Artificial Neural Network based implementation of Space Vector Modulation for Three Phase VSI

Vishnu V Bhandankar
Electrical and Electronics Dept.
Goa College of Engineering
Farmagudi, Ponda Goa, India- 403401
E-mail id: vishnu.bhandankar@gmail.com

Anant J Naik
Electrical and Electronics Dept.
Goa College of Engineering
Farmagudi, Ponda, Goa, India-403401
Email id: ajn@gec.ac.in

***Abstract*— SVM (Space Vector Modulation) is among the most common PWM technique for three phase Voltage Source Inverter ,SRM (switched reluctant motor), BLDC(Brushless DC) motor, and permanent magnet motor. Space vector PWM (SVPWM) has better harmonics performance along with higher rms voltage. Command voltage reference for all the three phases of three phase SVPWM is actuated as a whole. The logic behind this algorithm is that it averages the output vector of the inverter equal to the reference voltage vector. Due to complex nature of its operation, there is a computational delay involved in SVPWM, this often bounds its working up to few kHz of switching frequency. An Artificial Neural Network is used to solve this particular problem in this paper. The computational delay is negligible in case of feedforward neural network especially when a parallel architecture based dedicated application- specific IC (ASIC) chip is used. The conventional back propagation method undergo drawback such as overfitting the network. In this paper an alternate learning algorithm Bayesian Regularization method is used for training of the Neural Network. Bayesian regularized artificial neural networks (BRANNs) does not require cross-validation and are extra robust than conventional back-propagation neural network.**

Keywords—Artifical Neural Network, Neuron, Space Vector Modulaion,Bayesian regularization.

I. Introduction

SVPWM is one of the most popular PWM technique for DC to AC conversion for the following reasons:

- Wide linear range of operation.
- Better DC link utilization.
- 15% more output voltage than conventional modulations.
- Less harmonics content.

Due to the nature of working of SVPWM, the computational delay restricts its working up to several kHz of switching frequency. The operation complexity increases especially when SVM needs to work in all the three regions (i.e. undermodulation, overmodulation mode I and overmodulation mode II). The algorithm required for each mode of operation (undermodulation, overmodulation mode I and overmodulation mode II) is different [2].

The application of Artificial Neural Networks (ANN) in field of power electronics has been growing in recent years. A nonlinear input–output mapping is possible to be implemented using Neural Network. The neural network can be tuned by updating its weights and bias for a particular application. With use of a feed-forward neural network, a very fast implementation of SVM is possible when a dedicated application- specific IC chip is used. The optimal tuning of weights and bias of neural network is known as training neural network. The optimization technique for minimization of performance function (MSE) is done by calculating the gradient known as Backpropagation. The data generated using conventional SVM can be used for training the neural network in a convenient offline manner. Unlike the normal look-up table the neural network has an inherent characteristics of improved precision in interpolation [1].

Bayesian regularized artificial neural networks (BRANNs) does not require the long cross-validation and are extra robust than conventional back-propagation neural network. Bayesian regularization was first proposed in [10]. BRANN is difficult to overfit as it calculates & trains the network on effective net parameters, switching off those which are not required. In a standard feed-forward network these effective number of parameter is usually considerably low [6].

A Three phase for two level VSI with a balanced load has been shown in Fig. 1. The paper is organized in the following manner in Section I Introduction, Section II Operation of conventional SVPWM (Space Vector PWM) has been covered for undermodulation and overmodulation mode I, In Section III Implementation of SVPWM using a controller based on Artificial Neural Network has been discussed, Section IV Simulation, and Section V concludes paper.

