Prediction of Cascading Collapse Occurrence due to the Effect of Hidden Failure Protection System using Different Training Algorithms Feed-Forward Neural Network

N. H. Idris, N. A. Salim, M. M. Othman and Z. M. Yasin

Abstract—**Protection system plays a significant role in power system and operation of electrical networks especially in transmission system. The outage in transmission line that causes from hidden failure in protection system should be avoided. Artificial Neural Network (ANN) is one of the problem solver with variety of training algorithms that helps to predict the cascading collapse occurrence due to the hidden failure effect. The historical data obtained from NERC report is analyzed and being used in ANN for prediction purposed. This paper compares the supervised training algorithms of feed-forward neural network with backpropagation include Lavenberg- Marquadt (LM), Scale Conjugate Gradient (SCG) and Quasi Newton Backpropagation (BFG). IEEE 14 bus system is used as a case study. The performance of the training algorithms is analyzed based on Correlation Coefficient (R) and Mean Square Error (MSE)**

Index Terms—**ANN, Cascading Collapse, Hidden Failure, Training Algorithms Neural Networks, Prediction.**

I. INTRODUCTION

THE ROLE of transmission line is to provide reliable and transmit electricity with lower power losses in power system networks. In recent years, the outage of power transmission line suffered from the cascading collapse is even more crucial. From the studies, [1] cascading collapse is the main reasons leading to the blackout events. Blackout tend to affect huge economic losses, power system equipment damage and can be disastrous when it comes to life-support systems in places such as coordination facilities, hospitals and traffic control. One of the factors that cause the cascading collapse is the hidden failure in protection system. According to the NERC (North American Electric Reliability Council) studies, [2] more than 70% of major disturbances involved the relay protections which causes by the hidden failure. Hidden failures are defined as equipment’s defects or human factors tied to weakening the equipment’s reliability [3]. The failures in protection system equipments could happen due to the technology limitations, miss-operations and weak management system maintenance.

Therefore, scientists pay close attention and identify a method to detect the cascading collapse occurrence due to the hidden failure effect in order to reduce the risk of blackout phenomena and create an awareness during the system outages might happened. A solution to overcome these problems is the application of ANN for prediction purposed. The application of ANN in determining the cascading collapse occurrence is based on the tripping line in transmission line considering the hidden failure in the protection system. The simulation of the hidden failure model is applied to determine the failure in transmission line. Trip index has been implemented in the simulation whereas the value of ‘1’ indicated the line tripping while the value of ‘0’ indicated the line is not tripping. The data has been collected and Artificial Neural Network (ANN) will predicted the line outages based on the trip index considering the hidden failure effect.

A neural network is a huge parallel network of interconnected along processing elements which called neurons. Neurons that receives one or more inputs to produce an output and has its own ability to learn from data with linear and non linear problem solving [4]. The transfer function of neuron converts the input to the output of the neuron. The transfer function will generate the output and pattern recognition for training process.

There are variety of learning algorithms during information processing through biological neural networks. The

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backpropagation neural networks algorithms is used to modify the networks weights in order to improve the performance and minimize the error. The back propagation learning algorithm with gradient based approach in neural network training has numerous drawbacks such as the fact that performance depends on initial weights and that the likelihood of solution reaching global optimum [4]. Therefore, this paper proposes a method to predict the cascading occurrence in a transmission line considering the hidden failure effect in a protection system by using ANN. Three learning algorithms backpropagations is investigated which are LM, SCG and BFG. All the results are compared in terms of MSE, R and Mean Absolute Percentage Error (MAPE).

II. METHODOLOGY

A. Data from Hidden Failure Model

Protection system hidden failure have been identified as a contributing factor in spreading power system disturbances. It may cause many components outages that are reliant on each other. Hidden failure also known as a permanent defect of protection system to incorrectly and inappropriately trip during the switching event [5]. An initial component outage may result in a cascading tripping by affecting the neighboring components. Hidden failures cannot be detected during normal system operating condition. But, when a fault occur, it will expose and causing unnecessary outages to the other equipment. The existence of hidden failure in a protection system will intensify the stress on a system which makes it even worse and finally reduces the level of system reliability.

