

# ARTIFICIAL NETWORK BASED HARMONICS REDUCTION OF SOLAR FED CASCADE INVERTER

ShanmugapriyaM, PG student/EEE Dept.  
Erode Sengunthar Engineering College

Shymalagowri.M, ASP/EEE  
Erode Sengunthar Engineering College  
mshyamalagowri2011@gmail.com

## Abstract:

The selective harmonic elimination problem using Artificial Neural Network (ANN) to generate the switching angles of 11 level full bridge cascaded multilevel inverter powered by four varying dc input sources. A solar panel was connected to get the dc input source in the inverter. For a given dc sources, the lowest THD is generated using trained neural network. The odd harmonics 5<sup>th</sup>, 7<sup>th</sup>, 11<sup>th</sup> in the cascaded inverter is eliminated by using the ANN trained network. The back propagation algorithm has been used, in feed forward method for computing switching angle. Theoretical concepts have been validated in simulation results in MATLAB using artificial neural network technique.

Index:- Gate turn off thyristor (GTO), Active power filter, distributed energy resources (DERs), Total Harmonic Distortion (THD), selective harmonics elimination (SHE).

## INTRODUCTION:

For implementations of medium and high power inverters the developments of different types of distributed generation, such as photo voltaic, wind turbines and fuel cells. The high dv/dt is problem arised in this type of system because of switching losses and electromagnetic interferences. To overcome this problem, selective harmonic elimination (SHE) method is used in multilevel inverters to decrease the switching frequency and the total harmonic distortion (THD) [1]–[14].

At the present time, multilevel inverters are extensively used due to their lower switching frequency, lower switching losses, high voltage rating and lower electromagnetic interfaces [1]–[3]. In generally, multi level inverter has been used in many industries for its less voltage stress and capability of reducing harmonic. In the recent literatures studied extensively for utility and drive applications. The series connected H-bridges are predominantly attractive because of their modularity and scalability of control. Adding a energy storage and backup power interface is as convenient as adding another source module [1], [2]. More than a few switching algorithm such as space-vector modulation (SVM), pulse width

modulation (PWM), Sinusoidal Pulse Width Modulation (SPWM), selective harmonic eliminated pulse width modulation (SHEPWM) are extensively to control and establish switching angles to achieve the required output voltage [4]–[5]. From the above mentioned methods the low order harmonics are completely eliminated by SHE method. The optimum switching angles are calculate using SHE method in mathematical techniques such as iterative methods or mathematical theory of resultant can be applied, such that lower order dominant harmonics are eliminated [3], [4]. The purpose of ANN is recently growing in power electronics and drives area. In the control of dc–ac inverters, ANNs have been used in the voltage control of inverters for ac motor drives. A artificial neural feed forward network essentially implements nonlinear input-output mapping. The desired modulation index is used to produce optimal switching pattern

To generate the optimum switching angles of multilevel inverters, a new training algorithm is developed which is used as an alternative for the switching angles look-up table. This training algorithm used to simple control circuit, controlling the magnitude of output voltage continuously. There is no need to any lookup table after training the ANN. Back Propagation training Algorithm (BPA) is most generally used in the training stage. Without using a real time solution of nonlinear harmonic elimination equation, an ANN is trained off-line using the desired switching angles given by solving of the harmonic elimination equation by the classical method, i.e., the Newton Raphson method. After the termination of the training phase, the obtained ANN can be used to generate the control sequence of the inverter. The simulation results are presented MATLAB/Simulink software package for a single phase seven-level cascaded multilevel inverter to validate the accuracy of estimated switching angles generated by proposed ANN system.

## II SELECTIVE HARMONIC ELIMINATION AND POWER GENERATION

A proposed model with the 11-level cascade H-bridge (CHB) inverter and control is shown in Fig.

1. It has a five-full-bridge series-connected with five solar panels as its input dc supply that may

have different voltage levels.