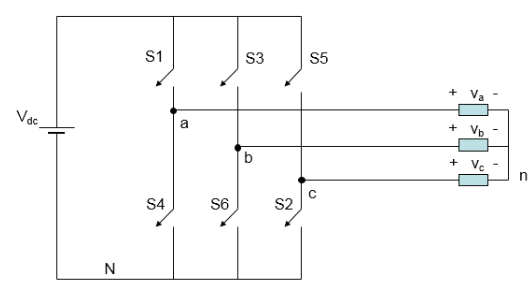

Fig. 1 Power circuit of three phase (2 level) voltage source inverter (VSI)

II. Space Vector PWM(SVPWM)

The output of two level inverter depends upon the switching state of switches S1-S6 of inverter shown in Fig. 1.The notation used for representing switching state is [Sw_a,Sw_b,Sw_c],Ex. [100] from upper half switch S1 is ON and from lower half S6 and S2 is ON. Considering all the switching states, the total switching states are: 2^3 =8.These switching states or vectors can be classified into 6 unit vector of magnitude 2/3 V_{dc} and 2 zero vectors .These vectors are represented as V_0[000]-V_7[111].Fig. 2 shows all eight vectors in dq frame. This results into splitting of dq frame into 6 equal sector and the hexagon form the boundary of the Space Vector modulation.

The first step towards implementation of SVPWM is identification of sector. An easy way for identification of sector is by using the phase angle α given by Eq. (1).

$$\alpha = \tan^{-1}\left(\frac{V_q}{V_d}\right) \tag{1}$$

Sector 1: $0 \le \alpha < 60$
Sector 2: $60 \le \alpha < 120$
Sector 3: $120 \le \alpha < 180$
Sector 4: $180 \le \alpha < 240$
Sector 5: $240 \le \alpha < 300$
Sector 6: $300 \le \alpha < 360$

The modulation index (mod) of inverter varies from 0-1 and can be given as:

$$mod = \frac{\bar{V}_{ref}}{V_{\mathrm{p}}} \tag{2}$$

Where V_p is peak value of fundamental of square wave while $\bar{V}_{ref}$ is the reference voltage magnitude. Depending upon the modulation index the working of SVM has been classified into three regions based: (1) undermodulation mode (mod < $\pi/2\sqrt{3}$) (2) overmodulation mode I ($\pi/2\sqrt{3}$ < mod < 0.952) (3) overmodulation mode II (0.952 < mod < 1).

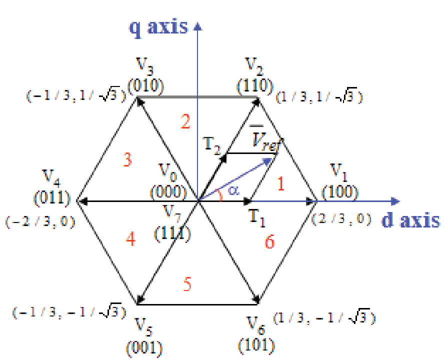

Fig. 2 Space Vector PWM

A. Undermodulation mode (0 < mod < $\pi/2\sqrt{3}$)

The voltage reference in case of the undermodulation mode or linear region, is confined within the hexagon boundary as shown in Fig. 3. The logic behind space vector PWM is that to estimate the command voltage vector $\bar{V}_{ref}$ using the eight switching patterns (eight vectors) of three phase (2 level) VSI. A simple way of estimating the command voltage vector is to generate the average VSI output for a small period t_s [3]. In one sampling interval, the output voltage vector reference $\bar{V}_{ref}$ can be given as:

$$\bar{V}_{ref} = \frac{t_0}{t_s}\bar{V}_0 + \frac{t_1}{t_s}\bar{V}_1 + \frac{t_2}{t_s}\bar{V}_2 + \ldots\ldots\ldots\frac{t_7}{t_s}\bar{V}_7 \tag{3}$$

Where t_0-t_7 is turn on time for each vector.

