Advances on System Identification Techniques for DC-DC Switch Mode Power Converter Applications

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ABSTRACT

System identification is fundamental in many recent state-of-the-art developments in power electronic such as modelling, parameter tracking, estimation, self-tuning and adaptive control, health monitoring, and fault detection. Therefore, this paper presents a comprehensive review of parametric, non-parametric, and dual hybrid system identification for DC-DC Switch Mode Power Converter (SMPC) applications. The paper outlines the key challenges inherent with system identification for power electronic applications; speed of estimation, computational complexity, estimation accuracy, tracking capability, and robustness to disturbances and time varying systems. Based on literature in the field, modern solutions to these challenges are discussed in detail. Furthermore, this paper reviews and discusses the various applications of system identification for SMPCs; including health monitoring and fault detection.

***Index Terms*— System Identification, Switch Mode Power Converters, Digital Control, Parametric Estimation, Non-Parametric Estimation.**

I. INTRODUCTION

A. System Identification Overview and Motivations

The objective of system identification is to capture the dynamic behaviour of a system based on measured data [1]. In a rigorous mathematical sense, system identification involves the construction of the model that most closely resembles the dynamic characteristics of the system (here, SMPC), based on observed data [2]. Typically, a frequency rich signal is injected into the control loop which, along with measurement of the resultant system output, is “processed” to derive a representative system model [3]. The system of interest is normally treated as a black-box model. The model structures are classified into two types: black box and grey box [2]. In the black box model, there is no prior information about the internal constituents of the system or the physical modelling of the system. Here, the choice of the model structure and the estimation of the parameters of the system are accomplished based on observed data from the system [4, 5]. When the error between the real system output and the corresponding model output is minimised an accurate model of deemed to have been obtained. In the grey box model, the system dynamics and the model structure are partially known in advance. The remaining unknown coefficients are estimated from the measured data. This prior information can be used as a benchmark to analyse the estimated model. In addition, it can improve the convergence of the applied algorithm. As an illustrative example, power converter parameters such as the output capacitance, or inductance, can be used as known coefficients and initially utilised to calibrate the grey box model [6].

In general, there are also two categories of system identification technique; on-line and off-line system identification [3, 7, 8]. In the on-line paradigm, real-time data is obtained and used immediately to identify the unknown characteristics of the system. Recursive Least Squares (RLS) is perhaps the most recognisable method of on-line system identification. Adaptive control schemes incorporate this approach to adapt the controller gains at regular intervals. This is accomplished in two phases. In the first step, system performance is monitored, and the dynamic characteristics of the closed loop system are actively identified, providing real time estimation of the model parameters. In the second step, the control parameters are fine-tuned according to the uncertainties of the system and this results in profound improvement in the dynamic performance of the system [9]. On-line health monitoring and fault detection are advanced features which can be incorporated into this structure. In the off-line paradigm, measured data is stored in memory; a typical approach uses a block array of memory. Once full, the array of observed signals is post-processed to establish the system model. This process is often referred to as “batch estimation” and can be adopted when modelling highly complex systems [7]. The estimated model is then used to design the desired control loop to achieve specific dynamics [3].

A large body of research has been carried out in the field of system identification for DC-DC Switch Mode Power Converter (SMPC) applications. Key motivations for applying system identification techniques, include:

1) Mathematical modelling: Many approaches establish an average model based on linear analysis. It is significantly more complicated to establish an accurate SMPCs model considering the intrinsic non-linearity of the system [10, 11].

2) Fundamental Control System Design: Many control approaches rely on an accurate model of the system (often represented as a transfer function) to design a robust controller; for instance, the well-established pole placement technique [12, 13].

3) Advanced self-tuning and real time adaptive control design. A major challenge in complex systems is overcoming system variability. In SMPCs uncertainties arise from ageing effects, component tolerances, parasitic elements, and unpredictable time varying load changes [14-16].

4) Real time monitoring of systems and devices. Real time monitoring facilitates, new condition monitoring, and fault detection schemes; for example, temperature monitoring of power devices, short/open circuit detection, and capacitor failure [17-20].

All these functions can now readily be implemented and applied in power electronics applications due to the proliferation of new low-cost, high performance Digital Signal Processors (DSPs) and Field Programmable Gate Arrays (FPGAs)[21]. Enhancements in digital hardware and modern software tools enable power electronics control engineers to develop a wide variety of system identification and control algorithms [22]. As a result, system identification for advanced SMPC design and control is gaining both academic and industrial interest [23].

B. Fundamental Challenges in System Identification of SMPCs

There are several fundamental challenges in system identification of SMPCs [24], these are linked to:

1) The computation complexity of the estimation algorithms.
2) Suitability for on-line and real time implementation with closed loop operation.
3) Speed and accuracy of the estimation process.
4) Cost of implementation.
5) Ability to deal with rapid real time changes.
6) Minimising the effect on the output of SMPC.

Fig.1 summarises recent innovations on system identification for SMPCs to address these implementation challenges. In this paper, we classify the literature according to the system identification methodology (parametric or non-parametric) adopted, and the fundamental technique applied. As shown in Fig.1, parametric estimation is divided into three schemes; iterative/recursive schemes, non-iterative schemes, parametric modelling schemes. Likewise, non-parametric schemes are divided into three: correlation estimation schemes, network-analyser schemes, and power spectrum density (PSD) schemes. Finally, dual estimation methods are also shown Fig.1, which use both system identification structures (parametric/ non-parametric).

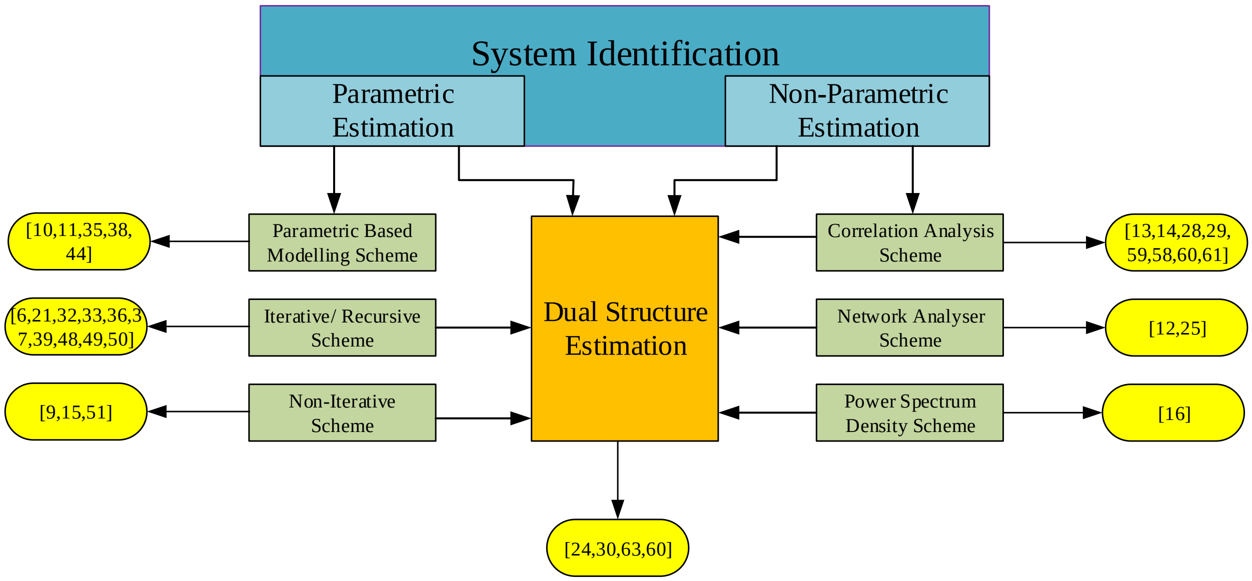

Fig.1. Advances in system identification for SMPCs.

C. Contributions and Paper Structure

Given recent developments, this paper presents a comprehensive review of parametric, non-parametric, and dual hybrid system identification techniques for SMPC applications. This is an area where significant research is currently being carried out to develop improved identification algorithms and advanced control techniques for next generation power electronic products. Thus, such a review is timely. Finally, the existing research challenges in the field are defined and areas for further research investigation are identified. The paper is structured as follow: Generic architecture for parametric and non-parametric system identification of SMPCs is presented in Section II. Modelling scheme-based system identification are presented in Section III. Iterative / non-iterative methodologies are explained in Sections IV and V. Non-parametric methodologies for SMPCs are demonstrated in Section VI. Section VII presents a dual estimation scheme of SMPCs. Furthermore, application of system identification in SMPCs system such as abrupt load estimation scheme and fault detection scheme are discussed in Section VIII. Finally, conclusions and discussion are summarised in Section IX.

II. Generic System Identification Architecture & Methodology for SMPCs

Fig. 2 shows a typical SMPC closed loop controller, incorporating a generic system identification mechanism. Here, a frequency rich signal is injected into the control loop to excite the system and the response of the system to this excitation is observed. From this, an estimation of the system characteristics can be accomplished. Both system identification approaches described in this paper (*ie.* parametric & non-parametric) utilize the structure depicted in Fig. 2. Typically, a Pseudo- Random- Binary- Sequence (PRBS) is applied to excite the dynamics of the SMPC as it is simple to implement, frequency rich, and has similar spectral properties to white noise [13]. Alternatively, other external perturbations can be applied such as multitone sinusoid signal [25], blue noise signal [26], pink noise signal [6], and chirp signal [12].

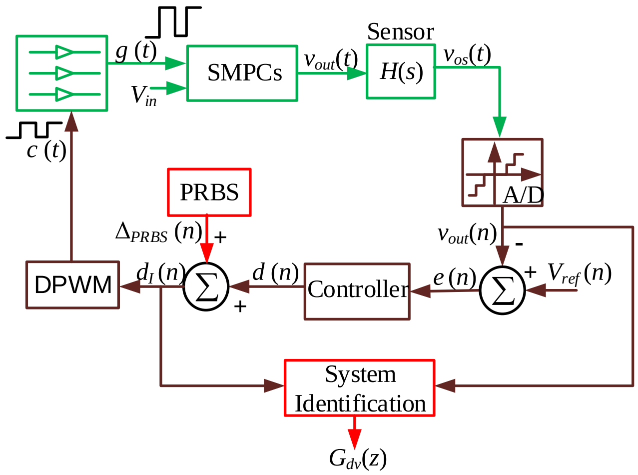

Fig. 2. Closed loop system identification for SMPCs.

