Abstract—This work proposes and experimentally verifies a novel Virtual Flux (VF) estimation method for predictive control of back-to-back voltage source power converters with Space Vector Modulator (SVM). The novelty of the proposed approach is the development of a time domain Initial Bias Compensation Virtual Flux (IBC-VF) estimation method and its combination with a predictive control scheme with constant switching frequency. Theoretical analysis and implementation procedures of the proposed method are detailed in this work. Compared to a conventional band-pass filter-based VF estimation methods, the proposed IBC-VF method shows an improved dynamic response. The whole IBC-VF based predictive control scheme is realized in the \(\alpha\beta\) frame and, so, does not require Park’s transformation. The proposed control scheme is implemented on a commercial off-the-shelf FPGA based platform. By using a Single-Cycle-Timed-Loop (SCTL) technique, the whole computation is finished within \(2.6\mu s\) making compensation of the calculation time obsolete. Both, simulation and experimental results, emphasize the effectiveness of the proposed scheme.

Index Terms—Back-to-Back Power Converter, FPGA Digital Control, Predictive Power Control, Virtual Flux Estimation.

I. INTRODUCTION

BACK-TO-BACK voltage source power converters with Active Front End (AFE) offer many advantages compared to those with Passive-Front-End (PFE) [1], [2]: (i) controllable sinusoidal currents on grid side with low harmonic pollution, (ii) controllable DC-link voltage which allows to reduce the DC-link capacitor size, (iii) a bi-directional power flow, and (iv) controllable reactive power on grid side.

These properties of a back-to-back converter make it possible to serve as a multi-functional converter: A back-to-back converter with DC-link can supply the full output power to its linear or non-linear load while controlling the active and reactive power drawn from the grid (net). The net side converter (NSC) functions as an active power filter by compensating harmonics and reactive power, whereas the load side converter (LSC) can act at the same time as supplier of an AC-load (like AC-motor or RL(C)-load). Moreover, such a fully controllable converter achieves a bi-directional power flow. Therefore it represents a promising solution to applications where regenerative operation or reactive power and harmonic compensation are needed [1]–[4].

Control of the grid-connected AFE part (i.e. the net/grid side converter) is one of the most important control tasks for a back-to-back converter. Whether grid side voltage sensors are needed (or not) and whether active and reactive power are to be controlled, the AFE control schemes can be classified into four groups [5], [6]: (i) voltage sensor based Direct Power Control (DPC), (ii) cascaded (current) control (in the following named “indirect power control”), (iii) Virtual Flux (VF) based DPC and (iv) VF based indirect power control. Due to the fast dynamics of DPC and model predictive control schemes [7]–[9], recently many reports were published dealing with direct power control and model predictive control concepts: In [10] an improved DPC scheme with duty cycle optimization is used. In [8] a Finite-Control-Set Model Predictive DPC (FCS-MP-DPC) is developed and in [11] a Sliding-Mode DPC (SM-DPC) is proposed. In [12] a constant-switching-frequency model predictive DPC is realized utilizing SVM. In [13] a predictive current controller for grid-tied wind turbine applications with extended state observer is proposed with fast dynamics and constant switching frequency. Besides, model predictive control becomes more and more popular in power electronics and electrical drives due to its promising results (see e.g. [14]–[18]).

All control schemes which rely on a voltage sensor depend on the measurement accuracy provided by the sensor hardware. Moreover, voltage sensor based schemes are costly
and vulnerable to noise and may complicate the system setup [1]. In [19] a voltage sensorless method utilizing a switching table in DPC is firstly proposed. By using virtual flux estimation schemes, several publications extended Voltage Oriented Control (VOC), DPC (with look-up table) and FCS-MP-DPC methods such that a voltage sensor is not required anymore (see e.g. [1]). Most of these VF estimation schemes rely either on a band-pass or high-pass filter to extract the related component(s) of the estimated VF. However, due to the inevitable transient time (time delay) of the filters, a relatively long delay occurs at the beginning and during the transient phases of the estimation yielding inaccurate control during these phases. E.g., a huge overshoot in the estimation error will be observed and the control system might suffer from limitation problems.

This work presents a novel VF estimation method with Initial Bias Compensation (IBC-VF). The proposed method numerically analyzes the estimated VF components and eliminates the initial bias due to the converter voltage integration and due to the initial flux in the filter inductance. The proposed algorithm makes the VF estimation fast and accurate, achieving a dynamic response within one sampling step. The proposed IBC-VF estimation method is combined with a predictive control scheme with SVM operating with constant switching frequency for a back-to-back power converter. Note that, for grid-connected power converters, constant-switching-frequency operation brings multiple benefits (for details see [12]). Main contributions of this work are the following:

(i) A novel Initial Bias Compensation Virtual Flux (IBC-VF) estimation method is proposed and derived. The proposed method is compared with two conventional band-pass filter-based methods and the comparison results are theoretically analyzed;

(ii) The proposed VF method is combined with a predictive control scheme for a back-to-back power converter. All computations for the proposed estimation and control scheme are performed in the $\alpha\beta$ reference (stationary) frame. Hence no Park’s transformation is needed;

(iii) The proposed combination of VF estimation and predictive control scheme is verified by experimental results on a FPGA based platform. The implementation steps are explained in detail.

The paper is organized as follows: In Section II a back-to-back converter with RL-load and net/grid side line choke (RL-filter) is modeled. Section III re-visits two band-pass filter based VF estimation methods and proposes the novel IBC-VF estimation method. Their performances are compared and analyzed. Section IV introduces the predictive control scheme with the proposed IBC-VF estimation for a back-to-back converter. Section V deals with the FPGA implementation and the experimental verification of the proposed method. Section VII concludes this paper.

II. SYSTEM DESCRIPTION AND MODELING

A typical two-level back-to-back converter with grid side RL-filter and RL-load is shown in Fig. 1. According to the circuit diagram in Fig. 1, the system can be modeled in the $\alpha\beta$ reference frame as follows (for details see [4] or, in great detail, the book chapter [20]).