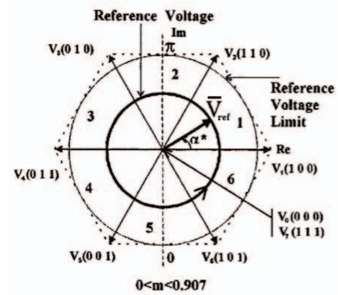

Fig. 3 Operation in Undermodulation

Hence $\bar{V}_{ref}$ can be defined in infinite number of ways depending upon the various switching time (t_0-t_7) of the vectors. But the command vector $\bar{V}_{ref}$ is resolved into two adjacent active vectors and zero vectors .This is to reduce the number of switching commutations per switching period thereby reducing the switching losses and making full utilization of active vectors. Using sector identification it is possible to find the two adjacent vector .Consider $\bar{V}_{ref}$ lies in sector 1 between V_1[100] and V_2[110],hence the switching will occur between V_1 and V_2 depending on magnitude of $\bar{V}_{ref}$ and remaining switching time is split between V_0 and V_7 . Hence $\bar{V}_{ref}$ now can be given as [4]:

$$\bar{V}_{ref} = \frac{t_0}{t_s}\bar{V}_0 + \frac{t_1}{t_s}\bar{V}_1 + \frac{t_2}{t_s}\bar{V}_2 + \frac{t_7}{t_s}\bar{V}_7 \tag{4}$$

The effective times for switching for sector 1 can be given as [4]:

$$\begin{aligned} T_1 &= T_s.a.\left(\sin\left(\frac{\pi}{3} - \alpha\right)/\sin\left(\frac{\pi}{3}\right)\right) \\ T_2 &= T_s.a.\left(\sin(\alpha)/\sin\left(\frac{\pi}{3}\right)\right) \\ T_0 &= T_s - (T_1 + T_2) \end{aligned} \tag{5}$$

Where a= $|\bar{V}_{ref}|/(2/3\,Vdc)$

Generalized equation for switching time duration at any Sector can be given by [4]:

$$\begin{aligned} T_1 &= \frac{\sqrt{3}T_s|V^*|}{V_{dc}}\left(\sin\frac{n}{3}\pi.\cos\alpha - \cos\frac{n}{3}\pi.\sin\alpha\right) \\ T_2 &= \frac{\sqrt{3}T_s|V^*|}{V_{dc}}\left(-\cos\alpha.\sin\frac{n-1}{3}\pi + \sin\alpha.\cos\frac{n-1}{3}\pi\right) \\ T_0 &= T_s - (T_1 + T_2) \end{aligned} \tag{6}$$

Where Where n=1 through 6 (that is, Sector 1 to 6)

$0 \le \alpha \le 60$

The SVPWM algorithm can be simplified by using dq components was proposed in [2]. The method proposes to simplify the algorithm of SVPWM by expressing the equations in terms of turn-on time for individual phase using 9 equations as shown in Eq. no (7) and it does not involve any look-up table [2].

$$T_{A-on} = \begin{Bmatrix} \frac{T_s}{4}\left(1+\frac{3}{2V_{DC}}\left[-V_d-\frac{V_q}{\sqrt{3}}\right]\right) & \\ \frac{T_s}{4}\left(1+\frac{3}{2V_{DC}}\left[-2V_d\right]\right) & \begin{matrix} S=1,4 \\ S=2,5 \\ S=3,6 \end{matrix} \\ \frac{T_s}{4}\left(1+\frac{3}{2V_{DC}}\left[-V_d-\sqrt{3}V_q\right]\right) & \end{Bmatrix}$$

$$T_{B-on} = \begin{Bmatrix} \frac{T_s}{4}\left(1+\frac{3}{2V_{DC}}\left[V_d-\sqrt{3}V_q\right]\right) & \\ \frac{T_s}{4}\left(1+\frac{3}{2V_{DC}}\left[-\frac{2V_q}{\sqrt{3}}\right]\right) & \begin{matrix} S=1,4 \\ S=2,5 \\ S=3,6 \end{matrix} \\ \frac{T_s}{4}\left(1+\frac{3}{2V_{DC}}\left[V_d-\frac{V_q}{\sqrt{3}}\right]\right) & \end{Bmatrix} \quad (7)$$

