Deadbeat Control with Bivariate Online Parameter Identification for SPS-modulated DAB Converters

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ABSTRACT  
Deadbeat control is considered an efficient method of controlling dual active bridge (DAB) converters among the different control methods presented in recent years. The conventional deadbeat control is heavily reliant on the precise values of the system model parameters. However, in DAB converters, system model parameters such as series inductance and output capacitance suffer from mismatches due to operating conditions, manufacturing tolerance, and aging. Thus, the inevitable result is degradation in the steady-state and dynamic performance of the output voltage. In order to compensate for this drawback of deadbeat control, this study proposes an adaptive online parameter identification approach for DAB converters operating under single phase-shift (SPS) modulation. From the matrix form of linear equations in deadbeat control, the least-squares analysis (LSA) approach is utilized to solve the solution by a simple 2-by-2 matrix inverse calculation. Thus, series inductance and output capacitance are identified straightforwardly. Meanwhile, the predicted value of the phase-shift ratio is updated using sampled measurement values in deadbeat control after every sampling step, which can control the output voltage. The benefits of the proposed algorithm are demonstrated by theoretical analysis, simulation, and experimental results under a variety of parameter mismatches and operational circumstances.

INDEX TERMS  
Deadbeat control, Dual active bridge, Least-squares analysis, Parameter identification, Single phase-shift.

I. INTRODUCTION  
The dc microgrid and its demand are growing quickly nowadays. For flexible energy distribution, many renewable energy sources are linked to energy storage systems (ESSs) and solid-state transformers (SSTs). Besides, dc-dc converters are increasingly capable of meeting power transmission requirements. One of the bi-directional converter topologies that has attracted much attention is the dual active bridge (DAB) converter. DAB converters are widely used due to their advantages, including high efficiency, high performance, wide control range, high voltage step-up/down ability, and galvanic isolation [1], [2]. Furthermore, the size and volume of a DAB converter are reduced by using leakage inductance and high-frequency transformers. For the purpose of controlling the output voltage of the DAB converter, many prevailing modulation methods have been performed, like single phase-shift (SPS), extended phase-shift (EPS), dual phase-shift (DPS), or triple phase-shift (TPS) [3], [4].

In recent years, many control methods have been introduced, such as proportional-integral (PI) control [5], model-based phase-shift control [6], feedforward control [7], model predictive control (MPC) [8], peak current control [9], and current stress optimization control [10]–[12]. These methods have the ability to stabilize and improve the output voltage performance while guaranteeing the achievement of fast transient dynamic and steady-state performance with a simplified model or more accurate model. However, most model-based control method causes performance degradation when there is a mismatch between the model and actual parameters. In practical hardware, the inductor [13] and capacitor [14] values slightly change according to temperature drift, manufacturing tolerance, aging, and operating conditions, and parameter mismatches of up to 20% sometimes occur [15], [16]. The authors in [17] and [18] proved that deadbeat control is an effective way to control the output voltage of DAB converters. Nevertheless, they have limitations when parameter mismatches are not solved satisfactorily in implementations because deadbeat control significantly depends on accurate system model parameter values.

To find the actual value of the system model parameters, the authors in [19] proposed a method of model-based feedforward control combined with recursive least-squares (RLS). However, in this method, the output capacitor also affects the performance, but it is not considered. Moreover, the phase-shift ratio is compensated by a PI controller. Thus, when the feedforward input such as load current suffers from a sudden change, that causes performance degradation. Another approach is to calculate the actual value of the parameters proposed in [20]. This method uses MPC combined with least-squares estimation to find state values by solving the gradient of the least-squares error function. However, all of the available data, including historical data
and present measured data, are used to find the solution. Thus, a significant change in the system model parameters or a large degree of disturbance can also lead to overcompensation or undercompensation, resulting in performance degradation. This problem was pointed out in [21], which added a forgetting factor to increase convergence speed and control robustness. Furthermore, in [20], the least-squares solution was found by solving a 3-by-3 matrix; this causes calculation to become complicated because only two variables of system model parameters need to be found. Note that, in the least-squares analysis (LSA), the noise caused by model inaccuracy and parasitism can be eliminated in the least-square solution [20]. Other approaches, such as the instantaneous phasor method [22] and RLS-based parasitic parameter extraction [23], can be used to identify the transformer parameters in the DAB converter. Nevertheless, these approaches cannot identify the value of the capacitor on both sides, and the algorithm is complicated.

