Harmonic Mitigation of a Solar FED Cascaded H-Bridge inverter using Artificial Neutral Network

Priya.G, Ramani.G, Revathy.G

PG Scholar, Nandha Engineering College, Erode

Associate Professor, Nandha Engineering college, Erode

Assistant Professor, Erode Sengunthar Engineering College, Erode

Abstract- A concept of application of Artificial Neural Network (ANN) for estimating switching angle in an 11 level full bridge cascaded multilevel inverter with optimal pulse width modulation , which was powered by five varying dc input sources. A solar panel was connected to each cascaded inverter. For a given modulation index the optimal switching angles with lowest THD is generated using trained neural network by replacing look-up table is proposed in this paper. The odd harmonics(5,7,11) in the inverter is eliminated by using the trained network. Theoretical concepts have been validated in simulation results using artificial neural network technique which shows the high performance and technical advantages of the developed system.

keywords- Active power filter, distributed energy resources (DERs), harmonics injection, optimal pulse width modulation (OPWM), selective harmonics compensation (SHC), Artificial Neural Network(ANN)

INTRODUCTION

For implementations of medium and high power inverters the development of different types of distributed generation, such as fuel cells, photo voltaics, and wind turbines, have provided. The switching losses and electromagnetic interferences caused by high dv/dt is problem arised in this type of system. Thus, to overcome these problems, selective harmonic elimination (SHE) based optimal PWM (OPWM) are used in multilevel inverters to minimise the switching frequency and the total harmonic distortion (THD) [1]–[14].

Nowadays, multilevel power inverters are widely used in AC motor drives, uninterruptible AC power supplies (UPS), high voltage and high power applications due to their lower switching frequency, lower switching losses, high voltage rating and lower electromagnetic interfaces (EMI) than conventional two level inverters [1]-[3]. In most cases, low distortion sinusoidal output voltage waveforms are required with controllable magnitude and frequency. Numerous topologies and modulation strategies have been introduced and studied extensively for utility and drive applications in the recent literatures. In the family of multilevel inverters, topologies based on series connected H-bridges are particularly attractive because of their modularity and simplicity of control [1], [2]. Several switching algorithm such as pulse width modulation (PWM), Sinusoidal Pulse Width Modulation (SPWM), space-vector modulation (SVM), selective harmonic eliminated pulse width modulation (SHEPWM) or programmed-waveform pulse width modulation (PWPWM) are applied extensively to control and determine switching angles to achieve the desired output voltage [4]-[5]. Among the mentioned techniques only SHE method is able to eliminate low order harmonics completely. In the SHE method, mathematical techniques such as iterative methods or mathematical theory of resultant can be applied to calculate the optimum switching angels such that lower order dominant harmonics are eliminated [3], [4]. The application 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 feed forward ANN basically implements nonlinear input-output mapping. For any chosen objective function, the optimal switching pattern depends on the desired modulation index.

In this paper, a new training algorithm is developed which is used as an alternative for the switching angles look-up table to generate the optimum switching angles of multilevel inverters. The advantages of this method are simple control circuit, controlling the magnitude of output voltage continuously versus modulation indexes and there is no need to any lookup table after training the ANN. 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. Back Propagation training Algorithm (BPA) is most commonly used in the training stage. 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

