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Neural Network based Modeling and Simulation of Transformer Inrush Current

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***Abstract*—**Inrush current is a very important phenomenon which occurs during energization of transformer at no load due to temporary over fluxing. It depends on several factors like magnetization curve, resistant and inductance of primary winding, supply frequency, switching angle of circuit breaker etc. Magnetizing characteristics of core represents nonlinearity which requires improved nonlinearity solving technique to know the practical behavior of inrush current. Since several techniques still working on modeling of transformer inrush current but neural network ensures exact modeling with experimental data. Therefore, the objective of this study was to develop an Artificial Neural Network (ANN) model based on data of switching angle and remanent flux for predicting peak of inrush current. Back Propagation with Levenberg-Marquardt (LM) algorithm was used to train the ANN architecture and same was tested for the various data sets. This research work demonstrates that the developed ANN model exhibits good performance in prediction of inrush current's peak with an average of percentage error of -0.00168 and for modeling of inrush current with an average of percentage error of -0.52913.

***Index Terms*—**Inrush Current, ANN, switching angle, Remanent flux, Modeling, Simulation, Transformer.

I. INTRODUCTION

Inrush current is very important issue for transformer designer. It effects on relay coordination because of ten to twenty times (even more) of rated current during transient period. These abnormal behaviors of inrush current causes relay to operate. Second harmonic based relay discriminate this abnormality in power system [1].Transient period of current (exponential decay) depends on circuit time constant. Transformer is R-L circuit with time constant of L to R. Resistance is very small for large rating of transformer, causes large transient period but it is relatively higher for small rating of transformer and also causes fast decay action in inrush current. Intensity of the inrush current depends on the instance of the sinusoidal voltage in which it is switched on as well as on characteristics of the ferromagnetic core such as its residual magnetism and its magnetization curve [2]. Magnetizing characteristic of core explained by ANN model [8-9]. Peak inrush current of nonlinear inductor in series with resistor is calculated by analytic formula [3]. Jameli [5] showed transformer inrush current with different operating conditions. Ali [10] showed analytic computation of inrush current using FEM modeling. Various protective systems for transformers, based on the differential relaying system were developed in recent years [4]. Various techniques based on complex circuits or microcomputers are proposed to distinguish inrush current from fault current. However, the transformer still must bear with large electromagnetic stress impact caused by the inrush current.

In this paper, first transformer equation is presented which was used for calculation of Inrush current. Then a single-phase transformer was simulated in MATLAB. Simulation was performed to obtain various data sets. These data sets were then utilized to develop two neural networks (ANN). One network was used for inrush current modeling and second network for modeling of inrush current's peak.

II. INRUSH CURRENT

Equivalent circuit of single phase transformer [2] during no load condition is shown in figure 1.

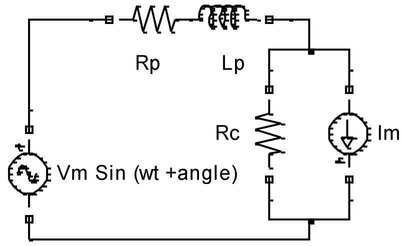

Figure 1: Equivalent circuit of Single phase transformer

Inrush Current can be determined by following equations.

$$Vm\ Sin(\omega t+\theta) = (r_p . i) + (L_p \frac{di}{dt}) + \frac{d\lambda}{dt} \quad (1)$$

$$i = \left(\frac{1}{r_c}\frac{d\lambda}{dt}\right) + i_m \tag{2}$$

$$i_m = \alpha\, Sinh(\beta\lambda) \tag{3}$$

Where r_P, L_P and r_c represents primary winding resistance, primary winding inductance, and core losses resistance respectively. i_m (eq^n 3) is magnetizing current.

A. Data collection

Data sets were collected using semi-analytic solution with the help of MATLAB programming. These sets including different values of inrush current at particular remanent flux, magnetizing current, time and switching angle. One data set was prepared for inrush current value based on different value of remanent flux, magnetizing current, and time but at constant switching angle. Second data set was prepared for inrush current's peak value based on different switching angle and ramanent flux.