$$T_{C-on} = \begin{Bmatrix} \frac{T_s}{4}\left(1+\frac{3}{2V_{DC}}\left[V_d+\frac{V_q}{\sqrt{3}}\right]\right) & \\ \frac{T_s}{4}\left(1+\frac{3}{2V_{DC}}\left[\frac{2V_q}{\sqrt{3}}\right]\right) & \begin{matrix} S=1,4 \\ S=2,5 \\ S=3,6 \end{matrix} \\ \frac{T_s}{4}\left(1+\frac{3}{2V_{DC}}\left[V_d+\sqrt{3}V_q\right]\right) & \end{Bmatrix} [2]$$

B. Overmodulation mode II ($\pi/2\sqrt{3}$<mod<0.952)

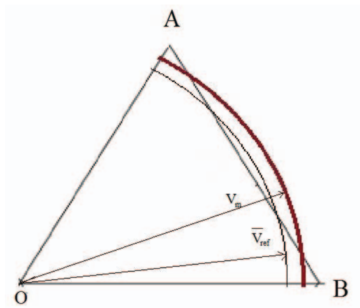

Fig. 4 Operaion in Overmodulation

In overmodulation the reference vector $\bar{V}_{ref}$ exceeds the hexagon boundary. The reference vector $\bar{V}_{ref}$ cuts the hexagon at two different points in each sector as shown in Fig. 4. The operation of Space Vector is classified into circular region and a linear region along line AB as shown in Fig. 4. In the circular region the operation remain same as the undermodulation region. On the hexagon trajectory, time t_0 vanishes, giving t_1 and t_2 expressions as [1]:

$$t_1 = \frac{T_s}{2}\left(\frac{\sqrt{3}\cos\alpha - \sin\alpha}{\sqrt{3}\cos\alpha + \sin\alpha}\right) \quad (8)$$
$$t_2 = \frac{Ts}{2} - t_1$$

To compensate for the loss a new reference vector Vm(Vm>$\bar{V}_{ref}$) is used. Pre calculation using computer program can be used to find the compensation required due to loss occurring in linear region. For the new extended reference V_m crossover angle as a function of modulation factor is plotted in Fig. 5[5][2].

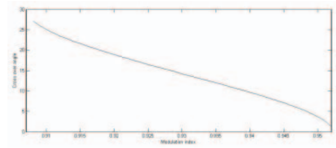

Fig. 5 Crossover angle (°) v/s modulation index

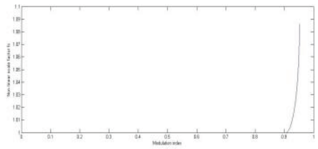

Fig. 6 fc v/s modulation index

For simplification, a nonlinear scale factor fc is used which extends the working of undermodulation mode to overmodulation mode I. This nonlinear scale factor can be given as [2]:

$$f_c = \frac{V_m}{\bar{V}_{ref}} \quad (9)$$

Where V_m is new extended reference in case of overmodulation mode 1, $\bar{V}_{ref}$ is reference voltage. The Fig. 6 shows the plot of fc v/s modulation index. The nonlinear scale factor fc is stored in terms of lookup table and on multiplication with the command voltage, will give the modified reference resulting into extended linear characteristics.

