Analysis of Total Harmonic Distortion and implementation of Inverter Fault Diagnosis using Artificial Neural Network

T G Manjunath¹, A C Vikramathithan¹, H Girish²

¹ Associate Professor, Sai Vidya Institute of Technology, Bangalore.
² Associate Professor, Cambridge Institute of Technology, Bangalore

Email: tgmnath@gmail.com

Abstract. As power electronics devices dependability is very significant to guarantee Multi Level Inverter (MLI) systems stable functioning, it is imperative to identify and position faults as promptly as possible. Due to the fault occurrences, the Total Harmonic Distortion (THD) on the system gets a hit. In this perspective, to improve fault diagnosis accuracy and efficient working of a Cascaded Multi level Inverter System (CHMLIS), a quick and accurate fault diagnosis strategy with an optimized training algorithm using Artificial Neural Network (ANN) is presented. Also, Total Harmonic Distortion (THD) is analyzed for each switch Fault simulated using MATLAB/Simulink and the results are presented. Results show the efficacy of Algorithm in identifying the fault. The auxiliary cell is replaced while the fault occurs in the main cell thus making the uninterrupted working of the Multi-Level Inverter (MLI) in the Induction Motor Drive (IMD).

1. Introduction

The multilevel inverters have turn out to be prevalent in cutting-edge machineries for high-power and medium voltage applications. As power electronics devices dependability is very significant to guarantee Multi Level Inverter (MLI) systems stable functioning, it is imperative to identify and position faults as promptly as possible.

Different Engineering and non-Engineering fields apply ANN for approaches that involve classification using multi-perceptron models [1-4]. Although intrinsic behavior of the back propagation network is advantageous with, inbuilt forecasting dynamism, tolerance to data error and independent of any external data for convergence, it pronounces some disadvantages. The convergence of training in this gradient descent-based method is slow and has more chances of converging to a local minimum.

Thus, to resolve the convergence problem many algorithms are considered [5-11]. PSO is a bio inspired optimization technique emulating the bird flock behavior or fish schooling. The potential solutions are spread throughout the hyperspace and they are accelerated in order to find the best point in the hyperspace to attain the solution. The requirement of memory and the computation are inexpensive while the implementation can be carried out using simple programming. PSO is an amalgamation of both GA and Evolutionary programming. A common thing between GA and PSO is that both the algorithm starts with the random population. GA uses binary variables which are shifted and rotated to get the new population while PSO uses real numbers as particles. Again, a randomized velocity is used to move the particles in search space. The momentum which modifies the velocities
adds up to the detailed exploration of the problem space. The particles update in the search space while GA updates using the crossover operation.

A multi-probabilistic method like PSO is used for optimizing the weight updating in the ANN training. PSO based network has proved to provide the prediction rate of around 80%. The optimized network model using PSO has proved superior to the ordinary BP based perceptron both in terms of precision and rate of convergence [12]. ANN experiments need a shorter and efficient way of choosing input parameters or the features for the compact ANN.

It is observed that the feature reduction techniques are used for the stability assessment algorithm [13]. ANN applications are assumed to be advantageous if a proper feature reduction technique is used. An optimized ANN using GA [14, 15, 16] is applied to estimate the margin of voltage stability. Capability of the ANN to learn and the capability of the optimization algorithms to search are combined for a better and efficient classification algorithm. The FDA of MLI is analyzed using the ANN in. A prototype for fault diagnosis of five level MLI connected to IMD is validated with the simulation results [17][18].

2. ANN Training

The ANN topology that is used in the current implementation is as given in the following Figure. As there is a single input for the classification of fault location in the implementation the input node is one. The input is the THD of the output voltage of the CHMLIS. And the output is the switch number where the fault occurs for the corresponding THD.

A neural network model with n hidden layer excluding single input and output layer is developed, we have taken n value as 100 as shown in the Figure 1. The input for the ANN training is the THD obtained from the output voltage of the MLI and the target is the switch position where the switch failure occurs. The input and the target pair are tabulated and given to the ANN to be trained by the optimized ANN. The optimized Back propagation neural network using the GA and MGA algorithm is trained using the parameter estimation methodology. The procedure how the Back-Pro NN Algorithm is applied on the FDA of the CHMLIS is as given below in the form of Pseudo code.