In order to overcome such limitations, this paper proposes a deadbeat control-based algorithm to simultaneously find the actual value of the series inductor and output capacitor. On the other hand, SPS modulation is the simplest and most widely used. Thus, it is adopted to show the effectiveness of the proposed algorithm. A matrix form of the model system is constructed, including historical data and present measured data. Then it is solved by LSA because LSA is considered the most simplified method to find an optimal solution to a set of linear equations [24]. Moreover, this paper finds system model parameters differently from existing studies by solving a 2-by-2 matrix. As a result, online parameter identification is performed and compatible with low-cost digital signal processors (DSP).

This paper is organized into six sections. Section II briefly reviews deadbeat control under the SPS modulation scheme. In Section III, the proposed algorithm is presented in detail. Section IV shows simulation results of the effect of parameter mismatches and the proposed algorithm. Section V presents and discusses experimental results that demonstrate the benefits of the proposed algorithm. Lastly, Section VI provides the conclusions.

II. SPS MODULATION-BASED DEADBEAT CONTROL

The topology of the DAB converter is shown in Fig. 1. Assume that power is transmitted from the input voltage $v_1$ side to the output voltage $v_2$ side via the high-frequency transformer $T$ with the turn ratio $n$. Capacitors $C_1$ and $C_2$ are connected to the input and output sides, respectively, and $L$ is the series inductor, which may consist of the leakage inductor of the transformer and the additional inductor. There are two H–bridges (bridges H1 and H2) that include eight switches (S1 – S8), and the current flows from bridge H1 ($i_p$ – primary current) to H2 ($i_d$ – secondary current). A square pulse with a 50% duty cycle is provided in every half-switching period. Waveforms of the DAB converter under SPS modulation are depicted in Fig. 2.

In-depth analyses of DAB converters can be found in [9], [25], and [26]. On the other hand, according to the authors in [3] and [8], the DAB converter is considered a first-order system. The reduced-order model [25], [27] has been proved to be a good compromise between complexity and accuracy compared with other models, like the improved reduced-order model [28], the generalized average model [29], and discrete-time model [30]. Thus, the reduced-order model is used in this paper. The output power and secondary current in the steady-state can be expressed as

$$P = \frac{nv_1v_2}{2L}D(1-D), \quad (1)$$

$$i_s = \frac{nv_1}{2L}D(1-D). \quad (2)$$

When the value of $D$ is in the range of $[0 \sim 1]$, power is transmitted from bridge H1 to bridge H2 with a maximum value at $D = 0.5$. The output capacitor is in parallel with the load, so the dynamic equation of the output current is given by

$$C_2 \frac{dv_2}{dt} = i_s - i_2, \quad (3)$$

Discretizing (3) according to the forward approximation [8], obtained

$$v_2[k] = i_s[k-1] + \frac{v_2[k-1]}{fC_2} - i_2[k-1], \quad (4)$$

where $v_2[k]$ and $v_2[k-1]$ are the output voltages at the $k^{th}$ and $(k-1)^{th}$ sampling step, respectively; $i_s[k-1]$ and $i_2[k-1]$ are the secondary current and output current at the $(k-1)^{th}$
sampling step, respectively.

This paper sets the phase-shift ratio as $0 < D < 0.5$ to simplify the analysis. From (3) and (4), the related constraint between $v_2[k]$ and $v_2[k - 1]$ is derived as

$$v_2[k] = \frac{nv_1[k-1]}{2f^2LC_2}D[k-1](1-D[k-1]) - \frac{1}{fC_2}i_m[k-1] + v_1[k-1], \quad (5)$$

where $v_1[k-1]$ and $D[k-1]$ are the input voltage and phase-shift ratio at the $(k-1)^{th}$ sampling step, respectively.

The reference value of output voltage $v_{2\text{ref}}$ is considered as a goal to achieve

$$v_2[k] = v_{2\text{ref}}. \quad (6)$$

Combining (5) and (6), the predicted value of $D$ at the $k^{th}$ sampling step is obtained as

$$D[k] = \frac{1}{2}\left(\frac{1}{4} + \frac{2f^2LC_2}{nv_1[k]}\left(v_2[k] - v_{2\text{ref}} - \frac{i_m[k]}{fC_2}\right)\right)^{1/2}. \quad (7)$$

A block diagram of SPS modulation-based deadbeat control is depicted in Fig 3. All system model parameters and the measured values are adopted to calculate the predicted value of $D$ at the $k^{th}$ sampling step from (7). Clearly, the predicted value of $D$ strongly depends on the values of the $L$ and $C_2$, so the exact determination of these parameters is essential. The mismatch in system model parameters can degrade the steady-state performance, which will be discussed in the next section.

