Design of a Prediction-Accuracy-Enhanced Continuous-Time MPC for Disturbed Systems via a Disturbance Observer

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***Abstract*—This paper addresses the prediction accuracy enhancement problem in the context of continuous-time model predictive control (MPC) by using a disturbance observer. The disturbance estimation is introduced in the output prediction to correct the errors caused by disturbances and uncertainties, which eventually leads to the desired offset-free tracking performance. Due to such a different design philosophy, the computational burden of the proposed method will be significantly reduced as compared with the existing offset-free MPCs for disturbed systems. Another promising feature of the proposed method lies in its nominal performance recovery property. The workability of the proposed method is validated by its application to a dc–dc buck converter system.**

***Index Terms*—Continuous-time model predictive control (MPC), disturbance observer (DOB), offset-free tracking, prediction accuracy enhancement.**

I. Introduction

A. Literature Review: MPC Under Disturbances

Model predictive control (MPC) has been known as one of the most famous practical control approaches in industrial applications, due to its conceptual simplicity and, in particular, optimized tracking performance and powerful ability to handle constrained systems [1]–[14], [16]–[20]. The early applications of MPC are mainly constrained within the process control community, where the process generally behaves in slow time-varying dynamics [2]. A key issue restricting the penetration of MPC to industrial electronic systems (IES) with fast dynamics would be the contradiction between the requirement of fast responses and heavy computational burden caused by online optimization [3]. With the rapid development of computing hardware and convex optimization technique, implementation of MPC to IES with fast dynamics has become feasible and attracted a great deal of attentions [3], [4], [6]. For example, see servo motors [6], [14], [21], [22], power converters/rectifiers [7]–[9], helicopters [10], and industrial engines [23], for the recently successful and fruitful applications of MPC for systems with fast time-varying dynamics.

Disturbances and uncertainties always bring undesirable influences on the closed-loop control performance of most industrial systems or processes [6], [11], [21], [22], [24]–[30]. In spite of the promising feature and cheerful results on application of MPC to IES, similar to most of the other advanced feedback control methods, MPC usually asymptotically suppresses the disturbances and uncertainties through a manner of feedback regulation in a relatively slow way [11], [13]. Note that integral control action is one of the most practical approaches utilized for early MPC algorithm to counteract the undesirable influences of disturbances and uncertainties, e.g., see dynamic matrix control [2], generalized predictive control [5], and MPC embedded with an integrator [4]. For those integral MPCs, the utilization of an integrator to remove the offset would pay the price of sacrificing other control performances of the closed-loop system. The reason is that the integral action also has coupled interactions with other performances, such as transient behaviors, tracking, stability, and robustness. This also may cause additional efforts on control parameter tuning for integral MPCs. As a practical alternative approach, disturbance observer (DOB)-based control (DOBC) has been proved to be effective in compensating the effects of unknown external disturbances and model uncertainties in control systems and received an increasing interest in control society [31]–[35]. The major merit of DOBC is that the robustness of the resulting closed-loop system is obtained without sacrificing its nominal performance [31].

With the growing interests in smarter and higher precision industrial devices, the development of advanced disturbance rejection approaches becomes a hot topic in the field of control engineering. To this end, the combination of MPC with DOBC has been extensively investigated to enhance the

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antidisturbance performances of various kinds of systems (see, e.g., [6], [7], [9]–[13], [15]–[20], and references therein). In general, those MPC approaches can be classified into the following two categories.

The first category mainly focuses on feedforward compensation for the effects of disturbances and uncertainties [6], [9]–[13], [15]. The design philosophy of those MPC methods is quite straightforward. A DOB is first utilized to estimate the lumped disturbances possibly consisting of external disturbances and unknown model uncertainties. In addition to the feedback MPC, an additional feedforward control action based on the disturbance estimation is then implemented to compensate the effects of disturbances and uncertainties. However, it is usually difficult for those controllers to obtain optimized performance since the feedforward control law is designed separately and not taken into account in the receding optimization process.

The second category is referred to as offset-free MPC [7], [16]–[20]. The basic idea behind those controllers is the two-phase design process, which is illustrated as follows. First, online constrained optimization utilizing disturbance estimations and real-time state estimations as initial conditions is implemented to obtain optimized target states and control inputs in the presence of disturbances and uncertainties. Second, a receding optimization procedure is utilized to derive the final control sequence, such that the target states can be followed by the real states. It is also noticed that much efforts in this area focus upon discussing the feasibility to achieve zero offset for systems with different dimensions of states, inputs, and outputs. However, in order to achieve the desired target trajectory, solving such an additional online constrained optimization problem will bring about undesirable real-time computational burdens for practical applications.

B. Motivations

We consider a class of single-input–single-output (SISO) systems with multiple disturbances described by

$$\begin{cases} \dot{x} = Ax + Bu + Dw \\ y = Cx \end{cases} \tag{1}$$

where $x = [x_1, \ldots, x_n]^\top \in \mathbb{R}^n$ is the state, $u \in \mathbb{R}$ is the control input, $y \in \mathbb{R}$ is the controlled output, and $w = [w_1, \ldots, w_p]^\top \in \mathbb{R}^p$ is the lumped disturbances consisting of external disturbances and sources of mismatch between the linear model and the real plant. For example, if the true plant is presented by

$$\dot{x} = f(x, u, d)$$

where $d \in \mathbb{R}^l$ is a vector of external disturbances, then we can express this system as (1) by defining $Dw = f(x, u, d) - Ax - Bu$, where D is generally an identity matrix.

