# Computationally Efficient Self-Tuning Controller for DC-DC Switch Mode Power Converters Based on Partial Update Kalman Filter

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***ABSTRACT*__ In this paper, a partial update Kalman Filter (PUKF) is presented for the real-time parameter estimation of a DC-DC switch-mode power converter (SMPC). The proposed estimation algorithm is based on a novel combination between the classical Kalman filter and a M-Max partial adaptive filtering technique. The proposed PUKF offers a significant reduction in computational effort compared to the conventional implementation of the Kalman Filter (KF), with 50% less arithmetic operations. Furthermore, the PUKF retains comparable overall performance to the classical KF. To demonstrate an efficient and cost effective explicit self-tuning controller, the proposed estimation algorithm (PUKF) is embedded with a Bányász/Keviczky PID controller to generate a new computationally light self-tuning controller. Experimental and simulation results clearly show the superior dynamic performance of the explicit self-tuning control system compared to a conventional pole placement design based on a pre-calculated average model.**

*Index Terms*— **System Identification, Switch Mode Power Converters, Digital Control. Parametric Estimation, Kalman Filter, Self-Tuning Controller.**

## I. INTRODUCTION

Adaptive and self-tuning controllers for switch mode power converter (SMPC) applications, based on system identification of the power converter parameters, are receiving increasing research attention [1-3]. This is in part due to the continuous fall in price, and improved processing performance of modern microprocessor platforms. However, due to the high computational complexity of many existing adaptive algorithms, this kind of control scheme is often not fully implemented in real-time for low-cost low-power SMPCs. Instead, the identification step is demonstrated offline using real-time data, and then the results obtained are used in the digital control design for the SMPC [4, 5]. For this reason, it is desirable to reduce the computational overhead of these adaptive algorithms to facilitate full implementation on low cost hardware and promote industrial take-up [6].

There are many self-tuning control techniques based on system identification of SMPC have been presented in the literature [4, 5, 7]. Both parametric and non-parametric identification methods have been utilised in this scheme to show the feasibility of integrating system identification in digital control design. In non-parametric identification methods, the system frequency response is determined by means of correlation analysis and used to construct an auto-tuning digital PID controller on a Xilinx Virtex-IV FPGA controlling SMPC [7, 8]. A non-parametric system identification method using the power spectrum density (PSD) computation was introduced and validated on a digitally controlled buck converter in [1]. The proposed method was verified experimentally on a high-cost Virtex6 FPGA using a VHDL-MATLAB co-simulation model. Despite the good performance achieved using the non-parametric identification methods, the implementation cost is still high as more complicated and costly embedded systems are required, which is undesirable, in particular, for small and high volume systems.

On the other hand, an indirect self-tuning adaptive controller based on parametric estimation method has been introduced in [9, 10]. Here, the discrete transfer function coefficients of SMPC are estimated using Recursive Least Squares (RLS) algorithm and the controller is designed following a pole-placement method. However, the overall complexity of this combination is high due to the requirement of a high number of mathematical operations used in RLS estimation. For this reason, the sampling frequency is selected to be much lower than the switching frequency in order to realise the proposed scheme on low-cost microcontrollers. In addition, the RLS estimation in real-time is highly affected by measurement noise and necessitates a sufficient level of perturbation to enhance the estimation accuracy and prevent estimator wind-up algorithm [3, 11]. In [3], the Kalman filter (KF) configured for parameter estimation of SMPC is introduced. The simulation and real-time results show that the KF algorithm can handle the parameter estimation task efficiently with several advantages over the classical RLS adaptive algorithm. However, this performance comes with increased computational complexity, which is proportional to the number of parameters to be estimated; in particular, the computation of adaptation gains and the covariance update. These two steps are known as the bottlenecks of the recursive algorithm, where multiplications of matrix vectors are required to update the parameter vector in each iteration. In addition, the overall complexity is prone to increase if the identification algorithm is combined with an adaptive controller such as pole-placement method.

To overcome the above mentioned issues, a new computationally efficient self-tuning control scheme based on Partial Update Kalman Filter (PUKF) is proposed in this paper. This structure uses a promising approach to controlling the computational cost of adaptive algorithms, known as a partial update (PU) scheme. In this scheme, a subset of the adaptive filter coefficients is updated at each iteration based on the data vector analysis. In parametric system identification, the achievable complexity reduction by partial coefficient updates is significant, as the number of arithmetic operations is considerably reduced [12]. Several types of partial update have been presented in the literature including sequential PU, periodic PU, M-Max PU, stochastic PU, and selective PU [13]. Here, M-Max PU methods are applied to the KF for the first time in order to reduce the computational overhead of the identification algorithm while maintaining comparable performance to the full KF. The estimated parameters of the SMPC are then used to compute and adaptively tune the control loop gains in real time based on the Bányász/Keviczky method. The effectiveness of the proposed scheme is experimentally verified on a synchronous DC-DC buck converter operating in continuous conduction mode (CCM); however, it can be easily transferred to other converter topologies. Results demonstrate the feasibility of using the PU approach in parameter estimation for SMPC, since the parameter variations are detected and estimated accurately.

In comparison to the widely used pole-placement technique, this PID controller is computationally more efficient. Therefore, the overall complexity of the self-tuning control (STC) scheme is reduced. The final solution is very well suited to power electronic applications where low cost, high performance systems are desirable.

## II. Partial Update Adaptive Filter and M-max Adaptive Algorithms Theory

Incorporating adaptive filtering algorithms in control system design has become an area of active research over the last two decades. One area of particular interest is the adaptive control of systems involving real-time system identification and robust controller tuning methods. Fig.1 shows an adaptive filter used within a typical system identification structure. Here, the parameters vector $\hat{h}(k)$ is adjusted at each iteration cycle using a recursive algorithm. However, as the dimensions of the parameter vector increase the complexity of the implemented algorithm grows accordingly, leading to a higher implementation cost for the target application. Therefore, the partial-update (PU) scheme is presented as a straightforward method to reduce the computational complexity of the adaptive filtering algorithms. In this approach, the adaptive algorithm updates part of the parameter vector instead of updating the full filter vector [12, 14].

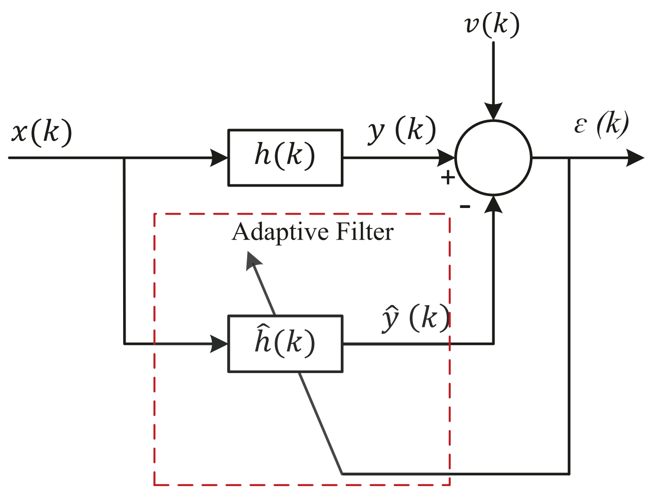



Fig. 1. An Adaptive Filter configured for system identification.

