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PWM CONTROLLER USING ARTIFICIAL NEURAL NETWORK FOR VOLTAGE FED INVERTER INDUCTION MOTOR DRIVE

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ABSTRACT
The paper describes feed forward ANN based SVM that fully control three phase inverter in the linear region. A back propagation –type feed forward ANN is trained offline with data generated by this simple algorithm, and then extensively evaluated on V/Hz controlled induction motor drive.

KEYWORDS: space vector pulse width modulation, artificial neural network, Induction Motor.

INTRODUCTION
Space vector modulation (SVM) is a very popular pulsewidth modulation (PWM) method for voltage-fed converter ac drives because of its superior harmonic quality and extended linear range of operation. However, a difficulty of SVM is that it requires complex online computation that usually limits its operation up to several kilohertz of switching frequency. However, switching frequency can be extended by using a high-speed digital signal processor (DSP) and simplifying computations with the help of lookup tables. Lookup tables, unless very large, tend to reduce the pulsewidth resolution. Power semiconductor switching speed has improved dramatically in recent years. Modern ultrafast insulated gate bipolar transistors (IGBTs) demand switching frequency as high as 50 kHz. The DSP-based SVM practically fails in this region where artificial-neural-network (ANN)-based SVM can possibly take over.

The application of ANNs is recently growing in power electronic systems. A feedforward ANN implements nonlinear input–output mapping. A feedforward carrier-based PWM technique, such as SVM, can also be looked upon as a nonlinear mapping phenomenon where the command phase voltages are sampled at the input and the corresponding pulsewidth patterns are established at the output.Therefore, it appears logical that a backpropagation-type ANN which has high computational capability can implement an SVM algorithm. The ANN can be conveniently trained offline with the data generated by calculation of the SVM algorithm. ANN has inherent learning capability that can give improved precision by interpolation unlike the standard lookup table method.

SPACE VECTOR PWM FOR VOLTAGE SOURCE INVERTER
This section is devoted to the development of Space vector PWM for a two-level voltage source inverter in linear region of operation. As seen from Fig 1, there are six switching devices and only three of them are independent as the operation of two power switches of the same leg are complimentary. The combination of these three switching states gives out eight possible space voltage vectors. The output voltage vector is synthesized by using six active vectors $V_1 \sim V_6$ and two zero vectors V_0, V_7 as shown in Fig. 2. Each voltage vector represents the switching state of the set of three upper switches of three legs, e.g., the voltage vector V_1 (100) represents for switching state of the set of switching functions (S_1, S'_2, S'_3).

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$$\vec{V}^* = \frac{2}{3}(v_{oA} + v_{oB}e^{j\frac{2\pi}{3}} + v_{oC}e^{j\frac{2\pi}{3}}) = V_o e^{j\theta_0} \tag{1}$$