III. CASE STUDY

This study was carried on 120-VA, 60-Hz, (220/120) V transformer [2] and inrush current obtained from equations (1) and (2) using a discrete time, with 83.333µs. The equivalent circuit of this transformer is shown in Figure 1and its parameters (220-V winding) are r_P = 15.476Ω; L_P = 12 mH; r_c =7260Ω. For the transformer magnetization curve, as given in equation (3), the following parameters determined experimentally were used: α = 63.084mA; β = $2.43Wb^{-1}$.

IV. NEURAL NETWORK

Neural Network consists of three layers namely input layer, hidden (Processing) layer(s), output layer. Input data fed to network through input layer, after that processing takes place. Output value comes out at output layer which will compare with target value to find out error. Back propagation with LM algorithm is used to minimize this error or reducing tolerance range. Neural Network has beauty to give accurate value depends on input value after well training of network [6,7].The flow chart of modeling of inrush current is accomplished by ANN network is shown in figure 2.Since these data have their own ranges, therefore the data has been normalized at same scale in between 0.1 to 0.9 for well training. Trained Network represents modeling of inrush current. After training, output of network gives normalized values which will convert back to their original values to ensure practical values of inrush current.

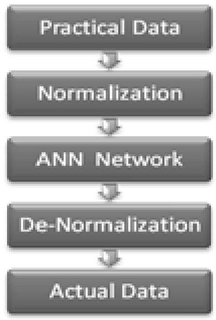

Figure 2: Flow chart of ANN Modeling

A. ANN Model for Modeling of Inrush current

ANN1 structure shown in figure 3 consists of three neurons at input layer (i_m, λ_n & t_n), six and three successive neurons in hidden layers 1 and 2, and one output neuron at output layer (i_{inrush}).

Mathematically, it can be defined by equation 4.

$$i_{inrush} = f_{ANN1}\,(t_n\,,\,\lambda_n, i_m,) \tag{4}$$

Where, n = number of iteration,
t_n= time,
i_m = Magnetizing current and
λ_n = flux linkage.= N. flux

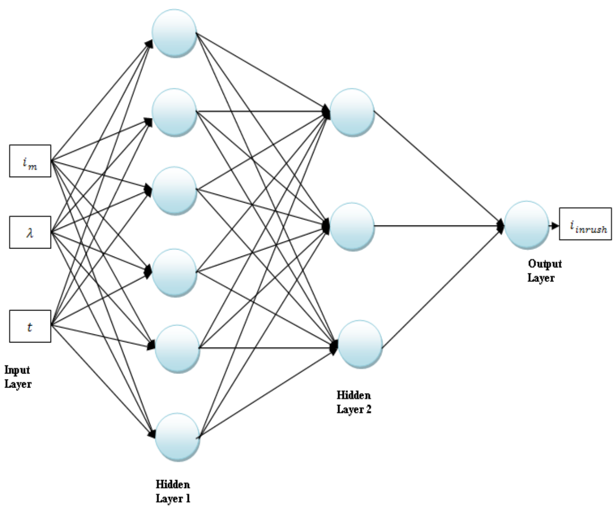

Figure 3: ANN1 Structure (3-6-3-1) for Inrush current Modeling

f_{ANN1} is ANN Structure (3-6-3-1) for inrush current Modeling. Data sets (i_m, λ_n & t_n) were used to train ANN1 so that it able to predict inrush current value based on magnetizing current, flux linkage, and time.

B. ANN model for modeling of inrush current's peak

ANN2 structure shown in figure 4 consists of two neurons at input layer (θ_n , Br_n), eight and six successive neurons in hidden layers 1 and 2, and one output neuron at output layer ($i_{peak,}$).

Mathematically, it can be defined by equation 5.

$$i_{peak,n} = f_{ANN2}\,(\theta_n\,, Br_n) \tag{5}$$

Where n = number of iteration,
θ = Switching angle, and
Br = remanent flux.

f_{ANN2} is ANN Structure (2-8-6-1) for modeling of inrush current's Peak. Data sets (θ_n , Br_n) were used to train ANN2 so that it able to predict inrush current's peak based on switching angle and remanent flux.

Switching angle is that angle at which transformer gets energized. Switching angle was considered in between 0^o to 180^o.

Remanent flux is that flux which remains in core from switch off to next switch on. As stage of switch on comes, remanent flux will add with flux wave which leads to saturation region of magnetization curve because of adding flux i.e. approximate double of flux which becomes more than maximum flux density of core material. Therefore switching angle and remanent flux plays important role in transformer inrush current.