A. Non-Parametric Structure of SMPCs

In non-parametric estimation, no prior knowledge of the model structure is required to estimate the system dynamics. This is perhaps the most significant advantage of non-parametric estimation schemes [3]. In addition, the level of complexity of non-parametric methods is often quite low, making them relatively easy to implement [2, 5, 8]. However, non-parametric methods are sensitive to noise and an appropriate excitation signal is normally required to achieve accurate estimation. Therefore, acquisition of long data sequences is essential to overcome these issues and as a result the identification process can take significant time to complete [3, 27]. Practically, this restricts a non-parametric schemes ability to identify rapid system variations, such as an abrupt load change in an SMPC system. Also, it hinders the continuous iterative estimation of the system model, which is imperative for real-time adaptive control design. Furthermore, inaccuracies in the estimated parameters may be more significant in the discrete domain, as a consequence of the transformation from the *s*-to-*z* domain and the effects of quantization [3, 27]. Normally, the identification process is activated during the steady-state period, facilitating the determination of the average linear model of the SMPC [28]. In any system identification scheme, the identification procedure starts with injecting an excitation signal, and then sampling the experimental input and output data of the unknown system. In DC-DC SMPCs, the output-to-voltage control model is commonly identified, thus the data to be processed is the output, $v_{out}(n)$, and the excited signal, $d_I(n)$, (see Fig. 2). The measured data is passed to the pre-processing stage, where signal conditioning and filtering takes place to remove unwanted noise components (Fig. 3) [3]. The dynamic characteristics of the SMPC can be estimated using conventional time-domain or frequency domain analysis [2]. However, in SMPC literature, the frequency response of the system can be estimated by initially determining the impulse response using cross correlation techniques and then applying FFT analysis (as shown in Fig. 3). This facilitates a simpler, lower cost solution, which is essential in these applications [29]. However, in this approach, direct correlation between the input and output signals cannot be assumed [3].

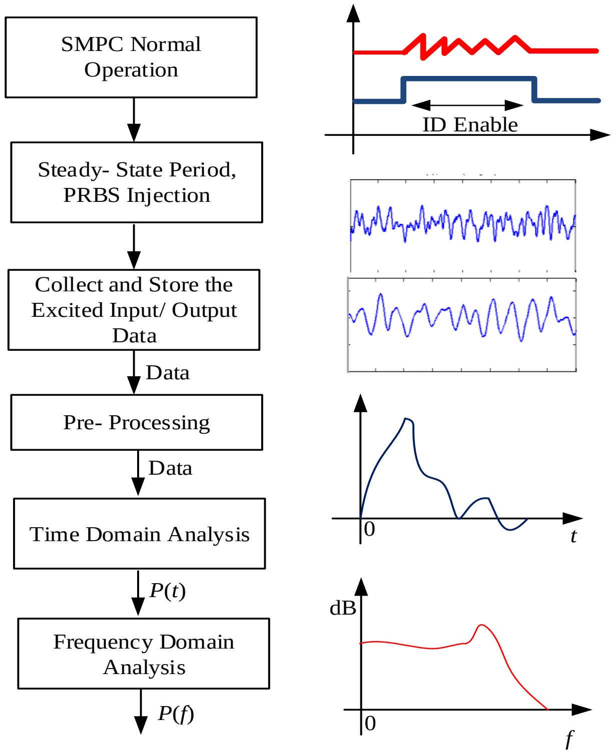

Fig. 3. Non-parametric identification procedure of SMPC.

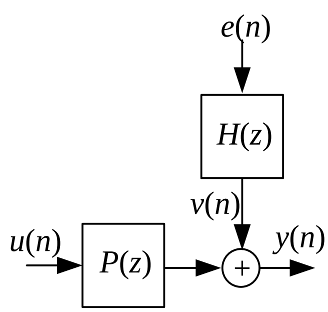

Fig. 4. General linear model transfer function.

As shown in Fig. 4, the linear time invariant discrete system can be expressed as [29]:

$$y(n) = \sum_{k=1}^{\infty} p(k)u(n-k) + v(n) \tag{1}$$

Here, $u(n)$ is the sampled input signal, $y(n)$ is the discrete output signal, $p(k)$ is the discrete impulse response of the system, $e(n)$ is noise and $v(n)$ is the disturbance signal (in Fig. 4, $h(n)$ is the discrete impulse response of the noise). From (1), the cross-correlation between the input $u(n)$ and the output $y(n)$ can be described as:

$$\mathbf{R}_{uy}(m) = \sum_{n=1}^{\infty} u(n)y(n+m) = \sum_{n=1}^{\infty} p(n)\mathbf{R}_{uu}(m-n) + \mathbf{R}_{uv}(m) \tag{2}$$

Where, $\mathbf{R}_{uu}(m)$ is the auto-correlation of $u(n)$ and $\mathbf{R}_{uv}(m)$ is the cross-correlation between the input and the disturbance. Two conditions should be considered for valid non-parametric estimation of the impulse response [29]:

1) The input $u(n)$ and disturbance $v(n)$ are uncorrelated, therefore $\mathbf{R}_{uv}(m) = 0$.

2) $\mathbf{R}_{uu}(n)$ is the auto-correlation of a white noise input signal and thus $\mathbf{R}_{uu}(m) = \delta(n)$. Consequently, equation (2) can be written as [5]:

$$\mathbf{R}_{uy}(m) = p(m) \tag{3}$$

If the conditions in (1 & 2) are met, then the frequency response of the SMPC can be identified by performing frequency analysis on the output to (3), for example by taking the FFT [29]:

$$FFT\{\mathbf{R}_{uy}(m)\} = P(f) \tag{4}$$

B. Parametric Estimation of SMPCs

In parametric estimation schemes, the main objective is to determine the optimal parameters that best describe the unknown model of the system. One of the main drawbacks of this scheme is that a model structure must be defined in advance [14]. Fortunately for many SMPCs topologies, such as DC-DC buck, boost, or buck-boost converter, the candidate model is well recognised and normally represented as a simple second order model [30]. Higher order models can be applied, which may lead to enhanced model accuracy, however they increase computation burden. Likewise, to alleviate issues such as electromagnetic interference in SMPCs, additional harmonic filtering elements are added to the circuit [31]. This can potentially change the candidate model (e.g. higher order model, or input to output voltage model is required) and thus increase the complexity of the identification process. Identical to non-parametric approaches, proper excitation is imperative to ensure accurate convergence of the estimated parameters. Many different algorithms can be used to estimate the system parameters; Least Mean Square (LMS), Recursive Least Square (RLS), and subspace based methods are perhaps some of the dominant algorithms [2, 5, 32]. These algorithms provide a simple adaptive scheme which is capable of rapid convergence rate, good estimation accuracy, and robust tracking ability in the event of system parameter changes [33]. However, the final solution is normally dependent upon a matrix inversion operation, which is computationally heavy and presents implementation difficulties. For RLS algorithms, matrix inversion can usually be avoided using matrix inversion lemma, there is still considerable operational complexity at each sampling instant [34]. To reduce the computation burden, an approximation method to the matrix inversion operation such DCD-RLS algorithm can be considered [3]. With parametric estimation techniques, advanced control techniques such as pole placement and model reference control can easily be integrated with the estimation method [14]. Furthermore, direct digital control design methods can be applied [3]. This can substantially reduce errors attributable to *s*-domain to *z*-domain transformation approximations [35]. Furthermore, the model can be estimated on-line and in closed loop form, and typically has low sensitivity to noise and disturbance. This is a distinct advantage over many non-parametric identification techniques [3].

As previously described, the candidate model of the unknown system is derived in advance. Fig. 5 represents the modelling procedure of the unknown system. After a pre-processing step the model structure is selected, and the order of the model is defined. This may be accomplished from prior knowledge of the system. Thus, the selected model may be considered as a “grey box” model [6]. The optimisation algorithm is then applied to estimate the parameters of the model. The estimated model provides a best fit with the pre-processed data. This can be achieved by comparing the estimated output data with the measured data. The difference is known as a modelling error. If the modelling error is within a defined specification, the model is deemed acceptable and the parameters may be estimated. Otherwise, the process is repeated by selecting a new model or carefully considering the input and output data to determine whether any pre-processing or filtering is required [3]. Fortunately, the analytical discrete model for many common SMPC topologies is understood and well defined in existing literature. For simplicity, the Auto Regressive Moving Average (ARMA) filter is a popular model employed to estimate the parameters of conventional SMPC topologies. The generic ARMA model is represented in (5) [3].

$$G(z) = \frac{Y(z)}{U(z)} = \frac{\sum_{k=1}^{N} b_k z^{-k}}{1 + \sum_{k=1}^{M} a_k z^{-k}} = \frac{b_1 z^{-1} + \; b_2 z^{-2} + \; \ldots + b_N z^{-N}}{1 + a_1 z^{-1} + \; a_2 z^{-2} + \; \ldots + a_M z^{-M}} \tag{5}$$

Equation (5) can also be written in difference form as:

$$y(n) = \sum_{k=0}^{N} b_k u(n-k) - \sum_{k=1}^{M} a_k y(n-k) \tag{6}$$

From which, the data and parameters vectors may be expressed as:

$$\begin{gathered} \boldsymbol{\varphi} = [-y(n-1) \quad \ldots \quad -y(n-N), u(n-1) \quad \ldots \quad u(n-M)]^T \\ \boldsymbol{\theta} = [a_1 \quad \ldots \quad a_N, b_1 \quad \ldots \quad b_M]^T \end{gathered} \tag{7}$$

And the estimated output is calculated in regression form by:

$$\hat{y} = \boldsymbol{\varphi}^T \boldsymbol{\theta} \tag{8}$$

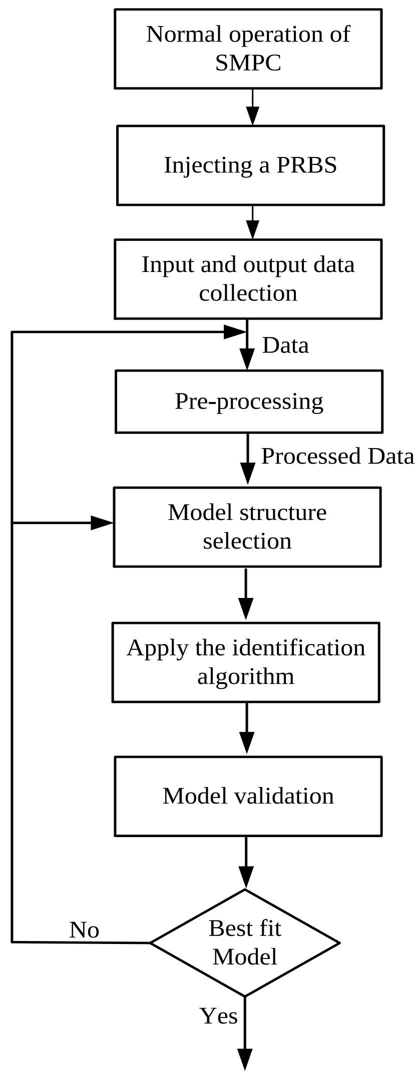

Fig. 5. Parametric identification procedure of SMPC.

