Application of Neural Networks to Power Converter Control

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Abstract - This paper discusses application of neural networks to power converter control. In this system, the networks can get knowledge about control rules for inverter. We confirm the effectiveness of the proposed method by computer simulations.

1 Introduction

Applications of switching power devices, such as power MOSFET and SITh, achieve very high frequency carrier of PWM power converters and improve the control performances: fast response and low distortion in output waveform. It is true that the output current ripple in a high frequency carrier inverter becomes smaller than that in a low frequency carrier inverter. However, the application of the high frequency carrier inverter with fast switching power devices does not always improve the power conversion efficiency. Particularly in high voltage applications, as the number of power devices turn on/off per unit time interval increases, the switching power loss becomes larger. Therefore, in order to reduce the switching power loss, a new PWM control strategy should be devised, whose switching frequency is low and the current error is small.

Several control strategies are used in industrial applications. Among them, the sub-harmonic modulation method and the instantaneous value comparison method are noted. These control methods are realized in simple circuits. These systems, in particular for the instantaneous value control method, do not cope with switching loss, because they generate high frequency switching signals to reduce the current harmonics.

Recently parallel distributed processings such as neural networks have received wide attentions to process complex data in short time [1]-[3]. Remarkable features of neural networks are fast processing speed and fault tolerance to some of miss connections in the network system. Moreover, some of networks have learning capability.

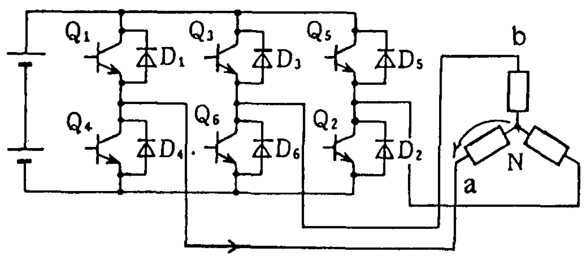
The outline of this paper is as follows: First, the concept of applications of neural networks to the on-off pattern control of a PWM inverter is described. Secondary, an example of applications of neural network to inverter control is proposed with simulation results. In the proposed system, the neural network is applied to generate the on-off switching pattern of a 3-phase PWM inverter. Lastly, concluding remarks are presented.

2 Neural Network Approach to On-Off Control of Inverter

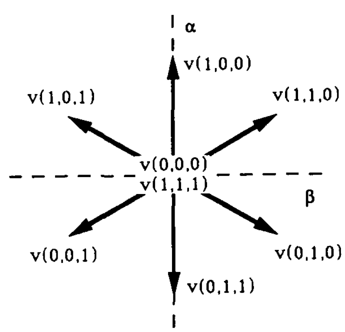
This chapter presents the concept of application of neural networks to the on-off pattern control of a PWM inverter.

2-1 Non-linear function of on-off control

Figure 1 shows a three-phase PWM inverter. Since the triggering signal of each power device in the inverter is digital signal, the outputs of the controller must be binary values. On the other hand, the input data to the inverter controller have analogue values such as current error or voltage error. Therefore, the controller of the inverter must



(a) Circuit



(b) Voltage vector

Fig.1 Three-phase PWM inverter

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have some non-linear functions to convert the analogue inputs into the binary outputs. For this reason, the on-off pattern controller of the inverter conventionally includes non-linear functions such as hysteresis comparators and/or comparators in the sub-harmonic modulation method.

The operation of the inverter controller can be considered as a kind of non-linear data mapping from analogue inputs to binary outputs. The problem in the conventional design of on-off pattern controller is in the way how to combine non-linear functions so as to realize the desired non-linear data mapping. It can be solved when the data mapping is not so complex one. For example, the instantaneous space vector method [4] to generate the on/off signals is designed successfully and applied for several PWM inverters. This kind of design approach, however, may not be powerful enough to actualize the more complicated data mapping. An example is the case that multiple performance indexes, such as both current ripple and switching loss of an inverter, should be compromised.

