Journal of Engg. Research **Vol. 5 No. (6) March 2018 pp.** *1-14*

تحديد الأعطال بالاستخدام المدمج لنظام الاستدلال العصبي –الضبابي التكيفي وخوارزمية غوستافسون– كيسيل

أمالينا عبد الله*، تشانارونغ بانمونكول*، نيبون هونشاريون*، كونيهيكو هيداكا**

* كلية الهندسة، قسم الهندسة الكهربائية، جامعة شولالونغكورن، بانكوك 10330، تايلاند.

** قسم الهندسة الكهربائية ونظم المعلومات، جامعة طوكيو، طوكيو،8656-113، اليابان.

مراسلة المؤلف بالبريد الالكتروني: amalina1979@gmail.com

الخلاصة

إن المسائل المتعلقة بالكشف عن حدوث عطل ما، تثبيت النوع، وتخمين المكان الدقيق للعطل ينبغي أن تحل للقضاء الفوري على الأعطال واستعادة تجهيز القدرة بأقل الانقطاعات. ساهمت المناهج التقليدية في مساعدة مؤسسات الطاقة على التغلب على تلك المشاكل. ومع ذلك فإن تلك المناهج تعتمد على معاملات الخط وتشتمل على عدد قليل من المعادلات الرياضية المعقدة. في هذه الورقة، تم اقتراح طريقة جديدة لتحديد وتصنيف العطل ومكانه وذلك بالاستفادة من الدمج بين نظام الاستدلال العصبي–الضبابي التكيفي (ANFIS) و خوارزمية التكتل غوستافسون– كيسيل(GK) . لقد استعرضت فعالية وعملية هذه الطريقة من خلال نتائج المحاكاة. تستخدم هذه الطريقة خوارزمية التكتل الضبابي (GK) لتقرير الترتيب المسبق ومعامله ويحدد معامله اللاحق باستخدام التربيع الأصغر المتعامد. إن الطريقة المفترضة لا تعتمد على معلومات معامل الخط ويمكنها الحصول على دقة عالية في تخمين مواقع الأعطال.

Fault identification usingcombined adaptive neuro-fuzzy inference system and Gustafson–Kessel algorithm

Amalina Abdullah*, ChannarongBanmongkol*, NaebboonHoonchareon* and Kunihiko Hidaka**

**Faculty of Engineering, Department of Electrical Engineering,Chulalongkorn University, Bangkok 10330, Thailand*

***Department of Electrical Engineering and Information System, The University of Tokyo, Tokyo113-8656,Japan*

**Corresponding Author: amalina1979@gmail.com*

ABSTRACT

Issueson detecting the occurrence of a fault, justifying the type, and estimating the exact location of the faultshould be resolved to eliminate faults promptly and restore power supply with minimum interruption. Conventional approaches have contributed toassisting power utility in overcomingthese issues. However, these approaches rely on line parameters and involve a few complex mathematical equations. In this paper, a new method for fault identification pertinent to classification and location is proposed by utilizing the combined adaptive neuro-fuzzy inference system (ANFIS) and Gustafson–Kessel (GK) clustering algorithm. The effectiveness and practicability of this method aredemonstrated by the simulation results. This method uses the GK fuzzy clustering algorithm to decide on the premise configuration and its parameter and identifies itssucceeding parameter usingthe orthogonal least square. The proposed method is independent of the line parameter information and obtains high accuracy on estimation of fault locations.

Keywords: Adaptive neuro-fuzzy inference system;fault identification;Gustafson–Kesselalgorithm; power system protection.

INTRODUCTION

Deterministic conventional approaches in identifying faults of power systems have a few drawbacks. First, a lack of accuracy attributed to extensive variation exists in the respective system and power network. Second, the conventional approach requires a complex mathematical calculation in the algorithms,in which an expert personnel-in-charge is necessary. In addition, the dependence of line parameters, such as the value of system voltage, fault resistance, and line length, can limit the performance of such approaches.

An independence from the factor of fault resistance value and a parameter-free algorithm can overcome the above problems by using artificial intelligence (AI) technique (Radojevic*et al.*, 2009;Raval, 2008). Among the well-known AI techniques, the artificial neural network (ANN) is efficient and practical when a mathematical model of the system is unavailable. By contrast, fuzzy logic (FL) can copy the sensing, generalizing, operating, processing, and learningcapability of a human operator(El-Sayed, 2010). The issues on reliability, increasing physical dimensions, and the size of transmission lines have motivated several researchers to investigate further. Jang(1993) explained that these two beneficial approaches can be used together, because they possess some similarities on the basic structure of a neuron. ANN uses supervised training to plot the unknown relations between the unknown fault distance and available data through the collected training data(Fernandez *et al*., 2002; Jain *et al*.,2008, 2010;Majid*et al*. 2015; Ramadoni, 2013).

A combination of fuzzyand neural network (FNN)—known as adaptive neuro-fuzzy inference system (ANFIS)—has been used in identifying fault in power systems(Coury, 1998)and contributed tonumerous inventions through research. The training approaches of ANN on theparameters for FL networks transform the FL systems into an efficient and useful tool. Researchers have taken interest in the estimation capability of ANN to locate faults in the transmission line and distribution network (El-Sayed, 2010;Gracia*et al*., 2005;Majid*et al*., 2016; Ngaopitakkul&Pothisan, 2009; Sadeh&Afadi, 2009).