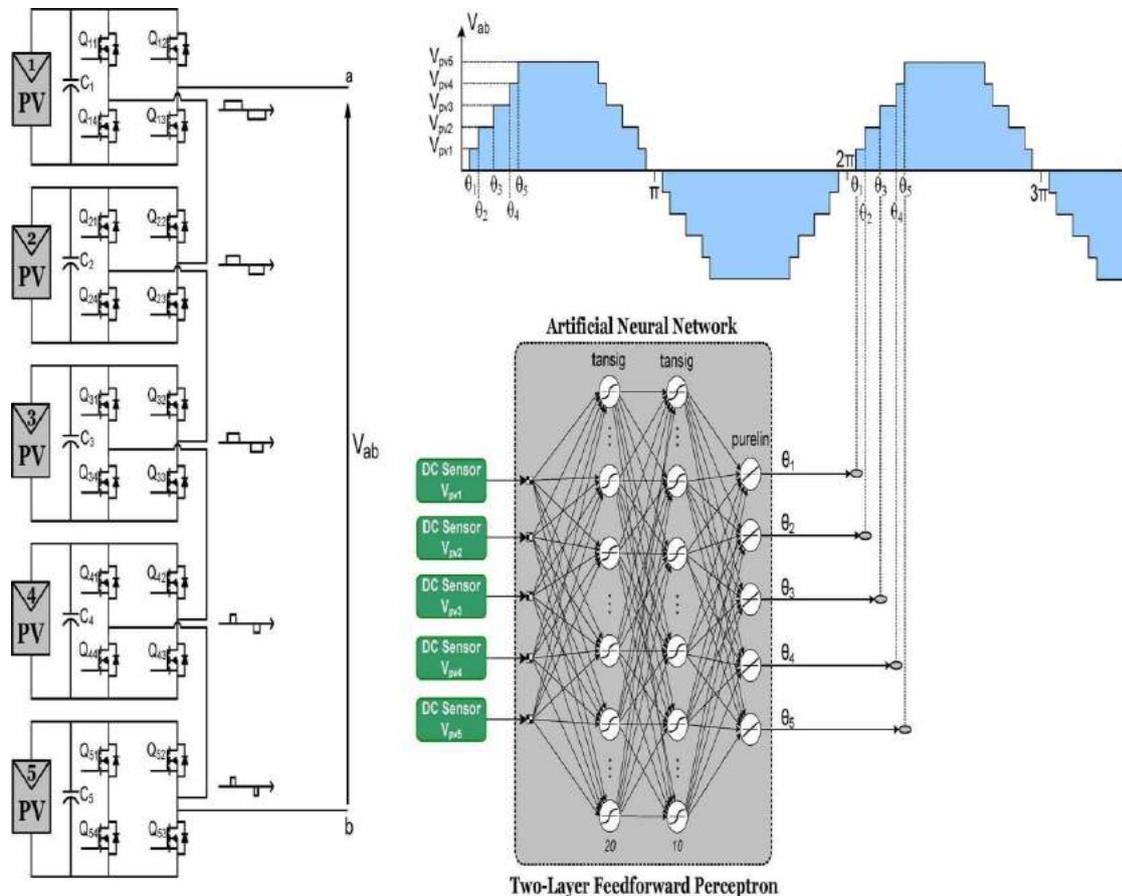


Fig. 1. Single-phase ML cascade inverter topology and ANN-based angle control.

**A . SHE and Unequal DC Sources**

The systematic of the output voltage at infinite frequencies is shown in equation 2. This equation have only odd harmonics. The module voltages  $VPV1$ – $VPV5$  are related to their particular switching angles  $\theta_1$ – $\theta_5$ . The reason for that lies on the assumptions of wave symmetry that cancels out the even components. The target harmonics can be capriciously set, a new data set can be found, and a new ANN can be trained for the system. The selection of target harmonics is depend on the application requirements. Equation (2) is the main equation and also the initial for SHE. The target harmonics in (2) will define the set of transcendental equations to be solved. It is desired to solve (2) so maintained and the lowest harmonics (in this case 5<sup>th</sup>, 7<sup>th</sup>, 11<sup>th</sup> and 13<sup>th</sup>) are cancel

