

Adaptive DOCR Coordination in Loop Electrical Distribution System With DG Using Artificial Neural Network LMBP

¹Daeng Rahmatullah, ¹Belly Yan Dewantara, and ¹Iradiratu D.P.K

¹Department of Electrical Engineering
Universitas Hang Tuah,
Surabaya, Indonesia

daengrahmatullah@gmail.com, bellyyandewantara@yahoo.com, Iradiratu@hangtuah.ac.id

Abstract - To design the coordination protection for passive distribution system is not the tough work, while active or mesh distribution system which consists many distributed generators is quite more challenge for protection engineers. Additionally, the short circuit current will also vary if any DG in the system is offline, which causes to re-coordinate the relay protection in the system. To reset the relay protection, the engineers need more time. However In order to reduce the time of relay setting calculation, the adaptive protection coordination is proposed in this study by using artificial neural network. The study bases on the combinations of DGs' state and the current short circuit levels as the input data and low setting of the directional overcurrent relays (DOCR) as the output data training. This research is conducted on modified IEEE 9-bus system equipped with distributed generators. After reaching convergence of Levenberg-Marquardt Back Propagation (LMBP) learning process, the results of weights and biases are compiled into the master controller to control all of the relays in the whole system. It will generate the relay setting automatically base on the results of ANN training. The results of this research have been testified in Etap simulation successfully and it is obvious that LMBP neural network is a robust method to model adaptive relay coordination system.

Keyword – *Neural Network, Directional Over Current Relay, Distributed Generation, Loop system.*

I. INTRODUCTION

Protection of power system are installed in electric power systems such as generators, transmissions, and distribution in order to improve reliability of the system. In radial system, the relay protection can be used such as inverse curve, definite curve, or both. The protection in loop coordination system is more complex than the radial system due to the direction of current flowing from various directions. So, that must be required directional over current relay (DOCR). Adding DG to the system can result the varying level of fault current. needed protection scheme with an efficient estimation error signal and intelligent decision-making in the event of disruption Protection in the distribution system is to detect current short circuit and overload from various causes in the field, one of them for their DG [1]. The coordination of relay protection for DG using directional systems has been discussed by several papers [2] and [3]. However, the variation of the DG conditions changes over time resulting in a change in the direction and value of the fault current. To

protect the system in every DG condition by using coordination of multi-curve relay protection. Good coordination is the coordination that has the operating time relay as small as possible. To obtain such coordination, the optimum coordination of the protection relay is proposed by following [4], [5], [6], and [7]. However, that is not enough, the power supply changed by DG will change the amount of fault current in the whole system. As a result, the relay setting values have to be resetting as well. Even a slight change of power generation in the system, the relay setting must be reconsidered due to the sensitivity of the mesh system. The more complex the plan is, the longer the time is needed. Adaptive coordination of relay settings using artificial intelligence (AI) is proposed to solve the problem. By using ANN, the calculation of relay setting will be much faster. That can cover on every combination of generation in the system. All of relay setting calculation results will be the target of an algorithm. If there is a change in combination generation, then the algorithm can accurately predict the appropriate relay settings.

Some papers have suggested intelligent and adaptive protection mechanisms as discussed in [8], [9], and [10]. The learning process data of this paper using ANN Levenberg-Marquardt backpropagation (LMBP). Protective coordination will be obtained the right setting for any change in the in term of generation conditions by using adaptive setting. The data obtained by ANN is less than that of look up table. So master control does not need large memory space.

LMBP algorithm is used here to obtain adaptive protection settings in case of system conditions change. The proposed adaptive scheme is tested on modified-IEEE-9-bus system. After the simulating with a variety of case studies, the simulation results will be testified in Etap simulation to make sure that the appropriate of setting protection has been obtained [11].

The purpose of this research to obtaining adaptive algorithms to get the settings DOCR for protection in the loop distribution network connected with DG and Simulation results from the implementation of the settings relay protection with neural network LMBP.