Referring back to Fig. 2, and once the model of the unknown system is selected, parametric identification algorithms begin processing the input and output signals on a sample-by-sample basis. Unlike non-parametric schemes, any system changes can usually be detected quickly based on the real time measurement data. In SMPC digital control loop design, the captured data is typically the output voltage, $v_{out}(n)$, and the excited control action signal, $d_I(n)$ (leading to the duty cycle-to-output voltage transfer function); however, inductor current or capacitor voltage can also be used [6]. As shown in Fig. 6, at each iteration cycle prediction error methods such as RLS algorithms seek to minimise the error between the real system $y(n)$ and the estimated model $\hat{y}(n)$. This error is known as the prediction error $\varepsilon(n)$ [3, 33]:

$$\varepsilon(n) = y(n) - \hat{y}(n) \tag{9}$$

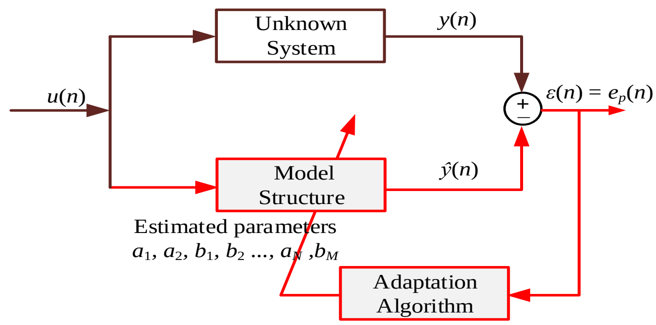

Fig. 6. General block diagram of parametric identification.

As discussed, much research has been carried out in the field of parametric system identification of SMPCs [20, 36-39]. Unfortunately, many of the presented methods require significant signal processing to implement and this eventually has a cost penalty for the target application. Furthermore, the computational complexity impacts upon microprocessor execution time, and this in turn makes it difficult to adopt in continuous parameter estimation for adaptive control applications [33].

III. MODELING METHODOLOGIES BASED SYSTEM IDENTIFICATION FOR SMPCS

The state space average model is the most common approach to obtain the linear system of SMPCs:

$$\begin{aligned} \dot{x} &= \mathbf{A}\boldsymbol{x}(t) + \mathbf{B}\boldsymbol{u}(t) \\ y &= \mathbf{C}\boldsymbol{x}(t) + \mathbf{D}\boldsymbol{u}(t) \end{aligned} \tag{10}$$

Here, **A**, **C**, and **D** are the system matrices/vectors, y is the output, and $\boldsymbol{x}(t)$ is the state vector. Once the linear state space model of the converter is defined, it is possible to apply the Laplace transform for obtaining the frequency domain linear time model. This model is essential in linear feedback control design, such as the root locus control approach. In voltage mode control of the SMPC, the control-to-output voltage transfer function (11) [40, 41] plays the important role of describing the locations of poles/zeros for optimal voltage response. Consider the case for the buck DC-DC converter:

$$G_{dv}(s) = \frac{V_{in}(CR_C s + 1)}{s^2 LC\left(\frac{R_o + R_C}{R_o + R_L}\right) + s\left(CR_C + C\left(\frac{R_o R_L}{R_o + R_L}\right) + \frac{L}{R_o + R_L}\right) + 1} \tag{11}$$

Where, V_{in} is the input voltage, C is the output capacitance, L is output inductance, R_o is the load resistance, R_L is the inductor equivalent series resistance (ESR), and R_C is the capacitance ESR.

To derive the discrete model of SMPC, the continuous time dynamic model must be defined. Then, by sampling the states of the converter at each time instant the continuous time differential equations are transformed into a discrete time model. A discrete time model is necessary for digital implementation. Different techniques have been proposed for discrete time modelling of DC-DC converters and for obtaining the control-to-output transfer function [42, 43]. In general, a zero-order-hold (ZOH) transformation approach (12), is used to convert the linear model described in (11) to a discrete equivalent model (13) [5]:

$$G_{dv}(s) = (1 - z^{-1})\mathfrak{I}\left\{\frac{G_{dv}(s)}{s}\right\} \quad (12)$$

$$G_{dv}(z) = \frac{b_1 z^{-1} + \quad b_2 z^{-2} + \quad ... + b_N z^{-N}}{1 + a_1 z^{-1} + \quad a_2 z^{-2} + \quad ... + a_M z^{-M}} \quad (13)$$

The following section presents two effective methods of SMPCs modelling suitable for the purposes of system identification.

A. Black Box Modelling

A non-linear black box model of a DC-DC converter, based on Least Square (LS) techniques, is presented in [10, 11, 38]. The techniques presented are centred on the Hammerstein model. As shown in Fig.8, this model consists of a non-linear static model in combination with a Linear Time Invariant (LTI) ARX model.

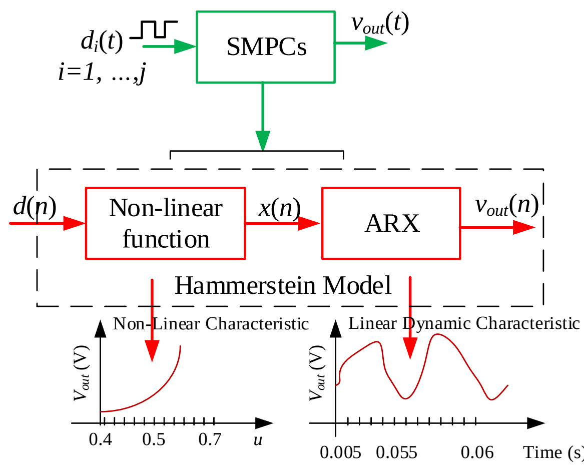

Fig.7. Hammerstein black box scheme.

The dynamic characteristics of the SMPC are captured by the ARX model (14). To identify the system model, the estimation process must pass two phases [10, 38] (Fig.7). In the first phase, and during the steady-state period, the converter is supplied by a constant input voltage with a variable duty cycle signal. The corresponding output voltage is measured; as a result, the non-linear static model will be identified. In the second step, a PRBS is injected to excite the system dynamics, and the measured values of the control-to-output voltage data are observed to identify the candidate second order ARX model (14-to-20). The suggested process effectively defines the DC-DC converter model; from this, a robust controller is developed [10, 38]. The authors in [44] utilise the same paradigm demonstrated in [10, 38] to identify a complex 4th order DC-DC converter transfer function.

In [11], the dynamic characteristic of the DC-DC converter is excited by a step load change and the output response is captured. Two outcomes are possible; when the resultant dynamic is evaluated as an LTI response, the DC-DC model is estimated using LS (20); otherwise a non-linear method such as the Hammerstein model is applied.

$$A(z)y(n) = B(z)x(n) + e(n) \quad (14)$$

Where,

$$x(n) = f(d(n)) \tag{15}$$

Here, $x(n)$ is the ARX input, $y(n)$ is the ARX output, and $e(n)$ is the added error. The parameters of $A(z)$ and $B(z)$ are defined in (17). Equation (14) can also be re-written as:

$$y(n) - x(n) = \begin{array}{c} a_1[x(n) - y(n-1) + \cdots + \\ +a_N[x(n) - (y(n-N)] \\ +b_1[x(n-1) - x(n)] + \cdots + \\ +b_M[x(n-M) - x(n)] + e(n) \end{array} \tag{16}$$

From which, the data and parameters vector may be stated as:

$$\boldsymbol{\theta} = [a_1 \quad \ldots \quad a_N, b_1 \quad \ldots \quad b_M]^T \tag{17}$$

Accordingly, the LTI model depicted in (16) can be described as:

$$\hat{y} = \boldsymbol{\varphi}^T\boldsymbol{\theta} + e \tag{18}$$

Where,

$$\begin{aligned}
&\hat{\mathbf{y}} = [\hat{y}(n_i+1) \quad \cdots \quad \hat{y}(n_i+K)]^T \\
&\boldsymbol{\varphi} = [r(n_i+1) \quad \cdots \quad r(n_i+K)]^T \\
&\mathbf{e} = [e(n_i+1) \quad \cdots \quad e(n_i+K)]^T \\
&\hat{\mathbf{y}} = y(n) - x(n) \\
&\mathbf{r}_a(n) = [x(n) - y(n-1) \quad \cdots \quad x(n) - y(n-N)]^T \\
&\mathbf{r}_b(n) = [x(n-1) - x(n) \quad \cdots \quad x(n-M) - x(n)]^T \\
&\mathbf{r} = [\mathbf{r}_a \quad \mathbf{r}_b]^T
\end{aligned} \tag{19}$$

Here, K is the index of the captured data. To determine the unknown parameters of the ARX model, LS solution is applied:

$$\boldsymbol{\theta} = (\boldsymbol{\varphi}^T\boldsymbol{\varphi})^{-\mathbf{1}}\boldsymbol{\varphi}^T\hat{y} \tag{20}$$

B. Steiglitz IIR Model

An open loop system identification approach to estimate the control-to-output voltage model of a DC-DC converter is presented in [35]. In this scheme, the SMPC is perturbed by a step change in the duty cycle signal (Fig. 8). The same injection sequence is repeated five times in total. The DSP is then used to capture the sampled averaged input and output data. The collected data is used to estimate the system parameters. Here, Steiglitz model (21), based on iterative least squares method is employed [35]. The authors in [45] concluded that the digital control model relying upon discrete estimation provides better performance than the mathematically calculated model.

$$min \sum es^2 = \oint \left| d(z)\frac{B_j(z)}{A_{j-1}(z)} - v_{out}\frac{A_j(z)}{B_{j-1}(z)} \right| \frac{dz}{z} \tag{21}$$

Where,

$$\frac{B(z)}{A(z)} = \frac{b_1 z^{-1} + \quad b_2 z^{-2} + \quad ... + b_N z^{-N}}{1 + a_1 z^{-1} + \quad a_2 z^{-2} + \quad ... + a_M z^{-M}} \tag{22}$$

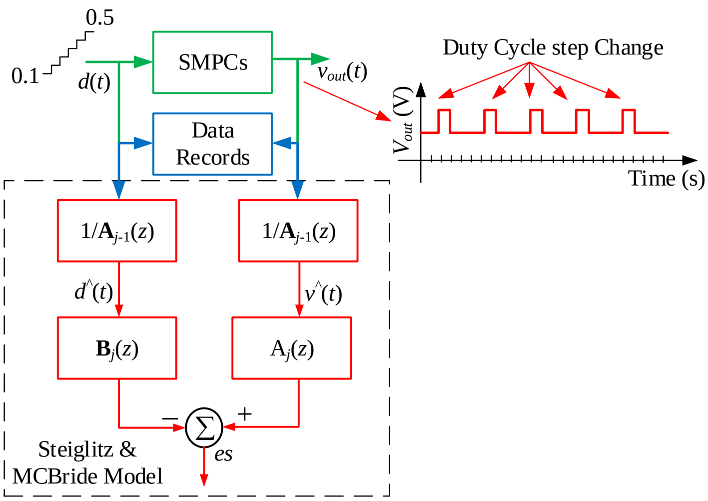

Fig. 8. Steiglitz IIR estimation scheme.

