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Offset-free adaptive nonlinear model predictive control with disturbance observer for DC-DC buck converters

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Abstract: The aim of this paper is to design a nonlinear model predictive control for DC-DC buck converters to track constant reference signals with zero steady-state error. The online trained neural network (NN) model is employed as the predictor and the steady-state error, which is called the offset, is studied in the presence of the changes in system parameters and the external disturbances. The stability of the closed-loop system is investigated using the Lyapunov direct theory. The proposed method can provide offset-free behavior in the presence of constant disturbances. For rejecting nonconstant disturbances, a nonlinear disturbance observer based on the NN inverse model is proposed. Due to wide applications of the DC-DC converter in power electronics, control of its output voltage is considered in this paper. The effectiveness of the proposed control method is demonstrated by experimental results.

Key words: Model predictive control, offset-free control, neural network, disturbance observer, DC-DC power converter

1. Introduction

Regulating the output voltage of DC-DC converters has been an interesting subject in the research area of power electronics and automatic control for many years. The wide applications of the converters in industrial electronics, computers, power supplies, and motor drivers make them important from the control-engineering viewpoint. The model predictive control (MPC) method is one of the advanced control algorithms that is widely used in industrial applications due to its ability in control of constrained and nonlinear systems [1]. MPC is employed in the power control area, especially in control of converters [2,3]. This control strategy utilizes an explicit process model to predict the future response of the system and provides the control signal by solving an online constraint optimization problem [4]. Accuracy of the predictor model is an important issue in MPC. Hence, due to the nonlinear nature of almost all plants, using nonlinear models can improves the MPC performance in different industrial applications [5]. Neural networks (NNs) as general approximators are widely used in nonlinear MPC (NMPC) [6]. NNs are cascaded recursively in the NMPC structure to provide the output predictions over the prediction horizon.

Model–plant mismatches and external disturbances deteriorate the control performance and cause steady-state error in the output response. Eliminating the steady-state error in the presence of the model–plant mismatches and disturbances is widely studied in the literature and different approaches are proposed for it. One of these approaches is adaptive control that adjusts the changes of the system and the disturbances, which reduces the influence of these factors [7]. Another approach is offset-free control, which tries to reject the effect of the disturbance by augmenting the system model with the disturbance fictitious model and employing an

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observer to estimate the states of the augmented system [8–10]. In some offset-free approaches the difference between system and predicted model outputs is utilized to correct the predictions in the multistep output recursive prediction [11]. In [12,13], the classical control structure along with the resonant controller is used to achieve zero steady-state tracking error in the current control of the inverters and converters. A robust approach for estimating and rejecting the disturbance uses a disturbance observer (DOB) that is studied in both time and frequency domains [14]. In the frequency domain, which is mostly used in the linear control area, the inverse model of the system is utilized; then, by comparing the system input and the output of the inverse model, the disturbance is estimated. The estimated disturbance is used in the feedforward structure to modify the controller output [15]. The time domain approach, which is used mostly in nonlinear control, is based on the design of the observer gain for nonlinear augmented systems [16]. In order to provide a robust current model predictive control of the converters, the feed-forward compensation of disturbances was employed and a disturbance observer such as a Luenberger observer or extended state observer was utilized to estimate the uncertainties, system model errors, and disturbances in [17,18].

The three basic switch-mode DC-DC power converters are the buck, the boost, and the buck–boost configurations. The buck (step-down) converter produces an output voltage lower than the input. A typical buck converter works in continuous current mode. The most important problem in these converters is to achieve good tracking accuracy [19].

In this paper, the offset-free tracking control of DC-DC buck converters in the presence of model–plant mismatches and external disturbances is considered. The NMPC controller based on the adaptive NN predictor model is utilized. The adaptive structure of the model helps the controller to reject the model–plant mismatches (internal disturbances) as well as external constant disturbances. For nonconstant disturbances a DOB is added to the adaptive NN-based NMPC (ANNMPC) to reject the effects of other types of disturbances. The structure of the frequency domain DOB with some modifications is used and the NN model is employed to obtain the inverse model of the converter. Moreover, stability of the closed-loop system is studied using the Lyapunov direct method. Experimental results show substantial improvements of the proposed controller as compared with the standard NMPC.

This paper is organized as follows. Section 2 gives the problem statement. The NMPC strategy and the structure of the adaptive NN predictor are explained in this section. Disturbance rejection of constant and ramp disturbances using the DOB along with the stability of the closed-loop system is explained in Section 3. Experimental results of the buck DC-DC converter are given in Section 4. Section 5 concludes the paper.

