Parameter Monitoring for Degradation and Fault
Detection of DC-DC Converter in a Satellite
Power Supply System

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A thesis submitted to the Nanyang Technological University
in fulfilment of the requirement for the degree of
Doctor of Philosophy

2016

ACKNOWLEDGEMENT

First of all, I would like to thank my supervisor Prof Low Kay Soon for his generous support and helpful guidance. I would also like to thank Prof Ling Keck Voon and Prof Justin Dauwels for the kindly help they provided to solve many problems that I encountered in my research.

I would like to thank the administration staffs in Satellite Research Centre, Mrs. Tham Suet Mei, Mrs. Chong-Eng Puay Cheng and Ms. Low Siew Kheng for their administrative support in the course of my PhD candidature period. They brought us a safe and productive research environment.

Lastly I would like to thank all my friends, my seniors and my parents who always encourage me to get through the difficulties in the course of my study. I would like to thank my husband especially for his care and understanding.

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ABSTRACT

Once injected into the orbit, the satellites operate in space all the time and they are exposed under very harsh space environment such as extreme temperature variation in vacuum condition, radiation etc. As a satellite requires significant amount of investment, it is desired to understand its lifespan and performance degradation before a replacement satellite is launched. The degradation process of an electronic component is strongly related to the thermal, radiation and pressure conditions in the low earth orbit. This research focuses on the degradation and fault monitoring of the electronics components in the DC-DC converters of satellite power system. The main contributions of this research are listed below.

Main Contributions
<ul style="list-style-type: none">• Developed a low sampling rate online power converter circuit parameter estimation method. The estimation accuracy is compatible with the conventional high sampling rate methods as indicated in both simulation and experimental results.
<ul style="list-style-type: none">• Derived the interleaved boost converter's state space model to include the most important parasitic effects.
<ul style="list-style-type: none">• Developed a grouped immigration algorithm to accelerate the solution convergence rate in highly inter-relative multi-variable problems using biogeographical based optimization (BBO).

The degradations in the converters are detected through the online parameter estimation. The previously reported fault detection methods for the DC-DC converter require a sampling frequency to be at least 25 times of the switching frequency. In this thesis, the new parameter estimation methods are developed based on the averaged converter circuit model. This allows the measurements to be taken only once in every few switching cycles. Therefore, this method can be implemented

using low cost and low power processor. This is particular important for miniaturized satellites which have limited power budget due to the limited area of the solar array available for the satellite. The low sampling rate method has been verified through simulation and experimental study for a buck converter. The average estimation error for the circuit components are less than 5.17% in the simulation and 7.5% for the experimental results.

The parameter estimation method can be extended to other converter topologies. To provide redundancy in the power system, the multi-phase interleaved converter has been developed for various applications. Such feature is useful for satellite to eliminate single point failure. To develop an online parameter monitoring system, a general state space based interleaved DC-DC converter averaged model is formulated in this thesis. Moreover, the number of measurements and unknowns in this model are scalable

. As additional unknowns are added into the optimization problem for multiphase interleaved converter, the convergence rate of the conventional BBO approach dropped. To accelerate the convergence rate of BBO with moderate calculation complexity, the grouped immigration method is proposed in this research. Results have demonstrated that the convergence rate improved significantly such that the estimation error deviation for the circuit component is less than 2% and the averaged error is less than 7% when the function evaluation is restricted to 200,000. Thus it outperformed the conventional BBO method, in which the estimation error is greater than 100% due to premature termination under the same function evaluation limit.