III. Implementation of Artifical Neural network

A. Model

In this Section we propose a two layer feedforward ANN model as shown Fig. 9 with two input (1) modulation index (2) reference vector phase α.The basic building block of neural network is a neuron, see Fig. 7. The output of the neuron is given as:

$$y = f(\varphi) = f\left(\sum_{i=0}^{N_0} a_i w_i\right) \quad (10)$$

The activation function used for hidden layer in this case is a sigmoidal function given as:

$$f(\varphi) = \frac{1}{1+e^{-\beta\varphi}} \quad (11)$$

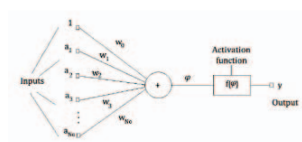

Fig. 7 Model of Neuron

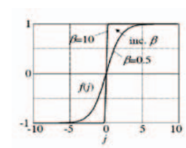

Fig. 8 Sigmoidal Function

The proposed model consists of two input neuron, 50 hidden neuron and three output neuron .The network is trained to generate reference signal for each phase, these reference signal is compared with triangular wave to generate gating pulses for the three phase inverter.

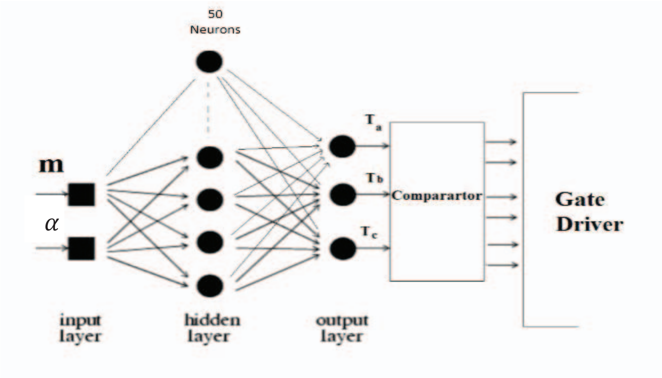

Fig. 9 Neural Network Model for SVPWM

B. Training of Neural Network

In general training algorithm for neural network can be classified into two methods: Cross Validation Early Stopping (CVES) and Bayesian Regularization.

1) Cross Validation Early Stopping (CVES)

Cross Validation Early Stopping (CVES) is the most popular method to achieve generalization through using cross-validation. In CVES, the total data available is divided into two sets: (1) training set and (2) validation set. Weights and bias updating is carried out using the training set while the validation set monitors the changes in error while training process. In the initial training phase the validation error with the cross validation set will decrease. In case if neural network starts to overfit the data, the error with validation will increase and when validation error exceeds the specified number of iteration the training process comes to halt. [9].A similar problem is faced in case of implementation of SVM using CVES, the training stops at 230 epoch because of increase in error with cross validation after initial phase. See Fig. 10 the mean square error achieved is 1.1081e-4.

2) Bayesian Regularization

Large weight can cause excessive variance of the output. By use of regularization this excessive variance caused by large weight can be dealt. The objective function of standard Backpropagation algorithm is minimization of error, the error are susceptible to weights. To make the response of the neural network flatter, the standard objective function is modified by adding penalty factor which consists of squares of all network weights. These penalty factors decreases the tendency to overfit of neural network model during training process and it also favors small values of network weights and bias [9].

In Bayesian Regularization the weights and bias are updated in an iterative manner using Lavenberg-Marquardt(LM) optimization technique [10]-[12]. As discussed in previous para the objective function involves combination of network error and network weights, this results in better generalization. The objective function F(ω) can be given in terms of the following equation [13][15].

$$F(\omega) = \alpha' E_{\omega t} + \beta E_e \tag{12}$$

Where $E_{\omega t}$ is the squared neural network weight sum and E_e is the neural network training error sum. The goal function parameters are α' and β. The neural network weights and bias are seen as random variables and the training set along with distribution of neural network is taken as Gaussian distribution in case of Bayesian Regularization framework [15].

Bayes theorem is used to find out the values of α' and β factors. Consider two events X and Y then Bayes theorem is given by the following equation [14] [15].