$$V_{ab}(wt) = \sum \times [4 \cdot (VPV1 \cos(n.\theta_1) + VPV2$$

$$n=1,5,7,11, \pi n \cos(n.\theta_2) + VPV3$$

$$\cos(n.\theta_3) + VPV4 \cos(n.\theta_4) + VPV5 \cos(n.\theta_5)]$$

Varying output voltages from many dc sources such as solar panel, fuel cells etc. depends on varying sunlight intensity, load, or other factors. Either a dc–dc converter or the modulation index of the grid-interface inverter is used to regulate this dc voltage in grid connection. For example, the solar panel output voltage may differ based on the amount of energy available during a day, and the grid-interface system should be able to respond to this variation in the switching angles to keep the fundamental regulated at its reference value and the low-order harmonics minimized. The approach in this work is to maintain the fundamental at the desired level by means of choosing the low

∞

frequency switching angles in (2) as shown in Fig. 1. This paper uses a non-deterministic approach to solve for the angles instead of using an analytic method to determine the angles offline. This

method gives solution where analytical solution cannot proceed.

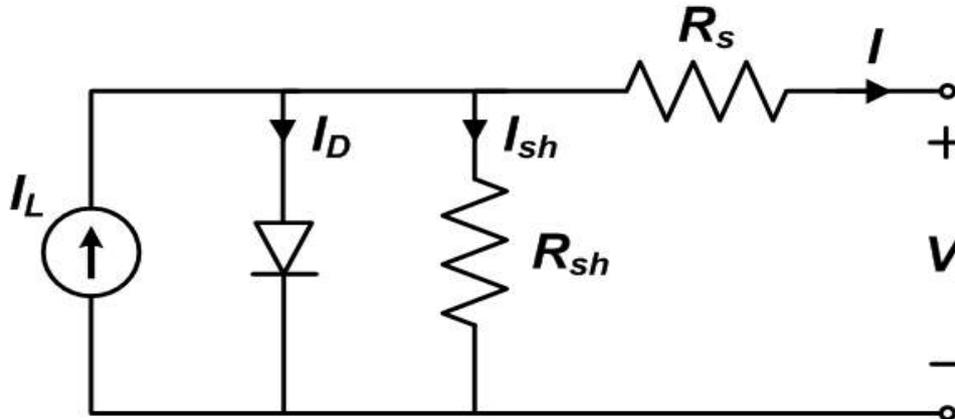


Fig. 2. PV cell single-diode model representation

### B. Solar Cell Modeling

A suitable model was designed to simulate the PV module that reflects the curves of the solar panel with relative exactness. The single-diode model is shown in Fig. 2 to simulate the PV module under different irradiance and temperature levels. The suitable model becomes application dependent. The PV cell model used in this work is a more innate model based on the single-diode cell (Fig. 2). From the PV module data sheets the inputs are utilised. This model greatly reduce the modeling task once the iterations and nonlinear equations are solved. Equation (1) is the basic formula, and the solar panel's data sheet provides the parameters to solve for the unknowns

$$I = IPV - I_0 \left[ e^{\left( \frac{V + R_s I}{V_t} \right)} - 1 \right] - V + \frac{R_s I}{R_p} \quad (1)$$

where,

- I -PV module output current;
- V -PV module output voltage;
- IPV- PV current;
- $I_0$  -saturation current;
- $V_t$  -thermal voltage

### III. ANNs

ANNs are computational models that were motivated by the biological neurons. It has a series of nodes with interconnections, for input/output

mapping the mathematical functions are used. Due to its flexibility to lead in its domain and outside it, as well as work with the non-linear nature of the problem, the ANN is suitable. Although the data set presented to the ANN is not complete and not all combinations were obtained by the GA, the ANN has flexibility enough to interpolate and extrapolate the results. Because of this features, it make ANN's appropriate for problems commonly encountered in power electronics such as fault detection and harmonic detection. If it is properly trained the time consuming will be fast to run and parallelized easily.