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List of Abbreviations

ADC	Analogy-to-digital converter
BBO	Biogeography Based Optimization
BBOGI	Biogeography Based Optimization with grouped immigration
CBBO	Cooperative coevolution Biogeography Based Optimization
DSP	Digital signal processor
EMI	Electro-magnetic interference
ESR	Equivalent serial resistance
FDIR	Fault detection isolation and reconfiguration
HSI	Habitat suitability index
KCL	Kirchhoff's current law
KVL	Kirchhoff's voltage law
LBBO	Linearized Biogeography Based Optimization with local search
PRBS	Pseudo random binary sequence
PWM	Pulse width modulation
RCBBO	Real coded Biogeography Based Optimization
RLS	Recursive least square
SIV	Suitability index variables
ZOH	Zero order hold

CHAPTER 1

Introduction

As the satellite orbits around the earth, it is exposed to various thermal and radiation stresses. The components of the satellite may degrade faster than expected if these stresses become severe sometimes, for example when the satellite orbits over the South Atlantic Anomaly area. However, once the satellite is launched into space it is impossible to retrieve it back for maintenance. Therefore it is necessary for the satellite operators to know the fault and health condition of the critical components of the satellite. They can then correct the fault or plan ahead to finish the main missions if degradation is found. If redundancy is available, the reconfiguration could be activated before the fault occurs.

To detect and identify the failures and degradations, analysis at the component level must be performed. This has already been applied on many satellite attitude determination and control hardware such as the gyroscope and reaction wheels [1, 2]. For the satellite power system, its reliability maintenance is still restricted to the system level [3, 4]. The focus of system fault detection in the satellite power context is to maintain the battery charged and handling the trip event. In order to achieve this, the reconfigurations such as safe hold protection and reboot are used. An example is the fault detection, identification and reconfiguration (FDIR) developed for the power system of TerraSAR-X and TanDEM-X mission [5]. While the fault detection techniques at power electronics component level have not been applied in

the space system, they have been investigated intensively in recent years for other industries [6-11]. Nevertheless, carrying out component level FDIR in the stand alone satellite system is different. Firstly, there is limited system information available at limited sampling bandwidth. Secondly, the system works in a dynamical thermal and radiation environment.

1.1 Background

The main functionality of the satellite power system is to generate, regulate and distribute the power through the power bus at the required voltage level. Fig. 1.1 shows a typical block diagram of the DC-DC converters used in a satellite power system.

Fig. 1.1 Typical structure of satellite DC power system.

As shown in Fig. 1.1, the DC-DC converters play an important role. In the power generation unit, it extracts the solar energy from the solar array with the maximum power point tracking algorithm. In the power distribution unit, it converts the power

bus voltage to the desired load voltages. Components such as capacitors and MOSFETs are commonly used in the DC-DC converters. During the operation of these DC-DC converters, the capacitors and MOSFET switches are continuously exposed to load and environmental stresses. Redundancy hardware is usually designed for the critical DC-DC converters so that a “switch to redundancy” command can be performed if the output voltage level is lower than the system’s threshold value. Although this implementation is able to protect the power system in many failure scenarios, it cannot overcome some critical failures such as the capacitor short circuit failure. On the other hand, the failed component in the system is not identified and therefore the satellite operators have very little information about the failure. To overcome these issues, the component level fault handling for power electronics is required. This topic has been brought out in the power electronics society in the recent years [12-16] following the increasing needs of the safety and robustness.

The power electronics’ reliability has been shifted from the conventional testing to pass the handbook standard into analysing the physics-of-failure (PoF) approaches [14-16]. The procedure of PoF normally includes the following steps:

1. Identify the potential failure mechanisms.
2. Find the dominant cause of the failure.
3. Model the dominant failure mechanism with acceleration test [17-20] or cycle test [21, 22].
4. Derive the mean time-to failure (MTTF).

The field data or mission profile based lifetime estimation is more accurate than the data collected under the acceleration tests. For example in the wind turbine application [12] and metro systems [13]. Unfortunately, both field data and the

acceleration test results are not available for the space power electronics in step 3 due to the time and cost constraints. Therefore after step 2, this procedure can no longer be used. The works in this research are aimed for closing-up this gap by developing a feasible online monitoring method for the space power electronics systems.

From the data gathered in the recent industrial survey [23], the distribution of failures in the power electronic system is illustrated in Fig. 1.2.

Fig. 1.2 Failure rates distribution in the power electronic system.