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)} \tag{13}$$

Where P (X) and P(Y) are individual probabilities of event X and Y without regard of each other. P (X|Y) is the conditional probability of X given that Y is true. Similarly P (Y|X) is the probability of Y when X is true. To train the network by tuning it's weight and bias Eq no (12) needs to minimized, which is equivalent to maximizing the probability function given in Eq no (14) [15] :

$$P(\alpha', \beta|D, M) = \frac{P(D|\alpha', \beta, M)P(\alpha', \beta|M)}{P(D|M)} \tag{14}$$

Where D is the weight distribution of the neural network and M corresponds to neural network architechure. The aim is to find the optimal value of α' and β. $P(D|M)$ is the normalization factor, $P(\alpha',\beta|M)$ is the uniform prior density for the regularization parameters and $P(D|\alpha',\beta,M)$ is the likelihood function of D for given α',β,M. So to maximize the probability function (α', $\beta|D,M$) , $P(D|\alpha', \beta,M)$ needs to maximized. By this process for a given weight space the optimal value of α' and β are found. Algorithms moves into LM phase where weights are updated in order to minimize objective function, then in case if convergence is not meet new values of α' and β are estimated and process is repeated [12] [15].

MATLAB tool was used for creating and training purpose of Space Vector PWM. Both training algorithm were implemented with Input as modulation index and reference phase angle θ going from 0 to 360 deg. and target output using Eq (7). Network was trained at 1000 Epoch using CVES (Lavenberg-Marquardt) and Bayesian Regularization.3600 data of different modulation index and reference phase angle has been used. Fig. 11 shows the Best training Performance of the network obtained by Bayesian Regularization, the mean square error of the proposed network is 1.3837e-6.Table I & Fig. 12 shows comparison of the results obtained by both the methods.

Table I COMPARISION OF NETWORK OBTAINED BY LM AND BR

Training method	Mean Sq. Error	Regression
LM	1.1081e-4	9.99793e-1
BR	1.3837e-6	9.99997e-1

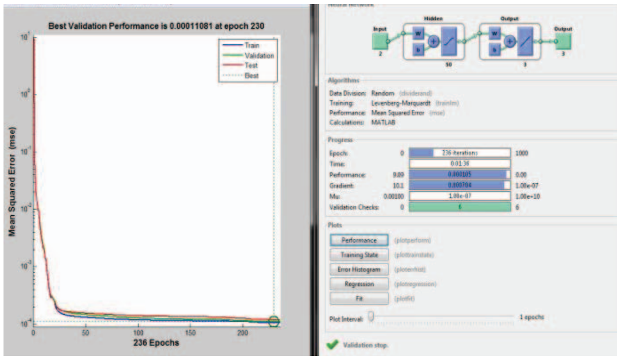

Fig. 10 Training Neural Network using Lavenberg-Marquardt.

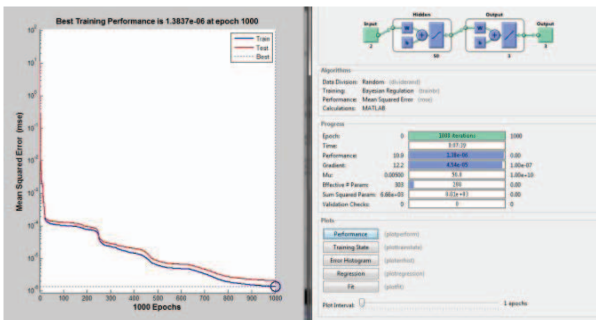

Fig. 11 Training Neural Network using Bayesian Regularization

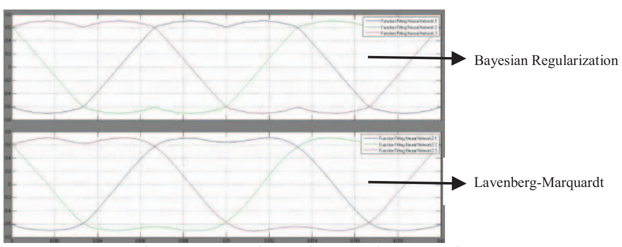

Fig. 12 Comparison of Output by BR and LM

IV. SIMULATION

A simulation of ANN based SVPWM for Three phase VSI was carried out in MATLAB. For this model, switching frequency of 3 kHz and RL load (R=0.23ohm and L=30.7mH) was used. The operation of the Space vector was further extended into overmodulation using nonlinear scale factor (Fig. 6).The Fig. 13 shows the model of ANN based SVPWM in MATLAB. Fig. 14-Fig. 18 shows the results for undermodulation (m=0.7) while Fig. 19-Fig. 23 shows results for overmodulation mode I (m=0.94).