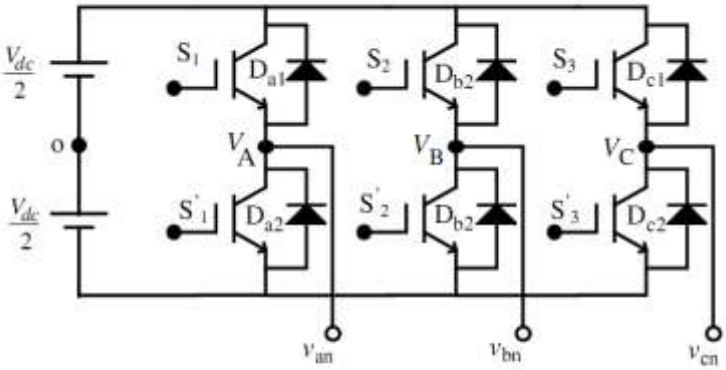

Fig.1. Power circuit topology of a three-phase voltage source inverter

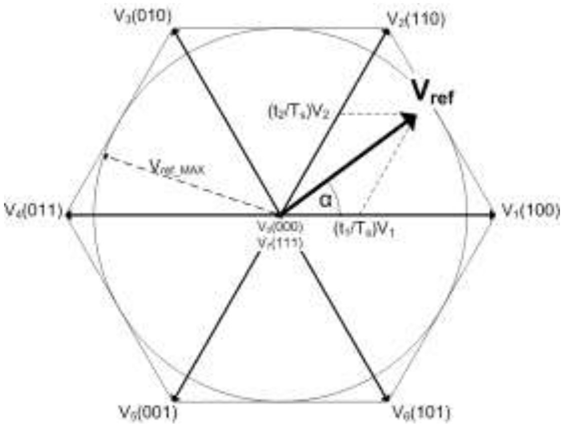

Fig. 2. Voltage space vector locations corresponding to different switching states

Assuming the reference output voltage vector is also located in sector 1, the equations for effective time of active vectors V_1, V_2 and zero vectors V_0, V_7 are calculated as follows:

$$t_a = 2.K.V^* \sin(\frac{\pi}{3} - \alpha^*) \tag{2}$$

$$t_b = 2.K.V^* \sin\alpha^* \tag{3}$$

$$t_0 = \frac{T_s}{2} - (t_a + t_b) \tag{4}$$

Where,

t_a : time of switching vector that lags V^*, t_b : time of switching vector that leads V^*, t_0 : time of zero switching vector, α^* : angle of V^* in 60° sector, T_s :sampling time, $K = (\sqrt{3}T_s)/(4V_d)$.

NEURAL NETWORK BASED SPACE VECTOR PWM

The SVM algorithm described in the previous section will be utilized to generate training data for ANN-based SVM. In the timer-based method, discussed in this section, the algorithm will be somewhat modified and then simplified.

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Consider for all six sector, the phase A turn-on time can be expressed as:

$$T_{A-ON}=\begin{cases}\frac{t_0}{2}=\frac{T_S}{4}+K.V^*\left[-\sin(\frac{\pi}{3}-\alpha^*)-\sin(\alpha^*)\right], & S=1,6\\ \frac{t_0}{2}+t_b=\frac{T_S}{4}+K.V^*\left[-\sin(\frac{\pi}{3}-\alpha^*)+\sin(\alpha^*)\right], & S=2\\ \frac{t_0}{2}+t_a+t_b=\frac{T_S}{4}+K.V^*\left[\sin(\frac{\pi}{3}-\alpha^*)-\sin(\alpha^*)\right], & S=3,4\\ \frac{t_0}{2}+t_a=\frac{T_S}{4}+K.V^*\left[\sin(\frac{\pi}{3}-\alpha^*)-\sin(\alpha^*)\right], & S=2\end{cases} \tag{5}$$

The phase A turn-on time can be written in the general form:

$$T_{A-ON}=T_S/4+f(V^*).g(\alpha^*) \tag{6}$$

Where $f(V^*)$ is the voltage amplitude scale factor, $T_s/4$ is the bias time and $g(\alpha^*)$ is called the turn-on signal at unit voltage and is given as:

$$g(\alpha^*)=\begin{cases}K\left[-\sin(\pi/3-\alpha^*)-\sin(\alpha^*)\right], S=1,6\\ K\left[-\sin(\pi/3-\alpha^*)+\sin(\alpha^*)\right], \ S=2\\ K\left[+\sin(\pi/3-\alpha^*)+\sin(\alpha^*)\right], S=3,4\\ K\left[-\sin(\pi/3-\alpha^*)-\sin(\alpha^*)\right], \ S=5\end{cases} \tag{7}$$

SIMULATION

ANN-based space vector pulse width modulation

The MATLAB/Simulink model for implementing the ANN-based SVPWM is shown in Fig. 3.Initially a neural network is trained with the reference voltage input and the turn-on time as output using equations (2–4). The ANN model is then generated in the Simulink, as shown in Fig. 4. The input signal is the reference voltage position angle α^* which is normalized and then pulsewidth functions at unit amplitude are solved (or mapped) at the output for the three phases. The model uses a multilayer perception-type network with sigmoidal-type transfer function in the first and second layers. The number of hidden nodes can be chosen 12 and four output neurons. The weights are generated during the training mode.

