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A NOVEL MULTIVARIABLE OUTPUT ERROR STATE SPACE MODEL BASED PREDICTIVE CONTROL APPROACH

Huimin Jin, Weilin Yang* and Dezhi Xu

School of Internet of Things Engineering
Jiangnan University
No. 1800, Lihu Avenue, Wuxi 214122, P. R. China
6191915003@stu.jiangnan.edu.cn; xudezhi@jiangnan.edu.cn
*Corresponding author: wlyang@jiangnan.edu.cn

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Abstract. *A subspace identification based model predictive control (MPC) approach is proposed in this paper for systems with unknown dynamics. The system model is predicted directly based on the known input and output data, which simplifies modeling procedure, especially for complicated systems. Specifically, the MOESP algorithm is employed in our work, based on which the state space model is derived. The infinite-horizon min-max MPC approach is considered to optimize the system performance. The proposed method involves offline training and online identifying of the system model, with moderate computation requirements. This approach is further applied to a boost converter control problem. Simulations demonstrate the effectiveness of the method.*
Keywords: Subspace identification, MOESP, Model predictive control, State-space model

1. **Introduction.** Model predictive control (MPC) originates from process industries, such as petrochemical, and smelting. It has profound engineering background and theoretical significance. This method is widely investigated in academic community and various practical industrial applications. It is featured by three basic characteristics: prediction model, rolling optimization and feedback correction [1]. However, with the progress of science and technology, the scale of modern industrial equipment is becoming larger and larger, and the modeling work becomes more and more complicated. It is desirable to effectively build dynamic models for control systems. Therefore, a data-driven MPC approach is investigated in this work.

Van Overschee and De Moor introduced the subspace identification algorithms [2] for deterministic and random systems, respectively. When the prior structure information is unknown, the direct identification of the system model by using the input and output data obtained from the experiment has the robustness of numerical calculation, which makes the subspace method widely used in multivariable systems. Due to the above advantages, data-driven control methods, including predictive control, have been widely studied based on subspace identification techniques.

In the development of subspace identification algorithms, the classical algorithms mainly include three identification methods: MOESP (multivariable output error state space) [3], CVA (canonical variate analysis) [4] and N4SID (numerical algorithm for subspace state space system identification) [5]. MOESP was proposed by Verhaegen in 1993 [3], and its identification procedure generally consists of two steps. The first step is to construct the Hankel matrix with data and decompose it by QR technology. Then obtain the consistency estimation of the extended observable matrix through the mutually orthogonal subspace decomposed. The second step is calculating the system correlation matrix

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by estimating the extended observable matrix. Although MOESP needs to construct a larger matrix when solving the input matrix B and feedback matrix D, compared with the N4SID process using least squares to solve the system matrix and output matrix, this method is easier to solve and has higher accuracy. Therefore, MOESP is employed in this paper.

A genetic algorithm (GA) is used in [6] for optimal estimation. In a data-driven control system based on online subspace identification and the MPC method, the relationship among the output saturation step, prediction horizon and subspace matrix is obtained. An optimal tuning method of unconstrained data-driven subspace predictive control is proposed for non-minimum phase open-loop stabilization [7]. In [8], an MPC approach was developed for a class of nonlinear systems based on subspace identification of bilinear models. Compared with the above papers, this paper obtains the coefficient matrix of the system state space equation based on the method of combining offline and online subspace identification. The proposed MOESP algorithm is simple and accurate. On the basis of dealing with the constraint problem of the control input, the predictive control is adopted. The parameters of the system are identified online using the input and output data groups generated in real time during the control process, so that the identification results of the system are more accurate than the original identification results.

The flowchart diagram shown in Figure 1 mainly reveals the approach proposed in this paper. This paper is devoted to getting the model of the unknown system and controlling the plant to make it run stably and achieve a good running state through the simple method of combining subspace identification and predictive control. The method proposed in this paper is applied to the control problem of boost converter. Simulation results demonstrate the effectiveness of the proposed method.