2. Problem statement

Consider the following SISO nonlinear nonaffine dynamic system with unknown external disturbance:

$$y(k) = f\left(y(k-1),\ \ldots,\ y(k-n_y),\ u(k-1),\ \ldots,\ u(k-n_u), d(k)\right) \tag{1}$$

where f is an unknown nonlinear function, y and u are the output and input of the system, n_y and n_u respectively refer to the maximum lags in the system output and input, and $d(k)$ is an unknown but bounded disturbance.

2.1. Nonlinear model predictive control formulation

Model predictive control utilizes the explicit model of the system and provides the control signal based on the online constraint optimization problem. The performance index of the NMPC contains the tracking error over the prediction horizon (N_P) and the changes of the control signal over the control horizon ($M \leq N_P$) as follows:

$$\begin{aligned} L_{NMPC} \quad = \quad & \min_{\Delta u(k|k),\ldots,\Delta u(k+M-1|k)} \left[\sum_{i=1}^{N_P} \left(y_{sp}(k+i) - y_m(k+i\,|k) \right) Q \left(y_{sp}(k+i) - y_m(k+i\,|k) \right) \right. \\ & \left. + \sum_{j=0}^{M-1} \left(\Delta u(k+j\,|k) \right) R \ \left(\Delta u(k+j\,|k) \right) \right] \end{aligned} \tag{2}$$

subject to:

$$\begin{array}{ll} y_{\min} \leq y_m(k+i\,|k) \leq y_{\max} & 1 \leq i \leq N_P \\ u_{\min} \leq u(k+i\,|k) \leq u_{\max} & 0 \leq i \leq M-1 \\ \Delta u_{\min} \leq \Delta u(k+i\,|k) \leq \Delta u_{\max} & 0 \leq i \leq M-1 \end{array} \tag{3}$$

where $y_{sp}(k)$ is the desired reference signal, $y_m(k)$ is the output of the model, and Q and R are the weighting factors on the predicted error and the control effort, respectively. Moreover, it is considered that $\Delta u(k+j|k) = 0$ for $j > M-1$.

In this paper, the NN model is employed as the predictor in the NMPC structure, which is trained online. The NN model is described by the following nonlinear autoregressive moving averaging model:

$$y_m(k) = f_{NN} \left(y(k-1),\ \ldots, y(k-\hat{n}_y), u(k-1),\ \ldots, u(k-\hat{n}_u) \right) \tag{4}$$

where f_{NN} represents the nonlinear mapping function, and $\hat{n}_y$ and $\hat{n}_u$ are the maximum lags in the model output and input, respectively. A multilayer perceptron (MLP) NN with one hidden layer is considered. In each step, the NN weights are trained via the new data obtained from the system by solving the following optimization problem:

$$\min_{\mathbf{w}(k)} E_{NN}(k) = \min_{\mathbf{w}(k)} \frac{1}{2} \left(e_M(k)^2 + e_T(k)^2 \right) \tag{5}$$

where $\mathbf{w}(k)$ is the NN weights vector and

$$e_M(k) = y(k) - y_m(k), \quad e_T(k) = y_{sp}(k) - y_m(k) \tag{6}$$

Since the NN model is used as a predictor in the NMPC problem, in addition to the modeling error, the tracking error is also used for training the NN model parameters. The online minimization problem of Eq. (5) is solved by the Levenberg–Marquardt (LM) algorithm and the NN weights are updated by the following equation:

$$\mathbf{w}(k+1) = \mathbf{w}(k) - \eta \left(\mathbf{J}^T(k)\mathbf{J}(k) + \mu \mathbf{I} \right)^{-1} \mathbf{J}^T(k) e(k) \tag{7}$$

where η is the learning rate, μ is the regularization parameter of the LM algorithm, $\mathbf{J}(k) = -\partial y_m(k)/\partial \mathbf{w}(k)$ is the Jacobian vector, and $e(k) = e_M(k) + e_T(k)$ is the instantaneous training error. The NN input vector is considered as $\phi(k-1) = [y(k-1)\ \cdots\ y(k-\hat{n}_y)\ u(k-1)\ \cdots\ u(k-\hat{n}_u)]^T$.

The NN model is a one-step-ahead predictor for the system output. To produce the predictions of the output over the prediction horizon, the past output samples in the vector $\phi(.)$ are gradually replaced by their predicted values. That is, by updating the vector $\phi(.)$, the one-step-ahead NN model is recursively cascaded to generate the future predictions, as depicted in Figure 1. The NN weights are considered fixed and are not trained over the prediction horizon. That means:

$$\mathbf{w}(k+i|k) = \mathbf{w}(k) \qquad 1 \leq i \leq N_P \tag{8}$$

The structure of the closed-loop system is illustrated in Figure 1.