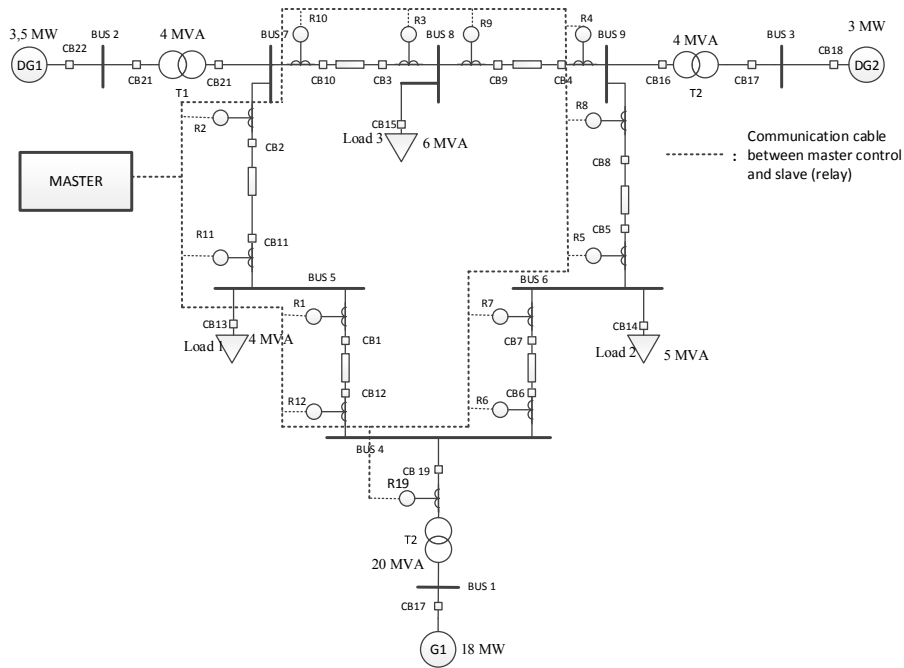


Fig.1. IEEE-9 bus

II. PROTECTION SCHEME

A. Setting Relay Protection

For protection coordination loop and multi-loop system using inverse time curve only. Each relay has at least one backup relay to prevent failure protection. Inverse curve has a characteristic where the greater the fault current relay operating time is shorter. Conversely, if the fault current is small then relay operating time is longer [12].

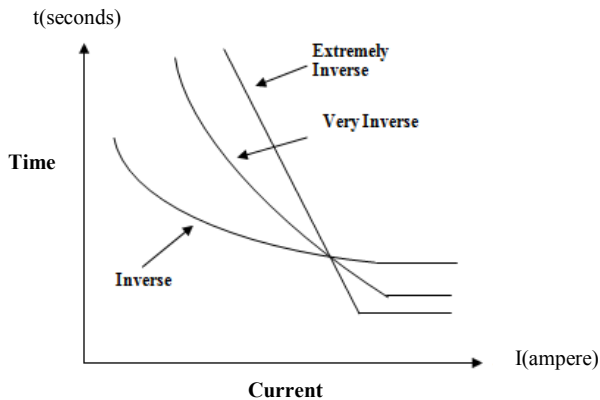


Fig.2. Characteristics standard inverse, very inverse, and extremely inverse[12]

It is stated in reference [12], for inverse time DOCR setting can be set up two parts as the pickup setting and time dial setting. In DOCR I_{pickup} current value is determined by:

$$I_{pickup} = \frac{I_{set}}{CT_{primary}} \times CT_{secondary} \quad (1)$$

I_{set} is the current in the CT primer in ampere. According to the British Standard BS 142 adjustment limit is $1.05I_{FLA} < I_{set} < 1.4I_{FLA}$, where I_{FLA} is current when the equipment has maximum load[12].

$$td = \frac{k \times TDS}{\left[\left(\frac{I_{scmax}}{I_{set}}\right)^\alpha - 1\right]} \quad (2)$$

TDS is a time dial setting and td is the time the operational relay when the maximum short circuit happens. Relay protection using a standard curve is inverse to the value of k is 0.14 and α is 0.02 in reference [13].