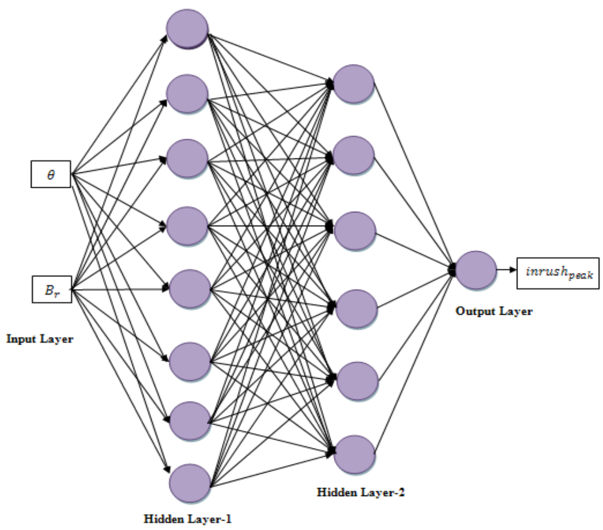

Figure 4: ANN2 structure (2-8-6-1) for modeling of inrush current's peak

V. RESULTS AND DISCUSSION

A. ANN1 Model for Modeling of Inrush current

Inrush current data was obtained using semi analytic solution with assuming maximum initial flux-linkage value 0.826-Wb coil, and the excitation angle corresponds to θ = 0^o. To know accuracy of ANN1 Model, Output data of ANN1 was compared with data which was used to train ANN1 as shown in figures 5 and 6.

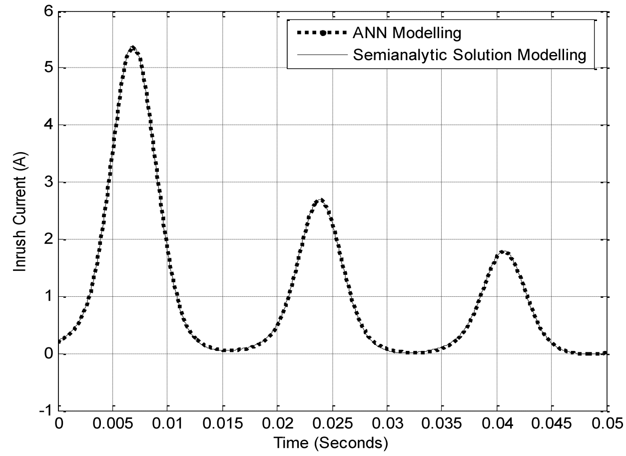

Figure 5: Inrush current with ANN1 Modeling (points) and semi analytic Solution (Line)

Different weights associate with f_{ANN1} is described here:

a) Weights between Input layer to Hidden Layer-1

$W_{i\text{-}h1}$	Input Layer (Neurons)		
Hidden layer1	1.0847	-5.0678	3.5285
	-3.4451	-4.2004	1.1627
	-11.095	-3.3678	-0.42559
	-0.1392	-1.2362	0.0018401
	10.316	-1.4722	-2.9265
	-27.369	-3.2762	8.1826

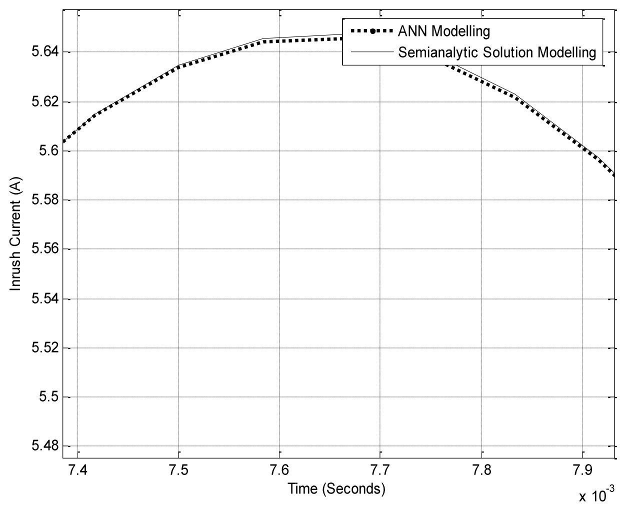

Figure 6: Zooming of first cycle of Inrush current shows difference in ANN1 modeling and semi analytic solution modeling