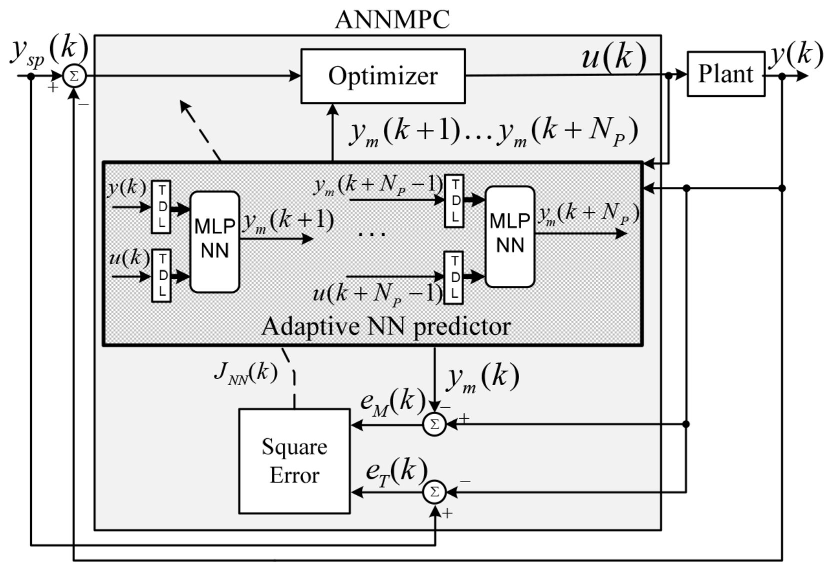

Figure 1. Closed-loop system with ANNMPC and recursive NN predictor.

3. Disturbance rejection

Model mismatches and external disturbances lead to tracking error, which can deteriorate the performance of control systems. Adaptation ability of the online modeling helps the controller to adjust the changes of the system parameters in each time step and attenuate the tracking error. Moreover, the constant external disturbances can be rejected by adaptive control methods. This issue is investigated in the following theorem.

Theorem 1 *The ANNMPC controller with the cost function of Eq. (2) and online model training rule of Eq. (7) leads to the asymptotically stable closed-loop system in the presence of the model mismatches and the external step disturbances if the NN learning rate satisfies the following condition:*

Table. Parameter values of the buck DC-DC converter.

Parameter	Value	Unit
Input voltage	12	V
Inductance	100	μH
Capacitance	220	μF
Load resistance	72	Ω
Switching frequency	20	kHz

$$0 < \eta(k) < \frac{1}{\mathbf{J}(k)\left(\mathbf{J}^T(k)\mathbf{J}(k) + \mu\mathbf{I}\right)^{-1}\mathbf{J}^T(k)} \tag{9}$$

Proof The candidate Lyapunov function is considered as:

$$V(k) = e_T(k)^2 + e_M(k)^2 \tag{10}$$

Since the stability of the closed-loop system is investigated in the presence of the model mismatches and external disturbances, the Lyapunov function contains both the tracking and the modeling error. The first difference of Eq. (10) is:

$$\Delta V(k) = V(k+1) - V(k) = 2e_T(k)\Delta e_T(k) + \Delta e_T(k)^2 + 2e_M(k)\Delta e_M(k) + \Delta e_M(k)^2 \tag{11}$$

After some calculations, Eq. (11) can be written as

$$\begin{aligned} \Delta V(k) \quad = \quad & 2e_T(k)\left(\partial e_T(k)/\partial \mathbf{w}(k)\right)^T \Delta\mathbf{w}(k) + \left(\left(\partial e_T(k)/\partial \mathbf{w}(k)\right)^T \Delta\mathbf{w}(k)\right)^2 \\ & +2e_M(k)\left(\partial e_M(k)/\partial \mathbf{w}(k)\right)^T \Delta\mathbf{w}(k) + \left(\left(\partial e_M(k)/\partial \mathbf{w}(k)\right)^T \Delta\mathbf{w}(k)\right)^2 \end{aligned} \tag{12}$$

According to the definition of the Jacobian vector $(\mathbf{J}(k) = -\partial y_m(k)/\partial \mathbf{w}(k))$ and using Eq. (7), Eq. (12) can be rewritten as:

$$\begin{aligned} \Delta V(k) = \; & \left(2\eta(k)\mathbf{J}(k)\left(\mathbf{J}^T(k)\mathbf{J}(k) + \mu\mathbf{I}\right)^{-1}\mathbf{J}^T(k)\left(e_T(k) + e_M(k)\right)^2\right) \\ & \left(-1 + \eta(k)\left[\mathbf{J}(k)\left(\mathbf{J}^T(k)\mathbf{J}(k) + \mu\mathbf{I}\right)^{-1}\mathbf{J}^T(k)\right]\right) < 0 \,. \end{aligned} \tag{13}$$