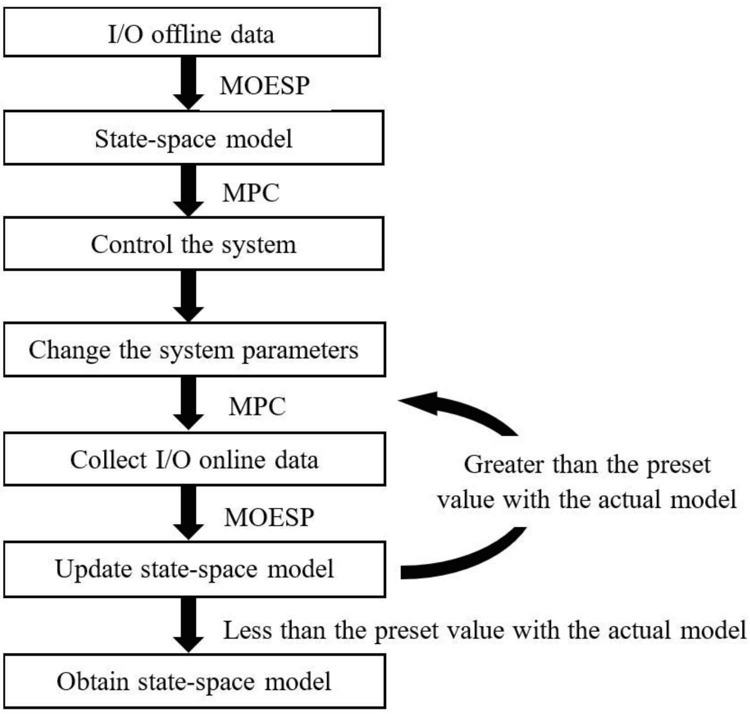


Figure 1. The overall flowchart diagram of the proposed method

The structure of this paper is organized as follows: Section 2 describes the subspace identification method; Section 3 shows the design of MPC strategy; Simulations on boost converter control are provided in Section 4; Section 5 draws some conclusions.

2. **Subspace Identification Method.** In this section, we will introduce the subspace identification method of MOESP. We will show the composition of data matrices and the

LQ decomposition method which are used in model identification. Then, the detailed implementation procedure of MOESP method [9] is given.

The state-space model to be obtained using the data-driven approach is shown below:

$$\begin{aligned} x(t+1) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + Du(t), \quad t = 0, 1, \ldots \end{aligned} \tag{1}$$

where $x(t) \in \mathbb{R}^n$ is the state vector, $u(t) \in \mathbb{R}^m$ the control input, $y(t) \in \mathbb{R}^p$ the output vector, and $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{n\times m}$, $C \in \mathbb{R}^{p\times n}$, $D \in \mathbb{R}^{p\times m}$ are constant matrices. The following MOESP method for subspace identification is based on the above system model.

2.1. **Data matrices.** Given the following input-output data

$$(u(0), u(1), \ldots, u(k+N-2)), (y(0), y(1), \ldots, y(k+N-2)),$$

where k is greater than the dimension of the state vector n, and N is sufficiently large. The block Hankel matrices are built based on the input and output data,

$$U_{0|k-1} = \begin{bmatrix} u(0) & u(1) & \cdots & u(N-1) \\ u(1) & u(2) & \cdots & u(N) \\ \vdots & \vdots & \ddots & \vdots \\ u(k-1) & u(k) & \cdots & u(k+N-2) \end{bmatrix},$$

$$Y_{0|k-1} = \begin{bmatrix} y(0) & y(1) & \cdots & y(N-1) \\ y(1) & y(2) & \cdots & y(N) \\ \vdots & \vdots & \ddots & \vdots \\ y(k-1) & y(k) & \cdots & y(k+N-2) \end{bmatrix}.$$

The matrix input and output equations are derived by repeating Equation (1), which is particularly important in identification. Then we can obtain

$$\begin{bmatrix} y(t) \\ y(t+1) \\ \vdots \\ y(t+k-1) \end{bmatrix} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{k-1} \end{bmatrix} x(t) + \begin{bmatrix} D & & & \\ CB & D & & \\ \vdots & \ddots & \ddots & \\ CA^{k-2}B & \cdots & CB & D \end{bmatrix} \begin{bmatrix} u(t) \\ u(t+1) \\ \vdots \\ u(t+k-1) \end{bmatrix}. \tag{2}$$