![Figure 1. ANN Topology](image)

2.1. Pseudo Code

1. The model of the Feed Forward NN(FFNN) is developed with right number of inputs, hidden and output layers.
2. The activation function is chosen arbitrarily and can be changed if does not converge for the training model.
3. Tolerance value that regulates the training is chosen along with the connection weight initialization.
4. The observed THD and the corresponding switch failure is tabulated and split for training and testing implementation.
5. The error is calculated between the traversed input at the output node and the target output which is the desired output. If the target output doesn’t counterpart with the actual output, then the error has to be propagated to update the weights in the previous nodes.
6. Before the error propagation, the error is matched with the tolerance assessment to decide whether the iteration of training has to stop or continue. If the error value is higher than the tolerance value, then the iteration continues.

7. The weight correction term is calculated for each node and the resulting weight correction term is updated for the previous layer. This updating continues till the input layer and the updated weights are modelled.

8. The weight updation would reduce the error term to be reduced for each iteration and the steps 5, 6 and 7 are repeated till loss value comes well below tolerance.

9. The entire process is repeated until all the I/O pairs are trained using the previous steps. An ANN model is ready with all the weight and the bias values updated that is ready to be tested with the new data that is not in the training data set. This model is the trained model of ANN.

3. Optimizing ANN using Parameter Optimization

The stochastic nature of the ANN training paradigm and the stochastic nature of the FDA applied in this implementation lead to the Parameter Optimization Algorithm to be implemented on the FDA algorithm. The process of parameter optimization is extensively dealt in many literatures. The process of enhancing any control algorithm by improving the parameters involved in the control or decision is called Parameter Optimization.

In this implementation the ANN parameters including the weight and bias prices are augmented for training the FDA on the CHMLIS in the three phase IMD. The learning accuracy and speed of the ANN in this FDA paradigm is targeted. The weight and bias values are searched in the hunt space in order to obtain the least MSE value during the FDA training on the ANN. The parameter estimation or optimization algorithm exhibits the following advantages,

- Mathematical model of the plant under control is not needed and thus does not need the calculations related to it and previous knowledge related to it.
- A comparison with other algorithms can be carried out
- Complex problems can be solved without the plant model of the system.

3.1. GA Based ANN Parameter Optimization

The constructed ANN thus developed in the previous segment with the initialized weight and the bias values are obtained. The ANN structure thus developed has to be trained by parameter estimation method using the optimization algorithm instead of the gradient descent method inbuilt in the ANN. The quick and accurate training of the ANN is targeted.

GA and MGA are used on the ANN optimization algorithm to obtain the quickly trained accurate ANN. The procedure followed for the parameter estimation method on an ANN using the meta heuristics method is as shown below. As there are two variables (weight and bias) that are optimized this is a multi-varied meta heuristics algorithm. The GA based ANN optimization algorithm is as discussed below.

3.2. Pseudo Code

1. Initial weights and the bias values are chosen from the ANN model thus developed.
2. Two arrays containing the weight and the bias values are obtained by unwrapping the matrices.
3. These two arrays are considered as the initial chromosomes.
4. The chromosomes are populated for a particular population size chosen randomly by means of intuitive selection.
5. These populated weight and bias values thus obtained are converted to weight and the bias matrices.
6. The updated weight and the bias matrices are applied on the ANN to obtain the MSE at the training paradigm.
7. The MSE obtained from the ANN after each weight and bias obtained is tabulated in an array.
8. New set of weight population and bias population is created for the chromosomes thus there in the previous iteration.
9. From the newly populated chromosomes two parents are chosen.
10. These parents are taken and the crossover probability is applied to get the new offspring.
11. These new offspring is applied with mutation probability which produces new children in place of the parent chromosome.
12. Then the fitness function is applied for MSE optimization by repeating the steps 5,6 and 7, until the total number of iterations is obtained or until the MSE does not minimize further.
13. The weight and the bias values that provides the lowest MSE is saved in an array.
14. The weight and the bias with lower MSE are chosen and applied on the ANN after the final iteration and an ANN model is generated.
15. The objective function of MSE is checked with the updated weight and bias values and the performance of ANN prediction are updated.
16. The initial parent selection for crossover phenomena is done using the Roulette Selection.

Recombination solutions which are worthwhile potentially, Genetic algorithm that has Roulette wheel selection as a genetic operator is preferred.
Probability of i\textsuperscript{th} individual is obtained from, 
\[ p_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \]

Where f\textsubscript{i} is fitness of the individual i and individuals in the population is taken as N.

Above process is compared to a casino Roulette wheel. Considering fitness, a sector of wheel will be selected. This could be achieved by considering mean value of the fitness, followed by normalization. Random selection is performed same as Roulette wheel rotation.

