# A Neural Network Based Reference Modified PID Control with Simple Duration Design for Digitally Controlled DC-DC Converters

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**Abstract-** The aim of this paper is to propose a neural network based reference modified PID control which has a simple duration design method for transient characteristics improvement of digitally controlled dc-dc converters. In renewable energy network systems, various types of dc-dc converters are widely used for power conversion and such converters require a superior control method for a stable operation. Especially, transient characteristics should be improved since they heavily affect the stability of the system. For such purposes, designing of conventional control methods becomes a difficult task since the optimization of control parameters needs complicated analysis and it is affected from variations of circuit components of converters. Therefore, simple and easy design of control is widely required for a stable operation of power converters. The neural network can provide a suitable control methodology for such situation since it treats the plant as a black box and it can realize a non-linear control based on training of the input-output relation without complicated modelling and analysis. On the other hand, the neural network based method has a disadvantage caused from the fact that the neural network is trained with data obtained in advance and an overcompensation phenomenon occurs in the transient response. In this paper, the neural network control is adopted to control the dc-dc converter in coordination with a conventional PID control. The neural network predicts the output voltage of the converter and the reference value in the PID control is modified with the predictions to reduce the error of the output voltage. To avoid overcompensation, a simple duration design for the neural network control is also provided to improve the transient response effectively. From prototype testing in simulation and experiment, it is revealed that the proposed method contributes to obtain a superior transient performance compared with the conventional PID control.

**Keywords** dc-dc converter, digital control, neural network, reference modification.

## 1. Introduction

In renewable energy network system, several types of power energy sources such as solar and wind power plants are connected to battery, electric equipment and other loads through grid connection. Also, various types of dc-dc converters are adopted in such system for power conversion among components in the system. Therefore, superior control methods of dc-dc converters are required to realize a stable and efficient operation of the system. Especially, transient responses of dc-dc converter are important since the improvement of them can have a large contribution to such purposes.

For the power conversion in such system, digitally controlled pulse-width-modulated (PWM) switching dc-dc converters are widely used since it can provide stable and efficient operation with simple control strategy. The most popular way to control digital PWM dc-dc converters is PID control method and the control design mainly focuses on modelling and analysis of the plant and the controller and gain parameter setting of them. In the control design, variations of circuit elements and parasitic elements become a problem since it is hard to consider such effects into the modelling and the conventional analytical result does not become the optimal one. Therefore, the flexible control and its design method are required to handle such circuit parameter variations caused from, for example, production process and aging degradation.

A training based method is one of the possible ways to realize such flexible control method since it can tune the control parameter setting by training even parameter variations exist. For the control of the power converter, neural network based methods [7-14] are widely adopted as the training based method. The neural network treats the plant and the controller as a black box and it can approximate them as a non-linear dynamical system obtained by training using its input-output relation. It is expected to provide a powerful solution to improve the transient characteristics due to its flexible capacity of non-linear prediction compared to the conventional analytical design of the controller. As the neural network can work as a non-linear time series predictor, it is also expected to handle delay time effect caused from the digital calculation process.

The neural network control can realize the flexible control using its non-linear prediction, however, it needs a complicated computation. Therefore, it is difficult to realize in real time computation using a real use computation component such as DSPs. In [15], the neural network prediction control is adopted without real time computation of the neural network calculation in coordination with the conventional PID control. Instead of the real time computation, prediction results of the neural network are stacked as look-up tables into array memory and they are called in the control calculation process in the transient state to improve the transient response. The array based approach contributes to reduce computation complexity and resource effectively. However, the error between output and prediction result of the array based method becomes larger compared to the on-line calculation. To address such problem, duration and timing of the neural network control is devised [16], however, the design of them is done manually and it is a difficult task. Hence, a simple and easy designing method is needed to adopt it to various types of dc-dc converters used in the renewable energy network system.

In this paper, the neural network based reference modification which is realized with a simple duration designing method is adopted to improve the transient response. In the proposed method, duration and timing of the neural network control are designed based on area information of the transient response which is easily obtained. A simple criterion for duration and timing designing allows us to adopt the proposed method to improve the transient response easily and effectively. The proposed method is evaluated by a buck-type dc-dc converter which is the most popular and basic converter. From results in simulation and experiment, it is revealed that the proposed method can improve the transient response effectively compared to the conventional PID control. It is also confirmed that the proposed method has a superior performance against the variation of the circuit parameter compared to the conventional one.

## 2. Operation principle of proposed method

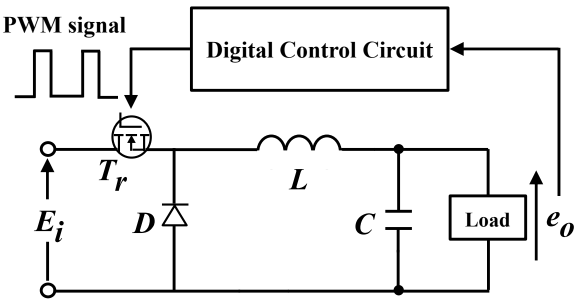



**Fig. 1.** Digitally controlled buck-type dc-dc converter.

Since a buck-type is the most fundamental and popular converter in dc-dc power conversion, it is selected to use as a prototype testing of the proposed method. Figure 1 shows a digitally controlled pulse-width-modulated (PWM) buck-type dc-dc converter used in this study. The output voltage of the converter is regulated with the digital controller. In Fig. 1, symbols represent circuit parameters as following; $E_i$ and $e_o$ are input and output voltages; $T_r$ is a switch; $D$ is a diode; $C$ is an output capacitor, $L$ is an inductor. In this study, a load shown in Fig. 1 is assumed as a fixed value resistor. In the $n$-th switching period, the sensed $e_o$ is converted its digital value $N_{e_o}$ as follows;