A. Net and Load Side Dynamics

The net (grid) and load side dynamics in the $\alpha\beta$ reference frame are given by

$$\ddot{\vec{e}}_n(t) = \vec{e}_n(t) + \vec{i}_n(t) + L_n \cdot \frac{d\vec{i}_n(t)}{dt}, \quad \vec{v}_n(0) = \vec{v}_n^0 \in \mathbb{R}^2$$  \hspace{1cm} (1)$$

and

$$\dot{\vec{i}}_l(t) = R_l \cdot \vec{i}_l(t) + L_l \cdot \frac{d\vec{i}_l(t)}{dt}, \quad \vec{i}_l(0) = \vec{i}_l^0 \in \mathbb{R}^2,$$  \hspace{1cm} (2)$$

where $\vec{e}_n = (i_{n_a}, i_{n_b})^\top$ and $\vec{i}_l = (i_{l_a}, i_{l_b})^\top$ are current vectors of grid and load side, respectively; $\vec{v}_n^0$ and $\vec{i}_l^0$ are the initial current vectors of grid and load side, respectively (often set to zero); $\vec{e}_n = (v_{n_a}, v_{n_b})^\top$ is the grid side source voltage vector and $\vec{v}_l = (v_{l_a}, v_{l_b})^\top$ and $\vec{i}_l = (v_{l_a}, v_{l_b})^\top$ are the grid side and load side converter voltage vectors, respectively. All quantities in the $\alpha\beta$ reference frame can be obtained from the corresponding quantities in the abc reference frame as follows:

$$\vec{x}_y(t) = \begin{bmatrix} \frac{\sqrt{2}}{3} & \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ 0 & \sqrt{\frac{2}{3}} & -\frac{1}{2} \end{bmatrix} \cdot \vec{x}_{abc}(t)$$  \hspace{1cm} (3)$$

where $x$ can represent a current $i$ or a voltage $v$. The subscript $y$ may indicate load $l$ or net $n$ (grid) side. For $y \in \{n, l\}$, the voltage vector $\vec{v}_y$ is a function of the DC-link voltage $V_{dc}$ and the corresponding switching vector $\vec{G}_{y,abc}$ in the abc reference frame. More precisely, for an ideal switching behavior of the power switches in Fig. 1, the following holds

$$\vec{v}_{abc}(t) = \frac{V_{dc}}{3} \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} \cdot \vec{G}_{y,abc}(t)$$  \hspace{1cm} (4)$$

with switching vector $\vec{G}_{y,abc}(t) = (G_{y,a}^u, G_{y,b}^u, G_{y,c}^u)^\top$ where $G_{y,a}^u, G_{y,b}^u, G_{y,c}^u \in \{0, 1\}$.

B. DC-Link Voltage Dynamics

Considering the DC-link current $I_{dc}$ of a back-to-back converter (see Fig. 1), the DC-link dynamics can be modeled as follows

$$\frac{dV_{dc}(t)}{dt} = \frac{1}{C} I_{dc}(t) = \frac{1}{C} [I_n(t) - I_l(t)],$$  \hspace{1cm} (5)$$

where $I_n(t) = \vec{v}_{abc}(t) \cdot \vec{G}_{y,abc}(t)$ and $I_l(t) = \vec{v}_{abc}(t) \cdot \vec{G}_{y,abc}(t)$ are DC-link components of the net (grid) and load side currents, respectively.
III. VIRTUAL FLUX ESTIMATION SCHEMES

The concept of virtual flux (VF) estimation was originally proposed to improve the VOC schemes (see [21]), and was developed further for AC voltage sensorless instantaneous active and reactive power estimation. This concept allows to replace AC voltage sensors by a VF estimator. This has advantages like hardware cost reduction and system simplification. By treating the net/grid side line choke (RL-filter) and the grid voltage as the stator circuit of an AC machine (see Fig. 1 and (1)), one may introduce the virtual flux as follows

\[
\vec{\psi}_{\text{in}}(t) := (\psi^e_{\text{in}}(t) \quad \psi^\beta_{\text{in}}(t))^T := \int_0^t \vec{e}_n(\tau) \, d\tau (6)
\]

Normally, \(\vec{v}_n\) is not measured. However, it can be estimated by invoking the switching sequence (4) or the on-duty time of each phase \(T_{SW}^{abc}\) and the Clarke transformation \(T_C\) as in (3), i.e.

\[
\vec{\psi}_{\text{in}}^{(3)} = T_C \vec{v}_{\text{abc}}^{(4)} = T_C T_{SW} T_n^{abc},
\]

where \(T_n^{abc} := (T_n^a, T_n^b, T_n^c)^T\) with \(T_n^a, T_n^b, T_n^c \in [0, T_{SW}]\). \(T_{SW}\) is the switching period. \(T_n^{abc}\) can be obtained from the modulator for the indirect control schemes (e.g. VOC or DPC-SVM and MPC-SVM). Moreover, in most practical applications, the resistance of the choke (RL-Filter) on the net/grid side is very small, i.e. \(R_n \approx 0\). Hence, inserting (8) and \(R_n = 0\) into (7), yields

\[
\vec{\psi}_{\text{in}}(t) = \int_0^t \vec{e}_n(\tau) \, d\tau = \int_0^t \vec{e}_n(\tau) \, d\tau + L_n \cdot \vec{i}_n(t) - L_n \cdot \vec{i}_n(0). (9)
\]

For the remainder of this paper, it is assumed that the grid is balanced (ideal) but unknown. Hence, the grid voltage has the following form

\[
e_n = A(\cos(\omega_n t + \theta_0), \sin(\omega_n t + \theta_0))^T (10)
\]

with constant amplitude \(A\), constant initial phase \(\theta_0\) and constant angular frequency \(\omega_n\). Now the virtual flux may be written as follows

\[
\hat{\vec{\psi}}_{\text{in}}(t) = \int_0^t \vec{e}_n(\tau) \cdot d\tau = \int_0^t A \cdot (\cos(\omega_n \tau + \theta_0) \quad \sin(\omega_n \tau + \theta_0))^T \cdot d\tau
\]

\[
= A \cdot \left[ \frac{\sin(\omega_n t + \theta_0)}{\omega_n} - \frac{\cos(\omega_n t + \theta_0)}{\omega_n} \right] + \frac{A}{\omega_n} \cdot \left[ -\sin(\theta_0) \quad \cos(\theta_0) \right] \cdot \vec{\psi}_{\text{bias}}(t) = \hat{\vec{\psi}}_{\text{in}} = (\hat{\psi}_{\text{in}}^e, \hat{\psi}_{\text{in}}^\beta)^T
\]

Equations (9) and (11) are the key equalities to obtain an estimate of the net/grid voltage.

