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Improvement of Fault Identification and Localization Using Gustafson-Kessel Algorithm In Adaptive Neuro-Fuzzy Inference System

Amalina Abdullah, Channarong Banmongkol and Naebboon Hoonchareon

Chulalongkorn University, 254 Phayathai Road, Pathumwan, Bangkok 10330.

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ABSTRACT

Most of the techniques on identifying fault location depend on parameters of power transmission line. Thus, a complex mathematical solution will be considered which at such conditions, the dependence on line parameters will limit performance of algorithms. An independent or parameters free algorithm is an option to overcome this problem by using an artificial intelligent technique. This paper presents a recent scheme including of fault identification, and fault localization to estimate the distance of fault. A 115 kV parallel transmission line system has been used to develop and implement the proposed scheme. We used the approach of hybrid intelligent method called adaptive neuro-fuzzy inference system (ANFIS) combine with discrete wavelet transform (DWT) to obtain a great performance. A novel approach of implementing Gustafson-Kessel (GK) clustering algorithm has improved the stability and accuracy of performance. Results show that the proposed scheme can contributes as an efficient tool to overcome the obstacles in analysis of fault data.

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INTRODUCTION

One of the problems in power system protection is to accurately classify the fault data and estimate the exact location where the fault occurs.The increasing complexities of the modern power transmission systems have greatly raised the significance of the fault location research studies. It is very important issue in order to clear faults quickly and restore power supply as soon as possible with minimum interruption. Solution to this problem will help the service operator, increase the reliability of power utility performance and reduces economic damage to the network by reducing restoration time. Most of the techniques on identifying fault location depend on parameters of transmission line. Thus, a complex mathematical solution will be considered which at such conditions, dependable on line parameters will limit the performance of algorithms. Fault identification and diagnosis based on conventional deterministic approach face a few problems in achieving the desired speed, selectivity and accuracy. This is due to inability to adapt the dynamically to the variation of operating conditions. Examples of the problems are, system loading level, fault inception instance and fault resistance, etc. An independent or parameters free algorithm is an option to overcome these problems by using an artificial intelligent technique such as Fuzzy logic based by (Biswarup *et al*. 2005 and Mahanty *et al*. 2007), Artificial neural network (ANN) based by (Samantray *et al*. 2007), Fuzzy neural network based by (Huisheng Wang *et al*. 1998) , Wavelet based by (Chunju Fan *et al*. 2006, Osman H. *et al*. 2004, El Safty S. *et al*. 2009), and combined Wavelet-ANN techniques based by (Sami Ekici *et al*. 2008, Chiradeja P. *et al*. 2009, Nan Zhang *et al*. 2007, Abdollahi A. *et al*. 2010, and Meisam *et al*. 2011). The advantage of this solution will increase the robustness and flexibility of such techniques.

This paper presents a recent scheme including of data reduction, fault identification, and fault localization. A 115 kV parallel transmission line system has been used to develop and implement the proposed scheme. We used the approach of hybrid intelligent method called adaptive neuro-fuzzy inference system (ANFIS) combine with discrete wavelet transform (DWT) to obtain a great performance. ANFIS is intelligent techniques based on combination of artificial neural network (ANN) and fuzzy inference system (FIS) has been used on detection and classification of faults since the last 20 years. Recently, the researchers have started the investigation on its

Corresponding Author: Amalina Abdullah, Chulalongkorn University, 254 Phayathai Road, Pathumwan, Bangkok 10330.
E-mail: amalina1979@gmail.com

capability on estimating fault localization. Wavelet transform is one of the efficient tools for analyzing non stationary signals such as transients, and has been widely applied to solve numerous problems in power systems. DWT with the mother wavelet of Daubechies-4 is used to extract the features of data. The data is pertinent to single line to ground fault which is the most fault in transmission and distribution networks. More than 700 data is used in this study including the pre-fault data. The development of simulation data involved variety value of fault resistances and fault locations to increase the accuracy performance. A novel approach of implementing Gustafson-Kessel (GK) clustering algorithm (R. Babuska *et al* 2005) has improved the stability and accuracy of performance. Results show that the proposed scheme can contributes as an efficient tool to overcome the obstacles in analysis of fault data.

