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Root cause detection of call drops using feedforward neural network

K R Sudhindra* V Sridhar

People's Education Society College of Engineering, Mandya 571401, India

* E-mail of the corresponding author: sudhindra_kr@rediffmail.com

Abstract

Call drop rate in GSM (Global System for Mobile Communication) network is an important key performance indicator (KPI) that directly affects customer satisfaction. The delay in identification of exact call drop reason because of multiple reasons involved in it would results in poor customer satisfaction. The TCH (traffic channel) call drops due to three different hardware causes are collected from live GSM network for 10 days and are represented in time domain. Time domain features such as mean, maximum, standard deviation etc. are extracted from each type of call drop signal which is used to train the feedfoward neural network. FF neural network is made as decision making classifier, feature vector is inputted and root cause detection information is outputted.

Keywords: TCH call drops, neural network, GSM

1. Introduction

TCH (Traffic channel) drop rate is one of the major KPI that affect the performance of live GSM network. The TCH drop is the abrupt disconnection of call after traffic channel is allocated. The multiple causes of call drops in live network will delay the process of call drop detection and its elimination from the network which will result in poor customer satisfaction. The relation of call drops with handover and its effects on performance is exclusively discussed in (Wahida Nasrin and Md Majharul Islam, 2009). The effect of user mobility on call drops in live GSM network considering different patterns for user mobility was discussed in (A.G. Spilling and A.R. Nix, 2000). The influence on handover failures on TCH call drops for different types of calls are discussed in (D.Lam, D.C Cox and J.Widom,1997).In [A. Kolonits,1997] the lognormal hypothesis for distribution of the call holding time of both the normally terminated and the abnormal dropped calls has been studied. The phenomena of TCH call drops have been classified, verifying that handover failure become negligible in a well-established cellular network. All the previous works implicitly assumes that proper radio planning has been done and there is no equipment failure or network outage. In live network there are multiple causes for call drops identifying of which requires rich hands on experience on the network. In many cases root cause detection of call drops will consume lot of time which results in customer dissatisfaction. A novel method of root cause detection of TCH call drops using artificial neural network is discussed in this paper.

2. Methodology

Root cause detection of TCH call drop based on feed forward (FF) neural network using Levenberg-Marquardt training algorithm is designed. The block diagram of proposed system is shown in Figure 1. The TCH call drop trends due to three different hardware causes are collected for 10 days and are represented in time domain. The next step is to extract features from the signal representing TCH call drops and construct eigenvector for each cause using extracted features. FF neural network is made as decision making classifier, signal eigenvector is inputted and root cause detection information is outputted.

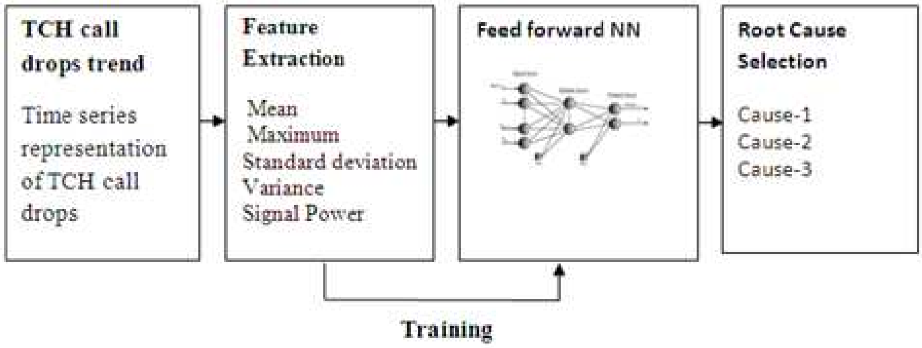

Figure 1. Block diagaram of root cause detection of TCH call drops

2.1Time domain representation of TCH call drops

The three major BTS hardware faults such as HDLC (High Level Data Link Control) communication between CMB (control and maintenance board) and FUC(frame unit control) broken, Abis control link broken alarm and PA(Power Amplifier) forward Power (3 db) alarm contributed for call drops in live network are considered for study in the proposed system. The TCH call drops due to three different causes are collected for duration of 10 days with a sampling time of 15 minutes and are represented in time domain as shown in Figure 2 to Figure 4. The time domain representation TCH call drops shows unique characteristics for different hardware faults which are significant finding that is used for feature extraction required for root cause identification. These data is used as input for proposed root cause detection system.