The digital words corresponding to turn-on time are generated by multiplying the output of the neural network with V^*T_S and then adding $T_s/4$, as shown in the Fig. 3. The PWM signals are then generated by comparing the turn-on time with a triangular reference having a time period of T_s and amplitude $T_s/2$, and the PWM signals thus obtained are then applied to the inverter.The simulation results for different voltage transfer ratios are shown in Fig. 6. This shows that the designed ANN-based SVPWM works well with linear range modulation.

RESULTS AND DISCUSSION

The ANN-bases SVPWM is applied for induction motor drive with V/f controller as shown in Fig.7. The simulation parameters are given as follows:

- Induction motor: 5 hp 220 V four pole, frequency range: 0–60 Hz
- Stator resistance: $R_s=0.5814\Omega$
- Rotor resistance: $R_r=0.4165\Omega$

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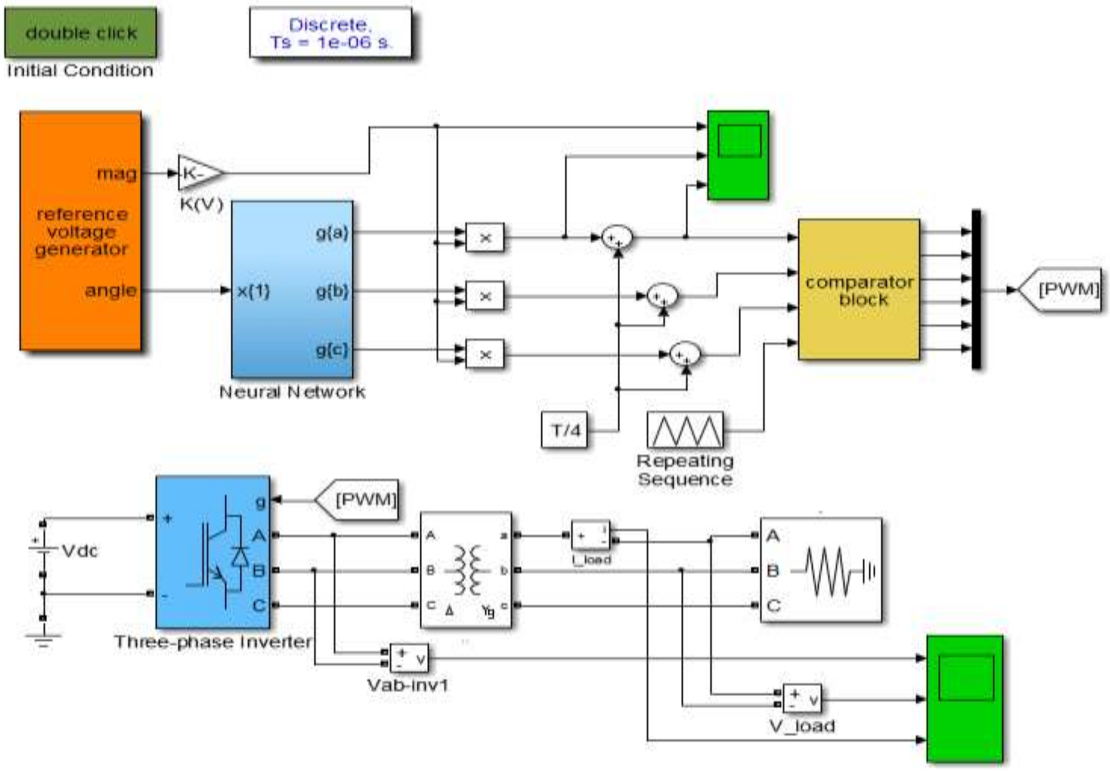