MATERIAL AND METHODS

A. System Structures:

Transmission line is a component of electrical power systems that are most frequently experienced faults compared to other power system elements. Parallel transmission lines are used in the transmission system due to their economic and environmental benefits. The robustness and reliability of double circuit/ parallel line is important since the faults are commonly happen at this type of system voltage. However, the protection of parallel lines are always challenging due to the mutual coupling effect of the two lines.

B. Wavelet transforms implementation:

Wavelet transforms are fast and efficient means of analyzing transient voltage and current signals (S. Sajedi *et al* 2011). This technique has extensively used in AI approach but also for improving two-terminal fault location algorithm in conventional approach (Wutthikorn *et al* 2010). The wavelet transform not only decomposes a signal into frequency bands, but also, provides a non uniform division of the frequency domain. The application of wavelet transform in engineering areas usually requires discrete wavelet transform (DWT), which represented as:

$$DWT(m,n) = \frac{1}{\sqrt{a_0}^{m}} \sum_k x(k)\psi\left(\frac{k-nb_0a_0^m}{a_0^m}\right) \tag{1}$$

Wavelet Coefficients are used for pre-processing of data input to the proposed scheme. These coefficients are obtained by applying DWT on the data under study. The DWT considerably simplifies the input signal which reduces the volume of input data without loss of information. In order to reduce the input data, in connection with accuracy and speed but retaining important feature of the wavelet signals, features have been extracted. This dramatically reduces the training stage in the artificial neural network ANN and increases the overall performance of the digital relay. Technique of identifying maximum wavelet coefficient of ¼ cycles of the signals immediately after fault occurs has been used. It can improve algorithm's performance if they are used as inputs instead of actual values of voltages and currents of three phase transmission line system. One of the most popular mother wavelets found for power system transient analysis in the literature is Daubechies's wavelet family. Wavelet analysis deals with expansion of functions in terms of a set of basic functions (wavelets) which are generated from a mother wavelet by operations of dilatations and translations (C. Sydney *et al* 1998). The mother wavelet daubechies (db4) is employed to decompose high frequency components from the signal. After applying DWT to voltages and currents signals, coefficients are obtained. Wavelet analysis is a relatively new signal processing tool and is applied recently by many researchers in power systems due to its strong capability of time and frequency domain analysis (C.H. Kim and R. Aggarwal, 2000 and 2001).

C. Modelling of Adaptive Neuro-Fuzzy Inference System (ANFIS):

ANFIS is a hybrid intelligent system which combines the fuzzy logic qualitative approach and adaptive neural network capabilities towards better performance (Jang 1993). ANFIS has been used in fault detection and fault classification in power system during last 2 decades (Ramadoni 2013). Recently, the researchers have spend their interest on its capability for fault location in transmission line and distribution network (Ramadoni 2013, Javad *et al* 2009, El Sayed 2010). A few advantages in application of ANFIS are better balance between credibility and understandable, also it is proficient to adjust the membership function parameters and linguistic rules directly from the data. Other advantage is that the neural networks become more transparent, while fuzzy systems become competent for learning. The basic structure of Fuzzy Inference System (FIS) as shown in Figure 1 is a model that maps input characteristics to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single valued output or a decision associated with the output. Fuzzy inference can also be employed to model systems whose rule structure is essentially predetermined by the user's interpretation of the characteristics of variables in the model. However, it cannot be distinguish what the FIS membership functions should look like simply from the data for some situations. Parameters of FIS could be chosen so as to tailor the membership functions to the input and output data rather than choosing the parameters associated with a given membership function arbitrarily in order to account for these types of variations in the values of data.