Based on NERC reports, the historical data obtained for 16 years from 1984 to 1999 acquired is 400 number of events cascading collapse occurrence due to the hidden failure of protection system [6]. Thus, the probability for one cascading collapse occurrence can be calculated as shown in equation (1) below:

$$P_{HF} = \frac{Ecc}{tcc \times 365 days \times 24 hours \times 60 \min \times 60 \sec} \tag{1}$$

Where:
Ecc = Total number of events for the cascading collapse occurrence
Tcc = Total years of observation translated in second

Therefore, the probability of hidden failure due to the historical information from NERC reports given by:

$$P_{HF} = \frac{400 events}{16 years \times 365 days \times 24 hours \times 60 \min \times 60 \sec} = 8 \times 10^{-7} event / \sec ond \tag{2}$$

The accumulation of the data probability of hidden failure is selected based on the analysis for the most severe total loading condition that could provide critical system cascading collapse. Based on the [5], there are three cases studies which aim to obtain the most severe total loading condition. The case study proved that $P_{HF} = 1 \times 10^{-2}$ is the most severe total loading condition.

The impact of hidden failure causing to an incorrect tripping of other protection system equipments. The line is stressed which its loading line is disseminated among neighboring lines that also known as exposed line. The probability of hidden failure and exposed line are used as the input in ANN acquired from the historical data. The other input is the random number of line limit power flow that is obtained through the simulation of hidden failure model where the output of ANN is the tripping line index '1' indicate the line trip and '0' indicate the line is not trip.

B. Training Algorithms

This paper proposed feedforward backpropagation neural network algorithm with activation function *purelin* and *sigmoid* functions. *Sigmoid* function is used for the hidden layer while *purelin* function used for output layer. The neural networks composed with three layers which are input layer, hidden layer and output layer [7] . Feedforward neural network consists one or more hidden layers which function to allow the network to learn the relationship between inputs and output with update the weights between the nodes. In ANN, there are learning rate, momentum rate and number of hidden layer that help in accelerating the convergence of ANN model, speeding up the training process and lastly, helps in reduce error between targeted and predicted output. The structure of ANN is constructed with input layer, hidden layer and output layer as shown in Fig. 1.

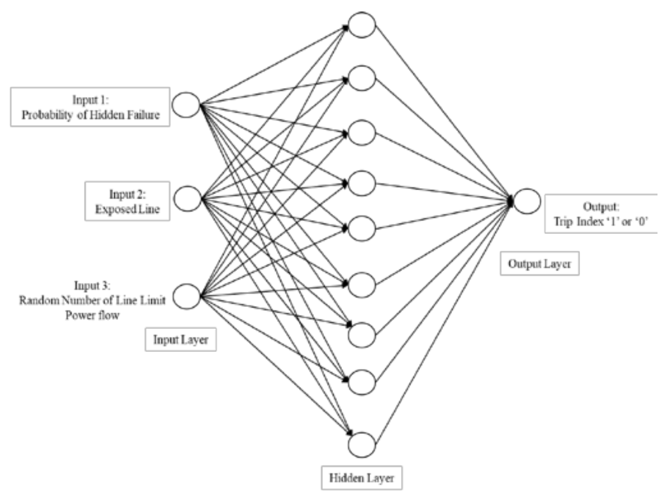

Fig. 1 General structure of ANN

Generally, backpropagation neural network commonly used for supervised training process with Multi-Layer Perceptron (MLP). Backpropagation is commonly used in ANN because of its accuracy and versatility. It solved the problem by propagating training values backward from output to hidden and input layers.

