VOL. 10, NO. 22, DECEMBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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TIME–CURRENT CHARACTERISTIC CURVE PREDICTION FOR DIRECTIONAL OVERCURRENT RELAYS IN INTERCONNECTED NETWORK USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT
The desired accuracy level of the nonlinear time-current characteristic curve prediction of each overcurrent protective relay can best be obtained from the practical coordination scheme data, applied for the optimal prediction of the relay operation time, rather than empirical data application as mostly seen in most computational applied method for the neural network training and relay operation time prediction. This paper presents a global optimal determination of relay operational parameters settings for time dial setting (TDS) and plug setting (PS) as apply for the time-current characteristic curve prediction for each relay in a propose IEEE 9 bus test system for optimal determination of individual relay response time to fault within its protection zones. A propose hybrid genetic algorithm with artificial neural network (GA-ANN) technique is propose for the prediction of the time-current characteristic curve obtained from global accurate operational parameter settings of each relay to short circuit fault. The GA is applied for global optimal operational parameter determination for each relay by solving a modified objective function (MOF) equation for accurate training data extraction. These valid obtained operation parameters are supplied as training inputs data for the training of ANN to predict accurately the time-current characteristic for each relay. The level of obtained accuracy of the nonlinear time-current characteristic curves will predict accurately the operation time of each relay to different fault current level with minimum mean square errors (mse) obtained from the applied Levenber-Maequardt algorithm as compared with the obtained outputs from other two applied ANN nonlinear function fitting training algorithm.

Keywords: modify objective function, genetic algorithm, artificial neural network, time dial setting, plug setting.

INTRODUCTION
In order to isolate the damaging effect of short circuit overcurrent fault in power system transmission and distribution network, protective relay should respond quickly as possible to eliminate the damaging effect of the short circuit fault and also eradicate miscoordination among relay pairs at different location within the network [1]. DOCR is commonly use in power system protection scheme, due to its unique ability to trip short circuit overcurrent fault in unidirectional manner and its low procurement cost when compared with distance relay in transmission line system. The two basic operational parameter settings (TDS & PS) must be optimally selected to guarantee adequate and effective operation and coordination scheme [2]. These will ensure that the backup relay trips the same fault at minimal coordination time margin (CTM) in case the primary relay fails to achieve this purpose [3][4]. However, for mesh distribution network (MDN) protection coordination scheme, it is a highly constraints nonlinear optimization problem, difficult to solve by conventional coordination techniques[5][6]. The following factors are considered for effective protection coordination scheme; the selectivity and reliability qualities of the relay element, the discrimination of operation time between the primary and backup relay pairs, the objective function (OF) formulation, the optimization technique to be apply, the nature of network topology and the relay time-current characteristic curve formulation are the few requirement considered for effective protection coordination scheme achievement [7]. Furthermore, when the OF is linearly formulated, only one control variable (TDS) of the fitness function can be optimize as mostly applicable in earlier research work [8]. However, nonlinear OF formulation will allow the two operational control variables (TDS and PS) to be optimize simultaneously for actual determination of the nonlinear time-current characteristic curve for the relay operation time determination [9]. The TDS is directly proportional to the relay operation time response while the PS is inversely proportional to the same time, thereby increasing the optimization complexity for the nonlinear OF formulation and sound knowledge of programming is a requirement in this case [10].

The artificial intelligence (AI) application in relay coordination scheme under different AI algorithm application for optimal determination of the operational parameters settings for protective relay coordination schemes as proposed in several reviewed literatures. An improved GA in combination with linear programming (LP) method was earlier introduced for the robust coordination and determination of operational parameter settings for the DOCRs to mitigate against the miscoordination problems for both discrete and continuous TDS settings in MDN [11]. Another author proposed the particle swarm optimization algorithm (PSO) in variable topologies in solving the pending extremely constraints

VOL. 10, NO. 22, DECEMBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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coordination problem with changing topologies [12]. Also, an improved fitness equation was formulated as a mixed integer nonlinear programming problem (MINLP) by some authors in their publications [13] and [14] with the General Algebraic Modelling Software (GAMS) applied in solving the MINLP. However, all these proposed methods could only optimized operational parameter setting reduction but could not effectively address miscoordination elimination problem among selected protective relay pair due to external constraint violations and the complexity in the optimal determination of the relay operational parameters setting due to simultaneous optimization of both TDS and PS [15]. Hence, a MOF with embedded operation time difference among relay pairs within the function fitting equation is proposed for the elimination of the pending miscoordination problems among relay pair due to external coordination constraint violations from earlier applied techniques as seen in [16]. The GA was applied in solving a new proposed MOF to determine the global optimal values of each relay operational parameter settings and elimination of the pending miscoordination problems among relay pairs as seen also in [17].

