A VECTOR CONTROLLED INDUCTION MOTOR DRIVE WITH NEURAL NETWORK BASED SPACE VECTOR PULSE WIDTH MODULATOR

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ABSTRACT

A neural network based implementation of space vector modulation of a voltage-sourced inverter has been proposed in this paper. Use of ANN based technique avoids the direct computation of trigonometric function (e. g. sine function) as in conventional space vector modulation implementation. The main disadvantages with conventional implementation are, use of any look-up table implies the need for additional memory, interpolation of non-linear functions lead to poor accuracy and thus to increased harmonics in the PWM waveforms, the use of a look-up table and interpolation demands additional computing time that limits the maximum inverter switching frequency. The proposed scheme is simple and straight forward and avoids the direct computation of non-linear functions. This scheme is evaluated under simulation for a variety of operating conditions of the drive system and comparison is made with the conventional method of implementation. Results show improved performance and robustness of the drive system.

Keywords: Space Vector Pulse Width Modulation (SVPWM), Modulation Index, Voltage Space Vectors, Kohonen's Competitive Net.

1. INTRODUCTION

PWM control of the inverter switches requires to synthesize the desired reference stator voltage space vector in an optimum manner with the following objectives [1]:

- A constant switching frequency f_s.
- Smallest instantaneous deviation from its reference value.
- Maximum utilization of the available dc-bus voltages.
- Lowest ripple in the motor current and
- Minimum switching loss in the inverter.

The above conditions are generally met if the average voltage vector is synthesized by means of the two instantaneous basic non-zero voltage vector that form the sector (in which the average voltage vectors to be synthesized lies) and both the zero voltage vectors, such that each transition causes change of only one switch status to minimize the inverter switching loss.

It is possible to use a competitive type of ANN [2] which has six output nodes in the competitive layers. Two of these largest net inputs are the winner nodes which are associated with the two adjacent switching vectors. The second task is to compute the on-times (pulse times) of the adjacent switching vectors. Since the two net values contain information of the position (θ) of the reference voltage vector with respect to the two adjacent switching vectors, it is possible to use these net values for the estimation of the on-times of the switching vectors. The details are discussed in the following sections. Space vector modulation was comprehensively investigated in [3]-[7]. Neural network based space vector PWM is implemented in [8]. Here neural network was trained before implementation in actual scheme. In the classification algorithm, when classes are known a prior, there is no need of training the net as detailed in [9]-[10].

A difficulty of conventional space vector modulation is that it requires complex and time consuming online computation in DSP based implementation. The online computational burden of a DSP can be reduced by using lookup tables. However the lookup table method tends to give reduced pulse width resolution unless it is very large. The proposed scheme can be used to obtain reduced sampling time and thus higher switching frequencies, higher bandwidth of the control loops and reduced harmonics in all the PWM waveforms.

2. CONVENTIONAL SPACE VECTOR PULSE WIDTH MODULATION (SVPWM) IN A VOLTAGE SOURCE INVERTER

For A.C. drive application sinusoidal voltage source are not used. They are replaced by six power IGBT's that act as on/off switches to the rectified D.C. bus voltage. Owing to the inductive nature of the phases, a pseudo-sinusoidal current is created by modulating the duty-cycle of the power switches [3],[5]. Fig. 1. shows a three phase bridge inverter induction motor drive.

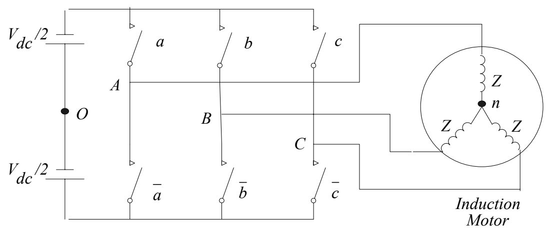


Fig. 1. Three phase voltage source inverter.

For the three phase two level PWM inverter the switch function is defined as

SW_i = 1, the upper switch is on and bottom switch is off.
= 0, the upper switch is off and bottom switch is on.
where $i = A,B,C$.