To simplify the notations, define

$$\mathrm{y}_k(t) = \begin{bmatrix} y(t) \\ y(t+1) \\ \vdots \\ y(t+k-1) \end{bmatrix} \in \mathbb{R}^{kp}, \quad \mathrm{u}_k(t) = \begin{bmatrix} u(t) \\ u(t+1) \\ \vdots \\ u(t+k-1) \end{bmatrix} \in \mathbb{R}^{km}.$$

The extended observability matrix O_k, and the block Toeplitz matrix Ψ_k are given as

$$\mathrm{O}_k = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{k-1} \end{bmatrix}, \quad \Psi_k = \begin{bmatrix} D & & & \\ CB & D & & \\ \vdots & \ddots & \ddots & \\ CA^{k-2}B & \cdots & CB & D \end{bmatrix} \in \mathbb{R}^{kp\times km}.$$

And then we get

$$\mathrm{y}_k(t) = \mathrm{O}_k x(t) + \Psi_k \mathrm{u}_k(t), \quad t = 0, 1, \ldots \tag{3}$$

with $\mathrm{u}_k(t)$ and $\mathrm{y}_k(t)$, the block Hankel matrices $U_{0|k-1}$ and $Y_{0|k-1}$ are represented as $U_{0|k-1} = \begin{bmatrix} \mathrm{u}_k(0) & \mathrm{u}_k(1) & \cdots & \mathrm{u}_k(N-1) \end{bmatrix}$, $Y_{0|k-1} = \begin{bmatrix} \mathrm{y}_k(0) & \mathrm{y}_k(1) & \cdots & \mathrm{y}_k(N-1) \end{bmatrix}$, respectively. Therefore, it can be obtained from Equation (2) that

$$Y_{0|k-1} = \mathrm{O}_k X_0 + \Psi_k U_{0|k-1}, \tag{4}$$

where $X_0 = \begin{bmatrix} x(0) & x(1) & \cdots & x(N-1) \end{bmatrix} \in \mathbb{R}^{n\times N}$ is the initial state matrix.

It is assumed that the external input and the initial state matrix meet the following conditions.

Assumption 2.1.
1) $\mathrm{rank}(X_0) = n$
2) $\mathrm{rank}(U_{0|k-1}) = km$, *where* $k > n$
3) $\mathrm{span}(X_0) \cap \mathrm{span}(U_{0|k-1}) = \{0\}$, *where* $\mathrm{span}(\cdot)$ *denotes the space spanned by the row vectors of a matrix.*

2.2. **MOESP method.** The LQ decomposition method is applied to a rectangular data matrix to obtain a partitioned lower triangular matrix with zero upper right corner, i.e.,

$$\begin{bmatrix} U_{0|k-1} \\ Y_{0|k-1} \end{bmatrix} = \begin{bmatrix} L_{11} & 0 \\ L_{21} & L_{22} \end{bmatrix} \begin{bmatrix} Q_1^{\mathrm{T}} \\ Q_2^{\mathrm{T}} \end{bmatrix}. \tag{5}$$

L_{11}, L_{22} are the lower triangular, and $Q_1 \in \mathbb{R}^{N\times km}$, $Q_2 \in \mathbb{R}^{N\times kp}$ are orthogonal.