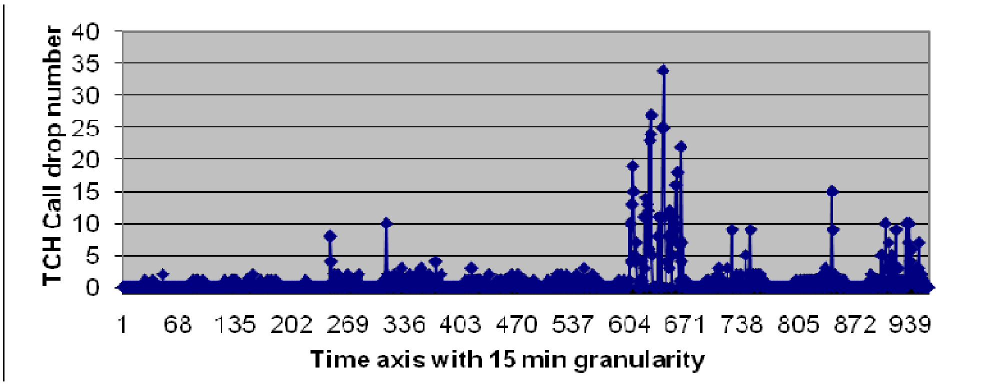

Figure 2. HDLC Communication between CMB and FUC broken

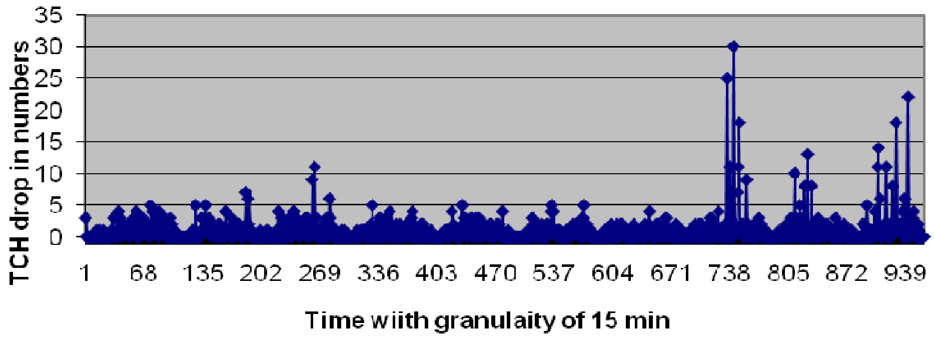

Figure 3. Abis control link broken alarm

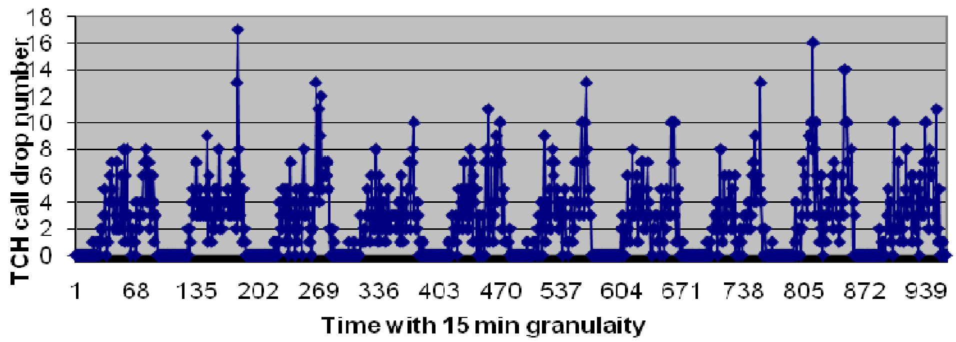

Figure 4. PA Forward Power (3 db) alarm

2.2 Feature Extraction

Five feature parameters such as mean, minimum, maximum, standard deviation, variance and signal power are determined for each signal sample and standard feature vector is constructed for each fault type. Euclidean distance of every two feature vectors can be calculated with the Euclidean distance formula and then compare the size of the Euclidean distances. If Euclidean distances are significantly different and balanced between them, then feature vectors are ideal (Yanhua Zhang and Lu Yang, 2010). These feature vectors are used for fault detection.

2.3 Root cause detection of call drops using feedforward neural network

Three layer feedforward artificial neural network (ANN) which is used in the proposed model is discussed in this section. Computation nodes are arranged in layers and information feeds forward from layer to layer via weighted connections as illustrated in Figure 5. Circles represent computation nodes (transfer functions), and lines represent weighted connections. The bias threshold nodes are represented by squares. Mathematically, the typical feedforward network can be expressed as shown in equation (1).

