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Prediction of Cascading Collapse Occurrence due to the Effect of Hidden Failure of a Protection System using Artificial Neural Network

Transmission line act as a medium of transportation for electrical energy from a power station to the consumer. There are many factors that could cause the cascading collapse such as instability of voltage and frequency, the change of environment and weather, the software and operator error and also the failure in protection system. Protection system plays an important function in maintaining the stability and reliability of the power grid. Hidden failures in relay protection systems are the primary factors for triggering the cascading collapse. This paper presents an Artificial Neural Network (ANN) model for prediction of cascading collapse occurrence due to the effect of hidden failure of protection system. The ANN model has been developed through the normalized training and testing data process with optimum number of hidden layer, the momentum rate and the learning rate. The ANN model employs probability of hidden failure, random number of line limit power flow and exposed line as its input while trip index of cascading collapse occurrence as its output. IEEE 14 bus system is used in this study to illustrate the proposed approach. The performance of the results is analysed in terms of its Mean Square Error (MSE) and Correlation Coefficient (R). The results show the ANN model produce reliable prediction of cascading collapse occurrence.

Keywords: Hidden Failure; Protection System; Artificial Neural Network (ANN); Cascading Collapse.

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1. Introduction

Electrical power system is a huge system that is being interconnected together with hundred thousand networks of electrical components which consists of generation, transmission and distribution components. It is designed to transmit and distribute electrical energy produced by generators and feed the power to any load such as residential, commercial and industrial [1]. Power system plays an important role in the country's economic and social development. High demand of electricity from consumers may affect the social and economic growth and near its power system stability limit. High power consumption that exceeds the maximum limit could cause overloaded in power transmission system [2, 3]. Hence, transmission lines form a vital part in the power system to ensure there is no over loaded that pass through the power grid.

Transmission line provides the medium of transportation for electrical energy from a power station to load [4]. Theoretically, the cascading collapse occurrence are considered to be absolutely dependable because it helps to ensure the continued safe, reliable and efficient delivery of electricity to consumers. However, power system network is a wide range of complex network that involve many interconnected components that have their own tendency to failure [5]. There are many factors that cause the cascading collapse such as instability of

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voltage and frequency, the change of environment and weather, the software and operator error and also the failure in protection system.

The increasing numbers of electrical equipment especially in manufacturers and residential areas may contribute an issue in power system disturbances. Protection system plays an important function in maintaining the stability and reliability of the power grid [6]. According to the study conducted by NERC [7] more than two-third of the major disturbances that occurred between 1984 and 1988 involved the misoperation or hidden failure in protection system relays [6].

Hidden failures in relay protection systems are the primary factors for triggering the cascading collapse. Hidden failures are permanent defects that exist in relay protection systems, but they can only be exposed when the power systems are under faulty or abnormal conditions [8]. Cascading collapse have been the cause of major blackouts in power systems which lead to economical loss and system instability [9].

Cascade collapse is a complex and complicated phenomena which occurs due to a sequence of line outages that tend to increase the stress of the system [10]. Cascading collapse can be seen rarely happening in the system but somehow, once it occurs it not just affecting the system but also may interfere with the entire system in the line. Consequently, it will lead the whole system to blackout. In order to maintain the robustness of the large scale-network, the root cause of the blackout have to be investigated to create a countermeasure and to be aware of the failure when it occurs. This is to prevent any losses either in matter of time and economy that may lead to business collapse.

Therefore, it is important to identify a method to detect and predict any failure that might occur. As a result, it will create an awareness during the system outages in order to reduce risk of interruption when disturbance occur. Therefore, this paper proposes a technique by using ANN in order to predict and analyze the power system cascading collapse occurrence due to the effect of hidden failure protection sysem and the risk of network failures.

2. Notation

The notation used throughout the paper is stated below.

Constants:

T	the total number of the data
P_a	the actual the transmission line outage
P_p	the predicted the transmission line outage
N	the total number of prediction
X_i	the actual vector
X'_i	the vector of N prediction

3. Methodology

3.1. Hidden Failure Model

The hidden failure of a protection system is defined as a permanent defect of a relay unit or protection system which will incorrectly trip and remove the circuit elements as direct consequences of another switching event [11]. In this study, line protection hidden failure is adopted to model the operation of protection relays. DC load flow study is involved in simulation and tripping line is performed until the system collapse due to instability of the power grid.