In this paper, a novel continuous-time MPC approach is proposed as an alternative solution for disturbed system (1) to achieve offset-free tracking. The design philosophy of the proposed method is clear, which is briefly summarized as follows. First, a state-space DOB is introduced to estimate the lumped disturbances of the system, and then, the disturbance estimations are employed to correct the output prediction online, which will substantially enhance the prediction accuracy under disturbances and uncertainties. This is the essential difference in the design philosophy between the proposed method and the existing offset-free MPCs. Second, a receding-horizon optimization is proposed to derive the desired control law. It is shown by rigorous stability analysis that the resultant control law can achieve offset-free tracking performance under disturbances and uncertainties. Furthermore, it is discussed that the proposed method can be extended to an output-feedback case and multi-input–multi-output (MIMO) systems with few changes. The main contributions of this paper include the following.

1) A continuous-time offset-free MPC approach based on prediction accuracy enhancement via a DOB is developed for a general disturbed system, which can be viewed as a parallel continuous-time analog to the existing discrete-time offset-free MPC.
2) The prominent disturbance rejection performance of the proposed method is achieved without sacrificing the nominal tracking performance.
3) Moreover, unlike the existing offset-free MPC approach, the online optimization problem for the target state and input planning is not required to be solved by the proposed method, which significantly reduces the computational load.

Finally, a dc–dc buck converter application example is implemented to show the feasibility and effectiveness of the proposed control scheme.

II. Controller Design

Here, we consider designing the desired model predictive controller. To begin with, a generalized cost function for system (1) is defined as

$$J = \frac{1}{2}\int_0^{T_P} \left[\|\hat{y}(t+\tau) - \hat{y}_c(t+\tau)\|_{\mathcal{Q}}^2 + \|\hat{u}(t+\tau)\|_{\mathcal{R}}^2\right] d\tau \tag{2}$$

where T_P is the predictive period, $\hat{y}(t+\tau)$ is the predicted output, $\hat{y}_c(t+\tau)$ is the desired future reference trajectory, $\hat{u}(t+\tau)$ is the future control decision to be determined, $\mathcal{Q}$ is a symmetric positive-definite matrix weighting on the predictive tracking error, and $\mathcal{R}$ is a symmetric semipositive-definite matrix weighting on the control input.

A. DOB Design

The DOB proposed in [12] provides an adequate way to estimate the disturbances in system (1) and is given by

$$\begin{cases} \dot{z}_w = -L\left[D(Lx + z_w) + Ax + Bu\right] \\ \hat{w} = z_w + Lx \end{cases} \tag{3}$$

where $\hat{w} = [\hat{w}_1, \ldots, \hat{w}_p]^\top$ is the estimation of the disturbance w, z_w is the internal state vector of the observer, and L is the observer gain to be designed.

For DOB (3), introduce its estimation error as $e_w = w - \hat{w}$. Then, for system (1), the disturbance estimation error system is described by

$$\dot{e}_w(t) = -LDe_w(t) + \dot{w}. \tag{4}$$

Assumption 1: The dimension of the lumped disturbances is no higher than that of the states, i.e., $p \le n$. In addition, the matrix D is of full rank, i.e., $\text{rank}(D) = p$.

Assumption 2: The derivatives of the disturbances in system (1) are bounded, i.e., $\|\dot{w}(t)\| < \infty$.

Lemma 1 ([29]): Under Assumptions 1 and 2, it is always possible to choose an observer gain L (e.g., taking $L = \gamma D^\top$ for simplicity, where γ is a positive constant) such that

$$\dot{e}_w(t) + LDe_w(t) = 0 \tag{5}$$

is asymptotically stable. Then, the disturbance estimation error system (4) is locally input-to-state stable (ISS).

Assumption 3: The disturbances in system (1) are slowly time varying and bounded and satisfy $\lim_{t\to\infty} \dot{w}(t) = 0$.

Lemma 2: Under Assumptions 1 and 3, if the observer gain L is chosen, such that (5) is asymptotically stable, then the disturbance estimator $\hat{w}$ of DOB (3) can asymptotically estimate the disturbance w in system (1).

Proof: This lemma follows readily from Lemma 1 together with the use of the ISS definition given in [38]. ■

B. Output Prediction With Disturbance Compensation

The input relative degree (IRD) of system (1) is defined as σ [39]. The future output $y(t+\tau)$ in the moving horizon is predicted by Taylor series expansion

$$y(t+\tau) \doteq y(t) + \tau y^{[1]}(t) + \cdots + \frac{\tau^{\sigma+r}}{(\sigma+r)!} y^{[\sigma+r]}(t) \tag{6}$$

where r is the control order (see [36] for detailed definition). The derivatives of the output under consideration of the disturbances are calculated as 考虑扰动的输出导数

$$y^{[i]} = CA^i x + \sum_{k=0}^{i-1} CA^{i-1-k} D w^{[k]}, \quad i = 1, \ldots, \sigma - 1$$

$$y^{[\sigma]} = CA^\sigma x + \sum_{k=0}^{\sigma-1} CA^{\sigma-1-k} D w^{[k]} + CA^{\sigma-1} Bu. \tag{7}$$

Differentiation of (7) with respect to time yields

$$y^{[\sigma+1]} = CA^{\sigma+1}x + CA^\sigma Bu + CA^{\sigma-1}Bu^{[1]} + \sum_{k=0}^{\sigma} CA^{\sigma-k} D w^{[k]}. \tag{8}$$

Similarly, the higher derivatives of the output can be calculated as

$$y^{[\sigma+i]} = CA^{\sigma+i}x + \sum_{k=0}^{i} CA^{\sigma+i-1-k} B u^{[k]} + \sum_{k=0}^{\sigma+i-1} CA^{\sigma+i-1-k} D w^{[k]} \tag{9}$$

for $i = 2, \ldots, r$.