Fig. 3. Model for implementing the ANN-based SVPWM

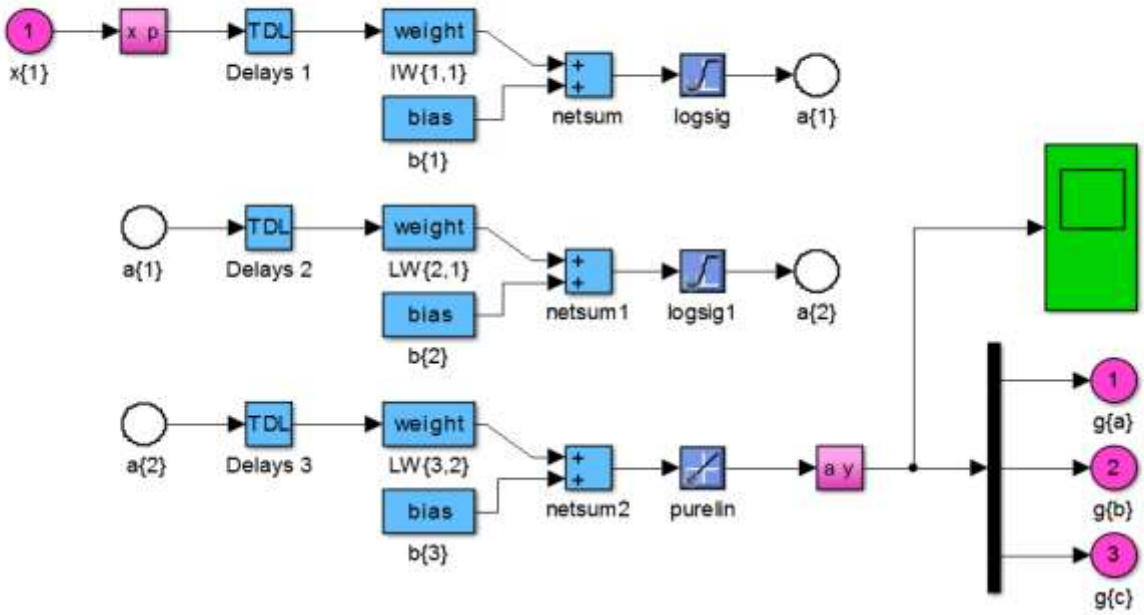

Fig. 4. The neural network model

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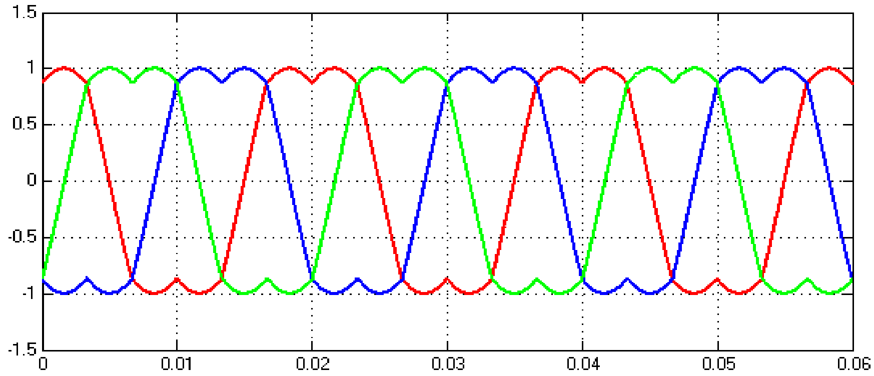
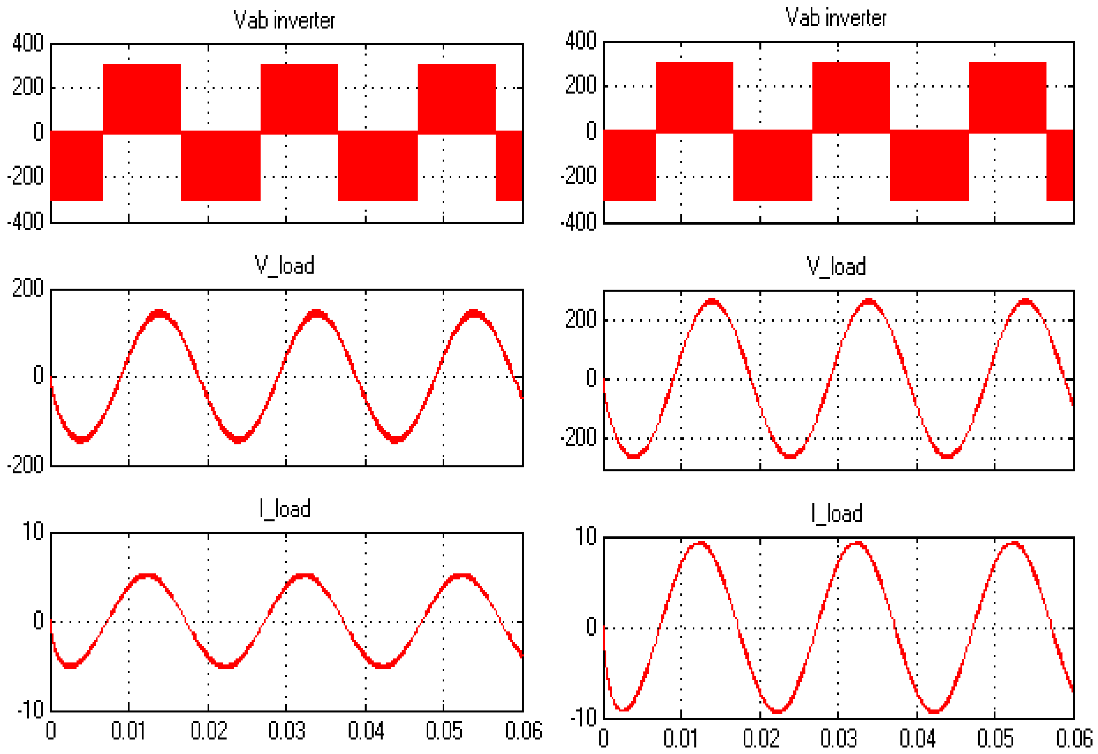


Fig. 5.Turn-on pulse width function as a function of angle α in different sectors



a) mf =0.5 b) mf=0.9

Fig.6. Response of ANN-SVPWM with V_{dc}=300V

- Stator leakage inductance: $L_{ls} = 3.479$ mH
- Rotor leakage inductance: $L_{lr} = 4.15$ mH
- Magnetizing inductance: $L_m = 78.25$ mH
- Three-phase R-L load: R = 20 Ω, L = 15 mH
- PWM frequency: 5 kHz (Ts = 200 µs).

As seen in the figure 8 the Induction is first referenced at 100 rpm/sec and after 1 minute again referenced at 160 rpm/sec. As we can see the actual speed is almost synchronized. However it takes 0.2 second to achieve steady state.