The model uses DC load flow to estimate power flows through an AC system, assuming that the entire system has a voltage magnitude of 1.0 per unit. It also neglects the transmission line resistance. DC load flow solution is non-iterative. It has the solution of convergence at every simulation [13]. Each line has a different probability of tripping depends on the load increment. The probability is at a pre-determined value below the line limit and will increase linearly up to 1.4 times of the line.

The hidden failure that caused to a tripping of an exposed line is selected based on the probability of an incorrect tripping curve as shown in Fig. 1.

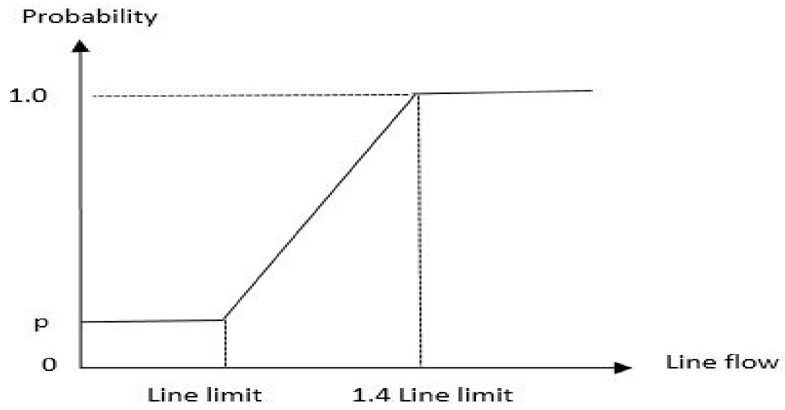

Fig. 1 The curve of probability of an exposed line tripping incorrectly

3.2. ANN Model

In this study, a two-layer of neural network with backpropagation has been applied to predict the cascading collapse occurrence in the IEEE 14 bus system. Basically, the backpropagation neural network is a multilayer, feedforward neural network which commonly used for supervised training process. Multi-Layer Perceptron (MLP) approach is used in the ANN model network. It functions by approximating the nonlinear relationship between the input and output. The training technique used is Lavenberg-Marquardt *(trainlm)* algorithm. This algorithm is a network training function that updates weight and bias values with the fastest backpropagation algorithm with supervised ANN model training in Matlab software.

The ANN model is developed in two stages which is training and testing process. Basically, the ANN model consists of three layers of neurons which are input neurons, which send data through synapses to the second layer of neurons and then through other synapses to the third layer of output neurons [13]. During training of supervised ANN model, the number of neurons in the learning rate, momentum rate and hidden layer is determined heuristically. In ANN, learning rate helps in accelerating the convergence supervised ANN model training. In addition, momentum rate assists in speeding up the training process of supervised ANN model. Generally, the range of learning rate and momentum rate is from 0 to 1. The hidden layer helps in reducing the error between targeted and predicted value. However, too many neurons in the hidden layer can result in over-fitting conflict and very small number of neurons can cause failure of the ANN model to learn a pattern.

The learning algorithm used is Levenberg-Marquardt (trainlm) in order to improve the learning speed and avoid local minimum. For hidden layer, the Sigmoid transfer function (logsig) is used meanwhile, purely linear (purelin) transfer function used for output layer. These transfer function commonly used for multilayer network. Logsig functions to generate outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity while for function fitting conflict purelin is used.

The data had been collected and classified into two set namely training and testing data set. The ANN trained and tested using Multilayer Perceptron (MLP) approach. This approach will give result in mean absolute percentage error (MAPE) as in equation (1). The best result should be less than 10% in MAPE.

$$MAPE = \frac{100}{T} \frac{\sum \left| Pa - Pp \right|}{Pa} \tag{1}$$

On the other hand, the accuracy of the prediction is evaluated in terms of Means Square Error (MSE) as in equation (2) and Regression Analysis. The ratio used is 80:20 for training and testing process.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (X_i' - X_i)^2 \tag{2}$$

3.3. Flowchart ANN 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, random number of line limit power flow and exposed lines are identified as input while trip index of cascading collapse occurrence 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 and also number of hidden layer of the network.
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 does not converge, modify the value of train parameter and retrain again the ANN model.
5) Tabulate and save all the output for next testing process. The flowchart of training ANN model is shown in Fig. 2 below:

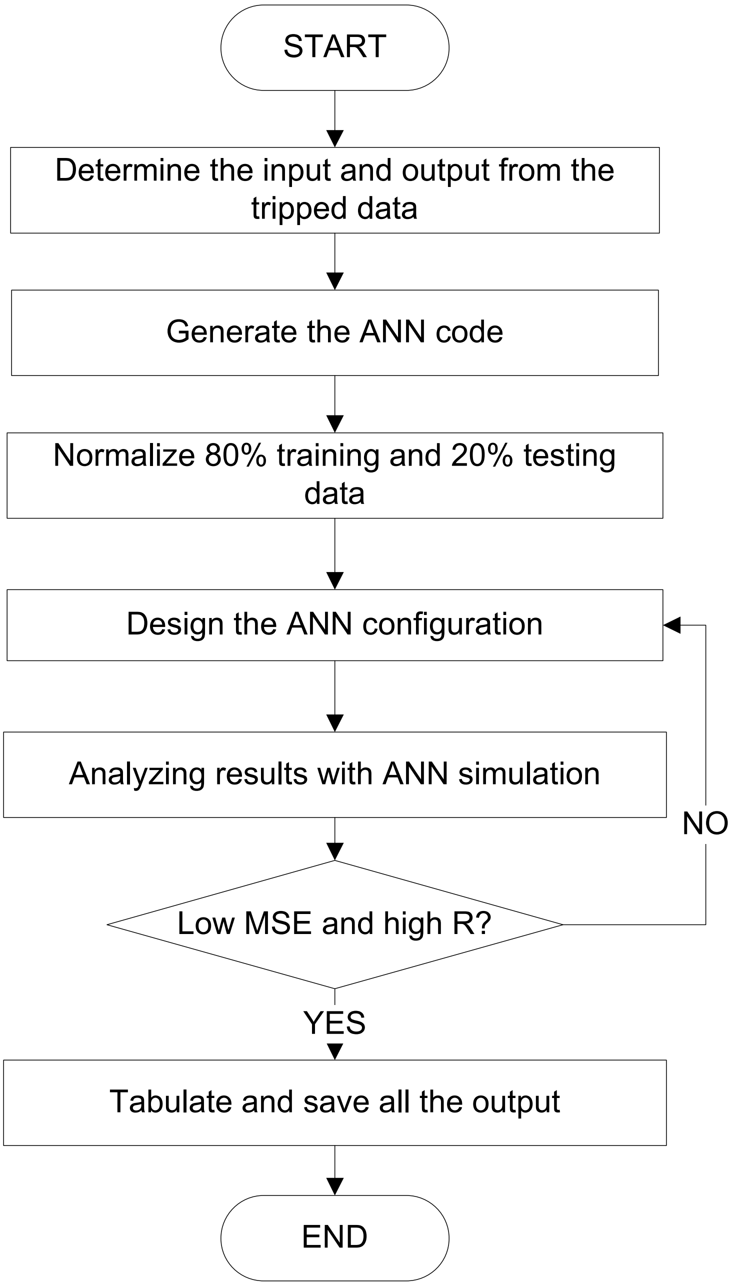

Fig. 2. The flowchart of training ANN algorithm

The procedure for testing 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. Run for the testing simulation process.
3) Compare the result. The convergence of the result based on the highest R and the MSE. The mean absolute percentage error (MAPE) is also calculated. The result show the value of MAPE which is below than 10% error.
4) If the result still does not converge, retrain again the network followed the training procedure from previous steps.

5) Finally, save all the results. The flowchart of testing process is shown in Fig. 3 below:

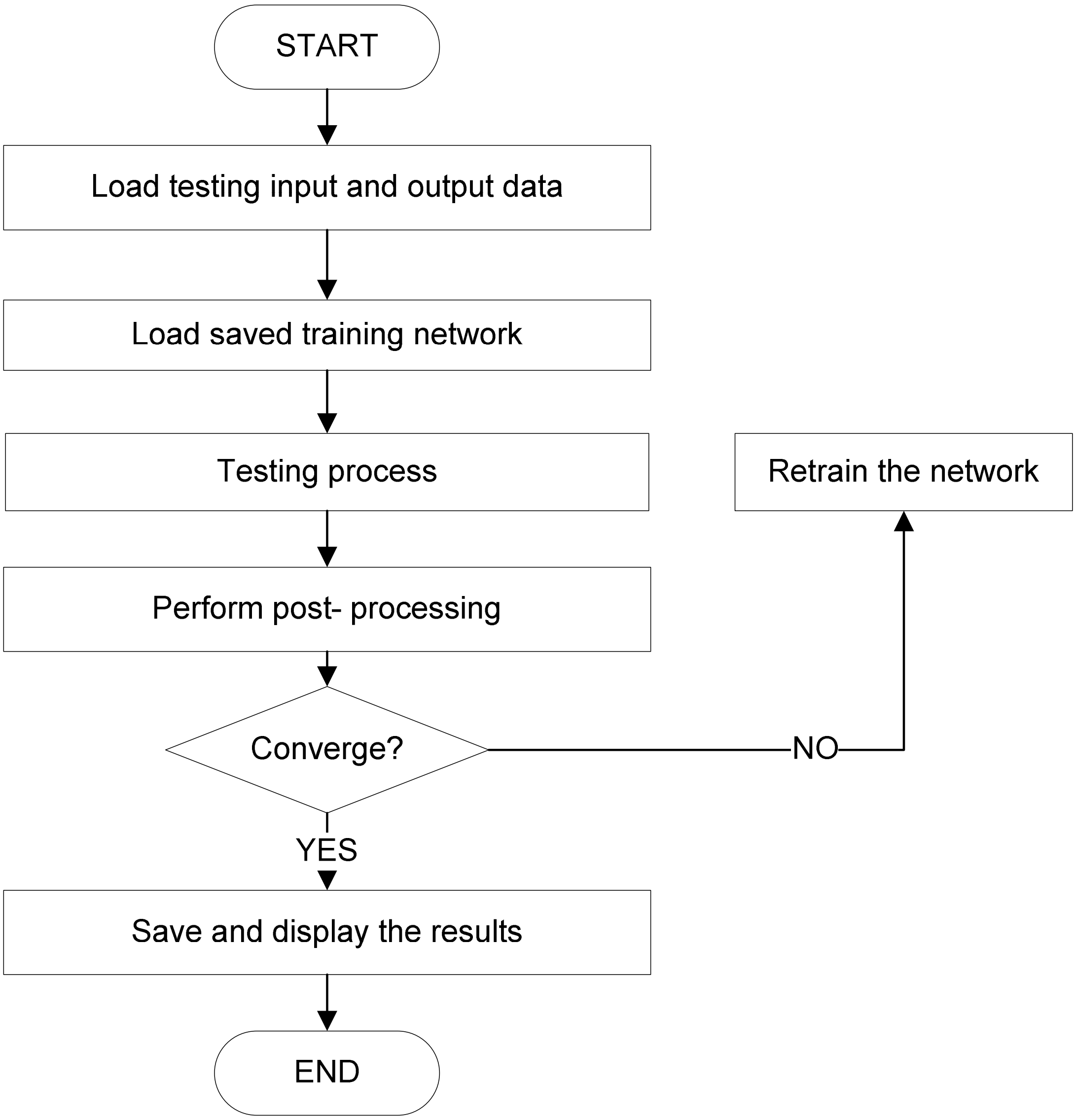

Fig. 3. The flowchart of testing ANN algorithm

4. Result and Discussion

This section will explain on the results of probability of exposed line and trip index of cascading collapse occurrence in term of MSE and R analysis determined by taking into consideration the effects of hidden failure of a protection system. The test system that is used as case study is the IEEE 14 bus system as shown in Fig. 4 [14]. The total load for this test system is 259MW. This test system consists of 5 generators, 14 buses, 20 transmission lines and 11 loads.