$$N_{e_o}[n] = G_{AD} e_o[n] \tag{1}$$

$$G_{AD} = \frac{2^Q - 1}{E_{AD}} \tag{2}$$

where $E_{AD}$ is a input range of the A/D converter and $Q$ is a resolution of the A/D converter. To regulate $e_o$ to its desired output voltage $E_o^*$, the conventional digital PID control calculate the digital on-time duration $N_{T_{on}}$ is calculated for PWM by Eqs. (3) and (4)

$$N_{T_{on}}[n] = N_B - N_{PID}[n] \tag{3}$$

$$\begin{aligned} N_{PID}[n] = {} & K_P\left(N_{e_o}[n-1] - N_R\right) \\ & + K_I \sum\left(N_{e_o}[n-1] - N_R\right) \\ & + K_D\left(N_{e_o}[n-1] - N_{e_o}[n-2]\right) \end{aligned} \tag{4}$$

where $N_B$ is a bias; $N_R$ is a reference value; $K_P$, $K_I$ and $K_D$ are proportional, integral and differential coefficients respectively.

In the conventional PID control, $N_R$ is the digital value of $E_o^*$. In the reference modified PID control [15,16], the reference value in the P term is modified with the neural network prediction to improve the transient response effectively due to the fact that the P term is dominant in the calculation of $N_{T_{on}}$ in the transient state. Since the reference modification is adopted in the transient state, therefore, the steady-state characteristics are regulated with the PID control. The reference modified PID control is represented by Eq. (5)

$$\begin{aligned} N_{PID}[n] = K_P \{ & N_{e_o}[n-1] - (N_R + \Delta N_R[n]) \} \\ & + K_I \sum \left( N_{e_o}[n-1] - N_R \right) \\ & + K_D \left( N_{e_o}[n-1] - N_{e_o}[n-2] \right) \end{aligned} \quad (5)$$

In Eq. (5), $\Delta N_R[n]$ is calculated with the digital predicted value by neural network $\hat{N}_{e_o}^{(1)}[n]$ as shown in Eqs. (6) and (7).

$$\Delta N_R[n] = N_R - \hat{N}_{e_o}^{(1)}[n] \quad (6)$$

$$\hat{N}_{e_o}^{(1)}[n] = G_{AD} \hat{e}_o{}^{(1)}[n] \quad (7)$$

The neural network adopted in this study is a three-layer feedforward type and it is trained with the back propagation algorithm [6] to minimize the least square error of the predicted output voltage. A sigmoid function is used in non-linear calculation of output of each unit. The neural network consists of an input layer with three units, a hidden layer with six units and an output layer with one unit. It is trained to predict the output voltage in the n-th switching period $\hat{e}_o{}^{(1)}[n]$ from its former sensed information of output voltage $e_o[n-1]$, $e_o[n-2]$, $e_o[n-3]$. For the training, the sensed output voltage data in the transient state are used. The advantage of the neural network based reference modification is that the training of neural network proceeds iteratively. By the iterative training, transient characteristics are gradually improved and the superior performance is achieved. Figure 2 shows a control diagram of the reference modification with the neural network.

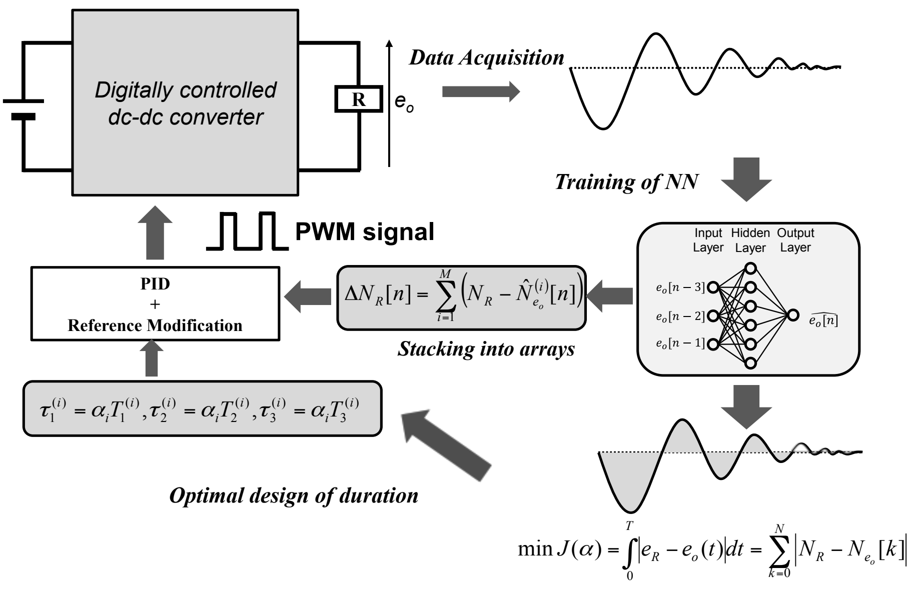



**Fig. 2.** Control diagram of proposed control method.

In addition to the reference modification, the duration and timing of the neural network control is also devised for the effective improvement as shown in Fig. 3. In the reference modification with the neural network, the duration and timing are designed from peak points of undershoot and overshoot of the output voltage ideally [15,16] since it is the most effective way to suppress the transient response. However, it is difficult to sense the peak point due to time delays of A/D conversion and calculation processes. Also, the sensing noise affects to the ideal peak points detection.