D. Implementation of Gustafson-Kessel algorithm:

The Gustafson-Kessel (GK) algorithm (D.E. Gustafson *et al* 1979) is a powerful clustering technique with a large number of applications in various domains including image processing, classification and system identification (R.N. Dave *et al* 1992, R. Babuska 1992). The important characteristic of this algorithm is the local adaptation of the distance metric to the shape of the cluster by estimating the cluster covariance matrix. Another main feature is ability on adapting the distance-inducing matrix correspondingly, when the GK algorithm is implemented in the extraction of Takagi–Sugeno fuzzy model from data. Overfitting is able to be reduced when the number of training samples is low in comparison to the number of clusters. This is achieved by adding a scaled unity matrix to the calculated covariance matrix. Mostly, the Gustafson-Kessel clustering algorithm is applied to identify Takagi Sugeno models (D.E. Gustafson *et al* 1979). A drawback of this algorithm is that only clusters with equal volumes can be found and the resulted clusters cannot be directly used to form membership functions. The Gustafson-Kessel algorithm allows calculating an adaptive distance as a way to detect clusters with different geometries within a data set. A special GustafonKessel algorithm, called modified GK algorithm (Robert Babuska, 2005) has been used. The advantage of this algorithm is it can improve the performance of training stage and able to find a partitioning of the data. The explanation below describes the steps on implementing modified Gustafson Kessel algorithm.

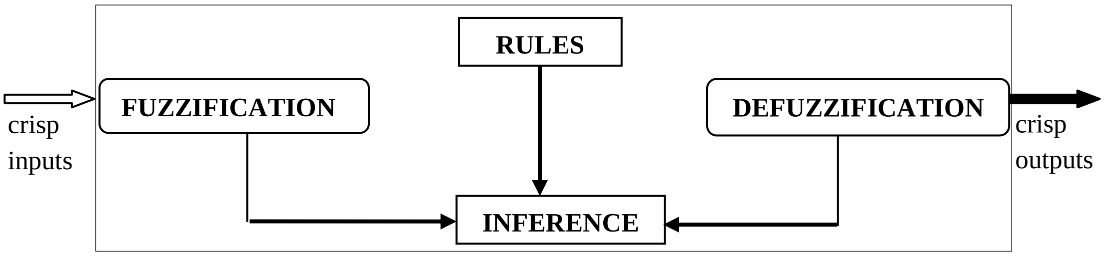


Fig. 1: Basic structure of the Fuzzy Inference System.

$step$ 1: Compute cluster prototypes (means):

$$V_i^{(l)} = \frac{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m Z_k}{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m}, \quad 1 \le i \le K$$

$step$ 2: Compute the cluster coverience matrices:

$$F_i = \frac{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m (z_k - V_i^{(l)})(z_k - V_i^{(l)})^T}{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m}, \quad 1 \le i \le K.$$

Add a scaled identity matrix:

$$F_i = (1-\gamma)F_i + \gamma \det(F_0)^{\frac{1}{n}} \mathrm{I},$$

Extract eigenvalues λ_{ij} and eigenvectors ϕ_{ij} from F_i. Find $\lambda_{i\,max} = max_j \lambda_{ij}$ and set:

$$\lambda_{ij} = \lambda_{i\,max} / \beta \qquad \forall j \text{ for which } \lambda_{i\,max} / \lambda_{i\,j} > \beta$$

Reconstruct F_i by :

$$F_i = [\phi_{i1} \dots \phi_{in}] diag(\lambda_{i1}, \dots, \lambda_{in}) [\phi_{i1} \dots \phi_{in}]^{-1}$$

$Step$ 3: Compute the distances :

$$D^2_{ikA_i} = (z_k - V_i^{(l)})^T \left[\rho_i \det(F_i)^{\frac{1}{n}} F_i^{-1}\right] (z_k - V_i^{(l)}), \qquad 1 \le i \le K, \; 1 \le k \le N.$$

$Step$ 4: Update the partition matrix:
for $1 \le k \le N$
if $D_{ikA_i} > 0$ for $1 \le i \le K$,

$$\mu_{ik}^{(l)} = \frac{1}{\sum_{j=1}^{K} (D_{ikA_i}/D_{jkA_i})^{2/(m-1)}},$$

Otherwise

$$\mu_{ik}^{(l)} = 0 \text{ if} D_{ikA_i} > 0 \text{ , and} \mu_{ik}^{(l)} \in [0, 1]$$