The MOESP method is mainly employed in this paper for model identifications. From Equation (5), one has

$$U_{0|k-1} = L_{11}Q_1^{\mathrm{T}}, \tag{6a}$$

$$Y_{0|k-1} = L_{21}Q_1^{\mathrm{T}} + L_{22}Q_2^{\mathrm{T}}. \tag{6b}$$

Based on Assumption 2.1, it can be known that L_{11} is nonsingular, so $Q_1^{\mathrm{T}} = L_{11}^{-1}U_{0|k-1}$. Thus, (6b) is written as

$$Y_{0|k-1} = L_{21}L_{11}^{-1}U_{0|k-1} + L_{22}Q_2^{\mathrm{T}}. \tag{7}$$

In a word, in (6b) the right side of $Y_{0|k-1}$ is the orthogonality and decomposition of $Y_{0|k-1}$ on $U_{0|k-1}$ and its complement. By Equation (4) and Equation (6b)

$$\mathrm{O}_kX_0 + \Psi_kL_{11}Q_1^{\mathrm{T}} = L_{21}Q_1^{\mathrm{T}} + L_{22}Q_2^{\mathrm{T}}. \tag{8}$$

It is important to note that both sides of Equation (8) are the sum of two terms. Note that they have different meanings. The right side is an orthogonal sum, and the other side is a direct sum. Then we can know that $\mathrm{O}_kX_0 \neq L_{22}Q_2^{\mathrm{T}}$, $\Psi_kL_{11}Q_1^{\mathrm{T}} \neq L_{21}Q_1^{\mathrm{T}}$. Post-multiplying Equation (8) by Q_2 yields $\mathrm{O}_kX_0Q_2 = L_{22}$, where $Q_1^{\mathrm{T}}Q_2 = 0$, $Q_2^{\mathrm{T}}Q_2 = I_{kp}$. We will get O_k, also the order of the system is obtained by decomposing $L_{22} \in \mathbb{R}^{kp\times kp}$ by SVD (singular value decomposition).

Let the SVD of $L_{22} \in \mathbb{R}^{kp\times kp}$ be obtained by

$$L_{22} = \begin{bmatrix} U_1 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_1^{\mathrm{T}} \\ V_2^{\mathrm{T}} \end{bmatrix} = U_1\Sigma_1V_1^{\mathrm{T}}, \tag{9}$$

where $U_1 \in \mathbb{R}^{kp\times n}$, $U_2 \in \mathbb{R}^{kp\times(kp-n)}$, Σ_1 is a diagonal matrix. Then, we have

$$\mathrm{O}_kX_0Q_2 = U_1\Sigma_1V_1^{\mathrm{T}}. \tag{10}$$

Therefore, O_k is defined as

$$\mathrm{O}_k = U_1\Sigma_1^{1/2}, \tag{11}$$

and $n = \dim \Sigma_1$. And then it is easy to get the matrix C

$$C = \mathrm{O}_k\left(1 : p, 1 : n\right). \tag{12}$$

A is obtained by solving the following linear equation

$$\mathrm{O}_k(1 : p(k-1), 1 : n)A = \mathrm{O}_k(p+1 : kp, 1 : n). \tag{13}$$

Next, the estimations of B and D are considered. Since $U_2^{\mathrm{T}}L_{22} = 0$, $U_2^{\mathrm{T}}\mathrm{O}_k = 0$, pre-multiplying (8) by $U_2^{\mathrm{T}} \in \mathbb{R}^{(kp-n)\times kp}$ yields, then we can get $U_2^{\mathrm{T}}\Psi_kL_{11}Q_1^{\mathrm{T}} = U_2^{\mathrm{T}}L_{21}Q_1^{\mathrm{T}}$. Then post-multiplying the above formula by Q_1 yields

$$U_2^{\mathrm{T}}\begin{bmatrix} D & 0 & \cdots & 0 \\ CB & D & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ CA^{k-2}B & CA^{k-3}B & \cdots & D \end{bmatrix} = U_2^{\mathrm{T}} L_{21} L_{11}^{-1}. \tag{14}$$

Equation (14) shows a linear equation about B and D, and then we adopt the least square method to solve for them. In reality, set

$$U_2^{\mathrm{T}} := \begin{bmatrix} L_1 & L_2 & \cdots & L_k \end{bmatrix}, \quad U_2^{\mathrm{T}} L_{21} L_{11}^{-1} := \begin{bmatrix} M_1 & M_2 & \cdots & M_k \end{bmatrix},$$

where $L_i \in \mathbb{R}^{(kp-n)\times p}$, $i = 1, \ldots, k$, $M_i \in \mathbb{R}^{(kp-n)\times m}$.