The performance of the training process is determined based on the minimum error in MSE and MAPE as shown in equation (3) and (4) respectively.

$$MSE = \frac{1}{N}\sum \frac{|Pa - Pp|}{Pa} \quad (3)$$

Where:
N = The total number of prediction
X_i = The actual vector
X'_i = The vector of N prediction

$$MAPE = \frac{100}{T}\sum_{i=1}^{N}(X'_i - X_I)^2 \quad (4)$$

Where:
P_a =The actual the cascading collapse occurrence
P_p = The predicted the cascading collapse occurrence
T = The total number of data

In this paper, we focused on the training algorithms for backpropagation neural networks which consists of three classes, Lavenberg- Marquadt *(trainlm)*, Scale Conjugate Gradient *(trainscg)* and Quasi Newton Backpropagation *(trainbfg)* as described below:

1) Lavenberg-Marquadt (trainlm)

This Lavenberg-Marquadt training algorithm is an estimation to the Newton method for training ANN. It is the most faster training that can converge faster than other training algorithms with momentum Backpropagation. This algorithm is most suitable for heuristic technique and known as the most accurate in reducing the error. The propose of this algorithm is to minimize the error [8], as shown in the equation (5) and (6) shown below:

$$x^* \in E^N \quad (5)$$

Where:
x^* = Contained among the zeros of $\frac{1}{2}\nabla\phi(x) = J(x)^T F(x)$
$\nabla\phi(x)$ = Gradient of ϕ
$J(x)$ = Jacobian matrix of F

$$\phi(x) = \|F(x)\|_2^2 = \sum_{i=1}^{M}|fi(x)|^2 \quad (6)$$

Where:
$F(x)$ = Residual vector obtained from dataset by a nonlinear form

2) Scale Conjugate Gradient (trainscg)

Leonard and Kramer proposed conjugate gradient combine with line search strategy for the fast speed convergence. Generally, the training algorithms used learning rate to update weights and thresholds. The conjugate gradient algorithm functions update automatically using their own step [9]. The equation (7) below shows the search direction, P_o of the algorithm started from the steepest descent direction, g_o:

$$P_o = -g_o \quad (7)$$

The weight and threshold value is calculated using the equation in (8):

$$X_{k+1} = X_k + \alpha_k P_k \quad (8)$$

Where:
P_o = Search direction
g_o = Steepest descent direction
X = Weight and threshold value
α = Decrease the gradient in the search direction

3) Quasi Newton Backpropagation (trainbfg)

The newton training algorithm which has high accuracy rate efficiently with its advantage of the faster convergence speed compared to scale conjugate gradient.

The computation of iteration is obtained as shown in (9) below, where the Hessian matrix is used for the performance of the iteration. Due to the computation each iteration is expensive for feedforward neural network, Quasi Newton method is proposed which is the second derivatives at each step is neglect [9].

$$X_{k+1} = X_k - H_K^{-1} g_K \quad (9)$$

Where:
k = Iteration k
H_k = Hessian matrix of the performance function at iteration k

C. Hidden Failure Algorithm

The simulation procedure starts from a base case flow and follow the following steps. The procedure is repeated for several times. Below the following steps:

1) Load IEEE 14 bus system for an initial tripping event for probability hidden failure and other parameters
2) Increase load, P and Q at each bus with every 50% increment. Select an initial line as the triggering line and trip that line.
3) Perform the DC load after each tripping. Check for line flow violations.
4) If there is no line violate at the load bus, increase the load bus with 50% increment again.
5) If there is line violate, determine the currently exposed lines and determine the probability of incorrect tripping for each exposed line.
6) For each exposed line, generate a random number to determine whether the line tripped with the condition the probability of incorrect tripping is greater than the random number generated.
7) Finally, collect all the parameter and probability of hidden failure obtained from the simulation.