The general concept of PU scheme can be applied using many different methods. Among these methods, data-independent approaches such as the periodic PU and the sequential PU method, and the data-dependent M-Max PU technique are popular [12]. The latter approach was originally proposed by Aboulnasr *et al*. [15] with the intention of reducing the computational cost of the Normalised Least Mean Squares (NLMS). Here, the update technique is based on data vector analysis by finding a subset of the parameter vector that makes the greatest contribution to the filter output $\hat{y}(k)$ and minimise the error $\varepsilon(k)$ [15]. In other words, for a filter with $N$ coefficients, only the taps corresponding to the $M$ largest magnitudes of the data vector are updated at each time iteration [16]. This requires a prior knowledge of the application under consideration. In an SMPC system, this kind of prior knowledge can be acquired from modelling techniques such as the state space average model and by selecting an appropriate model structure. For this reason, in this paper the M-Max PU technique is adopted and developed to provide a computationally efficient parameter estimation scheme for a synchronous DC-DC buck converter based on the self-tuned KF presented in [3].

### *A. M-Max NLMS Algorithm*

Fig.1 shows an adaptive filter of length *N* used in system identification structure, in which the input regression vector is defined as $x(k) = [x(k), x(k-1), \ldots., x(k-N+1)]^T$, and the filter coefficients vector is given by $\hat{h}(k) = [\hat{h}_1(k), \hat{h}_2(k), \ldots., \hat{h}_N(k)]^T$. During the identification procedure an adaptive algorithm is used to identify the parameter vector of unknown system $h(k) = [h_1(k), h_2(k), \ldots., h_N(k)]^T$ by means of minimising the square of the error signal as follows [16]:

$$\varepsilon(k) = y(k) - \hat{y}(k) + v(k) \tag{1}$$

Where: $\hat{y}(k) = x^T(k)\hat{h}(k)$ and $v(k)$ is measurement noise. In the M-Max NLMS algorithm, the parameter vector is updated each time iteration based on a specific selection criterion where only coefficients corresponding to the largest amplitude samples in the regression vector $x(k)$ are updated [12]. Therefore, at each time instant $k$ the estimation update is computed in a recursive manner and described by:

$$\hat{h}(k) = \hat{h}(k-1) + \mu \frac{I_M(k)\, x(k) \varepsilon(k)}{\|x(k)\|^2 + \vartheta} \tag{2}$$

Here: $\mu$ and $\vartheta$ are the step-size and regularisation parameter respectively, and $I_M(k)$ is the tap selection matrix defined as:

$$I_M(k) = \begin{bmatrix} i_1(k) & 0 & 0 & 0 \\ 0 & i_2(k) & 0 & 0 \\ 0 & 0 & i_3(k) & 0 \\ 0 & 0 & 0 & i_N(k) \end{bmatrix}, i_j(k) = \begin{cases} 1 & |x(k\text{-}j\text{+}1)| \in \{\text{M maxima } |x(k)| \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Thus, the M-max updates are simply given by the *M* maxima of the magnitude of the input regression vector entries, which does not require computation of the full update vector. This results in complexity reduction for the M-max

NLMS algorithm defined by a factor of $B = M/N$, which results in significant improvement in performance compared to the fully updated NLMS if $0.5N \leq M < N$ is selected [12, 16].

*B. M-Max Kalman Filter Algorithm*

The Kalman Filter is a recursive method widely used to estimate unmeasured states and/or unknown parameters in a linear dynamic system [3, 17]. In the KF configured for parameter estimation, the state-space model for parameter estimation problem is given by:

$$\begin{aligned} y(k) &= \varphi^T(k)\theta(k) + v(k) \\ \theta(k) &= \theta(k-1) + w(k) \end{aligned} \tag{4}$$

Here, changes in the parameter vector $\theta$ are driven by random vector $w$ with covariance matrix $Q \in \mathrm{R}^{N\times N}$ , $v(k)$ is the observation noise with variance $r > 0, y$ is the measured output, and $\varphi$ denotes the regression vector. As a recursive algorithm, the KF updates the adaptive filter coefficients lumped in a vector $\hat{\theta}$ at each time iteration $k$ as [3]:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + K(k)\varepsilon(k) \tag{5}$$

where $K(k)$ is the Kalman gain, which can be computed via using a direct extension of the M-Max approach and expressed as:

$$K(k) = \frac{P(k-1)\varphi(k)I_M(k)}{r + I_M(k)\varphi(k)P(k-1)\varphi^T(k)} \tag{6}$$

In (6), $P$ is defined as the error covariance matrix that is updated at each sampling interval by the additional inclusion of a diagonal matrix $Q$ known as process noise covariance matrix to account for time-varying parameters. From which:

$$P(k) = I_M(k)P(k-1)[I(k) - K(k)\varphi^T(k)] + Q(k)I_M(k) \tag{7}$$

The diagonal elements in the matrix $Q$ are computed using the tuning method introduced in [3], which employs an iterative algorithm based on the innovation term to enhance the tracking ability of the filter in the event of any abrupt change in system parameters.

$$Q(k) = dig\{[\hat{\theta}_1(k) - \hat{\theta}_1(k-1)]^2, [\hat{\theta}_2(k) - \hat{\theta}_2(k-1)]^2, \ldots\ldots [\hat{\theta}_N(k) - \hat{\theta}_N(k-1)]^2\} \tag{8}$$

From (5) to (7) it can be seen that, when the M-Max algorithm is extended to KF, the number of multiplications required to update the error covariance matrix and hence the Kalman gain is reduced due to the presence of zero elements in the tap selection matrix $I_M$. As a result, the M-Max KF updates only the set of $M$ coefficients corresponding to the largest amplitude samples in the regression vector $\varphi(k)$ to facilitate maximum reduction in the prediction error $\varepsilon(k)$. As a result, the computational complexity of the derived M-Max KF is lower than the self-tuned KF presented in [3].

## III. Parameter Estimation of DC-DC Power Converter Using M-Max Kalman Filter

In this paper, the proposed M-Max KF approach is used in parameter estimation of a synchronous DC-DC buck converter (see Fig.2), to reduce the computational overhead of the full version introduced in [3] and to produce a new light adaptive algorithm suitable for low cost implementation.

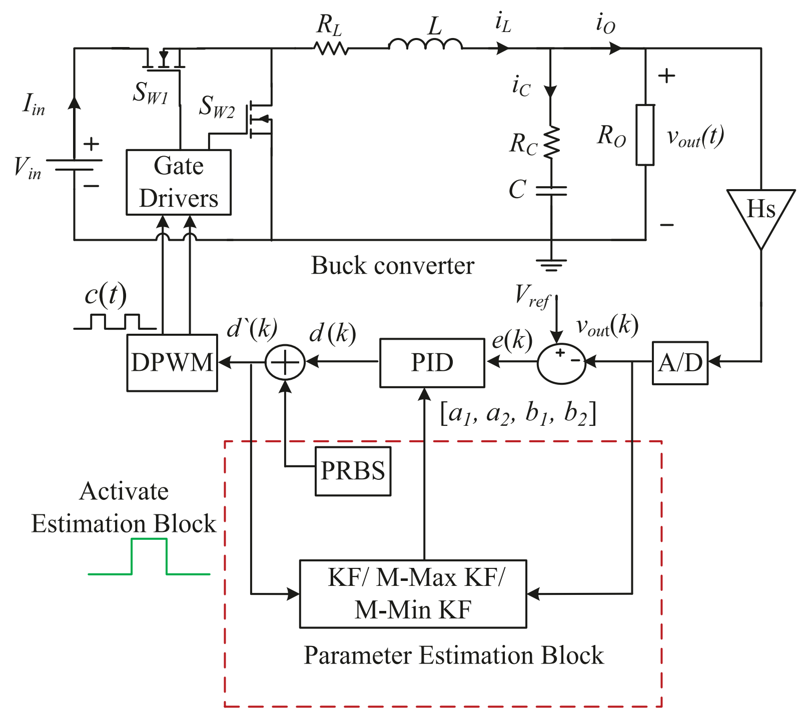



Fig. 2 The proposed STC scheme using PUKF.