Plan using IEEE-9-bus system that has been modified into a distribution system is shown in Fig.1. The protective coordination system has been designed as primary relay and backup relay. The grouping of the main relay and backup relay is shown by the table I.

TABLE I. COORDINATION RELAY

Fault Bus	Clockwise		Counter Clockwise	
	Main Relay	Back up Relay	Main Relay	Back up Relay
5	1	6 19	5	1
7	2	1	7	2
8	3	2	8	3
9	4	3	9	4
6	5	4	6	5 12
4	6	5	4	6

The main relay and back up relay must have coordination time interval (CTI) $> 0.2s$ [13].

$$td_{backup} - td_{main} < 0,2 \quad (4)$$

Where td is the time of operational relay in the event of the maximum short circuit.

B. Neural Network Levenberg-Marquart (LM)

Backpropagation neural network is using Levenberg-Marquardt algorithm. This method is a combination of Newton algorithm with the steepest descent method (gradient descent). The weight equation of the Levenberg-marquardt method (LM) in [14] is written as follows:

$$W_{k+1} = W_k - (J_k^T J_k + \mu I)^{-1} J_k^T e \tag{3}$$

Where W is the weight, I is the identity of matrix and μ is the training rate. Differences between this algorithm and backpropagation is about weight improvement. When the value of learning rate is equal to 0 ($\mu = 0$), then the LM method will be the same as the Gauss newton. However, if the value of μ is greater, then LM method with backpropagation method is alike. Modifications of this method is to reduce the matrix J jacobian. ANN is used 1 input layer, 1 hidden layer with *tansig* activation function, and 1 output layer with *purelin* activation function. Architecture of Artificial Neural network design is shown in Fig. 3.

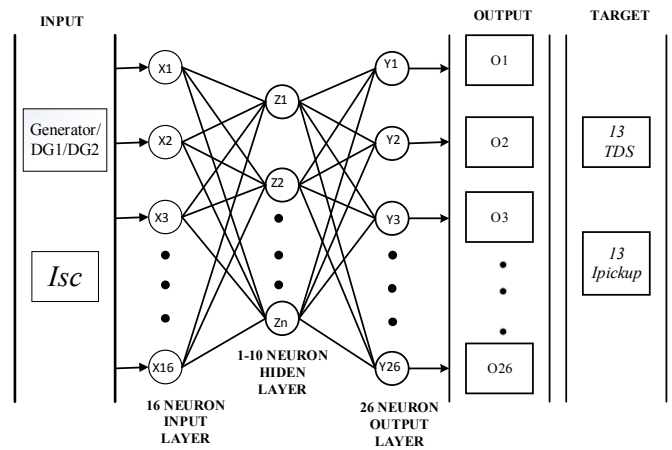


Fig. 3. Architecture of Artificial Neural Network

Combination of generation, and current short circuit data are used as input data in Fig. 3. X_n is neuron of input layer, Z_n is neuron of hidden layer and Y_n is neuron of output layer. On other hand, 13 TDS and 13 Ipickup setting from 13 relays are used as target. Table II shows input data and table III shows target data.

TABLE II. TRAINING DATA

Case	INPUT															
	Combination of Generation			Current Short Circuit												
	G	DG1	DG2	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R19
1	1	1	1	0	0	0	195	549	935	0	0	0	125	538	907	1930
2	1	0	1	0	0	0	54	405	790	0	0	0	272	272	651	1920
3	1	1	0	0	0	0	310	310	696	0	0	0	12	424	800	1920
4	1	0	0	0	0	0	165	165	550	0	0	0	158	158	593	1920
5	1	1	1	2210	0	0	0	0	327	0	53	404	721	1130	0	1880
6	1	0	1	2130	0	0	0	0	248	0	131	484	802	802	0	1880
7	1	1	0	2030	0	0	0	0	147	0	234	234	552	966	0	1880
70	1	0	1	428	833	833	1200	0	0	1500	1940	0	0	0	0	1920
71	1	1	0	282	680	1150	0	0	0	1650	2090	1510	0	0	0	1920
72	1	0	0	428	833	833	1200	0	0	1500	1940	0	0	0	0	1920