Fig. 1.2 shows that the capacitor and semiconductor switches are the most fragile components in the power electronics systems, which are widely used in the satellite power system. The degradation of the electrolytic and ceramic capacitor have been studied through tests in [24] and [25]. The results for KM25VB-470 capacitors at 105 °C working temperature and 25 V rated DC voltage show that as an electrolytic capacitor degrades, its equivalent serial resistance (ESR) will increase, and its capacitance will decrease as illustrated in Fig. 1.3 [24]. For ceramic

capacitors, the cracks propagation and the loss of insulation resistance will also cause the capacitance to drop [26].

Fig. 1.3 (a) Degradation of ESR. (b) Degradation of capacitance. [24]

The MOSFET failures are quite common and critical in the power industries. The acceleration test had been performed on a batch of IRF520Npbf MOSFETs with TO-220 package. In [18, 19], the thermal stress and electrical stress were applied on the separate testing batches and the prognostic study had shown many meaningful results. One of them is shown in Fig. 1.4. In that study, the temperature was gradually increased beyond the MOSFET's rated temperature and then dropped to room temperature in each test run. During this process the MOSFET ON-state resistance was measured.

Fig. 1.4 Degradation of MOSFET ON state resistance under thermal cycling [19]

As shown in Fig. 1.4, the suddenly increase of the MOSFET ON state resistance was observed in each cycle from the 5th cycle onwards, and the degradation was not fully recovered when the temperature dropped back to the room temperature. Through the X-ray investigation, it was found that this effect is caused by the die-attach degradation. The study also observed a shift at the MOSFET threshold voltage in the test batch that went through another electrical stress test.

1.2 Objectives

The objectives of this research are as follows:

- Survey the existing component level fault detection and system identification methods that have been applied on the power electronic systems in various applications. Evaluate their feasibility for the satellite power system.
- Investigate the modelling method for different converter topologies. Develop an appropriate model for the fault detection method. The accuracy for these

models need to be verified so that the modelling errors will not affect the fault identification result.

- Develop an online component level fault detection method for the DC-DC converter through online components' electrical characteristics identification and parameters estimation. This estimation needs to be stable against system disturbances and measurement noise so that the fault prognosis is reliable.
- Verify the performance of the fault detection method on the multi-phased interleaved converter topology to enable hot redundancy and fault reconfiguration.

1.3 Main Contribution

The contributions of this research are listed in Table 1. 1

Table 1. 1 Contributions of the research

Chapter No.	Key contributions
Chapter 4	Derived the component parameter model of a DC-DC buck converter in the form of the achievable RLS regression coefficients.
Chapter 5	Developed a general method to estimate the component values in a DC-DC converter through Biogeographical Base Optimization (BBO) approach with local search.
Chapter 6	Derived a general state space model for the multi-phased interleaved DC-DC converter.
Chapter 6	The convergence rate of the BBO method is improved in solving for non-separable problems by adopting the proposed group immigration method with dynamic random grouping.

1.4 Outline of Thesis

The rest of this thesis is organized as follows:

Chapter 2 provides a literature review in two aspects. Firstly, a brief study on the possible failure mechanisms of different components in the power electronic circuit is investigated and summarized. This is followed by a review of the previous works on the power electronics fault detection and system identification are introduced.

Chapter 3 introduces the different modelling techniques which are commonly used by the previous research. A new average modelling approach is proposed in this research. As the averaged model has not been used for fault detection of power electronic component, the accuracy of the model is verified and the sensitivity of the averaged model against parameter variations is investigated.

Chapter 4 presents the direct mapping method to estimate the component characteristics from the system identification results using recursive least square (RLS) technique. The derivation of the mapping equations are presented in detail. Both the simulation and experimental results on parameter estimation are discussed.

Chapter 5 introduces a general online identification method which views the component characteristics as the features to be optimized. The BBO is proposed to solve the problem numerically. Both the simulation and experimental results on parameter estimation are presented. As compared with the RLS method, the estimation accuracy has been improved at the expense of higher computational cost.