As an essential step in parametric identification procedure, the discrete time model of buck converter is required. To accomplish this step, the transfer function relating the output voltage ($v_{out}$), to input duty cycle ($d$) is introduced first and expressed as follows [11]:

$$\frac{v_{out}(s)}{d(s)} = \frac{V_{in}\,(CR_C s+1)}{s^2 L\, C\left(\frac{R_C+R_o}{R_L+R_o}\right) + s\left(CR_C + C\left(\frac{R_O R_L}{R_O+R_L}\right) + \frac{L}{R_O+R_L}\right) + 1} \tag{9}$$

Where, $V_{in}$ is the input voltage, $R_O$ is the load resistance , $L$ is the inductance with DC resistance $R_L$, and $C$ is the output capacitance with equivalent series resistance $R_C$. Then, the digital equivalent transfer function is computed using a zero-order-hold mapping technique and given by:

$$G_{vd}(z) = \frac{b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \tag{10}$$

Here, $a_1$, $a_2$, $b_1$, and $b_2$ are the parameters to be estimated, which dependent on the Laplace transfer function coefficients defined in (8), and on the digital sampling time. By using the simple autoregressive model with exogenous input (ARX) model, the discrete transfer function (10) can be described as a linear difference equation in order to formulate the identification problem. This model takes into account measurement noise and modelling approximations via adding the error term $\varepsilon(k)$ as follows [18]:

$$v_o(k) + a_1 v_o(k-1) + a_2 v_o(k-2) = b_1 d(k-1) + b_2 d(k-2) + \varepsilon(k) \tag{11}$$

For system identification purposes, the system parameters are lumped in one vector $\theta = [a_1, a_2, b_1, b_2]^T$ hence equation (11) may be rewritten in vector form:

$$v_o(k) = \varphi^T(k)\theta(k) + \varepsilon(k) \tag{12}$$

In the considered buck converter, the data vector $\varphi(k)$ consists of the lagged sampled output voltage $v_o(k)$ and the lagged sampled control signal $d(k)$ as follows:

$$\varphi(k) = [-v_o(k-1), -v_o(k-2), \; d(k-1), d(k-2)]^T \tag{13}$$

From (10) and (11), the ARX model can be represented as an IIR adaptive filter employed in system identification structure with predicted output $\hat{v}_o(k \mid \theta)$ given by:

$$\hat{v}_o(k \mid \theta) = \sum_{n=0}^{m} b_n(k)\, d(k-n) + \sum_{n=1}^{l} a_n(k)\, v_o(k)(k-n) \tag{14}$$

In buck converter model $m = l = 2$ and $b_0 = 0$, and the prediction error $\varepsilon(k)$ which needs to be minimised during the identification process can be introduced as:

$$\varepsilon(k) = v_o(k) - \hat{v}_o(k \mid \theta) \tag{15}$$

According to the basics of M-Max algorithm, the adaptive filter coefficients corresponding to the largest samples $M$ in the regression vector $\varphi(k)$ are selected to be updated in the recursive identification block shown in Fig.2. This means, the update step will consider only the coefficients with the highest error contribution. To clarify that, the predicted converter output is described as a composition of two components and each component represents the corresponding contribution of the sub-filter in the overall output. As the parameter vector $\theta$ is unknown, the estimated vector $\hat{\theta} = [\hat{a}_1, \hat{a}_2, \hat{b}_1, \hat{b}_2]^T$ is used in this expression and expressed as:

$$\begin{aligned} \hat{v}_o(k \mid \hat{\theta}) &= \hat{v}_1(k \mid \hat{\theta}) + \hat{v}_2(k \mid \hat{\theta}) \\ \hat{v}_1(k \mid \hat{\theta}) &= [-v_o(k-1), -v_o(k-2)]\,[\hat{a}_1, \hat{a}_2]^T \\ \hat{v}_2(k \mid \hat{\theta}) &= [\,d(k-1), d(k-2)]\,[\,\hat{b}_1, \hat{b}_2]^T \end{aligned} \tag{16}$$

Practically, the duty cycle is selected to be $0.1 < d(k) < 0.9$ that means when the desired output voltage is higher than 1V, the filter coefficients corresponding to the lagged output voltage are selected to be updated each time iteration. For instance, the investigated model in [3, 6], the targeted output voltage ($v_o$) is 3.3 V and the control signal ($d$) is around 0.33 in steady state operation. Accordingly, the denominator coefficients $[a_1, a_2]$ are chosen for the update step as their contribution in the filter output and hence in the prediction error $\varepsilon(k)$ (see 15) is higher than the numerator coefficients $[b_1, b_2]$ contribution in the filter output as described in (16). Therefore, the parameters $[b_1, b_2]$ are considered less important, and the algorithm performance is only slightly affected if they are not updated at a given iteration as addressed in the M-Max NLMS when $0.5N \leq M < N$ is selected. This results in 50 % complexity reduction compared to the full KF ( $B = M / N$ ; with $N = 4$ and $M = 2$).

Importantly, in some applications the accuracy of the estimated parameters is crucial hence the performance of the PU estimator is required to be the closest to the full version. For that reason, the PU algorithm proposed in [19] is extended here and used to produce a modified version of the original M-Max algorithm. This modification entails the full estimator to be run early in the identification process for a short time (see Fig.3), then the less important parameters are fixed for the rest of identification period. This means, the only term will be computed using the full parameter vector with length *N* is the prediction error every time iteration and the rest of algorithm sequence is performed on the sub filter coefficients with length *M*. From this, the prediction error used in the update step describes the contribution of all parameters in the filter output $\hat{v}_o(k)$ that will produce more accurate estimation as the lees important filter coefficients are considered. In the same manner, the less important coefficients can be updated periodically if required to monitor any slow variation such as ageing in the passive components in the DC-DC converters. This is accomplished by means of adjusting the corresponding elements in the tap selection matrix $I_M(k)$ in the following order:

$$I_M(k) = \begin{bmatrix} i_1(k) & 0 & 0 & 0 \\ 0 & i_2(k) & 0 & 0 \\ 0 & 0 & i_3(k) & 0 \\ 0 & 0 & 0 & i_N(k) \end{bmatrix}, i_j(k) = \begin{cases} 1 & |x(k\text{-}j\text{+}1)| \in \{\text{M minima } |x(k)|\} \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