b) Weights between Hidden Layer1 to Hidden Layer2

	$W_{h1\text{-}h2}$		Hidden Layer1 (Neurons)			
Hidden layer2	0.11459	2.3128	0.07225	2.0329	0.08479	0.21367
	0.11139	1.3542	0.10149	-3.030	-1.4033	0.16277
	0.34714	7.9291	28.492	5.0615	-7.3575	-40.717

c) Weight between Hidden layer-2 to output layer

$W_{h2\text{-}o}$	Input Layer (Neurons)		
Output Neuron	-9.8719	7.2919	2.219

d) Bias Values of hidden layer1

Hidden Layer1 (Neurons)					
-1.8686	5.1622	6.3852	-1.3332	1.78	0.22031

e) Bias Values of hidden layer2

Hidden Layer2 (Neurons)		
1.3763	-0.96866	-5.7563

f) Bias Values of Output Layer

Output Layer (Neurons)	0.41341

Performance during training of ANN1 with respect to number of epochs is shown by figure 7.

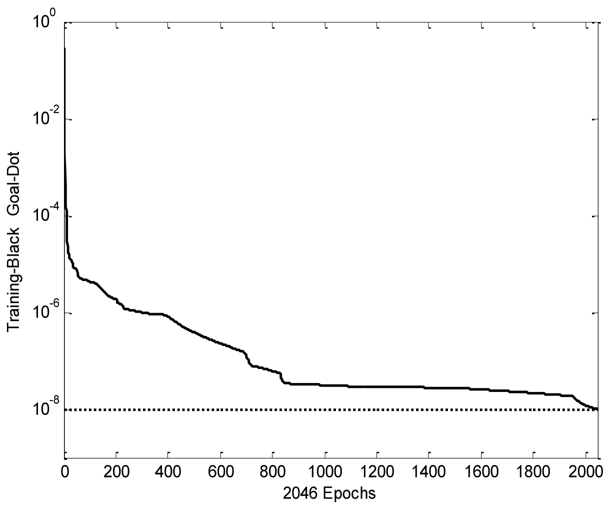

Figure 7: Performance with epochs during training of ANN1 Modeling for inrush current

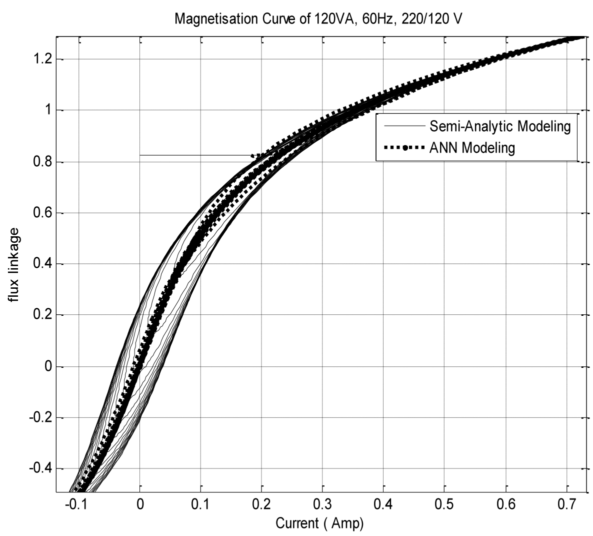

Figure 8: Magnetization curve with ANN1 Modeling (dotted)

Magnetization characteristic is shown in figure 8 using data obtained from semi analytic solution and ANN1. Some part of data for comparison is shown in table-1

Table-1 Comparison of inrush current using semi-analytic and ANN1

S.No	Time	i_m	Flux	semi-analytic i_{inrush}	ANN1 i_{inrush}	% Error
1	0.0007	0.2454	0.8509	0.25289	0.2515	-0.5526
2	0.0015	0.3084	0.9425	0.3208	0.3212	0.13072
3	0.005	2.5786	1.8123	2.4908	2.4903	-0.0200
4	0.01	2.9514	1.8678	3.0465	3.0461	-0.0131
5	0.02	0.2792	0.9026	0.30319	0.3036	0.16464
6	0.03	0.1627	0.6899	0.13254	0.1320	-0.3482
7	0.04	1.3891	1.5579	1.3673	1.3667	-0.0439
8	0.05	-0.003	-0.025	-0.0039	-0.002	-36.632