Since the sum of two positive definite (PD) matrices is PD, hence $\left(\mathbf{J}^T(k)\mathbf{J}(k) + \mu\mathbf{I}\right)$ and its inverse are PD as well. Then, using the Sylvester criterion, it can be written as:

$$\mathbf{J}(k)\left(\mathbf{J}^T(k)\mathbf{J}(k) + \mu\mathbf{I}\right)^{-1}\mathbf{J}^T(k) > 0 \tag{14}$$

Therefore, the first term in Eq. (13) has a positive value and the second term must be negative. Hence, the stability bound for η is obtained as in Eq. (9). □

Remark 1 *In this paper, the NN is utilized as an adaptive predictor model in ANNMPC. This model is trained in each time step using new data obtained from the system. Therefore, this NN model may learn the disturbances (in output or in system parameters) along with the disturbed system response. The model mismatch is included in the modeling error and the disturbance exists in both the tracking and modeling error due to the NN modeling. Hence, using the Lyapunov function of Eq. (10) for the stability of the closed-loop system, the effect of model mismatch and disturbances is considered. According to Theorem 1, if* η *is selected in the stability region of Eq. (9), for* $k \to \infty$ *(the steady-state behavior), the Lyapunov function and consequently the modeling and tracking error tend to zero:*

$$\lim_{k\to\infty} V(k) = 0 \Rightarrow \begin{cases} \lim\limits_{k\to\infty} e_T(k) = 0 \\ \lim\limits_{k\to\infty} e_M(k) = 0 \end{cases} \tag{15}$$

Therefore, the error between the reference signal and the real plant output tends to zero in the presence of the model–plant mismatches and disturbances, which provides offset-free behavior for the system response:

$$\begin{cases} \lim_{k\to\infty} y_{NN}(k) = y_{sp}^{\infty} \\ \lim_{k\to\infty} y_{NN}(k) = \lim_{k\to\infty} y_p(k) \end{cases} \Rightarrow \lim_{k\to\infty} y_p(k) = y_{sp}^{\infty} \tag{16}$$

It should be noted that the Lyapunov theory considers the steady-state behavior of the system. Hence, step disturbances (i.e. external disturbances with constant values) can be successfully rejected. However, no such conclusion can be drawn about the nonconstant disturbances. Typically, nonconstant disturbances in real applications are ramp or sinusoidal signals [20,21]. NMPC based on the adaptive NN model cannot reject these types of disturbances. An important approach for dealing with nonconstant disturbances is using the feedforward control algorithm with the DOB. The DOB-based control methods utilize the inverse model of the system and estimate the disturbance by comparing the output of the inverse model and the input signal of the system. The estimated disturbance is subtracted from the controller output and therefore rejects the disturbance from the control signal. The structure of the proposed ANNMPC method using the DOB is depicted in Figure 2.

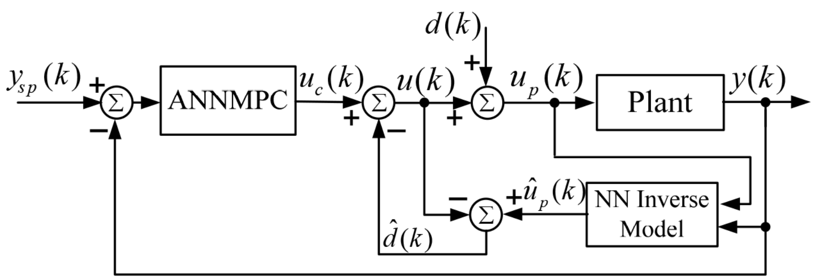

Figure 2. Structure of the proposed ANNMPC with disturbance observer.

Since the inverse model of the system is utilized in the nonlinear disturbance observer method, the nonlinear system must be in minimum phase. A NN model with the MLP structure is used to obtain the inverse model of the system. According to Figure 2, the estimated disturbance ($\hat{d}(k)$) is given by:

$$\hat{d}(k) = \hat{u}_p(k) - u(k) = g\left(\mathbf{Y}(k), \mathbf{U_p}(k)\right) - u(k) = g\left(\mathbf{Y}(k), \mathbf{U}(k) + \mathbf{D}(k)\right) - u(k) \tag{17}$$

where $g(\cdot)$, the inverse model of the system, is a MLP NN, which is trained offline using the LM algorithm. Moreover:

$$\hat{u}_p(k) = g\left(y(k-1),\ \ldots, y(k-\tilde{n}_y), u_p(k-1),\ \ldots, u_p(k-\tilde{n}_u)\right) \tag{18}$$

and

$$\begin{aligned} &\mathbf{Y}(k) = [y(k-1),\ \ldots, y(k-\tilde{n}_y)], \quad \mathbf{U_p}(k) = [u_p(k-1),\ \ldots, u_p(k-\tilde{n}_u)], \\ &\mathbf{U}(k) = [u(k-1),\ \ldots, u(k-\tilde{n}_u)], \quad \mathbf{D}(k) = [d(k-1),\ \ldots, d(k-\tilde{n}_u)]. \end{aligned} \tag{19}$$