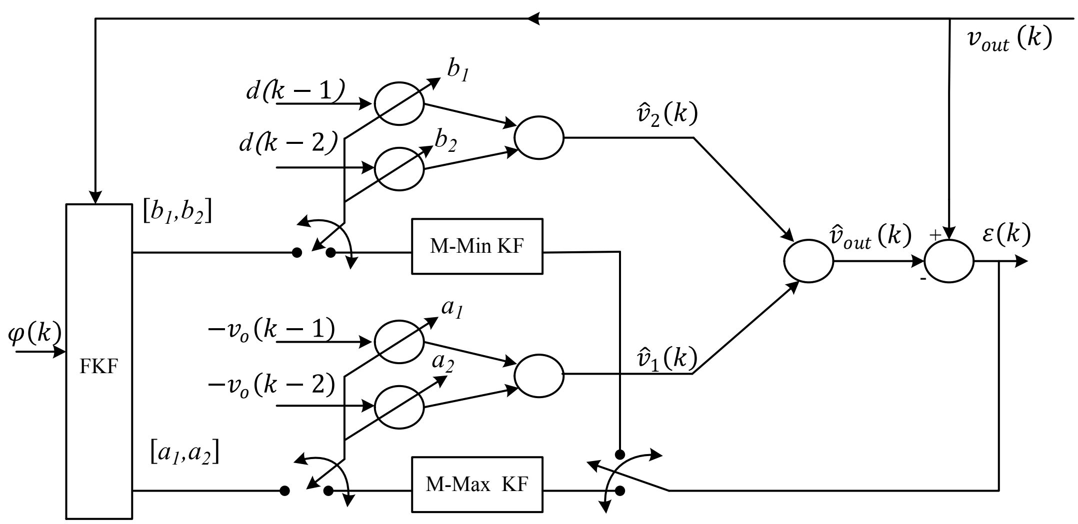



Fig. 3. Block diagram of the proposed PU structure.

To demonstrate the advantages of the proposed algorithm, Table I illustrates the required number of arithmetic operations when the proposed M-Max KF is applied and compared with the full version KF in Table II. In Table I the initial choices of the system parameters $\hat{\theta}(0)$ and covariance matrix $P(0)$ are selected by the designer, and the role of experience and intuition is paramount.

TABLE I

RELATIVE COMPUTATIONAL COMPLEXITY OF THE PROPOSED M-MAX PUKF

| Step | Formula | × | + | ÷ |
|---|---|---|---|---|
| Initialisation | $P(0) = g * I,\ and\ \hat{h}(0) = 0,$ where $I$ is an $N \times N$ identity matrix, g is large number, $r$ is scaler > *0,* $Q$ is diag $[Q_{11}, Q_{22}, .., Q_{NN}]$ | | | |
| | *Do for k* $\geq 1$ | | | |
| 1 | $\varepsilon(k) = y(k) - \varphi^T(k)\hat{\theta}\ (k-1)$ | $N$ | $N$ | - |
| 2 | $K(k) = \dfrac{P(k-1)\varphi(k)I_M(k)}{r + I_M(k)\varphi(k)P(k-1)\varphi^T(k)}$ | $2M^2+M$ | $2M^2-M$ | 1 |
| 3 | $\hat{\theta}(k) = \hat{\theta}(k-1) + K(k)e(k)$ | $M$ | $M$ | - |
| 4 | $Q_{ii}(k) = [K(k)e(k)]^2$ | $M^2$ | $M$ | - |
| 5 | $P(k) = I_M(k)P(k-1)[I(k) - K(k)\varphi^T(k)] + QI_M(k)$ | $2M+M^3$ | $2M+M^3$ | - |

TABLE II

RELATIVE COMPUTATIONAL COMPLEXITY IN TERMS OF COMPARISON

| Algorithm $N > M$ | × | + | ÷ |
|---|---|---|---|
| Full update KF | $5N+3N^2+N^3$ | $4N+2N^2+N^3$ | 1 |
| M-Max PUKF | $N+4M+3M^2+M^3$ | $N+3M+2M^2+M^3$ | 1 |

## IV. THE PROPOSED DIGITAL SELF-TUNING CONTROLLER BASED ON BÁNYÁSZ/KEVICZKY SCHEME

Due to the rapid and significant development in digital signal processors and microcomputers, designing and implementing a complete explicit STC, as illustrated in Fig.4, has become achievable even for low-cost applications such as SMPC. A direct digital control design approach can be used to compute the controller gains online relying entirely on the estimated discrete model as it is common in this design scheme to construct the regulator based on the inverse of the process model [20].

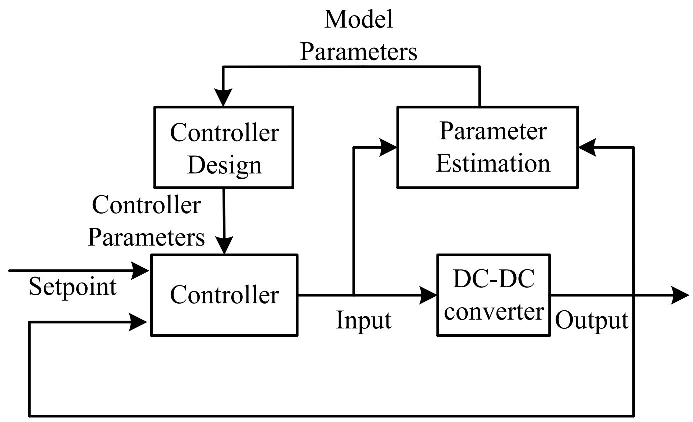



Fig.4. Explicit self-tuning control for SMPC.

For a voltage-mode buck regulator, two zeros are needed to compensate for the second order plant (power stage) and a pole at the origin is needed to minimise steady-state error [21]. In practice, the discrete PID regulator is the commonly used strategy in buck DC-DC converters. Therefore, the discrete PID controller in its direct form as a two zeros, one pole transfer function is selected and expressed as:

$$G_{PID}(z) = \frac{q_0 + q_1 z^{-1} + q_2 z^{-2}}{1 - z^{-1}} = \frac{Q(z^{-1})}{1 - z^{-1}} \tag{18}$$

In (18), the controller parameters are computed using only the estimated discrete transfer function. This approach is known as Bányász/Keviczky PID controller [22]. Here, the discrete transfer function in (10) is assumed to be stable, second order dead-time lag and given by:

$$G_P(z) = \frac{B(z^{-1})}{A(z^{-1})} = \frac{b_1(1 + \gamma z^{-1})}{1 + a_1 z^{-1} + a_2 z^{-2}}\ z^{-de} \tag{19}$$

Where: $de > 0$ is the time delay steps of the process, $\gamma = \frac{b_2}{b_1}$, and $b_1 \neq 0$. For the given process specifications, the controller polynomial $Q(z^{-1})$ is chosen to be proportional to the denominator of the controlled process and can be defined as:

$$Q(z^{-1}) = q_0(1 + a_1 z^{-1} + a_2 z^{-2}) = q_0 + q_1 z^{-1} + q_2 z^{-2} \tag{20}$$

This implies:

$$q_1 = q_0 a_1, \qquad q_2 = q_0 a_2 \tag{21}$$

Consequently, the control loop is simplified and given by:

$$G_P(z)\ G_{PID}(z) = \frac{k_I(1 + \gamma z^{-1})}{1 - z^{-1}}\ z^{-de} \tag{22}$$