This study attempts to investigate the capability of GK algorithm in identifying faults in power systemsand proposes a novel scheme of fault identification in power transmission line according to the problems pertinent to a complex algorithm in the previous fuzzy modeling methods based on the combined ANFIS and GK algorithm for nonlinear system. It considered the balanced fault in a transmission line (symmetric fault) and unbalanced fault (asymmetric faults):single line-to-ground (SLG), line-to-line (LL), and double line-to-ground (DLG) faults. At power transmission line, 70% of the fault that occurred was in the type of SLG, which is very often caused by physical contact.

This paper is organized as follows. Section 1presents the introduction. Sections 2 and 3 provide a brief descriptionofthe simulation and transmission line model using electromagnetictransient program (EMTP), followed by a description of the scheme related to fault identification and location. Simulation findings and performance analysis are covered in Section 6. Finally, Section 7 provides the conclusions of the research study

FEATURE EXTRACTION AND DATA REDUCTION USING WAVELET

Feature extraction and data reduction are among the most beneficial in the implementation of wavelet transform (Andries, 2007; Ekici, 2009;Han *et al*., 2004; F. Martin. 2003; Reddy &Dohantra, 2006).Discrete wavelet transform (DWT) is applied to the data under study. It is used to find wavelet transform of samples waveforms (Sushma, 2014) and is given by

$$DWT(f,m,n) = \frac{1}{\sqrt{a_0^m}} \Sigma_m f(m) \Psi^* \left(\frac{n-ka_0^m}{a_0^m}\right) \quad (1)$$

where a_0^m is the scaling (dilation) constant, ka_0^m is the time shift constant, Ψ is the mother wavelet function, and k, m are integers.DWTanalyzes the signal prevalent at various frequencies to obtain the detailed coefficient bands by facilitating the decomposition of the signal into the detail coefficient (Cd) andcoarse approximation. Breaking the signal into simpler forms, such as various frequency bands, is achieved through sequential high pass and lowpass filtering of the time domain signal.

The current signal has a higher frequency of π/2 radians instead of π, which is in accordance with the Nyquist's rule.Thus, half of the samples can be eliminated when the signal passes through the lowpass filter of the half band. The fault data pass through wavelet transform to obtain their detailed coefficient. This research also focuses on the implementation of wavelet transform for data reduction, as shown in Figure 1. The raw signal of fault data comprises 150000 signal pointsand isreduced with the process of sampling frequency. Removing each sample is considered to result in sub-samplingthe signal by two, wherein the signal can then possess a reduced (half) number of points. Hence, the sampling frequency should be twice or higher than the maximum frequency present in the signal according to the Nyquist's rule.

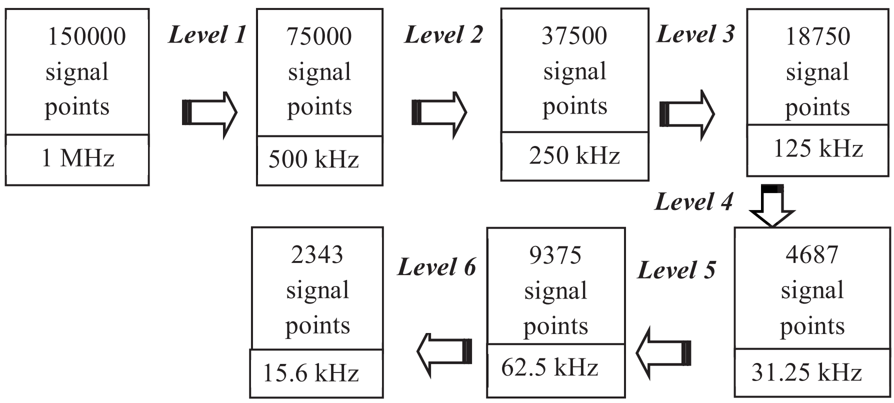

Figure 1. Reduction of point signal and sampling frequency.

ANFIS

The ANFIS architecture incorporates a feed-forward neural network that possesses five layers, as illustrated in Figure 2(Jang, 1993). Layer 1 is acknowledged as a fuzzification,in which each set of inputs depends on the fuzzy membership function (MF). Layer 2 comprises the output nodes,which are engaged in the firing of the rule reciprocal to the product of the membership grades. Layer 3 is known as the "normalized firing strengths," wherein the output of the ith nodes is equivalent to the ratio of the firing strength of the ith rule to the sum of all the firing strengths of the rules. Layer 4 comprises the output of the node, and Layer 5 is denoted as a single output.A distance-relaying approach based on an FNN is developed by Han *et al*.(2004), which focuses on the fuzzy viewpoint;however, the FNN measures the fault location within 80% of the line.

Anenormous training set and a large number of neurons are important for a better fuzzy-neuro architecture. Errors could be increased due to the condition of too small or too large number of neurons. It will always be an open discussion. One can check using a few methods such as k-fold cross-validation and structural risk minimization (SRM). In this study, we have implemented Levenberg-Marquardt and validation (test and error) while doing each testing and training.The optimized parameters will be the reference to shape the membership functions.