$$\text{with} \sum_{i=1}^{K} \mu_{ik}^{(l)} = 1 \text{ otherwise.}$$

Until $\left\| U^{(l)} - U^{(l-1)} \right\| < \in$

- ***Fault Identification:***

The inputs, which are the six wavelet coefficients of the single line to ground fault data. Then it clusters the data into two clusters using modified GK algorithm which is better than FCM or hard partitioning like K-means algorithm. Membership of each data point is calculated for each defined class. Since it is the fuzzy clustering, the data point may belong to more than one class with certain degree of membership. The membership to one class is assigned based on the highest value of the membership value. For example, if the data point 1 has the following membership in two clusters;
Cluster 1 : 0.8
Cluster 2 : 0.2 (the sum should be equal to 1)
Then, it is assigned to cluster 1 due to higher membership value. Since there are two clusters, the task was to create a cluster for a fault case, and a cluster for no fault case.

- ***Fault Localization:***

In this part, the same strategy has been used. We knew that our aim is to identify faults data pertinent to phase to ground (AG), phase B to ground (BG) and phase C to ground (CG). These are the class of fault data. The input is six wavelet coefficients. The same strategy on membership value and clustering are used in the program. The distance of fault location will be predicted based on the developed algorithm.

RESULTS AND DISCUSSION

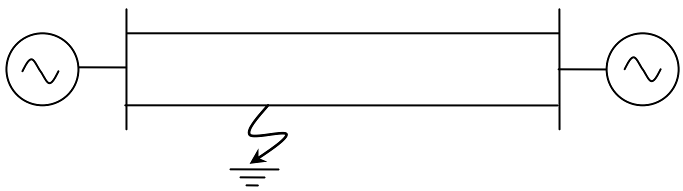


Fig. 2: One-line diagram of the system.

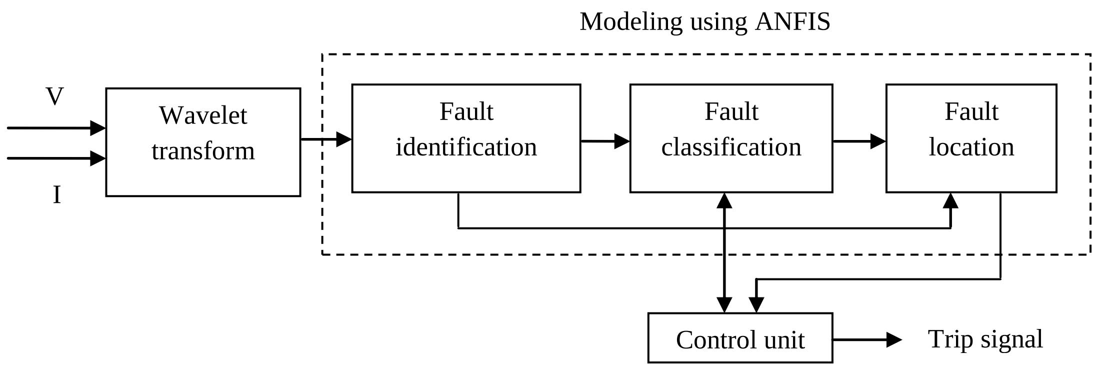


Fig. 3: Proposed model of protection scheme.

Figure 2 shows a one-line diagram of 115 kV double-circuit transmission lines used in this study. The transmission lines with 100 km in length are supplied from both sides. They are modeled and simulated by using Electromagnetic Transient Program (EMTP) to obtain a large amount of data of fault currents and voltages. A fault is created at every 2 km along the full length. The purpose on creating fault at a lot of locations is to increase the reliability on accuracy of fault distance estimation. For each distance taking into account, fault resistance is varying with the values of 0.5 Ω, 5 Ω, 25 Ω, 100 Ω and 200 Ω. The simulation fault data is then transferred to Matlabenvironment for further process and analysis. To accomplish the task, features of voltages and currents signals are extracted based on discrete wavelet transform with daubechies4 (db4) as mother wavelet. These features are then used as an input to train and test the algorithm. Technique of identifying maximum wavelet coefficient of ¼ cycle of the signals immediately after fault occurs has been used.