The obtained transfer function in (22) involves a pure time delay connected in series with an integrator gain that given by the following relationship:

$$k_I = q_0 b_1 \tag{23}$$

The controller parameters can finally be computed by the application of the following formula:

$$q_0 = \frac{k_I}{b_1} \tag{24}$$

$$q_1 = q_0 a_1 \tag{25}$$

$$q_2 = q_0 a_2 \tag{26}$$

$$\text{for } \gamma = 0 \rightarrow k_I = \frac{1}{2de - 1} \tag{27}$$

$$\text{for } \gamma > 0 \rightarrow k_I = \frac{1}{2de(1+\gamma)(1-\gamma)} \tag{28}$$

The relations tips (23-28) and (18) are then used to calculate the controller output (the duty cycle) by:

$$d[k] = q_0 e[k] + q_1 e[k-1] + q_2 e[k-2] + d[k-1] \tag{29}$$

## V. Simulation Results

To investigate the overall performance of the proposed STC scheme including the M-Max PUKF and the Bányász/Keviczky PID controller, a voltage controlled synchronous DC-DC buck SMPC circuit is simulated using MATLAB/Simulink identically to that in Fig. 2. The circuit parameters of the buck converter are the following: $R_O$ = 5 Ω, $R_L$ = 63 mΩ, $R_C$ = 25 mΩ, $L$ = 220 μH, $R_{DS(on)}$ = 18 mΩ, $C$ = 330 $\mu$F, the sensing gain is $Hs$ = 0.5, and $V_{in}$ = 10 V. The buck converter is switched at 20 kHz using conventional pulse width modulation and the output voltage is also sampled every 50 μs. To justify the identification results, the discrete model of the buck converter is calculated in advance, at a sampling time of 50 μs and given by:

$$G_{vd} = \frac{0.2262 + 0.1119\, z^{-2}}{1\text{-}1.913\, z^{-1} + 0.946\, z^{-2}} \tag{30}$$

The output voltage is regulated at 3.3V using a digital PID voltage controller. The fixed PID parameters are computed using the well-recognised pole-placement technique and expressed in the following transfer function:

$$G_C(z) = \frac{4.672 - 7.539\, z^{-1} + 3.184\, z^{-2}}{(1 - z^{-1})(1 + 0.374\, z^{-1})} \tag{31}$$

In addition to the step-down converter, the simulated model is constructed identically to that in Fig. 2, and the system identification sequence is performed step by step as described by the flowchart in Fig. 5. Firstly, the identification procedure is enabled whilst the converter is in steady-state operation. Simultaneously, a 9-bit Pseudo Random Binary Sequence (PRBS) is injected into the feedback loop as a frequency rich excitation signal for 25 ms as shown in Fig.6 (a). This is adequate to demonstrate the convergence time for full KF and PUKF. In order to avoid causing large ripples in the output voltage, the magnitude of PRBS signal is selected to be ΔPRBS = ± 0.025. This perturbation signal is approximately ± 2.5% with respect to the nominal DC output voltage under normal operating conditions. During this period, the full KF is activated for 10 ms, to identify the full parameter vector $[a_1, a_2, b_1, b_2]$ as shown in Fig. 6. After the first stage is accomplished, the numerator coefficients $[b_1, b_2]$ are fixed and exported to the M-Max KF and to the PID block as depicted in Fig. 2.

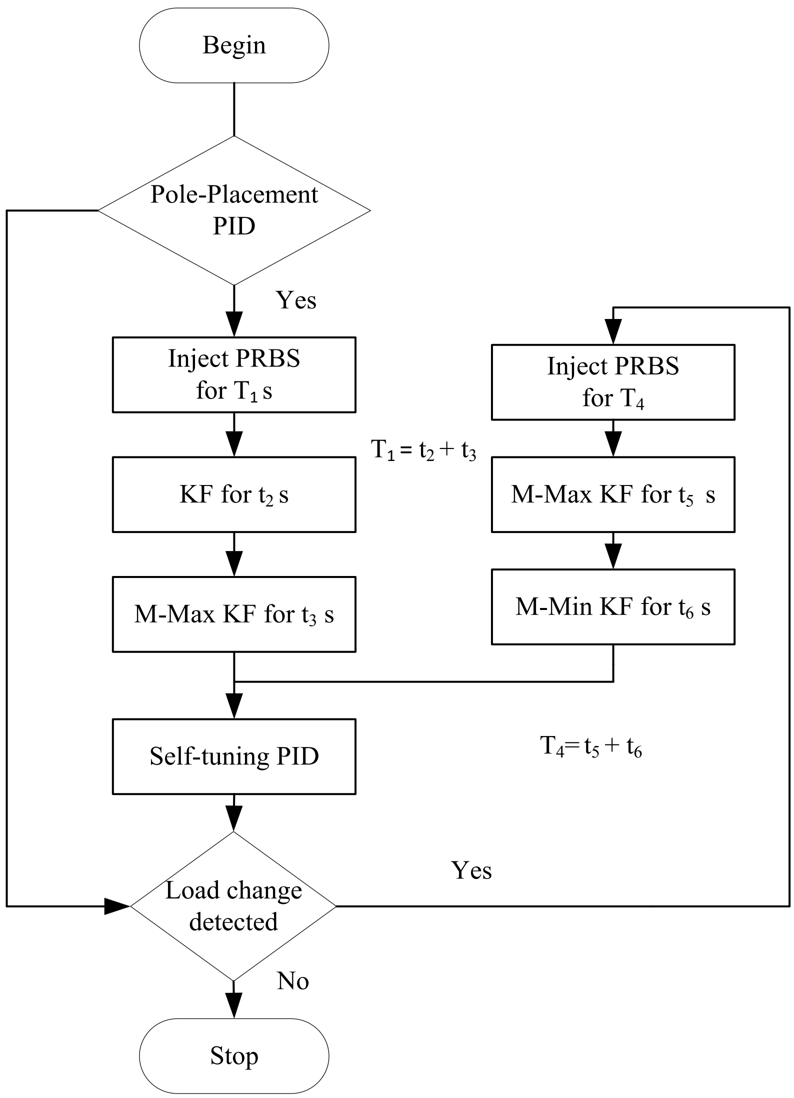



Fig. 5. Parameter estimation and STC flowchart.

Once the full update KF is disabled, the M-Max KF is enabled, and the update of the denominator coefficients [$a_1$,$a_2$] commences at each time iteration for the rest of the identification procedure. Fig.7 illustrates the online parameter estimation results obtained using the M-Max KF algorithm. Here, the proposed adaptive algorithm rapidly identifies the selected subset of the adaptive filter coefficients [$a_1$,$a_2$] with final estimation values very close to the full KF and within the same convergence time about 1 ms (see Fig.7(a)). Additionally, the prediction error converges to very small value close to zero indicating a good performance of the PUKF (Fig.7 (b)).

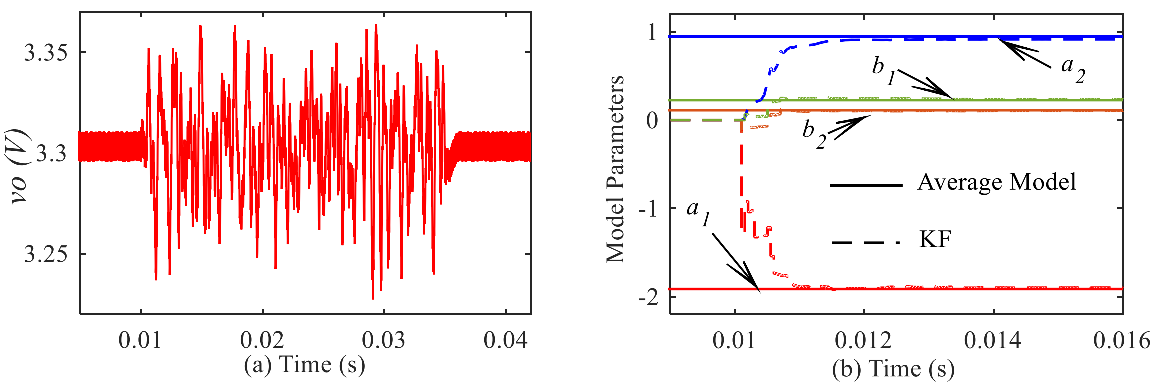



Fig. 6. Identification sequence, a: output voltage during enable 1 period, b: estimated model parameters using full KF.