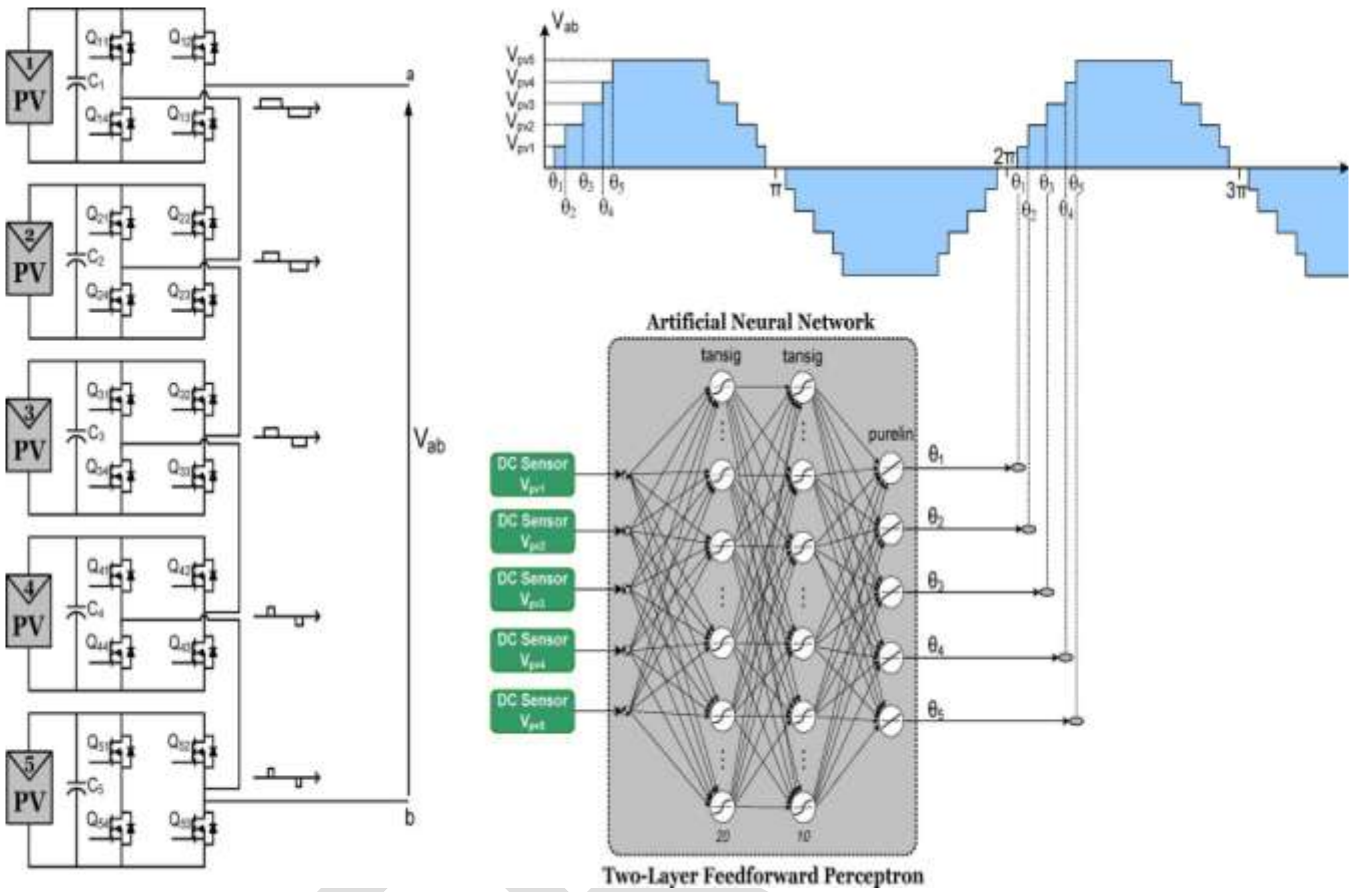

Fig 1-phase ML cascade inverter topology and ANN-based angle control

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.

A. 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 utilisied. 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

$$I = IPV - I_0[e^{(V + RsI\ Vta)} - 1] - \frac{V + RsI}{Rp} \qquad ....(1)$$

where,

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

B. SHE and Unequal DC Sources

The contents of the output voltage at infinite frequencies is shown in equation 2. The module voltages VPV1–VPV5 are associated to their particular switching angles θ1–θ5. This equation have only odd harmonics. 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

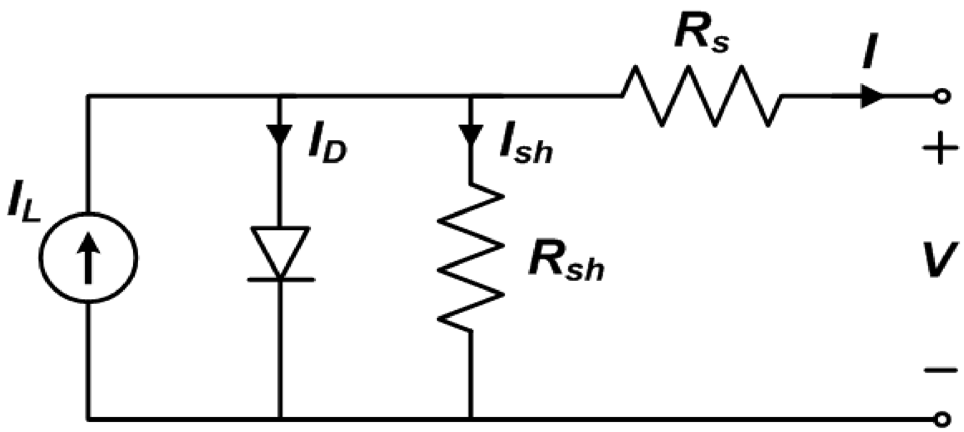

Fig. 2. PV cell single-diode model representation

maintained and the lowest harmonics (in this case, the 5th, 7th, 11th, and 13th) are cancel

$$V_{ab}(wt) = \sum_{n=1,5,7,11,..}^{\infty} \times \left[\frac{4}{\pi n} \left(V_{PV1}\cos(n.\theta 1) + V_{PV2}\cos(n.\theta 2) + V_{PV3}\cos(n.\theta 3) + V_{PV4}\cos(n.\theta 4) + V_{PV5}\cos(n.\theta 5)\right)\right]$$

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 nondeterministic 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 .