In another way to design the duration and timing is to use the array data for prediction. In the proposed method, the peak points can be determined from the array data since they are prediction results obtained in advance. However, it arises another problem that the array data are calculated in advance and it cannot reflect the progressing output since it is not a real time computation method. Figure 4 shows an example of the difference of the duration where $T_1^{(1)}$ represent durations btained from the peak point of the array data and $\tau_1^{(1)}$ are the optimal duration. Therefore, the array based reference modification requires the designing method of the duration and timing. The easiest way is to set $\tau_j^{(1)} = \alpha \cdot T_j^1$ $(j = 1,2,3)$ is to use a fixed ratio $\alpha$ $(0 < \alpha \le 1)$ which is determined manually [16]. However, the parameter tuning is expected to be systematic, i.e., the design of $\alpha$ needs to have a reasonable criterion to tune since the aim of the designing method aims to apply the proposed method various situations simply and easily.

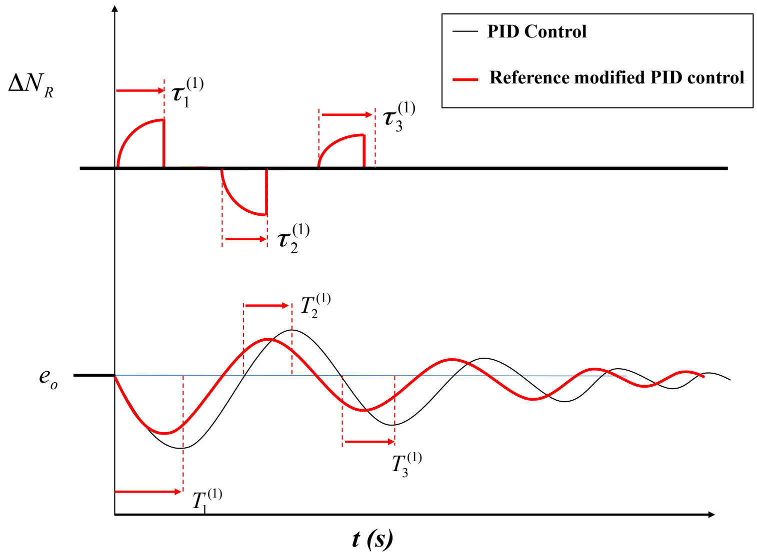



**Fig. 3.** Duration and timing of reference modification with neural network.

To design the duration and timing for the optimal reference modification, an objective function $J(\alpha)$ is defined as an area measure of the transient output voltage as shown in Fig. 5. Since $J(\alpha)$ can be easily obtained by observation, it is also used to tune other conventional control methods. From its definition, the value of $J(\alpha)$ is affected from duration $\tau_j^{(1)}$.

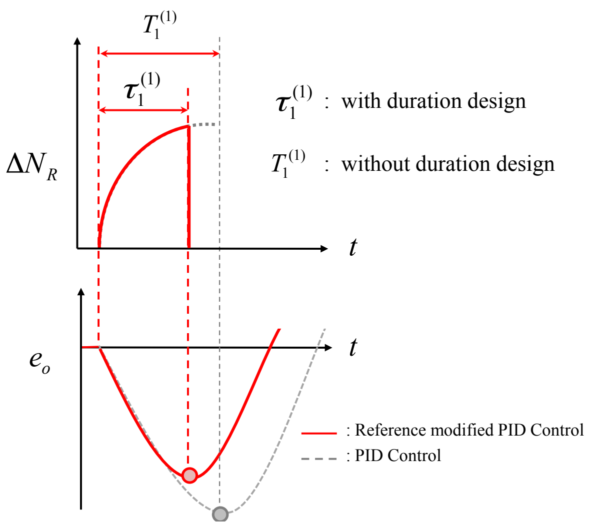
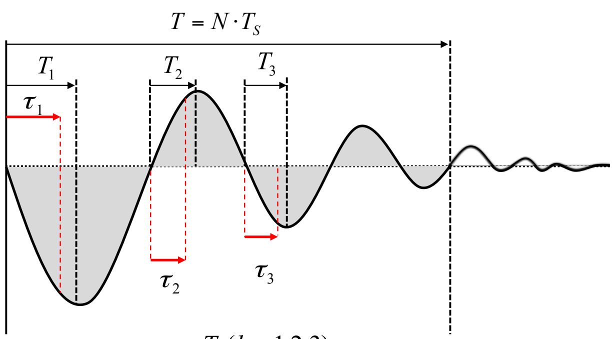