### III. PROPOSED ONLINE PARAMETER IDENTIFICATION

#### A. STEADY-STATE ERROR OF THE OUTPUT VOLTAGE

In order to examine the effect of parameter mismatch on the output voltage $v_2$, the mismatch ratio of the series inductance $m_L$ and the mismatch ratio of the output capacitance $m_{C2}$ are defined as

$$m_L = \frac{L}{L_a} \quad (8)$$

and

$$m_{C2} = \frac{C_2}{C_{2a}}, \quad (9)$$

where $L_a$ is the actual value of the $L$ and $C_{2a}$ is the actual value of $C_2$.

The output current $i_k = v_2/R$ is substituted into (2), and the average value of the current passing through $C_2$ is assumed to be zero in the steady-state [10]. Consequently, $v_2$ in the steady-state is rewritten as

$$v_2 = \frac{fRC_m m_{C2} v_{2\text{ref}}}{1 - m_L + fRC_m m_{C2}}. \quad (10)$$

From (10), the percentage of steady-state error $\Delta v_2\%$ is derived as

$$\Delta v_2 \% = \frac{v_2 - v_{2\text{ref}}}{v_{2\text{ref}}} \times 100\% = \frac{m_L - 1}{1 - m_L + fRC_m m_{C2}} \times 100\%. \quad (11)$$

As mentioned in Section I, $L$ and $C_2$ vary up to 20% in practical experiments. Thus, $\Delta v_2\%$ was calculated with respect to $m_L$ and $m_{C2}$ changing from 0.8 to 1.2. The results of $\Delta v_2\%$ are shown in Fig. 4, with all parameters shown in Table I. Obviously, if there is no mismatch in $L$ ($m_L = 1$), the value of $\Delta v_2\%$ is zero even if $C_2$ has a mismatch (red line). However, whenever $L$ has a small mismatch, $\Delta v_2\%$ strongly depends on $m_{C2}$. When $m_L$ and $m_{C2}$ are chosen as 0.8, $\Delta v_2\%$ becomes $-0.5047\%$. When $m_L$ is chosen as 1.2 and $m_{C2}$ as 0.8, $\Delta v_2\%$ becomes 0.3394%, which could be the worst-case mismatch scenario.

#### B. ONLINE PARAMETER IDENTIFICATION WITH LEAST-SQUARES ANALYSIS

In (5), if the parameter mismatch occurs, the predicted value on the left-hand side is different from that on the right-hand side, so the predicted output voltage differs from the reference value; as a result, not only the steady-state but also the dynamic performance deteriorates rapidly. Therefore, the emergent issue here is how to identify the actual values of $L$ and $C_2$ in the next sampling step. The equation (5) can be rewritten as

$$E[k-1] = -C_2 F[k-1], \quad (12)$$

where

$$E[k-1] = \frac{nv_1[k-1]}{2f^2}D[k-1](1-D[k-1]), \quad (13)$$

and
\[ F[k-1] = -\frac{1}{f} i_z[k-1]. \] (14)

It is easy to see that the measured values will be employed as input data for the next sampling step. Rearranging (12) to the matrix form, obtained

\[ Kx = h, \] (15)

where

\[
K = \begin{bmatrix}
E[k-1] & -(v_2[k]-v_z[k-1]) \\
\varepsilon E[k-2] & -(v_2[k]-v_z[k-2]) \\
\vdots & \vdots \\
\varepsilon^k E[1] & -(v_2[2]-v_z[1])
\end{bmatrix}_{(k-1) \times 2}, \tag{16}
\]

\[
x = \begin{bmatrix}
\frac{1}{L} \\
C_2 \varepsilon_{j=1}^1
\end{bmatrix}, \tag{17}
\]

\[
h = \begin{bmatrix}
-F[k-1] \\
-\varepsilon F[k-2] \\
\vdots \\
-\varepsilon^{k-2} F[1]
\end{bmatrix}_{(k-1) \times 1}. \tag{18}
\]

The vector \( h \) is the predicted data, and the matrix \( K \) is the measured data with sizes of \((k-1)\)-by-1 and \((k-1)\)-by-2, respectively, and the vector \( x \) has a size of 2-by-1. The constant \( \varepsilon \) is the forgetting factor, which will be discussed at the end of this section. Since matrix \( K \) is not square (i.e., the number of rows is different from the number of columns), (15) cannot be solved in the traditional inverse matrix to find the solution. In addition, after every sampling step, the system model parameters need to be updated to obtain the predicted output voltage accurately.