There is another synthetic approach to actualize the non-linear data mapping. That is the application of neural network . The neural network automatically learns the non-linear data mapping from the desired input and output data given as teaching signals.

2-2 Features of neural network

Remarkable features of neural networks are both fast processing speed and fault tolerance to some of miss connections in the network system. Moreover, some of networks have learning capability.

Because of parallel processing mechanism of neural networks, it is expected that the neural networks can execute the non-linear data mapping in very short time. At this time, however, the computation speed of the neural network with simulator is not so fast, because the operation of the neural network is simulated in a series sequential computer at present. In the near future, a neural network chip with parallel processing mechanism will be available in low price. Then the fast processing speed will be utilized in many applications.

Because of distributed network structure, the performance of the neural network may not be influenced by some of miss connections in the network itself. And a control system with multi-input neural network may not be affected by partial fault in the system, because some other correct input data may compensate the influence of wrong input data. An example of fault tolerance of the neural network control system is shown in the next chapter.

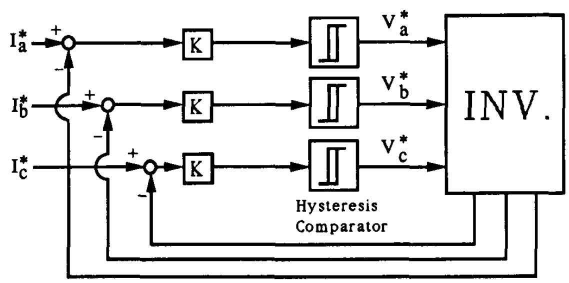
Some kinds of neural networks are known to have learning capability with appropriate learning rules. Among several learning rules, the error back propagation algorithm is well known and powerful because it can be applied to multi-layered networks. The error back propagation algorithm requires the teaching signal of input data and requested output data to learn the desired data mapping. The teaching signal should be determined carefully so as to include sufficient information to learn the essential characteristics of the desired data mapping. An example of teaching signal is proposed in the next chapter, in which the neural network learns the operation of the on-off pattern controller of three-phase PWM inverter.

3 Simulation Results

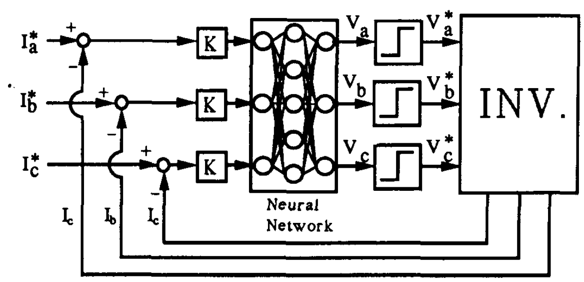
An example of applications of neural networks to inverter control is proposed in this chapter. In the proposed system, the neural network is applied to generate the on-off switching pattern of a 3-phase PWM inverter. This chapter consists of four sections. The first section explains the block diagram of the proposed system with a neural network. The second is the method of training the neural network. And the last two sections are the control performance comparison between the control system with the neural network and that with instantaneous value comparison method.

3-1 Current control system with neural comparator

Figure 2(a) is the block diagram of the



(a) Hysteresis comparator



(b) Neural comparator

Fig.2 Current control of three phase PWM inverter instantaneous value comparison method with hysteresis comparators. Figure 2(b) shows the current control system with a neural network. In the system, the neural network operates like the hysteresis comparator of Fig. 2 (a). So the control method of Fig. 2(b) is called the neural comparator method in this paper. The inputs of the neural comparator are the errors between reference currents and actual currents. The K is coefficient for scaling. As shown in Fig. 2 (a), three inputs of hysteresis comparators are independent of each other. On the contrary, three inputs of the neural comparators are connected each other in the structure of network as shown in Fig. 2 (b). Since the output function of each neural unit is a continuous sigmoid function for applying the error back propagation algorithm, the neural network outputs are not always exactly 0 or 1. So the comparators without hysteresis are introduced to make the neural network outputs into binary values as shown in Fig. 2 (b). The system parameters are listed in Table 1.