$$y_i = \Phi_o\left[C\Phi_h\left(Bu_i + b_h\right) + b_o\right] \qquad (1)$$

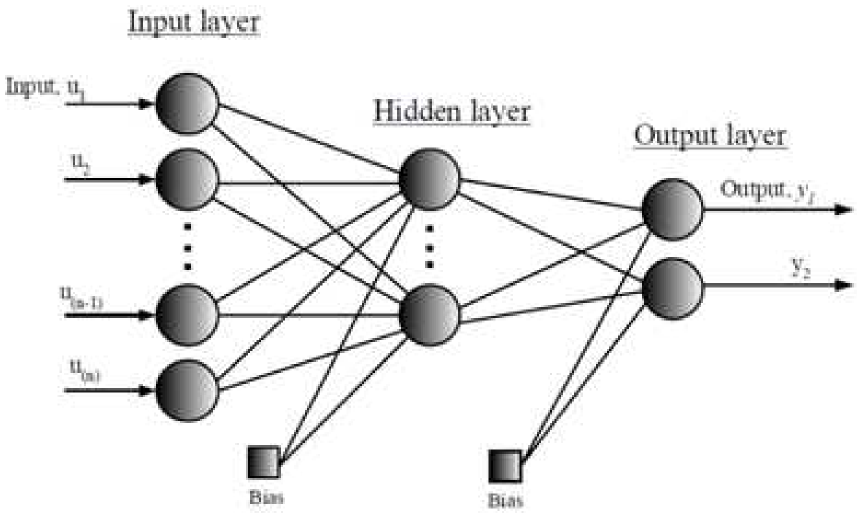

Figure 5. Three layer feed forward neural network

Where y_i is the output vector corresponding to input vector u_i , C is the connection matrix (matrix of weights) represented by arcs(the lines between two nodes) from the hidden layer to the output layer. B is the connection matrix from the input layer to the hidden layer, and b_h and b_o are the bias vector for the hidden and output layer, respectively, $\Phi_h(\cdot)$ and $\Phi_o(\cdot)$ are the vector valued function corresponding to the activation(transfer) functions of the nodes in the hidden and output layers, respectively. Thus, feedforward neural network models have the general structure of equation (2).

$$y_i = f(u) \qquad (2)$$

where f(·) is a nonlinear mapping. The continuous activation functions allow for the gradient based training of multilayer networks [.K. Mohamad, S. Saon, M.H. Abd Wahab et al., 2008]. Various learning algorithms were developed and only a few are suitable for multilayer neuron networks. Levenberg-Marquardt (LM) (Magali R. G. Meirele and Paulo E. M. Almeida, 2003) learning is used in the proposed model of root cause detection of call drops. TCH call drops due to three types of causes are collected for 10 days from OMC and used to construct feature vector for training the neural network. Six unique group of feature vector from each type of signal are constructed. 18 groups of data that are obtained are used as training sample to be inputted into network to train the network. In addition feature vectors are also constructed as detecting sample to test whether the network is working as per design.

The specific structure of FF neural network consist '15' neurons at hidden layer and '3' neurons at output layer. Hyperbolic secant S-transfer function "tansig" is adopted as transfer function of hidden layer and linear transfer function "purelin" is adopted as transfer function of output layer. Levenberg-Marquardt BP training function is adopted as network training function whose performance index is "mse" and training target is 0.01. After training, the neural network can be given problems that are similar to the ones that it was trained on and it would make decisions about the data that it is currently processing.

3. Results and discussion

Five feature parameters such as mean, maximum, standard deviation, variance and signal power are found using TCH call drop time series signal and used as feature vector for fault detection. Table 1 shows the characteristics parameters of TCH call drop time series signal.

Table 1. Characteristics parameters of TCH call drop time series signal

Sl. No.	Fault Type	Mean	Max	Std	Var	Power
1	HDLC Communication between CMB and FUC broken	0.97	34.00	3.10	10.00	13
2	Abis Control link broken	0.59	14.00	1.14	1.13	0.93
3	PA forward power (3 dB) alarm	0.62	23.00	1.60	2.60	2.48

Root cause codes for HDLC communication between CMB and FUC broken (type1), Abis control link broken alarm (type2) and PA forward Power (3 db) faults (type 3) are designed in Table 2. Part of training samples is shown in Table 3. LM algorithm is used to train the feed forward neural network. Network training error curve is shown in figure 6.

Table 2. Fault type code design

Parameters	Fault Types		
	Type-1	Type-2	Type-3
Flaw codes	001	010	100

Table 3. Training Sample

Fault Types	Input Vectors					Fault codes for input vector
	U1	U2	U3	U4	U5	
Type-1	0.971	34	3.107	9.476	13.780	100
Type-1	1.060	42	1.484	3.534	7.070	100
Type-1	1.822	13	3.077	9.473	20.803	100
Type-1	1.414	20	3.280	10.790	25.94	100
Type-1	0.945	32	3.201	10.24	11.66	100
Type-1	1.240	51	3.801	14.400	13	100
Type-2	0.589	14	0.934	1.140	0.93	010
Type-2	0.523	16	1.260	1.611	1.128	010
Type-2	0.714	17	1.618	2.618	2.123	010
Type-2	0.669	17	1.223	1.49	1.180	010
Type-2	0.228	7	0.681	0.464	0.473	010
Type-2	0.363	13	1.013	1.021	0.534	010
Type-3	0.514	59	2.078	4.319	4.120	001
Type-3	0.547	22	1.446	2.091	1.648	001
Type-3	1.036	21	2.439	6.041	9.610	001
Type-3	1.170	21	2.144	4.591	6.840	001
Type-3	0.417	23	1.700	2.653	2.482	001
Type-3	0.640	10	1.130	1.270	1.96	001