**Fig. 4.** Optimal duration design for reference modification.

In the proposed method, the reference modification with time duration control proceeds as follows. Firstly, the conventional PID control is adopted and the neural network is trained with the acquired data of the output voltage. After the training, the prediction results are stacked into the memory as an array (look-up table) $\left\{\hat{N}_{e_o}^{(1)}[n]\right\}$ and $T_j^{(1)}$ are determined. Secondly, the optimal duration ratio $\alpha$ is calculated to minimize $J(\alpha)$ as Eq. (8):




$$\tau_k = \alpha \cdot T_k \, (k = 1,2,3)$$

$$J(\alpha) = \int_0^T \left| e_R - e_o(t) \right| dt = \sum_{k=0}^{N} \left| N_R - N_{e_o}[k] \right|$$

**Fig. 5.** Objective function for designing duration and timing of neural network control.

$$\begin{aligned} \alpha &= \arg\min_{\alpha} J(\alpha) = \arg\min_{\alpha} \int_0^T \left| e_R - e_o(t) \right| dt \\ &= \arg\min_{\alpha} \sum_{k=0}^{N} \left| N_R - N_{e_o}[k] \right| \end{aligned} \quad (8)$$

Thirdly, the optimal duration $\tau_j^{(1)}$ are designed using the optimal $\alpha$. After these three procedures, the reference modification is completed using $\left\{\hat{N}_{e_o}^{(1)}[n]\right\}$ and $\tau_j^{(1)}$ as shown in Fig. 2. As shown in Fig. 5, it is noted that the reference modification is adopted to three overshoots and undershoots to suppress the transient response. Also, time duration of the transient state is defined from the transient state starts till

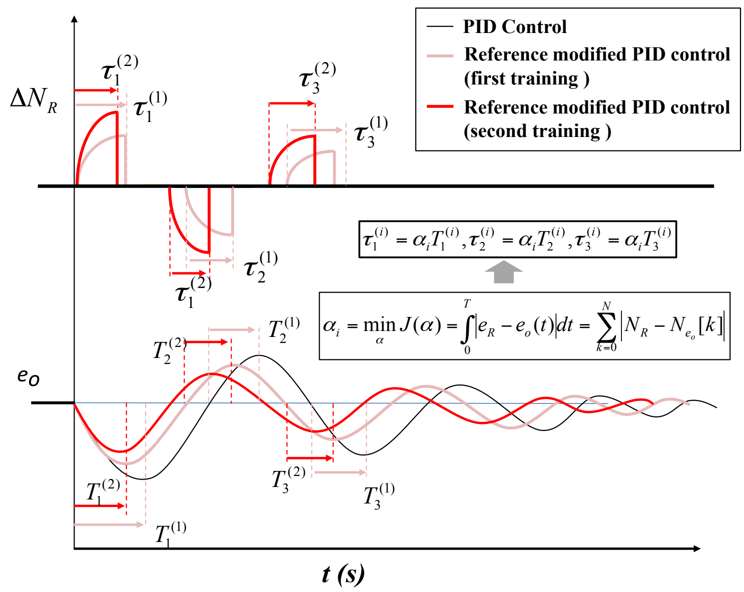



**Fig. 6.** Duration and timing of reference modification with repetitive training.

five undershoots and overshoots occurs to calculate $J(\alpha)$ in this study. These numbers are not limited and users can select suitable ones for their applications.

The advantage of the neural network based reference modification is that the data acquisition and training procedure can repeat in the same manner as above. Therefore, iterative training proceeds, the transient characteristics are gradually and effectively improved without any change of the PID control parameters. After M-th iteration, the reference modification term $\Delta N_R[n]$ becomes as Eq. (9):

$$\Delta N_R[n] = \sum_{i=1}^{M} \left( N_R - \hat{N}_{e_o}^{(i)}[n] \right) \tag{9}$$

The iterative training can proceed until the improvement of the reference modification reaches its limitation and enough suppression of transient characteristics are obtained.

Figure 6 shows duration and timing of the reference modification the iterative training of the neural network proceeds. When the number of iterative training is M, array data $\left\{ \hat{N}_{e_o}^{(i)}[n] \mid i = 1,2,\cdots M \right\}$ and durations $\left\{ \tau_j^{(M)} \mid j = 1,2,3 \right\}$ are finally obtained for the reference modification. It is noted that all durations for each prediction result are controlled by $\tau_j^{(M)}$ as shown in Fig. 6.

All required information for the reference modification such as $\hat{N}_{e_o}^{(i)}[n]$ and $\tau_j^{(i)}$ are stacked into the memory and it is called in the transient state. Therefore, the proposed method can be realized in a small computational resource and it can be easily implemented in real use computation processors.

**Table 1.** Circuit parameter setting.

| Circuit Parameter | Value |
|---|---|
| $f_S$ | 100 kHz |
| $C(=C_0)$ | 831 uF |
| $L$ | 189 uH |
| $E_i$ | 20 V |
| $E_o^*$ | 5 V |
| $E_{AD}$ | 20 V |
| $Q$ | 12 bit |
| rated $I_o$ | 1.0 A |

**Table 2.** Control parameter setting.

| Control Parameter | Value |
|---|---|
| $K_P$ | 4 |
| $K_I$ | 0.015 |
| $K_D$ | 4 |

## 3. Simulated and experimental evaluation

### 3.1. Circuit and control parameter setting

To evaluate the proposed method, the transient characteristics are evaluated in simulation and experiment. Table 1 shows circuit parameter setting of the dc-dc converter for evaluation used in this paper. Table 2 shows the control parameter values of the PID control. PID control parameters are tuned so as to regulate the steady-state characteristics and to improve the transient characteristics as much as possible. These parameter values are remained same in the reference modification and repetitive training of the proposed method.