This paper proposes a novel hybrid GA-ANN approach to determine the Time–Current characteristics curve for the prediction of the actual optimal operation time for each protective relay for different station buses by using the valid experimental result output from the GA solution of the MOF, which addresses the global optimal parameter settings determination and miscoordination elimination among relay pair as the input training data to the ANN. A propose IEEE 9 bus Test system will be model and simulated in DigSilent Power Factory software and subjected to power load-flow and short circuit fault analysis.

PROBLEM FORMULATION

The relay coordination OF is formulated as the minimization of the total weight sum of the operation time for all primary relays for short circuit fault within their respective protection zones coverage [18]. Mathematically expressed as:

$$(OF): \ \mathrm{MinZ} = \sum_{i=1}^{M} \mathrm{W} \times t_{i,j} \tag{1}$$

Three main linear inequality bound constraints must be satisfied for miscoordination elimination for the formulated OF in Equation. (1), two of these constraints are based on the operation parameter settings of the relay while the third attends to the coordination constraints between the primary and back up relay pair's selection. The first operational constraint is on the parameter boundary restriction settings for TDS and PS. While the second constraints bound is on the acceptable operation time range for each relay operation to fault within its primary protection zone without much time delay. These bound constraints are illustrated in equation Equation. (2), Equation. (3) and Equation. (4) respectively. The third, is the coordination constraints between primary and backup relay pair selection with appropriate coordination time margin (CTM) of selection in Equation. (5) which enables backup relay trip faults always with minimal CTM in case the primary relay fail to isolate same fault.

$$\mathrm{TDS}_{min} \le \mathrm{TDS} \le \mathrm{TDS}_{max} \tag{2}$$

$$\mathrm{PS}_{max} \le \mathrm{PS} \le \mathrm{PS}_{min} \tag{3}$$

$$t_{min} \le t \le t_{max} \tag{4}$$

$$t_{bk,j} \ge t_{pr,j} + \mathrm{CTM} \tag{5}$$

Where,
t_{min} minimum operation time of the relay
t_{max} maximum operation time of the relay
CTM coordination time margin between relay pair

The operation time of a protective relay is mathematically expressed in Equation. (6), with several constant illustrated on Table-1. The operation time of protective relay is a function of nonlinear characteristic curve selection with stated constants. These constants determine the shape and steepness of the curve as shown on Table1.The standard inverse IEC characteristics is selected for this research study stated as applied in Equation. [6] where, β = 0.14, α = 0.02, L= 0.

$$t = \frac{(\beta \times \mathrm{TDS})}{[(\mathrm{PSM})^{\alpha} - 1]} + L \tag{6}$$

Table-1. IEC inverse time curve characteristic constant.

Curve description	Standard	α	β	L
Standard inverse	IEC	0.02	0.14	0
Very inverse	IEC	1.0	13.5	0
Extremely inverse	IEC	2.0	80.0	0
Long-time inverse	UK	1.0	120	0

Where, PSM is the plug setting multiplier

$$\mathrm{PSM} = \frac{I_{\text{short circuit}}}{I_{\text{pickup}}} \tag{7}$$

Substituting Equation (6) in (1) lead to conventional OF

$$(OF): \ \mathrm{MinZ} = \sum_{i=1}^{M} [\, K \times (\mathrm{TDS})] \tag{8}$$

Where;

$$K = \frac{0.14}{[(\mathrm{PSM})^{0.02} - 1]} \tag{9}$$

Solving OF in Equation. (8) with linear programming (LP) optimization technique will produce a solution that is trapped in a local minimum and with miscoordination among primary and backup relay pair still pending, due to some constraint violation. When such solution obtained is applied for the training of the ANN, then a wrong predictor will be produce. Furthermore, to avoid this problem, modification of this fitness equation will eliminate constraints violations leading to an