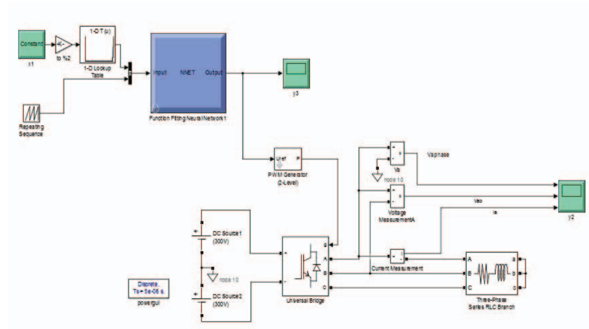

Fig. 13 Model of ANN based SVPWM in MATLAB

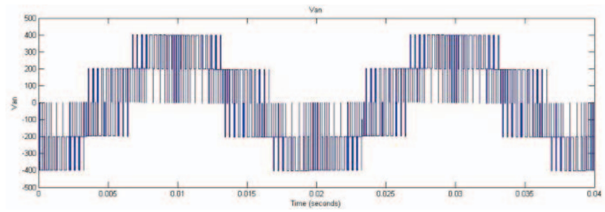

Fig. 14 Phase voltage Van for undermodulation (mod = 0.7)

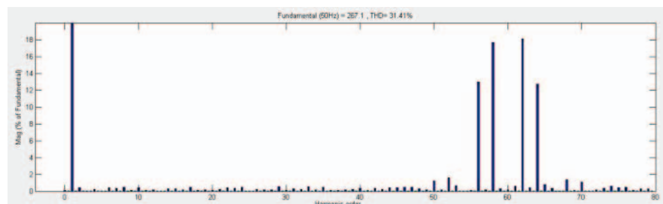

Fig. 15 FFT Phase voltage Van for undermodulation (mod = 0.7)

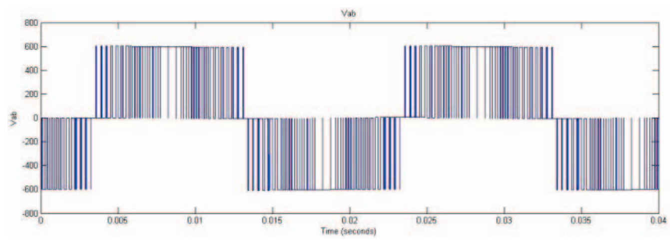

Fig. 16 Line-Line Voltage Vab for undermodulation (mod = 0.7)

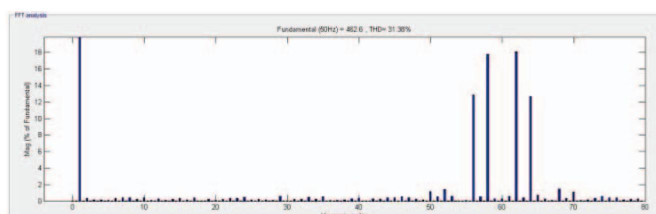

Fig. 17 FFT Line-Line Voltage Vab for undermodulation (mod = 0.7)