Where, $\tilde{n}_y$ and $\tilde{n}_u$ are the maximum lags in the model input and output, respectively.

The weights of the NN inverse model are adjusted using the following objective function:

$$L_{off-line} = \frac{1}{2}\sum_n e_{inv}(n)^2 \tag{20}$$

where $e_{inv}(n) = u_p(n) - \hat{u}_p(n)$ is the training error. By minimizing the objective function of Eq. (20), the weights of the NN inverse model are given by

$$\mathbf{v}(n+1) = \mathbf{v}(n) - \rho \left(\mathbf{J}_{inv}^T(n)\mathbf{J}_{inv}(n) + \gamma\mathbf{I}\right)^{-1} \mathbf{J}_{inv}^T(n) e_{inv}(n) \tag{21}$$

where ρ is the learning rate, γ is the regularization parameter of the LM algorithm, and $\mathbf{J}_{inv}(n) = \partial e_{inv}(n)/\partial \mathbf{v}(n)$ is the Jacobian vector.

It can be shown that for the specific bound on the learning rate of the NN model weights, the NN inverse model converges asymptotically to the actual value of the plant input. This is shown in the following theorem.

Theorem 2 *If the weights $\mathbf{v}(n)$ of the offline trained NN inverse model are trained using Eq. (21), then the NN inverse model will converge to the actual value of the plant input asymptotically if the learning rate satisfies the following condition:*

$$0 < \rho(n) < \frac{2}{\mathbf{J}_{inv}(n)\left(\mathbf{J}_{inv}^T(n)\mathbf{J}_{inv}(n) + \gamma\mathbf{I}\right)^{-1} \mathbf{J}_{inv}^T(n)} \tag{22}$$

Proof The candidate Lyapunov function is considered as:

$$V(n) = e_{inv}(n)^2. \tag{23}$$

The first difference of Eq. (23) is:

$$\Delta V(n) = 2e_{inv}(n)\Delta e_{inv}(n) + \Delta e_{inv}(n)\Delta e_{inv}(n) \tag{24}$$

The first difference of the tracking error can be written as:

$$\Delta e_{inv}(n) = \left(\partial e_{inv}(n)/\partial \mathbf{v}(n)\right)^T \Delta\mathbf{v}(n) \tag{25}$$

Using the definition of the Jacobian vector, it gives $\Delta e_{inv}(n) = \mathbf{J}_{inv}^T(n)\Delta\mathbf{v}(n)$. Substituting Eq. (21) into Eq. (25) yields:

$$\begin{aligned}\Delta V(n) = \quad & -\rho e_{inv}(n)^2\, \mathbf{J}_{inv}(n)\left(\mathbf{J}_{inv}^T(n)\mathbf{J}_{inv}(n) + \gamma I\right)^{-1} \mathbf{J}_{inv}^T(n) \\ & \left[2 - \rho\, \mathbf{J}_{inv}(n)\left(\mathbf{J}_{inv}^T(n)\mathbf{J}_{inv}(n) + \gamma I\right)^{-1} \mathbf{J}_{inv}^T(n)\right]\end{aligned} \tag{26}$$

To ensure that the output of the NN converges to the desired output, it is required to have $\Delta V(n) < 0$. Finally, a procedure similar to the proof of Theorem 1 follows the assertion. □

According to Theorem 2, it can be written that $g(\cdot) = f^{-1}(\cdot)$. Substituting this equation into Eq. (17), the estimated disturbance is calculated as:

$$\begin{aligned}\hat{d}(k) &= g\left(\mathbf{Y}(k), \mathbf{U}(k) + \mathbf{D}(k)\right) - u(k) \\ &= f^{-1}\left(\mathbf{Y}(k), \mathbf{U}(k) + \mathbf{D}(k)\right) - u(k) = u(k) + d(k) - u(k) = d(k)\end{aligned} \tag{27}$$