C. Summary and Discussion

The modelling procedure in black box techniques is relatively complex and time-consuming for real-time operation [38]. The experimental data is captured using dSpace (DS1103 platform) and then processed by MATLAB environment. The work in [11] requires many steps and advanced analysis prior to estimation, thus it is more suitable to off-line scenarios and accurate control design. In Steiglitz IIR model, a discrete model of SMPC can be directly obtained but high perturbation in the output during identification process can be observed. According to [35], a 5 % step change in the duty cycle causes a change of 1 V at the output of the DC-DC converter. The time for the identification procedure to complete is about 120 ms. As a result, the approach is not pertinent for on-line controller design in SMPC applications, or for real-time parameter tracking. The identification scheme was implemented on a TMS320F2808-DSP involving MATLAB Real-Time Workshop toolbox. The resultant open loop discrete model was incorporated for the direct digital control design method by Ragazzini's [45]. The proposed controller has been implemented experimentally by DSP platform. However, the design steps necessitated an off-line optimisation or curve fitting method, to convert the resultant high order Ragazzini controller to match the desired second order digital PID controller.

IV. ITERATIVE AND RECURSIVE ESTIMATION METHODS OF SMPCS

Different parameters estimation algorithms based on iterative and recursive scheme for on-line system identification of SMPCs are presented in the literature. Classical RLS algorithm (Table I) is the typical example utilizing this methodology. Again, low complexity, simplicity of implementation, convergence rate of the estimated parameters, accuracy of the estimated model, and cost are the main challenges for developing an effective recursive estimation scheme for SMPCs application. This section will exemplify the recent and effective algorithms relied upon iterative approach.

Table I. Exponential RLS algorithm description.

Step	Formula
Initialization	$P(0) = g * I$, and $\hat{\theta}(0) = 0$, 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-Kalman gain	$K_k = P^{+}_{k-1}\varphi_k[\varphi_k P^{+}_{k-1}\varphi^{T}_{k} + r_k]^{-1}$
2-Parameters estimate	$\hat{\theta}_k = \hat{\theta}_{k-1} + K_k[\, y_k - \varphi^{T}{}_{k}\hat{\theta}_{k-1}]$
3-Estimate dispersion update	$P_k = P^{+}_{k-1}\left(I - K_k\varphi^{T}{}_{k}\right)$
4-Covariance matrix project ahead	$P^{+}_{k} = P_k + Q$

A. DCD-RLS Algorithm

Hardware efficient real time algorithm to reduce the computation complexity that exists with the classic RLS method (Table I) was introduced in [33]. The proposed algorithm is known as Dichotomous Coordinate Descent (DCD), and is employed in [3, 33] for the first time in SMPC application. An equation error infinite-impulse-response (IIR) filter is proposed to validate the system modelling of the synchronous buck SMPC (see Fig.9). Adaptive filter techniques are used to identify the filter coefficients in (13).

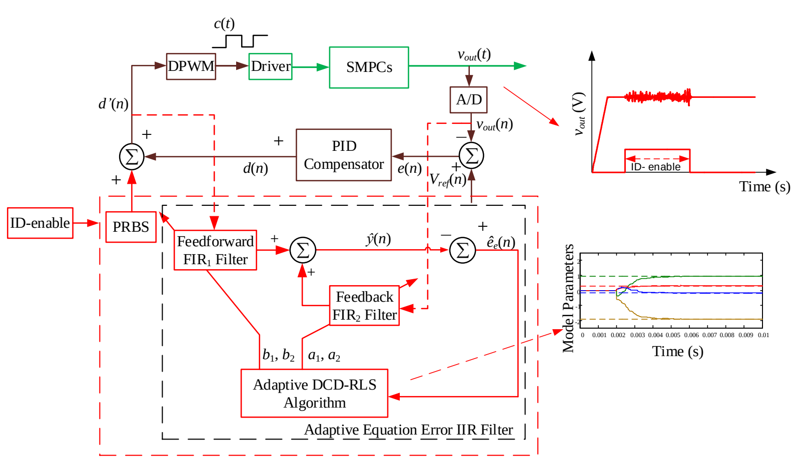

Fig.9. Equation error IIR filter based on DCD-RLS estimation scheme.

At steady state, a small amplitude PRBS signal is injected into the closed loop and the algorithm processes the excited input and output signals at each time instant. Once the prediction error is minimized (ideally zero) (23), the optimal parameters are obtained. As presented in [3, 33], the estimation accuracy for the denominator coefficients in (13) are excellent, whilst the numerator coefficients fluctuate slightly around the expected values. This is mainly due to the effect of noise and the inherently small numerical values of the numerator parameters. Also, the proposed DCD algorithm contains no multiplication operations (Table. II), unlike the classical RLS algorithms; hence it is a much more computationally efficient solution with similar performance [46, 47].

$$J(n) = \sum_{k=1}^{n} e_p^2(k) = \sum_{k=1}^{n} [d_r(k) - \boldsymbol{\theta}^T \boldsymbol{\varphi}(k)]^2 \tag{23}$$

Where,

$$e_p(n) = d_r(n) - \hat{y}(n) \tag{24}$$

Here, e_p is the error prediction, $\hat{y}$ is the estimation output signal, $\boldsymbol{\theta}$ is the filter parameters, $\boldsymbol{\varphi}$ is data vector, and $d_r(n)$ is the desired signal.

Table II. Leading DCD algorithm description.

Step	Equation
Initialisation	$\Delta\ \boldsymbol{\theta} = 0$, $\mathbf{r} = \boldsymbol{\beta}_o$, $\mu = H$, $m = 1$
	for $k = 1,\ldots, N_u$
1-Check the leading parameters	$i = arg\ max_{p=1,..,N}\ \lvert r_p\rvert$,go to step 4
2-Update the step size	$\mu = \mu / 2$, $m = m + 1$
3-Check the number of iteration	if $m > M$, algorithm stops
4- Check the residual value	if $\lvert r_i\rvert \leq (\mu / 2)R_{i,i}$, then go to step 2
5- Update the Parameters	$\Delta\boldsymbol{\theta}_i = \Delta\ \boldsymbol{\theta}_i + \text{sign}\ (r_i)\ \mu$
6- Update the residual vector	$\mathbf{r} = \mathbf{r} - \text{sign}(r_i)\mu\mathbf{R}^{(i)}$

In Table. II, $\mathbf{R}$ is an auto-correlation matrix of size $N \times N$ (25), $\boldsymbol{\beta}$ is the cross-correlation vector of length N (26), $\mathbf{r}$ is the residual vector (27), u is the step size, m is the number of bits, and N is the number of iterations.

$$\mathbf{R}(n) = \mathbf{R}(n-1) + \boldsymbol{\varphi}^T(n)\boldsymbol{\varphi}(n) \tag{25}$$

$$\boldsymbol{\beta}(n) = \boldsymbol{\beta}(n-1) + d_r(n)\boldsymbol{\varphi}(n) \tag{26}$$

$$\mathbf{r}(n) = \boldsymbol{\beta}(n-1) - \mathbf{R}(n)\widehat{\boldsymbol{\theta}}(n) \tag{27}$$

B. BBO-RLS Algorithm

The research in [39] incorporates the Biogeographical Based Optimization (BBO) algorithm , with the RLS algorithm (Table I) to estimate the parameters of DC-DC converters and then to determine the circuit coefficients of the converter, such as the inductance and output capacitance for failures detection (see Fig.10). To improve the accuracy of estimation under different measurement noise, a state-space model of the DC-DC converter with full state observation is deployed. Here, BBO is proposed to enhance the optimization solution of the multivariable problem. According to [39], the solution presented is more accurate than alternative works; nonetheless it is best suited to low sampling rate applications and requires high specification microprocessor hardware for real time implementation. Consequently, this method has limited application potential in real time systems and is again more suitable for off-line identification. For on-line estimation, the authors assumed that components in the circuit change slowly; therefore, this scheme is not suitable for tracking abrupt changes such as abrupt load changes in point of load converter (POL) applications.

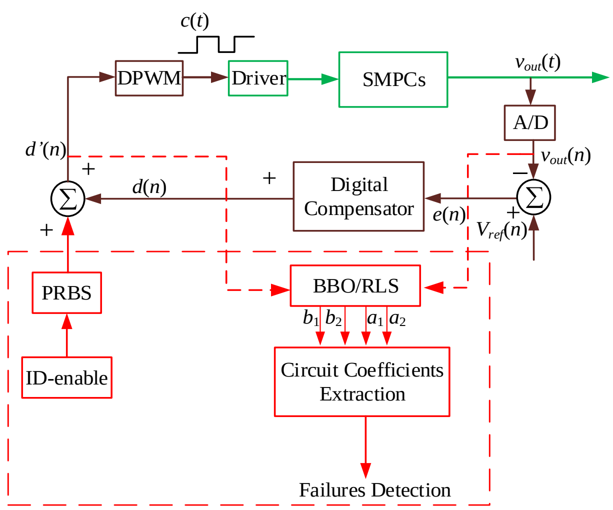

Fig. 10. BBO-RLS Estimation Scheme.

C. KF Techniques

In [36], real-time estimation of the DC-DC buck converter parameters is performed using a Kalman filter scheme (KF) (Table. III). The functional block diagram is similar to Fig.9; however, the IIR filter in Fig.9 is replaced by a KF. This research sets out to accurately estimate the SMPCs parameters as rapidly as possible, and to eliminate the need to inject a continuous excitation signal during the identification process, as discussed in Section II. Unlike the classical RLS algorithm, linear growth of the covariance matrix elements (P, Table III) is observed in the KF method. This allows the estimator to work for long periods of time without any significant output perturbation. This makes the KF approach a good choice for real-time applications such as DC-DC converters where long periods of perturbation in the output voltage are highly undesirable. Furthermore, unlike RLS approaches, the effects of system parameter uncertainty are considered in the KF. This in turn enables greater accuracy parameter estimation in addition to faster convergence speed and reduced execution time compared to the classic RLS algorithm. By using a forgetting factor scheme, estimator wind-up occurs causing a significant fluctuation in the estimated parameters. Therefore, this kind of recursive implementation cannot provide reliable estimation once the excitation signal is disabled or disconnected for any reason. Therefore, employing the RLS algorithm in parameter estimation requires a periodic output perturbation to guarantee converter stability. Most recently, the work in [48] proposed combining the classical Kalman filter with a M-Max partial adaptive filter to form a partial update Kalman Filter (PUKF) scheme. This scheme reduces the computational effort of the conventional KF by 50 %.

Table III. KF algorithm description.