"1" denotes $V_{dc}/2$ at the inverter output, "0" denotes $-V_{dc}/2$ at inverter output with respect to neutral point of the d.c. bus. The eight switch states $S_i = (SW_A, SW_B, SW_C)$ where i=0,1,…..7 are shown in Fig. 2. There are eight voltage vectors $\overline{V_0}$ - - - - - $\overline{V_7}$ corresponding to the switch states $\overline{S_0}$ - - - - - $\overline{S_7}$ respectively. The lengths of vectors $\overline{V_1}$ - - - - - $\overline{V_6}$ are unity and the length of $\overline{V_0}$ and $\overline{V_7}$ are zero. These eight vectors form the voltage vector space as depicted in Fig. 3. The six non-zero

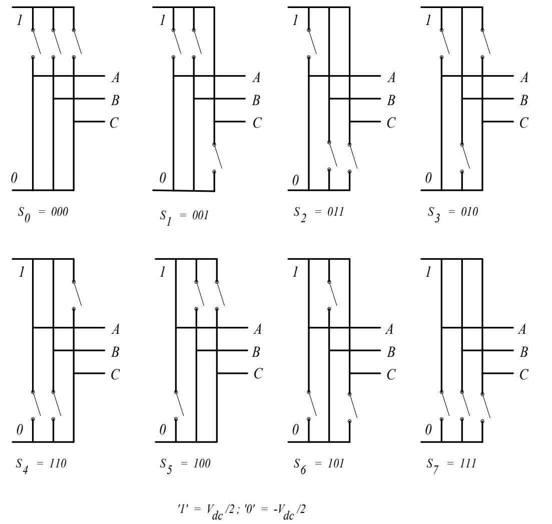


Fig. 2. Eight switching states of VSI.

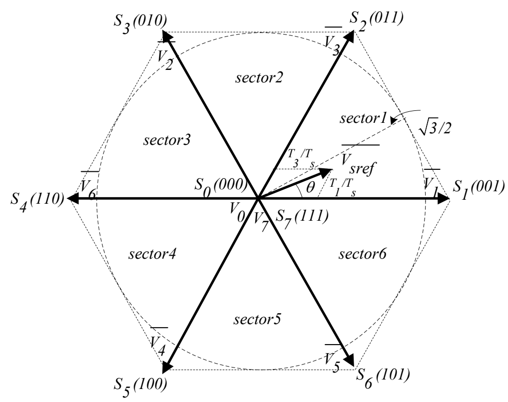


Fig. 3. Voltage space vectors.

voltage space vectors form a hexagonal locus. The voltage vector space is divided into six

sectors. It can be seen that when the space vector moves from one corner of the hexagon to another corner, then only the state of one inverter leg has to be changed. The zero space vectors are located at the origin of the reference frame. The reference value of the stator voltage space vector $\overline{V}_{sref}$ can be located in any of the six sectors. Any desired stator voltage space vector inside the hexagon can be obtained from the weighted combination of the eight switching vectors. The goal of the space vector modulation technique is to reproduce the reference stator voltage space vector ($\overline{V}_{sref}$) by using the appropriate switching vectors with minimum harmonic current distortion and the shortest possible cycle time. The eight permissible states are summarized in Table I.

TABLE I
SUMMARY OF INVERTER SWITCHING STATES

Voltage vector	sw_A	sw_B	sw_C	V_{An}	V_{Bn}	V_{Cn}
$\overline{V_0}$	0	0	0	0	0	0
$\overline{V_1}$	0	0	1	$-V_{dc}/3$	$-V_{dc}/3$	$2V_{dc}/3$
$\overline{V_2}$	0	1	0	$-V_{dc}/3$	$2V_{dc}/3$	$-V_{dc}/3$
$\overline{V_3}$	0	1	1	$-2V_{dc}/3$	$V_{dc}/3$	$V_{dc}/3$
$\overline{V_4}$	1	0	0	$2V_{dc}/3$	$-V_{dc}/3$	$-V_{dc}/3$
$\overline{V_5}$	1	0	1	$V_{dc}/3$	$-2V_{dc}/3$	$V_{dc}/3$
$\overline{V_6}$	1	1	0	$V_{dc}/3$	$V_{dc}/3$	$-2V_{dc}/3$
$\overline{V_7}$	1	1	1	0	0	0

