Proceedings of the Fourth IASTED International Conference
POWER AND ENERGY SYSTEMS (AsiaPES 2008)
April 2-4, 2008 Langkawi, Malaysia
ISBN CD: 978-0-88986-732-1

NEURAL PREDICTIVE CONTROL FOR A THREE-PHASE POWER CONVERTER SVPWM WITH CURRENT REGULATOR

Hari Sutiksno, Mochamad Ashari, and Mauridhi Hery Purnomo
Institut Teknologi Sepuluh Nopember
Kampus ITS Sukolilo Surabaya
Indonesia
hari@stts.edu, ashari@ee.its.ac.id , hery@eepis-its.edu

ABSTRACT
This paper presents the application of predictive control technique using artificial neural networks for a three-phase power converter space vector PWM with current regulator. Predictive control is an algorithm to minimize the performance index of prediction model of the power converter to generate control action. The model of three-phase power converter which is used to predict the future values, is based on artificial neural network. The simulation results of the proposed method are shown by using Matlab Simulink.

KEY WORDS
Predictive Control, Power Converter, Current Regulator, Neural Networks

1. Introduction

Many three-phase rectifiers with a diode bridge rectifier circuit and capacitor on dc side are used in industrial applications. These rectifiers are very simple and low in cost. However, these rectifiers perform only unidirectional power flow and are characterized poor power factor and high harmonic line currents [1]. Therefore, a three-phase power converter space vector PWM gives a good solution for industrial application. The advantages of three-phase converters are bidirectional power flow, sinusoidal line current, possible to regulate the power factor of input line, and to stabilize the dc link voltage[1-2],[8-9],[10]. To perform a unity power factor of line current and good performance of dc link volage of a three-phase power converter, control design is required. Proportional and Integral (PI) controllers have been used to solve the problem[3]. However, it is difficult to optimise the performance of the plant. Another approach is based on the predictive control. With this strategy, plant model to predict future behaviour of plant, and an optimization algorithm is required.

As known that neural networks have been applied very sucsessfully in the identification and control of dynamic systems [4]. Multilayer perceptron is the most popular neural network that used to be applied as a universal approximator for modelling of nonlinear systems and controllers.

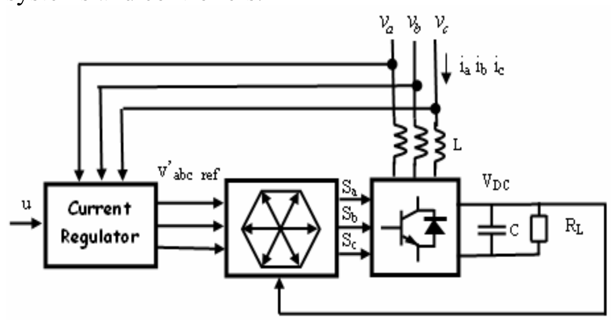


Figure 1. Three-Phase Power Converter SVPWM with Current Regulator

In this paper, it is proposed to use neural predictive control for three-phase power converter with current regulator. With this method, a neural network model is used by controller to predict the future dc voltage of converter response, so that the line currents can be controlled. An optimization algorithm computes the control signal to optimize the future plant performance. The neural network plant model is a time delayed neural network (TDNN) and trainned offline.

.

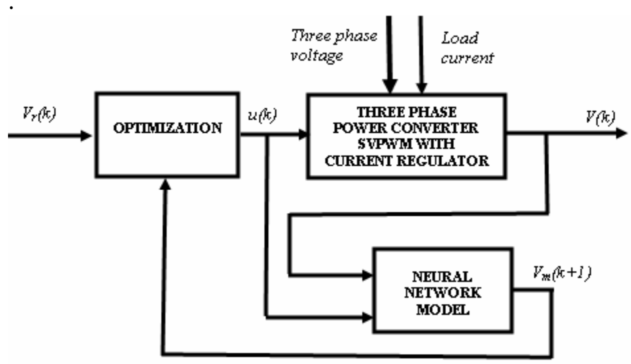


Figure 2. Neural Predictive Control of Three-Phase Converter SVPWM with Current Regulator