Define the control sequence (also known as decision variables) as $\hat{\bar{u}} = [\hat{u}(t)^\top, \hat{u}^{[1]}(t)^\top, \ldots, \hat{u}^{[r]}(t)^\top]^\top$. Suppose that the disturbances satisfy the conditions provided in Assumption 3. Moreover, similar with most of the existing offset-free MPCs [3], [5], we assume that $w^{[k]}(t) \approx 0$ for $k = 1, \ldots, \sigma + r - 1$. Substituting the disturbance estimation $\hat{w}$ into (7)–(9), the output prediction $\hat{y}(t+\tau)$ under the control sequence $\hat{\bar{u}}$ is approximated by

$$\hat{y}(t+\tau) = \left[\bar{\mathcal{T}}(\tau), \tilde{\mathcal{T}}(\tau)\right] \begin{bmatrix} \bar{Y} \\ \tilde{Y} \end{bmatrix} \tag{10}$$

where

$$\bar{\mathcal{T}}(\tau) = \left[1, \tau, \cdots, \frac{\tau^{\sigma-1}}{(\sigma-1)!}\right]$$ 没有u的事情的

$$\tilde{\mathcal{T}}(\tau) = \left[\frac{\tau^\sigma}{\sigma!}, \cdots, \frac{\tau^{\sigma+r}}{(\sigma+r)!}\right]$$ 和u有关的

$$\bar{Y} = \begin{bmatrix} \hat{y} \\ \hat{y}^{[1]} \\ \vdots \\ \hat{y}^{[\sigma-1]} \end{bmatrix} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{\sigma-1} \end{bmatrix} x + \begin{bmatrix} 0 \\ CD \\ \vdots \\ CA^{\sigma-2}D \end{bmatrix} \hat{w}$$

$$\tilde{Y} = \begin{bmatrix} \hat{y}^{[\sigma]} \\ \vdots \\ \hat{y}^{[\sigma+r]} \end{bmatrix} = \tilde{Y}_{x,w} + \tilde{Y}_u \hat{\bar{u}}$$

with

$$\tilde{Y}_{x,w} = \begin{bmatrix} CA^\sigma \\ \vdots \\ CA^{\sigma+r} \end{bmatrix} x + \begin{bmatrix} CA^{\sigma-1}D \\ \vdots \\ CA^{\sigma+r-1}D \end{bmatrix} \hat{w}$$

$$\tilde{Y}_u = \begin{bmatrix} CA^{\sigma-1}B & 0 & \ldots & 0 \\ CA^\sigma B & CA^{\sigma-1}B & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{\sigma+r-1}B & CA^{\sigma+r-2}B & \ldots & CA^{\sigma-1}B \end{bmatrix}.$$

C. Receding Optimization and Control Law Design

The future reference signal and the control input can be written in a similar way as

$$\hat{y}_c(t+\tau) = \left[\bar{\mathcal{T}}(\tau), \tilde{\mathcal{T}}(\tau)\right] \begin{bmatrix} \bar{Y}_c \\ \tilde{Y}_c \end{bmatrix} \tag{11}$$

$$\hat{u}(t+\tau) = \hat{\mathcal{T}}(\tau)\hat{\bar{u}} \tag{12}$$

where

$$\hat{\mathcal{T}}(\tau) = \left[1, \tau, \ldots, \frac{\tau^r}{r!}\right].$$

By virtue of (10)–(12), the performance index (2) is expressible as

$$
\begin{aligned}
J =& \frac{1}{2}\int_0^{T_P} \left[(\bar{Y}-\bar{Y}_c)^\top, (\tilde{Y}-\tilde{Y}_c)^\top\right] \begin{bmatrix} \bar{\mathcal{T}}^\top(\tau)\sqrt{\mathcal{Q}} \\ \tilde{\mathcal{T}}^\top(\tau)\sqrt{\mathcal{Q}} \end{bmatrix} \\
&\times \left[\sqrt{\mathcal{Q}}\bar{\mathcal{T}}(\tau), \sqrt{\mathcal{Q}}\tilde{\mathcal{T}}(\tau)\right] \begin{bmatrix} \bar{Y}-\bar{Y}_c \\ \tilde{Y}-\tilde{Y}_c \end{bmatrix} d\tau + \frac{1}{2}\int_0^{T_P} \hat{\hat{u}}^\top \hat{\mathcal{T}}^\top(\tau)\mathcal{R}\hat{\mathcal{T}}(\tau)\hat{\hat{u}}\, d\tau \\
=& (\bar{Y}-\bar{Y}_c)^\top \mathcal{T}_1(\bar{Y}-\bar{Y}_c) + 2(\tilde{Y}-\tilde{Y}_c)^\top \mathcal{T}_2^\top(\bar{Y}-\bar{Y}_c) \\
&+ (\tilde{Y}-\tilde{Y}_c)^\top \mathcal{T}_3(\tilde{Y}-\tilde{Y}_c) + \hat{\hat{u}}^\top \mathcal{T}_4 \hat{\hat{u}}
\end{aligned} \tag{13}
$$

where

$$
\begin{aligned}
\mathcal{T}_1 &= \frac{1}{2}\int_0^{T_P} \bar{\mathcal{T}}^\top(\tau)\mathcal{Q}\bar{\mathcal{T}}(\tau)d\tau \\
\mathcal{T}_2 &= \frac{1}{2}\int_0^{T_P} \bar{\mathcal{T}}^\top(\tau)\mathcal{Q}\tilde{\mathcal{T}}(\tau)d\tau \\
\mathcal{T}_3 &= \frac{1}{2}\int_0^{T_P} \tilde{\mathcal{T}}^\top(\tau)\mathcal{Q}\tilde{\mathcal{T}}(\tau)d\tau \\
\mathcal{T}_4 &= \frac{1}{2}\int_0^{T_P} \hat{\mathcal{T}}^\top(\tau)\mathcal{R}\hat{\mathcal{T}}(\tau)d\tau.
\end{aligned}
$$