4. Analysis of THD and Inverter switch Fault Diagnosis Implementation
To improve fault diagnosis accuracy and efficient working of a Cascaded H-bridge Multi level Inverter System (CHMLIS), a quick and accurate fault diagnosis strategy with an optimized training algorithm is presented. Also, Total Harmonic Distortion (THD) is analyzed for each switch failure and tabulated.

A fault diagnosis model developed using Artificial Neural Network (ANN) is generated for a Seven level three phase CHMLIS. The ANN model is optimized using the GA algorithm using parameter estimation algorithm. The parameters that control the ANN training like the weight and the bias value is optimized by the use of Genetic Algorithm (GA) current implementation. The three phases IMD utilized is equipped with 5HP motor drive. The overall circuit illustration of the IMD is as shown in Figure 2.

![Figure 2. Proposed Block Diagram](image-url)
The speed of convergence during training is the major requirement in the implementation. The implementation carried out used Mean Square Error (MSE) as the neutral function to be reduced. The parameters like the weight and the preconception values were optimized to obtain the minimized MSE while training the ANN for fault diagnosis.

A performance evaluation of the ANN training on the Fault Diagnosis Algorithm (FDA) is delivered in this paper and results are discussed in detail. While training the input and the target is selected as THD and the position of the switch respectively. The tabulated THD and the switch position with different working conditions are supplied to the ANN for training. For each switch failure position, different THD is obtained. As the occurrence of the fault is not uniform in nature and so it is randomized problem to be unraveled, thus requiring ANN to solve the fault prediction problem. This relation between the obtained THD and the fault at any switch is fitted on the ANN model.

5. Results and Discussion

A MATLAB model which has the MLI model with auxiliary legs for replacing while failure in the switches occurs is developed and the FDA implementation is carried out. The auxiliary cell is replaced while the fault occurs in the main cell thus making the uninterrupted working of the MLI in the IMD. The detection of the fault is predicted from the fitted ANN model and reconfiguration is carried out using the auxiliary cell. The Back Propagation network is implemented for the ANN. The multilevel inverter topology simulations are carried out on MATLAB/SIMULINK platform shown Figure 3.

The constraints used for GA (modified) execution,

- Min. error Th. =0.03.
- Pop. size= 100. Max. of epochs=1800.
- Fit. function= MSE. Number of layers=2.
- No. of neurons in input layer = 4. epochs trained= 88.
- Mean squared error: = 0.008744818256473

![Figure 3. Output of 3-phase 7 MLI without fault](image)

Without fault THD =31.09. When there is a fault in switch S2 and S12, the corresponding THD value is same and for these two cases it is severe compared to other switch faults as publicized in Figure 4.
Figure 4. Output obtained during switch faults, (I) THD when switch S2 is Faulted (II) THD when switch S12 is Faulted (III) Output when switch is faulted at Phase-A

Table 1. THD values for each switch fault

| Sl. no. | Faulty switch | % THD   |
|---------|---------------|---------|
| 1       | No Fault      | 31.09   |
| 2       | S1            | 46.43   |
| 3       | S2            | 113.21  |
| 4       | S3            | 29.00   |
| 5       | S4            | 46.43   |
| 6       | S5            | 35.63   |
| 7       | S6            | 68.24   |
| 8       | S7            | 35.63   |
| 9       | S8            | 68.24   |
| 10      | S9            | 29.00   |
| 11      | S10           | 46.43   |
| 12      | S11           | 46.43   |
| 13      | S12           | 113.21  |

Table 2. MSE for the 20 Iteration

| Sl. no. | GA (modified) with ANN | ANN |
|---------|------------------------|-----|
| 1       | 0.008744818256473      | 1.2378e-008 |
| 2       | 0.016569798565873      | 1.6401e-007 |
| 3       | 0.03684922124476       | 1.1747e-010 |
| 4       | 0.03900683678980       | 8.8295e-008 |
| 5       | 0.028214233993611      | 1.3922e-009 |
| 6       | 0.025954975655545      | 2.6955e-010 |
| 7       | 0.02466346793999       | 6.7710e-010 |
| 8       | 0.034720373725770      | 2.1662e-009 |
| 9       | 0.023586805197258      | 3.4198e-008 |
| 10      | 0.032668187608547      | 6.7636e-010 |
| 11      | 0.039077233089494      | 6.9386e-013 |
| 12      | 0.016923061624203      | 6.7710e-010 |
| 13      | 0.038761728049251      | 3.8834e-010 |
| 14      | 0.038403166474452      | 3.4912e-010 |
| 15      | 0.03171295319183       | 9.5231e-009 |
| 16      | 0.039787671660570      | 1.9748e-009 |
| 17      | 0.035801775255144      | 4.3747e-010 |
| 18      | 0.038249568911908      | 4.9736e-012 |
| 19      | 0.034758617723503      | 1.3351e-009 |
| 20      | 0.030514183397513      | 3.2446e-014 |
6. Conclusion
The THD is analyzed for each faulty switch and is applied to ANN fault verdict arrangement to get finest results. The arrangement is tested with MATLAB and by considering MSE as the objective function. A fault diagnosis model developed using Artificial Neural Network (ANN) is generated for a Seven level three phase CHMLIS. The ANN model is optimized using the GA algorithm (modified) using parameter estimation algorithm. The parameters that control the ANN training like the weight and the bias value is optimized by the use of Genetic Algorithm (GA) current implementation. The algorithms are Coded and result displays the efficacy of Algorithm in identifying the fault accurately.