2. Neural Predictor

In neural predictive control, neural network model of three-phase power converter will be used as a predictor. As known, that neural networks have been used very succesfully in the identification and control of dynamic systems [5]. A nonlinear system generally can be expressed in NARMAX model (Fig 3) as:

$$V(k) = f[V(k-1), V(k-2), \ldots V(k-n), u(k-d-1), \ldots \\ u(k-d-2), \ldots u(k-d-m)] \qquad (1)$$

where $f(.)$ is a nonlinear function
d is dead-time
n and m is the order of the system
u is the input of the system
V is the output of the system

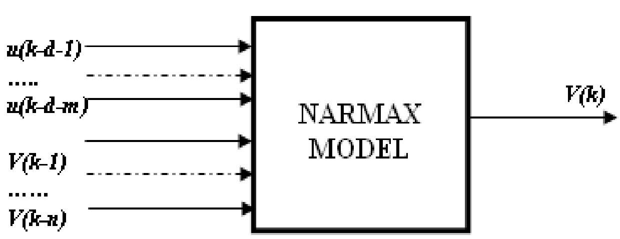


Figure 3. NARMAX Model

In many applications, time-delayed neural networks (TDNN) have been used to model of the plant with NARMAX. The structure of two-layer neural networks as shown in Fig.4 with sigmoid transfer functions in hidden layer, and linear transfer functions in the output layer are commonly used [6]. The number of neurons in hidden layer and output layer respectively is *N* and one. The size of matrices of weights $\boldsymbol{W_1}$ dan $\boldsymbol{W_2}$ respectively is $N \times (m+n)$ and $1 \times N$, that connect inputs to hidden layer, and connect hidden layer to the output. Then $b_{11}, \ldots b_{N1}$ are the biases of neurons in hidden layer, and b_2 is the bias of output neuron. The output of neural networks can be expressed as follow.

$$V_p(k) = \begin{bmatrix} w_2(1,1) & w_2(1,2) & \ldots & w_2(1,N) \end{bmatrix} \begin{bmatrix} f(X_1) \\ f(X_2) \\ \ldots\ldots \\ f(X_N) \end{bmatrix} + b_2 \qquad (2)$$

where

$$\begin{bmatrix} X_1 \\ X_2 \\ \ldots \\ \ldots\ldots \\ X_N \end{bmatrix} = \begin{bmatrix} w_1(1,1) & w_1(1,2) & \ldots\ldots & w_1(1,m) & w_1(1,m+1) & \ldots\ldots & w_1(1,m+n) \\ w_1(2,1) & w_1(2,2) & \ldots\ldots & w_1(2,m) & w_1(2,m+1) & \ldots\ldots & w_1(2,m+n) \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ w_1(N,1) & w_1(N,2) & \ldots\ldots & w_1(N,m) & w_1(N,m+1) & \ldots\ldots & w_1(N,m+n) \end{bmatrix} \begin{bmatrix} u(k-1) \\ u(k-2) \\ \ldots \\ u(k-m) \\ V(k-1) \\ \ldots \\ V(k-n) \end{bmatrix} + \begin{bmatrix} b(1,1) \\ b(1,2) \\ \ldots\ldots \\ \ldots\ldots \\ b(1,N) \end{bmatrix} \qquad (3)$$

and $f(X_i)$ is sigmoid function.