TABLE III. TARGET DATA

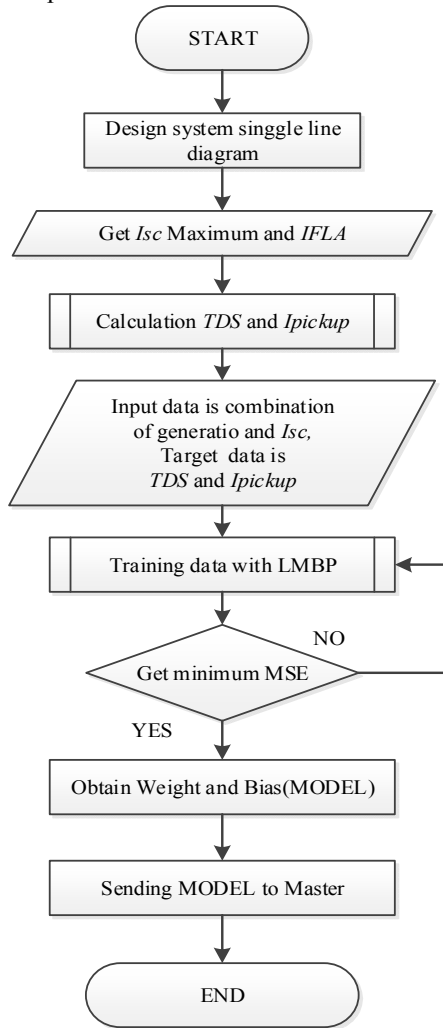
Case	TARGET																									
	TDS													Ipickup												
	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R19	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R19
1	0.141	0.139	0.116	0.093	0.079	0.100	0.145	0.144	0.115	0.089	0.078	0.098	0.130	4.52	4.20	4.20	4.20	4.20	3.15	4.52	4.20	4.20	4.20	4.20	3.15	6.44
2	0.145	0.144	0.100	0.090	0.155	0.220	0.153	0.161	0.137	0.137	0.122	0.198	0.167	4.52	4.20	4.20	4.20	2.10	1.05	4.52	4.20	4.20	3.15	2.11	1.05	5.77
3	0.147	0.152	0.134	0.113	0.131	0.201	0.162	0.166	0.119	0.132	0.169	0.242	0.168	4.52	4.20	4.20	4.20	2.10	1.05	4.52	4.20	4.20	3.15	2.11	1.05	5.77
4	0.136	0.140	0.097	0.147	0.096	0.203	0.144	0.150	0.106	0.150	0.097	0.211	0.148	4.52	4.20	4.20	1.89	1.89	0.74	4.52	4.20	4.20	1.89	1.89	0.74	5.77
5	0.141	0.139	0.116	0.093	0.079	0.100	0.145	0.144	0.115	0.089	0.078	0.098	0.130	4.52	4.20	4.20	4.20	4.20	3.15	4.52	4.20	4.20	4.20	4.20	3.15	6.44
6	0.145	0.144	0.100	0.090	0.155	0.220	0.153	0.161	0.137	0.137	0.122	0.198	0.167	4.52	4.20	4.20	4.20	2.10	1.05	4.52	4.20	4.20	3.15	2.11	1.05	5.77
7	0.147	0.152	0.134	0.113	0.131	0.201	0.162	0.166	0.119	0.132	0.169	0.242	0.168	4.52	4.20	4.20	4.20	2.10	1.05	4.52	4.20	4.20	3.15	2.11	1.05	5.77
70	0.145	0.144	0.100	0.090	0.155	0.220	0.153	0.161	0.137	0.137	0.122	0.198	0.167	4.52	4.20	4.20	4.20	2.10	1.05	4.52	4.20	4.20	3.15	2.11	1.05	5.77
71	0.147	0.152	0.134	0.113	0.131	0.201	0.162	0.166	0.119	0.132	0.169	0.242	0.168	4.52	4.20	4.20	4.20	2.10	1.05	4.52	4.20	4.20	3.15	2.11	1.05	5.77
72	0.136	0.140	0.097	0.147	0.096	0.203	0.144	0.150	0.106	0.150	0.097	0.211	0.148	4.52	4.20	4.20	1.89	1.89	0.74	4.52	4.20	4.20	1.89	1.89	0.74	5.77

