ARTIFICIAL NEURAL NETWORK-BASED SPACE VECTOR PWM FOR MULTI-LEVEL VOLTAGE-FED INVERTERS

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***Abstract*: This paper proposes an artificial neural network (ANN) based space vector pulse width modulation (SVM) for a multi-level voltage-fed inverter. Basically, the approach uses two multilayer perceptron (MLP) type of neural network. The first ANN uses the amplitude and angle of the reference voltage vector to determine the nearest three vectors (NTV) by finding the triangle where the reference vector lies. The second ANN is used to calculate the duty cycles of the three space vectors. An erasable programmable logic device (EPLD) synthesizes the PWM waves. The main advantage of this approach is the fast and simple implementation of the highly complex SVM algorithm for multi-level inverters without loosing precision compare to the conventional DSP-based SVM algorithm. Simulation results for a five-level inverter using the proposed ANN-based SVM are given and shown to be excellent.**

KEYWORDS: Multilevel inverter, space vector modulation, artificial neural network

I. INTRODUÇÃO

The neutral-point-clamped (NPC) multi-level voltage-fed inverters (VFI) are becoming very popular recently for multi-megawatts power applications. The main advantage of such inverter topology is voltage division, i. e., the output voltage is produced through small steps of voltage, and therefore the individual switches are submitted only to these small voltages steps [1]. The others advantages are: low harmonic distortion of the output voltage and low *dv/dt*. The SVM algorithm for this inverter provides the additional advantages of harmonic reduction and higher range of undermodulation. In conventional SVM for multi-level inverter, the identification of the nearest three voltage vectors used to synthesize the reference vector is very complex. This involves tasks such as: identification of the sector and the triangle where the reference vector lies [3]; look-up table check; and many trigonometric operations for duty-cycle calculation [2]. Some simplifications of this algorithm have been proposed by [4] and [5]. Basically, these papers propose the use of the non-orthogonal reference system. These contributions are undeniable for simplification of the algorithm. However, even with these simplifications, the complexity of the algorithm is quite high.

This paper proposes an artificial neural network (ANN) based space vector pulse width modulation (SVM) for a multi-level voltage-fed inverter. Basically, the approach uses two multilayer perceptron (MLP) type of neural network. The first ANN uses the amplitude and angle of the reference voltage vector to determine the nearest three vectors (NTV) by finding the triangle where the reference vector lies. The second ANN is used to calculate the duty cycles of the three space vectors.

The switching state sequence times are calculated using the duty cycles, sextant and the triangle information. The switching times are then fed to an erasable programmable logic device (EPLD) that generates the PWM waves, which drive the inverter switches. Therefore, the most complex part of the algorithm is replaced by two simple feedforward multi-layer perceptron type ANN.

II – MULTI-LEVEL INVERTER SPACE VECTOR PWM

As mentioned in section I, the conventional SVPWM algorithm, due to its nature of handling the reference voltage vector as a whole, is very complex. This complexity increases even more as the number of levels (n) of the inverter increases, since the number of switching states increases with n.

In a n-level inverter, although the number of switching states N_s is given by:

$$N_S = n^3 \qquad (1)$$

The actual number of voltage space vectors Nv is given by:

$$N_V = n^3 - (n-1)^3 \qquad (2)$$

These voltage vectors divide the d-q plane into N_T triangles. The relation between the number of triangles and the number of levels of the inverter is given in equation (3).

$$N_T = 6.(n-1)^2 \qquad (3)$$

For instance, the five-level inverter, shown in Fig. 1, has 125 switching states, of which only 61 are effective space vectors, whose divide the d-q plane into 96 triangles.

In the SVM algorithm, out of the Nv space vectors, only the nearest three vectors (NTV), whose are the adjacent vectors of the triangle where the reference vector lies, are used to compose the output vector. Fig. 2 shows the space vectors and triangles for the five-level inverter.