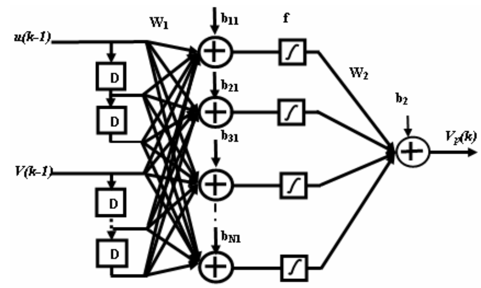


Figure 4. The Structure of TDNN

To determine the parameters $\boldsymbol{W_1}$, $\boldsymbol{W_2}$, $b_{11}, \ldots b_{N1}$, and b_2, it can be done by training procedure. With this procedure, training data of *u(k-1)* and *V(k-1)* is required. Fig.5 shows the training procedure for the plant. The value of *u(k-1)* and *V(k-1)* can be obtained respectively from *u(k)* and *V(k)* through a delay element. With initial weights and biases, the output of the neural network and the plant produces an error value. This value is used to correct the parameters of the network. Backpropagation is one of the training procedures in multilayer neural networks. With the new parameters, it will produce new error signal. The recursive process will continue until the minimum error is reached.

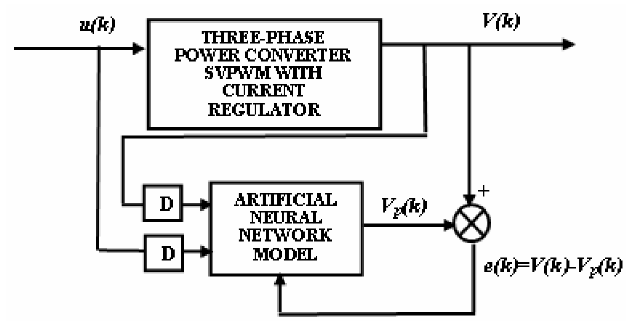


Figure 5. The diagram for Training of the Plant Model

Now a neural network predictor of the plant has been obtained as shown in fig.6. With input values of *u(k)* dan *V(k)*, the neural network will produce one step prediction value of *V(k+1)* . It can be expressed as follow.

$$V_p(k+1) = \begin{bmatrix} w_2(1,1) & w_2(1,2) & \ldots & w_2(1,N) \end{bmatrix} \begin{bmatrix} f(X_1) \\ f(X_2) \\ \ldots\ldots \\ f(X_N) \end{bmatrix} + b_2 \qquad (4)$$

where

$$\begin{bmatrix} X_1 \\ X_2 \\ \ldots \\ \ldots\ldots \\ X_N \end{bmatrix} = \begin{bmatrix} w_1(1,1) & w_1(1,2) & \ldots\ldots & w_1(1,m) & w_1(1,m+1) & \ldots\ldots & w_1(1,m+n) \\ w_1(2,1) & w_1(2,2) & \ldots\ldots & w_1(2,m) & w_1(2,m+1) & \ldots\ldots & w_1(2,m+n) \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ w_1(N,1) & w_1(N,2) & \ldots\ldots & w_1(N,m) & w_1(N,m+1) & \ldots\ldots & w_1(N,m+n) \end{bmatrix} \begin{bmatrix} u(k) \\ u(k-1) \\ \ldots \\ u(k+1-m) \\ V(k) \\ \ldots \\ V(k+1-n) \end{bmatrix} + \begin{bmatrix} b(1,1) \\ b(1,2) \\ \ldots\ldots \\ \ldots\ldots \\ b(1,N) \end{bmatrix} \qquad (5)$$

Of course, it is possible to predict several steps of output by extending equation (4) and (5). The neural predictors will be used by predictive algorithm for calculating the future control signal to be applied to the power converter.

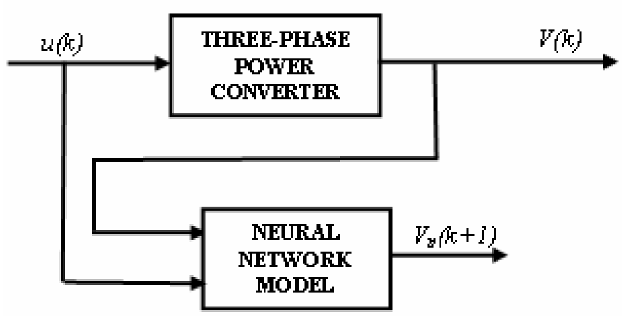


Figure 6. One Step Neural Predictor

3. Optimization Algorithm

In neural predictive control, it is expected that the time response of the output dc voltage of power converter respect to load change can be optimised. The function to be optimised is a function or error. The cost function is defined as follow:[7]