Figure 3 shows the proposed model of protection scheme discussed in this paper. It begin with raw signal from the fault pertinent to voltages and currents. The signals then being through data reduction process using wavelet transform method. Now, the data is ready for the input for the system of ANFIS. The occurrence of fault will be identified to confirm the existence of fault. Then, the fault will be classify either single line to ground, double line, double line to ground or three phase. In this paper, fault classification will concern on specific of single line to ground; AG, BG or CG. Then, distance of fault will be estimated. Basically, the estimated result will be compared with the actual distance to identify the accuracy of performance. The steps below summarize the proposed model in general description.

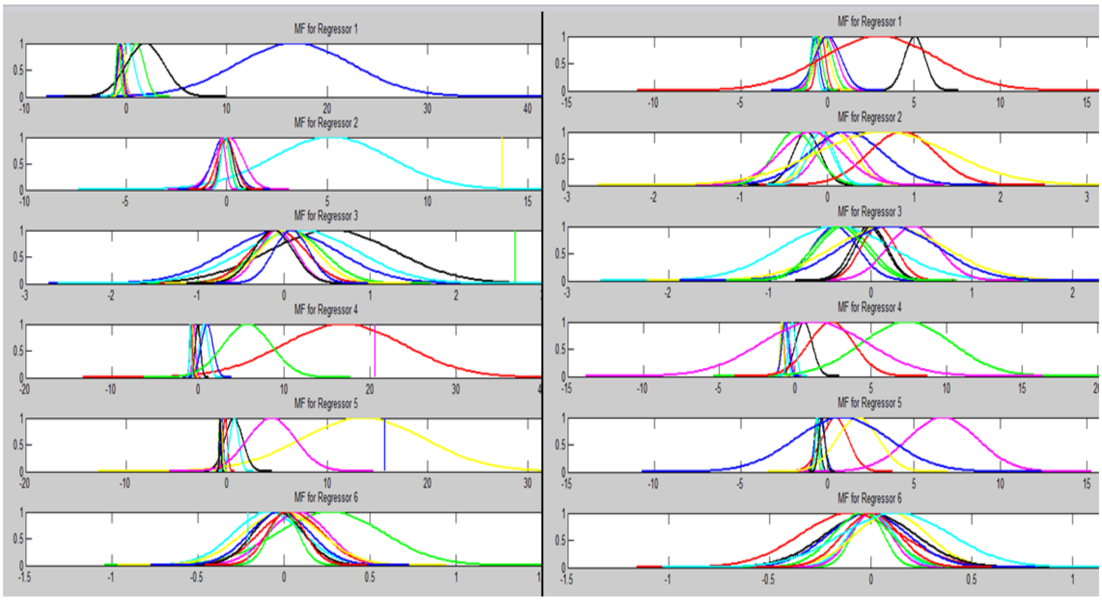
Step 1: Create the architecture of fuzzy inference system (FIS) in Matlab environment. The architecture consist of two inputs (i.e. voltages and currents fault measured in the locator end of transmission line) and one output.

Step 2: Determine the membership functions for ANFIS input and output. In this work, gbell membership function has been chosen for each input and output of FIS architecture.

Step 3: Collecting or producing suitable information (data) to train ANFIS. The data for training process should have same form and the various conditions of a real power system is included. A power system simulation using EMTP has been carried for achieving the suitable data.