The performance index in (13) is further rewritten as

$$
J = J_0 + J_1 \tag{14}
$$

where

$$
\begin{aligned}
J_0 =& (\bar{Y}-\bar{Y}_c)^\top \mathcal{T}_1(\bar{Y}-\bar{Y}_c) + 2(\bar{Y}-\bar{Y}_c)^\top \mathcal{T}_2(\tilde{Y}_{x,w}-\tilde{Y}_c) \\
&+ (\tilde{Y}_{x,w}-\tilde{Y}_c)^\top \mathcal{T}_2(\tilde{Y}_{x,w}-\tilde{Y}_c) \\
J_1 =& \hat{\hat{u}}^\top\left(\tilde{Y}_u^\top \mathcal{T}_3 \tilde{Y}_u + \mathcal{T}_4\right)\hat{\hat{u}} \\
&+ 2\left[(\bar{Y}-\bar{Y}_c)^\top \mathcal{T}_2 + (\tilde{Y}_{x,w}-\tilde{Y}_c)^\top \mathcal{T}_3\right]\tilde{Y}_u\hat{\hat{u}}.
\end{aligned}
$$

Taking partial derivative of J with respect to $\hat{\hat{u}}$ gives

$$
\frac{\partial J}{\partial \hat{\hat{u}}} = 2\left(\tilde{Y}_u^\top \mathcal{T}_3\tilde{Y}_u + \mathcal{T}_4\right)\hat{\hat{u}} + 2\tilde{Y}_u^\top\left[\mathcal{T}_2^\top(\bar{Y}-\bar{Y}_c) + \mathcal{T}_3(\tilde{Y}_{x,w}-\tilde{Y}_c)\right]. \tag{15}
$$

Let $(\partial J/\partial\hat{\hat{u}}) = 0$. Then, the optimized control law $\hat{\hat{u}}^*$ is obtained from (15) as

$$
\hat{\hat{u}}^* = \left(\tilde{Y}_u^\top \mathcal{T}_3\tilde{Y}_u + \mathcal{T}_4\right)^{-1}\tilde{Y}_u^\top\left[-\mathcal{T}_2^\top(\bar{Y}-\bar{Y}_c) + \mathcal{T}_3(\tilde{Y}_c-\tilde{Y}_{x,w})\right]. \tag{16}
$$

Taking the first row of the optimized control law (16), the continuous-time MPC law to be applied to the plant is given by

$$
\hat{u}^*(t) = C_u\hat{\hat{u}}^* \tag{17}
$$

where $C_u = [1, 0, \ldots, 0]_{1\times(r+1)}$.

Remark 1: The control weighting has been explicitly included in the cost function (2), and the derived control law (17) can be directly implemented for practical plants. However, it is not easy to derive rigorous stability and robustness analysis for systems under such a general formulation of predictive control law. On the other hand, as suggested in [36] and [37], instead of applying the control weighting $\mathcal{R}$, the control effort can also be restricted by adjusting the parameters of control order r and predictive time T_P. In fact, it has been indicated in [36] that the excessive control effort can be reduced by increasing the predictive time and choosing a lower control order. To this end, the control weighting $\mathcal{R}$ will not be considered in the following discussion of this paper for convenience of analysis and implementation.

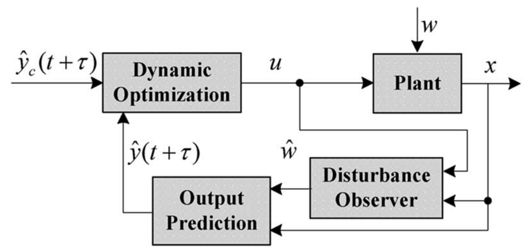

Fig. 1. Block diagram of the proposed continuous-time offset-free MPC method.

With the discussion in Remark 1, we suppose that $\mathcal{R} = 0$ and derive a simpler version of control law from (16) and (17) as

$$
\begin{aligned}
\hat{u}^*(t) = (CA^{\sigma-1}B)^{-1}&\left[-K(\bar{Y}-\bar{Y}_c)\right. \\
&\left.+\left(y_c^{[\sigma]} - CA^\sigma x - CA^{\sigma-1}D\hat{w}\right)\right]
\end{aligned} \tag{18}
$$

where K is the first row of the matrix $\mathcal{T}_3^{-1}\mathcal{T}_2^\top$. Note that the matrix $\mathcal{T}_3$ is positive definite [36]. It follows from [36] that the optimized control gain K has the following form:

$$
K = [k_0, \quad k_1 \quad \cdots \quad k_{\sigma-1}]
$$

and the predictive period T_P and the control order r are used to determine the parameters k_i $(i = 0, \ldots, \sigma-1)$. The block diagram on implementation of the proposed method is shown in Fig. 1.

III. Performance Analysis

A. Stability Analysis

Assumption 4: The zero dynamics of system (1) is stable.

First, the following lemma is presented as a preliminary result for stability analysis of the proposed method.

Lemma 3 ([36]): Suppose that the condition of Assumption 4 holds for system (1). In the absence of disturbances, it is always possible to select an appropriate control order r, such that the closed-loop system under the baseline MPC of (18) without disturbance compensation is asymptotically stable, i.e., the polynomial

$$
p(\sigma, s) = s^\sigma + k_{\sigma-1}s^{\sigma-1} + \cdots + k_0 = 0 \tag{19}
$$

is Hurwitz stable.

Now, the stability of the proposed method is established by the following theorem.

Theorem 1: Suppose that the control order r and the observer gain L in (3) are selected, such that the polynomial $p(\sigma, s) = 0$ in (19) is Hurwitz stable, and the error system (5) is asymptotically stable, respectively. Then, the closed-loop system, which consists of the plant (1) under disturbances satisfying Assumptions 1 and 2, the continuous-time MPC law (18), and the DOB (3), is bounded-input–bounded-output (BIBO) stable.

Proof: Define a new group of coordinate transformation for system (1) as

$$z = \Phi(x) = \begin{bmatrix} \xi \\ \eta \end{bmatrix}$$

where

$$\xi = [\xi_1, \xi_2, \ldots, \xi_\sigma]^\top = \left[Cx, CAx, \ldots, CA^{\sigma-1}x\right]^\top$$

and $\eta = [C_{\sigma+1}x, \ldots, C_n x]^\top$ is selected, such that the mapping $\Phi(x)$ has a Jacobian matrix, which is nonsingular, and $C_i B = 0$ for all $\sigma + 1 \le i \le n$.