The fundamental network is shown in Fig. 3. The network is multilayer with one input stage, two hidden layers, and one output layer. The computational model of a biological neuron is highlighted in Fig. 3, and the interconnections also shown in the network. Its inputs are the five voltage magnitudes measured at the terminals, and its output is the input for all the neurons in the next layer. Each neuron  $aj$  computes a weighted sum of its  $n$  inputs  $V_k$ ,  $k = 1, 2, \dots, n$ , and generates an output as shown in

$$a_j = \text{tgsig} \left( \sum_{K=1}^n w_k V_k + \text{bias} \right) \quad \dots(3)$$

The output can be given by the tangent sigmoid of the final weighted sum that usually has a bias associated to it that can be considered as an additional input.

**A. knowledge From Data:**

A network has to be found the desired output for the trained data and also should have the ability to simplify for points inside the hypercube space determined by the data. By updating the network weights according to given data will generalize data set so it helpful in learning for the computational neuron.

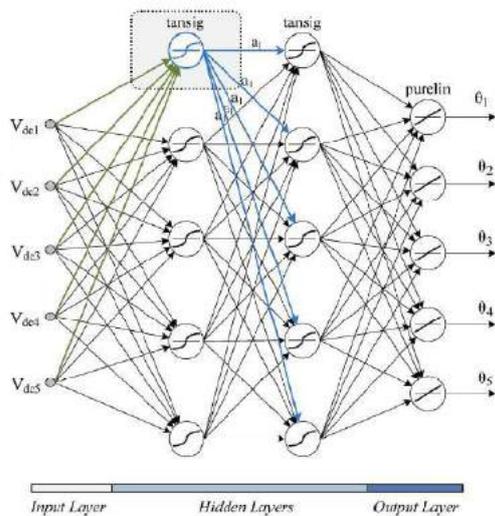


Fig. 3. Multilayer feedforward perceptron neural network model.

Performance is measured by calculating the mean-square error (mse) as shown in

$$e = \frac{1}{p} \sum_{i=1}^p \|y^{(i)} - d^{(i)}\|^2 \quad \dots(4)$$

where

- $p$ - number of training data entries;
- $y$  - ANN output vector-current ANN output;
- $d$  - desired output vector-switching angles.

To minimize the error obtained in (4), the ANN back propagation training algorithm is used. A well-trained ANN would output switching angles that are very close to the desired values, giving an error near zero in (4), for a given set of input voltages. The desired switching angles are those that minimize the harmonic components.

**B. ANN Training:**

The new data set was divided into three subsets: training, validation, and test. By using the scaled conjugate gradient algorithm the first subset of the ANN is trained. An establishment subset is used to stop the training to avoid generalization. If the validation error starts to increase, then results in over fitting data. A third subset is used to verify

that the data are not poorly divided. When this error gets a low value in a different iteration than the validation and training subsets, it might be an indication of poor data division. The proportions adopted in this work were 0% for validation, 55% for training, 3, and 15% for test. All the 32 different networks were trained 50 times each, and their performance values are shown in Fig. 5. The ANN that was implemented was shown in Figs. 1 and 4 which is a feed forward multilayer acuity with one hidden layer of 20 neurons. It is configured with single- and multiple-hidden layer ANN's. The two-hidden-layer performance is shown in Fig. 5. The two hidden layer was chosen because of better performance, training time, memorization, and learning ability.

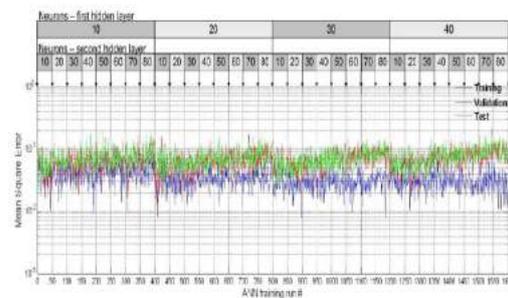


Fig. 5. ANN performance results for different numbers of hidden layer neurons.