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improved protection coordination scheme and global optimal parameter setting with miscoordination elimination as shown in Equation. (10) and Equation. (11) as published in [16].

$$MOF : \min(Z) = w_1 \times \sum_{i=1}^{M} (t_i)^2 + w_2 \times \sum_{j=1}^{P} [\Delta t_{pr,bk} - \gamma(\Delta t_{pr,bk} - |\Delta t_{pr,bk}|)] \quad (10)$$

Where,

$$\Delta t_{pr,bk} = \Delta t_{bk} - \Delta t_{bk} - CTM \quad (11)$$

i	Each relay number from 1 to M
P	Number of primary and backup relay pairs
$\Delta t_{pr,bk}$	Operation time difference for each relay pair.
M	Total number of relays
t_i	Operation time for i^{th} relays
t_{pr}	Primary relay operation time
t_{br}	Backup relay operation time
CTM	coordination time margin, taken as 0.3s
w_1	Weighting control of $\sum_{i=1}^{M}(t_i)^2$
w_2	Weighting control $\sum_{j=1}^{P}(\Delta t_{pr,bk} - \gamma(\Delta t_{pr,bk} - \lvert\Delta t_{pr,bk}\rvert))^2$
γ	Added constant factor to handle miscoordination.

IEEE 9 BUS TEST SYSTEM

Considering the modelling and simulation of a 33KV distribution system in Figure-1 for propose IEEE 9 Bus Test system, with three electrical distribution generators (DG) power supply sources. Individual current measurement at each relay location and relay pair selection for effective coordination scheme is displayed on Table-2 for several faults simulated location (A-F) on all primary relay protection zones. The electrical power-load flow and short circuit fault analysis execution on the test model for fault at different location from A-F in sequence within the individual relay primary protection zone for different operational mode; as either the primary or backup protection element. Moreover, the extracted data from these simulation results are applied in global optimal determination of the relay operational parameter settings by the application of GA optimization method. This will produce a global optimal solution of the MOF of Equation. (10).

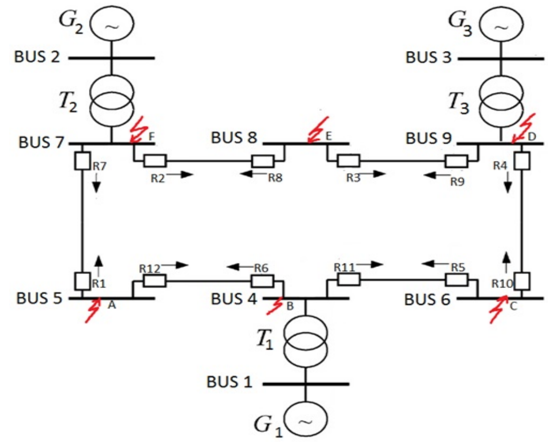

Figure-1. Single line diagram for IEEE 9 bus test system.

Table-2. Relay pairs selection and current readings.

Fault Location	Primary relay	Backup Relay	Primary current (A)	Backup current (A)
Bus 5 (A)	R6	R5	3048	1075
	R7	R8	3427	1238
Bus 4 (B)	R5	R4	2508	2577
	R12	R7	2050	2110
Bus 6 (C)	R4	R3	3736	732
	R11	R12	3129	1030
Bus 9 (D)	R3	R2	2007	2035
	R10	R11	1931	1990
Bus 8 (E)	R2	R1	3344	1022
	R9	R10	3525	543
Bus 7 (F)	R1	R6	1961	2007
	R8	R9	3525	2509

METHODOLOGY

Ga application on MOF

Solving relay protection coordination optimization problem with GA evolutionary computational method involves the searching through of a decision space from set of feasible and non-feasible solution with the aim of convergence to a global optimal solution of the relay operational parameters, through a fitness evaluation process [19]. The solution is achieved by penalizing any obtained fitness value that violates the coordination constraints between primary and backup relay pair selection as expressed in Eqn. (11), which enhances a feasible solution from the decision region. But if the problem do not have any feasible solution in the search space, the GA will then select the solution with minimum or less violation as the case maybe. GA select individual with better fitness values as parents and uses the current population to create the new offspring for the next generation at every stage. This is applied in solving both constraint and unconstraint global optimization problem by adapting three main rules at each stage to create the next generation from the current populations as seen in [20]. The three applied rules are selection, crossover and

VOL. 10, NO. 22, DECEMBER 2015 ISSN 1819-6608
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mutation rules. Figure-2 gives a flow chart on the research procedures adopted in relay operational parameter determination with GA solution of the MOF in this work.