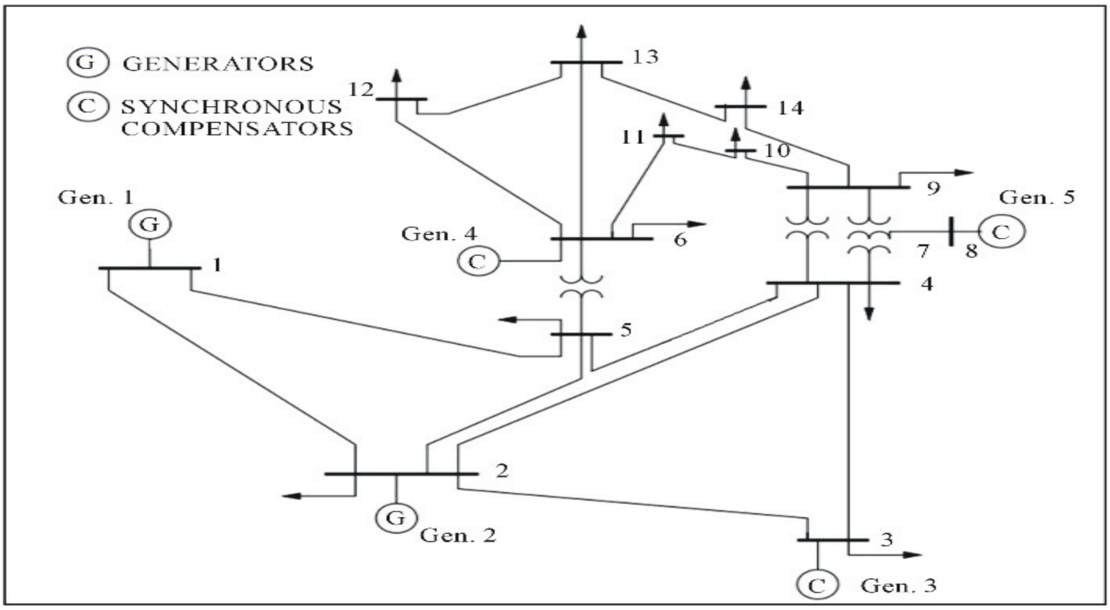

Fig. 4 Single line diagram for IEEE 14 bus system

Upon prediction of cascading collapse occurrence, the ANN model is implemented by developing the Matlab code with ratio of 80:20 for training and testing with normalize data process. The heuristic method is used to find the value of learning rate, momentum rate and number of hidden layer. The procedure starts by determining the learning rate by fixing the first of hidden layer to maximum which is 10 and the value of momentum rate to 0.5. Increase the value of learning rate from 0.1 to 1. The best value of learning rate is obtained based on the lowest MSE and highest R. This value of learning rate is fixed in order to find the value of momentum rate for the next procedure.

Next, the momentum rate is determined by varying the value from 0 to 1. The number of first hidden layer is fixed to 10. The same step is repeated in determining the number of first hidden layer. The best value for learning rate and momentum rate is fixed. The number of hidden layer is varied from 1 to 10. Choose the best number of first hidden layer with the lowest of MSE and also highest R. Noted that the second of hidden layer is fixed to 1 for all the procedures. Table 1, 2, and 3 show the optimum value of learning rate, momentum rate and number of first hidden layer. The optimum value for learning rate is 0.7, momentum rate is 0.5 and the number of hidden layer is 8. The less error is better for the data to converge.

Table 1: Optimum value for learning rate

Learning Rate	MSE	R
0.1	0.0312	0.98632
0.2	0.0306	0.98732
0.3	0.0254	0.99120
0.4	0.0318	0.98306
0.5	0.0472	0.97416
0.6	0.0241	0.98773
0.7	0.0189	0.99693
0.8	0.0345	0.98618
0.9	0.0335	0.99342
1.0	0.0261	0.98979

Table 2: Optimum value for momentum rate

Momentum Rate	MSE	R
0.1	0.0412	0.98271
0.2	0.0277	0.98725
0.3	0.0340	0.98742
0.4	0.0267	0.99649
0.5	0.0197	0.99147
0.6	0.0322	0.98467
0.7	0.0475	0.97496
0.8	0.0435	0.97469
0.9	0.0261	0.98666
1.0	0.0229	0.99325