Step	**Formula**
Initialization	$P_0 = g * I$, and $\hat{\theta}_0 = 0$, where I is an $N \times N$ identity matrix, g is large number usually >1, $(\lambda) \in (0,1]$,
	Do for k ≥ 1
1- Prediction error calculation	$ep_k = y_k - \varphi^T{}_k \hat{\theta}_{k-1}$
2-Calculate Kalman gain	$K_k = \dfrac{P_{k-1}\varphi_k}{\left(\lambda + \varphi^T{}_k P_{k-1}\varphi_k\right)}$
3-Update the parameter vector $\hat{\boldsymbol{\theta}}$	$\hat{\theta}_k = \hat{\theta}_{k-1} + K_k \left(y_k - \varphi^T{}_k \hat{\theta}_{k-1}\right)$
4-Update the covariance matrix $\boldsymbol{P}$	$P_k = \dfrac{1}{\lambda}\left[P_{k-1} - P_{k-1}K_k\varphi^T{}_k\right]$

D. FAP-RLS Algorithm

A Fast Affine Projection (FAP)-RLS algorithm (28-to-32) is also proposed to estimate the model parameters of the DC-DC converter [21, 32]. Again, the general architecture in Fig.2 is adopted in this work. The aim is to find a very fast way of identifying the parameters of the DC-DC converter and to adapt the control loop rapidly in response to dynamic changes within the system. This research addresses this point, and the FAP estimation algorithm as a parameter estimator for SMPC applications is validated in [21, 32]. In [32], MATLAB Simulink is used to estimate the parameters of the buck converter in (13),while in [21] the FAP-RLS algorithm is experimentally validated on a DC-DC buck converter and successfully incorporated with a charge balance adaptive controller to optimize the output voltage during abrupt load changes. It is shown that a first order model of the buck converter can be used to optimize the output response; given most techniques rely upon a second order model this offers an advantageous low computation complexity solution.

$$e_i = \mathbf{d}_i - U_i w_{i-1} \tag{28}$$

$$G_i = U_i U_i^* \tag{29}$$

$$y_i = \mathbf{U}_i \boldsymbol{\theta}_{i-1} = z_i + \mathbf{G}_i \varepsilon_i \tag{30}$$

$$z_i = \mathbf{U}_i \boldsymbol{\theta}_{i-2} \tag{31}$$

$$\mathbf{R}_i = [\varepsilon + \mathbf{U}_i \mathbf{U}_i^*] \tag{32}$$

$$\boldsymbol{\theta}_i = \boldsymbol{\theta}_{i-i} + \boldsymbol{U}_i^* \boldsymbol{R}_i{}^{-1} e_i \tag{33}$$

Where, i is the iteration, U is input (here, represents duty cycle), y is the output, $\boldsymbol{\theta}$ is the parameters vector and, $\mathbf{d}$ is the filter desired vector. The regressor matrix is obtained as follows:

$$\mathbf{U}_i = \begin{bmatrix} u_i \\ u_{i-1} \\ \vdots \\ u_{i-K+1} \end{bmatrix} \quad (34)$$

$$\mathbf{d}_i = \begin{bmatrix} d_i \\ d_{i-1} \\ \vdots \\ d_{i-K+1} \end{bmatrix} \quad (35)$$

Here, K in FAP-RLS is a positive integer which defines the number of steps to be used in the estimation. Clearly, FAP-RLS rapidly estimates the system parameters making it appropriate for tracking abrupt system changes but requires higher computational effort. For example, for each iteration and for $K = 2$, FPA algorithm required 34 multiplication operations and 33 addition operations [32].

E. SALS Algorithm

Gietler *et.al.* [37], investigates low computation iterative algorithms (Step Adaptive Least Square (SALS), DCD-RLS, Batch Least Square (BLS)) for parametric estimation of buck converter at high sampling rates. Two excitation signals (PRBS and sinusoidal chirp signal) are applied. To improve convergence rate of the proposed SALS algorithm, the sampled data (output voltage and stimulus signal) is processed using a Randomized Kaczmarz algorithm. The method relies upon prior estimation; thus, an additional memory block is required to store the excitation data. The work states that using a chirp signal improves the convergence rate of the SALS algorithm. Comparing results, the DCD-RLS converges faster than SALS [37], however, SALS is less sensitive to noise. Additionally, the computational effort to generate the chirp signal is higher compared to a typical PRBS, as used with say the DCD-RLS. The SALS algorithm falls under the LMS category; therefore, it offers low computational complexity compared with other existing iterative methods; however, special attention should be given when selecting the step size (37) to ensure parameter convergence. As stated in [47], it is essential to carefully select the LMS step size to avoid instability in the estimation process mainly during any abrupt load change. For complete comparison between the algorithms, in term of estimation accuracy, robustness, and noise sensitivity greater investigation into the closed loop form should be carried out.

$$\boldsymbol{f_c} = \frac{\boldsymbol{f_s}\sqrt{\boldsymbol{log b_2^2} + \boldsymbol{4cos}\left(\frac{\boldsymbol{-2b_1}}{\boldsymbol{2\sqrt{b_2}}}\right)^{-1}}}{\boldsymbol{4\pi}} \quad (36)$$

$$\boldsymbol{\theta}(n) = \boldsymbol{\theta}(n-1) + 2\mu\boldsymbol{\varphi}(\boldsymbol{y}(\boldsymbol{n}) - \boldsymbol{\varphi}^{\boldsymbol{T}}\boldsymbol{\theta}(\boldsymbol{n}-\boldsymbol{1})) \quad (37)$$

Where, f_c is converter corner frequency, b_1 and b_2 are the estimated converter parameters in (13), f_s is the sampling frequency, $\boldsymbol{\theta}$ is the parameter vector and $\boldsymbol{\varphi}$ is the data matrix.

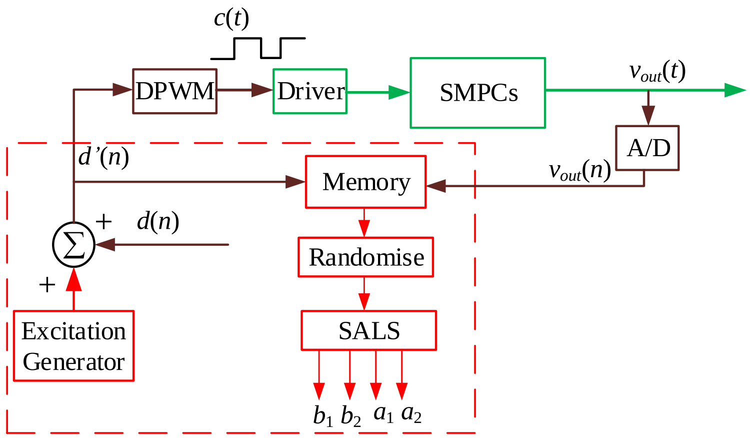

Fig.11. Open Loop SALS Estimation Scheme.

F. Summary and Discussion

The bottle neck in many schemes is the computational burden involved with recursive algorithms (Table IV). As shown, the exponential DCD-RLS algorithm has the lowest computation cost; in the worst case scenario the number of additions is limited to $A_n = (2N + 1)N_u + M$, and the number of multiplications is $M_n = 0$ [46]. In Table IV, N is the number of model parameters, N_u represents the number of iterations, M is the number of bits to represent each the parameters at fixed point DCD, and K is the projection order. As listed in Table IV, it is clear that the computation complexity of the KF and FAP algorithms is high relative to the DCD; however, they offer rapid parameter estimation performance.

The computational complexity of the BBO-RLS scheme [39] is highest among all the iterative methods. It has been shown that for each iteration, the BBO algorithm requires 2*npop* + *nls MaxIter* function evaluations, *npopD* habitat modifications, and two rounds of sorting with *npop* elements are involved. In each function evaluation, the number of addition and multiplication operation is given by 2*N* + Aeig and 2*N* +*Meig*. Here, $Aeig$ and $Meig$ are the number of operations required to obtain the eigenvalues and eigenvectors from the BBO generated circuit parameters. Reference [39] provides a comprehensive mathematical definition to calculating the computational burden of the BBO algorithm.

In terms of implementation, all the iterative schemes presented here use a floating-point processor (typically a TMS320F28335-DSP); therefore, finite word length effects on the estimation accuracy has not investigated. Also, all are practically tested on low frequency operation without clarifying the execution time of the proposed algorithms. For low computational effort and high frequency operation, DCD -RLS and SALS algorithm can be adopted (see Table IV). SALS itself requires $3N + 2$ multiplication operations; such low computational schemes are very well suited for on- chip implementation [37]. However, additional operations are required for the randomization process introduced by the Kaczmars algorithm, and cost is not fully considered in [37]. In addition, the proposed solution is not practically implemented in a way to measure the execution time and validate the high frequency of operation. Here, an FPGA platform is used to inject the excitation signal and an 8-bit ADC captures the excited signals. Practically, the main issue with iterative based estimation schemes is the selection of the step size and the forgetting factor. These parameters clearly affect the estimation speed and identification robustness, but the impact of this is often not considered in literature. A notable exception is the work presented in [47]. Finally, all test cases presented here are successfully implemented on low-power DC-DC buck SMPCs except the work in [32] which tested on 4 kW; however, the presented cases can be directly applied to high power converter applications without any changes in the procedure of identification and control loop tuning.

Table IV. Computational complexity of each algorithm.

Algorithms	×	+	÷
Classical exponential RLS **[49]**	$N^2 + 5N + 1$	$N^2 + 3N$	1
Exponential DCD-RLS **[3, 33]**	–	$(2N+1)N_u + M$	–
Kalman filter **[36, 50]**	$N^3 + 2N^2 + 5N$	$N^3 + 2N^2 + 2N - 1$	1
FAP-RLS **[21, 32]**	$(1 + K)N + K^2 + 2K^2 + 2K + 2$	$(1 + K)N + K^3 + 2K^2 + 2K + 1$	–
SALS [37]	$3N + 2$	$2N + 1$	–

V. NON-ITERATIVE ESTIMATION METHODS OF SMPCS

Non-regression methods have also been successfully proposed in the identification and auto-tuning control of DC-DC converters [9, 15, 51]. State-of-the-art shown two effective solutions to identify the system dynamics of SMPCs and then to auto-tune the control loop parameters.

Forward relay-feedback techniques are presented in [15, 51] (Fig.12,a). Here, the identification and tuning process are performed during start-up of the DC-DC converter. It introduces oscillations at a desired frequency into the output for a short period, then, the converter parameters are estimated based on the measured frequency of the oscillated signal. Significant ripple is introduced into the output voltage of the DC-DC converter during estimation [52]. The authors in [9] propose inserting a Limit Cycle Oscillation (LCO) into the regulated output voltage of the DC-DC during steady-state period (Fig.12, b). The LCO is generated by reducing the resolution of the Digital Pulse Width Modulator (DPWM) with aids of integral gain instead of using a relay in the feedback loop [33] (38). The converter's corner frequency, quality factor amplitude (39) and frequency information are then estimated from the desired LCO signal [52]. This method results in lower system identification accuracy, but it is a hardware efficient approach [54].

$$-1 = 1\angle 180^\circ = NPWM\,(A_{osc}, \varepsilon) G_{dv}(j2\pi f_{osc}) \times K_{AD}(j2\pi f_{osc}) \frac{K_I}{j2\pi f_{osc}} \quad (38)$$

Where,

$$NPWM\,(A_{osc}) = \frac{4Dr}{\pi A_{osc}} \quad (39)$$

Here, $NPWM(A_{osc})$ is the describing function of the DPWM, ε is the hysteresis width, K_{AD} is the ADC gain, A_{osc} and f_{osc} is the oscillated amplitude and oscillated frequency respectively, D_r is the quantization step of DPWM, and K_I is the integral gain.

$$\begin{aligned} f_c &= \frac{1}{2\pi\sqrt{LC}} \\ Q &= R\sqrt{\frac{C}{L}} \end{aligned} \quad (40)$$

Where, L and C are the DC-DC circuit components, and f_c, Q is the converter's corner frequency and quality factor respectively.