Considering the MOF fitness equation in Equation. (10) having the relay pair operational time difference ( ) as positive value, which is an indication of proper coordination between primary and backup relay pair, hence, the second part of the MOF in Equation. (10) becomes;

$$\sum_{i=1}^{P}[\Delta t_{pr,bk} - \gamma(\Delta t_{pr,bk} - |\Delta t_{pr,bk}|)]^2 = \Delta t_{pr,bk}$$

But, when is negative value, an indication of miscoordination between primary and backup relay pair. Then the second part of the same equation then becomes;

$$\sum_{i=1}^{P}[\Delta t_{pr,bk} - \gamma(\Delta t_{pr,bk} - |\Delta t_{pr,bk}|)]^2 = (2\gamma-1)(\Delta t_{pr,bk})$$

This condition is not needed for effective coordination scheme to take place and should be eliminated within any protection coordination scheme and this pending problem will be eliminated by GA application in solving the MOF to determine a valid coordination parameter setting which could be used as a valid experimental data for the training of the ANN for accurate time-current characteristic prediction and operation time determination for each relay within the network as shown in Figure-1.

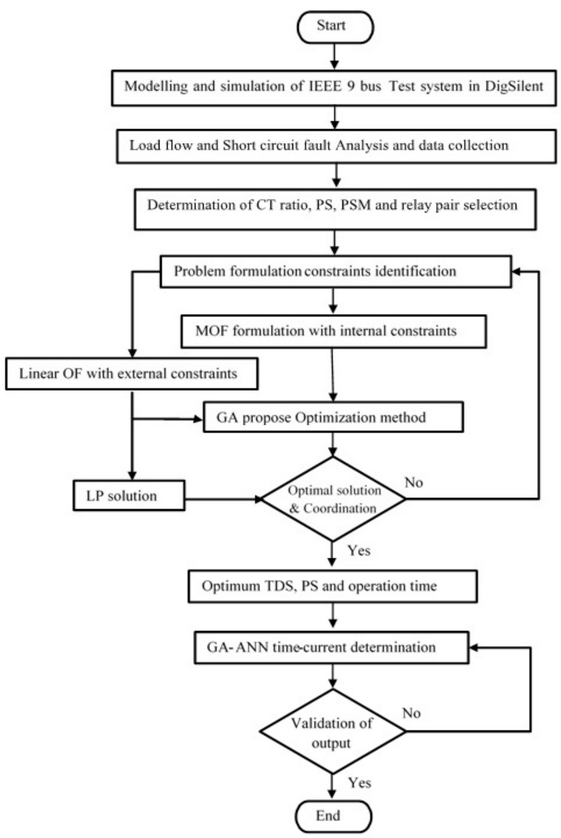

Figure-2. Research procedure flow chart.

GA-ANN time-current characteristic prediction

A hybrid GA-ANN is propose to predict the nonlinear Time-Characteristic curve used for the determination of the optimal operation time for individual relay. The obtained global operational parameters from the GA solution of the MOF as displayed in Table-3 are applied in the training of the supervised ANN model with TDS and PSM as the training input data and the obtained relay operation time as target data for the supervised learning of ANN model as shown in Figure-3. The total available data for each relay is divided into three main parts; the training, validation and test data. An effectively trained network will solve the nonlinear function fitting time-current characteristics curve prediction and optimal operation time determination at different short circuit current. Hence, several training algorithm are propose for the nonlinear function fitting training of the model. Hence, the error margin between the actual output and expected output of the trained network with reference to the convergence time will be observed during the supervised training of the network model for best algorithm selection with least square error (***mse)***.