Defining $\bar{L}_i = \begin{bmatrix} L_i & \cdots & L_k \end{bmatrix} \in \mathbb{R}^{(kp-n)\times(k+1-i)p}$, $i = 2, \ldots, k$. Thus, from Equation (14)

$$\begin{bmatrix} L_1 & \bar{L}_2 \mathrm{O}_{k-1} \\ L_2 & \bar{L}_3 \mathrm{O}_{k-2} \\ \vdots & \vdots \\ L_{k-1} & \bar{L}_k \mathrm{O}_1 \\ L_k & 0 \end{bmatrix} \begin{bmatrix} D \\ B \end{bmatrix} = \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_{k-1} \\ M_k \end{bmatrix}. \tag{15}$$

Calculate (D, B) from Equation (15), the block matrices have full column rank, and then $k(kp - n) \geq (p + n)$ is true.

In summary, we can solve B by providing the space identification method given I/O data $U_{0|k-1}$ and $Y_{0|k-1}$.

The MOESP algorithm follows the following steps:

Step 1 Calculate the LQ decomposition in Equation (5);

Step 2 Calculate the SVD of Equation (9), and let $n := \dim \Sigma_1$, and define the extended observability matrix as $\mathrm{O}_k = U_1 \Sigma_1^{1/2}$;

Step 3 Obtain C and A from Equation (12) and Equation (13), respectively;

Step 4 Solve Equation (15) to calculate B and D by the least square method.

3. Model Predictive Control.

Consider the following quadratic cost function:

$$J_\infty(s) = \sum_{i=0}^{\infty} \left[\|x(s+i|s)\|_W^2 + \|u(s+i|s)\|_R^2 \right], \tag{16}$$

where $W > 0$ and $R > 0$ are weighted matrices, and $\cdot(s + i|s)$ denotes the predicted quantities (e.g., the system state and the control input) corresponding to the time instant $s + i$ based on time s. The optimization problem to be solved online is

$$\begin{aligned} &\min_{u(s+i|s), i\geq 0} J_\infty(s) \\ &\text{s.t. } x(s+i+1|s) = Ax(s+i|s) + Bu(s+i|s) \\ &\quad\;\; -\bar{u} \leq u(s+i\,|s) \leq \bar{u}. \end{aligned} \tag{17}$$

3.1. Infinite-horizon min-max MPC.

The min-max approach is considered to optimize the performance, i.e., derive the maximum bound of the cost function, and then minimize it. To this end, the state feedback control law is employed,

$$u(s+i|s) = Fx(s+i|s), \quad i \geq 0, \tag{18}$$

where F is the control gain. Define a quadratic function $V(x) = x^{\mathrm{T}} P x$, $P > 0$. Considering the stability conditions, the upper bound of the infinite-horizon cost function is obtained:

$$V(x(s+i+1|s)) - V(x(s+i|s)) \leq -\left[\|x(s+i|s)\|_W^2 + \|u(s+i|s)\|_R^2 \right], \tag{19}$$

which further yields

$$\sum_{i=0}^{\infty}\left[\|x(s+i|s)\|_W^2+\|u(s+i|s)\|_R^2\right]\leq V(x(s|s)). \tag{20}$$

Hence, $V(x(s|s))$ is an upper bound of the cost function. At each time instant, minimizing $V(x(s|s))$ is carried out. In practice, we introduce a scalar variable γ and consider minimizing γ, subject to

$$V(x(s|s))\leq\gamma. \tag{21}$$

By defining a matrix $Q:=\gamma P^{-1}$, it is known from Schur complement that Equation (21) is equivalent to Equation (22):

$$\begin{bmatrix} 1 & x(s|s)^{\mathrm{T}} \\ x(s|s) & Q \end{bmatrix}\geq 0. \tag{22}$$

Substituting Equation (18) into Equation (19), one has

$$x(s+i|s)^{\mathrm{T}}\left[(A+BF)^{\mathrm{T}}P(A+BF)-P+F^{\mathrm{T}}RF+W\right]x(s+i|s)\leq 0. \tag{23}$$