Table 1 System parameters

System parameters
V : 50 V L :10 mH R :1.00Ω Sampling time : 52.1 μsec (19.2 kHz)

Before comparing the control performance of these two systems, the method of training the neural network is mentioned in the next section.

3-2 Training method of neural network

Figure 3 shows the neural network used which has 3 neurons for input layer , 5 neurons for hidden layer, and 3 neurons for output layer. The output function of each neuron is a continuous sigmoid function to apply the error back propagation algorithm as learning rule. We have tested a lot of types of neural networks. We decided to use the 3-5-3 network structure because the number of neurons was the least in the 3-5-3 network.

The input values are three phase current errors between the reference currents and the actual output currents. The output signals are switching patterns of the PWM inverter. Those output signals should be determined so as to decrease the current errors in the inverter system.

The neural network was applied to the current control after a hundred thousand sweeps of learning process with the eight stimulus patterns. The learning rule, used here, is the error back propagation algorithm. Figure 4 shows eight stimulus patterns of teaching signal. The notation, (0, 0, 0) - (1, 1, 1) , indicates the on-off pattern of the voltage vector (V_a^*, V_b^*, V_c^*). We selected eight patterns at the corners of eight areas as shown in Fig. 4. For example, if the I_a^*- I_a is 0.01, the V_a^* is set 1 to decrease the current error, on the contrary , if I_a^*-I_a is -0.01, the V_a^* is set 0. The input-output relation of these teaching signals is similar to that of the hysteresis comparator with the hysteresis width of 0.02. Table 2 summarizes the eight teaching signals. After the learning process, the output errors between the stimulus patterns and the actual neural network output patterns were less than 1%.

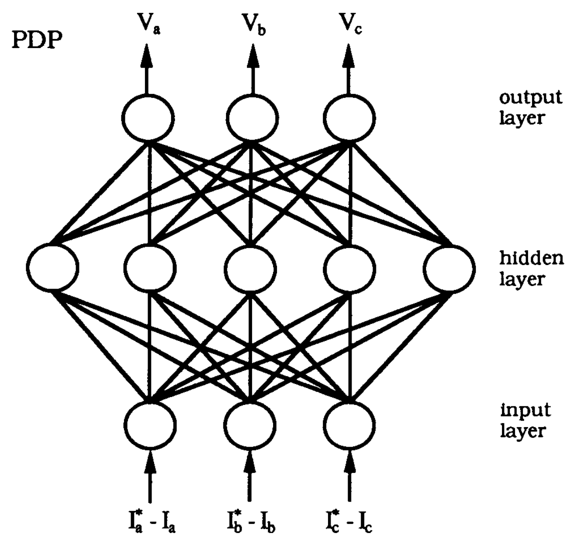


Fig.3 Structure of neural network

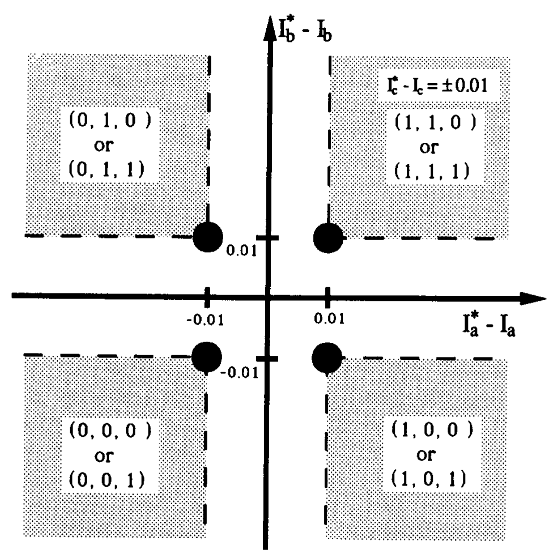


Fig.4 Teaching signal

When the neural network is applied to the current control, the connection weights of the neural network are fixed at the values obtained by the learning process. So the neural network does not continue the learning action during the current control process.