A. Estimation of Net Voltage by Filtering the Virtual Flux

From (11), due to constant \(\vec{\psi}_{\text{bias}}\), it is easy to see that \(\vec{e}_n\) can directly be computed with the knowledge of \(\vec{\psi}_{\text{key}}(t)\), since

\[
\vec{e}_n(t) = \frac{d}{dt} \vec{\psi}_{\text{in}}(t) = \omega_n \cdot \left[ -\hat{\psi}_{\text{key}}^e(t) \quad \hat{\psi}_{\text{key}}^\beta(t) \right]. (12)
\]

Now, the key question is how to extract \(\vec{\psi}_{\text{key}}\) from \(\vec{\psi}_{\text{in}}\), which can be computed by evaluating (9). Clearly, see (11), \(\vec{\psi}_{\text{bias}}\) is a constant which depends on the amplitude of the grid voltage and its initial phase. Moreover, without net/grid side voltage sensor(s), \(\vec{\psi}_{\text{bias}}\) is not available at system start. The simplest way, to extract \(\vec{\psi}_{\text{key}}\), is to use a high- or band-pass filter to filter out the constant influence of \(\vec{\psi}_{\text{bias}}\) in \(\vec{\psi}_{\text{in}}\).

Hereby, high-pass filters will be not further considered due to their undesirable amplification of noise (noise sensitivity). Moreover, first-order filters introduce an undesired phase shift (delay) to the closed-loop system dynamics, which is often not acceptable. So in recent publications (see e.g. [22]–[24]), a band-pass filter \(F_{bp}(s)\) has been proposed with a cut-off frequency at \(\omega_n\) to filter out the bias term \(\vec{\psi}_{\text{bias}}\) in (11). The (filtered) estimate \(\vec{\psi}_{\text{key}}\) of the key component \(\vec{\psi}_{\text{key}}\) in (11) is given by

\[
\vec{\psi}_{\text{key}}(t) := L^{-1} \{ F_{bp}(s) \} * \hat{\vec{\psi}}_{\text{in}}(t). (13)
\]

The proposed band-pass filter has the following transfer function (for both \(\alpha\) and \(\beta\) component)

\[
F_{bp}(s) = \frac{\hat{\psi}_{\text{in}}^\alpha(s)}{\hat{\psi}_{\text{in}}^\beta(s)} = \frac{\hat{\psi}_{\text{key}}^\alpha(s)}{\hat{\psi}_{\text{key}}^\beta(s)} = \frac{K \omega_n s}{s^2 + K \omega_n s + \omega_n^2}, (14)
\]
The frequency response (bode plot) of filter (14) is depicted in Fig. 2. The time response of (14) for sinusoidal input signals, e.g. \( \int_0^t e_n^\alpha(\tau) d\tau = \int_0^t A \cos(\omega_n \tau + \theta_0) d\tau \) as in (10), is given by: (i) for \( K = 2 \):

\[
\hat{\psi}_0^\alpha(t) = -A \frac{\cos(\theta_0) + \sin(\theta_0)}{\omega_n} \omega_n t + \sin(\theta_0) e^{-\omega_n t} + A \frac{\sin(\omega_n t + \theta_0)}{\omega_n} \tag{15}
\]

and (ii) for \( K \neq 2 \):

\[
\hat{\psi}_0^\alpha(t) = A \frac{\sin(\omega_n t + \theta_0)}{\omega_n} \tag{16}
\]

where \( M = \sqrt{K^2 - 4} \) and \( \lambda_{1,2} = \frac{\omega_n}{2}(K \pm \sqrt{K^2 - 4}) \).

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\hat{\psi}_0^\alpha(t) = -A \frac{\cos(\theta_0) + \sin(\theta_0)}{\omega_n} \omega_n t + \sin(\theta_0) e^{-\omega_n t} + A \frac{\sin(\omega_n t + \theta_0)}{\omega_n} \tag{15}
\]

and (ii) for \( K \neq 2 \):

\[
\hat{\psi}_0^\alpha(t) = A \frac{\sin(\omega_n t + \theta_0)}{\omega_n} \tag{16}
\]

where \( M = \sqrt{K^2 - 4} \) and \( \lambda_{1,2} = \frac{\omega_n}{2}(K \pm \sqrt{K^2 - 4}) \).

So, since \(-\omega_n, -\lambda_1\) and \(-\lambda_2\) have negative real parts, the terms \( e^{-\omega_n t}, e^{-\lambda_1 t}\), and \( e^{-\lambda_2 t}\) in (15) and (16) tend to zero for \( t \to \infty \). Hence, in steady state, the filter response gives the desired component \( \hat{\psi}_0 \). Analogously, for an input signal \( \int_0^t e_n^\alpha(\tau) d\tau = \int_0^t A \sin(\omega_n t + \theta_0) d\tau \), one obtains the component \( \hat{\psi}_0^\beta \). However, the initial accuracy of the filtered output depends on the filter dynamics which correlate with the real parts of the filter poles \( \Re\{-\lambda_1\} \) and \( \Re\{-\lambda_2\} \). More precisely, the transient response is related to the slowest pole, i.e. \( \max\{\Re\{-\lambda_1\}, \Re\{-\lambda_2\}\} \). For \( K = 2 \), the fastest transient response is obtained (\( \approx \frac{\omega_n}{2} = 0.016 s \)). In conclusion, in steady state, the band-pass filter (14) filters out the initial bias \( \hat{\psi}_{bias} \) without any phase shift (at \( \omega_n \)) which gives, for \( t \gg \frac{1}{\omega_n} \),

\[
\hat{\psi}_0^\alpha(t) = \hat{\psi}_0(t) \quad \text{and} \quad \hat{\psi}_0^\beta(t) = \hat{\psi}_0^\beta(t). \tag{17}
\]