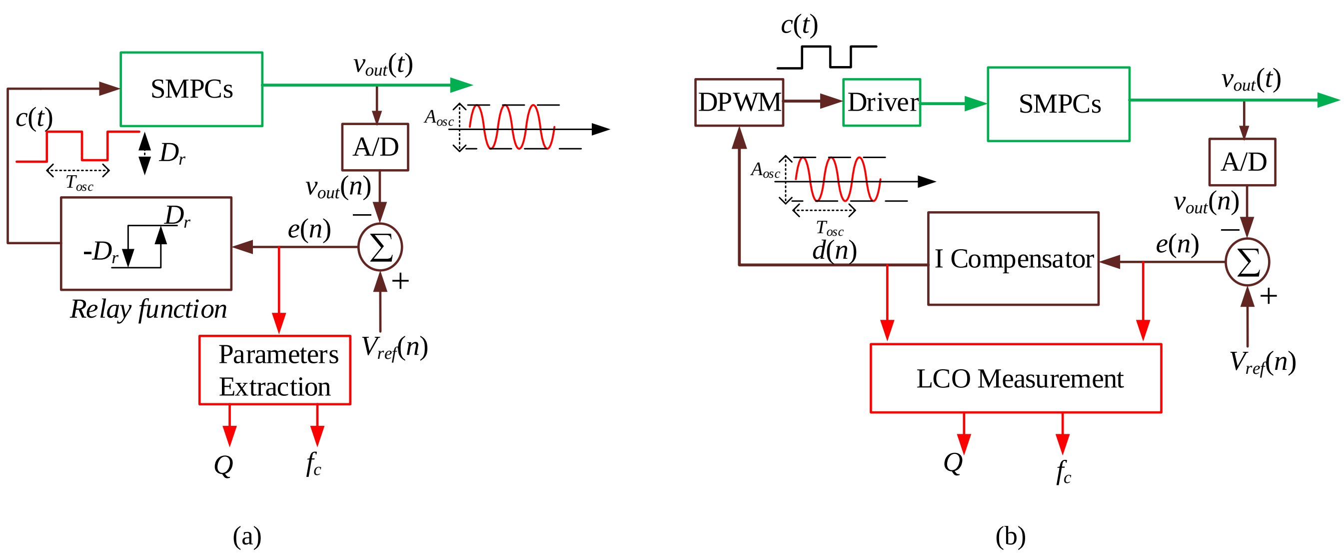

Fig. 12. (a) Relay estimation scheme. (b). LCO estimation scheme.

A. Summary and Discussion

For low hardware implementation and on-line estimation, LCO [9] or relay [15, 51] schemes can be adopted. Better estimation accuracy can be achieved by relay-based estimation, however, both techniques potentially suffer from estimation errors and risk of oscillation in the regulated output during the system identification process. LCO, requires less computational effort; to quantify this, the relay scheme takes 27 ms (sampling time = 50 μs) to estimate the system dynamics and tune the loop parameters, compared to 2.5 ms for the LCO method at the same sampling rate. To accomplish the estimation and control loop tuning, many processing steps are required; therefore, special attention is required when implementing each step in DSP software code or FPGA hardware. For example, in the LCO scheme and during the identification process, the main PID controller is converted to an integral only controller to amplify the LCO signal, and the PWM resolution is reduced to enhance this oscillation and further excite the system output. The test case in [9] is successfully implemented on 10 W DC-DC power converters, with 400 kHz switching frequency for computer SMPC applications, while in [15] a 200 kHz switching frequency is used; recently, the test case in [15] is employed to monitor the stability of DC-DC power converters in DC grid system [53].

VI. FREQUENCY RESPONSE IDENTIFICATION METHODOLOGIES FOR SMPCS

Many papers have presented to identify the frequency response characteristics of the control-to-output model of a DC-DC converters [55, 56]. Health monitoring and fault detection of DC-DC power converters has also been thoroughly examined using non-parametric approach [18, 28, 57]. However, further research focuses on improving specific aspects on this procedure, such as: reducing the computation complexity of the identification process in both time and frequency domain [14, 29], minimising the impact of disturbance and noise on the estimation accuracy [16, 28], introducing new types of perturbation signal to improve the identification performance [58], and novel on-line closed loop implementations [12, 14]. Therefore, this section presents distinct non-parametric algorithms for SMPCs and discusses the performance of these structures.

A. Correlation Estimation Scheme

An effective non-parametric method (Procedure in Fig. 3, Equations. 1-to-4) based on frequency response measurement of SMPC is presented in [14, 29]. In this method, a wide range of SMPC parameter uncertainty can be handled, but significant time is required to complete the identification process and long data sequences need to be managed [27]. According to [29], at 100 kHz sampling frequency, the procedure takes approximately 180 ms to complete; which is significant in an SMPC application. Also, during the identification process, the system runs in open loop form without adequate regulation. A low resolution ADC has been shown to have a substantial impact on the identification accuracy (quantisation effect) [3]. Therefore, research in [14] presents a complete identification procedure including a pre-emphasis and de-emphasis filtering technique to improve accuracy and smooth the estimated frequency response (see Fig.13). This work has been embedded with a digital controller to facilitate an auto-tuning SMPC voltage controller [59].

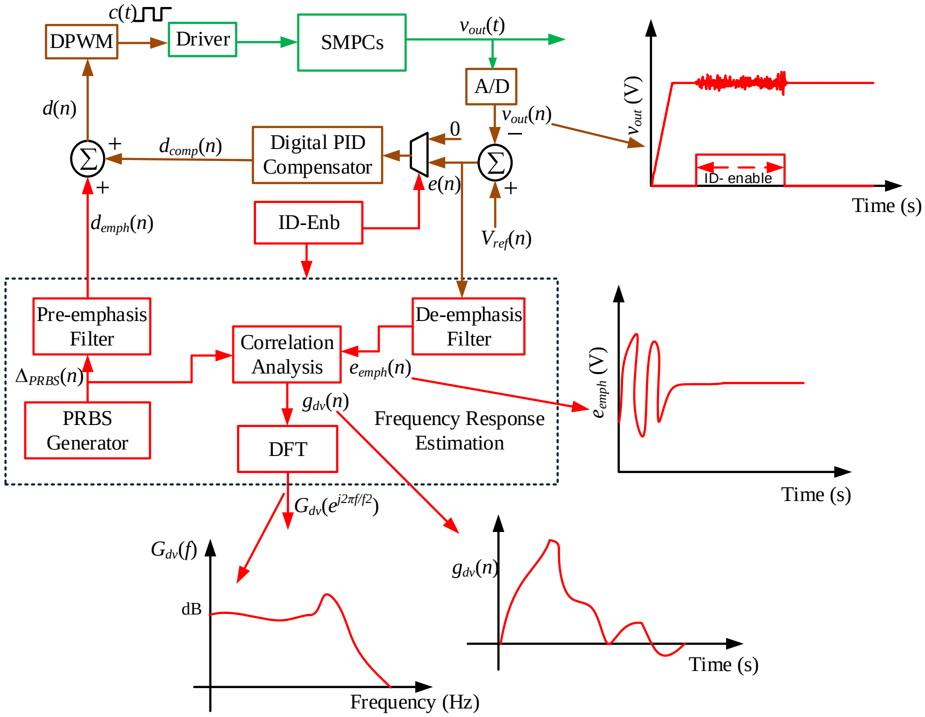

Fig. 13. Non-parametric correlation block diagram.

Further research to enhance the accuracy of the non-parametric cross correlation estimation in [14, 29] has been developed in [28]. In this method, the measured cross-correlation between the input and output of the DC-DC converter (2), is enhanced by using a windowing technique. This in turn leads to an improvement in the non-parametric frequency response estimation (4). Moreover, the authors suggest injecting blue noise into the control loop instead of a PRBS signal to mitigate the noise floor concern at high frequencies. Additional enhancement is also presented by Barkley and Santi [28], by taking an oversampling approach to avoid discontinuity in the input and output voltage and current signals. This strategy has also been integrated with an adaptive controller for an SMPC [60].

From literature, estimation results in non-parametric schemes are highly sensitive to system disturbances and quantization noise produced by low resolution A/D converters. To alleviate these problems, a good signal-to-noise ratio (SNR) is required; this can be achieved by injecting a large amplitude perturbation signal. However, a recognised and undesirable deviation in the regulated output voltage can disturb the steady state operation of the SMPC. One way to improve the robustness of the identification is to inject a different type of PRBS; such as the inverse repeat binary sequence (IRBS) or maximum length binary sequence (MLBS) [13, 61]. However, introducing these types of perturbation signals (IRBS & MLSB) requires an extra digital low pass filter and high-resolution Digital-to-Analogue Converter (DAC); the solutions presented are suitable for off-line testing of commercial DC-DC converter products. Furthermore, in the work by Roinila *et al*. [58], a circular cross-correlation method is proposed to improve the estimation of the impulse response, and minimise the impact of system disturbance. Fuzzy density technique is also proposed by the same authors in [58], this time to determine the uncertainty in the measurement.

B. Network Analyzer Scheme

An alternative technique, similar to that of a network analyser (Fig.14), is presented in [12, 25]; here, a non-parametric frequency domain technique is employed. The authors inject a sinusoidal signal (sine sweep) to directly estimate the frequency response of the control-to-output transfer function using DFT methods (41); loop gain can also be estimated by using (42). In this case, there is an inherent assumption that the disturbances are uncorrelated with the input and output signals. Therefore, the sensitivity issues with the previously described correlation analysis ((1) and (2)) are avoided [25]. However, windowing of the input and output signals is required prior to estimating the spectral density. The selected windowing technique will clearly affect the final estimation result from our review of the literature this is not always clearly reported and discussed in the level of detail necessary.

$$X(n) = \sum_{k=0}^{N-1} x_k e - j\frac{2\pi kn}{N} = \sum_{k=0}^{N-1} x_k \left(\cos(\frac{2\pi kn}{N}) - j\sin(\frac{-j2\pi kn}{N}) \right) \tag{41}$$

$$\begin{aligned} y &= \frac{G_{dv}H}{1+G_{dv}H} r \\ u &= \frac{y}{G_{dv}} = \frac{H}{1+G_{dv}H} r \end{aligned} \tag{42}$$

Where, G_{dv} is the control-to-output transfer function, H is the sensor transfer function, r is the reference signal, y is the output signal, u is the input signal, N is the number of samples, X is a complex spectrum.