D. Artificial Neural Network Algorithm

The ANN algorithm consists training and testing process. All the parameters undergo the 80% training and 20% testing process. The procedure for training process is explained in the steps below:

1) Identifying the input and output from the parameters obtained in the hidden failure algorithm simulation. The probability of hidden failure for exposed line, random number and exposed lines are identified as input while trip index for the tripping line is determined for output parameter.
2) A heuristic method which is trial and error method is used with ratio of 80:20 with normalize training data
3) Design the ANN configuration. Set the value of epochs, goal, momentum rate, learning rate, number of hidden layer of the network and also the training algorithm of backpropagation which are LM, SCG and BFG.
4) Analyze the result from the simulation ANN model. Compare the convergence result based on the lowest MSE and the highest R if the result still do not converge, modify the value of train parameter and retrain again the ANN model.
5) Tabulate and save all the output for next session.

The procedure for training process is explained in the steps below:

1) The testing process is conducted after the training process in ANN model. Load the testing input and output data in the simulation MATLAB.
2) Load the save network for training process in ANN model.
3) Run for the testing simulation process.
4) Compare the result. The convergence of the result based on the highest R and the lowest MSE. MAPE is also calculated. The result shows the value of MAPE which is below than 10% error.
5) If the result still does not converge, retrain again the network followed the training procedure from previous steps.
6) Finally, save all the results.

III. RESULTS AND DISCUSSION

This section will explain on the results of prediction of cascading collapse occurrence due to the effect of hidden failure of protection system is compared with different training algorithm backpropagation.

The result is analyzed based on the MSE, R and MAPE accuracy. The test system that is used as case study is the IEEE 14 bus system as shown in Fig. 2. The total load for this test system is 259MW. This test system consists of 5 generators, 14 buses, 20 transmission lines and 11 loads.

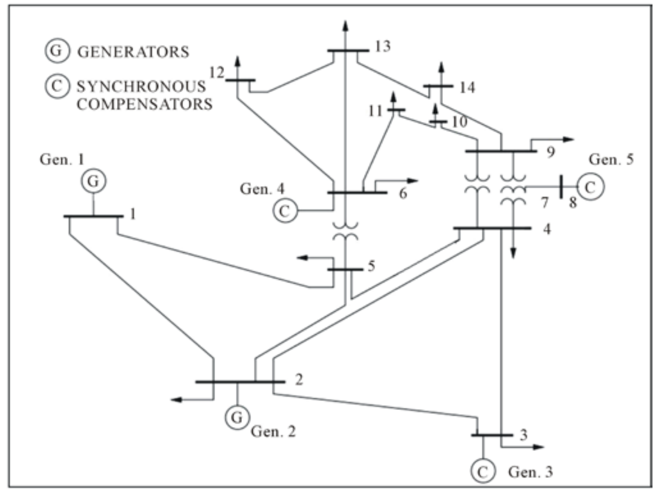

Fig. 2. Single line diagram for IEEE 14 bus system

TABLE I
COMPARISON OF DIFFERENT TRAINING ALGORITHMS OF ANN CONFIGURATION

Item	**Model**		
Network Configuration	‘logsig’, ‘purelin’	‘logsig’, ‘purelin’	‘logsig’, ‘purelin’
Learning Rate	0.2	0.2	0.2
Momentum Rate	0.9	0.9	0.9
Number of Hidden Layer	9	9	9
Training Technique	Lavenberg-Marquadt *(LM)*	Scale Conjugate Gradient *(SCG)*	Quasi-Newton Backpropagati on *(BFG)*
Training Goal	0.001	0.001	0.001
Epoch	100	100	100
No. of Training Data	888	888	888
No. of Testing Data	222	222	222
MSE Training	0.00113	0.0013	0.00089
MSE Testing	0.00072	0.0016	0.00082
MAPE	1.0194%	1.5327%	1.5327%
R	0.99951	0.99941	0.5684
Time (s)	0:00:00	0:00:02	0:00:01

Table I shows that the configuration of the ANN configuration with different training algorithms backpropagation. The learning rate, momentum rate and number of hidden layer is setting up with heuristic method based on the ANN algorithm explained in methodology section. The data consists of total 1110 data with 888 training data and 222 testing data. The goal and epoch is set to 0.001 and 100 iterations.