$$J = \sum_{i=N_1}^{N_2} [V_p(k+i) - V_r(k+i)]^2 + \lambda \sum_{i=1}^{N_u} \Delta u^2(k+i-1) \tag{6}$$

with $\Delta u(k+i-1) = 0, \quad 1 \le N_u < i \le N_2$ (7)

where *Nu* is the control horizon
N_1 is the minimum prediction horizon
N_2 is the prediction horizon
i is the order of the predictor
r is the reference trajectory
λ is weight factor

The command *u* may be subject to amplitude constraints.

$$u_{\min} \le u(k+i) \le u_{\max}, i = 1,...N_2 \tag{8}$$

The cost function is often used with λ=0, so J becomes:

$$J = \sum_{i=N_1}^{N_2} [V_p(k+i) - V_r(k+i)]^2 = \sum_{i}^{N} e(k+i)^2 \tag{9}$$

With predicted value of neural network and reference, the control action must be determined and updated based on the gradient descent method, It is simply expressed in equation:

$$u(k+1) = u(k) - \gamma \frac{\partial J}{\partial u(k)} \tag{10}$$

where γ is small number.

Based on equation (9), the term $\frac{\partial J}{\partial u(k)}$ for one-step ahead prediction can be calculated as follow.

$$\frac{\partial J}{\partial (k)} = \frac{\partial}{\partial u(k)} \{[V_p(k+i) - V_r(k+i)]^2\} \tag{11}$$

$$\frac{\partial J}{\partial (k)} = 2[V_p(k+i) - V_r(k+i)] \frac{\partial}{\partial u(k)} [V_p(k+i)] \tag{12}$$

where

$$\frac{\partial}{\partial u(k)}[V_p(k+i)] = \begin{bmatrix} w_1(1,m+n) \\ w_1(2,m+n) \\ ..... \\ .... \\ w_1(N,m+n) \end{bmatrix}^T \begin{bmatrix} f'(X_1) & 0 & 0 & 0 & 0 \\ 0 & f'(X_2) & 0 & 0 & 0 \\ ... & ... & ... & ... & ... \\ ... & ... & .... & ... & ... \\ 0 & 0 & 0 & 0 & f'(X_N) \end{bmatrix} \begin{bmatrix} w_2(1,1) \\ w_2(1,2) \\ ..... \\ .... \\ w_2(1,N) \end{bmatrix} \tag{13}$$

Finally, by subtituting equation (12) and (13) into equation (10).

$$u(k+1) = u(k) - \gamma 2[V_p(k+i) - V_r(k+i)] \begin{bmatrix} w_1(1,m+n) \\ w_1(2,m+n) \\ ..... \\ .... \\ w_1(N,m+n) \end{bmatrix}^T \begin{bmatrix} f'(X_1) & 0 & 0 & 0 & 0 \\ 0 & f'(X_2) & 0 & 0 & 0 \\ ... & ... & ... & ... & ... \\ ... & ... & .... & ... & ... \\ 0 & 0 & 0 & 0 & f'(X_N) \end{bmatrix} \begin{bmatrix} w_2(1,1) \\ w_2(1,2) \\ ..... \\ .... \\ w_2(1,N) \end{bmatrix} \tag{14}$$

Now, here is the optimization algorithm:

1. Select value γ
2. Compute the predicted value $V_{p(k+1)}$ from equation (4) and (5)
3. Compute the new control signal *u(k+1)* from equation (14)
4. Return to step 2.