B. ANN2 model for modeling of inrush current's peak

1) Effect of switching angle

It was observed that switching angle plays a very important role in peak of inrush current as well as time to settle down to no load current value. With zero degree switching, inrush current has highest peak relatively to other switching angles as shown in figure 9. According to this figure 9, highest peak appear with lowest switching angle as well as takes longer time to settle down at no load current value and lowest peak appear with higher switching angle as well as takes lesser time to settle down to no load values. In other words, peak of inrush current and settling time to no load current value, behaves as inversely proportional to switching angle.

Wave form of inrush current with different switching angle is shown in figure 9 and 10 at constant remanent flux i.e. 0.824 Wb. To understand clearly effect of switching angle on peak of inrush current and settling time to no load value is shown by figure 10.

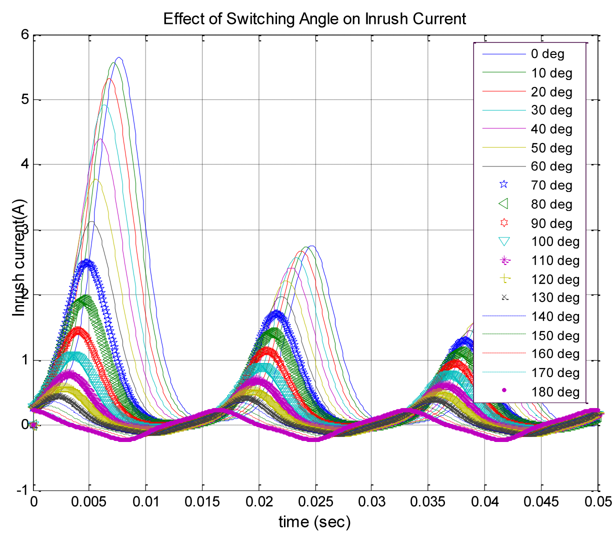

Figure 9: Effects of different switching angle on inrush current with time

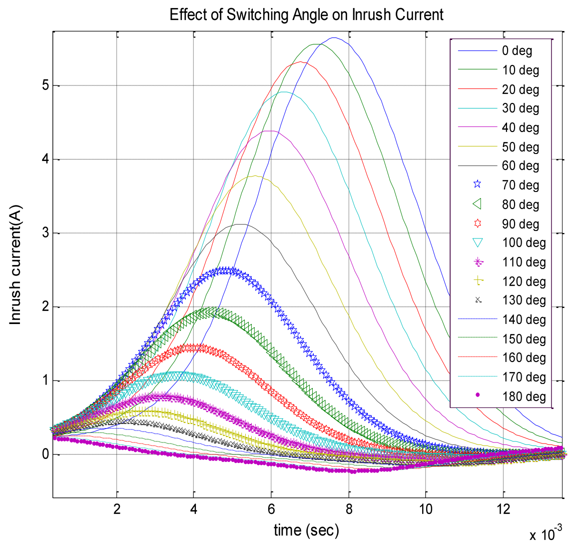

Figure 10: Zooming of first cycle with different switching angle of Inrush current with time

2) *Effect of Remanent Flux*

It was observed that Peak of inrush current is highest with high value of remanent flux & low value of remanent flux, and lowest with low value of remanent flux & high value of switching angle. In other words inrush current is directly proportional to the remanent flux but inversely proportional to switching angle as shown in figure 11.

Different weights associate with f_{ANN2} describes here:

g) Weights between Input layer to Hidden Layer-1

W_{i-h1}	Input Layer (2 Neurons)	
Hidden layer1(6 Neurons)	-3.8413	4.4941
	1.2163	-3.13
	1.8156	2.3123
	-2.1326	-4.6827
	-0.1166	26.895
	2.3082	4.199
	-0.31717	-1.0443
	3.9155	-6.2348