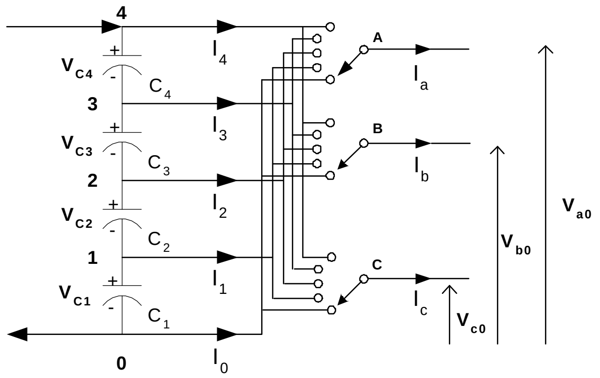


Fig. 1.– Simplified representation of a five-level inverter

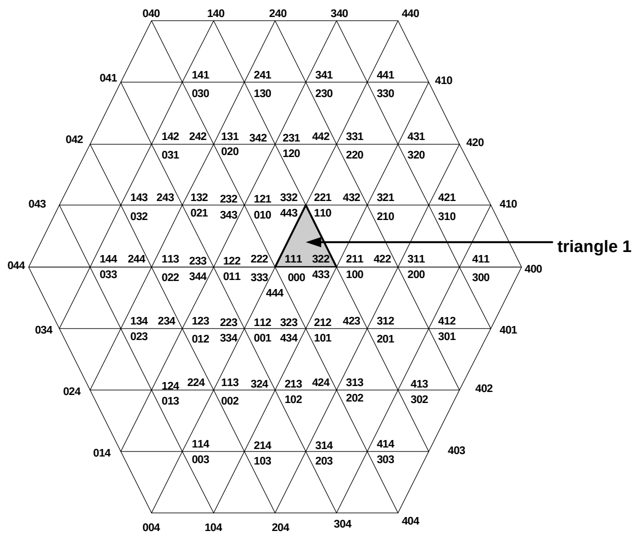


Fig. 2 – Switching states in d-q plane of a five-level inverter.

II.1– Triangle Identification

In order to assure the capacitor voltage balance, the correct sequence of the vectors used to compose the output vector is vital. This correct sequence is achieved by an accurate identification of the triangle where the reference vector lies. An convenient approach is to do the identification of triangle considering only one sextant, independently of the actual sextant where the command voltage vector V^* lies. The result of this method is a significant simplification on the calculation of the duty cycles t_a, t_b, and t_c. The simplification lies in the fact that the reference voltage vector can be considered to be always in the first sextant, which reduces considerably the number of triangles to be identified. For instance, in a conventional method for a five level inverter, the position where the reference vector lies should be identified in a 96 triangles universe. However, using the proposed simplification, this universe is only of 16 triangles.

An strategy to identify the triangle where the reference voltage vector lies is given in [3]. This strategy uses coordinates translation and a rotation factor to determine the sequence of the numbers of the triangles in the first sextant. The sequence goes horizontally from the left to the right. This is not a good approach since the numbering sequence changes for inverters with different number of levels. This problem is overcome in this proposed method, where the main idea is to use a diagonal ordination of the number of the triangle, in a crescent order from the center to the border of the hexagon. Basically, this is a masking in of the strategy done by [3]. Therefore, the triangle numbering sequence holds independently of the numbers of levels of the inverter.

Figure 3 presents the proposed approach for numbering the triangles and the vector sequence for each triangle. The duty cycle of each vector is obtained in accordance to the average value principle, which is given by equation (4):

$$\begin{aligned} V_1 t_a + V_2 t_b + V_3 t_c &= V^* \\ t_a + t_b + t_c &= 1 \end{aligned} \qquad (4)$$

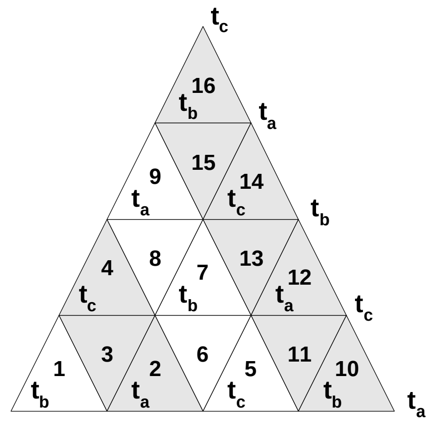


Fig. 3 – Triangles numbering and vector sequences (duty cycles t_a, t_b, and t_c) for sextant 1.