Reference
[1] Chinthamalla R, Sanjeevikumar P, Karampuria R, Sachin Jain, Ahmet H. Ertas and Viliam Fedak, Dec. 2016, Engineering Science and Technology: An International Journal Elsevier Journal Publications, vol. 19, no. 4, pp. 1731-1741,
[2] Rodriguez J, Lai J.S, and Peng F Z, IEEE Transactions on Industry Applications, vol. 49, no. 4, Aug. 2002, pp. 724-738.
[3] Lei Zhang, "Artificial Neural Network model design and topology analysis for FPGA implementation of Lorenz chaotic generator," 2017 IEEE 30th CCECE, 2017, pp. 1-4, doi: 10.1109/CCECE.2017.7946635.
[4] J. Rodriguez, P. W. Hammond, J. Pontt, R. Musalem, P. Lczana, and M. J. Escobar, Aug.2005,IEEE Transactions on Industrial Electronics, vol. 52, no. 4, , pp. 1080- 1085.
[5] Muttil N, Chau KW, 2006 , International Journal of Environment and Pollution 28 (3–4) 223–238.
[6] K.W. Chau 2006 ,Application of a PSO-based neural network in analysis of outcomes of construction claims DOI: 10.1016/j.autcon.
[7] W. Nakawiro and I. Erlich, April 2008,Proceedings of the 3rd International Conference on Deregulation and Restructuring and Power Technologies , pp. 941–947, Nanjing, China,
[8] Pandey S.N, Tapaswi S, and Srivastava L,2010 , Applied Soft Computing Journal, vol. 10, no. 1, pp. 251–260,
[9] Oh, W. Pedrycz S K , and Roh S B, 2011,Journal of the Franklin Institute, vol. 348, pp. 415–425,
[10] Kalpani Thantirige; 2016,Industrial Electronics Society, 42nd Annual Conf. of the IEEE.
[11] Anjali Anand,2016, (ICPS), 2016 IEEE 6th International conference.
[12] Hyun-Woo Simetal, 2016 JIEEE Industry Applications Magazine ( Volume: 22, Issue: 2),
[13] Pires V F , AmaraIT G , Foito D, Pires A J , Apr. 2017,Proc. 11th IEEE Int. Conf. Compat. Power Electron. Power Eng., pp. 193-198.,
[14] J. Lamb, B. MirafzalJune 2017, IEEE Trans. Ind. Electron., vol. 64, no. 6, pp. 4846-4856, Jun. 2017.
[15] Chinnasamy, V.A. and Shashikumar, D.R. (2020) ‘Breast cancer detection in mammogram image with segmentation of tumour region’, Int. J. Medical Engineering and Informatics, Vol. 12, No. 1, pp.77–94
[16] G., T. & Kusagur, Ashok. (2018). Robust Fault Detection of Multilevel Inverter using Optimized Radial Basis Function based Artificial Neural Network in Renewable Energy Power Generation Application. International Journal of Computer Applications. 180. 8-15. 10.5120/ijca2018917231.
[17] Manjunath, Dr & Kusagur, Ashok. (2018). Analysis of Different Meta Heuristics Method in Intelligent Fault Detection of Multilevel Inverter with Photovoltaic Power Generation Source. International Journal of Power Electronics and Drive Systems (IJPEDS). 9. 1214. 10.11591/ijpeds.v9.i3.pp1214-1222.
[18] Manjunath, Dr & Kusagur, Ashok. (2016). Fault Diagnosis and Reconfiguration of Multilevel Inverter Switch Failure-A Performance Perspective. International Journal of Electrical and Computer Engineering (IJEECE). 6. 2610-2620. 10.11591/ijece.v6i6.12112.