The following equation can guarantee that Equation (23) meets all requirements:

$$(A+BF)^{\mathrm{T}}P(A+BF)-P+F^{\mathrm{T}}RF+W\leq 0. \tag{24}$$

Define $F=YQ^{-1}$. Substitute $P=\gamma Q^{-1}$ and $F=YQ^{-1}$ into Equation (24), multiply Q on both sides of Equation (24), one has the following linear matrix inequality by resorting to the Schur complement,

$$\begin{bmatrix} Q & * & * & * \\ AQ+BY & Q & * & * \\ W^{1/2}Q & 0 & \gamma I & * \\ R^{1/2}Y & 0 & 0 & \gamma I \end{bmatrix}\geq 0, \tag{25}$$

where the symbol $*$ represents the blocks in the symmetrical positions. Now, solve the following optimization problem:

$$\begin{aligned}&\min_{\gamma,Q,Y}\gamma\\ &\text{s.t. Equation (22), Equation (25)}\end{aligned} \tag{26}$$

3.2. **Handling of constraints.** It is important to use the concept of set invariance to deal with the constraints. Consider the above definitions γ, Q, P, F, Y, and denote $\varepsilon=\left\{z\,\middle|\,z^{\mathrm{T}}Q^{-1}z\leq 1\right\}=\left\{z\,\middle|\,z^{\mathrm{T}}Pz\leq\gamma\right\}$. So ε is a set of ellipses. If Inequalities (22) and (25) are satisfied, ε is an invariant set, which yileds

$$x(s|s)\in\varepsilon\Rightarrow x(s+i|s)\in\varepsilon,\quad\forall i\geq 1. \tag{27}$$

The input constraint in the optimization problem (17), viz., $-\bar{u}\leq u(s+i\,|s)\leq\bar{u}$ is considered in the following. Since ε is an invariant set, in view of the j-th element of u, let ξ_j represent the j-th row of the identity matrix of order m, and then draw the following inferences:

$$\begin{aligned}\max_{i\geq 0}|\xi_j u(s+i|s)|^2&=\max_{i\geq 0}\left|\xi_j YQ^{-1}x(s+i|s)\right|^2\leq\max_{z\in\varepsilon}\left|\xi_j YQ^{-1}z\right|^2\\ &\leq\max_{z\in\varepsilon}\left\|\xi_j YQ^{-1/2}\right\|_2^2\left\|Q^{-1/2}z\right\|_2^2\leq\left\|\xi_j YQ^{-1/2}\right\|_2^2=\left(YQ^{-1}Y^{\mathrm{T}}\right)_{jj},\end{aligned} \tag{28}$$

where $(\bullet)_{jj}$ is the j-th diagonal element of the matrix, and $\|\bullet\|_2$ is 2-norm. If there exists a symmetric matrix Z such that the following inequality is satisfied,

$$\begin{bmatrix} Z & Y \\ Y^{\mathrm{T}} & Q \end{bmatrix}\geq 0,\quad Z_{jj}\leq\bar{u}_j^2,\quad j\in\{1,\ldots,m\}, \tag{29}$$

then one can ensure that the input constraint is satisfied by resorting to the Schur complement,

$$|u_j(s+i|s)|\leq\bar{u}_j,\quad j\in\{1,\ldots,m\}, \tag{30}$$

which is a sufficient condition for the input constraint. The whole optimization problem is summarized as follows,

$$\begin{aligned} &\min_{\gamma,Q,Y,Z} \gamma \\ &\text{s.t. Equation (22), Equation (25), Equation (29)} \end{aligned} \tag{31}$$

The optimal control input and output values can be obtained by solving Equation (31).

4. **Simulation Results.** The boost DC-DC converter circuit shown in [10] consists of a switching device S, an energy storage inductor L, a continuous current diode DD, a filter capacitor C, a load resistor R and an input voltage v_g. The inductance current is i_l and the output voltage is v. In the inductive current continuous mode, the circuit is divided into two phases: S on and S off.