Neural Network algorithm is used to evaluate TDS and Ipickup setting for relay 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11,12 and 19. Those firstly have been obtained by the manual calculation. TDS will be installed for four combination of generation sources. Combination of generator consist of,

Generator, DG1,2 On with Gen1 Off; Gen and DG2 On with DG1 Off; Gen and DG1 On with DG2 off; and Gen On with DG1, 2 Off. There are 26 outputs consisting 13 TDS and 13 Ipickup settings.

C. Reserching process

Fig. 4 is a process of reserch :



The research process begins with the design of single line diagram. After that, $I_{sc\ max}$ and I_{FLA} data are used to calculate TDS and I_{pickup} relays. Training input data is combination of generations and I_{sc} . The target data is TDS and I_{pickup} . The learning process and testing process by the LMBP is conducted to get the weight and bias with the smallest MSE. After terminating training process, the obtained weights and biases are sent to Master controller. Master controller can be personal computer, microcontroller or any controller which can save model (Wight and bias) from training ANN.

III. SIMULATION RESULT AND ANALYSIS

A. Training and Testing Neural Network

There is no specific algorithm to find the number of neuron in training process. So for this reserch, the number of neuron has been chosen based on the method of trial and error and observed for minimum MSE value.

In this paper, the process of training the neural network using 3 layers consists of 1 input layer, 1 hidden layer, and 1 output layer. the 72 items of data are formed randomly, 60% for the training process, 20% for validation, and 20% for

testing. Of the 72 items of data each row consists of 16 inputs and 26 outputs. Parameter for training can reach preferred results with maximum epoch 10^3 , gradient 10^{-7} , and maximum fail is 6. Parameter for training is based on reference [14]. Here is training performance of 15 tests using 15 variations of the neuron in hidden layer.

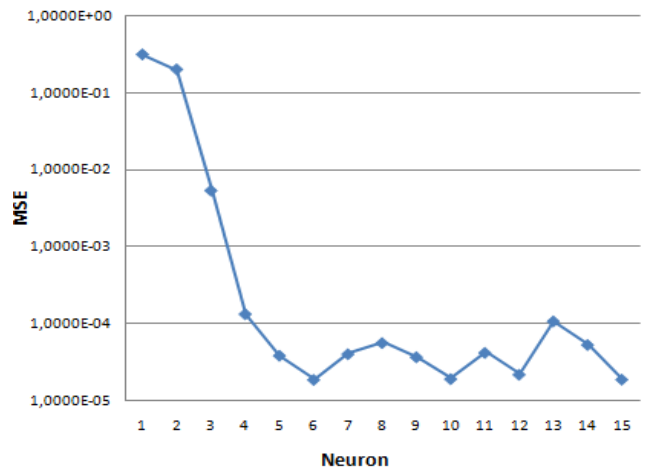


Fig 5. Curve of MSE

The testing results using 20% of 72 data obtained value of weight and bias, and the best training results can be obtained by using 6 neurons with 13 iterations. Mean Squared Error (MSE) = $1.8827e-005 = 1,8827 \times 10^{-5} = 0.01882\%$ and performant curves are shown in Fig. 6.

