

Optimization of Artificial Neural Network using Evolutionary Programming for Prediction of Cascading Collapse Occurrence due to the Hidden Failure Effect

N. H. Idris¹, N. A. Salim¹, M. M. Othman¹ Z. M. Yasin¹

¹Faculty of Electrical Engineering, Universiti Teknologi MARA, 40450, Shah Alam Selangor, Malaysia

norhazwaniidris@yahoo.com

Abstract. This paper presents the Evolutionary Programming (EP) which proposed to optimize the training parameters for Artificial Neural Network (ANN) in predicting cascading collapse occurrence due to the effect of protection system hidden failure. The data has been collected from the probability of hidden failure model simulation from the historical data. The training parameters of multilayer-feedforward with backpropagation has been optimized with objective function to minimize the Mean Square Error (MSE). The optimal training parameters consists of the momentum rate, learning rate and number of neurons in first hidden layer and second hidden layer is selected in EP-ANN. The IEEE 14 bus system has been tested as a case study to validate the propose technique. The results show the reliable prediction of performance validated through MSE and Correlation Coefficient (R).

1. Introduction

Cascading failure is a complicated and complex phenomena which occurs causes increase the stress of power system due to the sequence of line outages [1]. Normally, cascading failure is happen in power grids when one of the elements fails completely or unsuccessfully function and moves its load to nearby elements in the system. One of the main reasons for blackouts in power transmission grids is due to the cascading failure. These blackouts effect on the industrial growth, social and economic of the country [2]. Cascading failures may occurs due to loss of generating units at a station, voltage instability, the change of environment and weather, the software and the failure in protection system. As reported by [3], the most severe of disturbances in power grids convoluted hidden failure of a protection system. Two-third of the most serious disturbances that occurred on the year 1988 and 1984 involved the malfunction or hidden failure in protection system [4].

The severity of the occurrence has inspired to understand and analyze past blackout events and propose the new intelligent technique for prediction model to prevent massive blackouts. Artificial Neural Network (ANN) model is well known in prediction tasks because this model is nonlinear system modeling which capable by learning ability using collected data. ANN provides many advantages compared to the systems of conventional computational. Robustness, ability to memorize and rapidity are the most keen and interesting characteristics of ANN [5]. The architecture of an ANN depends on the type of activation functions which consists of bias and weights among neurons and number of neurons in training parameters.

The training parameters of the ANN model such as learning algorithm, the type of activation functions and number of hidden layer were determined heuristically. Therefore, the overall training



process for training parameters became very tedious and consume longer time [6]. This paper proposed with aim to optimize the momentum rate, learning rate and number of neurons in first and second hidden layer during training process for predicting cascading collapse occurrence due to the effects of hidden failure. With a hybrid of Evolutionary Programming (EP) and ANN, the training process becomes adaptable and faster because EP is well-known with fast convergence technique. EP has come out as a useful optimization tool for solving nonlinear programming problems.

2. Methodology

In this paper, a new contribution which is intelligent technique is suggested to predict cascading collapse occurrence due the effects of hidden failure model in steady state condition with hybrid method which is EP is employed to optimize training parameters.

2.1. Data Collection

The proposed models evaluates system performance probabilistically and predicted the historical data from the hidden failure simulation. The historical database is obtained through the cascading events occur in several years and being simulated in the hidden failure model. The probability of tripping for each line has different value depends on the increment of the load. The load is increased to 50% increment from the line bus system. The probability of the hidden failure has been trained and tested in the ANN model for prediction purposed. IEEE 14 bus system is used as a case study.

2.2. ANN-Based Prediction Model

ANN model has been chosen for prediction cascading collapse occurrence with two layer feedforward neural network. ANN with backpropagation was chosen because it can capture a variety of pattern accurately and can be used to perform nonlinear statistical modelling. ANN is an intelligence processing architecture that is inspired from biological nervous system similar with the brain that function for processing the information. ANN is one type of Artificial Intelligence (AI) that attempts to initiate the way a human brain works. It is used in various engineering field and demonstrated remarkable success.