Then, with the new coordinates $z = \Phi(x)$, system (1) is represented as

$$\begin{cases} \dot{\xi}_i = \xi_{i+1} + \phi_i w, \quad i = 1, \ldots, \sigma - 1 \\ \dot{\xi}_\sigma = \beta x + \alpha u + \phi_\sigma w \\ \dot{\eta} = q\xi + r\eta + sw \\ y = \xi_1 \end{cases} \tag{20}$$

where $\beta = CA^\sigma$, $\alpha = CA^{\sigma-1}B$, and $\phi_i = CA^{i-1}D$ for $i = 1, \ldots, \sigma$. Under the proposed MPC law (18), it follows from (20) that:

$$\dot{\xi}_\sigma = y_c^{[\sigma]} - \sum_{i=0}^{\sigma-1} k_i \left(\xi_{i+1} - y_c^{[i]}\right) - \sum_{i=1}^{\sigma-1} k_i \phi_i w + \left(\sum_{i=1}^{\sigma-1} k_i \phi_i + \phi_\sigma\right) e_w. \tag{21}$$

Introduce the following error signal:

$$e_{\xi,i} = \xi_i - y_c^{[i-1]}. \tag{22}$$

By combining (20) with (21) and (22), we have

$$\begin{cases} \dot{e}_\xi = A_\xi e_\xi + D_\xi w + \Gamma_\xi e_w \\ \dot{\eta} = q(e_\xi + y_{\xi,c}) + r\eta + sw \\ y = C\xi \end{cases} \tag{23}$$

where $e_\xi = [e_{\xi,1}, \ldots, e_{\xi,\sigma}]^\top$, $y_{\xi,c} = \left[y_c, \ldots, y_c^{[\sigma-1]}\right]^\top$

$$A_\xi = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ -k_0 & -k_1 & -k_2 & \cdots & -k_{\sigma-1} \end{bmatrix}$$

$$D_\xi = \begin{bmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_{\sigma-1} \\ -\sum_{i=1}^{\sigma-1} k_i \phi_i \end{bmatrix}, \quad \Gamma_\xi = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \sum_{i=1}^{\sigma-1} k_i \phi_i + \phi_\sigma \end{bmatrix}$$

$$C = [1, 0, \ldots, 0]_{1\times\sigma}.$$

It follows from Lemma 3 that there exists a symmetric positive-definite matrix P_ξ, such that:

$$A_\xi^\top P_\xi + P_\xi A_\xi = -I. \tag{24}$$

Similarly, the Hurwitz property of matrix $A_w = -LD$ indicates that there exists a symmetric positive-definite matrix P_w, such that

$$A_w^\top P_w + P_w A_w = -I. \tag{25}$$

As for the dynamics of the closed-loop system consisting of the state dynamics (23), regardless of the zero dynamics and the disturbance estimation error dynamics (4) together, a Lyapunov candidate function is defined as

$$V(e_\xi, e_w) = \frac{1}{2} e_\xi^\top P_\xi e_\xi + \frac{1}{2} \lambda e_w^\top P_w e_w \tag{26}$$

where $\lambda > 0$ is a constant. With (24) and (25) in mind, taking derivative of $V(e_\xi, e_w)$ along the closed-loop error dynamic systems (23) and (4) gives

$$\begin{aligned} \dot{V}(e_\xi, e_w) &= -\frac{1}{2} e_\xi^\top e_\xi - \frac{1}{2} \lambda e_w^\top e_w + e_\xi^\top P_\xi \Gamma_\xi e_w \\ &\quad + e_\xi^\top P_\xi D_\xi w + \lambda e_w^\top P_w \dot{w} \\ &\le -\frac{1}{2} \|e_\xi\|^2 - \frac{1}{2} \lambda \|e_w\|^2 + c_1 \|e_\xi\| \cdot \|e_w\| \\ &\quad + c_2 \|e_\xi\| \cdot \|w\| + \lambda c_3 \|e_w\| \cdot \|\dot{w}\| \end{aligned} \tag{27}$$

where $c_1 = \|P_\xi \Gamma_\xi\|$, $c_2 = \|P_\xi D_\xi\|$, $c_3 = \|P_w\|$ are positive constants. By Young's inequality, it further follows from (27) that:

$$\dot{V}(e_\xi, e_w) \le -\frac{1}{4} \|e_\xi\|^2 - \left(\frac{1}{2}\lambda - c_1^2\right) \|e_w\|^2 + c_2' \|e_\xi\| + \lambda c_3' \|e_w\| \tag{28}$$

where

$$c_2' = c_2 \cdot \sup_{t\in[0,\infty)} \|w(t)\|, c_3' = c_3 \cdot \sup_{t\in[0,\infty)} \|\dot{w}(t)\|.$$

Setting $\lambda > 2c_1^2$ and defining a bounded region as

$$\Omega = \left\{ (e_\xi, e_w) | \; \|e_\xi\| \le 4c_2', \|e_w\| \le \frac{2\lambda c_3'}{\lambda - 2c_1^2} \right\}$$

it can be derived that $\dot{V}(e_\xi, e_w) < 0$, provided that the closed-loop error system is located outside of the bounded region Ω, which shows BIBO stability of the closed-loop error system. Hence, the proof is complete. ■

B. Disturbance Attenuation Analysis

This subsection is concerned with analyzing the performance on disturbance attenuation of the proposed method.

Theorem 2: Suppose that the control order r and the observer gain L in (3) are selected, such that the polynomial $p(\sigma, s) = 0$ in (19) is Hurwitz stable, and the error system (5) is asymptotically stable, respectively. Then, the closed-loop system, which consists of plant (1) under disturbances satisfying

Assumptions 1–4, the continuous-time MPC law (18), and the DOB (3), achieves offset-free reference tracking.