Table 2 Teaching signal

	INPUT SIGNAL			DESIRED PATTERN		
1	0.01	0.01	0.01	1.0	1.0	1.0
2	-0.01	0.01	0.01	0.0	1.0	1.0
3	0.01	-0.01	0.01	1.0	0.0	1.0
4	0.01	0.01	-0.01	1.0	1.0	0.0
5	0.01	-0.01	-0.01	1.0	0.0	0.0
6	-0.01	0.01	-0.01	0.0	1.0	0.0
7	-0.01	-0.01	0.01	0.0	0.0	1.0
8	-0.01	-0.01	-0.01	0.0	0.0	0.0

3-3 Fault tolerance of neural comparator control

Figure 5 shows simulation results of two types of current control methods in the condition that the c-phase current error input is forced to be zero in the block diagrams shown in Fig. 2. In the control system with the hysteresis comparators of Fig. 2 (a), the lack of one-phase error input distorts the three-phase actual current outputs as shown in Fig. 5 (a). On the other hand, the control system with the neural comparator of Fig. 2 (b) works very well in spite of lack of the c-phase error input as shown in Fig. 5 (b). The reason is that the neural comparator has inter-connected network structure and other inputs of a-phase and b-phase compensate the lack of the c-phase input. This result shows that the parallel distributed processing mechanism of the neural comparator improves the fault tolerance of control system.

3-4 Reduction of switching loss and current ripple

Figure 6 shows the simulation results of the output current of three-phase inverter controlled by two methods shown in Fig. 2. For the sake of explaining these results, we define the ratio α as follows:

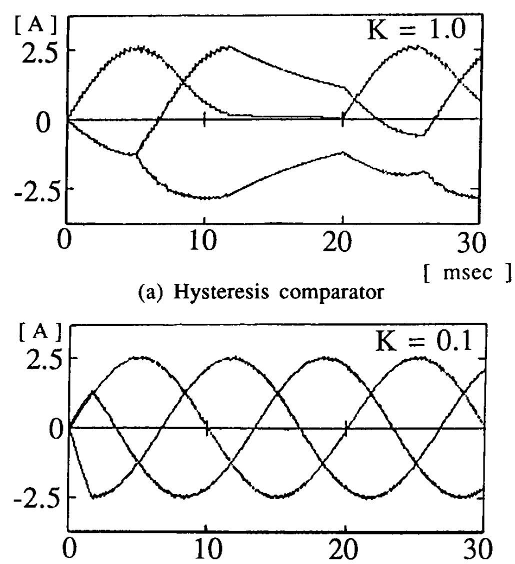
$$\alpha = \frac{A}{B}$$

A : number of actual device switching
B : number of possible switching instant

The α is in proportion to the number of actual switching per unit time interval. The reduction of α decreases the inverter switching loss. Then The inverter switching loss is represented by the α. Figure 7 shows the α and the peak-to-peak current error versus the K.

The current control performances of two types of control systems shown in Fig. 2 are almost the same at K=1.0. As shown in Fig. 6, at K=1.0, the controlled current waveforms of two types of systems are almost the same. By the data plotted in Fig. 7, the following comparison can be made. As for the control system with the hysteresis comparator, at K=1.0, then the α is 75.3 [%], and the peak-to-peak current error is 0.371 [A]. The corresponding data for the control system with the neural comparator are α=75.5 [%], and the peak-to peak current error is 0.378 [A]. Those data for the system with the neural comparator are in very good accordance with those for the system with the hysteresis comparator. Therefore, it can be mentioned that the control performance of these two control systems have almost the same control performance at K=1.0.