Hence, the disturbance can be observed exactly by the proposed NN-based DOB. Hence, it can be obtained from the Figure 2 that:

$$\hat{u}_p(k) = u_p(k) = u_c(k) \tag{28}$$

4. Experimental results

In this section, the performance of the proposed method in tracking the reference signals and disturbance rejection is demonstrated. The control of the DC-DC converter is considered here. DC-DC converters provide different DC voltage levels and are employed in power electronic equipment. The Buck DC-DC converter is depicted in Figure 3. Regulating the output voltage to the desired reference value is investigated in different converter applications. Changes in the output load and in the input voltage are mostly considered as the disturbances in the DC-DC converter [19]. The duty ratio of the power MOSFET is considered as the control signal. The comparing signal that is called OCR (Figure 3) is equal to the duty ratio of the MOSFET. The experimental prototype of the converter is implemented by the analog circuit. As depicted in Figure 3, the control system consists of the ANNMPC controller, an AVR microcontroller, the MOSFET gate driver (TLP250), and the converter. The AVR microcontroller is utilized for producing the PWM signal, reading the output voltage, and serial connection to the computer for receiving/transmitting data. The system parameters are selected as given in the Table. The waveforms of the buck converter are illustrated in Figure 4. It is considered that the inductor current is always positive. When the MOSFET is on, the diode is reverse-biased and when it is off, the diode conducts the current to the inductor [22].

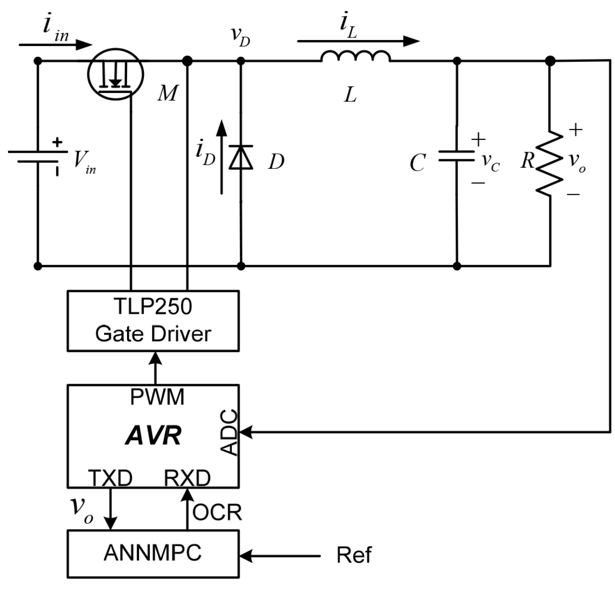

Figure 3. Closed-loop structure of the buck DC-DC converter.

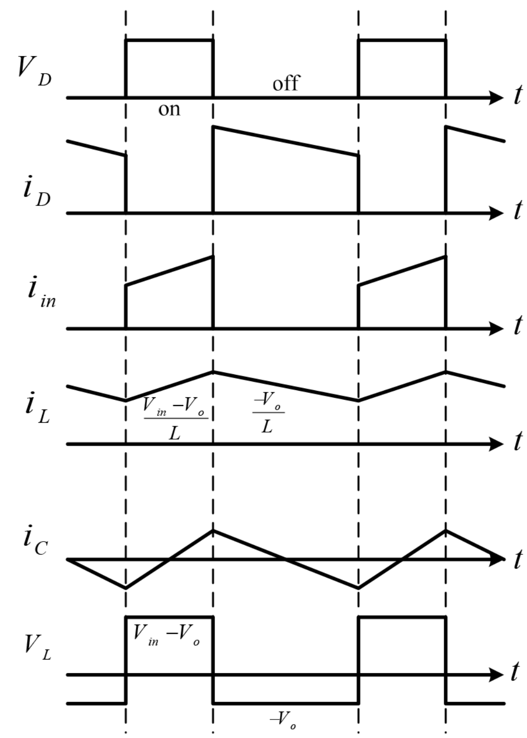

Figure 4. Waveforms of the buck converter.

4.1. Reference tracking

Here the proposed controller is applied to the DC-DC converter to study the performance of reference tracking for the output voltage. The number of neurons in the hidden layer of the NN predictor is equal to two with tangent hyperbolic functions; the tapped delays are selected as $\hat{n}_u = 2$, $\hat{n}_y = 3$ and the learning rates η and μ are set to one. The parameters of the ANNMPC are $N_P = 10$, $M = 2$, $Q = 1$, and $R = 0.01$. The tracking performance of the ANNMPC is depicted in Figure 5. As shown in this figure, the tracking response of the proposed algorithm is acceptable in both the transient and the steady-state responses. Moreover, the tracking is offset-free. For comparison, the NMPC controller based on a nonadaptive NN model (NNMPC) response is shown in this figure as well. As can be observed from this figure, the tracking responses of this controller have offsets.