However, initial deviations of the estimation are inevitable (i.e. for \( t \ll \frac{1}{\omega_n} \)). There are two ways to utilize the band-pass filter \( F_{bp}(s) \): (i) The use of a Partial Band-Pass (PBP) filter and (ii) the use of a Full Band-Pass (FBP) filter. In the following sub-sections, both filter approaches are explained in more detail and the novel Initial Bias Compensation Virtual Flux (IBC-VF) estimation scheme is introduced and compared with the conventional approaches.

B. Partial Band-Pass Filter Virtual Flux (PBP-VF) Estimation Method (see e.g. [25]–[27])

The PBP filter method applies band-pass filter (14) only to filter the integration of the (approximated) converter side voltage \( \tilde{v}_n \) as in (8), i.e.

\[
\mathcal{L}^{-1}\{F_{bp}(s)\} \ast \left( \int_0^t \tilde{v}_n(\tau) d\tau \right)
\]

\[
(1) \Rightarrow \mathcal{L}^{-1}\{F_{bp}(s)\} \ast \left\{ \int_0^t (\tilde{v}_n(\tau) - L_n \frac{d\tilde{i}_n(\tau)}{d\tau}) d\tau \right\}
\]

\[
\approx \mathcal{L}^{-1}\{F_{bp}(s)\} \ast \left\{ \tilde{\psi}_{e_n}(t) - L_n \tilde{i}_n(t) + L_n \tilde{\psi}_{bias}(t) \right\}. \tag{18}
\]

Clearly, \( \tilde{\psi}_{bias} \) will be filtered out in steady state. So an estimate for \( \psi_{key} \) is obtained by adding \( L_n \tilde{i}_n(t) \) to (18), i.e.

\[
\hat{\psi}_{key}(t) = \mathcal{L}^{-1}\{F_{bp}(s)\} \ast \tilde{\psi}_{e_n}(t) - \mathcal{L}^{-1}\{F_{bp}(s)\} \ast \left\{ L_n \tilde{i}_n(t) + L_n \tilde{\psi}_{bias}(t) \right\}. \tag{19}
\]

which gives an approximation of the desired filtered estimate as in (13).

C. Full Band-Pass Filter Virtual Flux (FBP-VF) Estimation Method (see e.g. [22], [28])

The FBP filter method applies band-pass filter (14) to filter the integration of the (approximated) converter side voltage \( \tilde{v}_n \) as in (8) and the current \( \tilde{i}_n(t) \) through \( L_n \). One obtains the following estimate \( \hat{\psi}_{key}(t) \) of the virtual flux

\[
\hat{\psi}_{key}(t) = \mathcal{L}^{-1}\{F_{bp}(s)\} \ast \left\{ \int_0^t \tilde{v}_n(\tau) d\tau + L_n \tilde{i}_n(t) \right\}
\]

\[
(1) \Rightarrow \mathcal{L}^{-1}\{F_{bp}(s)\} \ast \left\{ \int_0^t (\tilde{v}_n(\tau) - L_n \frac{d\tilde{i}_n(\tau)}{d\tau}) d\tau \right\}
\]

\[
+ \mathcal{L}^{-1}\{F_{bp}(s)\} \ast \left\{ L_n \tilde{i}_n(t) \right\}
\]

\[
\approx \mathcal{L}^{-1}\{F_{bp}(s)\} \ast \left\{ \tilde{\psi}_{e_n}(t) + L_n \tilde{\psi}_{bias}(0) \right\} = \hat{\psi}_{bias}, \tag{20}
\]

which approximates the desired filtered estimate as in (13). Inspection of (19) and (20) gives the following conclusions:

- **Steady state:** Since \( \tilde{i}_n(t) \) in (19) is a pure sinusoidal signal with frequency close to \( \omega_n \) (neglecting measurement and switching noise), \( F_{bp}(s) \ast \{ L_n \tilde{i}_n(t) \} \approx 0 \) holds true and, so, (19) equals (20).

- **Transient phase:** The FBP filter method with (19) is not accurate. Here the filter may loose information of \( L_n \tilde{i}_n(t) \) being not sinusoidal or having a different frequency than \( \omega_n \). In contrast to that, the FBP filter method in (20) is not affected.

- **Initial phase:** Due to the inevitable transient time of the filter dynamics, for both filter methods, the estimation is suffering from an initial delay time (\( \approx 1/\omega_n \)) yielding initial estimation errors. Any controller, using these
delayed estimates, will be affected and will output non-
ideal actuating signals and (large) overshoots are to be
expected e.g. in power output (see Fig. 3(a) and 4(a)).

D. Initial Bias Compensation Virtual Flux (IBC-VF) Estimation Method

Based on (9) and (11), a novel time-domain Initial Bias
Compensation Virtual Flux (IBC-VF) estimation method is
proposed in this paper. The proposed method is analyzed and
implemented in the discrete time-domain by introducing the
sampling period $T_s$ and the period

$$T_n := \frac{2\pi}{\omega_n}$$

(21)
of the grid fundamental voltage. For an arbitrary time instant
$t \geq 0$ and some signal $x(t)$, the discrete signal is written as
$x[k] := x(k T_s) \approx x(t)$. Moreover, it is assumed that $T_n$ is
a multiple of $T_s$. Hence, $T_n = N T_s$ for some fixed natural
number $N \geq 1$ (sampling instant). Now, for any $t \geq 0$ and for
a symmetrical grid, i.e. (10) holds (true in most applica-
tions), the following can be observed:

$$\sum_{i=0}^{N-1} \psi_{e,n}[i] = \sum_{i=0}^{N-1} \psi_{\text{key}}[i] + \sum_{i=0}^{N-1} \psi_{\text{bias}} = N \cdot \psi_{\text{bias}}.$$  