$$\overline{V_{sref}} = \frac{T_0}{T_s}\overline{V_0} + \frac{T_1}{T_s}\overline{V_1} + \dots\dots\dots + \frac{T_7}{T_s}\overline{V_7} \qquad (1)$$

where $T_0, T_1, \dots\dots T_7$ are the turn on time of the vectors $\overline{V_0}, \overline{V_1}, \dots\dots \overline{V_7}$ respectively and $T_0, T_1, \dots\dots T_7 \geq 0$, $\sum_{i=0}^{7} T_i = T_s$ where T_s is the sampling time.

In order to reduce the number of switching actions and to make full use of active turn on time for space vectors, the vector $\overline{V_{sref}}$ is split into the two nearest adjacent voltage vectors and zero vectors $\overline{V_0}$ and $\overline{V_7}$ in an arbitrary sector. For Sector 1 in one sampling interval, vector $\overline{V_{sref}}$ can be given as

$$\overline{V_{sref}} = \frac{T_1}{T_s}\overline{V_1} + \frac{T_3}{T_s}\overline{V_3} + \frac{T_7}{T_s}\overline{V_7} + \frac{T_0}{T_s}\overline{V_0} \qquad (2)$$

where $T_s - T_1 - T_3 = T_0 + T_7 \geq 0$, $T_0 \geq 0$ and $T_7 \geq 0$

The length and angle of $\overline{V_{sref}}$ are determined by vectors $\overline{V_1}, \overline{V_2}, \dots\dots \overline{V_6}$ that are called active vectors and $\overline{V_0}$, $\overline{V_7}$ are called zero vectors. In general

$$\overline{V_{sref}} T_s = \overline{V_i} T_i + \overline{V_{i+1}} T_{i+1} + \overline{V_7} T_7 + \overline{V_0} T_0 \qquad (3)$$

Where T_i, T_{i+1}, T_7, T_0 are respective on duration of the adjacent switching state vectors $(\overline{V_i}, \overline{V_{i+1}}, \overline{V_7} and \overline{V_0})$. The on durations are defined as follows:

$$T_i = mT_s Sin(60 - \theta) \qquad (4)$$

$$T_{i+1} = mT_s Sin(\theta) \qquad (5)$$

$$T_7 + T_0 = T_s - T_i - T_{i+1} \qquad (6)$$

Where *m* is modulation index defined as :

$$m = \frac{2}{\sqrt{3}} \frac{\left|V_{sref}\right|}{V_{dc}} \qquad (7)$$

V_{dc} is d.c. bus voltage and θ is angle between the reference vector $\overline{V_{sref}}$ and the closest clockwise state vector as depicted in Fig. 3.

In the six step mode, the switching sequence is $S_1 - S_2 - S_3 - S_4 - S_5 - S_6 - S_1 \dots\dots$. Further more it should be pointed out that the trajectory of voltage vector $\overline{V_{sref}}$ should be circular while maintaining sinusoidal output line to line voltage. In the linear modulation range, $\overline{V_{sref}} = \sqrt{3}/2\, V_{dc}$, the trajectory of $\overline{V_{sref}}$ becomes the inscribed circle of the hexagon as shown in the Fig. 3.

In conventional schemes, the magnitude and the phase angle of the reference voltage vector (i.e. V_{sref} and θ) are calculated at each sampling time and then substituted into (7) and (4), (5) to get the value of on duration. Due to *Sine* Function in (4) and (5) it produces a larger computing delay. Although the use of a lookup table and linear interpolation are used but it increase computation time and interpolation of non-linear function may lead to reduced accuracy and therefore contribute to the deterioration of PWM waveforms.

3. NEURAL NETWORK BASED SPACE VECTOR PWM IN VOLTAGE SOURCE INVERTER

In a voltage source inverter the space vector modulation technique requires the use of the adjacent switching vectors to the reference voltage vector and the pulse times of these vectors. For this purpose, the sector where the reference voltage vector is positioned must be determined. This sector number is then used to calculate the position θ of the reference voltage vector with respect to the closest clockwise switching vector (Fig. 4). The pulse time can than be determined by using the trigonometric function $Sin(\theta)$ and $Sin(60-\theta)$ as in

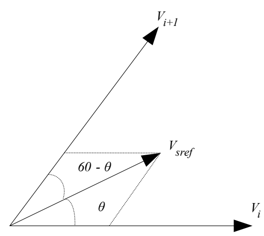


Fig. 4. Two winner neurons of the competitive layer closest to V_{sref} .