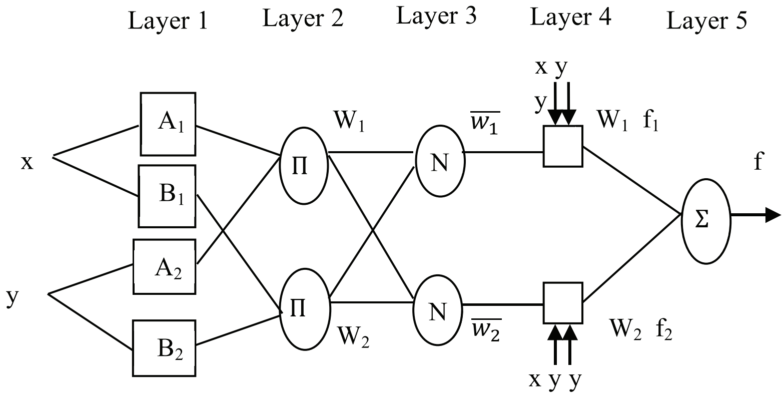

Figure 2. Five-layer architecture of ANFIS.

TAKAGI–SUGENO (TS) FUZZY MODEL

TS fuzzy model is effective in computingflexibility and fast computation. This model works well with adaptive and optimization techniques(Cichoki&Unbehauen, 1993). Thus, TS fuzzy model is used in problems related to a dynamic nonlinear system(Negnevitsky, 2005). The selection of respective architecture must be in line with the basic of general ANFIS, which contains a few layers. The member function is possible to be tuned using a back propagation algorithm or in permutation with a least square type method. In figure 2, layer 4 and layer 5, which represented the consequence parameters and defuzzification, respectively, have exactly the same function as a Takagi-Sugeno fuzzy model.The two main steps in problem solving using the TS type of neuro-fuzzy modeling are identifying the structure and optimizing the parameter. Structure identification is recognizingthe input–output space partition and the definite number of rules that should be used by the neuro-fuzzy system. Parameter optimization aims to identify the optimum values related to the parameters tangled in the TS type of neuro-fuzzy system, which refers to the

MF location in the foundation of each rule and the consequent of the imperative (Patel, 2014). The TS fuzzy inference system contains two rules:

Rule 1: If ($v\ is\ V_1$) **and** ($d\ is\ D_1$) **then** $f_1 = p_1 v + q_1 d + r_1$

Rule 2: If ($v\ is\ V_2$) **and** ($d\ is\ D_2$) **then** $f_2 = p_2 v + q_2 d + r_2$

where $p_1, p_2, q_1, q_2, r_1, and r_2$ are linear parameters and V_1, V_2, D_1 and D_2 are non linear parameters. In figure 2, the circle indicates fixed node,whereas square indicates adaptive node, which means that the parameter has the potential to be changed during adapting or training.

GK ALGORITHM

GK algorithm represents a principal clustering method that accompanies various applications in different domains, such as classification, image processing, and system identification (Wang *et al*., 2011). This algorithm can predict and anticipate local covarianceand divide data into subsets that can be aligned with linear sub-models. GK algorithm also identifies TS models(Castiollo&Melin, 2001; Kartalopoulos, 2004; Wang *et al.*, 2011).This algorithm has enhanced the typical fuzzy c-means algorithm by using an adjustable distance norm and adding a scaled unity matrix to the calculated covariance matrix.The product space of the regressors and regressand can be clustered to the partition of the data when the structure is identified. GK clustering algorithms can easily identify clusters that lie in linear subspaces, because each cluster is considered as a limited linear model of the system. Each group possesses its own norm-inducing matrix Ai. The matrices Ai are employed as optimization factors in the c-means functional,which allow every group to adjust the distance norm to the local systematicarrangement of the data. The GK algorithm is considerably dependent on the repetitive optimization of an objective function related to the c-means type:

$$J(Z;U, V, \{A_i\}) = \sum_{i=1}^{K} \sum_{k=1}^{N} (\mu_{ik})^m D_{ikA}^2. \quad (2)$$

Herein, $[\mu_{ik}] \epsilon [0,1]^{K\,X\,N}$ is a fuzzy partition matrix of the data, U = Z $\epsilon \mathbb{R}^{nxN}, V = [v_1, v_2, \ldots, v_k], v_i \epsilon \mathbb{R}^n$ is a k-tuple of cluster prototypes, and $m \epsilon [1, \infty]$ is a scalar parameter that identifies the fuzziness of the resulting clusters. The distance norm D_{ikA} can be considered for clusters dissimilar geometrical shapes in one data set:

$$D_{ikA_i}^2 (Z_k - v_i)^T A_i (Z_k - v_i). \quad (3)$$

mpleme

A modified GK algorithm that is capable ofimproving the performance of a training stage has been implemented andis explained in the steps below.