Recently, Bhardwaj *et al*. [12] designed a software tool to efficiently implement the frequency response technique presented in [25]. Additionally, the work in [12] proposes a mapping algorithm based on the Normalised Mean Square Error (NMSE) technique. Here, the estimated frequency response is mapped to the pole-zero location of the estimated transfer function. The purpose of this procedure is to estimate the frequency response for health monitoring of SMPCs. However, this requires the development of an effective and intelligent cost function to adequately fit the estimated results with the pole-zero locations and consequently calculate the SMPCs circuit parameters (*i.e*. *L* & *C* values). Estimating the pole-zero location and calculating the values of the SMPC circuit components can also be determined directly by parametric identification methods [62].

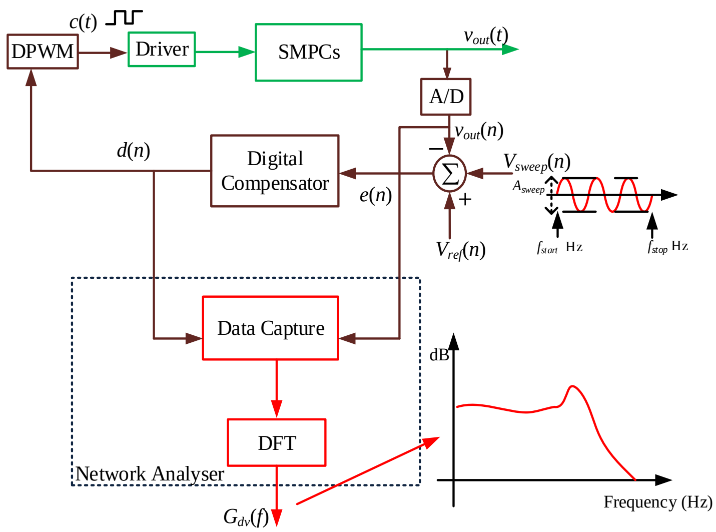

Fig. 14. Network Analyzer Scheme.

C. Power Spectrum Density Method

Based on the estimation process in [9], Congiu *et al.* [16] propose a new identification scheme using noise shaping and dither amplification techniques, instead of a LCO perturbation method, to improve the identification resolution (Fig.15). The work mainly focuses on extracting the output filter parameters of the buck converter. The identification process is accomplished in two phases; in the first phase, the system is operated in open loop with step increases in the reference signal to evaluate the impulse response of the DC-DC converter. The frequency response characteristic of the DC-DC buck converter is then estimated, and the resonant frequency is determined. In the second phase, the ESR zero of the output capacitor is extracted based on the estimated power spectrum density (PSD) of the SMPC during steady state operation of the DC-DC converter (43). Instead of generating an LCO perturbation signal, a 3rd order noise shaping filter is designed to excite the entire frequency range of interest (43). The PSD is applied to the error signal captured by the ADC chip and is computed by autocorrelation and FFT algorithms [16]. Compared to research in [9], the identification accuracy using this method is improved and the effect of ESR variation on the control loop is included. However, the computation demand is greater, and the identification process also requires multiple steps to complete. The estimated parameters are then used to tune the PID controller.

$$PSD\_e(n) = IFFT\left(FFT[e(n)]FFT[e(n)]^*\right) \tag{43}$$

$$G_{NS}(z) = (1 - z^{-1})(1 - 2\cos(2\pi \frac{f_n}{fs})z^{-1} + z^{-2}) \tag{44}$$

Where, G_{NS} is the discrete model of the noise shaper, f_s is the switching frequency and f_n is filter frequency.

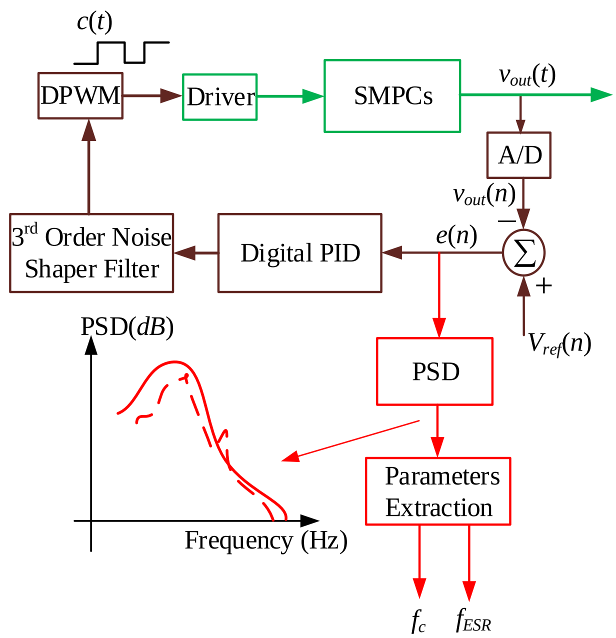

Fig. 15. PSD estimation block diagram.

F. Non-Parametric Structures Summary and Discussion

Correlation estimation scheme presented in [14, 29] was applied to buck and boost DC-DC converter with low speed of estimation and low estimation accuracy; actually, estimation can be realised in about 100 ms with simple signal processing resources. The implementation in this study was achieved through the Virtex-4 FPGA where the overall logic gates including pre/de-emphasis filter are 28.1 k and it required 9 kB RAM and 1.5 kB ROM to store the captured data. While, no details regarding processing time and hardware resources were given in the improved version [28], of correlation estimation scheme. Obviously, windowing techniques and using a classical correlation analysis (*ie*. not Walsh-Hadamard transform developed in [14, 29]) required higher hardware resources than the work in [14, 29], nonetheless the estimation accuracy was improved. Following on this, accurate model was accomplished in [13, 61] but requires an additional digital low pass filter and high resolution DAC, and transformer to couple the signal with the output voltage; accordingly, this scheme is unsuitable for on-line estimation.

To achieve an accurate dynamic estimation of SMPCs, the authors in [12, 25] proposed an alternative network analyzer scheme which can be easily developed for many power electronic applications, but for real time estimation it requires greater computational effort than other non-parametric methods. A software firework for network analyzer scheme based on Texas Instruments microcontrollers and code composer studio (CCS) was developed in [12]. To compare the execution time of the developed firework, the proposed scheme was implemented on both fixed and floating-point processors. According to [12], the number of cycles for the fixed-point processor is 126 cycles while floating processor takes 121 cycles at 50 µs sampling rate. For high frequency applications, authors proposed a dual-core architecture to implement the proposed algorithm.

To enhance the estimation accuracy for relay and LCO methods, PSD method was proposed in [16]; however, higher computation effort is required using PSD method. Virtex 6 FPGA is used to realize the proposed self-tuning algorithm. It is shown that integrating the PSD scheme with a self-tuning controller requires 7491 slice registers and 21583 slice look-up-tables (LUTs).

VII. Dual Estimation Structure

In this paradigm, both a non-parametric and a parametric method are combined to estimate a wide range of uncertainty in SMPCs (Fig.16) [30], to detect ageing mechanisms within the SMPC as presented in [63], and to directly design the digital control loop as demonstrated in [60]. As presented in [63], the identification procedure is accomplished in two steps. Firstly, the frequency response of the open loop converter is determined using FFT methods. Secondly, the system parameters are estimated from the frequency response data using parametric methods such as RLS algorithms. Clearly, implementing dual procedures is more complex and computationally intensive for on-line system identification purposes. In [60], a model fitting technique with an incorporated recursive parameterisation algorithm is used while in [63] a recursive weighted least square (WLS) technique (Table V) is deployed to estimate the parameters of the SMPC. As depicts in Fig.17, the aim is to find the candidate model which resembles the estimated frequency response data. Afterward, the controller parameters are re-tuned based on the estimated model. In [60], the estimate parameters are numerically processed to extract the converter coefficients; as a result, SMPC degradation can be detected.

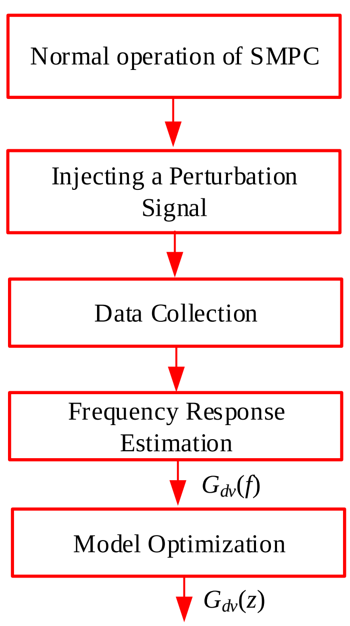

Fig.16. Dual estimation procedure.

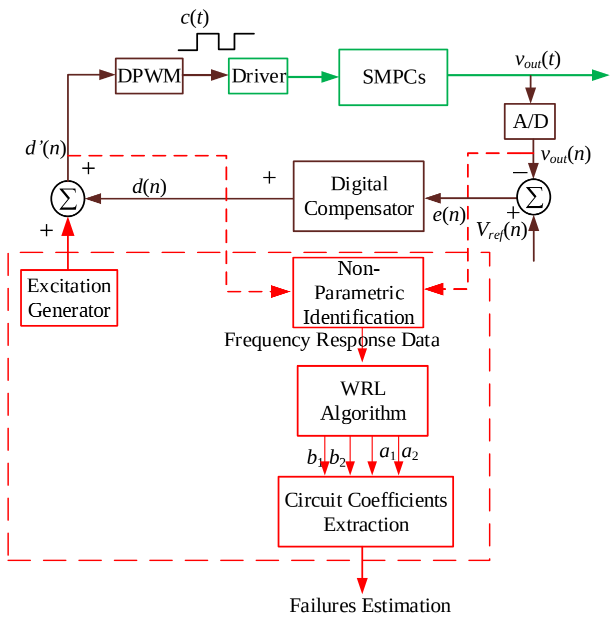

Fig. 17. Dual estimation scheme based on WLS algorithm.

Table V. Recursive WLS algorithm description.

Step	Formula
Initialization	$i = 0, W = 0, d_0 = 1, d_1 = 0, d_2 = 0, n = 0,$ where $d = [d_0 \quad d_1 \quad d_2]$ represents denominator parameters, $d = [n_0 \quad n_1]$, represents nominator parameters and w is the weighting matrix.
	Do for $i \geq 20$
1-Weighting matrix calculation	$W_{ik} = \frac{1}{\lvert D_{ik} \rvert \lvert H_n p_k \rvert}$
2-Calculate state variable vector	$S_{ik} = n_{ik} - d_{ik} H_{np_k}$, where H_{np} is the measured frequency response.
3-Update the estimated error	$e_{ik} = S_{ik} W_i$
4- Calculate the best model fit of parameters	$Bw = \sum_i \left[\left(\sum_{k=0}^{F} \overline{e_{ik}}^T e_{ik} \right)^{-1} \left(\sum_{k=0}^{F} e W_i^T H_{np_k} \overline{e_{ik}}^T \right) \right]$, where F is the frequency index.