Online parameter monitoring of an interleaved boost converter circuit is discussed in chapter 6. A general multiphase interleaved boost converter averaged model is first derived. The failure of MOSFET in the circuit is considered with the use of an independent inductor ESR estimator. The BBO method presented in Chapter 5 is improved by adding the group immigration (BBOGI) feature for faster

convergence. The simulation has been run for different BBO modifications to validate the effectiveness of the proposed BBOGI method and experiment has been conducted to verify the degradation detection and isolation capabilities of the proposed method.

Chapter 7 concludes the result and contributions achieved in this research work. The possible future research directions are discussed.

CHAPTER 2

Literature Review

Fault Detection Isolation and Reconfiguration (FDIR) is a well-established research topic. Many different FDIR methods have been developed in the past few decades [27-30]. The general failure in a system can be classified into three different fault types based on their nature as shown in Fig. 2.1. The three types of faults are the additive fault, the multiplicative fault and the parameter fault. Most of the FDIR methods focus on only one or two (but not all) of the fault types.

Fig. 2.1 Illustration of the failure types.

In the context of DC-DC converter, bias error of the ADC and PWM controller will cause additive fault. While gain error in the amplifiers will cause multiplicative fault. Component degradation in the converter circuit usually belongs to the parameter fault as the parameters in the circuit model are changed due to the degradation. Thus the component level fault detection problem is equivalent to the parameter estimation problem. The survey results on the components failure mechanisms are presented in the first part of this chapter to have an insight of the components' failure

modes. Then the following discussions are summarized from the methods in the literatures that are designed to detect these failures or identify the failure related parameters. Some of the methods only detect the failure qualitatively, and these methods are qualitative methods [31]. Most methods also provide quantitative estimation of the fault size. The degradation is normally a slow process at the beginning and it accelerates as the operating time accumulates (e.g. Fig. 1.3). This means that the small parameter degradations could reflect the remaining useful life. Therefore the quantitative methods are more favourable in the component fault monitoring context. In the next section the failure mechanism for the capacitor and MOSFET are briefly discussed.

2.1 Failure Mechanisms

2.1.1 Capacitor Failure Mechanisms

Different types of capacitors have different failure mechanisms. The electrolytic capacitor has the advantage of high capacitance per unit volume. It is most frequently used in the industries for the high current and low frequency applications. Its energy storage part is wounded with layers of anode aluminium foil, paper spacer and the cathode aluminium foil. The anode foil is covered with aluminium oxide and the paper spacer is impregnated with electrolyte. The failure mechanism of electrolytic capacitor is described by Table 2.1[32].

Table 2.1 Aluminium Electrolytic capacitor failure mechanism

Failure modes	Critical failure mechanisms	Critical stressors

Open circuit	Electrolyte loss	Operating voltage, operating temperature, ripple current
	Poor connection of terminals	Vibration
Short circuit	Dielectric breakdown of oxide layer	Operating voltage, operating temperature, ripple current
Wear out: drift of electrical parameters	Electrolyte loss	operating temperature, ripple current
	Electrochemical reaction (e.g. degradation of oxide layer, anode foil capacitance drop)	Operating voltage, operating temperature, ripple current

Table 2.1 shows the failure modes of electrolytic capacitor. The primary factors that induced the failure and internal causes. The electrolytic loss and degradation of the oxide layer will cause open and short circuit failures if they are not taken care of at the early phase. These degradations can be identified from the observation of the electrical parameters such as the ESR and capacitance.

In the aerospace electronics, the electrolyte capacitors are seldom used due to its outgassing in the vacuumed environment. The film capacitors are used instead and the failure mechanisms are summarized in the Table 2.2 [20, 33].