Proof: Substituting the control law (18) into (7) gives

$$y^{[\sigma]} - y_c^{[\sigma]} = -\sum_{i=0}^{\sigma-1} k_i \left(y^{[i]} - y_c^{[i]}\right) + \left(\sum_{i=1}^{\sigma-1} k_i\phi_i + \phi_\sigma\right) e_w. \tag{29}$$

The output tracking error is defined as

$$e_y = [e_{y,1}, \dots, e_{y,\sigma}]^\top$$

where

$$e_{y,i} = y^{[i-1]} - y_c^{[i-1]}, \quad i = 1, \dots, \sigma.$$

The output tracking error dynamics is then governed by the following compact form equation:

$$\dot{e}_y = A_\xi e_y + \Gamma_\xi e_w. \tag{30}$$

Let $E_{y,w} = [e_y^\top, e_w^\top]^\top$. Collecting the output dynamics (30) and the disturbance estimation error dynamics (4) together, the dynamics of the closed-loop system, regardless of the zero dynamics, is governed by

$$\dot{E}_{y,w} = A_\Sigma E_{y,w} \tag{31}$$

where

$$A_\Sigma = \begin{bmatrix} A_\xi & -\Gamma_\xi \\ 0 & A_w \end{bmatrix}.$$

Since A_Σ is Hurwitz stable, it is concluded from (31) that the proposed method could achieve offset-free reference tracking in the presence of disturbances. ■

Remark 2 (Nominal Performance Recovery): In the absence of disturbances, when the initial state of DOB (3) is taken as $z_w(0) = -Lx(0)$, DOB (3) provides the disturbance estimation as $\hat{w}(t) \equiv 0$. This shows that, in such cases, the proposed control law (18) is able to achieve the same control performance as the baseline MPC law proposed in [36] does. Thus, the proposed control law possesses the nice property of nominal performance recovery.

IV. Application to a DC–DC Buck Converter

Here, experimental studies of a dc–dc buck converter system are conducted to validate the feasibility and effectiveness of the proposed approach. To demonstrate the advantages of the proposed method, the baseline MPC proposed in [36] and an integral controller (that is extensively applied to remove the offset caused by load disturbance in MPC [4]) are employed for the purpose of comparison.

A. Dynamic Model Description

The dynamic model of generic pulsewidth modulation (PWM)-based dc–dc buck converters is described as follows [40]–[42]:

$$\begin{cases} \frac{dv_o}{dt} = \frac{1}{C} i_L - \frac{1}{CR_0} v_o + d_{v_o} \\ \frac{di_L}{dt} = -\frac{1}{L} v_o + \frac{V_{in}}{L}\mu \end{cases} \tag{32}$$

TABLE I
Parameters of DC–DC Buck Converters

Parameters	Meaning	Value
V_{in}	Input Voltage	20V
V_f	Reference Output Voltage	9V
L	Inductance	4.7mH
C	Capacitance	1000μF
R_0	Nominal Resistance	100Ω

Fig. 2. Experimental test setup of dc–dc buck converter example.

with

$$d_{v_o} = -\frac{1}{C}\left(\frac{1}{R} - \frac{1}{R_0}\right) v_o$$

where v_o is the average output voltage, i_L is the average inductor current, $\mu \in [0, 1]$ is the duty ratio of PWM signal, R is the load resistance, R_0 is the nominal value of R, L is the filter inductance, C is the filter capacitance, V_{in} is the dc input voltage, and d_{v_o} is the disturbance caused by load changes. The physical meaning and values of parameters on dc–dc buck converters (32) are listed in Table I.

In the controller design problem of dc–dc buck converter, the control input is the duty ratio μ, the controlled output is the output voltage v_o, and the reference signal is the reference output voltage V_f. The change of load resistance is deemed as one of the major disturbances in dc–dc converter systems [40], [41]. As such, the central goal of the controller design of dc–dc buck converters is to render satisfactory reference output voltage tracking even in the presence of large load resistance variation.

B. Simulation and Experimental Results

The proposed continuous-time MPC approach is implemented in a dc–dc buck converter to show the prominent robustness against disturbances. The simulation study is implemented by using MATLAB/Simulink/SimPowerSystems. The experimental test setup, consisting of a dc–dc buck converter, PC-LabView, NI myDAQ module, dc power, and voltage and current sensors, is shown in Fig. 2.

The control parameters are taken as the control order $r = 1(1)$, the predictive period $T_p = 0.0085(0.008)$, the observer