TABLE II
PERFORMANCE OF DIFFERENT TRAINING ALGORITHMS

Training Algorithm	**LM**	**SCG**	**BFG**
MAPE	0.99951%	1.5327%	1.5327%
MSE Training	0.00113	0.00130	0.00089
MSE Testing	0.00072	0.0016	0.00082
R	0.99951	0.99941	0.5684

Table II shows the performance of all the training algorithms, LM, SCG and BFG. The MAPE, MSE and R is analyzed and compared. From the study, the lowest value of MAPE is LM training algorithm which is 0.99951%. The SCG and BFG algorithm give the same value, 1.5327% whereas this value of MAPE still below than 10% for the most accurate prediction. The MSE training and testing for LM training algorithm are 0.00113 and 0.00072, for SCG training algorithm are 0.00130 and 0.0016, and lastly for BFG training algorithm are 0.00089 and 0.00082. The value of R obtained for LM, SCG and BFG training algorithms are 0.99951, 0.99941 and 0.56840. It is observed that BFG training algorithm proved less error during training and testing, however the value of R obtained is lowest compared to LM and SCG training algorithm. The value is 0.56840 which is less than 0.9. The performance of MSE, R and MAPE of all the training parameters is illustrated in bar chart as shown in Fig. 3, Fig. 4 and Fig. 5 below.