For evaluation, PSIM is used in the simulated study and the digital control part is implemented using TMS5320C6713 (Texas Instruments) in the experimental study.

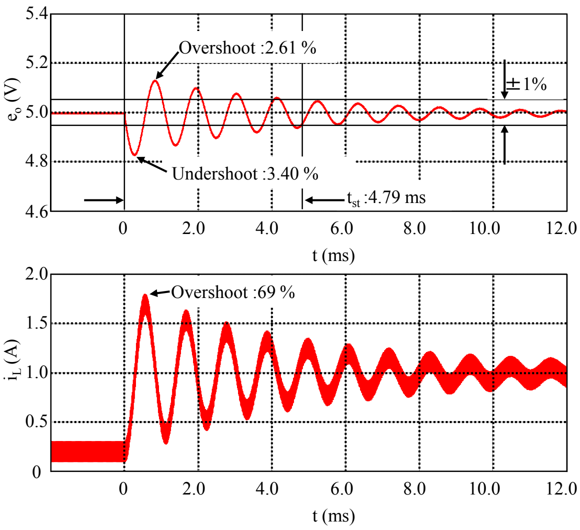
### 3.2. Evaluation of proposed method

In this evaluation, the step change of load from 0.2 A (25 Ω) to 1 A (5 Ω) is assumed in the transient state. It is noted that control parameters of the PID control shown in Table 2 remain same values in the reference modification and training of the proposed method. In each training procedure, one thousand points of sensed output voltage are acquired to training of the neural network.

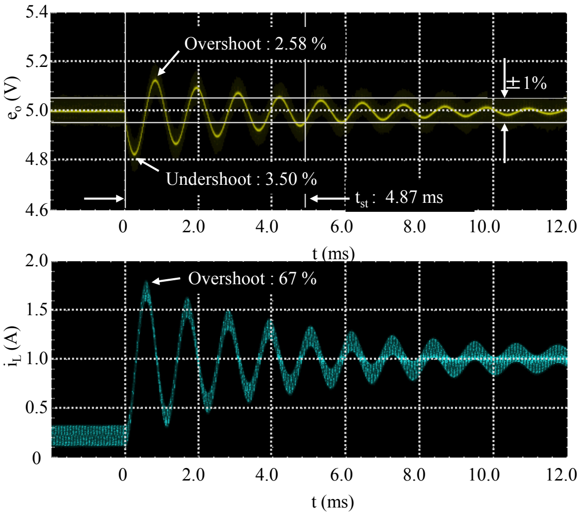
Figures 7 through 9 show simulated and experimental waveforms of $e_o$ and inductor current $i_L$ using the conventional PID control, the proposed control after the first iterative training and the proposed control after the seventh iterative training, respectively. Figures 10 through 13 show changes of the undershoot, overshoot, convergence time of $e_o$ and the overshoot of $i_L$ when the iterative training proceeds. The convergence time is defined as a time when the output voltage is settled in ±1% of the desired one in this study.

Figure 14 and Table 3 show results of the optimal $\alpha$ selection as the iterative training proceeds. From these results, the selected value of $\alpha$ is from 0.7 to 0.8 both in simulation and experiment.

From these results, it is seen that the transient characteristics are gradually improved as the iterative training proceeds. The effect of iterative training can be observed and the improvement by it converges in the seventh iteration. Finally, the propose method improves the transient characteristics effectively compared to the conventional PID control. For example, it is observed that the overshoot of the output voltage is improved from 3.50% to 1.62%, and the convergence time of the output voltage is improved from 4.87 ms to 0.248 ms in experiments.