4. Three-Phase Power Converter SVPWM with Regulator

Three-phase power converter that used in this paper is boost converter with three legs of phase, as shown in Fig.7. To understand the basic principle operation of the converter, the converter can be considered as a power inverter that connected parallel to three-phase line. Due to change load, the dc voltage of converter must be kept constant by regulating the line currents. The amount of current line can be controlled by determining the amplitude of and phase difference respect to the voltage source. By asuming that point *N* as zero voltage reference, the symetrical voltage of source is given as:

$$\begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} = \begin{bmatrix} v_m \cos\omega t \\ v_m \cos(\omega t - 2\pi\ )/3) \\ v_m \cos(\omega t + 2\pi/3 \end{bmatrix} \qquad (12)$$

The voltages v'_a, v'_b dan v'_c can be determined using the equation below:

$$\begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L & 0 & 0 \\ 0 & L & 0 \\ 0 & 0 & L \end{bmatrix} \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} v'_a \\ v'_b \\ v'_c \end{bmatrix} \qquad (13)$$

Then rectified current i_d can be obtained using this equation:

$$i_d = S_a i_a + S_b i_b + S_c i_c \qquad (14)$$

The dc voltage V_{DC} can be found the differential equation:

$$i_d = \frac{V_{DC}}{R_L} + C\frac{dV_{DC}}{dt} \qquad (15)$$

Using equations (12-15), it can be shown that dc voltage is affected by voltage source, load resistance, and control (S_a, S_b, and S_c).

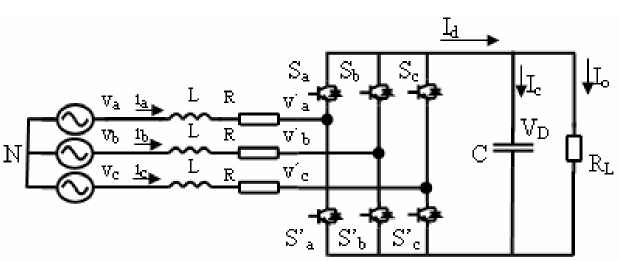


Figure 7. Three-phase Power Converter Circuit

Space Vector PWM is a method which is used to produce an three-phase ac voltage based on the space vector representation of voltages in the α, β plane. The α, β components can be obtained using Clarke transformation as follow:

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = \frac{2}{3}\begin{bmatrix} 1 & -0.5 & -0.5 \\ 0 & 0.866 & -0.866 \end{bmatrix} \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix}_{ref} \qquad (14)$$

Fig. 8 shows 8 space vectors in according to 8 switching positions of inverter, V' is the phase-to-center voltage which is obtained by proper selection of adjacent vectors $\boldsymbol{Vs_1}$ and $\boldsymbol{Vs_2}$.

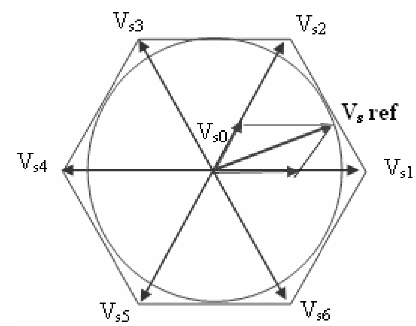


Figure 8. Space Vector Voltage

The reference space vector V' is given by

$$V' = \frac{Vs_1 T_1 + Vs_2 T_2}{T} \qquad (15)$$

where T_1, T_2 are the intervals of application of vector $\boldsymbol{Vs_1}$ and $\boldsymbol{Vs_2}$ respectively, and zero vectors V_0 ($S_a=0$, $S_b=0$ and $S_c=0$) and V_7 ($S_a=1$, $S_b=1$ and $S_c=1$) are selected for T_0.

They can be calculated using these equations:

$$T_1 = \frac{T_s}{V_{DC}}[v_{s\alpha}\sin(\frac{m\pi}{3}) - v_{s\beta}\cos(\frac{m\pi}{3})] \qquad (16)$$

$$T_2 = \frac{T_s}{V_{DC}}[-v_{s\alpha}\sin(\frac{(m-1)\pi}{3}) + v_{s\beta}\cos(\frac{(m-1)\pi}{3})] \qquad (17)$$

