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Research on Space Vector PWM Inverter Based on Artificial Neural Network

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***Abstract*—This paper proposed a Space Vector PWM algorithm based on artificial neural network for voltage-source inverters. When calculating the invert's three-phase turn-on time, the paper uses a three-layer forward-feed network which adopts the algorithm of Levenberg-Marquarde to train the network. This method uses artificial neural network's strong nonlinear approximation ability to avoid a lot of nonlinear calculation. At last, in the environment of MATLAB/Simulink, simulation model of the system was built. The simulation results show that the SVPWM algorithm of artificial neural network can improve the switching frequency and reduce the harmonic of output voltage and current.**

Keywords- Space Vector PWM; Artificial Neural Network; Inverter;Matlab/Simulink

I. INTRODUCTION

Space vector PWM (SVPWM) has recently grown as a very popular pulse width modulation (PWM) technology for voltage-source inverters, which can obviously reduce the inverter's output voltage harmonic and improve the utilization of DC voltage [1]. However, a setback of SVPWM is that it requires complex online computation that usually limits its operation only up to several kilohertz of switching frequency. Modern ultra-fast IGBT's allow operation at 50 kHz, the DSP-based SVPWM practically fails in this region where artificial neural network (ANN)-based SVPWM would probably take over [2][3]. To overcome this, the paper proposed a SVPWM algorithm based on ANN to avoid a lot of nonlinear calculation.

II. SPACE-VECOR PWM ALGORITHM

In the three-phase voltage-source inverter, three bridge arms has eight conducting states, including six nonzero vectors and two zero vectors, 1 of which represent the upper bridge arm conduction, 0 representatives of the lower bridge arm conduction[4][5]. Voltage space vector diagram is shown in Fig.1.

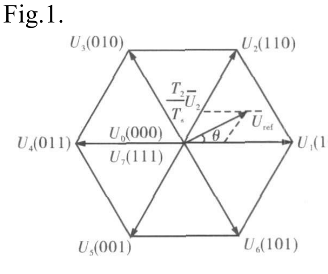

Figure 1. Voltage space vector diagram

In linear region, the rotating reference voltage remains in the hexagon [6][7]. The SVPWM strategy in this region is based on generating three consecutive switching voltage vectors in a sampling period (Ts) so that the reference voltage matches with the average output voltage, all the duty cycle can be described as follows:

$$\begin{aligned} d_1 &= \frac{2\sqrt{3}}{\pi} m \sin(\frac{\pi}{3} - \alpha) \\ d_2 &= \frac{2\sqrt{3}}{\pi} m \sin(\alpha) \\ d_0 &= 1 - d_1 - d_2 \end{aligned} \tag{1}$$

Where $d_1 = \frac{2t_1}{T_s}$, $d_2 = \frac{2t_2}{T_s}$, $d_0 = \frac{2t_0}{T_s}$

M - Modulation factor

For any command angle α^* , the duty cycles d_1, d_2, d_0 are given by (1). Similar duty cycle can be determined for all six sectors and the three-phase turn-on duty cycles can be calculated as:

1) For sector 1: （$0 < \alpha^* \le \frac{\pi}{3}$）

$$\begin{aligned} d_{A-ON} &= \frac{d_0}{2} = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(-\sin(\frac{\pi}{3} - \alpha) - \sin\alpha) \\ d_{B-ON} &= \frac{d_0}{2} + d_1 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(\sin(\frac{\pi}{3} - \alpha) - \sin\alpha) \\ d_{C-ON} &= \frac{d_0}{2} + d_1 + d_2 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(\sin(\frac{\pi}{3} - \alpha) + \sin\alpha) \end{aligned} \tag{2}$$

2) For sector 2: （$\frac{\pi}{3} < \alpha^* \le \frac{2\pi}{3}$）

$$\begin{aligned} d_{A-ON} &= \frac{d_0}{2} + d_2 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(-\sin(\frac{\pi}{3} - \alpha) + \sin\alpha) \\ d_{B-ON} &= \frac{d_0}{2} = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(-\sin(\frac{\pi}{3} - \alpha) - \sin\alpha) \\ d_{C-ON} &= \frac{d_0}{2} + d_1 + d_2 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(\sin(\frac{\pi}{3} - \alpha) + \sin\alpha) \end{aligned} \tag{3}$$