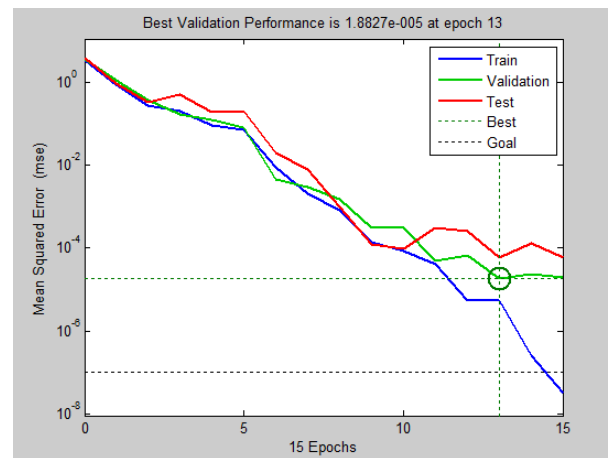


Fig. 6. Training Performance of ANN

B. TDS and Ipickup Setting Target VS Output ANN

TDS and I_{pickup} setting value is picked from the test results (20%) from 72 the data by using 15 iterations. After that, it has been used to compare between the actual data and ANN output. Table IV is comparison TDS and I_{pickup} target with output of testing Neural Network algorithm in each combination of generation.

Result comparison between target and output of ANN is quite similar. Some TDS and I_{pickup} are different but not affect to the coordination of relay. Relay coordination is testified by using ETAP application.

TABLE IV. TARGET VS OUTPUT OF ANN

RELAY	Generator, DG1 and DG2				Generator and DG2				Generator and DG1				Generator only			
	TDS	Ipickup	TDS	Ipickup	TDS	Ipickup	TDS	Ipickup	TDS	Ipickup	TDS	Ipickup	TDS	Ipickup	TDS	Ipickup
	Target		Output ANN		Target		Output ANN		Target		Output ANN		Target		Output ANN	
R1	0.1408	4.5238	0.1408	4.5238	0.1449	4.5238	0.1449	4.5238	0.1465	4.5238	0.1465	4.5238	0.1360	4.5238	0.1360	4.5238
R2	0.1394	4.2000	0.1394	4.2000	0.1439	4.2000	0.1439	4.2000	0.1524	4.2000	0.1524	4.2000	0.1398	4.2000	0.1398	4.2000
R3	0.1164	4.2000	0.1164	4.2000	0.0997	4.2000	0.0997	4.2000	0.1336	4.2000	0.1336	4.2000	0.0974	4.2000	0.0974	4.2000
R4	0.0930	4.2000	0.0930	4.2000	0.0895	4.2000	0.0895	4.1999	0.1127	4.2000	0.1127	4.2000	0.1471	1.8900	0.1471	1.8897
R5	0.0791	4.2000	0.0791	4.2000	0.1547	2.1000	0.1547	2.0999	0.1309	2.1000	0.1309	2.1001	0.0956	1.8900	0.0956	1.8899
R6	0.0996	3.1500	0.0996	3.1500	0.2203	1.0500	0.2203	1.0499	0.2007	1.0500	0.2007	1.0501	0.2031	0.7350	0.2031	0.7349
R7	0.1451	4.5229	0.1451	4.5229	0.1531	4.5229	0.1531	4.5229	0.1620	4.5229	0.1620	4.5229	0.1438	4.5229	0.1438	4.5229
R8	0.1437	4.2000	0.1437	4.2000	0.1614	4.2000	0.1614	4.2000	0.1657	4.2000	0.1657	4.2000	0.1500	4.2000	0.1500	4.2000
R9	0.1147	4.2000	0.1147	4.2000	0.1372	4.2000	0.1372	4.2000	0.1195	4.2000	0.1195	4.2000	0.1058	4.2000	0.1058	4.2000
R10	0.0889	4.2000	0.0889	4.2000	0.1371	3.1500	0.1371	3.1499	0.1316	3.1500	0.1316	3.1500	0.1498	1.8900	0.1498	1.8898
R11	0.0776	4.2000	0.0776	4.2000	0.1223	2.1105	0.1223	2.1105	0.1691	2.1105	0.1691	2.1106	0.0968	1.8900	0.0968	1.8900
R12	0.0983	3.1500	0.0983	3.1500	0.1981	1.0500	0.1981	1.0499	0.2420	1.0500	0.2420	1.0501	0.2107	0.7350	0.2107	0.7350
R19	0.1300	6.4432	0.1300	6.4432	0.1670	5.7700	0.1670	5.7700	0.1680	5.7700	0.1680	5.7700	0.1480	5.7700	0.1480	5.7700