ANN

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 nonlinear 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 ANNs appropriate for problems commonly encountered in power electronics such as fault detection and harmonic detection. If it is propoerly 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 Vk, k = 1, 2, . . . , n, and generates an output as shown in

n

$$a_j = tgsig\left(\sum_{K=1} w_k V_k + bias\right) \qquad ....(3)$$

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.

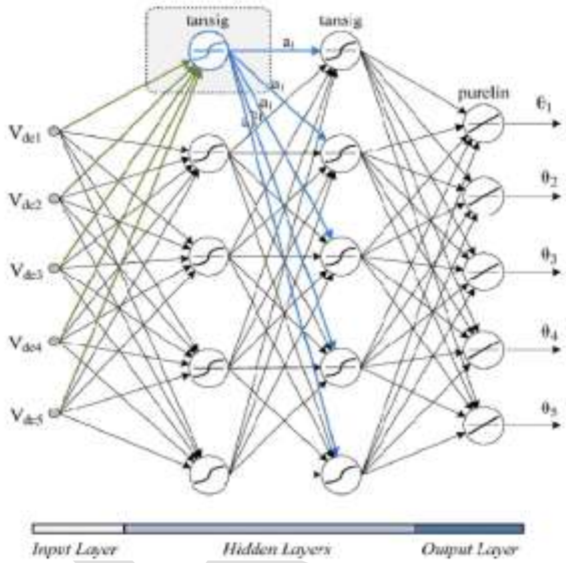

Fig. 3. Multilayer feedforward perceptron neural network model.

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

$$e = \frac{1}{p} \sum_{i=1}^{p} \left\| y^{(i)} - d^{(i)} \right\|^2 \qquad ....(4)$$

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 propogation 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. 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.

C. 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 trainned. A validation 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 55% for training, 30% for validation, 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

ANNs. 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.

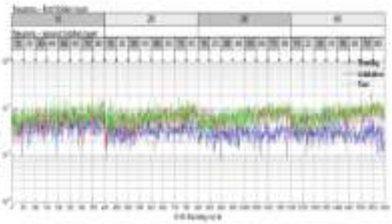

Fig. 5. ANN performance results for different numbers of hidden layer neurons

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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.

Modulation Index (M)	**Switching Angles**				
	θ_1 (rad.)	**θ_2 (rad.)**	**θ_3 (rad.)**	**θ_4 (rad.)**	**θ_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

Table I-Switching angles generated by ANN for 11-level

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

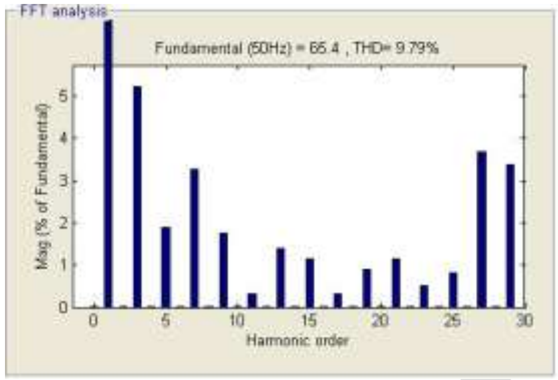

Fig 6. FFT analysis of 11 level inverter

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

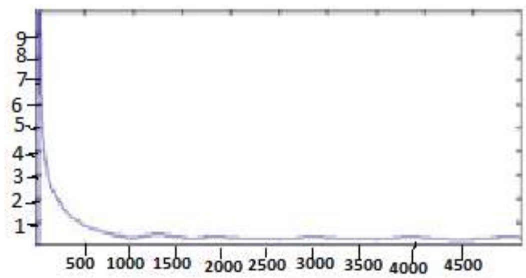

Fig.7. THD analysis of 11 level inverter.

CONCLUSION:

In this paper, the ANN is proposed to solve the selective harmonics elimination problem in inverters. The multilevel inverter used to generate staircase waveform by estimating the optimum switching angle using feed forward neural network was successfully demonstrated in this paper. The voltage control and harmonic suppression of selective set is successfully done by using this technique. 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. Then, 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 a eleven-level inverter to authenticate the accuracy of proposed approach to calculated the optimum switching angles which produce the lowest THD.

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