II.2 – Switching Patterns

The adequate strategy of using the redundant switching states guarantees the minimum number of switching, the optimum harmonic content, and best balance of the dc-link capacitor voltages. In the complete pattern, all the redundant vectors are used. The proposed algorithm is flexible in the sense that it can use either the complete or the reduced switching sequence pattern. In this work the complete switching pattern is used. The switching state sequence in a sampling period is pre-defined and depends on the number of the triangle in the hexagon where the reference voltage vector lies (T_{hex}). However, the number of the triangle can be obtained using the number of the sextant where the vector lies (*sext*) and the number of the correspondent triangle in the first sextant (*Tr*). Equation (5) shows this relation.

$$T_{hex} = (sext \quad 1).16 + Tr \qquad (5)$$

In this stage, the objective is to determine how much of each voltage level should be on in the switching period in analysis. For example, for phase *A*, the contribution of the voltage level 4 is the sum of the weighted duty cycles t_a, t_b and t_c, as shown in equation (6).

$$T_{4A} = K_{a4A}(T_{Hex})t_a + K_{b4A}(T_{Hex})t_b + K_{c4A}(T_{Hex})t_c \qquad (6)$$

Where the coefficients K_{a4A}, K_{a4A} e K_{c4A} are pre-defined and can be stored in a look-up table. Table 1 shows the direct and reverse sequences of the switching states necessaries to synthesize the reference vector lying in triangle 1.

TABLE 1: Switching state sequences for triangle 1

Phas	Direct Sequence													Reverse Sequence												
A	0	1	1	1	2	2	2	3	3	3	4	4	4	4	4	4	3	3	3	2	2	2	1	1	1	0
B	0	0	1	1	1	2	2	2	3	3	3	4	4	4	4	3	3	3	2	2	2	1	1	1	0	0
C	0	0	0	1	1	1	2	2	2	3	3	3	4	4	3	3	3	2	2	2	1	1	1	0	0	0
	Tb/10	Ta/8	Tc/8	Tb/10	Ta/8	Tc/8	Tb/10	Ta/8	Tc/8	Tb/10	Ta/8	Tc/8	Tb/10	Tb/10	Tc/8	Ta/8	Tb/10	Tc/8	Ta/8	Tb/10	Tc/8	Ta/8	Tb/10	Tc/8	Ta/8	Tb/10
													T_{4A}													
													T_{3A}													
													T_{2A}													
													T_{1A}													
													T_{0A}													

II.3 – Synthesis of the PWM signals

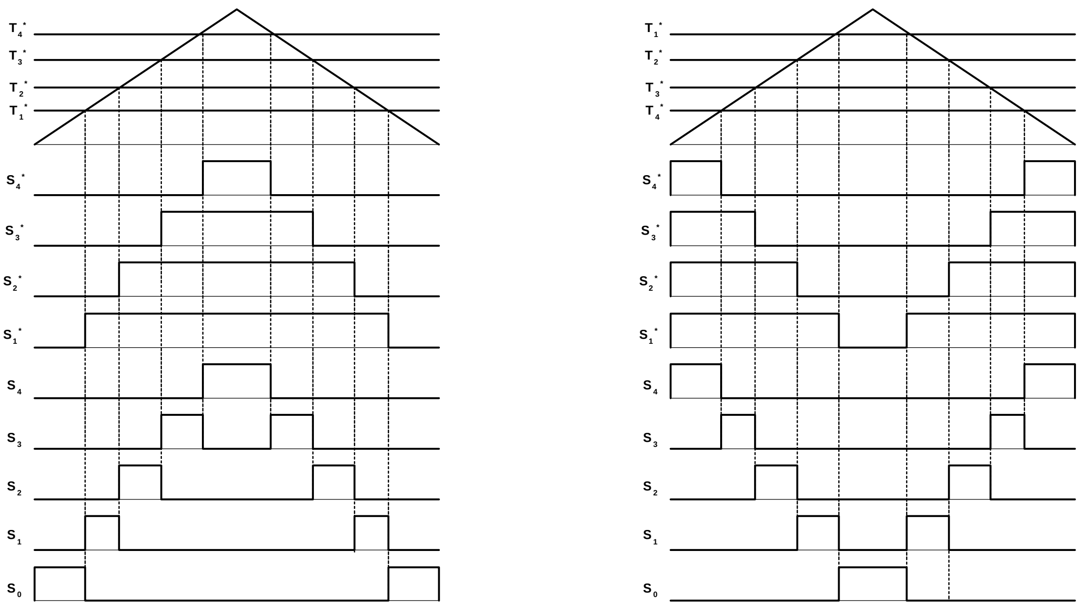
The PWM signals can be generated after obtaining the amount of time that each voltage level should be on for the three phases. An erasable programmable logic device (EPLD) is used to generate such signals.