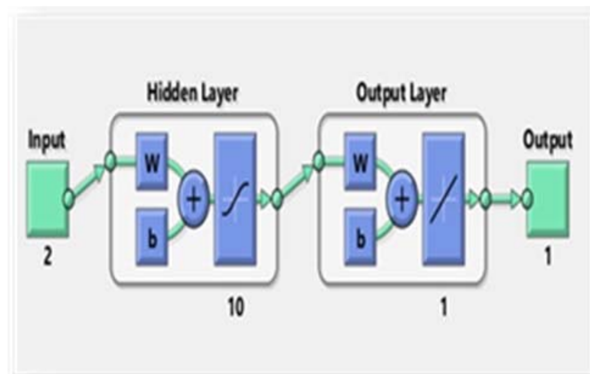

Figure-3. GA-ANN model network.

RESULT AND DISCUSSIONS

Table-3 displayed the obtained values for the calculated current transformer ratio (CT), the plug setting multiplier (PSM) and obtained TDS from the applied GA optimization technique. Several number of ANN training algorithm applied for the training and nonlinear curve fitting prediction of each relay operation time-current characteristic curve with least mean square error (***mse)*** between actual obtained output and the target operation time of trained GA-ANN model as displayed on Table-4 and Table-5. The Levenber-Maequardt algorithm is adopted for GA-ANN training to produce the best training fitting with least mean square error (mse) with the result displayed on Table-4 for the nonlinear function fitting algorithm of the modelled ANN. However, Table-5 displayed the validation result obtained from scaled conjugate gradient and Bayesian regularization training algorithm has been less effective and time consuming in the training of the ANN with higher number of iterative process and higher values of ***mse*** when compared to that

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obtained from the proposed Levenber-Maequardt algorithm.

Samples of fitting plot from Levenber-Maequardt algorithm is displayed on Figure-4 to Figure-7 which indicate the effective correlation between the training, validation and test sampled data as seen in the predicted time-current characteristic curve for five DOCR sampled relays after training of the ANN module.

Table-3. GA global optimal training parameter settings.

Relay	I_{sc}	CT ratio	PSM	TDS	Time
R1	1961	300:5	5.45	0.15	0.6088
R2	3344	200:5	20.90	0.30	0.6701
R3	2007	150:5	16.73	0.20	0.4831
R4	3736	400:5	9.34	0.15	0.4595
R5	2508	200:5	10.45	0.10	0.2914
R6	3048	200:5	19.05	0.05	0.1153
R7	3427	300:5	9.52	0.25	0.7592
R8	2485	200:5	16.57	0.25	0.6518
R9	3525	200:5	29.38	0.25	0.5313
R10	1931	400:5	4.83	0.10	0.4375
R11	3129	200:5	13.04	0.20	0.4032
R12	2050	150:5	13.67	0.30	0.7272

Table-4. Levenber-Maequardt algorithm training result.

Relay no	Target time	GA-ANN time	Mean square error (*mse*)	Epoch
R1	0.6088	0.6069	$4.5351x10^{-6}$	3
R2	0.6701	0.6799	$2.2932x10^{-4}$	2
R3	0.4831	0.4847	$5.332x10^{-5}$	5
R4	0.4595	0.4575	$2.4494x10^{-5}$	2
R5	0.2914	0.2960	$3.6520x10^{-5}$	3
R6	0.1153	0.1150	$1.5498x10^{-6}$	3
R7	0.7592	0.7521	$5.5761x10^{-3}$	2
R8	0.6518	0.65058	$1.7115x10^{-5}$	3
R9	0.5313	0.50133	$4.6788x10^{-5}$	2
R10	0.4375	0.4358	$1.4691x10^{-5}$	5
R11	0.4032	0.5327	$3.6799x10^{-4}$	2
R12	0.7272	0.7872	$3.6799x10^{-4}$	2

Table-5. ANN function fitting training algorithm.

Relay no	Scaled conjugate gradient (*mse*)	Bayesian regularization
R1	$3.7778x10^{-4}$	$6.2264x10^{-6}$ at 368 epoch
R2	$4.3426x10^{-5}$	$7.1258x10^{-11}$ at 149 epoch
R3	$4.6880x10^{-4}$	$1.3415x10^{-13}$ at 229 epoch
R4	$6.0847x10^{-5}$	$6.1769x10^{-12}$ at 77 epoch
R5	$1.1068x10^{-4}$	$2.3794x10^{-11}$ at 48 epoch
R6	$4.8930x10^{-6}$	$1.7231x10^{-11}$ at 65 epoch
R7	$1.0142x10^{-2}$	$7.2696x10^{-11}$ at 63 epoch
R8	$2.9025x10^{-5}$	$1.1272x10^{-11}$ at 212 epoch
R9	$1.202x10^{-3}$	$9.2882x10^{-14}$ at 224 epoch
R10	$3.3577x10^{-4}$	$7.0157x10^{-10}$ at 60 epoch
R11	$7.73078x10^{-3}$	$1.1557x10^{-13}$ at 156 epoch
R12	$1.2739x10^{-3}$	$1.5413x10^{-13}$ at 173 epoch