(4) and (5).

However, it is also possible to determine the two non-zero switching vectors which are adjacent to the reference voltage vector by computing the *cosine* of angles between the reference voltage vector and six switching vector and then by finding those two angles whose *cosine* values are the largest. Mathematically this can be obtained by computing the real parts of the products of the reference voltage space vector and the six non-zero switching vectors and selecting the two largest values. These are proportional to $Cos(\theta)$ and $Cos(60-\theta)$ respectively. Where θ and $(60-\theta)$ are the angles between the reference voltage vector and the adjacent switching vectors [9]-[10].

It is also possible to use an ANN based on Kohonen's competitive layers. In this paper modified Kohonen's competitive layers is proposed. It has two winner neurons and the outputs of the winner neurons are set to their net inputs. If normalized values of the input vectors are used, then the six outputs (six net values $n_1, n_2, \ldots\ldots n_6$) will be proportional to the *cosine* of the angle between the reference voltage vector and one of the six switching vectors. The two largest net values are then selected. These are n_i and n_{i+1}, proportional to $Cos(\theta)$ and $Cos(60-\theta)$. Since the space vector modulation is a deterministic problem and all classes are known in advance, there is no need to train the competitive layer.

$$net = V_{sref} . W = \left|V_{sref}\right| \left|W\right| Cos(\theta) \qquad (8)$$

Since the input vector and the weight vector are normalized, the instars net input gives the *cosine* of the angles between the input vector and the weight vectors that represent the classes. The largest instar net input wins the competition and the input vector is then classified in that class. The winner of the competition is the closest vector to the reference vector.

The six net values can be written in a matrix form for all neurons as:

$$\begin{bmatrix} n_1 \\ n_2 \\ n_3 \\ n_4 \\ n_5 \\ n_6 \end{bmatrix} = \begin{bmatrix} 1 & -1/2 & -1/2 \\ 1/2 & 1/2 & -1 \\ -1/2 & 1 & -1/2 \\ -1 & 1/2 & 1/2 \\ -1/2 & -1/2 & 1 \\ 1/2 & -1 & 1/2 \end{bmatrix} \begin{bmatrix} V_{Aref} \\ V_{Bref} \\ V_{Cref} \end{bmatrix} \qquad (9)$$

Where

$$\overline{W} = \begin{bmatrix} 1 & 1/2 & -1/2 & -1 & -1/2 & 1/2 \\ -1/2 & 1/2 & 1 & 1/2 & -1/2 & -1 \\ -1/2 & -1 & -1/2 & 1/2 & 1 & 1/2 \end{bmatrix}^T \quad \overline{V_{sref}} = \begin{bmatrix} V_{Aref} \\ V_{Bref} \\ V_{Cref} \end{bmatrix}$$

Assuming V_{sref} is applied to the competitive layer and n_i and n_{i+1} are the neurons who win the competition. Then from (8) we have

$$\begin{bmatrix} n_i \\ n_{i+1} \end{bmatrix} = \left|\overline{V_{sref}}\right| \begin{bmatrix} Cos(\theta) \\ Cos(60-\theta) \end{bmatrix} \qquad (10)$$

Also

$$\begin{bmatrix} Cos(\theta) \\ Cos(60-\theta) \end{bmatrix} = \frac{2}{\sqrt{3}} \begin{bmatrix} 1/2 & 1 \\ 1 & 1/2 \end{bmatrix} \begin{bmatrix} Sin(60-\theta) \\ Sin(\theta) \end{bmatrix} \qquad (11)$$