Step

Step 1: Calculate cluster prototypes (means).

$$V_i^{(l)} = \frac{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m Z_k}{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m}, \quad 1 \le i \le K. \quad (4)$$

$$F_i = \frac{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m (z_k - V_i^{(l)})(z_k - V_i^{(l)})^T}{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m}, \quad 1 \le i \le K. \quad (5)$$

Include a scaled identity matrix:

$$F_i = (1-\gamma) F_i + \gamma \det(F_0)^{\frac{1}{n}} I. \quad (6)$$

Extract eigenvalues λ_{ij} and eigenvectors ϕ_{ij} fromF_i.

Find $\lambda_{i\,max} = max_j \lambda_{ij}$ and set: $\lambda_{ij} = \lambda_{i\,max} / \beta \quad \forall j$ for which$\lambda_{i\,max} / \lambda_{i\,j} > \beta$. (7)

Reconstruct F_i by

$$= [\phi_{i1} \ldots \phi_{in}] \mathrm{diag}(\lambda_{i1}, \ldots, \lambda_{in}) [\phi_{i1} \ldots \phi_{in}]^{-1}.$$

Step 3: Compute the distances.

$$D_{ikA_i}^2 = (z_k - V_i^{(l)})^T [\rho_i \det(F_i)^{\frac{1}{n}} F_i^{-1}] (z_k - V_i^{(l)}), \quad 1 \le i \le K, \quad 1 \le k \le N. \quad (8)$$

Step 4: Check the partition matrix.

$$\text{for } 1 \le k \le N, \quad \text{if } D_{ikA_i} > 0 \text{ for } \quad 1 \le i \le K,$$

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

$$\mu_{ik}^{(l)} = 0 \text{ if} D_{ikA_i} > 0 \text{ , and } \mu_{ik}^{(l)} \in [0, 1] \tag{9}$$

with $\sum_{i=1}^{K} \mu_{ik}^{(l)} = 1$ otherwiseuntil $\left\| U^{(l)} - U^{(l-1)} \right\| < \in$.

THE PROPOSED ANFIS–GK FAULT IDENTIFICATION

The premise configuration and parameter of the fuzzy model are decided by the GK fuzzy clustering algorithm in the proposed method. The succedent parameter of the fuzzy model is identified using orthogonal least square. The training and testing procedure are utilized in the backpropagationneural network. Two main stages involved in this study are pertinent to fault and fault identification. ANFIS–GK is not yet implemented in the fault detection. The scheme described in Figure 3 begins with obtaining currents (I) and voltages (V). The first stage is detection, which aims to justify whetherthe signal is faulty or healthy. The coefficientsof respective signals will be obtained by implementing DWT. The daubechies 4 (DB4) are chosen as mother wavelets for this procedure.The next procedure ascertains the fault type and thenestimates the fault location, wherein the distance of the fault in the line is acknowledged. Fault detection isconducted by implementing fast Fouriertransform (FFT) and root mean square (RMS). RMS values are almost constant for healthy waveforms. Reduced RMS amplitude can assistin identifying the fault. Ifa fault exists, the RMS value of the voltage of the phase in the fault decreases,whereas the corresponding current RMS value increases. Fault waveforms that have strong peaks at 50 Hz for all the three phases with almost the same amplitude do not exist for FFT. For fault condition, the amplitude of the spectral component at 50 Hz in the voltage spectrumdecreasessignificantly compared with the FFT peak at 50 Hz of the voltage,which is non-existent in the fault. Conversely, the FFT peak value at 50 Hz of the current in the fault is significantly higher than that of the current with a non-existent fault.

The detail coefficient is ready for fault identification, whichis fault classification and fault location schemes. Both schemes are independent of each other; thus, the result of fault classification does not affect the fault location scheme. This technique can reduce time consumption in the real application at the power utility. The extracted data is given to the fault identification scheme, as shown in Figure 4. The flow of ANFIS–GK implementation is illustrated in Figure 6. In Figure 6, GK was implemented at step 4 with the detailed explanation as shown in Figure 5. This is the part that hasbeen improved compared to general ANFIS in practice.In a fault classification scheme, the GK clustering algorithm is used to identify the features of each type of fault and cluster them, respectively. However, in fault distance estimation, the aim is not only to cluster but also to estimate the exact fault. Thus, system identification is required in the development of algorithms.

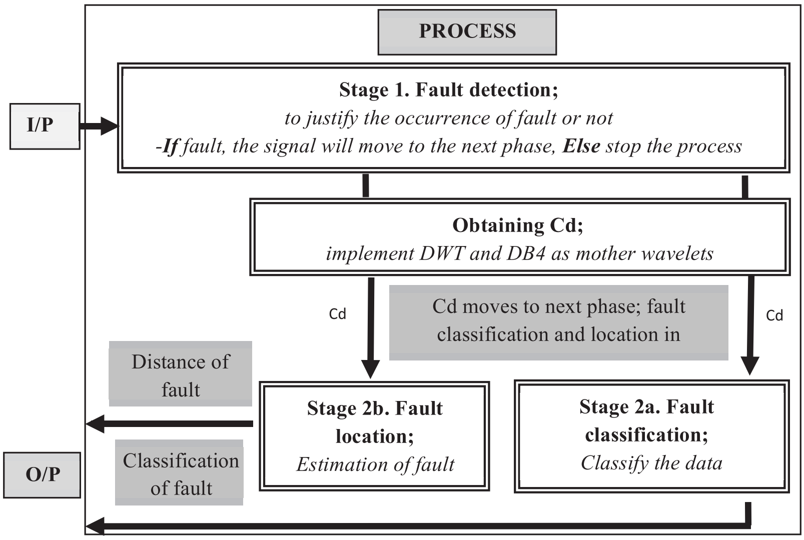

Figure 3. Structure of the proposed scheme.