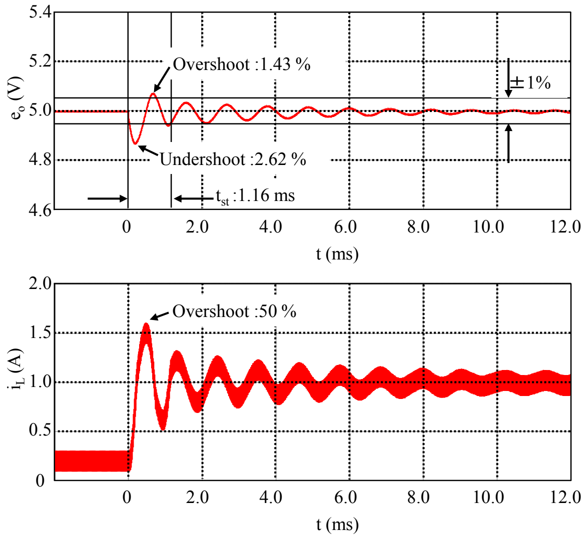



(a) Simulated waveforms

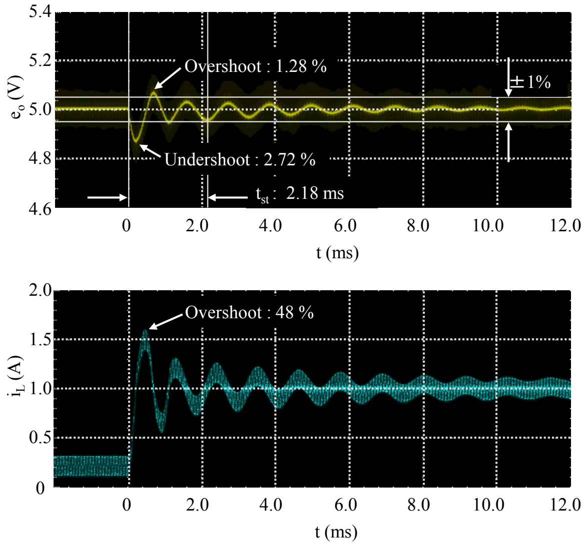



(b) Experimental waveforms

**Fig. 7.** Waveforms of output voltage $e_o$ and inductor current $i_L$ with conventional PID control when the step change of load from 25 Ω (0.2 A) to 5 Ω (1 A) occurs.

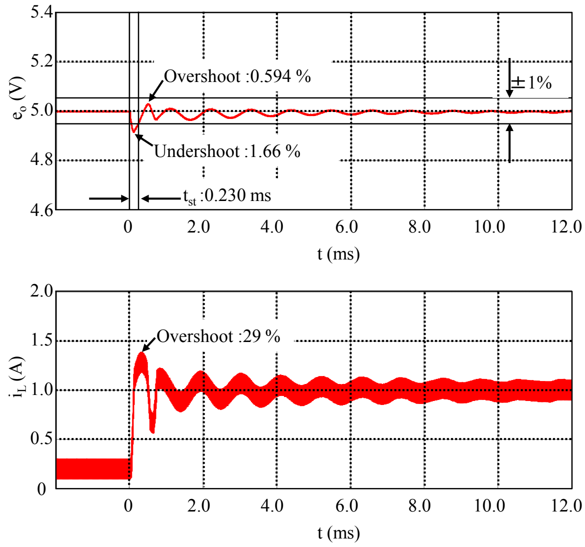



(a) Simulated waveforms

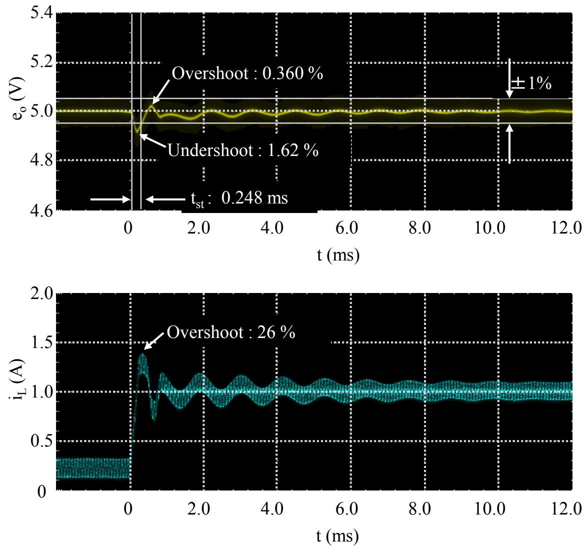



(b) Experimental waveforms

**Fig. 8.** Waveforms of output voltage $e_o$ and inductor current $i_L$ with proposed control after first training when the step change of load from 25 Ω (0.2 A) to 5 Ω (1 A) occurs.




(a) Simulated waveforms




(b) Experimental waveforms

**Fig. 9.** Waveforms of output voltage $e_o$ and inductor current $i_L$ with proposed control after seventh training when the step change of load from 25 Ω (0.2 A) to 5 Ω (1 A) occurs.