(22)

So, the constant$^1$ bias term $\psi_{\text{bias}}$ can be estimated after one
period $T_n$ (i.e. after $N$ samples) of the grid voltage by

$$\hat{\psi}_{\text{bias}}[N-1] = \frac{1}{N} \sum_{i=0}^{N-1} \psi_{e,n}[i].$$

(23)

So, in the $N^{th}$ sampling interval, the constant bias in (11)
can be compensated and the key component is given by

$$\forall k \geq N: \quad \hat{\psi}_{\text{key}}[k] = \psi_{e,n}[k] - \hat{\psi}_{\text{bias}}[N-1].$$

(24)

Clearly, in practice, measurement noise will deteriorate the
estimation. Therefore, to improve the VF estimate, the bias
term is updated for any new sampling instant $k > N$ by using
a shifting-average method as follows

$$\forall k > N: \quad \hat{\psi}_{\text{bias}}[k] = \frac{1}{N} \sum_{i=k-N}^{k} \psi_{e,n}[i] = \frac{\hat{\psi}_{\text{bias}}[k-1] + (\psi_{e,n}[k] - \hat{\psi}_{\text{bias}}[k-N])}{N}.$$ 

(25)

In conclusion, one may estimate the value of the key
component of the virtual flux by

$$\forall k > N: \quad \hat{\psi}_{\text{key}}[k] = \hat{\psi}_{e,n}[k] - \hat{\psi}_{\text{bias}}[k].$$

(26)

So far, still a problem remains: The estimated key compo-
nent $\hat{\psi}_{\text{key}}[k]$ of the virtual flux lags behind during the initial
estimation, i.e. for $0 \leq k \leq N$. In the following, a solution
which overcomes this drawback for all $k \geq 1$ is proposed.

$^1$Note that, $\psi_{\text{bias}}[0] = \hat{\psi}_{\text{bias}}[0] = \hat{\psi}_{\text{bias}}$ for all $t \geq 0$.

Hence, an estimation with a delay of no more than $T_s$ is
achieved. From (11) it is known that $\alpha$ and $\beta$ component of
the virtual flux are given by $\psi_{e,n}^\alpha(t) = \frac{\omega_n}{\alpha} \sin(\omega_n t + \theta_0)$ and $\psi_{e,n}^\beta(t) = \frac{\omega_n}{\beta} \sin(\omega_n t + \theta_0)$, respectively.
Considering the case $[\omega_n t \rightarrow 0$, one may rewrite the equations
above as follows

$$\lim_{\omega_n t \rightarrow 0} \psi_{e,n}^\alpha(t) = \lim_{\omega_n t \rightarrow 0} \frac{A}{\omega_n} (\sin(\omega_n t + \theta_0) - \sin \theta_0)$$

$$\lim_{\omega_n t \rightarrow 0} \psi_{e,n}^\beta(t) = \lim_{\omega_n t \rightarrow 0} \frac{A \omega_n}{\omega_n} (\cos(\omega_n t + \theta_0) - \cos \theta_0)$$

and

$$\lim_{\omega_n t \rightarrow 0} x[k] = \lim_{\omega_n t \rightarrow 0} \frac{A \omega_n}{\omega_n} (\cos \theta_0).$$

(27)

Now, for a small sampling time $T_s \ll 1$ (e.g. $T_s = 100 \mu s$ for
the employed setup) and $\omega_n t \rightarrow \omega_n T_s$ in (27), the virtual
flux is already estimated after one sampling interval by

$$\hat{\psi}_{e,n}^\alpha[1] = \lim_{\omega_n t \rightarrow \omega_n T_s} \left( \hat{\psi}_{e,n}^\alpha(t) \right) \approx \frac{AT_s}{\omega_n} \cos \theta_0.$$ 

(28)

Hence, for the initial estimation phase, the following esti-
mate of the bias component can be used:

$$\forall 1 \leq k \leq N: \quad \hat{\psi}_{\text{bias}}[k] = \hat{\psi}_{\text{bias}}[1] \equiv \frac{\hat{\psi}_{e,n}^\alpha[1]}{\omega_n T_s}.$$ 

(29)

To clarify and to ease implementation the proposed IBC-
VF estimation method, the necessary steps for the computa-
estimation/estimation are listed as quasi-code in Algorithm 1.