**C. SHE Data Set:**

Based on H- bridge topology, the possible number of data set for ANN training is desired. For a two-full-bridge case (five levels) a data set of four voltage levels for training, would generate a table of 42 rows. In a five-H-bridge converter with ten points equally spaced between 50 and 60 V, it may generate 105 different combinations. Instead of permutation the problem is faced as combination problem for reduce the size of the data set. In this way, the data set can be greatly reduced.

**SIMULATION RESULTS:**

The 5th, 7th, 11th and 13th harmonics are strongly suppressed it is cleared from the simulation result. The obtained switching angles for various values of modulation index using ANN for 11 level inverter is shown in Table I.

TABLE I SWITCHING ANGLES GENERATED BY ANN FOR 11-LEVEL

Modulation Index (M)	Switching Angles				
	$\theta_1$ (rad.)	$\theta_2$ (rad.)	$\theta_3$ (rad.)	$\theta_4$ (rad.)	$\theta_5$ (rad.)
0.6	0.0330	0.0665	0.5189	0.6717	0.7935

0.65	0.0423	0.1094	0.4929	0.6686	0.8402
0.7	0.0510	0.1494	0.4686	0.6658	0.8840
0.75	0.0591	0.1868	0.4458	0.6635	0.9249
0.8	0.0668	0.2216	0.4246	0.6615	0.9631
0.85	0.0740	0.2539	0.4048	0.6599	0.9988
0.9	0.0807	0.2840	0.3864	0.6586	1.0320
0.95	0.0870	0.3118	0.3692	0.6576	1.0630
1.0	0.0929	0.3377	0.3532	0.6568	1.0919

The FFT spectrum for 11-level inverters is shown in Fig. 6 respectively.

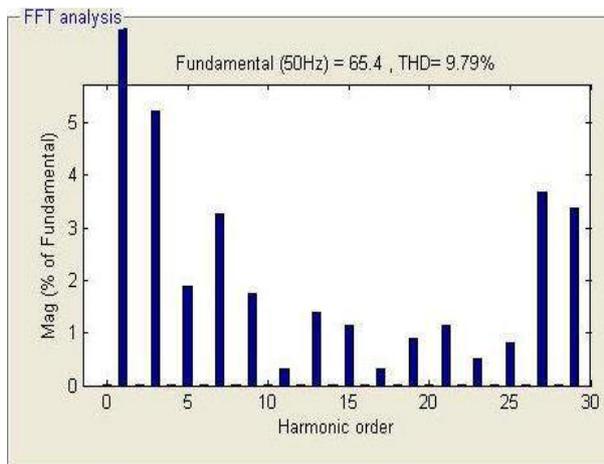


fig 6. FFT analysis of 11 level inverter

The THD analysis of 11-level inverter is shown in Fig. 7.

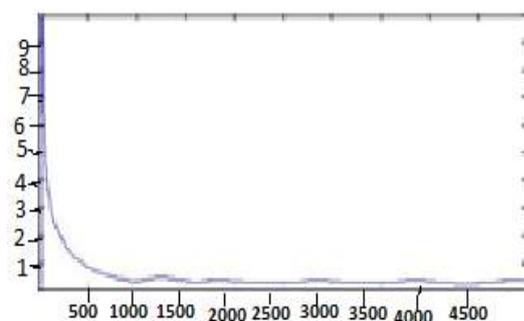


fig.7. THD analysis of 11 level inverter.

**CONCLUSION:**

In this paper, the ANN is proposed to work out the selective harmonics elimination problem in inverters. The multilevel inverter used to generate staircase waveform by computation the optimum

switching angle exploitation feed forward neural network was successfully demonstrated in this paper. The switching angles for eleven-level inverter is calculated based on SHE strategy in order to call off the 5, 7, 11 and 13 harmonics. The voltage control and harmonic suppression of selective set is successfully done by using this technique. An ANN is trained offline to reproduce these switching angles without constrain for any value of the modulation index. After the training process it is enough to obtain the network for real time control. Simulation results for an eleven-level inverter to demonstrate the accuracy of proposed approach to calculated the optimum switching angles which produce the lowest THD.