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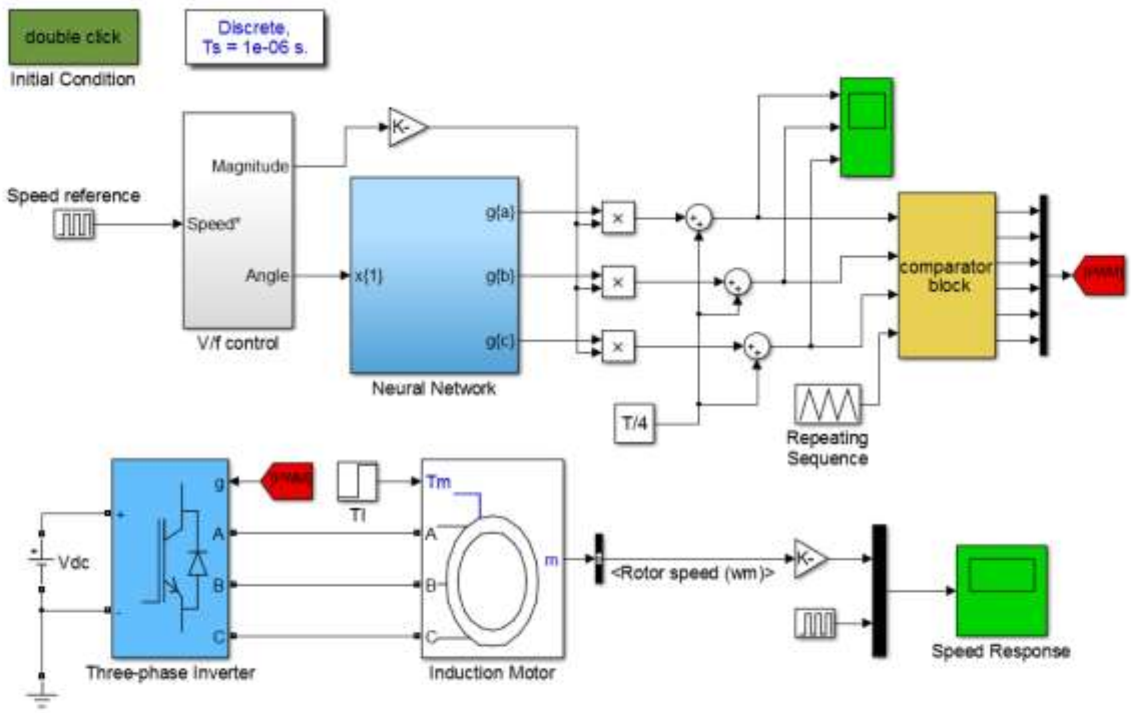

Fig. 7. Model ANN-SVPWM for induction motor with V/f control

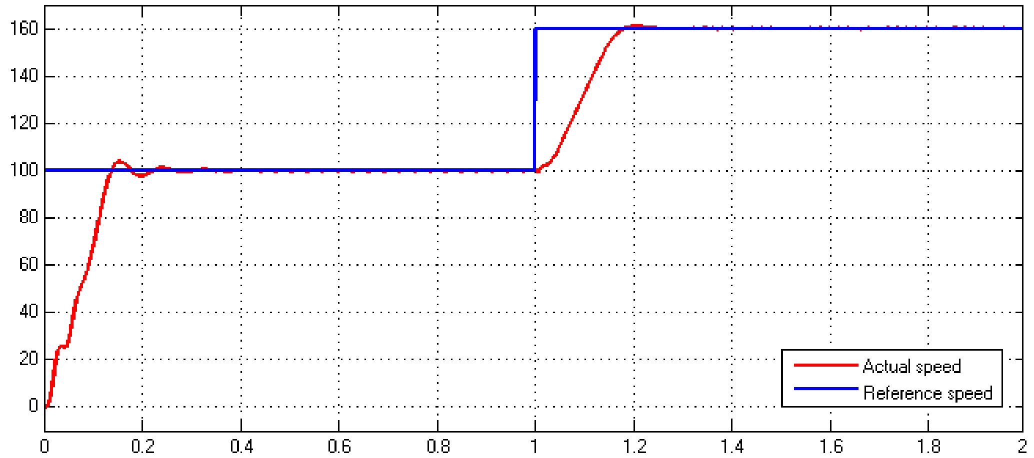

Fig. 8. Speed response of induction motor

CONCLUSION

A neural-network-based space-vector modulator has been described that operates very well in linear regions. The digital words corresponding to turn-on time are generated by the ANN and then converted to pulsewidths through a single timer. The scheme has been fully applied for a V/f-controlled induction motor drive, and gives good performance. The PWM controller can be used in a stator-flux-oriented vector-controlled induction motor drive in order to obtain a better performance.

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