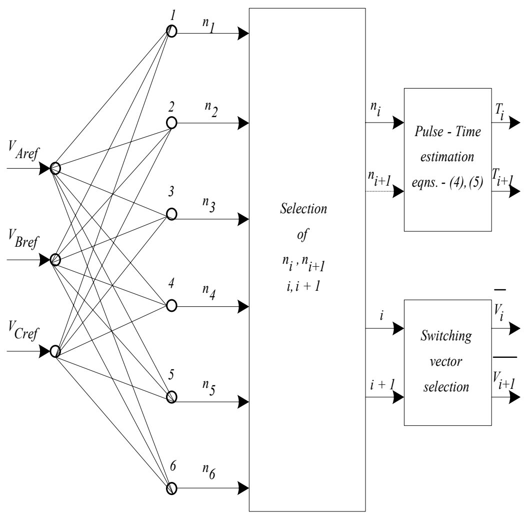
Substituting (11) in (10) we get

$$\frac{2}{3} \frac{T_s}{V_{dc}} \begin{bmatrix} -1 & 2 \\ 2 & -1 \end{bmatrix} \begin{bmatrix} n_i \\ n_{i+1} \end{bmatrix} = \frac{2}{\sqrt{3}} \frac{\left|\overline{V_{sref}}\right|}{V_{dc}} \begin{bmatrix} Sin(60-\theta) \\ Sin(\theta) \end{bmatrix} T_s \qquad (12)$$

Equation (12) is the on duration of the consecutive adjacent switching state vector V_i and V_{i+1}, which is same as (5) and (6).Therefore we have

$$\begin{bmatrix} T_i \\ T_{i+1} \end{bmatrix} = \frac{2}{3} \frac{T_s}{V_{dc}} \begin{bmatrix} -1 & 2 \\ 2 & -1 \end{bmatrix} \begin{bmatrix} n_i \\ n_{i+1} \end{bmatrix} \qquad (13)$$

The implementation of this method is depicted in fig. 5., first n_k for $k=1\ldots\ldots\ldots 6$ are calculated. Two



largest n_i, n_{i+1} and their corresponding indexes (i.e. i and $i+1$) are selected by Kohonen's

Fig. 5. Modified Kohonen's competitive layer based implementation of the space vector modulation technique for VSI.

competitive network. The on duration (T_i and T_{i+1}) of the two adjacent space vectors are computed. The space vector $\overline{V_i}$ and $\overline{V_{i+1}}$ are selected according to the value of i and $i+1$. When adjacent vectors and on times are determined the procedure for defining the sequence for implementing the chosen combination is identical to that used in conventional space vector modulation as depicted in Fig. 6. The proposed scheme for vector control induction motor drive with neural network based space vector modulated VSI is shown in Fig. 7.