In order to assure the voltage capacitors balance the appropriate switching pattern has to be used. The correct switching pattern will depend if the reference voltage vector lies either in an odd (A, C e F) or in an even (B, D e F) sextant [6]. If the reference voltage vector lies in any of the odd sextants the switching sequence has to go from lower to higher level (0, 1, 2 , 3, e 4), as shown in table 1. On the other hand, if the reference voltage vector lies in any of the even sextants, the switching sequence has to go from higher to lower level (4, 3, 2, 1, e 0). Therefore, the algorithm has to use an index to identify the sextant where the reference voltage vector lies. Figure 4 shows a logic diagram to obtain the PWM signals for the levels of one phase in the five-level inverter.

III – NEURAL-NETWORK-BASED SVPWM

As described in section II the space vector PWM algorithm is very complex and its complexity clearly increases as the number of level of the inverter increases. The algorithm complexity relies in two stage of the algorithm: i) identification of the triangle where the reference vector lies and ii) duty cycles calculation. These two stages of the SVM algorithm are the bottleneck of the algorithm.

Artificial neural networks were shown to be very useful in implementation of SVM algorithm [6], [7]. It was shown in [7] that the switching times can be calculated by using two neural networks. One ANN calculates the voltage amplitude function, and the other calculates the angle function. The outputs of the two ANN's are multiplied, and finally the switching times are obtained by summing a constant to that product. However, this strategy is valid only for two and three-level inverters. As the number of levels increases, the precision of this strategy deteriorates.



(a) Sextants A, C and E

(b) Sextants B, D and F

Fig. 4 – Logic used to obtain the PWM signals

This work proposes a improvement in the strategy proposed in [6] and [7], once it generalizes the strategy to implement the SVM algorithm for multilevel inverter with any number of levels. Here, two neural networks are also used, however they have different function in the SVM algorithm from those two neural networks used in [6] and [7]. The first ANN maps the amplitude and angle of the reference voltage vector to the number of the triangle where such vector lies. As discussed previously, the triangle identification is a way to determine which voltage space vector should be used to synthesize the command voltage vector. But, in this approach, this information is also used to do a weight update of the second ANN. The second ANN is used to map the amplitude and angle of the reference voltage vector to the duty cycles of the NTV. Figure 5 shows the block diagram of the ANN based SVM for multilevel inverter.