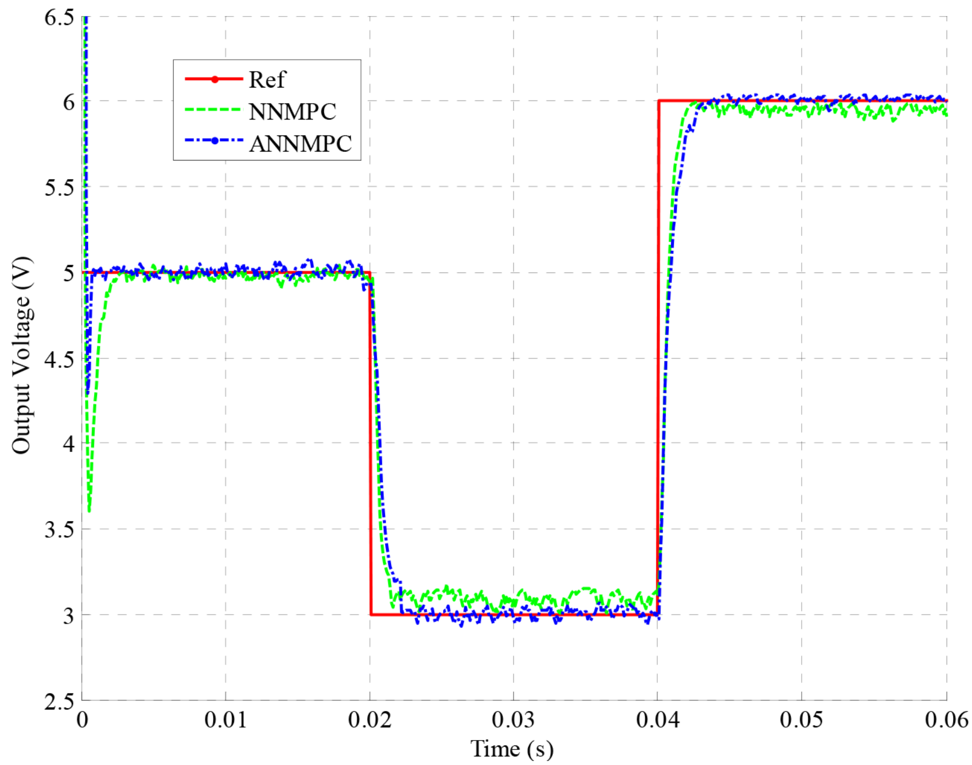

Figure 5. Reference tracking response of the converter.

4.2. Disturbance rejection

In this part, the disturbance rejection behavior of the ANNMPC in the presence of fluctuations on the output load and the input voltage is studied.

In Figure 6, the load is changed from 72 Ω to 160 Ω and the input voltage is changed from 12 V to 15 V and returns to 12 V. As this figure shows, the NNMPC algorithm that uses a nonadaptive predictor model has offsets for the step disturbance rejection. On the other hand, the ANNMPC strategy has good performance in the rejection of the step disturbances.

In addition to these step-like disturbances, the output load is changed from 72 Ω to 160 Ω slowly as a ramp disturbance. As proposed in this paper, for rejection of the ramp disturbances, the DOB is added to the control system in a feedforward control structure. In the DOB, the NN for the inverse model has one hidden layer with 15 neurons with tangent hyperbolic functions. Other parameters for this network are selected as $\tilde{n}_u = 2$, $\tilde{n}_y = 3$. Moreover, ρ and γ are set to one. The parameters of the ANNMPC are the same as in Section 4.1. The results of the disturbance rejection behavior of the proposed controller are depicted in Figure 7. For ramp disturbance rejection that is incurred to the converter in the output load, only the proposed algorithm in this paper has efficient behavior and provides zero steady-state error.