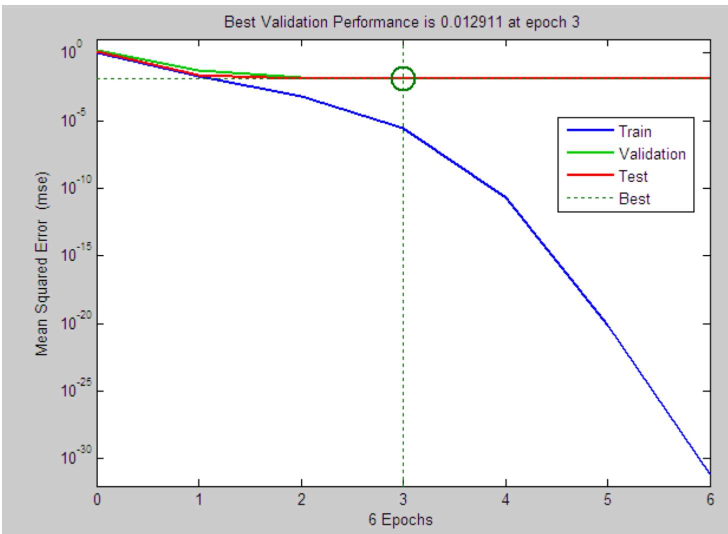

Figure 6. Train Error curve

From Figure 6 we observed that final mean-square error is small, the test set error and the validation set error have similar characteristics and no significant overfitting has occurred by iteration ‘3’ where the best validation performance occurs. In order to verify the accuracy of network, test samples with a total of ‘9’ sets of data are used to test network model and test results are shown in table 4. From table 4 it is found that the actual output of network is accordance with expectation output.

Table 4 Sample test results

Fault Types	Input Vectors					Expected outputs	Actual outputs			Results
	U1	U2	U3	U4	U5					
Type-1	0.9	34	3.1	10	13	100	0.9992	-0.0003	-0.0004	correct
Type-1	0.8	32	3.1	9	12	100	0.9994	-0.0003	-0.0003	correct
Type-1	0.7	28	2.7	12	13	100	0.9999	-0.0001	0.0002	correct
Type-2	0.5	14	0.14	1.13	0.93	010	-0.0268	0.8323	0.1885	correct
Type-2	0.6	12	1.12	2.87	1.12	010	0.0013	1.0014	0.0005	correct
Type-2	0.4	13	0.13	2.14	4.12	010	0.0008	1.0023	-0.002	correct
Type-3	0.6	23	1.57	3.61	2.48	010	0.0019	0.0012	0.9997	correct
Type-3	0.7	22	1.63	2.7	2.48	010	0.0020	0.0015	1.0000	correct
Type-3	0.6	24	1.61	4.3	2.23	010	-0.0009	-0.1082	1.1023	correct

4. Conclusions

The time series representation of TCH call drops shows unique characteristics for different hardware faults. These characteristics help to extract time domain features and construct Eigen vector for identifying root cause of call drops. Root cause detector of TCH call drops using feedforward neural network is designed and LM algorithm is used to train the network from the constructed feature vectors. The efficiency of the network can be improved by training the network with large number of samples.

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K R Sudhindra received Bachelor of Engineering degree in Electroncs and communication from Mysore University, India in 1999 and M.Sc (Engg). by research in faculty of Electrical Engineering sciences from Visvesvaraya Technological University, India in 2007. He is currently a Ph.D student of Department of Electronics and Communication Engineering, PESCE, Karnataka, India. He has total 5 years of experience in Telecom Industry. His research interests include operational research, signal processing & wireless communication.

V Sridhar has obtained his Ph.D from Indian Institute of Technology (IITD), New Delhi in the year 1996. He obtained his B.E (E&C) from University of Mysore in the year 1980 and M.E (Electronics & Telecommunications) from Jadavpur university, Calcutta in the year 1986. Presently he is serving as the Principal, PESCE, Mandya. He has more than 29 years of teaching, research and administrative experience.His major areas of research interest are Bio-medical instrumentation, Telemedicine, VLSI Design and Mobile communication. He has to his credit more than 40 research papers in national /international journals and conferences.