Data output from testing proses is compared with target data. The ANN learning process is good if target is similar to ANN output. Similarity of output and target is evidenced by MSE and simulation short circuit is used software ETAP.

C. Simulation of adaptive relay coordination using software.

To determine the accuracy of the *TDS* and *Ipickup* setting output of neural network, the *TDS* and *Ipickup* setting is entered into the relay. After that, the simulation of 3-phase-short circuit in 0.5 cycles tested in the bus 8 and the simulation results are shown in Fig. 7 and 8.

From the simulation results, it can be plotted relay coordination curves for relays 8, 9, 3, and 2 in Fig. 7 and 8.

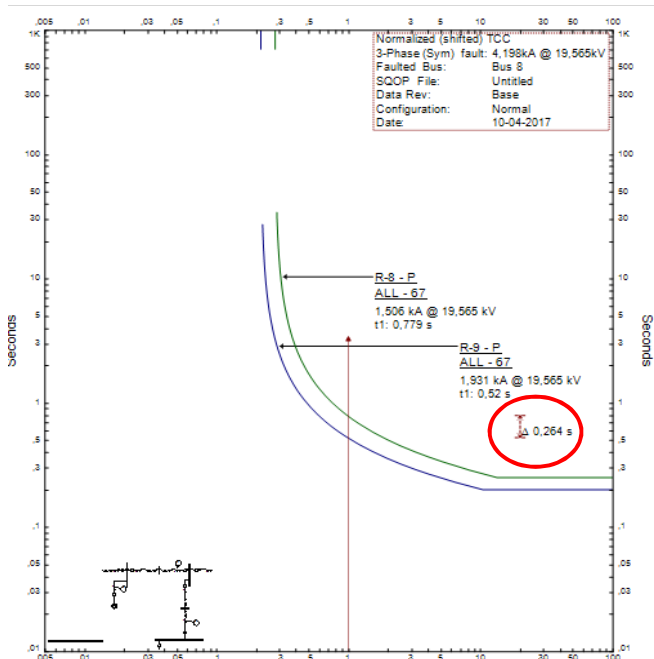


Fig. 7. Coordination Relay 9 and Relay 8

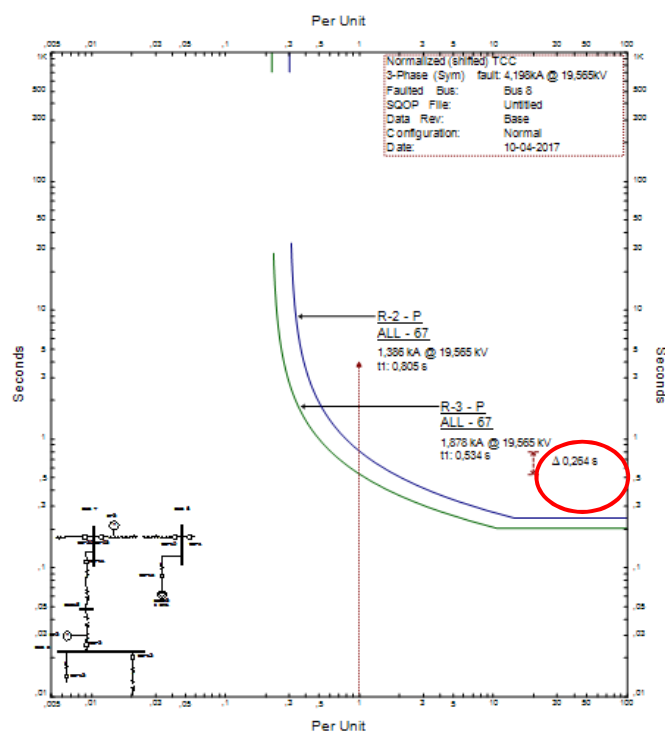


Fig. 8. Coordination Relay 3 and Relay 2

CTI value between the main relay and backup relay remained higher than 0.2s, so that the primary relay and backup does not work at the same time. Time operation of each relay can be shown in table V.

TABLE V. SIMULATION RESULT OF LMBP MODEL APPLIED ON THE DOCR USING SOFTWARE ETAP

Bus location	Couple Relay		Generator, DG1, and DG2			Generator and DG2			Generator and DG1			Generator only		
	Relay	Relay	td (seconds)		CTI	td (seconds)		CTI	td (seconds)		CTI	td (seconds)		CTI
	Fault	Main	Backup	Main	Backup	(seconds)	Main	Backup	(seconds)	Main	Backup	(seconds)	Main	Backup
5	1	6	0.640	2.364	1.724	0.677	1.309	0.632	0.712	1.938	1.226	0.679	2.707	2.028
5	1	19	0.640	0.865	0.225	0.677	1.150	0.473	0.712	0.955	0.243	0.679	0.946	0.267
7	2	1	0.601	0.883	0.282	0.622	0.912	0.290	0.685	1.003	0.318	0.631	0.928	0.297
8	3	2	0.534	0.805	0.271	0.552	0.796	0.244	0.632	0.919	0.287	0.557	0.803	0.246
9	4	3	0.483	0.764	0.281	0.567	0.948	0.381	0.587	0.882	0.295	0.532	0.920	0.388