3) For sector3: （$\frac{2\pi}{3} < \alpha^* \le \pi$）

$$\begin{aligned} d_{A-ON} &= \frac{d_0}{2} + d_1 + d_2 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(\sin(\frac{\pi}{3} - \alpha) + \sin\alpha) \\ d_{B-ON} &= \frac{d_0}{2} = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(-\sin(\frac{\pi}{3} - \alpha) - \sin\alpha) \\ d_{C-ON} &= \frac{d_0}{2} + d_1 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(\sin(\frac{\pi}{3} - \alpha) - \sin\alpha) \end{aligned} \tag{4}$$

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4) For sector 4: ($\pi < \alpha^* \le \frac{4\pi}{3}$)

$$\begin{aligned} d_{A-ON} &= \frac{d_0}{2} + d_1 + d_2 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(\sin(\frac{\pi}{3} - \alpha) + \sin\alpha) \\ d_{B-ON} &= \frac{d_0}{2} + d_2 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(-\sin(\frac{\pi}{3} - \alpha) + \sin\alpha) \\ d_{C-ON} &= \frac{d_0}{2} = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(-\sin(\frac{\pi}{3} - \alpha) - \sin\alpha) \end{aligned} \tag{5}$$

5) For sector 5: ($\frac{4\pi}{3} < \alpha^* \le \frac{5\pi}{3}$)

$$\begin{aligned} d_{A-ON} &= \frac{d_0}{2} + d_1 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(\sin(\frac{\pi}{3} - \alpha) - \sin\alpha) \\ d_{B-ON} &= \frac{d_0}{2} + d_1 + d_2 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(\sin(\frac{\pi}{3} - \alpha) + \sin\alpha) \\ d_{C-ON} &= \frac{d_0}{2} = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(-\sin(\frac{\pi}{3} - \alpha) - \sin\alpha) \end{aligned} \tag{6}$$

6) For sector 6: ($\frac{5\pi}{3} < \alpha^* \le 2\pi$)

$$\begin{aligned} d_{A-ON} &= \frac{d_0}{2} = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(-\sin(\frac{\pi}{3} - \alpha) - \sin\alpha) \\ d_{B-ON} &= \frac{d_0}{2} + d_1 + d_2 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(\sin(\frac{\pi}{3} - \alpha) + \sin\alpha) \\ d_{C-ON} &= \frac{d_0}{2} + d_2 = \frac{1}{2} + \frac{\sqrt{3}}{\pi} m(-\sin(\frac{\pi}{3} - \alpha) + \sin\alpha) \end{aligned} \tag{7}$$

Hence, the turn-on and turn-off time can be determined as following:

$$\begin{aligned} T_{A.B.C-ON} &= d_{A.B.C-ON} \cdot \frac{T_s}{2} \\ T_{A.B.C-OFF} &= (1 - d_{A.B.C-ON}) \cdot \frac{T_s}{2} \end{aligned} \tag{8}$$

Equation (2) - (7) can be transformed in general form:

$$\begin{aligned} d_{A-ON} &= \frac{1}{2} + \frac{\sqrt{3}}{\pi} . m . h_{10}(\alpha^*) \\ d_{B-ON} &= \frac{1}{2} + \frac{\sqrt{3}}{\pi} . m . h_{20}(\alpha^*) \\ d_{C-ON} &= \frac{1}{2} + \frac{\sqrt{3}}{\pi} . m . h_{30}(\alpha^*) \end{aligned} \tag{9}$$

Where

$$\begin{aligned} h_{10}(\alpha^*) &= [-\sin(\frac{\pi}{3} - \alpha) - \sin\alpha], \theta = 1,6 \\ h_{10}(\alpha^*) &= [-\sin(\frac{\pi}{3} - \alpha) + \sin\alpha], \theta = 2 \\ h_{10}(\alpha^*) &= [+\sin(\frac{\pi}{3} - \alpha) + \sin\alpha], \theta = 3,4 \\ h_{10}(\alpha^*) &= [+\sin(\frac{\pi}{3} - \alpha) - \sin\alpha], \theta = 5 \end{aligned} \tag{10}$$