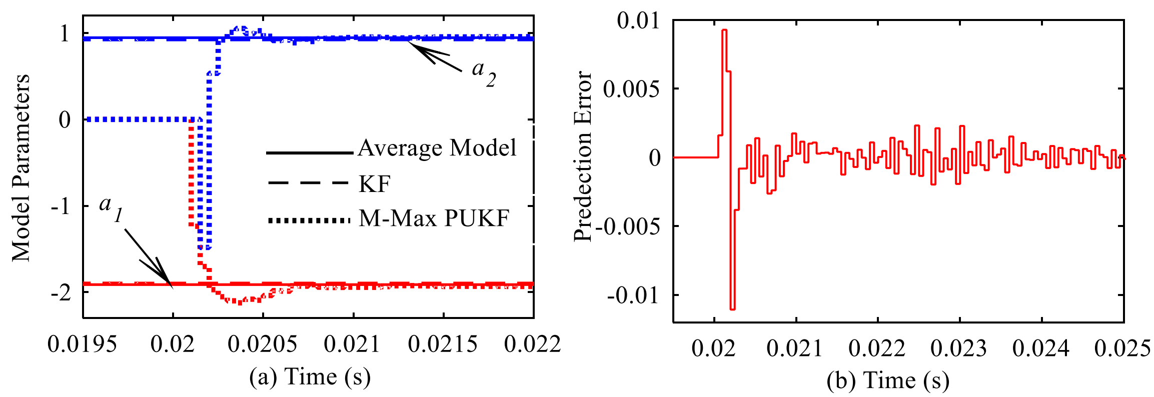



Fig. 7. Online parameter estimation results using M-Max KF. (a) Denominator coefficients. (b) Prediction error.

After the PRBS signal is disabled, and the discrete transfer function is fully estimated. Now the control action can be computed online using the previously described self-tuning Bányász/Keviczky PID controller in PID block, then the output voltage position is regulated by means of explicit STC designed using only the estimated discrete transfer function. In SMPC, a significant load variation can occur unexpectedly. Therefore, a derivative action is added to the designed STC to damp out any oscillation caused by the pure integral gain obtained in (22), accordingly, the controller output is computed as:

$$d[k] = q_0 e[k] + q_1 e[k-1] + q_2 e[k-2] + d[k-1] + K_D(e[k] - e[k-1]) \quad (32)$$

To demonstrate the dynamic behaviour of the proposed STC scheme, a periodic step load change from 5 Ω-to-2.5 Ω starting at 0.05 s is introduced. As depicted in Fig.8, when a repetitive load disturbance change is applied, a quick recovery with small overshoot and undershoot to the reference value is accomplished, with the maximum overshoot kept less than 5% of the desired output voltage. This performance demonstrates the successful design of the proposed STC scheme Bányász/Keviczky PID as a control method and the M-Max PUKF algorithm for online parameter estimation.

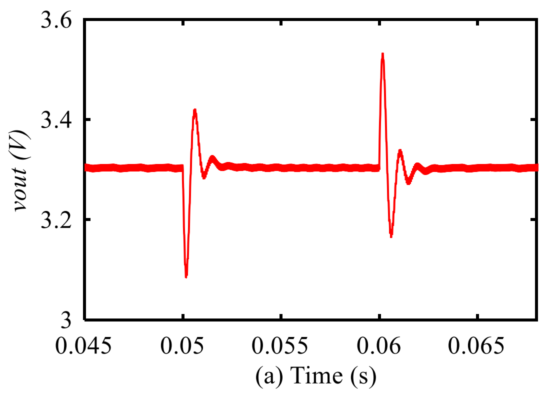



Fig. 8. Transient response of the proposed STC with *de* =2 and $K_D$= 0.5.

Secondly, the previous steps are repeated to evaluate the robustness of the STC and the proposed estimator by means of applying a significant load step from 5 Ω-to-1 Ω at 0.05 s. After the load change is detected, the PRBS block is enabled to perturb the output voltage as shown in Fig. 9 (a). This will improve the estimation accuracy and convergence time. At the same time, the M-Max PUKF is enabled to identify the selected subset of the adaptive filter coefficients $[a_1, a_2]$ every time iteration. Fig. 9 (b) illustrates the identification results using the M-Max PUKF technique. The transfer function poles are compared to the pre-calculated parameters at 1 Ω and show a very good match. Moreover, it can be seen that the estimation converges to steady state values in less than 2 ms and the prediction error converges to a small value very close to zero within the same time as shown in Fig. 9 (c). Having the new estimated load value, the controller action is updated online and the estimator block is disabled to reduce the computational load at steady state. This typical scenario is commonly applied in this field, as the estimator block can be activated again if a significant change in the loop error is detected.