and

$$T_0 = T_s - T_1 - T_2 \qquad (18)$$

The space-vector PWM current regulator is accomplished by estimating the appropriate duty cycles for the α-β space vectors adjacent to the reference vector in such a way that the line current is driven to the reference value at the end of period of time. In the case of steady-state operation, this is equivalent to calculating a reference voltage vector that accomplishes the deadbeat control and calculating the duty cycles for the appropriate states using space-vector PWM. Considering the voltage-source converter power circuit shown in Fig. 1, if T_s is assumed to be small in comparison with the period of the source voltage (V), then V can be assumed constant over the period Ts: Let t_n denote the time at the beginning of one Ts period. Then, the change in line current over one period (neglecting the source resistance) is

$$V(t_n) - V_{ac}(t_n) = L\frac{\Delta I}{\Delta t} = L\frac{I(t_n + T_s) - I(t_n)}{T_s} \qquad (19)$$

where V_{ref} is the average value of the ac-side rectifier voltage over T_s.

To obtain unity power factor condition, the reference current and the voltage at the end of switching period must be in phase or it can be written as

$$I(t_n + T_s) = KV(t_n + T_s) \qquad (20)$$

Substituting $I(t_n+T_s)$ from equation (20) into equation(19) and rearranging, the ac-side rectifier voltage is [9]:

$$V_{ac}(t_n) = (1 - \frac{2KL}{T_s})V(t_n) - \frac{KL}{T_s} I(t_n - T_s) - \frac{L}{T_s} I(t_n)$$

(21)

Using equation (20), input line current of the power converter can be regulated by means of the input K.

5. Simulation results

The predictive control of three-phase power converter SVPWM with current regulator has been simulated using Matlab Simulink R14 (Matlab 7.0). In this simulation, it is asumed that the data of three-phase power converter given below:

- Phase Voltage Source 100 Volt (max)
- Output Voltage (DC) = 300 volt
- Voltage Frequency = 50 Hz
- Input Inductance L = 3mH
- DC Link Capacitor C = 2200uF
- Switching Frequency 5kHz
- Full Load Resistance R_L = 35 Ohm

To compute the parameters of network, the training data will be required. This training data can be obtained using the method shown in fig.9.

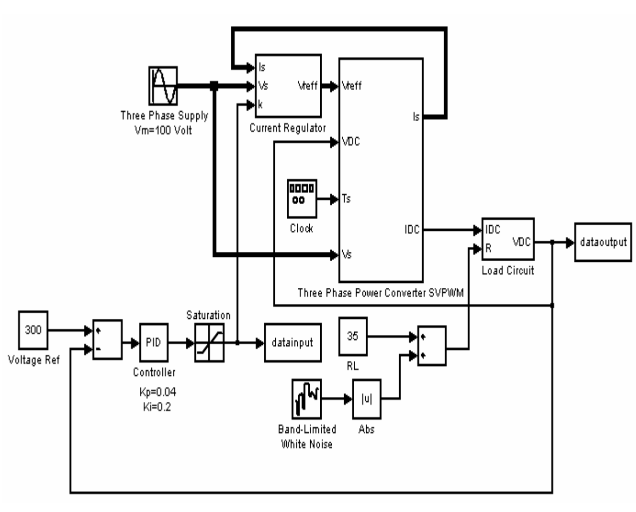
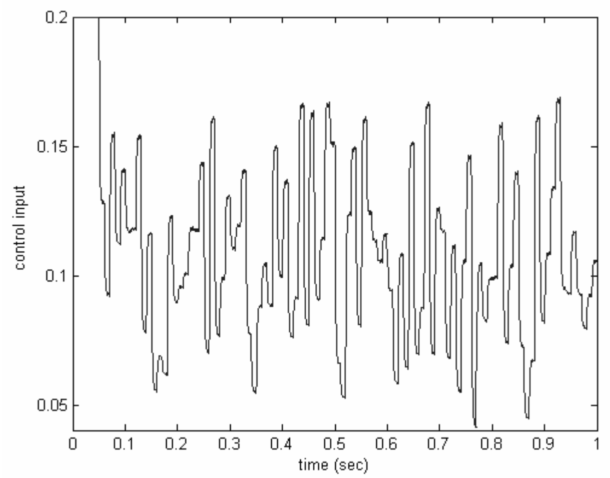
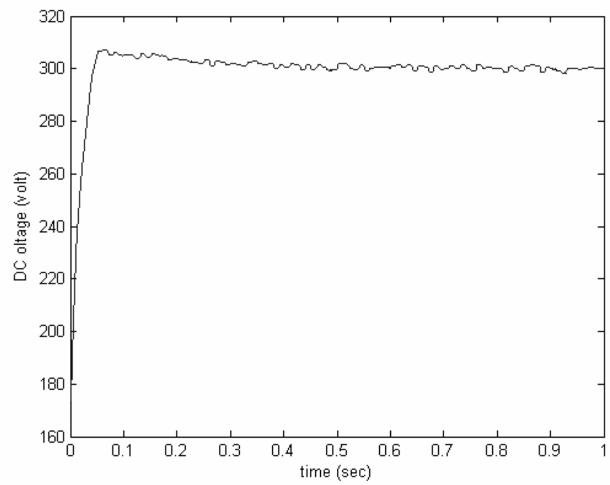