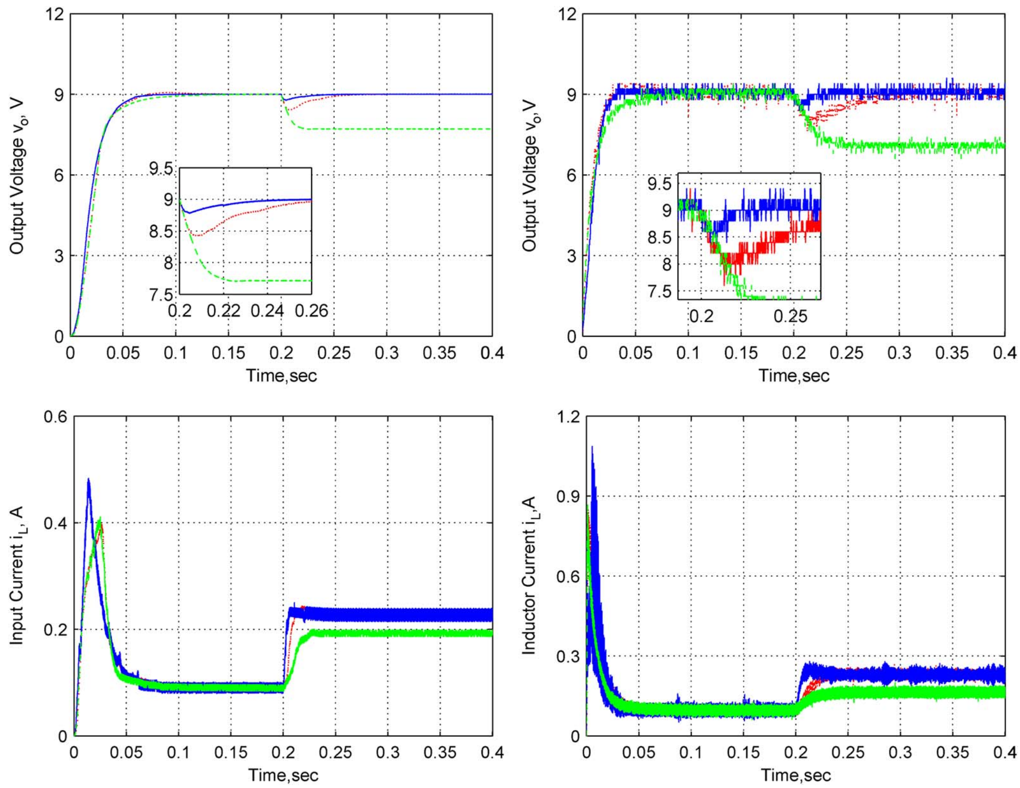

Fig. 3. Response curves of the dc–dc buck converter under the proposed controller (blue line), the integral controller (red line), and the baseline MPC (green line) in the presence of a sudden decrease of load resistance: top: output voltage; bottom: inductor current (left: simulation results; right: experimental results).

gain matrix $L = \mathrm{diag}\{1000, 1000\}(\mathrm{diag}\{1600, 1600\})$, the proportional gain $k_p = 0.035(0.095)$, and the integral gain $k_i = 7(6.5)$, for experimental (simulation) studies. Two cases, including a sudden decrease (from 100 to 40 Ω) and a sudden increase (from 100 to 180 Ω) of the load resistance, are considered in the experimental studies. The response curves of the dc–dc buck converter under the baseline MPC and the proposed MPC methods in the aforementioned two cases are shown in Figs. 3 and 4, respectively.

It is observed from Figs. 3 and 4 that the proposed composite MPC method has achieved offset-free regulation performance in the presence of the aforementioned two cases of load disturbances. In contrast, the baseline MPC method fails to track the desired target in the presence of load resistance variations, indicating that these disturbances exert significant influences on the control performance of the system. As shown in Figs. 3 and 4, the integral control approach could remove the offset caused by sudden the increase and decrease of load resistance. However, the maximum output voltage drop/raise of the integral control approach is larger than that of the proposed method. Furthermore, the recovery time after sudden load changes of the proposed method is much shorter than that of the integral control approach. The detailed comparison of performance indexes [including maximum output voltage drop/raise (MOVD/MOVR), recovery time (RT), and integral of absolute error (IAE)] between the proposed method and the integral control approach is listed in Tables II and III.

V. Discussions and Extensions

A. Extensions to Output-Feedback Case

Consider the following SISO systems:

$$\begin{cases} \dot{x} = Ax + Bu + Dw \\ y_m = C_m x, y = Cx \end{cases} \tag{33}$$

where $y_m \in \mathbb{R}^q$ denotes the measurable output. Suppose that the pair $(\bar{A}, \bar{C})$ is observable, where

$$\bar{A} = \begin{bmatrix} A & D \\ 0_{p\times n} & 0_{p\times p} \end{bmatrix}, \bar{C} = [C_m, 0_{q\times p}].$$

An extended state observer (ESO), which is able to estimate both states and disturbances, is designed as follows [25], [43]:

$$\begin{cases} \dot{z} = \bar{A}z + \bar{B}u + L(y_m - \hat{y}_m) \\ \hat{y}_m = \bar{C}z \end{cases} \tag{34}$$

where $z = [\hat{x}^\top, \hat{w}^\top]^\top$; L is the observer gain to be determined; $\bar{B} = [B^\top, 0_{1\times p}]^\top$; $\hat{x}$ and $\hat{w}$ denote the estimations of the states x and disturbances w, respectively. The stability analysis as well as guidance of observer gain tuning of the ESO (34) can be referred to [25] and [43].

With the estimations generated by the ESO in (34), we can refresh the continuous-time MPC design and analysis procedures in Section II by replacing all utilization of state variable x with