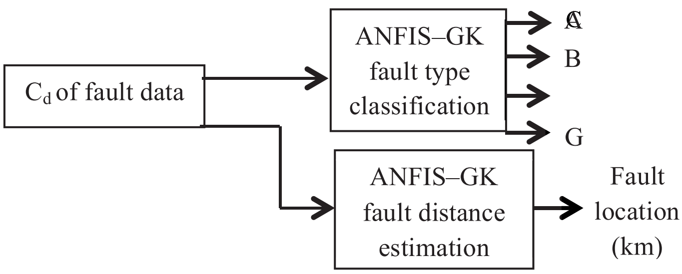

Figure 4. Fault identification scheme.

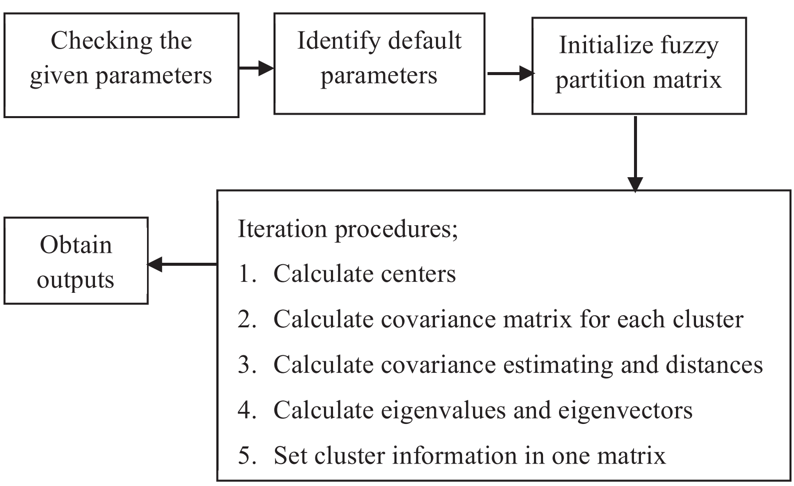

Figure 5. Illustration of GK algorithm implementation.

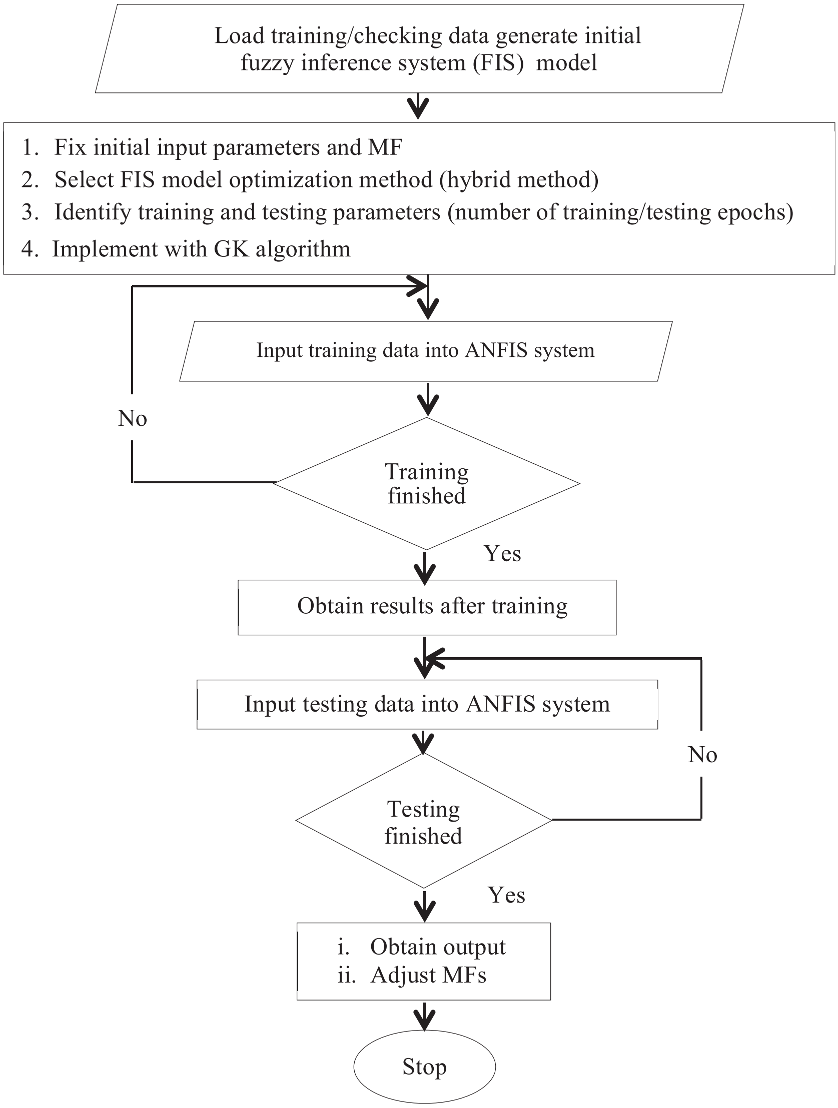

Figure 5. The proposed ANFIS-GK structure.