Algorithm 1 IBC-VF Estimation

1: function IBC-VF($\hat{\psi}_{e,n}[k], \hat{\psi}_{n}[k], k$)
2: Record first sampled values as $\hat{\psi}_{e,n}[0]$ and $\hat{\psi}_{n}[0]$;
3: if $k < 1$ then
4: Set $\hat{\psi}_{e,n}[0] = \hat{\psi}_{n}[0] = \hat{\psi}_{\text{bias}}[0]$;
5: end
6: if $k \geq 1$ then
7: Compute $\hat{\psi}_{e,n}[k]$ with (9), i.e.,
8: $\hat{\psi}_{e,n}[k] = \psi_{e,n}[k] + T_s \hat{\psi}_{n}[k] + L_n \cdot (\hat{\psi}_{e,n}[k] - \hat{\psi}_{e,n}[k-1]);$
9: if $1 \leq k \leq N$ then
10: Compute $\hat{\psi}_{\text{bias}}[1]$ with (29), i.e.,
11: $\hat{\psi}_{\text{bias}}[1] = \frac{1}{\omega_n T_s} \left( \hat{\psi}_{e,n}^\alpha[1] \right)^T$;
12: Set $\hat{\psi}_{\text{bias}}[k] = \hat{\psi}_{\text{bias}}[1]$;
13: end if
14: if $k > N$ then
15: Compute $\hat{\psi}_{\text{bias}}[k]$ with (25), i.e.,
16: $\hat{\psi}_{\text{bias}}[k] = \psi_{e,n}[k] - \hat{\psi}_{\text{bias}}[k-1] + \hat{\psi}_{e,n}[k] - \hat{\psi}_{e,n}[k-N]$;
17: end if
18: Compute $\hat{\psi}_{\text{key}}[k]$ with (26), i.e.,
19: $\hat{\psi}_{\text{key}}[k] = \hat{\psi}_{e,n}[k] - \hat{\psi}_{\text{bias}}[k]$;
20: end function
To illustrate and compare all three estimation schemes, i.e. PBP-VF (see Sec. III.B), FBP-VF (see Sec. III.C) and IBF-VF (see Sec. III.D) are implemented in Matlab/Simulink. To perform the comparison, all three estimation methods feed a Predictive Control scheme as shown in Fig. 6. Note that the design of the Predictive Control scheme is identical for all three virtual flux estimation methods (see Sec. IV). The simulation parameters are listed in Table I. The system topology is the same as depicted in Fig. 1. The simulation scenario is as follows: Within the interval [0, 0.08]s, the load side current reference has a frequency of 50Hz and a magnitude of 15A (peak). At $t = 0.04$s, the DC-link voltage reference steps up from 600V to 650V, whereas at $t = 0.08$s, the net/grid side current reference magnitude changes to 20A. The simulation results for the PBP-VF, FBP-VF and IBF-VF estimation methods are shown in Fig. 3, Fig. 4 and Fig. 5, respectively. In Fig. 3 and Fig. 4, both the PBP-VF and FBP-VF estimation methods exhibit an initial delay in the estimation response (see interval [0, 0.017]s in Fig. 3(c) & 4(c)). This delayed estimation leads to large deviations in the estimated power feedback (see interval [0, 0.017]s in Fig. 3(a) & 4(a)): System output power and reactive power show great over- or undershoots, which may become a serious issue (e.g. damaging the hardware) for real application. In contrast to that, the proposed IBC-VF method estimates the virtual flux after one sampling instant (see Fig. 5(c)). Hence, active and reactive power control show a very acceptable performance. To compare the transient performance of active and reactive power control, Fig. 3(a), Fig. 4(a) and Fig. 5(a) at $t = 0.04$s and $t = 0.08$s are inspected: Obviously, the predictive power controller using the FBP-VF estimation method, shows a better performance than that using the PBP-VF estimation method. Best performance has the predictive power controller fed by the proposed IBC-VF estimation method.

IV. PREDICTIVE CONTROL WITH IBC-VF ESTIMATION

A. Overall Control Strategy

The overall control strategy is depicted in Fig. 6. On net/grid side, a predictive power controller (PPC) is implemented which is fed by the proposed IBF-VF estimator and the output of the DC-link controller. On load side a predictive current controller (PCC) is implemented. Both predictive controllers are designed as dead-beat controllers and output reference voltages for net/grid and load side of the back-to-back converter, respectively. The corresponding switching patterns are generated by the respective SVM and so a constant switching frequency is assured. In the following the controller designs are explained in more detail.

B. Forward Euler discretization

For the discrete implementation of the predictive algorithms, prediction models are to be derived in discrete time. For sufficiently small sampling periods $T_s \ll 1$ (here: $T_s = 100\mu s$), the application of the first-order (forward) Euler discretization method

$$\frac{dX(t)}{dt} \approx \frac{X[k + 1] - X[k]}{T_s}$$

(30)

gives a sufficiently accurate approximation of time-continuous models (see e.g. [8], [29]). If the sampling interval is large...
The load side predictive (dead-beat) current controller has been considered. Estimation for a back-to-back converter with RL-load. Grid side estimated voltage in (b) and the predictive power controller (PPC on grid side) with IBC-VF estimation method in (c). Fig. 5. Simulation results for predictive control for back-to-back power converter with the proposed IBC-VF estimation method.

Fig. 6. Control structure of the predictive current controller (PCC on load side) and the predictive power controller (PPC on grid side) with IBC-VF estimation for a back-to-back converter with RL-load.

(larger than hundreds of $\mu s$ in the considered application). Euler discretization in (30) may not meet the required approximation accuracy, then more sophisticated discretization methods (like Runge-Kutta or linear multistage) should be considered.

C. Predictive Current Control (PCC) of the Load Side Converter (LSC)

Applying (30) to the load side dynamics (2) yields

$$\begin{bmatrix} v_l^\alpha[k] \\ v_l^\beta[k] \end{bmatrix} = R_l \begin{bmatrix} i_l^\alpha[k] \\ i_l^\beta[k] \end{bmatrix} + L_l \frac{T_s}{T} \begin{bmatrix} i_l^\alpha[k+1] - i_l^\alpha[k] \\ i_l^\beta[k+1] - i_l^\beta[k] \end{bmatrix}. \quad (31)$$

The load side predictive (dead-beat) current controller has the goal to drive the load side current to its reference $\vec{i}_l = (i_l^\alpha, i_l^\beta)^T$ in the very next interval, i.e.,

$$\vec{i}_l[k+1] = \hat{\vec{i}}_l[k+1]. \quad (32)$$

Inserting (32) into (31) and solving for the load side voltage gives the reference voltage

$$\begin{bmatrix} \hat{i}_l^\alpha[k] \\ \hat{i}_l^\beta[k] \end{bmatrix} = (R_l - L_l \frac{T_s}{T}) \begin{bmatrix} i_l^\alpha[k] \\ i_l^\beta[k] \end{bmatrix} + L_l \frac{T_s}{T} \begin{bmatrix} \hat{i}_l^\alpha[k+1] \\ \hat{i}_l^\beta[k+1] \end{bmatrix}, \quad (33)$$

which must then be modulated by the SVM. The future load side reference value is obtained by applying a second-order extrapolation algorithm (see [29] for more information):

$$\hat{i}_l[k+1] = 3(\hat{i}_l[k] - \hat{i}_l[k-1]) + \hat{i}_l[k-2]. \quad (34)$$