Given the previous statement, in order to find the actual value of the vector \( x \) more effectively, a new vector \( e \) is introduced as the error between the predicted data and the measured data; \( e \) is expressed as

\[
e = \begin{bmatrix}
e[k-1] \\
e[k-2] \\
e[1]
\end{bmatrix}_{(k-1) \times 1} = Kx - h. \tag{19}
\]

Meanwhile, the LSA function \( L(x) \) is defined as a mean square error as

\[
L(x) = \| e \|^2 = (Kx - h)^T (Kx - h), \tag{20}
\]

where the superscript symbol \( T \) represents the matrix transpose.

In order to find the LSA solution of \( L(x) \), a corollary is introduced as follows.

Corollary: Let \( \Omega \) be a subset of \( \mathbb{R}^n \) and \( f \in C^1 \) a real-valued function on \( \Omega \). If \( x^* \) is a local minimizer of \( f \) over \( \Omega \) and if \( x^* \) is an interior point of \( \Omega \), then \( \nabla f(x^*) = 0 \) (Chapter 1).

Proof: Suppose that \( f \) has a local minimizer \( x^* \) that is an interior point of \( \Omega \). Because \( x^* \) is an interior point of \( \Omega \), the set of feasible directions at \( x^* \) is the whole of \( \mathbb{R}^n \). Thus, for any \( d \in \mathbb{R}^n \), \( \partial^2 \nabla f(x^*) \geq 0 \) and \( -\partial^2 \nabla f(x^*) \geq 0 \). Hence, \( \partial^2 \nabla f(x^*) = 0 \) for all \( d \in \mathbb{R}^n \), which implies that \( \nabla f(x^*) = 0 \).

Therefore, the alternative way to evaluate the system using the LSA is to get \( L(x) \) gradient to zero. Additionally, because \( L(x) \) is a quadratic function, it is a positive definite. Thus, by solving the first-order necessary condition as mentioned in the above corollary, the unique minimizer of \( L(x) \) is obtained as follows

\[
\frac{\partial f(x)}{\partial x} = 2K^T Kx - 2K^T h = 0. \tag{21}
\]

As a result, the parameter vector is obtained as

\[
x = (K^T K)^{-1} K^T h. \tag{22}
\]

Because \((K^T K)^{-1}\) in (22) always exists. Thus, (22) is the LSA solution of online parameter identification based on deadbeat control.

By substituting (16)–(18) into (22), the actual values of \( L \) and \( C_2 \) are identified. However, the matrix and vector in (16) and (18) with ever-increasing rows lead to a tremendous computational burden and are impractical. Thus, (22) is rewritten as

\[
x = (U)^{-1} w, \tag{23}
\]

where the dimensionality of the matrix and vector is significantly reduced and given by

\[
U = \begin{bmatrix}
u_{11}[k-1] & u_{12}[k-1] \\
u_{21}[k-1] & u_{22}[k-1]
\end{bmatrix}_{2 \times 2} = K^T K, \tag{24}
\]

\[
w = \begin{bmatrix}
w_1[k-1] \\
w_2[k-1]
\end{bmatrix}_{2 \times 1} = K^T h. \tag{25}
\]

To find matrix \( U \) and vector \( w \), substitute (16) and (18) into (24) and (25), obtained

\[
u_{11}[k-1] = \sum_{k=1}^{k=1} \varepsilon^{k-1} E[h], \]

\[
u_{12}[k-1] = \sum_{k=1}^{k=1} \varepsilon^{k-1} E[h](v_2[h+1] - v_2[h]), \]

\[
u_{21}[k-1] = u_{12}[k-1], \]

\[
u_{22}[k-1] = \sum_{k=1}^{k=1} \varepsilon^{k-1} E[h](v_2[h+1] - v_2[h]), \tag{26}
\]

\[
w_1[k-1] = \sum_{k=1}^{k=1} \varepsilon^{k-1} E[h] F[h], \]

\[
w_2[k-1] = \sum_{k=1}^{k=1} \varepsilon^{k-1} F[h](v_2[h+1] - v_2[h]).
\]