Table 2.2 Metallized film capacitor failure mechanism

Failure modes	Critical failure mechanism	Critical stressors
Open circuit (typical)	Self-healing dielectric breakdown	Operating voltage, operating temperature, ripple voltage
	Connection instability by heat contraction of a dielectric film	Operating temperature, ripple current
	Reduction in electrode area caused by oxidation of evaporated metal due to moisture absorption	Humidity

Short circuit (with resistance)	Dielectric film breakdown	Operating voltage, ripple voltage
	Self-healing due to over current	Operating temperature, ripple current
	Moisture absorption by film	Humidity
Wear out: electrical parameter drift	Dielectric loss	Operating voltage, operating temperature, ripple current, humidity

Metallized film capacitors will not be destroyed after short circuit and it will self-heal. The main advantage of metallized film is low ESR and equivalent serial inductance (ESL) value. The ohmic loss is lower than other types. Therefore it is often used in high surge current and high frequency applications. Table 2.2 shows the failure mechanism of the metallized film capacitor. The film capacitor is more likely to have open circuit failure and it is more sensitive to the humidity and temperature as compared with other types of capacitor. The parameter drifts indicate dielectric losses, which gradually lead to breakdown. Although the metallic film capacitors has low ESR and wide capacitance range, the ceramic capacitors are usually preferred in the converter circuit for aerospace applications for the safety considerations. Table 2.3 shows the failure mechanism for ceramic capacitors.

Table 2.3 Ceramic capacitor failure mechanism

Failure modes	Critical failure mechanisms	Critical stressors
Short circuit (typical)	Dielectric breakdown	Operating voltage, operating temperature, ripple current
	Cracking; damage to capacitor body	Vibration
Wear out: electrical parameter drift	Oxide vacancy migration Dielectric puncture Insulation degradation Micro-crack within ceramic	Operating voltage, operating temperature, ripple current, Vibration

Table 2.3 shows that the short circuit failure is the typical failure mode for the ceramic capacitor. In particular, the vibration stress is experienced on the capacitor during testing, launching and ejection of the satellite. Therefore the wear out failure monitoring on the ceramic capacitor is essential to prevent the short circuit failure caused by the crack propagation. The relationship between the parameter degradation and the short circuit are obvious from the failure mechanism.

Depending on different failure mechanism, some scenarios in the wear out failure mode could be identified either by decrease in the capacitance or increase of capacitor ESR under the nominal operation voltage and temperature. The failure mechanisms that could be observed through ESR monitoring include electrolyte loss, dielectric loss, and insulation degradation. The electrolyte loss are also observable by monitoring the capacitance. The propagation of micro-cracks within dielectric material in ceramic capacitor are not observable through parameter estimation unless the cracks cut through part of the electrode. Depending on the dielectric materials used, 5% ~12% of capacitance change indicates the failure of a ceramic capacitor. The cracks that propagate through both electrode will cause short circuit failure.

2.1.2 MOSFET Failure Mechanisms

The failure mechanisms of power MOSFET have been presented in [17, 19, 34-40]. The failures have been studied with aging test, finite element simulation and failure component inspection. Their discussions are summarized in Table 2.4.

Table 2.4 MOSFET failure mechanism

Failure modes	Critical failure mechanisms	Critical stressors
On-state resistance increase	Die attachment de-lamination and bond-wire lift-off at the source terminal. Thermal runaway.	Temperature changes.

high drain to source leakage current	Void formation on die solder attachment. Floating gate. Thermal-runaway.	Operating temperature and temperature changes, Operating current.
Threshold voltage shift	Gate structure degradation	Operating temperature and operating voltage
Short circuits of gate	Propagation of a crack through the polyoxide. Avalanche effect.	Vibration, electrical static discharge (ESD), cosmic radiation.

As observed in Table 2.4, the failure modes of MOSFET are closely related to the thermal conditions. The failure modes are also inter-related. The short circuit in MOSFET are recoverable normally. However the total breakdown may happen when the degradations became serious under the thermal conditions it induced.

2.2 Related Research Works on Fault Diagnosis of Power Electronics

In this section, the previous works on power electronics fault diagnosis are introduced. The state of art on power electronics online monitoring is first presented and followed by the system identification and lifetime estimation.