$$\begin{aligned} h_{20}(\alpha^*) &= [+\sin(\frac{\pi}{3} - \alpha) - \sin\alpha], \theta = 1 \\ h_{20}(\alpha^*) &= [-\sin(\frac{\pi}{3} - \alpha) - \sin\alpha], \theta = 2,3 \\ h_{20}(\alpha^*) &= [-\sin(\frac{\pi}{3} - \alpha) + \sin\alpha], \theta = 4 \\ h_{20}(\alpha^*) &= [+\sin(\frac{\pi}{3} - \alpha) + \sin\alpha], \theta = 5,6 \end{aligned} \tag{11}$$

$$\begin{aligned} h_{30}(\alpha^*) &= [+\sin(\frac{\pi}{3} - \alpha) + \sin\alpha], \theta = 1,2 \\ h_{30}(\alpha^*) &= [+\sin(\frac{\pi}{3} - \alpha) - \sin\alpha], \theta = 3 \\ h_{30}(\alpha^*) &= [-\sin(\frac{\pi}{3} - \alpha) - \sin\alpha], \theta = 4,5 \\ h_{30}(\alpha^*) &= [-\sin(\frac{\pi}{3} - \alpha) + \sin\alpha], \theta = 6 \end{aligned} \tag{12}$$

III. MODEL OF ANN IMPLEMENTS SVPWM ALGORITHM

This paper uses a three-layer forward-feed neural network to implement the SVPWM algorithm. The first layer is the input layer, the number of neurons of second layer is 15*tansig* neurons and the third layer has 3 *purelin* neurons. Levenberg-Marquardt algorithm is used to train the neural network. The minimum error acceptable for training is 2e-5(Fig.2).

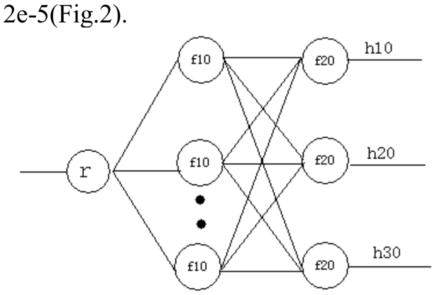

Figure 2. ANN model

The $h_{10,20,30}(\alpha^*)$ have been used for creating databases which are needed for training the neural network with one input (α^*) and three output (h_{10} h_{20} h_{30}). The angle step is 1 degree.

Training the network in the MATLAB environment by the program, the training results shown in Fig.3, the abscissa is the training cycles and the ordinate is the system error value. As can be seen from the Fig.3, the system converges at 530 times.

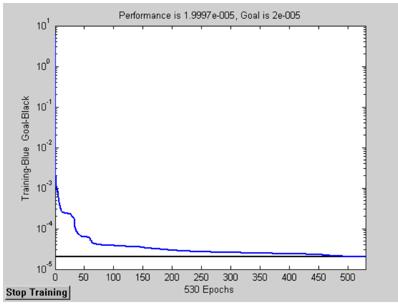

Figure 3. ANN training error convergence

IV. SIMULATION OF ANN-SVPWM INVERTER

A. The establishment of neural network sub-module

A neural network module can be built in the Neural Network Toolbox .For the network established in the MATLAB workspace, Can also use the function “gensim ()” to generate a corresponding Simulink network module. “Gensim ()” function call format is:

gensim(net,st)

In the Command Window, type

>>gensim(net1,-1) , it will generate a neural network module of net1,showing in fig. 4.

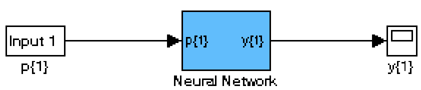

Figure 4. Neural network sub-module

Fig.4 is a Neural Network module, double-click the network module, it will pop up a new window where shown the network structure, as shown in Fig.5.

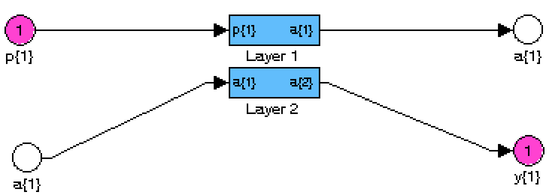

Figure 5. Structure of Neural network

B. Turn-on time to the duty cycle

The module can convert three-phase turn-on time to the PWM single which can control the IGBT to turn-on or turn-off (Fig.6).