The inputs consists of three variables which are random number generated with constrain 0 to 1, probability of hidden failure and exposed lines. All the data were separated with 80:20 rata for training and testing process. Training and testing data were normalized based on the type of the transfer function [5]. In this study the transfer function used is sigmoid and purely linear transfer function with *Levenberg-Marquardt* learning algorithm to improve the learning speed and avoid the local minimum. This approach will give result in Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE) as in equation (1) and (2) according to the highest correlation coefficient (R).

$$MAPE = \frac{100}{T} \sum \frac{|Pa - Pp|}{Pa} \quad (1)$$

Where:

- P_a The actual the transmission line tripping
- P_p The predicted the transmission line tripping
- T The total number of the data

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

Where:

- N The total number of prediction
- X_i The actual vector

X'_i The vector of N prediction

2.3. EP-ANN Model

Despite the ANN had been advantageous in prediction of cascading collapse occurrence, the trial and error method could causes the network to acquire a local optimal solution rather than a global optimal solution. As a result, hybrid model called EP-ANN combination is proposed for solving the optimal parameters during ANN training process that is used to predict the cascading collapse occurrence due to the effect of hidden failure model. The training parameters such as number of neurons in the hidden layer, the learning rate and momentum rate were optimized during the evolution of EP process.

The algorithm of EP consists of initialization of population, fitness computation, mutation, combination, selection, and convergence test. EP has been employed to optimize the three parameters with objective function to minimize the MSE during the training. The proposed EP-ANN model is summarized in the following steps below:

2.3.1. Step 1

Initialize the population with generate 20 random number that correspond to the number of neurons hidden layer1 and hidden layer 2, the learning rate and momentum rate denoted with x_1 , x_2 , x_3 and x_4 . x_1 and x_2 is produced within a range from positive integer 1 to 20 while x_3 and x_4 is generated from 0 to 1 value. After forms the initial candidates of the optimal solutions, this process finally known as parent [6].

2.3.2. Step 2

Fitness process is computed with the set of random number by training the parent in the ANN model called from the step 1. The computation in fitness value is according to the equation (2) which is the MSE value. The correlation coefficient, R and MAPE is also evaluated to check the validity of the error. MAPE should less than 10% error.

2.3.3. Step 3

Mutation process is performed to breed new offspring from the parent. The Gaussian mutation technique as in equation (3) is used to breed offspring.

$$x_{i+m.j} = x_{i.j} + N(0, \beta (x_{jmax} - x_{jmin}) (\frac{fi}{fmax})) \quad (3)$$

Where:

$x_{i+m.j}$	Offspring
$x_{i.j}$	Parents
N	Gaussian mutation
β	Search step
x_{jmax}	Maximum parents
x_{jmin}	Minimum parents
fi	Fitness 'i th '
$fmax$	Maximum fitness

2.3.4. Step 4

Fitness process is repeated same in the step 2 for each offspring.

2.3.5. Step 5

The process of combination occurred whereas the parents combined with offspring. After that, the population is ranked with the combination of parents and offspring. It is ranked according to the ascending order based on the fitness value. The selection process is performed. The highest MSE will be ranked at the bottom while the lowest MSE will be ranked at the top of the population.

2.3.6. Step 6

Convergence test is evaluated based on the stopping criterion which is the difference between the maximum fitness and minimum fitness should be less than 0.001. If the stopping criterion is violated, step 3 is repeated. Otherwise, the final parents in this step 6 is denoted as the final solutions.

The flowchart [7] of the whole steps is briefed in section 2.4 as shown below:

2.4. Flowchart

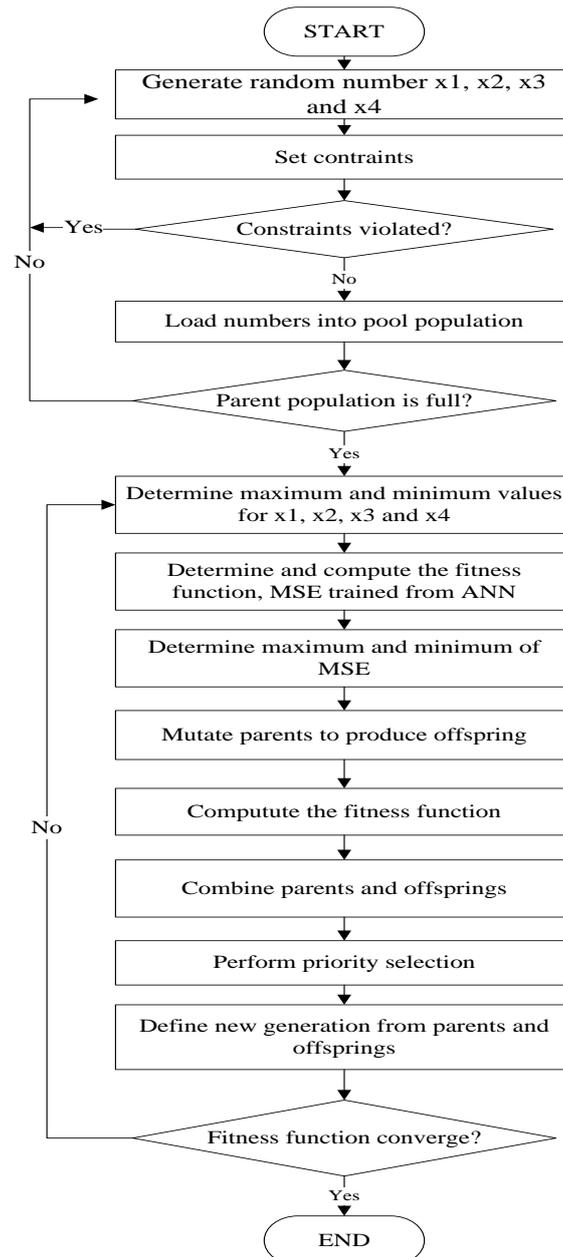


Figure 1. Flowchart of ANN-EP algorithm

3. Results and Discussion

The prediction of the cascading collapse occurrence due to the effects of hidden failure of a protection system is compared with the ANN and EP-ANN model. The IEEE 14 bus system is used as a case

study as shown as in Figure 2. The performance of the proposed EP-ANN model is tabulated in Table 1. Comparison of ANN model and EP-ANN model is tabulated in Table 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.

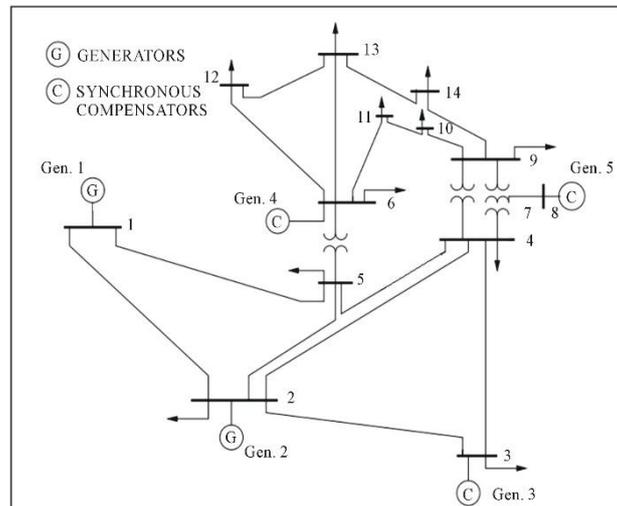


Figure 2. Single line diagram for IEEE 14 bus system

Table 1. ANN-EP Optimization of ANN Parameters and Configuration

Item	Model
Network Configuration	Logsig, logsig, purelin
Momentum Rate	0.01
Learning Rate	0.01
Number of Nodes in Hidden Layer 1	1
Number of Nodes in Hidden Layer 2	1
Training Algorithm	Lavenberg-Marquadt (lm)
Goal	0.001
Correlation Coefficient, R (Testing)	0.95817
Correlation Coefficient, R (Training)	0.98134
Training Number Pattern	888
Testing Number Pattern	222
MSE Training	0.0179
MSE Testing	0.0001
MAPE	0.68839%

The training process is conducted with 888 data patterns while testing process is conducted with 222 data patterns. The objective function is to minimize the MSE with optimal number of training parameters. The error is set to 0.001 with 1000 iterative updates (epochs). The training algorithm used in this algorithm is *Levenberg-Marquardt* with network configuration *logsig-logsig-purelin*. From table 1, the optimal MSE obtained is 0.0001. The best value for the number of nodes in hidden layer 1, x_1 and hidden layer 2, x_2 is 1, while the learning rate, x_3 and momentum rate, x_4 is 0.01 respectively.

The process stop at 9th iteration. The optimal MSE obtained is 0.0001 which is the best value after undergo the fitness computation with minimizing the error. During the optimization process, the 20 sets random numbers is generated and combined with the parents and offspring with 40 sets of random number. The selection process will select the best value from the best 40 sets of random numbers with the lowest fitness value from parents and offspring. The selection process yield the optimal MSE and also the ANN parameters respectively.

The R value obtained for training and testing are 0.98134 and 0.95817 which close to unity.

Table 2. Comparison Results of ANN-EP and ANN Model

Item	EP-ANN	ANN
Network Configuration	<i>logsig, logsig, purelin</i>	<i>logsig, logsig, purelin</i>
Momentum Rate	0.01	0.5
Learning Rate	0.01	0.7
Number of Nodes in Hidden Layer 1	1	8
Number of Nodes in Hidden Layer 2	1	2
Training Algorithm	<i>Lavenberg-Marquadt (lm)</i>	<i>Lavenberg-Marquadt (lm)</i>
Goal	0.001	0.001
Correlation Coefficient, R (Testing)	0.95817	0.96123
Correlation Coefficient, R (Training)	0.98134	0.99045
MSE (Testing)	0.0001	0.0073
MSE (Training)	0.0179	0.0265
Training Number Pattern	888	888
Testing Number Pattern	222	222
MAPE	0.68839%	0.6019%

In Table 2, the number of nodes in the first hidden layer and second hidden layer for EP-ANN is 1 while for ANN model the first and second hidden layer are 8 and 2. The details of the performance of EP-ANN had been conducted by evaluating the MSE and R for testing and training process. The error is reduced during the optimization process. The fitness is converged in 9th iteration which is the optimal solution as shown in Figure 3.