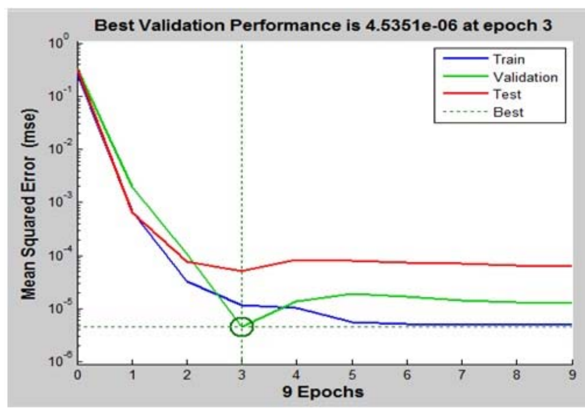

Figure-4. Relay R1 time current curve.

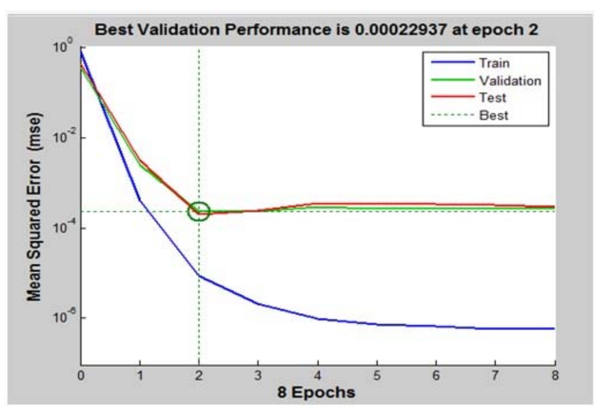

Figure-5. relay R2 time current curve.

VOL. 10, NO. 22, DECEMBER 2015 ISSN 1819-6608
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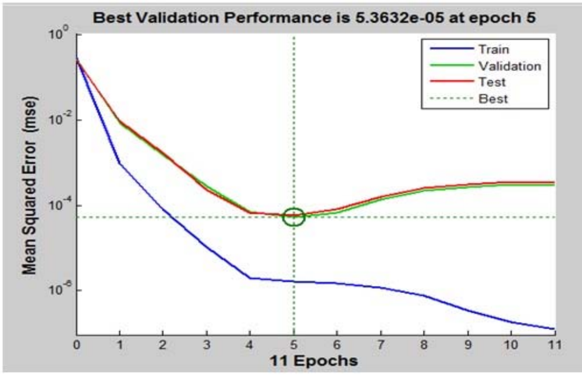

Figure-6. Relay R3 time current curve.

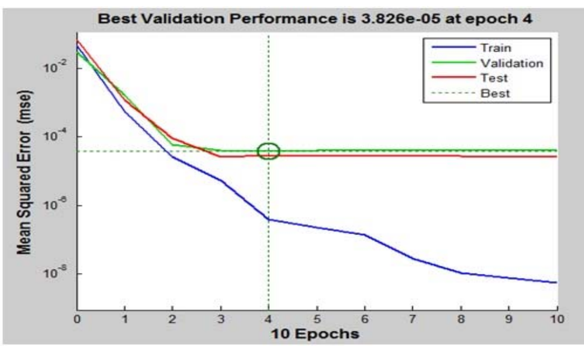

Figure-7. Relay R4 time current curve.

CONCLUSIONS

The Levenber-Maequardt algorithm produces the best prediction of time-current characteristic of all relay with least ***mse*** as displayed on Table-5. This algorithm produced the fastest convergence rate with minimum error. The outcome model could effectively predict the operation time of each relay at different short circuit current to effectively clear the fault at least minimal time without delay.

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