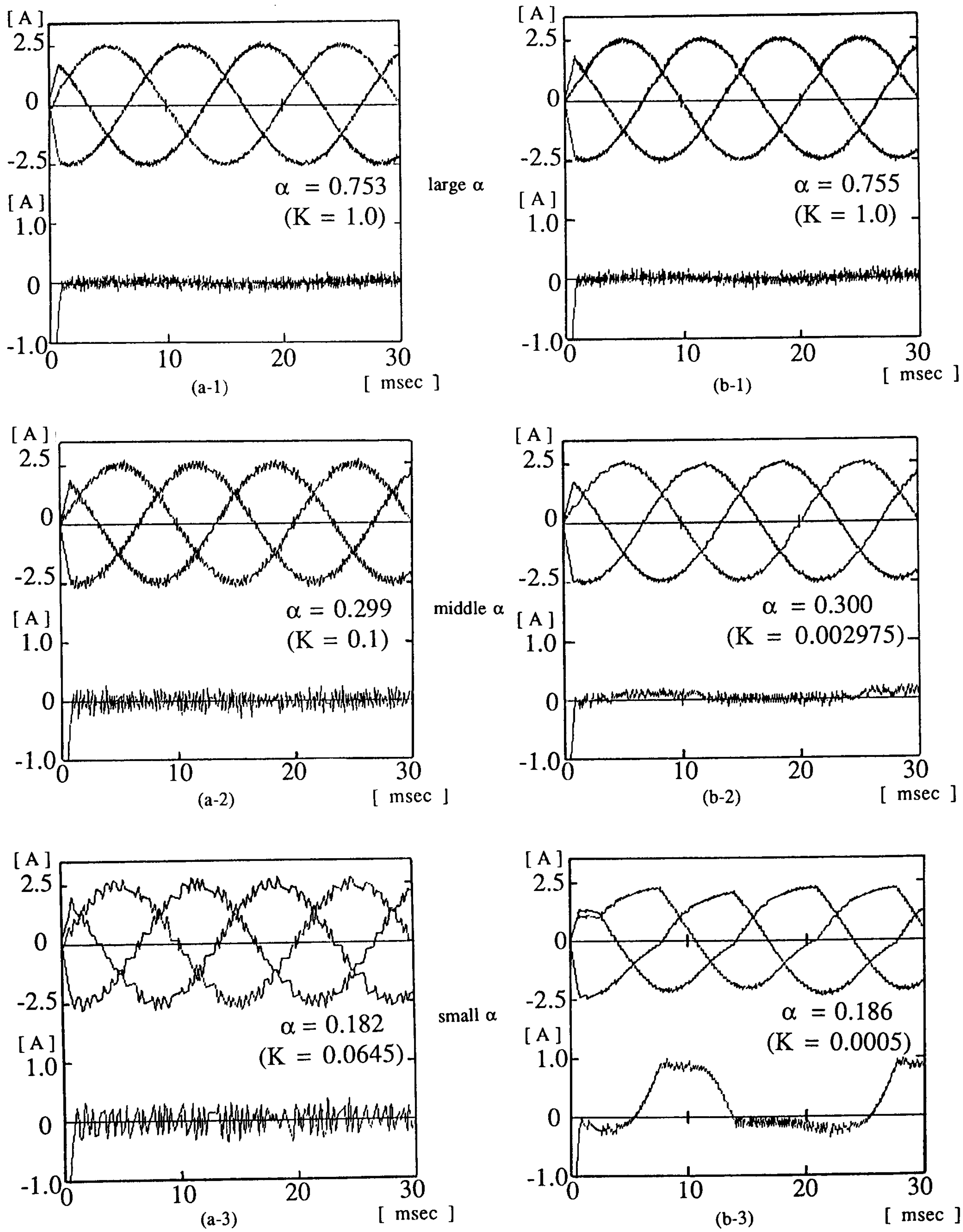
However, the system with the neural comparator presents interesting characteristics within the small value of K as shown in Fig. 7. As for the system with the neural comparator, at K=0.00298, then the α is 30 [%], and the peak-to-peak current error is 0.304 [A]. On the other hand, as for the system with the hysteresis comparator, when α=30 [%] the peak-to-peak current error is 0.563 [A] which is larger than that with the neural comparator. In this comparison, the values of α for two systems are the same to keep the switching