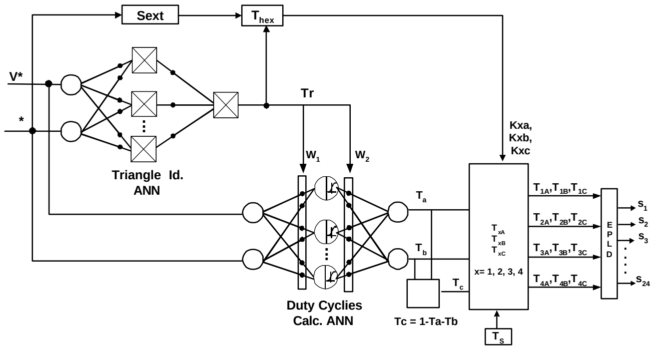


Fig. 5 - Neural network topology

III.1– Neural Network Based Triangle Identification

This ANN maps the amplitude (*V**) and angle (θ^*) of the reference voltage vector to the number of the triangle (*Tr*) where such vector lies. Notice that *Tr* is the number of the correspondent triangle in the first sextant. The output of this ANN will feed two blocks in the proposed approach. The block used to generate appropriate switching sequence for capacitor voltage balancing and the block of the second ANN. The ANN used for triangle identification is a multilayer perceptron (MLP). In order to train this ANN, a training data set was generated using the conventional algorithm given in [3]. The training data set was composed by 3361 input/output patterns. The ANN final topology was a 2-3-3-1 ANN, i. e., 2 inputs neuron, 2 hidden layers with 3 neurons each, and 1 output neuron. The transfer function used for all neurons was tan sigmoid type, except for the output neuron that uses a linear transfer function. Although the ANN could have only one hidden layer, the total number of neuron would be higher, and therefore the ANN would be bigger. The training stop criteria used was the maximum number of epochs. For this ANN, the training was done in 1250 epochs, and the sum squared error (SSE) after the 1250 epochs was 0.001. The ANN was tested using 200 input/output patterns chosen randomly, and the results were very good. Figure 6 shows the performance of the ANN based triangle identification for a modulation index of 0.53. The ANN identified the first sextant correspondent triangles correctly, which shows the success of the approach

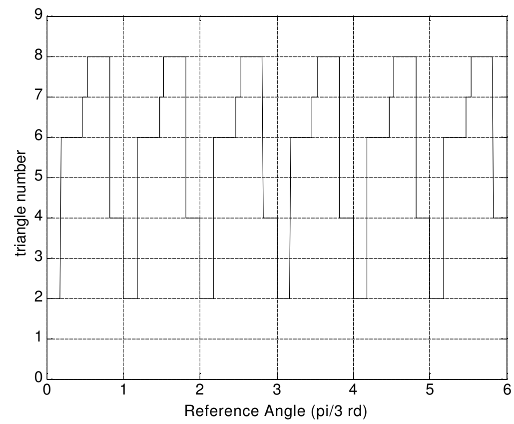


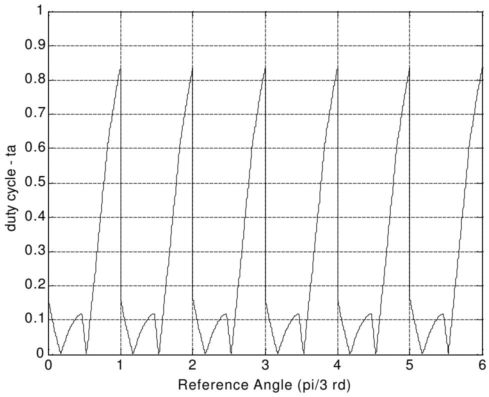
Fig. 6 – ANN based triangle identification for reference voltage vector trajectory with m=0.53

III.2– Neural Network Based Duty Cycle Calculation

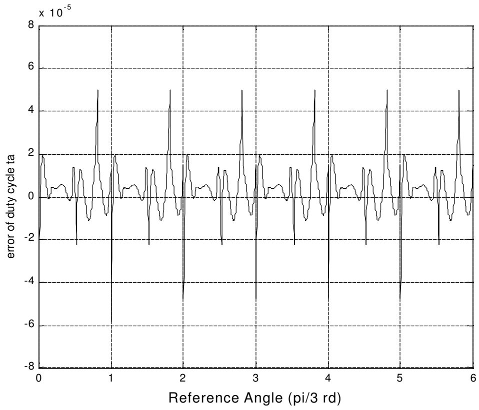
The second ANN used in the proposed approach maps the amplitude and angle of the reference voltage vector to the duty cycles of the NTV. However two problems must be overcome in order to train an ANN to do this mapping. The first problem is related to the size of training data, which is very large since the amplitude and angle range of the reference voltage vector in a multilevel inverter is very wide. The second problem is the highly nonlinear relation between the input variables (voltage and angle of the reference voltage vector) and the output variables (duty cycles of the NTV).

The strategy adopted was to use a “quasi-dynamic” ANN, i. e. the MLP-ANN has a set of weights and bias for each triangle in the first sextant, and they are changed depending on the position of the reference voltage vector. Therefore, this ANN also receives information of the triangle number (Tr) from the first ANN. The great advantage of this method is that instead of being trained to the whole operation range, the ANN is trained for each of the 16 triangles of the first sextant resulting in 16 sets of weights and bias. Although the training seems to be very hard, it is not since: i) the nonlinearities are much less in only one triangle, which increase the trainability of the ANN; and ii) the training set is much smaller than for the whole operation range. The training of each triangle handles a training set 96 times smaller, which makes the training process much easier and less time consuming. Therefore, the training for the 16 triangles is not as hard as seems to be and the 16 sets of weights and bias are easily obtained.