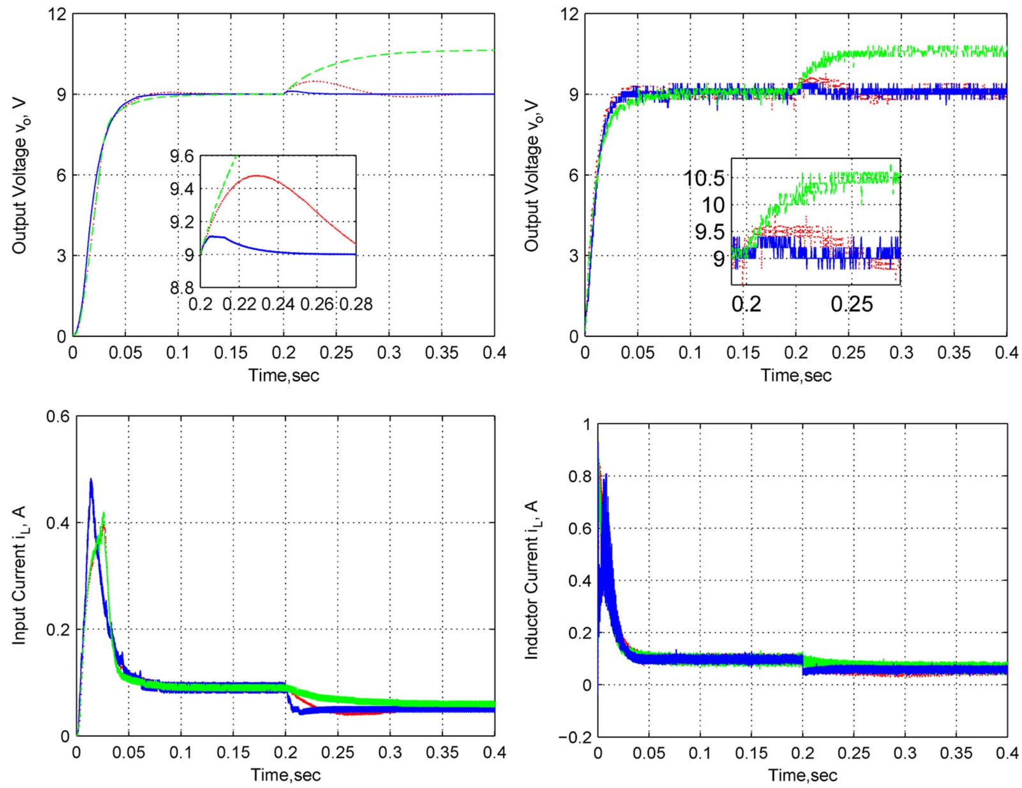

Fig. 4. Response curves of the dc–dc buck converter under the proposed controller (blue line), the integral controller (red line), and the baseline MPC (green line) in the presence of a sudden increase of load resistance: top: output voltage; bottom: inductor current (left: simulation results; right: experimental results).

TABLE II
COMPARISON OF PERFORMANCE INDEXES FOR LOAD INCREASE CASE

Test Type	Controller	MOVD	RT	IAE
Simulation	The Proposed	0.113V	0.0383s	0.0612
	Integral Controller	0.48V	0.17s	0.1795
Experiment	The Proposed	0.6V	0.02s	0.0052
	Integral Controller	1.2V	0.08s	0.042

TABLE III
COMPARISON OF PERFORMANCE INDEXES FOR LOAD DECREASE CASE

Test Type	Controller	MOVR	RT	IAE
Simulation	The Proposed	0.2212V	0.05s	0.0823
	Integral Controller	0.5776V	0.09s	0.1743
Experiment	The Proposed	0.4V	0.0288s	0.0058
	Integral Controller	0.6V	0.1s	0.027

its estimation $\hat{x}$, which yields a formulation of output-feedback continuous-time MPC scheme.

B. Extensions to MIMO Systems

Consider the following MIMO systems:

$$\begin{cases} \dot{x} = Ax + Bu + Dw \\ y_i = C_i x \end{cases} \tag{35}$$

for $i = 1, \ldots, m$ and $u \in \mathbb{R}^m$. Suppose that the relative degree vector of the MIMO system (35) is $\sigma = [\sigma_1, \ldots, \sigma_m]$. The ith output prediction can be expressed as

$$\hat{y}_i(t+\tau) = \hat{y}_i(t) + \tau \hat{y}_i^{[1]}(t) + \cdots + \frac{\tau^{\sigma_i + r}}{(\sigma_i + r)!}\hat{y}_i^{[\sigma_i + r]}(t)$$

where the derivatives of the output can be calculated in a similar way as that in Section II-B. The performance index for the MIMO system (35) can be straightforwardly derived as follows:

$$J_1 = \hat{\bar{u}}^\top H^\top \mathcal{T}_3 H \hat{\bar{u}} + \hat{\bar{u}}^\top H^\top \left[\mathcal{T}_2^\top (\bar{Y} - \bar{Y}_c) + \mathcal{T}_3 (Y_{x,w} - \tilde{Y}_c)\right] \tag{36}$$

where

$$H = \begin{bmatrix} \Lambda & 0 & 0 \\ * & \ddots & 0 \\ * & * & \Lambda \end{bmatrix}, \ \Lambda = \begin{bmatrix} C_1 A^{\sigma_1 - 1} \\ \vdots \\ C_m A^{\sigma_m - 1} \end{bmatrix}$$

and $\bar{Y}$, $\bar{Y}_c$, $Y_{x,w}$, $\tilde{Y}_c$, $\mathcal{T}_2$, and $\mathcal{T}_3$ can be formulated by referring to the definitions in Section II and [45], respectively. The control law can be derived by directly utilizing the design and analysis procedures presented in Sections II and III as well as [45], the details of which are omitted here for the sake of space.

Remark 3: For MIMO systems, there would be several controlled variables with different units and scales. The design of a weighting matrix $\mathcal{Q}$ provides an adequate way, in this case, to balance the control performance among different controlled variables.

VI. Conclusion

The prediction accuracy enhancement problem for a continuous-time MPC has been addressed in this paper via a DOB-based compensation technique. It has been proved that the offset raised by disturbances can be eliminated from the output channel by the newly proposed approach. The proposed MPC method has exhibited the following two remarkable features including: nominal performance recovery and low computational burden for disturbed systems. Simulation/experimental studies of a dc–dc buck converter example have been carried out to show the efficiency of the proposed method.

Similar with most of the existing disturbance-estimator-based control approaches [25], the proposed control approach could effectively deal with model uncertainties in practical engineering. However, a rigorous analysis of robust stability is nontrivial, and further researches will be conducted to work on this interesting issue.

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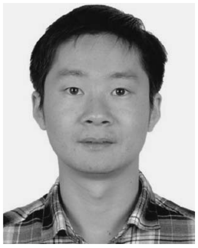

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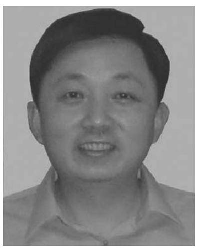

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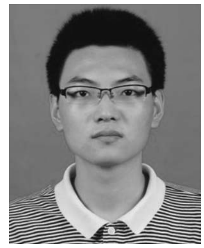

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