From (26), to guarantee hardware implementation of the proposed algorithm easily, the successive recurrence relation of the elements is implemented as

\[
u_{11}[k-1] = E^2[k-1] + \varepsilon^2 u_{11}[k-2], \]

\[
u_{12}[k-1] = -E[k-1](v_2[k] - v_2[k-1]) + \varepsilon^2 u_{12}[k-2], \]

\[
u_{21}[k-1] = u_{12}[k-1], \]

\[
u_{22}[k-1] = (v_2[k] - v_2[k-1])^2 + \varepsilon^2 u_{22}[k-2], \tag{27}
\]

\[
w_1[k-1] = -E[k-1] F[k-1] + \varepsilon^2 w_1[k-2], \]

\[
w_2[k-1] = F[k-1](v_2[k] - v_2[k-1]) + \varepsilon^2 w_2[k-2].
In the proposed algorithm, all elements in \( \mathbf{U} \) and \( \mathbf{w} \) are incrementally updated from the new measured data and the previous data, and thus controller memory is effectively utilized.

Contrary to the matrix \( \mathbf{K} \) and vector \( \mathbf{h} \) having a large size of elements, \( \mathbf{U} \) is a 2-by-2 matrix, and \( \mathbf{w} \) is a 2-by-1 vector. Thus, the calculated burden of the proposed algorithm is significantly mitigated by a simple matrix inverse operation with the size of 2-by-2, as shown in (23). Therefore, the proposed algorithm can be programmed into even a low-cost digital controller. When \( \mathbf{L} \) and \( \mathbf{C}_2 \) drift, the proposed algorithm provides an adaptive online parameter identification to trace the actual values.

By the way, since the sudden change in operating conditions or the system model parameters (for example, the failure of one of the parallel capacitors) makes the old measured data less important, their effects need to fade away. When \( \mathbf{v}_2 \) is close to \( \mathbf{v}_{2\text{ref}} \), the old measured data needs to be less required as \( k \) increases. Therefore, the forgetting factor \( \varepsilon \) directly affects the LSA solution, not only for convergence but also because it affects the performance of the proposed algorithm. Usually, \( \varepsilon \) is chosen as \( 0 < \varepsilon < 1 \) to guarantee adaptability. If \( \varepsilon \) is close to zero, the performance becomes more sensitive to noise, reducing the stability of the estimator. Conversely, if \( \varepsilon \) approaches unity, resulting in a weak forgetting effect, the solution of the proposed algorithm is determined mostly by the old measured data, thereby reducing the speed. In practice, \( \mathbf{L} \) and \( \mathbf{C}_2 \) change gradually. Therefore, parameter identification with the proposed algorithm requires a slow convergence rate, so \( \varepsilon \) needs to be set close to unity. In this paper, \( \varepsilon \) is chosen as 0.99.

The block diagram of the proposed algorithm is sketched in Fig. 5. First, the values of \( \mathbf{v}_1 \), \( \mathbf{i}_2 \), and \( \mathbf{D} \) at the \( (k - 1)^{\text{th}} \) sampling step and the parameters \( f \) and \( n \) are collected to compute \( E \) and \( F \) from (13) and (14). Then, \( \mathbf{U} \) and \( \mathbf{w} \) are calculated from (27). After that, \( \mathbf{x} \) is calculated from (23), and the values of \( \mathbf{L} \) and \( \mathbf{C}_2 \) are obtained from (17). Finally, the predicted value of \( \mathbf{D} \) at the \( k^{\text{th}} \) sampling step is calculated from (7) with the accurate model parameters.

**IV. SIMULATION RESULTS**

Simulation results in Fig. 6 show the steady-state error of \( \mathbf{v}_2 \) in several cases of parameter mismatch under conventional deadbeat control without parameter identification. Simulation parameters are shown in Table I. Cases \#1 to \#9 correspond to the values of \( m_L \) and \( m_{C2} \), which are described in Table II. In Fig. 6, the minimum value of steady-state error of \( \mathbf{v}_2 \) occurs in case \#1 where \( m_L = m_{C2} = 0.8 \) and maximum value in case \#7 where \( m_L = 1.2 \) and \( m_{C2} = 0.8 \). The remaining cases also result in a steady-state error. Clearly, the simulation result is the same as the theoretical analysis presented in Section III.A.