TEST PROCEDURE

Table 1. Simulation data.

No.	Type	No. of cases	Fault location	Fault resistance
1	No fault	100	Every 2 km along the line length	0.5Ω 5 Ω 25 Ω 100 Ω 200 Ω
2	A G	250		
3	B G	250		
4	C G	250		
5	A B G	250		
6	C A G	250		
7	B C G	250		
8	A B C	250		
9	A B	250		
10	C A	250		
11	B C	250		

A testing system is developed by using the EMTP to obtain a substantial amount of data through simulation. The power system model denotes a 115kV parallel transmission line, which is supplied from both sides. Figure 7 depicts a one-line diagram of the power system that is utilized for training purposes. The reliability of the parallel line is important,because faults commonly occur in this type of system voltage. The loading conditions over the protected transmission line are assumed to be nearly constant. Table 1 shows the parameter settings to obtain simulation data. In total, 2600 cases are obtained and are sent to the Matlab software for further analysis.

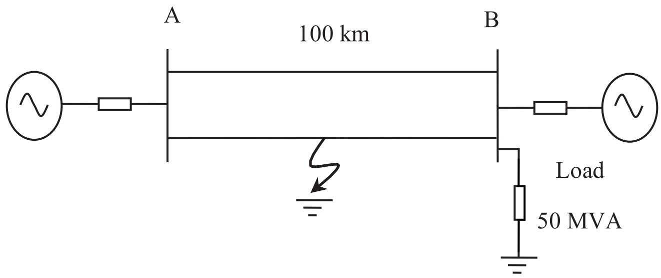

Figure 7. One-line diagram of the system.

The proposed scheme should be tested using a sizable amount of data. Data are divided into training and testing sets when sufficient data are obtained. The performance features in a neural network via the Matlabareused to justify that the amount of data required by the algorithm is sufficient. Basically, the amount of data is 70% for training and 30% for testing purposes. The input for the fault identification scheme is the detailed coefficients. Thus, the set of detailed coefficients of training is different than the testing set. Testing data are chosen randomly from the data that were included in the training process. The validation data are chosen at different conditions that are not included in the training process to ensure the proficiencyof the proposed method.

The selection is conducted using backpropagation neural network,which is implemented in the Matlab codes. The purpose of simulating the fault location is to predict the distance between the actual and predicted distances of the fault. Approximately 1600 samples are used for training, and approximately 300 samples are used for testing and validation.ANFIS–GK has a great learning process on the training data with regard to the optimization aspect.

RESULTS AND DISCUSSION

Three case studies were presented in this study, which are based on the simulation data, the IEEE 14-bus standard system, and the comparison with ANN method.

Case study 1: The simulation data

Figure 8represents the prediction of the distance that is close to the actualvalue of the TS neuro-fuzzy modeling on the fault location. A better model prediction can be obtained if the two points are closer.ANFIS models are used to generate data for computing the predicted value. Table 2 shows the performance of ANFIS-GK algorithm with the actual distance for all types of fault. The fault resistance considered is 5Ω,representing the general value of the fault resistance in a transmission line. The result from Table 2 is performed based onFigure 9 for better observation.

The result shows that the percentage of error is less than 0.6%. The calculation of error estimation (%) is as follows:

$$\%\,Error = \frac{|Actual\ location - Predicted\ location|}{total\ line\ length} \times 100.$$

Based on the results of the test system, the proposed ANFIS-GK scheme is confirmed to provide good performance for both fault classification and fault location estimation. Table 3 is also included to present the fault distance estimation for single line to ground pertinent to five different values of fault resistance involved in this study.