6	5	4	0.472	0.832	0.360	0.648	1.374	0.726	0.585	0.923	0.338	0.489	0.749	0.260
4	6	5	0.552	1.228	0.676	0.684	1.287	0.603	0.664	1.601	0.937	0.634	14.231	13.597
6	7	19	0.666	0.865	0.199	0.754	0.813	0.059	0.758	0.956	0.198	0.726	1.146	0.420
6	7	12	0.666	2.754	2.088	0.754	1.178	0.424	0.758	1.404	0.646	0.726	2.079	1.353
9	8	7	0.600	0.860	0.260	0.702	0.991	0.289	0.692	0.965	0.273	0.654	0.933	0.279
8	9	8	0.520	0.779	0.259	0.636	0.909	0.273	0.621	0.866	0.245	0.575	0.814	0.239
7	10	9	0.451	0.727	0.276	0.572	0.866	0.294	0.633	0.984	0.351	0.522	0.959	0.437
5	11	10	0.470	0.908	0.438	0.568	0.878	0.310	0.696	1.330	0.634	0.498	0.770	0.272
4	12	11	0.552	1.273	0.721	0.677	1.946	1.269	0.749	1.334	0.585	0.666	22.964	22.298

When combination of generation and current short circuit change and time operation relay must also change as well. From table V, all time operation of the main relay is under 1 second and CTI values are higher than 0.2 seconds (between main and backup relay) if fault happens on the bus internal loop. After testifying the results of ANN in Etap simulation, it can be seen briefly that Etap simulation interacted so well with the results of ANN.

IV. CONCLUSION

From the simulation results and analysis, DG in the distribution system has effect to the value current of short circuit in the system and makes relay settings change. The training process could reach the best performance in 15 iterations by using 60% for training, 20% for testing, and 20% for validating from 72 rows of input and output data. Plus, the Mean Squared Error (MSE) $1.8827e-005 = 1,8827 \times 10^{-5} = 0.01882\%$ is very small. The main relay operation time is under 1s and CTI Values $> 0.2s$ between main and backup relay, which are follow the constrain parameters in this study.

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