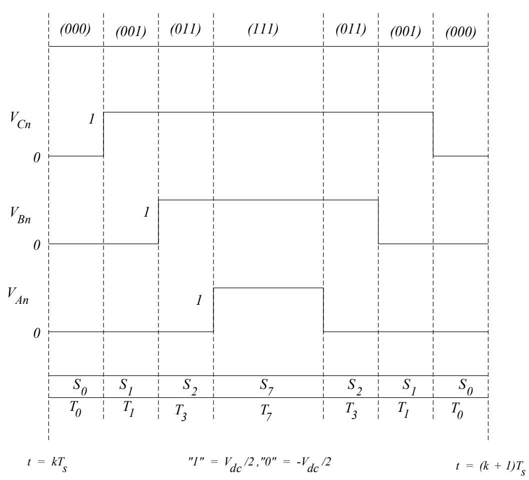


Fig. 6. Pulse patterns generated by space vector modulation in sector 1

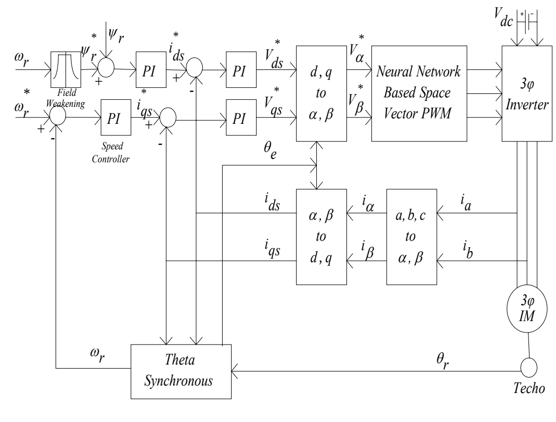
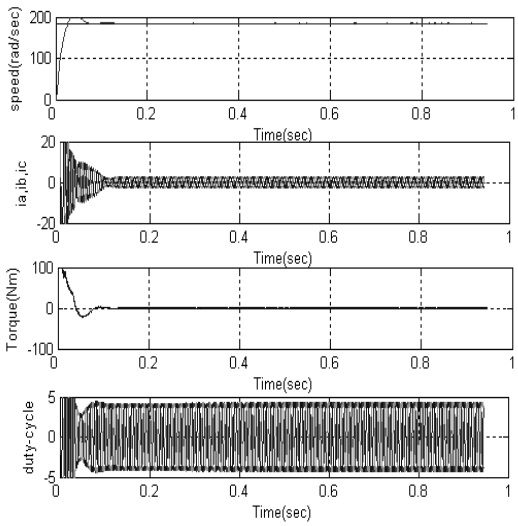


Fig. 7. Vector control Induction Motor Drive with neural network based space vector modulated VSI.

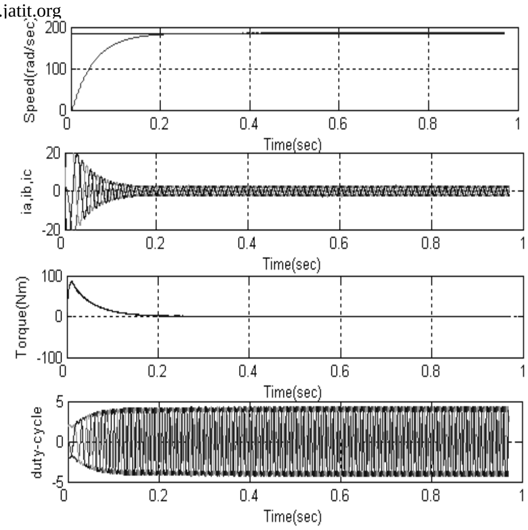
4. PERFORMANCE EVALUATION OF VECTOR CONTROLLED INDUCTION MOTOR DRIVE WITH NEURAL NETWORK BASED SPACE VECTOR PWM

Modified Kohonen's competitive layer based space vector PWM was integrated with the inverter for rotor flux oriented vector controlled induction motor drive. The inverter was operated at switching frequency of 10 kHz (i.e. T_s =0.1 ms). The parameters of the induction motor considered in this study are summarized in Appendix. The performance of vector control induction motor drive with neural network based space vector PWM is presented during starting, load perturbation and speed reversal.

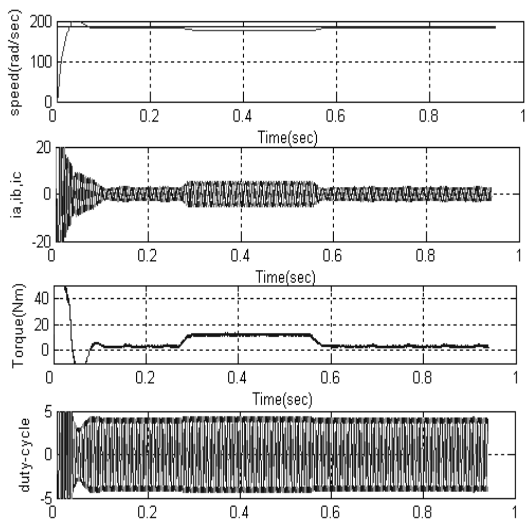
Fig. 8. shows time response of speed, current and duty cycle for no load condition for neural network based SVPWM and conventional SVPWM respectively. Fig. 9. shows time response of speed, current and duty cycle for load perturbation at 0.35 sec. to 0.55 sec. for neural network based SVPWM and conventional SVPWM respectively. Fig.10. shows time response of speed, current and duty cycle for speed reversal for neural network based SVPWM and conventional SVPWM respectively. Neural network based SVPWM vector control induction motor drive shows high level of performance during starting, speed reversal and load perturbation.