Figs. 7 and 8 show the steady-state error of \( \mathbf{v}_2 \) without and with the proposed algorithm under initial parameter mismatches. Initially, the conventional deadbeat control without parameter identification is adopted to control DAB under case \#1 \( (m_L = m_{C2} = 0.8) \) and case \#9 \( (m_L = m_{C2} = 1.2) \), in which system model parameters are the most different from the actual values. After the controller is switched to the proposed algorithm, \( \mathbf{v}_2 \) coincides nicely with \( \mathbf{v}_{2\text{ref}} = 95 \text{ V} \). The reason is that the system model parameters \( \mathbf{L} \) and \( \mathbf{C}_2 \) have been identified accurately, resulting in the predicted value of \( \mathbf{D} \) can be provided precisely after every sampling step. Therefore, in the proposed algorithm, the steady-state error of \( \mathbf{v}_2 \) is significantly mitigated by a simple matrix inverse operation with the size of 2-by-2, as shown in (23).

**TABLE I**

| Symbol | Quantity | Simulations | Experiments |
|--------|----------|-------------|-------------|
| \( f \) | Switching frequency | 10 kHz | 10 kHz |
| \( L_a \) | Series inductance (actual value) | 50 \( \mu \text{H} \) | 51 \( \mu \text{H} \) |
| \( C_{1a} \) | Input capacitance (actual value) | 440 \( \mu \text{F} \) | 431 \( \mu \text{F} \) |
| \( C_{2a} \) | Output capacitance (actual value) | 220 \( \mu \text{F} \) | 219 \( \mu \text{F} \) |
| \( v_1 \) | Input voltage | 100 V | 100 V |
| \( v_{2\text{ref}} \) | The reference value of the output voltage \( v_2 \) | 95 V | 95 V |
| \( n \) | Transformer turn ratio | 1 | 1 |
| \( R \) | Load | 28 \( \Omega \) | 28 \( \Omega \) |
performance is considerably improved.

Figure 9 shows the transient dynamic response of \( v_2 \) when \( v_{2\text{ref}} \) increases and decreases between 95 V and 100 V under mismatch case #2 (\( m_L = 0.8, m_{C2} = 1 \)). The steady-state error of \( v_2 \) is still present when \( v_{2\text{ref}} \) changes for the conventional deadbeat control, as shown in Fig. 9(a). Meanwhile, \( v_2 \) always traces \( v_{2\text{ref}} \) for the proposed algorithm, as shown in Fig. 9(b).

Simulation results in Fig. 10 show the transient dynamic response of \( v_2 \) when \( I_2 \) changes between 3.4 A and 4.4 A under mismatch case #7 (\( m_L = 1.2, m_{C2} = 0.8 \)). Obviously, \( v_2 \) also has a steady-state error for the conventional deadbeat control, as shown in Fig. 10(a). The steady-state error of \( v_2 \) is eliminated for the proposed algorithm, as shown in Fig. 10(b).

**V. EXPERIMENTAL RESULTS**

The experimental setup is built with a TMS320F28379D (Texas Instruments) as the digital controller. The experimental setup is depicted in Fig. 11, and the hardware components are shown in Table III. All experimental tests are carried out in a laboratory at room temperature (about 26°C). The LCR meter (Agilent) measures the actual system model parameters, including \( L \) and \( C_2 \), as given in Table I.

Fig. 12 illustrates the experimental results of the steady-state error of \( v_2 \) in several cases of parameter mismatch under conventional deadbeat control without parameter identification. The steady-state error of \( v_2 \) occurs with almost

![Simulation results when the proposed algorithm is activated under the parameter mismatch case #1 (\( m_L = m_{C2} = 0.8 \)).](image1)

![Simulation results when the proposed algorithm is activated under the parameter mismatch case #9 (\( m_L = m_{C2} = 1.2 \)).](image2)

![Simulation results of the steady-state error of \( v_2 \) in several parameter mismatch cases.](image3)
the same amount as theoretical analysis and simulation results when the values of $L$ and $C_2$ are mismatched.

In order to better illustrate the effect of mismatch and minimize the effect of uncertainty caused by measurement noises in practical work, the error must be obtained in a large number of sampling steps. So the average error $AE$ is defined as follows to describe the steady-state error of the measured output voltage

$$AE = \frac{1}{N} \sum_{i=1}^{N} \left| v_2(i) - v_{2\text{ref}} \right|,$$

(28)

where $N$ is the number of sampling data points and is set as 1000.