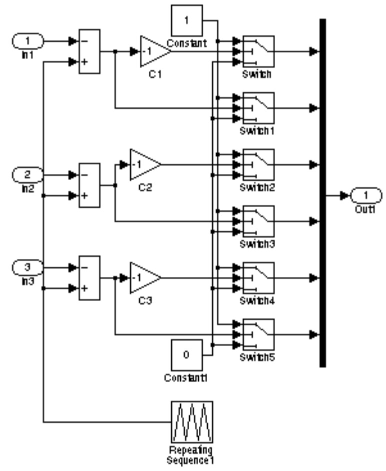

Figure 6. Turn-on time to duty cycle conversion

C. Simulation modle for ANN-SVPWM inverter

A simulink/Matlab program with the toolbox of neural-network is used to train and simulate the complete ANN-SVPWM inverter with the above-mentioned sub-module, as shown in Fig.7.

DC source voltage V_d=200V. The sample frequency f=9 kHz. Resistance R= 5Ω Inductance L=0.01H

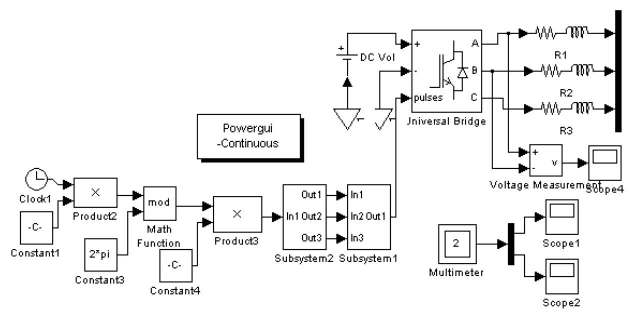

Figure 7. Simulation model for ANN-SVPWM inverter

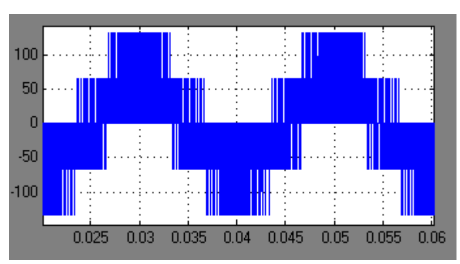

Figure 8. Phase voltage

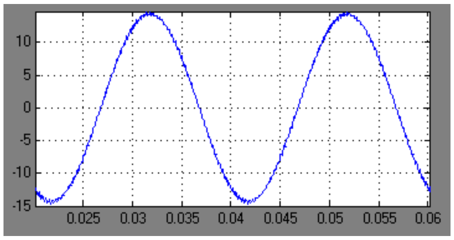

Figure 9. Phase current

The FFT analysis results in Powergui as shown in Fig.9 and Fig.10 that can be seen the THD of phase voltage and phase current are 0.98% and 0.07%.

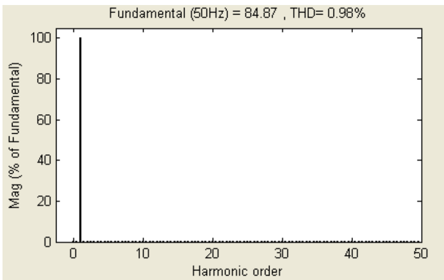

Figure 10. Spectrum of Phase voltage

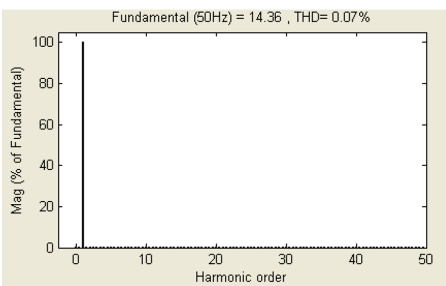

Figure 11. Figure11. Spectrum of Phase current

Simulation results demonstrate the excellent performance of the proposed ANN-SVPWM for the voltage-source inverter, while the good responses of the output voltage and current are obtained (Fig.8-Fig.11).

V. CONCLUSION

The paper proposed a Space Vector PWM algorithm based on artificial neural network for a voltage-source inverter that operates very well. The turn-on time are generated by the ANN and then converted to pulse widths. The ANN based SVPWM can yield higher switching frequency, which is not possible in conventional DSP-based SVPWM. ANN-SVPWM-Controller may be implemented in ASIC chip in the future.

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