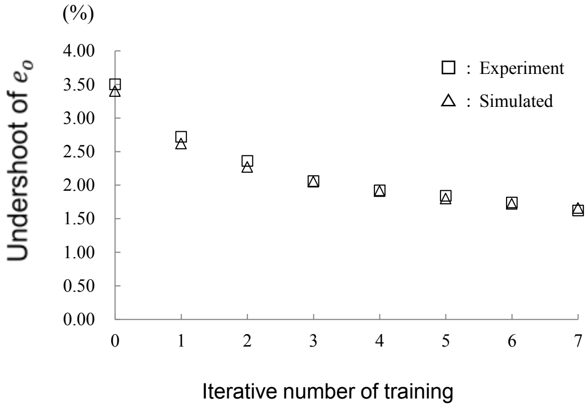



**Fig. 10.** Undershoot of output voltage when iterative training of neural network proceeds.

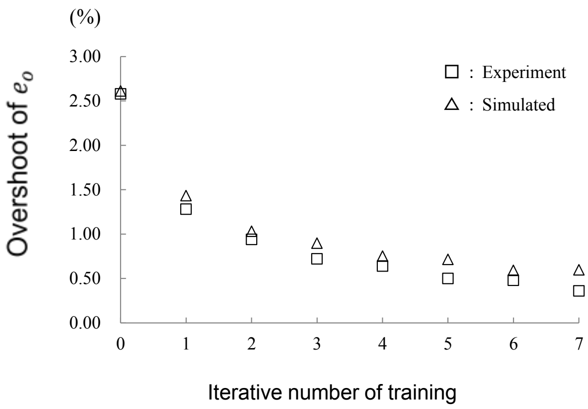



**Fig. 11.** Overshoot of output voltage when iterative training of neural network proceeds.

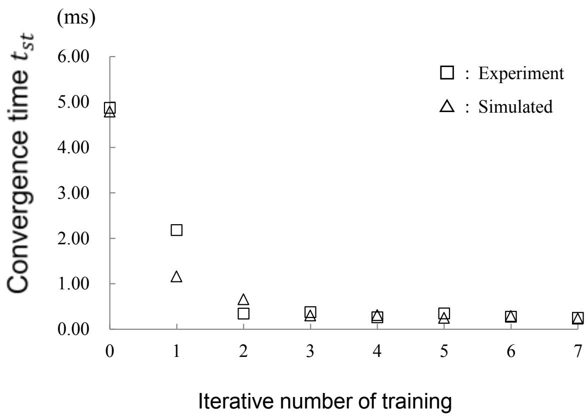



**Fig. 12.** Convergence time of output voltage when iterative training of neural network proceeds.

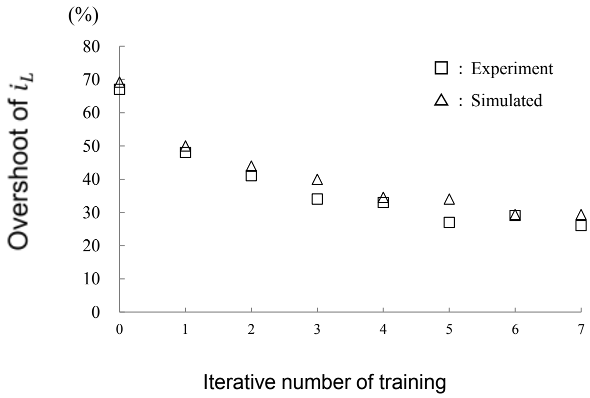
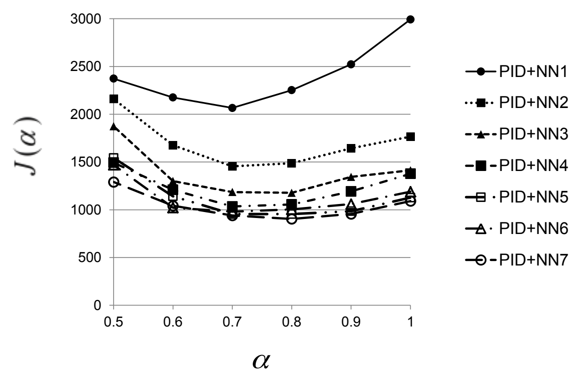
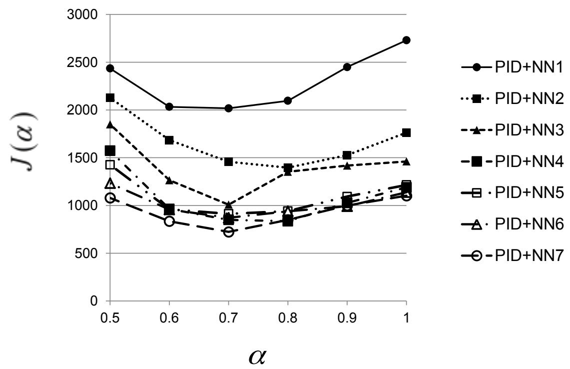



**Fig. 13.** Overshoot of inductor current when iterative training of neural network proceeds.




(a) Simulated result




(b) Experimental result

**Fig. 14.** Simulated and experimental results of optimal $\alpha$ selection.

**Table 3.** Selected optimal $\alpha$ in proposed design method.

| Iterative number | Selected optimal $\alpha$ | |
|---|---|---|
| | simulation | experiment |
| 1 | 0.7 | 0.7 |
| 2 | 0.7 | 0.8 |
| 3 | 0.8 | 0.7 |
| 4 | 0.7 | 0.8 |
| 5 | 0.8 | 0.7 |
| 6 | 0.7 | 0.7 |
| 7 | 0.8 | 0.7 |

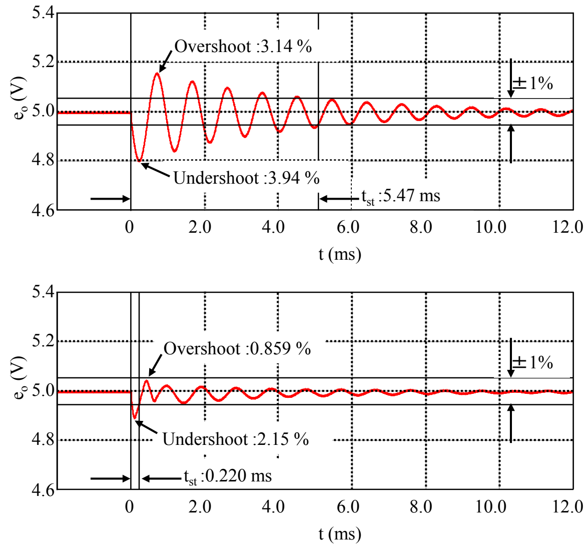
### *3.3. Evaluation on circuit parameter change*

When the circuit parameter condition is varied, the predicted results are not optimal since the training of the neural network does not consider such variation. It needs to evaluate that the proposed method can work under circuit parameter variation. One of the most important variations is concerned with the capacitor since it has aging degradation and product variation. Therefore, the proposed method is evaluated against the capacitance variation. It is noted that all parameters in the proposed method including PID control parameters, prediction results and the duration of the neural network control remain same settings.