(a) Hysteresis comparator

(b) Neural comparator

Fig.5 Current waveform in case $I_c^*-I_c = 0$

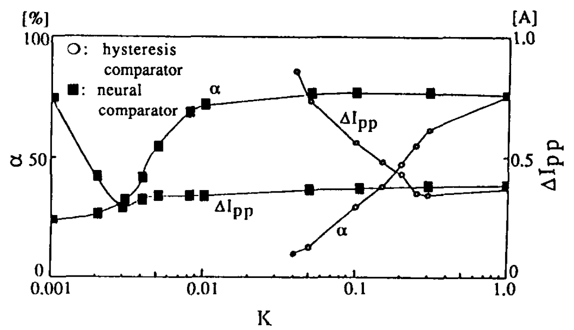


(a) Hysteresis comparator

(b) Neural comparator

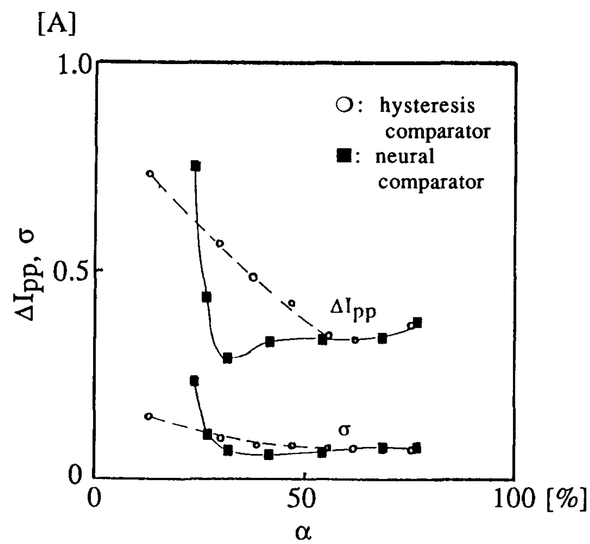
Fig.6 Three phase current and I_b^*-I_b

loss the same. From the comparison mentioned above, it may be said that the system with the neural comparator makes the current ripple smaller than that of the system with the hysteresis comparator in the condition of the same switching loss. In order to make this observation clearer, the data of Fig. 7 are plotted in another form as shown in Fig. 8. This figure clearly illustrates that the current error of the neural comparator system is smaller than that of the hysteresis comparator system.



$\Delta I_b = (I_b{}^* - I_b)$, $\Delta I_{pp} = (\Delta I_b)_{max} - (\Delta I_b)_{min}$

Fig.7 α and ΔI_{pp} vs. K



$\Delta I_b = (I_b{}^* - I_b)$, $\Delta I_{pp} = (\Delta I_b)_{max} - (\Delta I_b)_{min}$

$$\sigma = \sqrt{\frac{\Sigma(\Delta I_b)^2}{N}}$$

Fig.8 ΔI_{pp} and σ vs. α

4 Conclusion

A method of applying neural networks for power converter system is presented. Neural networks decompose comparator characteristics into network structure and have new interesting characteristics in themselves by learning. The validity of this approach is confirmed by simulation results. This approach is more effective than hysteresis comparator because switching loss in this neural comparator system is small.

The application of neural networks to inverter control is at the first stage of research. Many additional research in this area is needed. One of them is Hopfield's networks approach to optimization of PWM patterns. Hopfield's networks are known as a effective method to solve combinational optimization problems which need very long processing time with conventional sequential approach. We expect to apply these approaches for more complex control of power converter system.

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