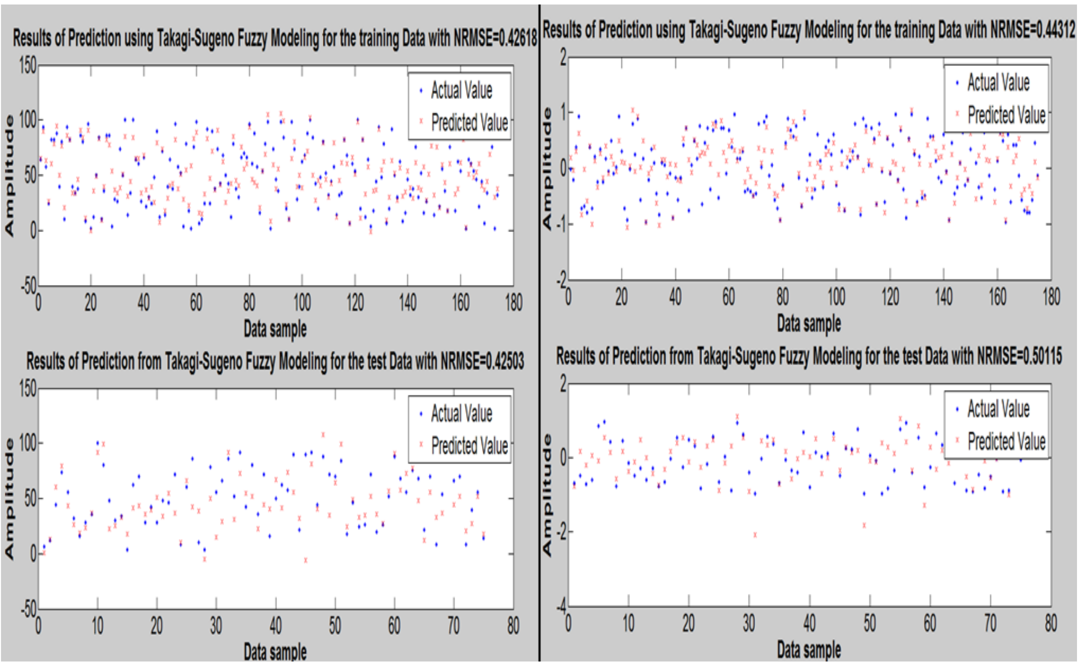
Figure 4 in the following part shows the G-Bell membership function of fault localization. The performance of a bell membership functions for specifying fuzzy sets. It is important to attain smoothness and symmetrical shape of plotting. The parameter locates the center of the curve width of the curve. It can be seen in figure 4 that implementation of GK algorithm has improved the shape of membership function. Thus, the further results will be much better and reliable.

Another results in figure 5 shows the prediction from Takagi-Sugeno for training and testing pertinent to fault localization. Figure 5a shows that the plotting is more scatter and amplitude is high. Thus, the result is less reliable. A better plotting can be seen in figure 5b. The amplitude is also reduced significantly. Numerical outputs in Matlab also proved the results. With this performance, further results will be more stable and obtain better accuracy.



a) b)

Fig. 4: G-Bell membership function a) Without GK algorithm b) With GK algorithm implementation.



a) b)

Fig. 5: Prediction from Takagi-Sugeno a) Without GK algorithm b) With GK algorithm implementation.

The percentage of error is then calculated based on the formula given below (El Sayed *et al* 2006)

$$\%\,Error = \frac{|Actual faultlocation - Predicted faultlocation|}{totallinelength} \times 100$$

Table 1 shows the recorded fault distance estimation for single line to ground studied in this paper. The distances are at 2km, 20km, 40km, 60km, 80km and 100km. Five different values of fault resistance are involved to observe the effect on accuracy. The results show a reasonably good performance for distance estimation of fault at power transmission line.

Table 1: Fault distance estimation for single line to ground fault (random selection of distances).

Actual distance	Estimation error (%)				
(km)	Rf = 0.5 Ω	Rf =5 Ω	Rf = 25 Ω	Rf = 100 Ω	Rf =200 Ω
2	0.022	0.067	0.088	0.083	0.131
20	0.006	0.029	0.012	0.042	0.091
40	0.019	0.021	0.032	0.072	0.029
60	0.009	0.041	0.062	0.066	0.062
80	0.023	0.031	0.044	0.057	0.060
100	0.026	0.036	0.052	0.049	0.075

Conclusion:

This paper has proposed a wavelet adaptive neuro fuzzy inference system approach that able to identify the fault, classify the types and estimate the distance of fault location. The input is based on voltages and currents which then extracted by using wavelet coefficient. The proposed algorithm is different from conventional algorithms that are based on deterministic computations on a well-defined model to be protected. The simulation results show that the proposed scheme provides a fast, accurate and reliable technique for fault identification and diagnosis. The successful of implementing neuro-fuzzy is heavily depends on prior knowledge of the system and the training data. The estimation error for single line to ground fault with the variation of fault resistances is less than 0.1%. The proposed scheme has been developed with aim for generalization output to avoid over fitting results.

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