, Vol. 13, No. 2, pp. 414-420, April 1998.

[2] W. P. Thomas and C. Christopulo, "Ultra-high speed Protection of series compensated lines," IEEE Transactionson Power Delivery, Vol. 7, pp. 139-145, January 1992.

[3] Jamil, M. Thomas, M. S. Moinuddin and P. Kumar,"Fuzzy approach to fault classification for transmissionline protection," Proc. IEEE Tencon 99 Conf., Vol. 2, pp. 1046-1050, September 1999

[4] Zheng-you, H.E., Yu-mei, C.A.I., Qing-quan, Q.: 'A study of wavelet entropy theory and its application in electric power system fault detection [J]'. Proc. CSEE, vol. 5, 2005.

[5] Megahed, A. I., Moussa, A. M., Bayoumy, A. E.: 'Usage of wavelet transform in the protection of series-compensated transmission lines', IEEE Trans. Power Deliv., 21, (3), pp.1213-1221, 2006.

[6] B. Das and J. V. Reddy, "Fuzzy-logic-based fault classification scheme for digital distance protection," IEEE Transactions on Power Delivery, Vol. 20, pp. 609-616, April 2005.

[7] R. N. Mahanty and P. B. Dutta Gupta, "A fuzzy logic based Fault classification approach using current samples only," Int. J. Elect. Power Syst. Res., Vol. 77, pp. 501-507, 2007.

[8] Sanaye-Pasand M. and Khorashadi-Zadeh H., "An extended ANN-based high speed accurate distance protection algorithm", *Int. Journal Electrical Power and Energy Systems*, Vol. 28, pp. 387-395, 2006.

[9] Martin F. and Aguado A., "Wavelet-based ANN approach for transmission line protection", *IEEETrans. of Power Deliver*, Vol. 18, No. 2, pp. 1572-1574, 2003.

[10] Silva K. M., Souza B. A. and Brito N. S. D., "Fault detection and classification in transmission lines based on wavelet transform and ANN", *IEEE Trans. of Power Deliver*, Vol. 21, No. 4, pp.2058-2063, 2006.

[11] Samantaray S. R. and Dash P. K., “Pattern recognition based digital relaying for advanced series compensated line”, *Int. Journal of Electrical Power and Energy System*, Vol. 30, No. 1, pp. 102-112, 2008.
[12] Chanda D., Kishore N. K. and Sinha A. K.,“Application of wavelet multi-resolution analysis for identification and classification of faults on transmission lines”, *Int. Journal of Electric Power Systems Research*, Vol. 73, No. 3, pp. 323-333, 2005.
[13] El Safty S. and El-Zonkoly A., “Applying wavelet Entropy principle in fault classification” *Int. Journal of Electrical Power and Energy System*, Vol. 31, No. 10, pp. 604-607, 2009.
[14] J.Z.Yang, C.W.Liu, ―A precise calculation of power system frequency and phasor, IEEE Transactions on Power Delivery 15 (2000) 494-499
[15] J.C.Gu, J.Z.Yu, ―Removal of DC offset in current and voltage signals using a novel Fourier filter algorithm‖, IEEE Transactions on Power Delivery 15 (2000) 73-79
[16] C.S.Yu,J.Z.Yang, C.W.Liu, ―New Fourier filter design for fault current filtering of series compensated lines‖, International Journal of Power & Energy Systems 28 (2008) 203-211
[17] D.C.Robertson, O.I.Camps, J.S.Mayer, W.B.Gish, ―Wavelets and electromagnetic Power system transients, IEEE Transactions on Power Delivery 11 (1996)
[18] P.D.Raval, ―ANN based Classification and Location of Faults in EHV Transmission Line‖, IMECS 2008 Vol.I.,19-21 Mar.2008, Hong Kong