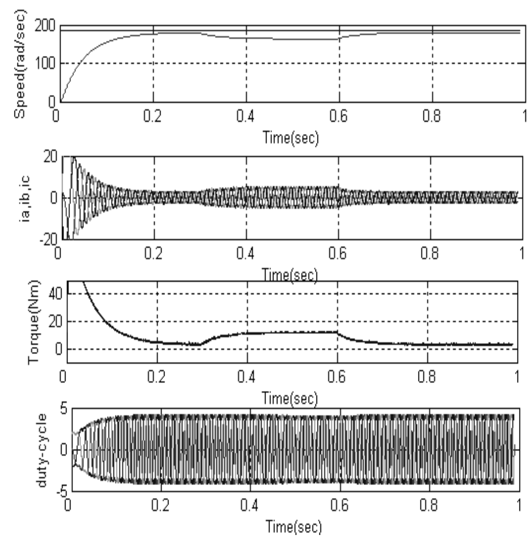
(a) Neural Network based SVPWM induction motor drive.



(b) Conventional SVPWM induction motor drive.



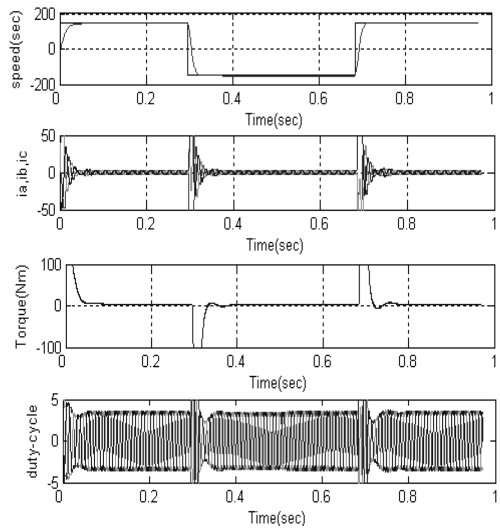
(a) Neural Network based SVPWM induction motor drive.



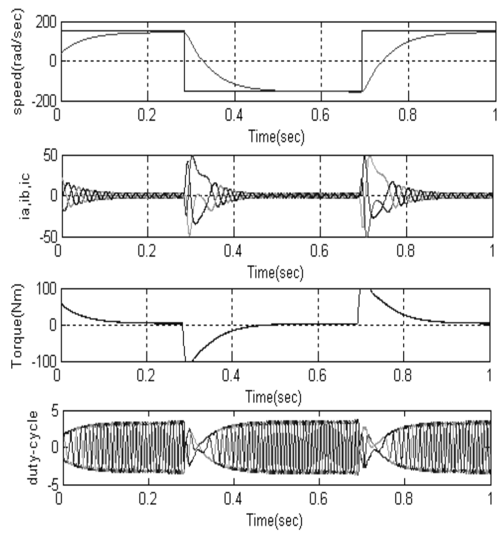
(b) Conventional SVPWM induction motor drive.

Fig. 8. Time response of speed, currents and duty cycle for no-Load

Fig. 9. Time response of speed, currents and duty cycle for load perturbation at 0.35 sec. to 0.55 sec.



(a) Neural Network based SVPWM induction motor drive.



(b) Conventional SVPWM induction motor drive.

Fig. 9. Time response of speed, currents and duty cycle for speed reversal at constant load.

5. CONCLUSION

Use of ANN based technique avoids the direct computation of non-linear function as in conventional space vector modulation implementation. The ANN based SVPWM can give higher switching frequency which is not possible by conventional DSP based SVPWM. Switching frequency can be easily extended up to 50 kHz with dedicated hardware ASIC chip. The results demonstrate the ability of the proposed scheme to improve the performance and robustness of the vector-control drives.

APPENDIX

The parameters of induction motor are as follows:

P	Nominal power	2.2KW
R_s	Stator resistance	1.77 ohms
R_r	Rotor resistance	1.34 ohms
X_{ls}	Stator leakage reactance	5.25 ohms
X_{lr}	Rotor leakage reactance	4.57 ohms
X_m	Mutual reactance	139 ohms
J	Rotor inertia	0.025 Kg.m^2
p	Number of pole	4

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