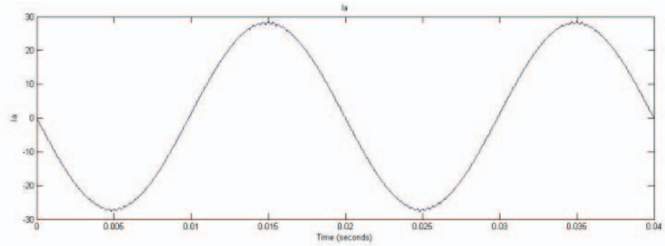

Fig. 18 Line-Line current Ia for undermodulation (mod = 0.7)

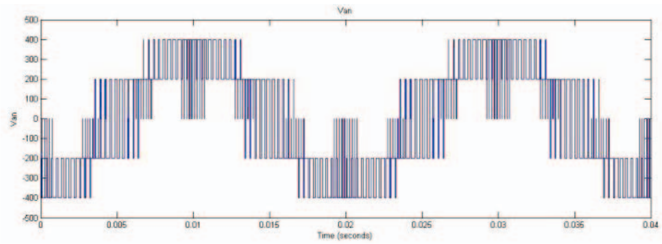

Fig. 19 Phase Voltage Van for overmodulation mode I (mod = 0.94)

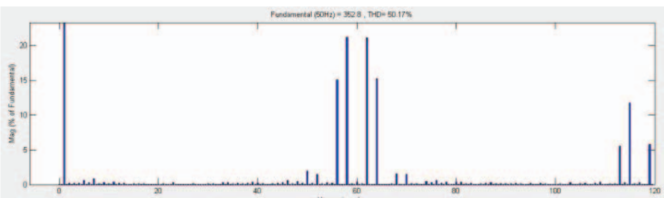

Fig. 20 FFT Phase volatage Van overmodulation mode I (mod = 0.94)

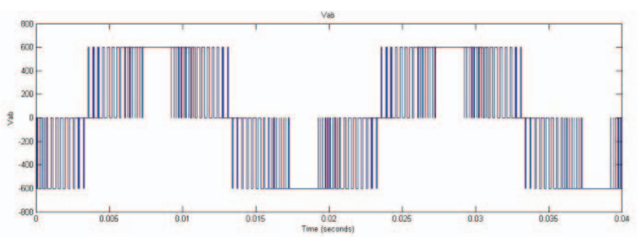

Fig. 21 Line-Line Voltage Vab for overmodulation mode I (mod = 0.94)

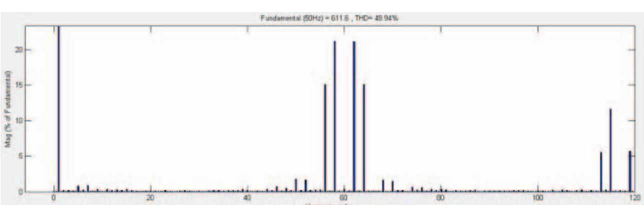

Fig. 22 FFT Line-Line Voltage Vab for overmodulation mode I (mod = 0.94)

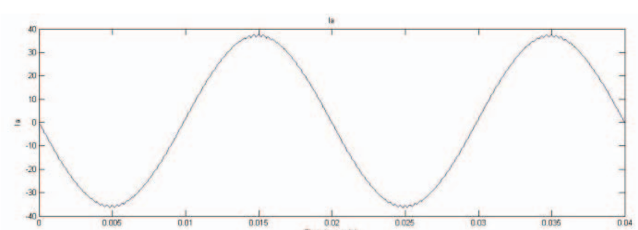

Fig. 23 Line Current Ia for overmodulation mode I (mod = 0.94)

V. Conclusion

The neural network based controller of space vector PWM operates very well. Further the operation of SVPWM is extended into overmodulation mode 1 using a look-up table. With using dedicated parallel architecture based ASIC it possible to implement SVM with negligible computational delay. To overcome the difficulty faced in CVES training algorithm, Bayesian Regularization was used to train the network giving result with better Regression. In this paper though a constant frequency operation and a RL load has been used, the operation can be implemented for a motor load with v/f control. The implementation for overmodulation mode-2 is in progress.

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