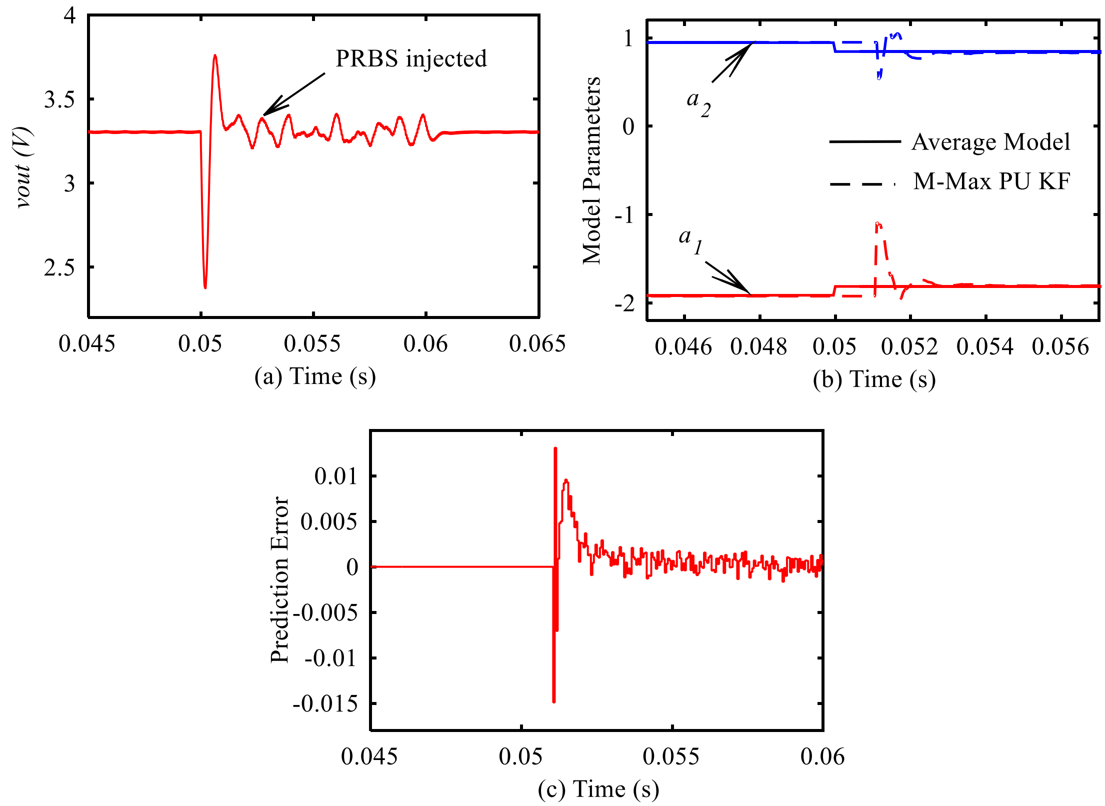



Fig. 9. Online parameters estimation during a step load change from 5 Ω to 1 Ω, a: Output voltage, b:M-Max PUKF estimation, c: Prediction error.

Following, the periodic M-Min KF is enabled to estimate the numerator coefficients $[b_1, b_2]$ using the same strategy applied in the M-Max KF. Fig. 10 shows the M-Min PUKF estimation convergence to steady state in less than 3 ms with accuracy range ± 4%.

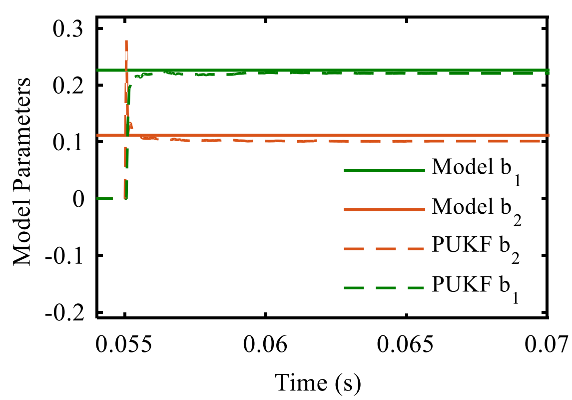



Fig. 10. The estimation results using M-Min PUKF.

According to the simulation results, the proposed M-Max PUKF is proven to be a reliable algorithm and can be employed in parametric system identification as well as in optimal explicit STC scheme. As the less important coefficients $[b_1,b_2]$ are fixed during the steady state and when the load change is applied, their small effect on the prediction error and on the accuracy of the proposed M-Max PUKF algorithm is clearly observed. The obtained estimation results using the identification scheme in Fig. 6 are compared and presented in Table III with the discrete average model and full KF estimation at 5 Ω and O.

TABLE III.

DISCRETE TIME CONTROL-TO-OUTPUT TRANSFER FUNCTION IDENTIFICATION

| Parameter | | KF | M-MAX PUKF | Model |
|---|---|---|---|---|
| | $a_1$ | -1.897 | -1.923 | -1.913 |
| | $a_2$ | 0.9233 | 0.950 | 0.945 |
| | $b_1$ | 0.2321 | fixed 0.2321 | 0.2259 |
| | $b_2$ | 0.1023 | fixed 0.1023 | 0.1118 |
| | $a_1$ | -1.8 | -1.840 | -1.814 |
| | $a_2$ | 0.822 | 0.852 | 0.8437 |
| | $b_1$ | 0.219 | fixed 0.2321 | 0.2243 |
| | $b_2$ | 0.096 | fixed 0.1023 | 0.1062 |

As illustrated in Table III and in Fig.8, the effect of load change on $b_1$ and $b_2$ is very small and can be ignored, which allows the estimator to identify the new values of $a_1$ and $a_2$ accurately after a step load change is applied with 0.002 s convergence time and 1.4% estimation error for $a_1$ and around 1% estimation error for $a_2$. Moreover, in SMPCs the absolute values of numerator coefficients are further minimised as the switching frequency is increased [23]. Therefore, their corresponding formulae (23, 24, and 28) in computing the controller parameters can be computed only once and used for all load values. This results in an additional 50% complexity reduction in the controller scheme. Here, only the denominator coefficients are updated in each time iteration as they are important in stability analysis and in the pole-zero cancellation technique adopted in the Bányász/Keviczky PID controller.

VI. EXPERIMENTAL VALIDATION OF THE PROPOSED STC BASED ON M-MAX KF

The experimental validation is performed using a prototype 5 W synchronous DC-DC buck converter. The converter parameters are selected to be the same as those outlined in Section V. The output voltage is initially regulated at 3.3 V using the digital PID voltage controller (31) embedded on a Texas Instruments TMS320F28335 digital signal processor (DSP) platform (Fig. 11). In addition to the digital controller, the DSP hosts the identification process and the STC scheme described in section IV. This is accomplished via using the Embedded Coder Support package in MATLAB/Simulink to generate C code for all related blocks in the Simulink model and to run the configured model in real time using 'External Mode'. Firstly, the converter operates in steady state and a practical implementation of the simulation procedure in section V is conducted on the DSP. This includes, the real-time implementation of the full KF, M-Max KF, and the online design of the STC.

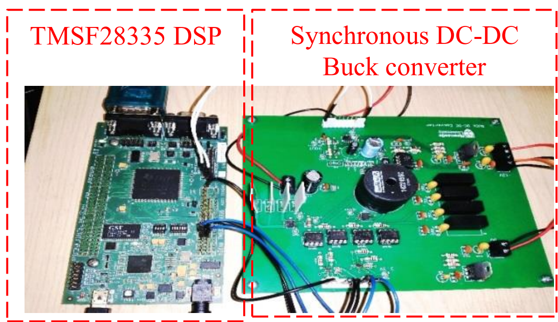



Fig. 11. Experimental setup of a synchronous buck converter for explicit STC.

### *A. Parameter Estimation Using M-Max PUKF*

Initially, the full update KF is activated to identify the coefficients of the discrete transfer function $[a_1, a_2, b_1, b_2]$ as shown in Fig.12 (a). Once full estimation is accomplished, the developed M-Max PUKF is enabled to estimate the selected subset of the adaptive filter coefficients $[a_1, a_2]$. Figure 12 (b) illustrates the estimation results using the developed M-Max PUKF. Apart from the small decrease in accuracy of coefficient $a_2$ , the selected parameters $a_1, a_2$ converge to steady state-values in less than 1 ms which demonstrates excellent agreement with the simulation results shown in Fig. 7 (a), thus confirming the successful real-time implementation of the proposed M-Max PUKF as a reliable estimator. Now, in order to update the full parameter vector, a periodic PUKF is enabled to estimate the less important coefficients, here $[b_1, b_2]$. As shown in Fig.12 (c), comparable results with those of the full estimator in terms of accuracy are achieved, while a longer convergence time approximately 3 ms is observed due to their small error contribution. Notably, the execution time of the proposed PUKF, measured in real time using Code Composer Studio, is about 18 μs which indicates around 50% complexity reduction compared to the full KF.