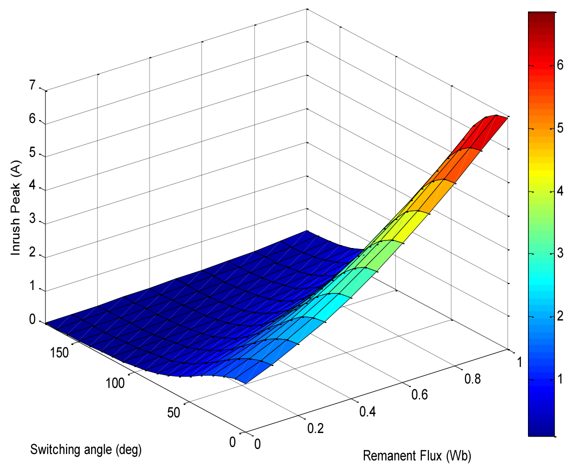

Figure 11: Effect of switching angle and remanent flux on peak of inrush current using semi-analytic solution approach.

h) Weights between Hidden Layer1 to Hidden Layer2

W_{h1-h2}	Hidden Layer1 (8 Neurons)							
Hidden layer2(6 Neurons)	0.61764	-0.4576	-0.086948	0.42496	-3.1017	-0.070111	-0.12957	0.51975
	0.048481	0.27697	0.14596	-1.3778	-0.4096	-1.1544	-1.0095	0.03801
	-2.2209	-0.3394	-4.0604	1.8096	-0.7601	1.3136	3.7157	0.16371
	0.66777	0.1803	0.74212	-2.10	3.4334	-1.0767	0.085525	-0.7761
	-1.554	0.50925	0.068421	-1.68	-0.3040	-1.4767	0.087242	0.06080
	-1.007	0.11706	-0.10481	0.46918	0.19474	0.34583	0.5819	-0.0078

i) Weight between Hidden layer-2 to output layer

W_{h2-o}	Hidden Layer2 (6 Neurons)					
Output Neuron	-4.092	4.9867	0.6031	-3.499	-2.510	3.138

j) Bias Values of hidden layer1

Hidden Layer1 (8 Neurons)							
3.9033	-0.110	-4.12	2.299	-16.14	-2.18	-0.34	4.630

k) Bias Values of hidden layer2

Hidden Layer2 (Neurons)					
-3.0764	-1.3229	-0.09180	2.0957	1.1932	1.3745

l) Bias Values of Output Layer

Output Layer (Neurons)	2.142

To know accuracy of ANN2 Model, Output data of ANN2 was compared with data which was used to train ANN2 as shown in figure 13.

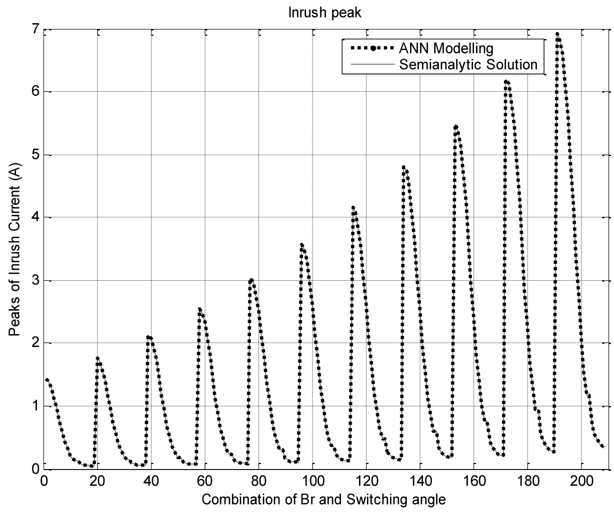

Figure 13: ANN2 Modeling of inrush current's peak

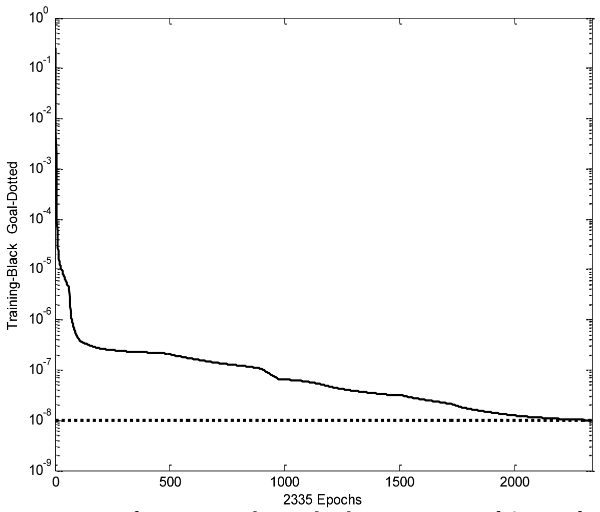

Figure 14: Performance with epochs during training of ANN2 for Inrush current's peak modeling