Comparisons of $\Delta v_2\%$ with respect to $m_L$ and $m_{C2}$ in theory, simulation, and experimental results are shown in Table IV. In Fig. 13, theory, simulation, and experimental results with respect to $m_L$ and $m_{C2}$ are compared. Note that the values of $\Delta v_2\%$ in simulation and experimental results are calculated form (28). Besides, Comparisons of the steady-state error of $v_2$ in simulations and experiments are shown in Fig. 14 in several cases of parameter mismatch, where the errors of $v_2$ in the simulation are calculated from Fig. 6, and the average errors of experimental results are calculated from (28). Obviously, the simulation and experimental results coincide well with the theoretical analysis.

Fig. 15 illustrates the experimental waveforms of the proposed parameter identification algorithm when the initial parameters have mismatches. When the proposed algorithm is activated, $m_L$ and $m_{C2}$ converge to the actual values ($m_L = 0.8$, $m_{C2} = 1$).
\( m_{C2} = 1 \) quickly. As a consequence, \( v_2 \) traces \( v_{2\text{ref}} \) accurately.

Experimental results in Figs. 16 and 17 indicate the dynamic performance of the proposed algorithm when compared to deadbeat control without the online parameter identification method and conventional PI control under SPS. Fig. 16 illustrates the experimental waveforms when \( v_{2\text{ref}} \) changes between 95 V and 100 V. When \( v_{2\text{ref}} \) changes in case #2 (\( m_L = 0.8, m_{C2} = 1 \)), as shown in Figs. 16(a) and (b), the steady-state error of \( v_2 \) remains for the conventional deadbeat control. In Figs. 16(c) and (d), although the steady-state error of \( v_2 \) is eliminated due to the integral compensator of the PI controller, the settling time is
Meanwhile, in the proposed algorithm, $v_2$ always traces $v_{2\text{ref}}$, as shown in Figs. 16(e) and (f). This is because when parameters are adaptively online identified, the predicted value of $D$ will be updated after every sampling step from the new measured data and the previous data. Furthermore, because the proposed algorithm does not include a compensating controller, it has a fast settling time and good dynamic performance.

Fig. 17 illustrates the experimental waveforms when $i_2$ changes between 3.4 A and 4.4 A. Initially, deadbeat control without parameter identification is executed under case #7 ($m_L = 1.2$, $m_{C2} = 0.8$) as shown in Figs. 17(a) and (b). It is easy to see that $v_2$ also has a steady-state error under the mismatch circumstances. Figs. 17(c) and (d) show the experimental results of conventional PI control with no steady-state error of $v_2$. However, $v_2$ has the settling time of 6 ms and the undershoot and overshoot of 3.8 V and 3.7 V as $i_2$ increases and decreases, respectively. Experimental results of the proposed algorithm are illustrated in Figs. 17(e) and (f), where the steady-state and dynamic performances of $v_2$ are excellent. Clearly, the benefits of the proposed algorithm, as demonstrated in simulations, are also confirmed by experimental tests.

**VI. CONCLUSIONS**

This paper presented an adaptive online parameter identification approach based on deadbeat control for the DAB converter under SPS modulation. Some observations and results are inferred as follows:

1) The theoretical analysis, simulation results, and experimental results have demonstrated steady-state errors of $v_2$ in cases of system parameter mismatch of the conventional deadbeat control. For example, when $m_L = m_{C2} = 0.8$, $\Delta v_2% = –0.52%$ in simulation and –0.54% in experiment, compared to the value of –0.5047% in theory with parameters shown in Table I.

2) The proposed algorithm accurately identifies $L$ and $C_2$, which significantly improves the steady-state error of $v_2$. Besides, the proposed method outperformed the conventional PI method in dynamic response.

3) Although the LSA is utilized in this paper, it is expected that other approaches for solving linear equations, such as RLS or Kaczmarz’s algorithm, will build on the original idea of this paper to enhance further the control theory of deadbeat control and parameter identification. The challenges are changing the forgetting factor adaptively to improve dynamic performance further and reducing the peak value of inductor current in the transient process of the deadbeat control.

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FIGURE 16. Comparison results when \( v_{2\text{ref}} \) changes between 95 V and 100 V under mismatch case #2 (\( m_L = 0.8, m_C = 1 \)).
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