D. DC-link Controller

The objective of a DC-link voltage controller is to regulate the DC-link voltage. For simplicity, a PI controller with the following transfer function is used:

$$H_{PI}(s) = \frac{I_n^*(s)}{V_{dc}(s) - V_{dc}(s)} = \frac{K_p}{s} + \frac{K_i}{s}. \quad (35)$$

The output of the PI regulator can be regarded as the net/grid side DC-link current reference $I_n^*$ with which the “PI part” of the active power reference $P^*$ for the grid side controller is computed (see Fig. 1). Clearly, the DC-link voltage (5) also depends on the load side DC-link current $I_l$ or the load side power flow $P_l$. To improve the DC-link control performance, a rough estimate $\hat{P}_l$ of the load side resistive losses is introduced and added as feed-forward term to the active power reference as follows

$$P^*(t) = V_{dc}(t) \cdot I_n^*(t) + R_l \cdot ||\hat{i}_l(t)||^2. \quad (36)$$

$$= P_{dc}(t) \cdot \frac{I_l(t)}{K_p} \cdot \frac{R_l}{K_i}.$$

E. Predictive Power Control (PPC) of the Grid Side Converter (GSC)

According to the instantaneous power theory [30], the net/grid side instantaneous power is given by

$$\begin{bmatrix} P(t) \\ Q(t) \end{bmatrix} = \begin{bmatrix} e_n^\alpha(t) \\ e_n^\beta(t) \end{bmatrix} \cdot \begin{bmatrix} P_n^\alpha(t) \\ P_n^\beta(t) \end{bmatrix} = \begin{bmatrix} e_n^\mu(t) \\ e_n^\nu(t) \end{bmatrix}. \quad (37)$$

Note that, in view of (12) and (1), the following hold:

$$\frac{d}{dt} \begin{bmatrix} e_n^\alpha(t) \\ e_n^\beta(t) \end{bmatrix} = \begin{bmatrix} -\omega_n \cdot e_n^\mu(t) \\ \omega_n \cdot e_n^\nu(t) \end{bmatrix} \quad (38)$$

and

$$\frac{d}{dt} \begin{bmatrix} e_n^\mu(t) \\ e_n^\nu(t) \end{bmatrix} = -\frac{1}{L_n} \begin{bmatrix} e_n^\alpha(t) - e_n^\mu(t) - R_n \cdot \hat{i}_n^\alpha(t) \\ e_n^\beta(t) - e_n^\nu(t) - R_n \cdot \hat{i}_n^\beta(t) \end{bmatrix}. \quad (39)$$
Taking the time derivative of (38) and invoking (39) and (40) yields the dynamics of active and reactive power in the \( \alpha \beta \) reference frame (see also [31]) as follows:

\[
\frac{d}{dt} \left( \begin{array}{c} P(t) \\ Q(t) \end{array} \right) = \frac{1}{L_n} \left( \begin{array}{c} e^\alpha_n(t) \\ e^\beta_n(t) \end{array} \right) \left( \begin{array}{c} e^\alpha_n(t) - v^\alpha_n(t) \\ e^\beta_n(t) - v^\beta_n(t) \end{array} \right) + \frac{P_n}{L_n} (P(t) - \omega_n Q(t)) + \frac{Q_n}{L_n} (Q(t) + \omega_n P(t)). \tag{41}
\]

Applying Euler’s method (30) to (41) and re-arranging the result gives the power dynamics in discrete time:

\[
\begin{align*}
\left( \begin{array}{c} P[k+1] \\ Q[k+1] \end{array} \right) &= T_s \left( \begin{array}{c} e^\alpha_n[k] \\ e^\beta_n[k] \end{array} \right) + \frac{1}{L_n} \left( \begin{array}{cc} e^\alpha_n[k] & -v^\alpha_n[k] \\ e^\beta_n[k] & -v^\beta_n[k] \end{array} \right) \\
&\quad \left( \begin{array}{c} P[k] - \frac{T_s R_n}{L_n} P[k] - \omega_n T_s Q[k] \\ Q[k] - \frac{T_s R_n}{L_n} Q[k] + \omega_n T_s P[k] \end{array} \right) \\
&\quad \left( \begin{array}{c} P[k+1] \\ Q[k+1] \end{array} \right) - \left( \begin{array}{c} P[k] \\ Q[k] \end{array} \right) + \omega_n T_s \left( \begin{array}{c} P[k] \\ Q[k] \end{array} \right). \tag{42}
\end{align*}
\]

For predictive (dead-beat) power control (similar to predictive current control), the control objective is to achieve tracking of the apparent power reference

\[
\hat{S}^*[k+1] := (P^*[k+1], Q^*[k+1])^T
\]

within the very next sampling step, i.e.

\[
\hat{S}[k+1] = (P[k+1], Q[k+1])^T = \hat{S}^*[k+1]. \tag{43}
\]

Here, similar to the load side current reference in (34), the apparent power reference in (43) is computed by the following second-order extrapolation scheme

\[
\hat{S}^*[k+1] = 3(\hat{S}^*[k] - \hat{S}^*[k-1]) + \hat{S}^*[k-2]. \tag{44}
\]

Inserting (44) into (42) gives the reference voltage on net/grid side:

\[
\begin{align*}
\left( \begin{array}{c} \hat{e}^\alpha_n[k] \\ \hat{e}^\beta_n[k] \end{array} \right) &= \left( \begin{array}{c} e^\alpha_n[k] \\ e^\beta_n[k] \end{array} \right) - \frac{L_n}{T_s ||\hat{e}_n[k]||^2} \left( \begin{array}{c} e^\alpha_n[k] \\ e^\beta_n[k] \end{array} \right) \\
&\quad \left( \begin{array}{c} P[k+1] - P[k] - \frac{T_s R_n}{L_n} P[k] + \omega_n T_s Q[k] \\ Q[k+1] - Q[k] + \frac{T_s R_n}{L_n} Q[k] - \omega_n T_s P[k] \end{array} \right) \\
&\quad \left( \begin{array}{c} P[k+1]* - P[k] \\ Q[k+1]* - Q[k] \end{array} \right) - \left( \begin{array}{c} P[k] \\ Q[k] \end{array} \right) + \omega_n T_s \left( \begin{array}{c} P[k] \\ Q[k] \end{array} \right).
\end{align*}
\]

which is to be modulated by the grid side SVM. If no grid side voltage information is available (as for the considered sensorless case), the virtual flux estimation in Algorithm 1 must be utilized to derive the estimate \( \hat{e}_n \) for the grid side voltage by invoking (12), i.e. in discrete time:

\[
\hat{e}_n[k] = \left( \begin{array}{c} \hat{e}^\alpha_n[k] \\ \hat{e}^\beta_n[k] \end{array} \right) = \omega_n \left( \begin{array}{c} -\hat{\psi}_\text{key}^\beta \\ \hat{\psi}_\text{key}^\alpha \end{array} \right). \tag{47}
\]