Figure 9. Diagram for Training Data Provider



(a) control

Figure 10. Training Data



(b) output

Figure 10. Training Data

In this case, the three-phase power converter must be operated in close loop system using PI controller. The training data represents relationship between input control and output voltage (dc voltage) with load changes as its parameter. Form the results of simulation as shown in fig.10, neural network can be trained using Levenberg and Marquard method. Neural model of the plant has been established succesfully using TDNN with 2 inputs, 8 neurons hidden layer, and single output.

Neural Predictive Control of Three-Phase Power Converter SVPWM using one-step ahead method has been simulated as shown in fig.11. The power converter operates on 300V and load changes from RL=35 ohm to 70 ohm at time t=0.5 sec. Fig.12 and 13 show respectively the time response of DC voltage and line current (line A) using Neural Predictive Control. Total harmonic distrotion (THD) of line current is about 2% on full load.

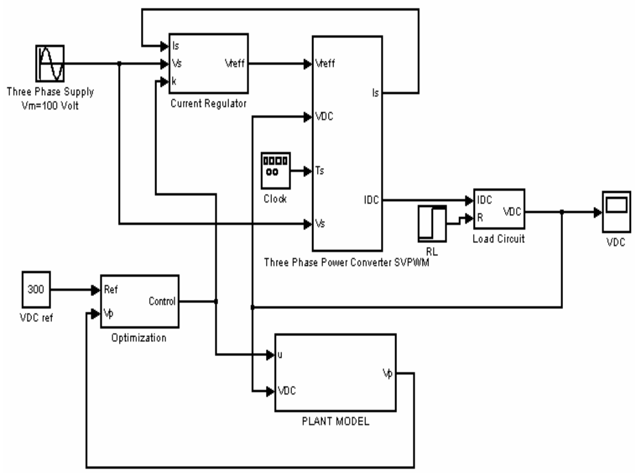


Figure 11. Simulink Diagram of Neural Predictive Control

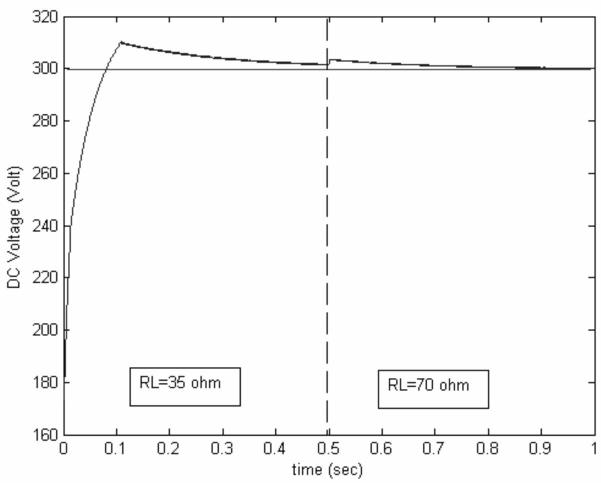


Figure 12. Time Response of DC Voltage respect to the load change

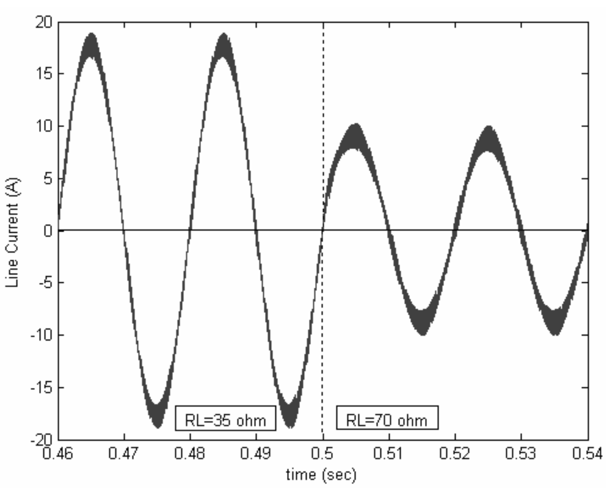


Figure 13. Line Current (line A)

6. Conclusion

With the use of current regulator in three-phase power converter SVPWM, it is possible to control the line currents with a dc value (not a sinusoidal function). Therefore, the neural model of the plant can be built simply using time-delayed neural network (TDNN).

From the simulations results, Neural Predictive Control for three-phase power converter SVPWM provides a good dynamic of controlled voltage, line currents in phase with line voltage, and gives low harmonic distortion.

References