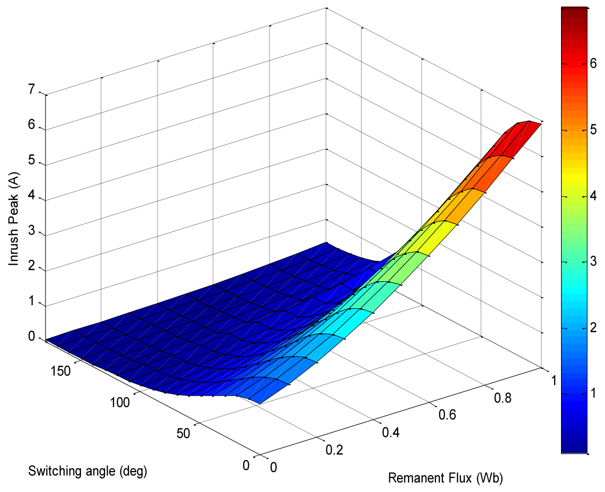

Figure 15: Effect of switching angle and remanent flux on peak of inrush current using ANN2.

Performance during training of ANN2 with number of epochs is shown in figure 14. Surface of ANN2 based inrush current's peak is shown in figure 15. Some part of data is shown in table-2.

Table2. Comparison of Inrush current's peak prediction using Semi-Analytic and ANN2

S.No.	Br	Switching angle	Semi-Analytic Peak of Inrush Current	ANN2 Based Peak of Inrush	Percentage Error
1	0	0	1.4375	1.4381	-0.04174
2	0	90	0.22458	0.2262	-0.72135
3	0	180	0.049339	0.050723	-2.80508
4	0.1	0	1.7554	1.7554	0
5	0.1	90	0.28484	0.28589	-0.36863
6	0.1	180	0.059083	0.059928	-1.43019
7	0.2	0	2.1266	2.127	-0.01881
8	0.2	90	0.36101	0.36142	-0.11357
9	0.2	180	0.07082	0.071761	-1.32872
10	0.3	0	2.5535	2.5543	-0.03133
11	0.3	90	0.45616	0.45652	-0.07892
12	0.3	180	0.085016	0.086269	-1.47384
13	0.4	0	3.0374	3.0378	-0.01317
14	0.4	90	0.57431	0.57523	-0.16019
15	0.4	180	0.10228	0.10356	-1.25147
16	0.5	0	3.5764	3.5765	-0.0028
17	0.5	90	0.72026	0.72165	-0.19299
18	0.5	180	0.12334	0.12406	-0.58375
19	0.6	0	4.167	4.1673	-0.0072
20	0.6	90	0.89931	0.90051	-0.13344
21	0.6	180	0.14903	0.14878	0.167751
22	0.7	0	4.8041	4.8043	-0.00416
23	0.7	90	1.1171	1.1177	-0.05371
24	0.7	180	0.18035	0.17978	0.316052
25	0.8	0	5.4806	5.4803	0.005474
26	0.8	90	1.3798	1.3798	0
27	0.8	180	0.21817	0.22033	-0.99005
28	0.9	0	6.1879	6.1892	-0.02101
29	0.9	90	1.6929	1.6931	-0.01181
30	0.9	180	0.27554	0.27528	0.09436
31	1	0	6.917	6.9168	0.002891
32	1	90	2.0612	2.062	-0.03881
33	1	180	0.35343	0.35282	0.172594

VI. CONCLUSION

From the results it is observed that Peak of inrush current and settling time to no load current value is inversely proportional to the switching angle but directly proportional to remanent flux. ANN Model has beauty to train network with data of non-linearity which gives almost exact matching with target values. Therefore ANN1 model gives inrush current value with an average of percentage error of -0.52913 and ANN2 able to predict inrush current's peak based on remanent flux and switching angle with an average percentage error of -0.00168, which is inacceptable limit. Results of the study suggest thatLM training is faster than the general delta rule and it needs less input pattern to training than the other one.

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