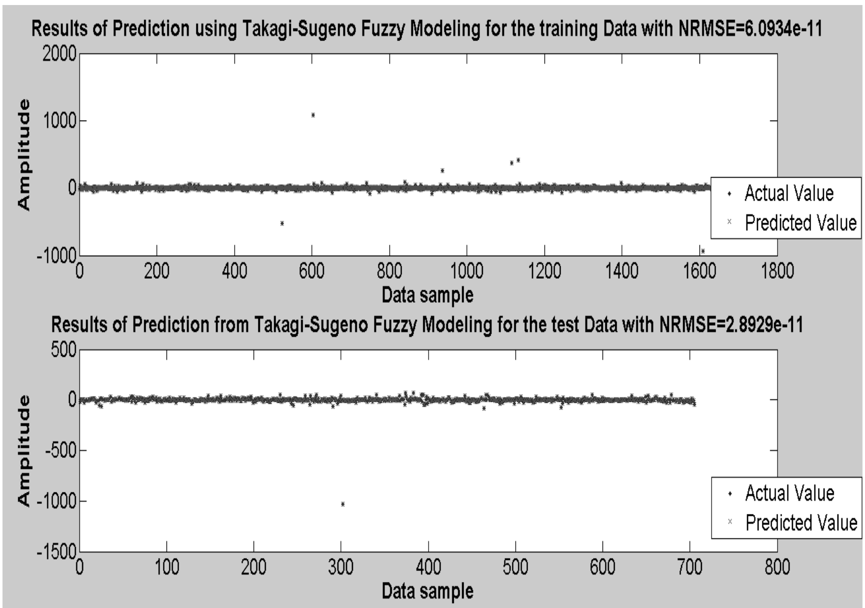

Figure 8. Distance prediction using TS fuzzy of AG fault for training and testing.

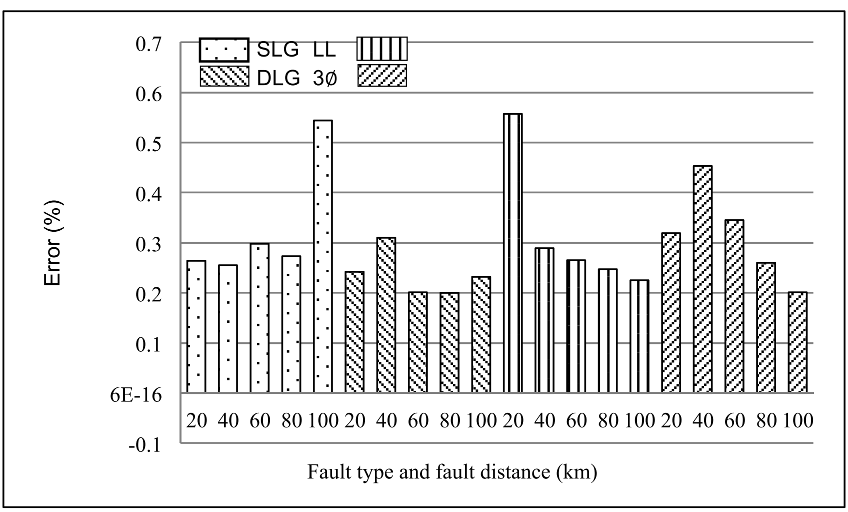

Figure 9. ANFIS–GK performance based on $R_f = 5\Omega$.

Table 2. ANFIS–GK performance based on $R_f = 5\ \Omega$.

Fault Type	Actual (km)	ANFIS–GK (km)	Error (km)	Error (%)
Single line to ground (SLG)	20	20.264	0.264	0.264
	40	39.745	0.255	0.255
	60	60.298	0.298	0.298
	80	79.727	0.273	0.273
	100	100.544	0.544	0.544
Double line to ground (DLG)	20	20.242	0.242	0.242
	40	39.690	0.310	0.310
	60	59.799	0.201	0.201
	80	80.200	0.200	0.200
	100	100.232	0.232	0.232
Line to line (LL)	20	20.557	0.557	0.557
	40	39.711	0.289	0.289
	60	59.735	0.265	0.265
	80	79.753	0.247	0.247
	100	99.775	0.225	0.225
Three phase (3Ø)	20	20.319	0.319	0.319
	40	40.453	0.453	0.453
	60	60.345	0.345	0.345
	80	80.260	0.260	0.260
	100	100.201	0.201	0.201

Table 3. Results of estimation error for single line to ground fault.

Fault Distance Estimation For Single Line to Ground					
Actual distance (km)	Estimation Error (Actual–Predicted)				
	$R_F = 0.5$	$R_F = 5$	$R_F = 25$	$R_F = 100$	$R_F = 200$
2.0	0.220	0.200	-0.296	-0.500	-0.532
10.0	0.242	0.296	-0.267	-0.309	-0.260
20.0	0.299	0.264	-0.384	0.203	-0.222
30.0	0.379	0.561	0.984	-0.253	-0.340
40.0	-0.274	-0.255	0.551	0.204	0.256
50.0	0.222	0.294	-0.462	0.580	-0.235
60.0	0.232	0.298	-0.235	0.270	-0.327
70.0	-0.511	-0.266	0.224	0.211	-0.222
80.0	-0.246	-0.273	-0.221	0.290	0.321
90.0	0.545	0.233	0.397	0.281	0.228
100.0	-0.221	0.544	0.220	0.224	0.431

Case study 2: The IEEE 14-bus standard system

The IEEE 14-bus standard system (IEEE Std C37,2004), which is developed through MATLAB/ SIMULINK software,is shown in Figure 10. The system is used to further verify the scheme. This system comprises five synchronous machines with IEEE type-1 exciters. Three of the five machines are synchronous condensers,which are used for facilitating reactive power support, and two are synchronous. The system comprises 11 loads, 14 buses, and 20 power lines,which account for the total of 259MW and 81.3 Mvar. Certain bus connections are selected.Fault resistance and fault distance are adjusted accordingly. After all the parameters areconfirmed, the model is run and the fault data produced by adjusting the parameters are obtained. The procedures continued for a few values of fault resistance and distance. The aim is to test the fault data obtained from IEEE 14-bus with the ANFIS–GK fault identification scheme. The presented results are pertinent to the single line to the ground fault tested between Buses 2 and 4. Table 4 shows the fault location results, whereas Table 5 shows the results pertinent to fault classification. The error is in the range from0.28km to 0.56km.