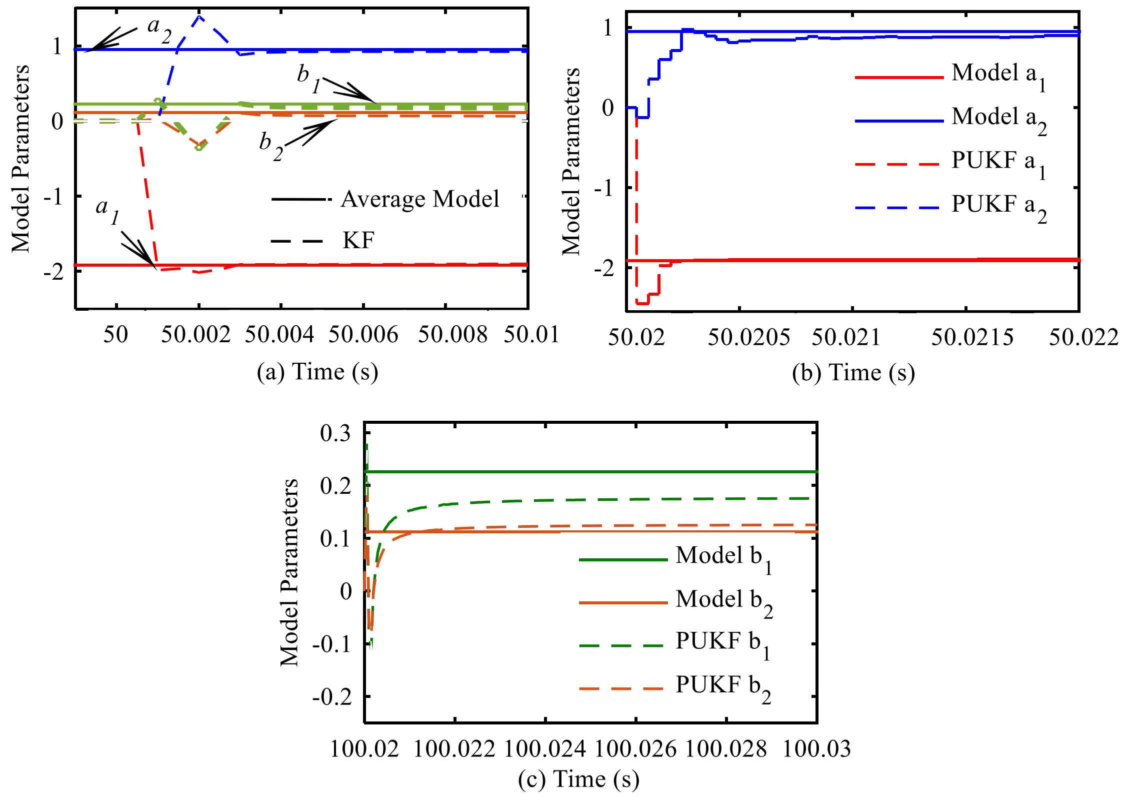
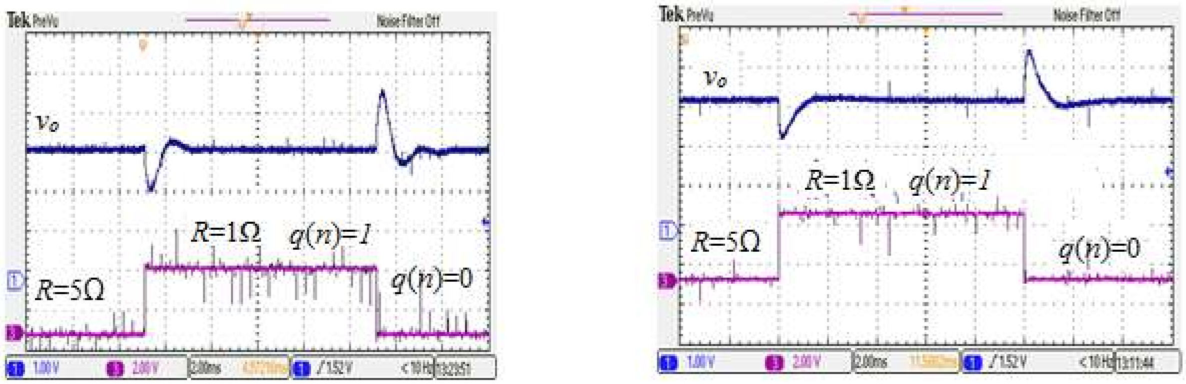



Fig. 12. Real-time parameter estimation using, a: full KF, b: M-Max PUKF, c: M-Min PUKF.

### *B. Improved Transient Response with Proposed STC*

Once the discrete transfer function is fully estimated, the self-tuning Bányász/Keviczky PID controller is then activated to regulate the output voltage at 3.3 V. As an important factor in assessing the designed STC, the converter is subjected to a step load change to investigate the dynamic performance. This test is conducted for a significant load change between 5 Ω to 1 Ω every 10 ms as shown in Fig 13. Here, the step load change is applied at regular intervals as desired using the GPIO pin configured as a digital output $q(n)$ (see Fig 13) to switch (Power MOSFET IRF7103PbF) controlling the load dynamics. To evaluate the transient characteristics of the designed STC, the same test is applied on the buck converter controlled using the well-recognised pole-placement technique. The waveforms in Fig 13 show a comparison of the load transient responses of the pole-placement PID controller and the designed explicit STC scheme respectively. In Fig. 13 (a), it can be seen that the output voltage transient shows significant oscillatory behaviour at the points of load change. Here the output voltage recovers to 3.3 V (reference value) in 1.8

ms with 48% overshoot. In contrast, the self-tuning improves the dynamic characteristics of the controller (Fig. 13 (b)), resulting in a significantly faster recovery time in 1.2 ms and lower transient overshoot of 38%.




(a)

(b)

Fig. 13. Transient response of the closed loop system with abrupt load change between 5Ω and 1Ω. (a) Pole placement controller. (b) The proposed STC.

## VII. Conclusions

This paper has presented a new computationally efficient self-tuning control scheme, which adaptively estimates the discrete transfer function of the DC-DC buck converter and compute the controller gains online. The proposed estimation algorithm is based on a novel combination between the classical Kalman filter and the M-Max partial adaptive filtering technique. This adaptive algorithm is based on the data vector analysis in partial update implementation. In DC-DC buck converter, the denominator coefficients $[a_1,a_2]$ are appointed as the more important parameters according to the data vector analysis and the importance of system poles in terms of stability and control design. As a result, the M-Max KF achieves around 50% computational complexity reduction in comparison with the full KF. In addition to the development of a low complexity estimation algorithm, the explicit STC scheme is constructed using a simple and robust control design method, which applies the discrete time model to calculate the controller elements. In doing so, there is a substantial reduction in the number of arithmetic operations compared to the well-known pole placement technique. Simulation and experimental results based upon a prototype synchronous DC-DC buck converter controlled by Texas Instruments TMS320F28335 DSP, show that the viability of adopting PU method in real-time parameter estimation for DC-DC converters. The developed M-Max KF provides fast convergence speed, small prediction error, and accurate parametric estimation very close to the full KF. Furthermore, the results confirmed the feasibility of integrating the PUKF with low complexity adaptive control scheme such as Bányász/Keviczky PID controller method in real-time. Additionally, the final set of experimental results demonstrate an enhancement in the overall dynamic performance of the closed loop control system compared to the conventional PID controller designed based on a pre-calculated average model. Noticeably, the identification procedure using full KF, PUKF, and controller design is completely executed on real-time hardware, without any remote intermediate post processing analysis.

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