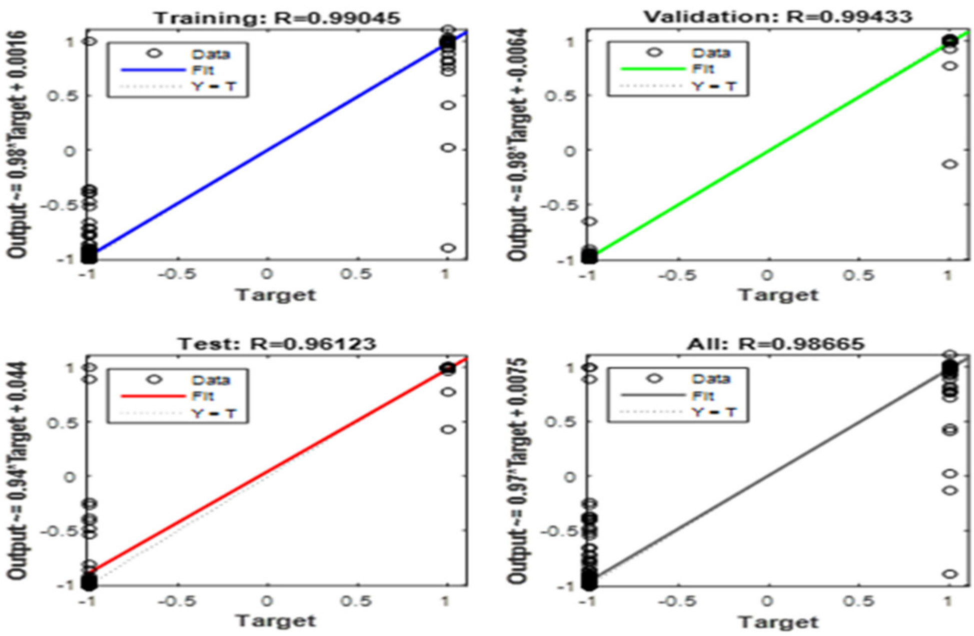

Fig 5. The correlation coefficient R

Table 4: Final design parameter for prediction

Item	Model
Network Configuration	'logsig', 'logsig', 'purelin'
Learning Rate	0.7
Momentum Rate	0.5
Number of Hidden Layer	8
Training Technique	Lavenberg-Marquadt *(lm)*
Training Goal	0.001
Regression Analysis, R	0.98665
Training Number Pattern	888
Testing Number Pattern	222
MAPE	0.6019%
Epoch	1000
MSE Training	0.0265
MSE Testing	0.0073

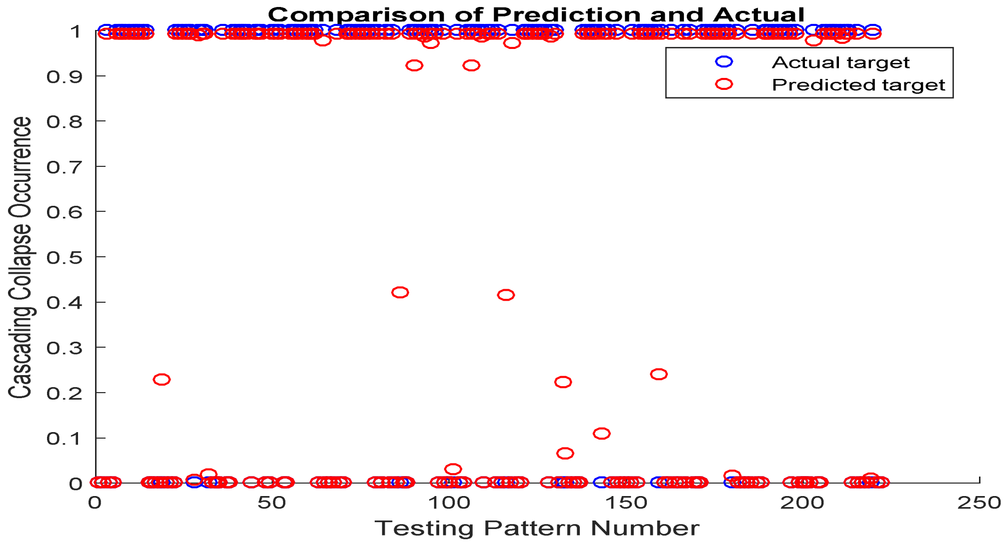

Fig. 6. Comparison of predicted and actual target

5. Conclusion

This study has presented a prediction of cascading collapse occurrence due to the effects of the hidden failure in protection system with the IEEE 14 bus system. ANN model can successfully use to determine the optimum number of neurons in the hidden layer, the learning rate and momentum rate with training algorithm Lavenberg-Marquadt. The prediction model also shows the lowest MSE with highest R. The results also show that the ANN model produce reliable prediction of cascading collapse occurrence due to the effect of protection system hidden failure.

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