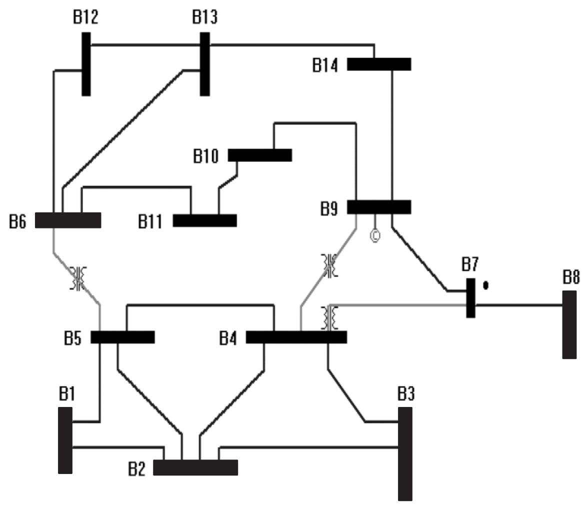

Figure 10. Electrical power network of the IEEE 14-bus.

Table 4. Fault location estimation on IEEE 14-bus network.

Fault type	Fault section	Fault location (km) from Bus 2	R_f (Ω)	Estimated fault location (km)	Error (km)
AG	2–4	20 km	5	20.37	0.37
AG	2–4	80 km	100	80.49	0.49
BG	2–4	20 km	5	20.56	0.56
BG	2–4	80 km	100	80.28	0.28
CG	2–4	20 km	5	20.25	0.25
C-G	2–4	80 km	100	80.43	0.43

Table 5. Fault classification on IEEE 14-bus network.

Actual fault type	Angle (δ°)	Fault resistance (Ω)	Fault type of the IEEE 14-bus
AG	45	5	AG
AG	45	100	AG
BG	45	5	BG
BG	45	100	BG
CG	45	5	CG
CG	45	100	CG
ABG	45	5	ABG
ABG	45	100	ABG
BCG	45	5	BCG
BCG	45	100	BCG

Case study 3: The comparison with ANN method.

The following observation is the comparison of fault distance with the ANN investigated from Pranav D.(2008),which implemented an ANN-based fault locator and fault classifier in their study. The simulation is set to justify the type and location of the fault using a number of fault data from the utility. The implemented ANN algorithm is illustrated in Figures 11 and 12, respectively. The comparison between the proposed scheme and ANN shows that ANFIS–GK performed better in obtaining the expected results. Essentially, ANFIS–GK providedprecise results in scheme identification using the index error.

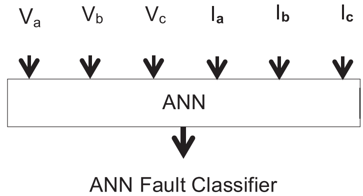

Figure 11. The scheme for ANN fault classifier.

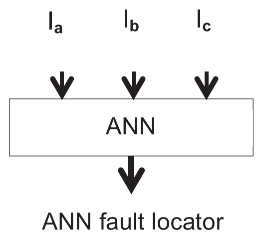

Figure 12. The scheme for ANN fault location.

The observation shows that ANFIS–GK is better than the ANN scheme, obtaining the best performance for the single line to ground. GK supported the result to be more generalized. Table 6presents the results when testing the real data pertinent to the single line to ground, double line,and double line to ground. The proposed ANFIS–GK scheme performed better when the range of error is from 0.2 km to 0.8km, compared to the range from 0.5km to 3.9km with the ANN method.

Table 6. Comparison with ANN-based method.

ANN/ANFIS fault type	Actual location	ANN		Proposed ANFIS–GK	
		Location	Error	Location	Error
BCG	74.6	72	2.6	73.8	0.8
AG1	71.6	70.3	1.3	71.1	0.5
AG2	89.5	88.6	0.9	88.9	0.6
BG	115.8	115.3	0.5	115.5	0.3
CG	41.9	40.7	1.2	41.7	0.2
BC	28.5	32.4	3.9	28.98	0.48
CG2	128.5	129	0.5	128.74	0.24
ABG	50.6	47.6	3.0	49.8	0.8

CONCLUSION

This paper presents an application of ANFIS–GK model for fault identification pertinent to fault classification and location. The proposed method is trained to classify the type of fault and separate ANFIS–GK scheme and is designed to estimate the actual fault position on a transmission line. The technique is tested using the data generated by EMTP at different distances along the length of transmission line. The results presented on the performance at fault location are verified with related case studies. In every test, the ANFIS–GK algorithm has performed the result of distance estimation within arange of error not exceeding 0.9km. More experimental studies should be determined for further works to reduce the error in minimum values, more real data from power utility should be tested, and the capability of the GK algorithm in power system analysis should be explored.

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Submitted: 04/11/2016
Revised : 20/01/2017
Accepted : 13/02/2017