[19] M.M. Saha, B. Kasztenny, E. Rosolowski, J. Izykowski, First zone algorithm forprotection of series compensated lines, IEEE Transactions on Power Delivery16 (2001) 200–207.
[20]M. Al-Dabbagh, S.K. Kapuduwage, Using instantaneous values for estimatingfault locations on series compensated transmission lines, Electric Power Sys-tems Research 76 (2005) 25–32.
[21] J. Sadeh, A. Adinehzadeh, Accurate fault location algorithm for transmissionline in the presence of series connected FACTS devices, International Journal ofElectrical Power & Energy Systems 32 (2010) 323–328.
[22] J.-Z. Yang, C.-W. Liu, A precise calculation of power system frequency and phasor, IEEE Transactions on Power Delivery 15 (2000) 494–499.
[23] D.L. Goldsworthy, A linearized model for MOV-protected series capacitors, IEEETransactions on Power Systems 2 (1987) 953–957.
[24] F. Ghassemi, J. Goodarzi, A. Johns, Method to improve digital distance relayimpedance measurement when used in series compensated lines protectedby a metal oxide varistor, in: Generation, Transmission and Distribution, IEEProceedings, IET, 1998, pp. 403–408.
[25] M. Saha, J. Izykowski, E. Rosolowski, B. Kasztenny, A new accurate fault locatingalgorithm for series compensated lines, IEEE Transactions on Power Delivery14 (1999) 789–797.
[26] Y. Chi-Shan, L. Chih-Wen, Y. Sun-Li, J. Joe-Air, A new PMU-based fault locationalgorithm for series compensated lines, IEEE Transactions on Power Delivery17 (2002) 33–46.
[27] A. Abdelaziz, S. Mekhamer, M. Ezzat, Fault location of uncompensated/series-compensated lines using two-end synchronized measurements, Electric PowerComponents and Systems 41 (2013) 693–715.
[28] D. Novosel, B. Bachmann, D. Hart, Y. Hu, M.M. Saha, Algorithms for locatingfaults on series compensated lines using neural network and deterministicmethods, IEEE Transactions on Power Delivery 11 (1996) 1728–1736.
[29] A. Hosny, M. Safiuddin, ANN-based protection system for controllable series-compensated transmission lines, in: IEEE Power Systems Conference andExposition, 2009. PSCE’09. IEEE/PES, 2009, pp. 1–6.

[30] A. Yusuff, C. Fei, A. Jimoh, J. Munda, Fault location in a series compensatedtransmission line based on wavelet packet decomposition and support vectorregression, Electric Power Systems Research 81 (2011) 1258–1265.
[31] J. Sadeh, A. Adinehzadeh, Accurate fault location algorithm for transmissionline in the presence of series connected FACTS devices, International Journal ofElectrical Power & Energy Systems 32 (2010) 323–328.
[32] F. Wang, Study on traveling-wave differential protection for series compensated line, Journal of International Council on Electrical Engineering 1 (2011)359–366.
[33] Mikel Galar, Alberto Fernandez, Edurne Barrenechea, Humberto Bustince,
A Review on Ensembles for the Class Imbalance Problem: Bagging, Boosting, and Hybrid-Based Approaches, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS, 2011
[34] L.I. Kuncheva, Combining Pattern Classifiers: Methods and Algorithms, Wiley-Interscience,2004
[35] Z. Zhou, Ensemble methods: foundations and algorithms, Chapman & HallCRC Data Mining and Knowledge Discovery Series,Taylor& Francis, 2004
[36] Niusvel Acosta-Mendoza, Alicia Morales-Reyes, Hugo Jair Escalante, Andres Gago-Alonso,learning to Assemble Classifiers via Genetic Programming, International Journal of Pattern Recognition and Artificial Intelligence, 2014
[37] Yong Liu, Error Awareness by Lower and Upper Bounds in Ensemble Learning, International Journal of Pattern Recognition and Artificial Intelligence, 2016
[38] Mohammad Ali Bagheri, Gholam Ali Montazer, Ehsanollah Kabir, A subspace approach to error correcting output codes", Pattern Recognition Letters, vol. 34, pp. 176–184, 2013
[39] Huang, G.-B., Q.-Y. Zhu & C.-K. Siew 2006. Extreme learning machine: theory and applications. Neurocomputing70(1): 489-501.
[40] Nan-Ying Liang, Guang-Bin Huang, P. Saratchandran, N. Sundararajan A Fast and Accurate Online Sequential Learning Algorithm for Feedforward Networks