2.2.1 Qualitative FDIR methods

In the hybrid bond graph (HBG) method [10], the bond graph model is derived from the causal relations between the system states and measurements. The casual relation can then be used to generate residues. As a result, component failures can be identified in the system based on the analysis of the residual pattern. In [9, 41, 42], similar method is applied on the power converter fault diagnosis. In [41] the parameter estimation with the detected mode is not included. Therefore only abrupt

parameter failure can be detected. The fault diagnosis procedure with HBG is shown in Fig. 2.2.

Fig. 2.2 HBG fault diagnosis procedure.

As shown in Fig. 2.2, to detect and isolate each component fault, the pattern of the residues derived from the bond graph needs to be detectable under at least one mode and unique. This requires special design for the sensor placement which might not be achievable in some cases. Although it is able to identify multiple component failures in the circuit, the sampling rate is generally much higher than the switching frequency. In addition, the result only gives the failure structure. A separate parameter estimation algorithm is required to generate the quantitative result. This method is designed for general hybrid electronic circuit in which the mode change is uncertain and therefore needs to be determined during the fault diagnosis. Whereas in the digital controlled converters the hybrid mode of the circuit can be extracted from the control signals. With this information, there should be a more efficient way to solve the parameter monitoring problem.

Multi-model method is proposed in [43]. Different residual generators are designed for presumed failure scenarios. If the presumed scenario does not occur the residue generated should be within the designed boundary (e.g. H_∞ norm). The generated residues can be compared with the fault signature matrix for fault identification. The fault signature matrix are used to specify the relationship between the residues and failure models. If the i^{th} residue is observable in the j^{th} failure model, then the corresponding element S_{ij} is one, otherwise the element is zero. The signature matrix is a diagonal matrix if all the failure scenarios are isolatable. The simulation result shows that a short circuit failure in the buck converter can be detected with this method, under the assumption that the possible failure scenarios are given.

2.2.2 Quantitative FDIR methods

Online monitoring of the converter electronics is not only required due to the inaccessibility of the components in the space industry, it is also required because the component electric characteristics changes under different operating conditions. For example the capacitor impedance changes significantly as the operating frequency changes. An example is shown in Fig. 2.3 [32] which is measured from an 4700 nF / 500V aluminium electrolytic capacitor.

Fig. 2.3 Dependence of capacitor impedance on the operating frequency. [32]

There are many quantitative methods that have been used in the power electronics community to achieve online component value estimations. However, most of the methods only detect the capacitor failures but not other components. As an example, the ripple analysis method [24] was proposed in 1993 to test the degradation of electrolytic capacitor in the operation. This method has been applied in many applications such as adjustable speed drives [44] and half-bridged converters [45]. The study for a buck converter in [8] had provided more experimental results with

reduced measurements required. To measure the ripples accurately, the experimental data was collected with an oscilloscope operating at 2 MHz for the buck converter switching at 20 kHz. This sampling frequency is too high for most of the low cost digital signal processors (DSP).

For DSP implementation, the real time monitoring of capacitor was achieved for a UPS system in [32]. The overall procedure for this system consists of four steps:

These four steps are involved to achieve the failure prognosis result. The thermal model and component ageing model are quite standard. The coefficients in these models were obtained from the thermal and acceleration experiment through least square error curve fitting. Therefore the most important step is to achieve accurate component parameter monitoring.

Fig. 2.4 Real time capacitor fault diagnosis block diagram.

The overall FDIR system block diagram in [32] is shown in Fig. 2.4. In the interface board, the capacitor voltage, inductor current, the ripple of them, as well as the ambient temperature are filtered at different cut-off frequencies and amplified before feed into the ADC channels on the DSP board. This is necessary to avoid the aliasing effect due to high switching frequency and low sampling rate. The DSP block in Fig. 2.4 contains mainly the software algorithms in the DSP other than the ADC block. This includes the Kalman filter estimation algorithm and aging algorithm. The blocks outside the boxes are user interfaces to display the estimated capacitance, ESR and the estimated remaining life time. In terms of performance, 2.2 % simulation error and $\pm 5\%$ experimental error can be achieved on capacitor ESR estimation. For capacitance estimation, experimental error is $\pm 10\%$. The estimation results at different temperature can be used to derive the thermal model coefficients. The thermal model identification is realised with a least square curve fitting method. For the capacitor's remaining life time prediction, the aging model follows the Arrhenius Equation, and the coefficient can be obtained by lifecycle test. The boost converter under testing was switching at 5 kHz, and the sampling frequency was 80 kHz. Such a low switching frequency will induce larger ripple at the output. Some loads on the satellite such as the inertia measurement unit (IMU) requires high quality power supply. Therefore the normal switching frequency for the PWM converters are designed at 20 ~ 100 kHz.