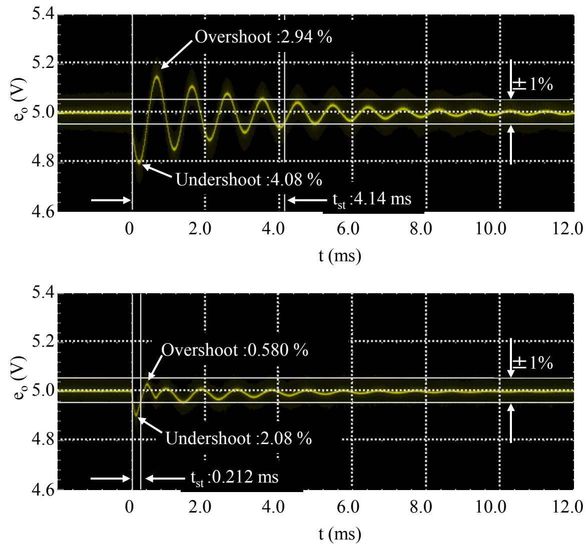
Figures 15 and 16 show simulated and experimental waveforms of the output voltage when the output capacitance varies to 75 % and 50 % of the original value $C_o$. Even the parameter condition differs from one when the training proceeds, the proposed method has a superior performance compared to the conventional PID control. From these results, the proposed method can work without re-training of the neural network under the variation capacitor and it is expected to have ability to adopt in real use situations.

## 4. Conclusion

This paper proposes a novel neural network based reference modification method to improve the transient characteristics of digitally controlled dc-dc converters. In the proposed method, the neural network reference modification is adopted in coordination with the PID control based on the predicted output voltage. Addition to the reference modification, duration and timing of the neural network control is devised to obtain effective compensation and avoid overcompensation. It is confirmed from evaluation results using the prototype that the proposed method can provide a superior transient performance compared to the conventional PID control. The proposed method can be applied to various type converters since it consists of simple and easy to design due to the fact of the flexibility of the neural network. Therefore, it is expected that the proposed method is widely applicable to various types of converters and it contributes to the stable and effective operation of the renewable energy network system.

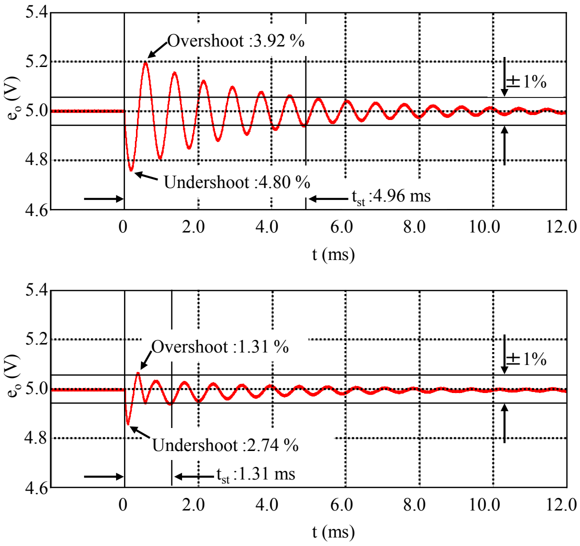



(a) Simulated waveforms

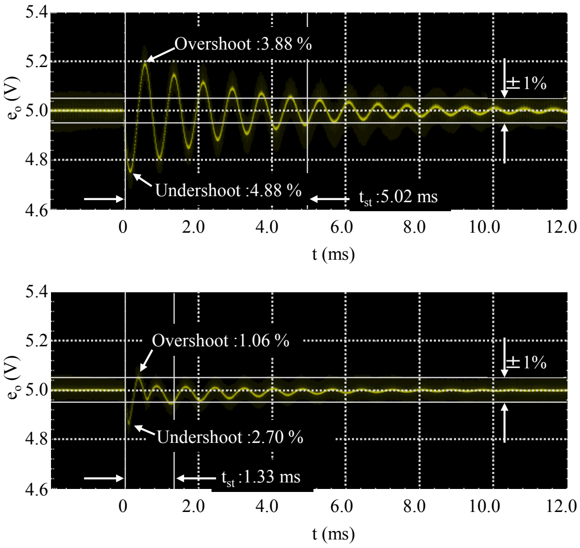



(b) Experimental waveforms

**Fig. 15.** Waveform comparison of PID control and proposed one when output capacitor varies to 75 % of $C_o$ (upper: PID; lower: proposed, step change of load from 25 Ω (0.2 A) to 5 Ω (1 A) ).




(a) Simulated waveforms




(b) Experimental waveforms

**Fig. 16.** Waveform comparison of PID control and proposed one when output capacitor varies to 50 % of $C_o$ (upper: PID; lower: proposed, step change of load from 25 Ω (0.2 A) to 5 Ω (1 A) ).

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