The ANN used for duty cycle calculation is a multilayer perceptron (MLP). The training of this ANN used 16 training dada set with 1327 input/output patterns each. The ANN final topology was a 2-10-2 ANN, i. e., 2 inputs neurons, 1 hidden layer with 10 neurons and 2 output neurons. The transfer function used for the hidden neurons was the tan sigmoid transfer function, while the output neurons used the linear type. The training stop criteria used was maximum number of epochs. The training of ANN for the each triangle, in the worst case, was done in 1500 epochs, and the SSE after 1500 epochs was $1x10^{-10}$. Figure 7 shows the performance of the ANN used to calculate the duty cycles for a modulation index of 0.53. The figure 7.(a) shows the duty cycle t_a calculated using the ANN. Figure 7.(b) shows the error between the duty cycle t_a calculated using the SVM equations and using the ANN. From the figure it is possible to see that the error is very small, and the maximum error is $5.0x10^{-5}$, which indicates the outstanding performance of the ANN.



(a)



(b)

Fig. 7 – Duty cycle calculation using ANN
(a) Duty cycle t_a for m=0.53
(b) Error of duty cycle t_a for m=0.53

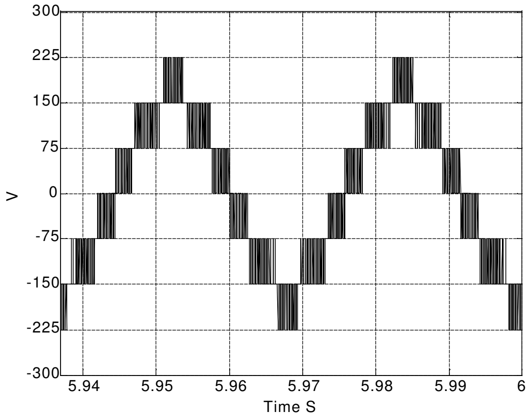
IV – SIMULATION RESULTS

A SIMULINK/MATLAB model of a Volts/Hertz induction motor drive using a five-level voltage-fed inverter was built to validate the proposed approach. The two neural networks were also included in the system using the MATLAB Neural Network Toolbox. The drive system parameters are given in table II.

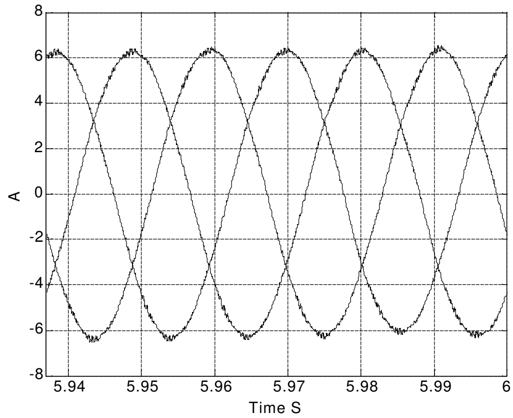
TABLE II : Drive system parameters

DC link voltage (V_{dc})	300 V
Sampling time (T_s)	500 S (f_s=2 kHz)
Induction motor	1 Hp, 230 V, 4-pole
	frequency range: 0 – 60 Hz
	Power factor (full load): 0.85
	Efficiency: (full load): 86%
	Stator resistance (Rs): 0.5814
	Rotor resistance (Rr): 0.4165
	Stator leak. inductance (Lls): 3.479 mH
	Rotor leak. inductance (Llr): 4.15 mH
	Magnetizing inductance (Lm):78.25 mH
	Rotor Inertia (J): 0.10 Kg.m^2
	Fan Load [T_L= r^2]: k= $8.25x10^{-5}$

The system was simulated for modulation index m=0.53 and for modulation index m=0.85. Figure 8 shows the line voltage waveform with the system operating with modulation index m=0.53. The figure also shows the current and the voltage line spectrum. It is possible to observe from these results that the proposed approach works very well when the reference voltage goes through the 3rd and 4th levels (triangles 2, 6, 7, 8 and 4).