Inserting (47) into (38) and (46), one finally obtains

\[
\begin{align*}
\left( \begin{array}{c} \hat{P}[k] \\ \hat{Q}[k] \end{array} \right) &= \omega_n \left[ \begin{array}{c} -\hat{\psi}_\text{key}^\beta \\ \hat{\psi}_\text{key}^\alpha \end{array} \right] \left( \begin{array}{c} \hat{\psi}_\text{key}^\alpha \\ \hat{\psi}_\text{key}^\beta \end{array} \right) \left( \begin{array}{c} \hat{e}^\alpha_n[k] \\ \hat{e}^\beta_n[k] \end{array} \right) \\
&\quad \left( \begin{array}{c} \hat{e}^\alpha_n[k] \\ \hat{e}^\beta_n[k] \end{array} \right). \tag{48}
\end{align*}
\]
predictive controllers (PCC & PPC) with the proposed initial bias compensation virtual flux (IBC-VF) estimation. The measurement results are shown in Fig. 9–14. Fig. 9 shows the estimates obtained by the proposed IBC-VF estimation method. Estimated virtual flux, estimated grid side voltage and estimated active and reactive power are almost identical to the real signals, which illustrates the effectiveness of the proposed IBC-VF method.

Fig. 11 shows control and estimation performance of the predictive power controller (PPC) with IBC-VF estimation scheme during changes in active power (by changing the load currents). The load side current reference changes from 2A to 4A at around 2.39s and back to 2A at around 6s. The DC-link voltage reference is kept constant at 200V. The reactive power reference is set to 0 var to perform an operation with unity power factor.

Fig. 10(a) shows the zoom of the load side predictive power control performance. Both the transient and the steady state response of the load side controller are fast. Fig. 10(b) shows the zoom of the a-phase voltage v.s. its current on the grid side. The good performance of the net/grid side controller – maintaining a unity power factor – is clearly visible.

Fig. 12 shows the control performance of the used DC-link controller and of the net side power controller. As can be seen in Fig. 12(a), the DC-link voltage follows the reference changes — from 180V to 230V at around 2s and from 230V back to 180V at 7s — with little overshoot and delay. The settling time is smaller than 0.3s. Fig. 12(b) shows the respective power control performance. The deviations in active power are caused by the step-like changes in the DC-link voltage.
The performance of the proposed IBC-VF scheme are shown. The load side current changes from 2A to 4A and back to 2A. The DC-link voltage reference is set to 200V and reactive power reference changes from 0var. 

In Fig. 13, reactive power control and estimation performance of the proposed IBC-VF scheme are shown. The load side current reference is kept at 4A (so the active power drawn from the grid is kept at around 280W), while the reactive power reference is changed from −50var to 100var at around 2s and then to −100var at 6s. Fig. 13(a) illustrates the decoupled dynamic performance of the proposed predictive power control scheme and the close match of estimated and real reactive power. Due to the changes in reactive power, the power factor also changes as illustrated in Fig. 13(b).

In Fig. 14 (a)–(d), the frequency spectra (with respective zooms) and the total harmonic distortions (THD) of (a) the load side current  \( i^a_l \), (b) the net side current  \( i^a_n \), (c) the estimated grid voltage  \( \hat{e}^a_n \) (each for phase  \( a \) ) and (d) the estimated net side active power  \( \hat{P} \)  are shown. In addition, Fig. 14 (e) illustrates the spectrum of the net side active power reference  \( P^e \). The THDs are computed with respect to a fundamental frequency of 50 Hz. All spectra in Fig. 14 (a)–(d) exhibit small peaks at 10kHz (see respective zooms of the spectra) which confirms a fixed (constant) switching frequency of 10 kHz of the predictive controllers with IBC-VF estimation scheme. The net side current in Fig. 14 (b) shows a noisy spectrum with frequencies ranging from 0 to 5kHz; this is due to the DC-link voltage measurement which induces measurement noise to the net side active power reference (the output of the DC-link controller, see Fig. 6 and Eq. (37)) and to the net side active power estimation (see Fig. 14 (d) & (e), resp.).

VI. CONCLUSION

This work has proposed a predictive control scheme with novel virtual flux estimation method and constant switching frequency for back-to-back power converters. The following have been realized: (i) A novel time domain initial bias compensation virtual flux (IBC-VF) estimation method has been proposed which achieves a VF estimation with time delay of only one sampling instant (instead of the time delay of filter-based VF estimation methods which require at least one period of the grid voltage). The proposed method has been compared with two band-pass filter-based methods and shows a better performance. In particular, during the initial/starting phase of the estimation, the transient and steady state accuracy are higher. (ii) The predictive current and power controller with the proposed IBC-VF estimation method have been realized in the (stationary) \( \alpha \beta \) reference frame. Park’s transformation is not required; (iii) Both, the novel virtual flux estimation and the predictive controllers have been implemented.
on a commercial-off-the-shelf FPGA platform with Single-Cycle-Timed-Loop (SCTL) technique. The implementation of the proposed scheme has been discussed in detail; (iv) The effectiveness of the proposed control scheme has been illustrated, both, by simulation and experimental results.

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