After 9th iteration, the error obtained is 0.0001 which is obviously reduce compared to the ANN model which is 0.0073. The optimal R value is 0.95817 for EP-ANN while the value of R in ANN model is 0.96123. Even though there is slightly different value for R, the objective function has been achieved in ordered to minimize the error. The best value for R is more than 0.95 to validate the performance is reliable and good.

The performance of MSE and R is illustrated in a bar chart with training and testing process and it is compared with ANN and EP-ANN model. For EP-ANN model, the MSE performance give 0.0179 for training and 0.0001 for testing process, while for ANN model, the MSE shown is 0.0265 for training while 0.0073 for testing process.

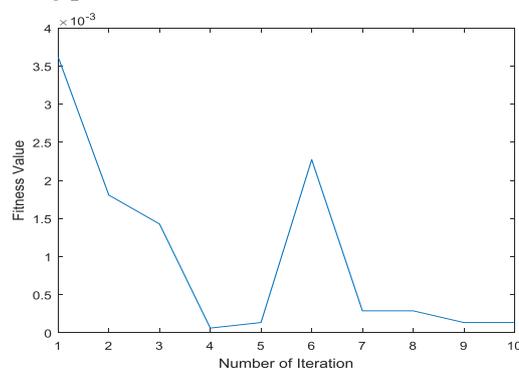


Figure 3. Fitness value with different number of iteration

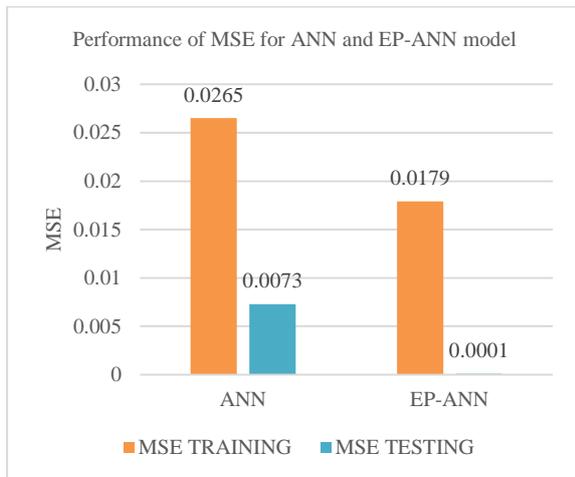


Figure 4. Performance of MSE for ANN and EP-ANN model

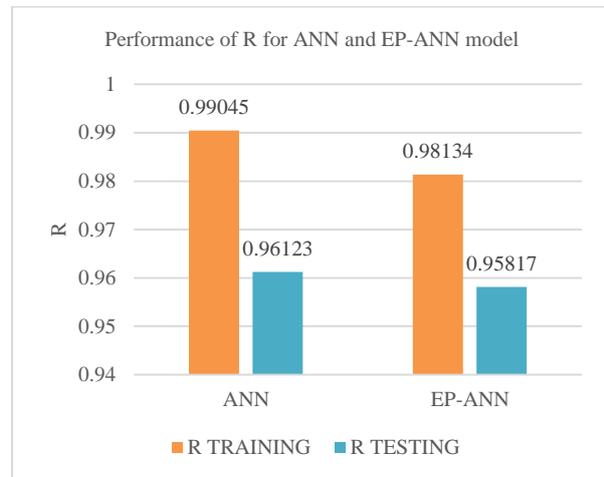


Figure 5. Performance of R for ANN and EP-ANN model

4. Conclusion

This paper has presented the novel of EP-ANN hybrid model for predicting the cascading collapse occurrence due to the effect of hidden failure in a protection system. The performance of MSE shows that the EP-ANN is proved for reliable model and fast convergence contrast to the performance of ANN model. EP-ANN model successfully determine the optimal number of hidden layer 1 and 2, learning rate and momentum rate with minimal error, and correlation coefficient close to unity. In short, the EP-ANN model is highly acceptable model for predicting the occurrence of cascading collapse in conjunction with the protection system hidden failure.

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