[1] P. Antoniewicz and M.P. Kazmierkowski, Predictive direct Power Control of Three-phase Boost Rectifier, *Bulletin of the Polish Academy of Sciences*, *Vol 54*, No.3, 2006, 287-292.

[2] S.Y. Ron Hui, Henry Shu-Hung Chung, A Bidirectional AC-DC Power Converter with Power Correction, *IEEE Transactions on Power Electronics*, *Vol.15*, No.5, 2000, 942-949.

[3] Vitor Fernao Pires and Jose Fernando A. Silva, Single-Stage Three-Phase Buck-Boost Type AC-DC Converter With High Power Factor, *IEEE Transactions on Power Electronics*, *Vol.16*, No.6, November 2001, 784-793.

[4] Orlando de Jesus and M. Hagan, Backpropagation Algorithms for a Broad Class of Dynamic Networks, *IEEE Transactions on Neural Networks*, Vol.18, No.1, January 2007, 14-27

[5] Shi Hong-li , Cai Yuan-li and Qiu Zu-lian, System Identification based on NARMAX Model using Hopfield Networks, *Journal of Shanghai University, Vol 10* no.4 June, 2006, 238-243.

[6] Bimal K.Bose, Neural Network Applications in Power Electronics and Motor Drives-An Introduction and Perspective, *IEEE Transactions on Power Electronics, Vol.54*, No.1, Februari 2007, 14-33

[7] Leizer Schnitman and Adhemar de Barros Fontes, The Basic of Neural Predictive Control, *Proceeding of the 7th Mediterranian Conference on Control and Automation(MED99)* Haifa, Israel, June 28-30, 1999.

[8] Yi-Hwa Liu, Chern-Lin Chen and Rong-Jie Tiu, A Novel Space Vector Current Regulation Scheme for Field-Oriented-Controlled Induction Motor Drive, *Trans IE, Vol. 45*, no.5, 1998.

[9] Suttichai Saetieo, and David A.Torey, Fuzzy Logic Control of a Space Vector PWM Current Regulator for Three-Phase Power Converters, *IEEE Transactions on Power Electronics, Vol13*, No.3, 1998, 419-426

[10] Woo-Cheol Lee, Dong-Seok Hyun, and Taeck-Kie Lee, A Novel Control Method for Three-Phase PWM Rectifiers Using a Single Current Sensor, *IEEE Transactions on Power Electronics, Vol.15*, No.5, 2000, 861-870