**REFERENCE**

- [1] Mitali Shrivastava" Artificial Neural Network Based Harmonic Optimization of Multilevel Inverter to Reduce THD"2012.
- [2] J. Rodriguez, J. Lai, and F. Z. Peng, "Multilevel inverters: A survey of topologies, control and applications," IEEE Trans. Ind. Electron., vol. 49, no. 4, pp. 724–738, Aug. 2002.
- [3] Faete Filho, Leon M. Tolbert, and Burak Ozpineci," Real-Time Selective Harmonic Minimization for Multilevel Inverters Connected to Solar Panels Using Artificial Neural Network Angle Generation" iee transactions on industry applications, vol. 47, no. 5, september2011.
- [4] B. Ozpineci, L. M. Tolbert, and J. N. Chiasson, "Harmonic optimization of multilevel converters using genetic algorithms," IEEE Power Electron. Lett., vol. 3, no. 3, pp. 92–95, Sep. 2005.
- [5] J. R. Wells, P. L. Chapman, and P. T. Krein, "Generalization of selective harmonic control/elimination," in Proc. IEEE Power Electron. Spec. Conf., Jun. 2005, pp. 1358–1363.
- [6] A. Pandey, B. Singh, B. N. Singh, A. Chandra, K. Al-Haddad, and D. P. Kothari, "A review of multilevel power converters," Inst. Eng. J. (India), vol. 86, pp. 220–231, Mar. 2006.
- [7] J. N. Chiasson, L. M. Tolbert, K. J. McKenzie, and Z. Du, "A unified approach to solving the harmonic elimination equations in multilevel converters," IEEE Trans. Power Electron., vol. 19, no. 2, pp. 478–490, Mar. 2004.
- [8] T. Tang, J. Han, and X. Tan, "Selective harmonic elimination for a cascade multilevel inverter," in Proc. IEEE Int. Symp. Ind. Electron., Jul. 2006, pp. 977–981.
- [9] Z. Du, L. M. Tolbert, J. N. Chiasson, and H. Li, "Low switching frequency active harmonic elimination in multilevel converters with unequal DC voltages," in Conf. Rec. IEEE IAS Annu. Meeting, Oct. 2005, pp. 92–98.
- [10] M. Dahidah and V. G. Agelidis, "Selective harmonic elimination multilevel converter control

**International Journal of Advanced Research in Basic Engineering Sciences and Technology (IJARBEST)**  
**Vol.3, Special Issue.24, March 2017**

with variant DC sources,” in Proc. IEEE Conf. Ind. Electron. Appl., May 2009, pp. 3351–3356.

[11] D. Ahmadi and J. Wang, “Selective harmonic elimination for multilevel inverters with unbalanced DC inputs,” in Proc. IEEE Veh. Power Propulsion Conf., Sep. 2009, pp. 773–778.

[12] Z. Du, L. M. Tolbert, and J. N. Chiasson, “Active harmonic elimination for multilevel converters,” IEEE Trans. Power Electron., vol. 21, no. 2, pp. 459–469, Mar. 2006.

[13] M. G. H. Aghdam, S. H. Fathi, and G. B. Gharehpetian, “Elimination of harmonics in a multi-level inverter with unequal DC sources using the homotopy algorithm,” in Proc. IEEE Int. Symp. Ind. Electron., Jun. 2007, pp. 578–583.

[14] J. N. Chiasson, L. M. Tolbert, K. J. McKenzie, and Z. Du, “Elimination of harmonics in a multilevel converter using the theory of symmetric polynomials and resultants,” IEEE Trans. Control Syst. Technol., vol. 13, no. 2, pp. 216–223, Mar. 2005.