(a)



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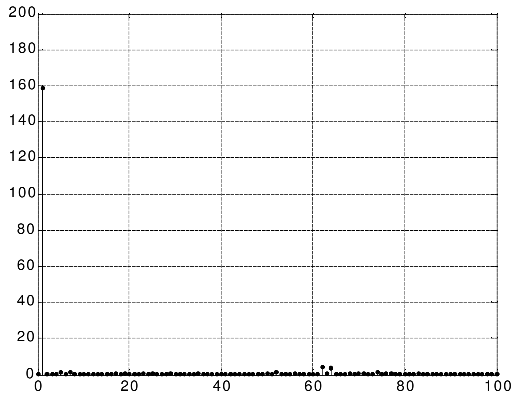
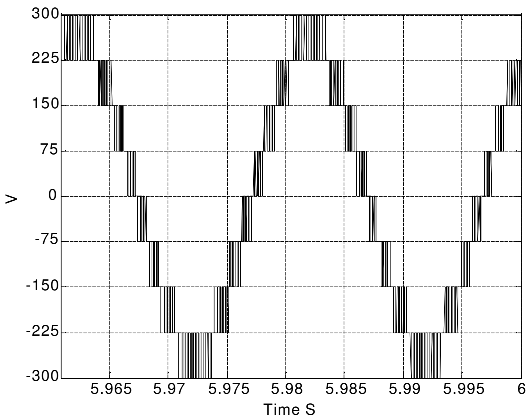


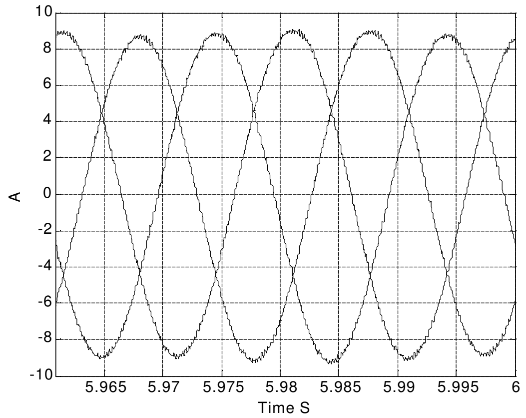
(c)

Fig. 8 – Simulation results for m = 0.53 (f=31.8 Hz)
(a) Line voltage
(b) Line current
(c) Line voltage spectrum

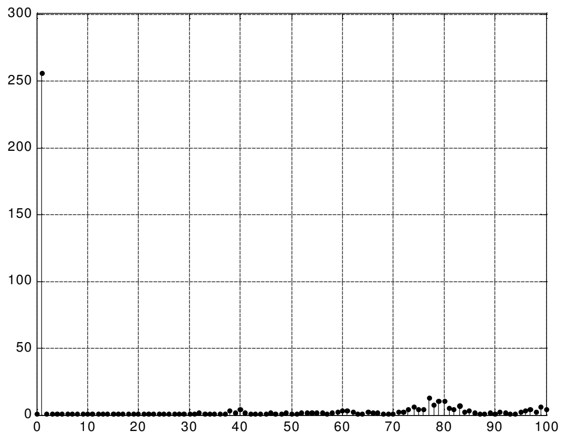
Figure 9 shows the line voltage waveform with the system operating with modulation index m=0.85. The figure also shows the current and the voltage line spectrum. The results are shown to be excellent for this modulation index as well. For this modulation index, the reference voltage goes through the 4th and 5th levels (triangles 5, 11, 12, 13, 15 and 9).



(a)



(b)



(c)

Fig. 9 – Simulation results for m = 0.85 (f=51 Hz)

(a) Line voltage
(b) Line current
(c) Line voltage spectrum

V – CONCLUSION

This paper proposed a Artificial Neural Network based Space Vector Pulse Width Modulation for multi-level inverters. The approach uses two ANN's to do the two most complex parts of the SVPWM algorithm. While one ANN was used for triangle identification, the other was used to calculate the duty cycles of the nearest three vectors. The ANN was designed, trained, and tested and gave excellent results. The simulation for a Volts/Hertz induction motor drive using a five-level voltage-fed inverter was given. The line voltage, the line current and the line voltage spectrum for modulation indexes that involves transition between two levels were given and shown to be excellent. Experimental results of the proposed approach using DSP and/or /FPGA will be given in the near future.

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