We now apply the proposed approach to the boost converter model to verify the feasibility of this approach. The two switched circuit models are shown in [10].

Steady-state (dc) model:

$$X = \begin{bmatrix} I \\ V \end{bmatrix} = \frac{V_g}{R_s} \begin{bmatrix} 1 \\ (1-D)R \end{bmatrix}, \quad Y = \frac{V_g(1-D)R}{R_s}, \tag{32}$$

in which I is the dc inductor current, V is the dc capacitor voltage, and Y is the dc output voltage.

Dynamic (ac small signal) model:

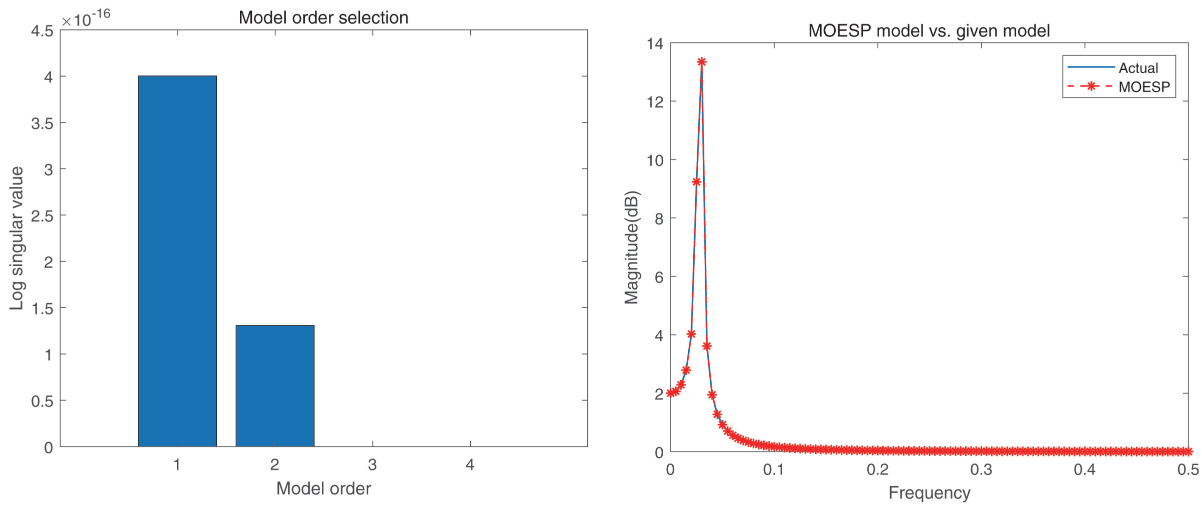
$$\begin{aligned} \frac{d}{dt}\begin{bmatrix} \hat{i}_l \\ \hat{v} \end{bmatrix} &= \begin{bmatrix} -\dfrac{R_l + (1-D)(R_c \| R)}{L} & -\dfrac{(1-D)R}{L(R+R_c)} \\ \dfrac{(1-D)R}{(R+R_c)C} & -\dfrac{1}{(R+R_c)C} \end{bmatrix} \begin{bmatrix} \hat{i}_l \\ \hat{v} \end{bmatrix} + \begin{bmatrix} \dfrac{1}{L} \\ 0 \end{bmatrix} \hat{v}_g \\ &\quad + \begin{bmatrix} \dfrac{R}{L}\dfrac{((1-D)R+R)}{R+R_c} \\ -\dfrac{R}{(R+R_c)C} \end{bmatrix} \frac{V_g \hat{d}}{R_s}, \\ \hat{y} &= \begin{bmatrix} (1-D)(R_c\|R) & \dfrac{R}{R+R_c} \end{bmatrix} \begin{bmatrix} \hat{i}_l \\ \hat{v} \end{bmatrix} - V_g \frac{R_c \| R}{R_s}\hat{d}, \end{aligned} \tag{33}$$

in which $R_s = (1-D)^2 R + R_l + D(1-D)(R_c\|R)$. $v_g = V_g + \hat{v}_g$, V_g is the dc line input voltage, $\hat{v}_g$ is the line voltage variations. $x = X + \hat{x}$, X is the dc value of the state vector, $\hat{x}$ the superimposed ac perturbation. In the same way, $y = Y + \hat{y}$. Assuming that the duty cycle varies from cycle to cycle, in other words, $d = D + \hat{d}$, where D is the steady-state (dc) duty ratio and $\hat{d}$ is a superimposed (ac) variation.