Recently, an efficient hardware on-chip identification scheme known as Built In Self-Test (BIST) is presented in [24]. Unlike the estimation procedure in [60]; here, the parameters of the SMPC are estimated, then the frequency response of the system is determined for health monitoring purposes. In this work, digital pseudo noise (PN) and mixed signal cross correlation-based analysis is used to compute the impulse response of the buck converter and to detect changes in converter circuit coefficients such as C, L, R. Furthermore, to minimize the computational complexity compared with the work in [14, 29], an analogue correlation circuit is proposed. The output of the correlation circuit is passed to the FFT process to compute the frequency response of the SMPC (see Fig.18). Likewise, in [13, 61], a circular correlation scheme and multi length PRBS is deployed to improve the estimation accuracy of the impulse response and the frequency response of the system. The estimated impulse response is compared with the 2nd order damped impulse response to parametrically estimate the damping factor (ζ) of the SMPC. By substituting the calculated ζ in (45), the phase margin of the system can be calculated. As given in (4), the frequency response of the system can be directly computed by FFT and then compared with the stored frequency response data of the healthy converter to detect the degradation in the SMPC.

$$\boldsymbol{PM} = \tan^{-1}\sqrt{\frac{1+\sqrt{1+\frac{4}{\zeta^4}}}{\frac{2}{\zeta^4}}} \tag{45}$$

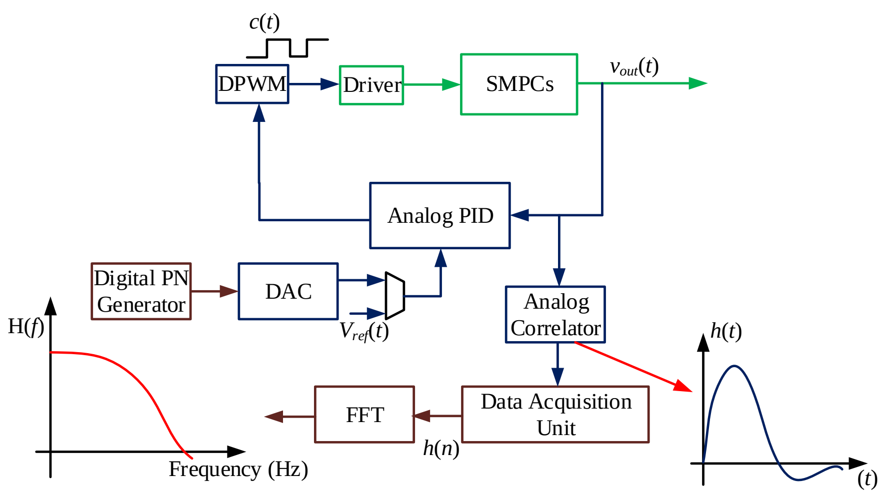

Fig. 18. BIST estimation scheme.

VIII. APPLICATION OF SYSTEM IDENTIFICATION ON LOAD CHANGES DETECTION & HEALTH MONITORING OF SMPCS

A. Abrupt Load Changes Detection of SMPCs

Sudden load changes can lead to the power converter operation switching from continuous conduction mode (CCM) to discontinuous conduction mode (DCM) [64]. As a result, without careful attention to the controller, the stability and performance of the system can be significantly compromised. Pitel and Krein [6], demonstrate a real time parametric system identification method for SMPC systems. An ordinary RLS method is used to monitor and estimate the abrupt load changes in DC-DC buck converter. To increase the estimation speed, the authors suggest using a control to inductor current transfer function of the buck converter instead of control to output voltage model:

$$G_{di}(s) = \frac{V_{in}R_o}{s^2LC\left(\frac{R_o+R_C}{R_o+R_L}\right)+s\left(CR_C+C\left(\frac{R_oR_L}{R_o+R_L}\right)+\frac{L}{R_o+R_L}\right)+1} \tag{46}$$

The work presented effectively identifies the parameters of the buck converter during the initial start-up of the system, and during periods of relatively slow load variations [33]. It clearly points out that a major challenge is to estimate the load value after an abrupt change. However, the estimation process using the RLS algorithm operates only with a very low sampling rate (approximately 4 kHz). Furthermore, in practice increased noise related to the high frequency inductor current ripple can potentially be experienced when using the current model, [6, 49].

Following on from [6], the authors in [49] proposed an adaptive variable forgetting factor RLS to estimate rapid load changes in a closed-loop buck DC–DC converter. The fuzzy part present to adjust the forgetting factor continuously depends on square predication error and variation square predication error $\left[{e_p}^2(k), \Delta e_p^2(k)\right]$ as shows in Fig.19.

$$\Delta e_p^2(k) = {e_p}^2(k) - {e_p}^2(k-1) \tag{47}$$

And the loss function describes as [2]:

$$J_k(\theta) = \sum_{i=1}^{n}\left[\sum_{j=1}^{n-1}\lambda(j-i)\right]\left[(y(k)-\boldsymbol{\varphi}^T(n-1)\widehat{\boldsymbol{\theta}}(n-1))^2\right] \tag{48}$$

Here, λ is the forgetting factor, y is the output signal, $\widehat{\boldsymbol{\theta}}$ is the estimated parameters, and $\boldsymbol{\varphi}$ is data vector.

Furthermore, the work in [49] presents a systematic procedure to map the numerical estimated discrete time parameters to the corresponding circuit components values. For simplicity and accuracy of parameter mapping, a typical control to output voltage model is employed (14) [49]. The scheme quickly identifies load changes, nonetheless the offered solution is computationally heavy, making it less suitable for high switching frequency power electronic applications. In [36, 50], KF algorithm has also been simulated to track and estimate the abrupt load changes in DC-DC buck converter.

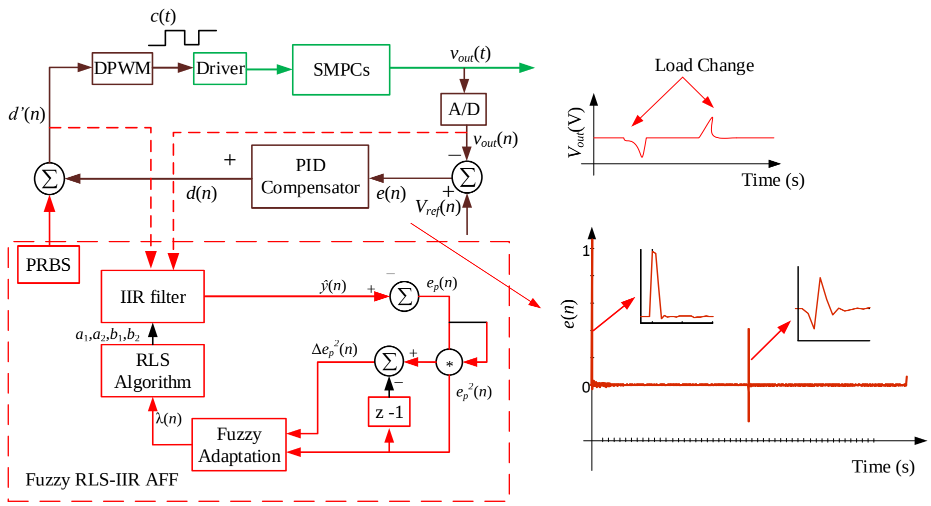

Fig.19. FRLS adaptive identification scheme.

B. Failure / Aging Detection of SMPCs

A substantial body of research has been presented in the literature to detect the degradation and resulting failure of DC-DC SMPCs using parametric schemes [17, 19, 39]. A recent example presented by J. Poon *et.al.*[18] employ a generalized gradient descent algorithm approach to detect faults in an interleaved boost DC-DC converter. Diagnosis of any faults depends on the specific circuit components (such as R_C, C and L). It is important to note that existing parametric estimation methods for SMPCs use the discrete average model (15); discretized using a zero-order-hold approach (13). However, in some cases extracting SMPCs circuit component values is very difficult using this discretization method. The work in [39, 49, 63] clearly describes the link between the estimated parameters and the circuit coefficients for the buck converter illustrated in (16), and sets out the challenges faced when employing this model for fault detection purposes For this reason, an alternative discrete model is proposed in [62]. As given in (49) for the buck converter and in (50) for the boost converter, the circuit components can be determined directly from the resultant estimated transfer function co-efficients. Initial testing of the proposed model based on RLS algorithm demonstrates the value of adopting this model for system identification of SMPCs [62]. The proposed technique can be applied to buck converter, but also non-minimum phase boost and buck-boost converters [43]. Analysis of non-minimum phase systems is rarely given consideration in literature, consequently most results are presented for the buck converter only. Importantly, all the state of art parametric techniques can directly utilize this model in the estimation/ loop control process.

$$G_{dv}(n) = \frac{\frac{V_{in}T_s}{LC}(T_s - t_d)\left(z + \frac{t_d}{T_s - t_d}\right)}{z^2 - \left(2 - \frac{T_s}{RC}\right)z + \left(1 - \frac{T_s}{RC} + \frac{T_s^2}{LC}\right)} \tag{49}$$

$$G_{dv}(n) = \frac{V_{in}T_s\left(\left(\frac{T_s}{LC} - \frac{1}{D'^2RC}\right)z + \frac{1}{D'^2RC}\right)}{z^2 - \left(2 - \frac{T_s}{RC}\right)z + \left(1 - \frac{T_s}{RC} + \frac{(D'T_s)^2}{LC}\right)} \tag{50}$$

Where, t_d is the delay time, special focus is required when selecting t_d for proper modelling, D is the dusty cycle and T_s is the sampling time.

IX. CONCLUSION

This paper presents an overview of the principles and techniques used in system identification for SMPCs. It provides details of the common parametric, non-parametric, and dual identification methods used in system identification for power electronic applications.

Non-parametric schemes are effective and cover a wide range of uncertainty within power converter; nonetheless, in many cases these methods are not ideal for rapid real time estimation that is vital for the development of advanced adaptive control for SMPC applications. Furthermore, abrupt changes within the system, such as load changes cannot readily be taken into account using these schemes. With parametric methods, real time identification of SMPC parameters can be easily and effectively achieved, making them well suited for component monitoring, on-line diagnosis tools, and adaptive control loop tuning. Typically, recursive estimation techniques, such as RLS, are used. However, the full capabilities of possible alternative estimation algorithms have not been fully investigated yet in power electronic applications. In particular, SMPC applications require high performance, computationally efficient, and low-cost solutions. This creates a challenging environment in which to develop advanced control solutions.

In addition, this paper considers several applications of system identification for SMPCs; and discusses the advantages and disadvantages of each. Going forward, intelligent integrated SMPC chip will continue to be developed by industry, facilitating greater integration between parameter estimation, digital control design, and advanced monitoring features. Greater research in this area is inevitable to reduce computation complexity, minimise digital hardware usage, and to introduce compact low cost intelligent SMPC devices. Furthermore, with the introduction of the new generation FPGA and multi-core microprocessor architectures new high-performance system identification algorithms will be developed for ultra-high switching frequency and sampling rate power converter topologies.

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