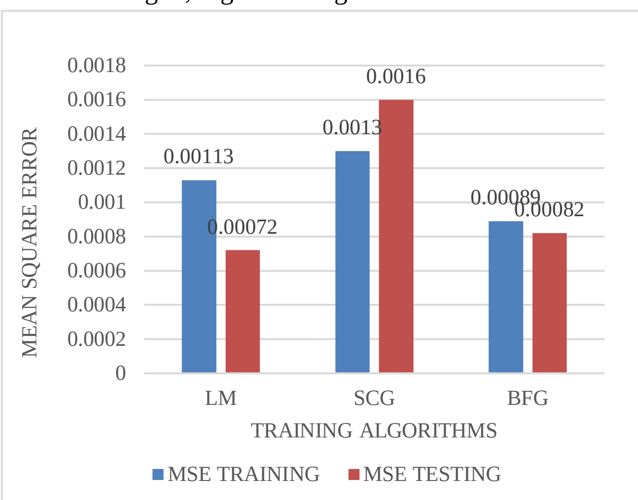

Fig. 3. Performance evaluation for MSE with different training algorithms

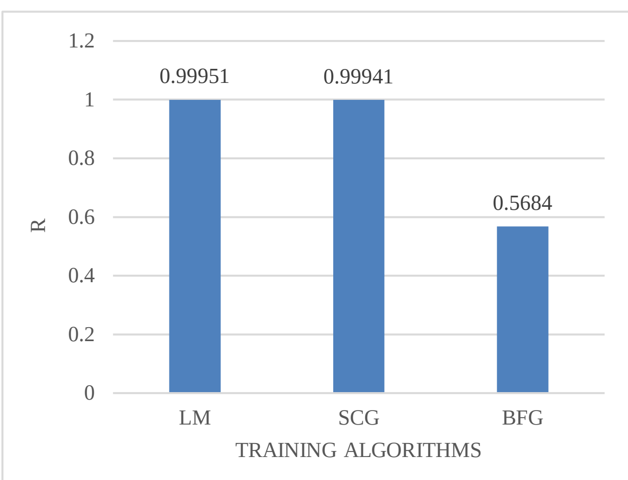

Fig. 4. Performance evaluation for R with different training algorithms

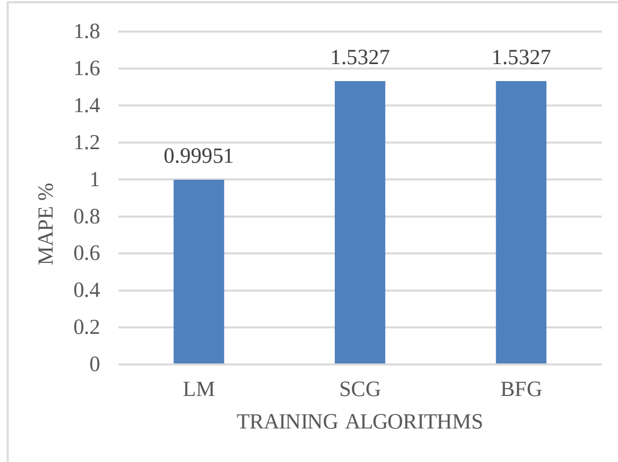

Fig. 5. Performance evaluation for MAPE with different training algorithms

IV. CONCLUSION

This paper has presented the use of backpropagation ANN for prediction of cascading collapse occurrence with hidden failure protection system effect with the goal to minimize the error and selecting the most suitable training algorithms. The backpropagation is chosen in this research because it has good prediction capability. From the result evaluation of these training algorithms, it is proved that LM training algorithm had performed well based on MSE, R and MAPE performance evaluation of prediction. The BFG training algorithm gave the best MSE but the R obtained is lowest which less than 0.9 of R. The SCG training algorithm gave average performance of R, MAPE and MSE. However, the LM training algorithm converge earlier than the SCG training algorithm.

From the case study, it is suggested that using LM backpropagation training algorithm as first choice to predict the ANN model for cascading collapse occurrence due to the effect of hidden failure protection system. LM training algorithm can give best accuracy of prediction and less computation time.

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REFERENCES

[1] Z. Shi, L. Shi, Y. Ni, L. Yao, and M. Bazargan, “Identifying Chains of Events During Power System Cascading Failure,” *Asia-Pacific Power Energy Eng. Conf. APPEEC*, no. 50977051, pp. 1–4, 2011.

[2] J. Chen, J. S. Thorp, and I. Dobson, “Cascading dynamics and mitigation assessment in power system disturbances via a hidden failure model,” *Int. J. Electr. Power Energy Syst.*, vol. 27, no. 4, pp. 318–326, May 2005.

[3] L. Zhao, X. Li, M. Ni, T. Li, and Y. Cheng, “Review and prospect of hidden failure : protection system and security and stability control system,” *J. Mod. Power Syst. Clean Energy*.

[4] E. Bashier, M. T. Orner, and A. I. Aziz, “Transmission Line Faults Detection, Classification and Location using Artificial Neural Network,” pp. 1–5, 2012.

[5] N. A. Salim, M. M. Othman, I. Musirin, and M. S. Serwan, "Identifying Severe Loading Condition During the Events of Cascading Outage Considering the Effects of Protection System Hidden Failure," *Proc. 2013 IEEE 7th Int. Power Eng. Optim. Conf. PEOCO 2013*, no. June, pp. 375–379, 2013.
[6] S. Wang, A. Chen, C. Liu, C. Chen, and J. Shortle, "Rare-event Splitting Simulation for Analysis of Power System Blackouts," 2011.
[7] M. Cilimkovic, "Neural Networks and Back Propagation Algorithm," *Inst. Technol. Blanchardstown, Dublin*, pp. 1–12, 2010.
[8] K. M. Brown, "Derivative Free Analogues of the Levenberg-Marquardt and Gauss Algorithms for Nonlinear Least Squares Approximation," vol. 297, no. x, pp. 289–290, 1972.
[9] X. Pan and B. Lee, "A Comparison of Neural Network Backpropagation Algorithms for Electricity Load Forecasting," 1990.

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