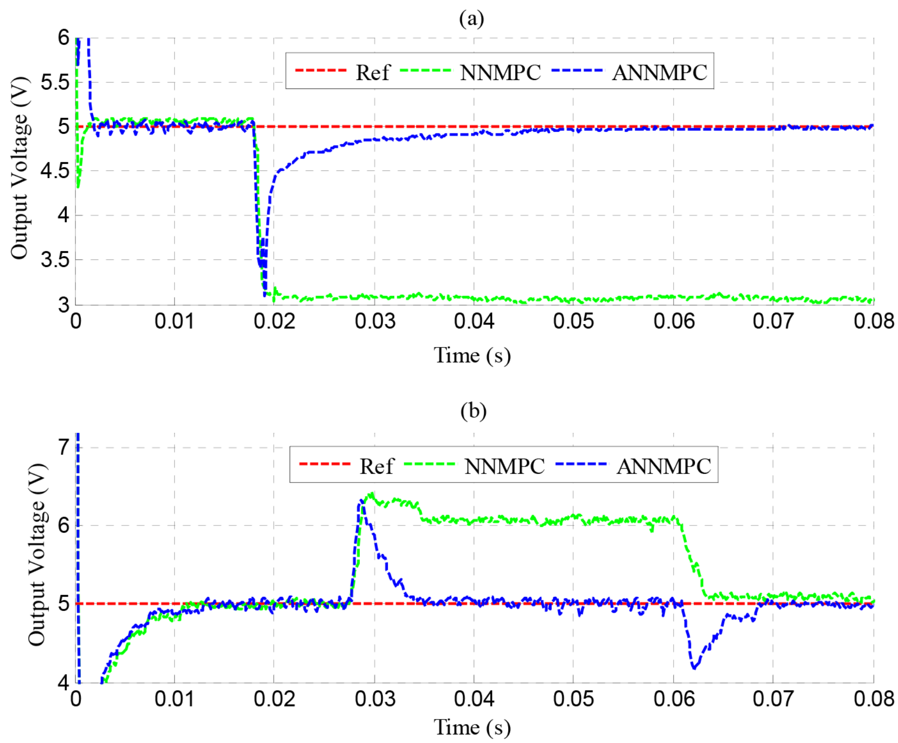

Figure 6. Step disturbance rejection responses of the converter: a) load changing from 72 Ω to 160 Ω, b) input voltage changing from 12 V to 15 V and then back to 12 V.

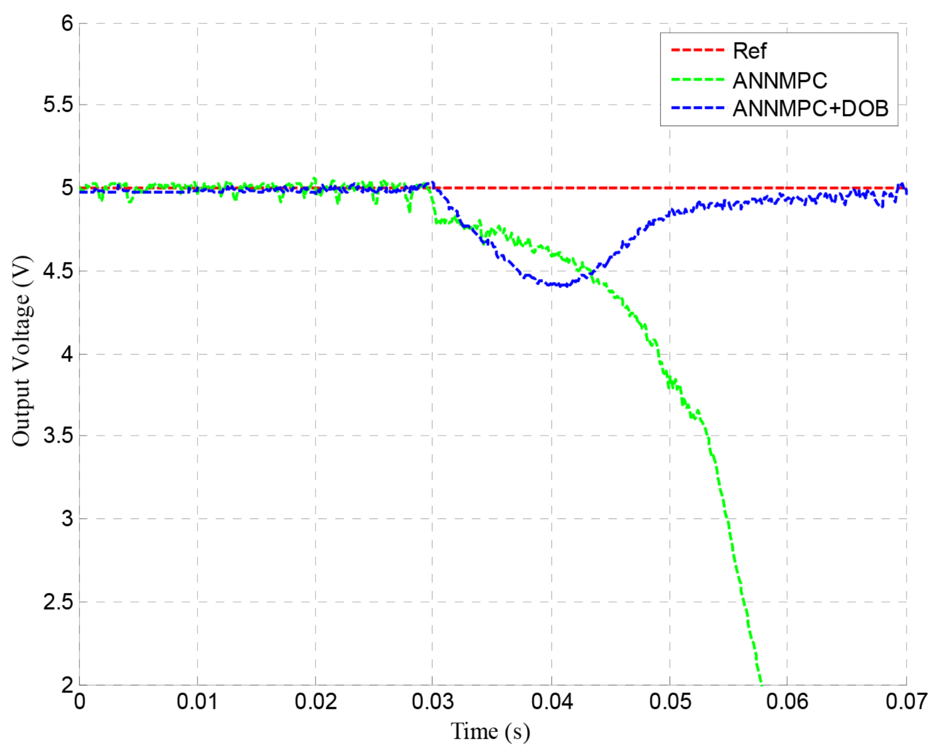

Figure 7. Rejection of ramp disturbance in output load.

5. Conclusion

In this paper, an NMPC strategy based on an adaptive NN predictor model was proposed to control the DC-DC buck converter in the presence of the external and internal disturbances caused by model–plant mismatches. The asymptotic stability and thus the offset-free behavior of the closed-loop system in tracking the constant reference signals in the presence of the constant disturbances was shown via the Lyapunov direct method. For nonconstant disturbances, a DOB based on the NN inverse model was proposed to estimate the nonconstant external disturbances and it was used as a feedforward compensation term in the ANNMPC approach. The experimental results for offset-free reference tracking as well as disturbance rejection on the voltage regulating show the effectiveness of the proposed control strategy.

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