The choice of parameters is very important for the accurate identification of the system. As can be seen from Figure 2(a), the order of the system is 2. As shown in Figure 2(b), the updated model identified by subspace identification method is consistent with the actual model of the system, and the difference of Bode amplitude diagram is small. It can be seen that MOESP method can be used to identify the plant model more accurately.

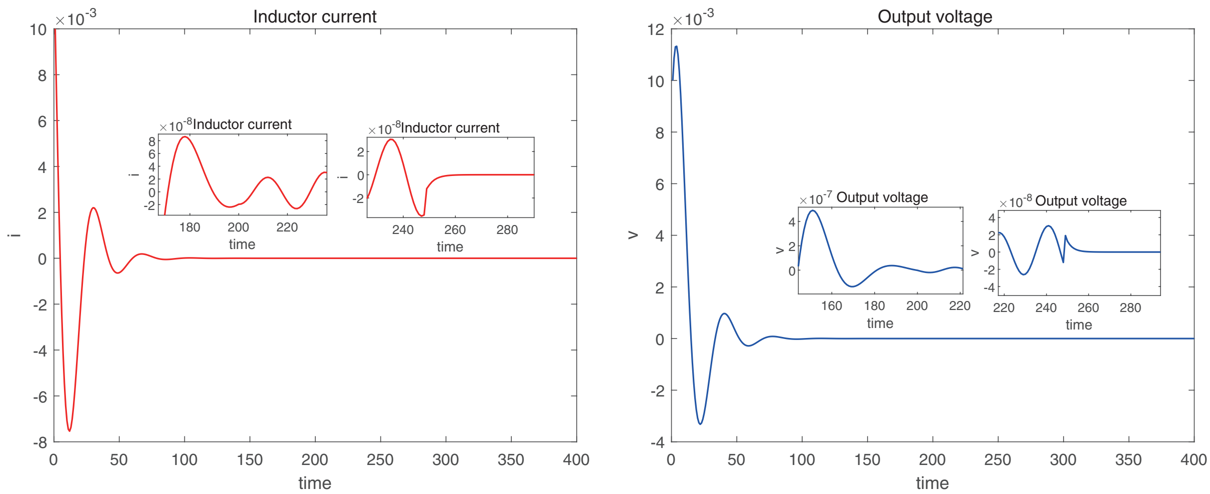
As can be seen from Figure 3, when the boost converter model is used, the load resistance of the old model is changed from 5 Ω to 50 Ω at the time of 247. After the model is changed, updated input and output data are collected, and the length of the new data set is 30 groups. The updated model can continue to control and run stably under the MPC method.

Compared with the existing research, the data identification method adopted in this paper is simple and efficient, and the influence of input constraints is also taken into account in predictive control. The identification and control are combined, and the offline



(a) (b)

Figure 2. (a) The order of the identification model; (b) identification model and actual model Bode diagram comparison



(a) (b)

Figure 3. (a) The MPC method identification model inductor current; (b) the MPC method identification model output voltage

control is transferred to online control, so that the accuracy of model identification is improved and the controlled object runs stably.

5. **Conclusion.** Subspace identification based MPC approach is proposed in this paper, which enables identifying the state-space model with input and output data using the MOESP method. The case that the system has varying parameters is considered, which is addressed by online identification based on the updated data. The proposed approach is able to identify the updated state-space model, and meanwhile, stabilize the closed-loop control system. Simulations of a boost converter control problem are carried out to show the effectiveness of the proposed method. The proposed method is suitable for control systems with complicated models that are difficult to obtain. Our future work will consider the disturbance estimation for the proposed subspace identification based MPC approach.

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