In [46] a polynomial fitting method is proposed. The data acquired near the switching are neglected to reduce the switching noise effect. As a result, accurate estimation for capacitance and capacitor ESR is achieved. 90% of the real time estimations are within the range of $\pm 1.4\%$ for capacitance and $\pm 2.7\%$ for ESR as compared with the averaged estimation. The sampling frequency is limited to 500

kHz for the DSP chip used in the experiment and the highest boost converter switching frequency achievable is 20 kHz.

The methods that have just been described only considered the capacitor failure but not the other components in the DC-DC converter. In [47], the full parameter estimation of a DC-DC buck converter is discussed. It obtained the hybrid model of the DC-DC converter and the recursive least square (RLS) method was used to estimate the correlation coefficients in this hybrid model. These coefficients were mapped into the component values. The data was collected at 3 MHz and the buck converter was switching at 20 kHz. The experimental error is less than 6% for the inductance, capacitance and capacitor ESR estimations.

In summary, the quantitative FDIR methods in the literature require a high sampling rate than the switching frequency. According to [48] the high switching frequencies (e.g. more than 50 MHz) are expected in the future converter-on-a-chip design. With limited sampling capability, the performance of these methods will be affected due to the aliasing effect.

2.2.3 Linear System Identification Methods

The linear system identification method is normally applied on the DC-DC converter for modelling and controller design purpose. It is also used for parametric fault detection in many applications such as the tank reactor, heating system and the industrial robots [30, 49, 50]. In these methods, the component values are not directly estimated and therefore they cannot be directly applied to monitor the component degradation. In [49] the subsystem identification method is used to identify the faults in the continuous stirred tank reactor (CSTR). The Nonlinear

Autoregressive with Exogenous Inputs (NARX) neural networks is used to approximate the nonlinear behaviour of the system so that the linear state space model is recursively updated. The fault is identified from the Eigenvalue residue but the degradation level is unknown. In [50] the identified system coefficients are further mapped into physical parameters. In [51, 52] the impulse response of the buck converter is retrieved from the online measurements by applying the Walsh-Hadamard transformation and the Discrete Fourier Transformation. The estimated loop gain obtained from the experiment for the DC-DC converter matches well with the network analyser measurement. In [53] the recursive dichotomous coordinate descent infinite impulse response filter (DCD-IIR) method is shown to have comparable parameter estimation accuracy as the conventional RLS method but at a more efficient computation. Both methods were used to identify the coefficients in the discretized transfer function of a DC-DC buck converter. The output voltage was sampled at 20 kHz, which was the same as the switching frequency of the converter.

Fig. 2.5 Experimental estimation of buck converter model parameters. [53]

shows the DCD-IIR and RLS parameter estimation performance based on an experiment with a buck converter switching at 20 kHz. The model parameters indicated by the solid lines are derived from the component values given in the components' datasheet. The poles indicated by a_1, a_2 are estimated accurately as the derived model. However there are some couplings found in the zero estimation result b_1, b_2 . This result is good enough for on-line adaptive controller design as shown in [53].

The identification results for these methods are generated based on the relationship between the circuit states change and the pseudo random binary sequence (PRBS) injected in the control signal. The PRBS sequence is a perturbation chosen to emulate the white noise. Hence, its autocorrelation is close to a delta function and its correlation with the output signal is close to the impulse response of the converter system. As the perturbation will affect the power quality at the output, the perturbation level is constrained.

The perturbation is required for most of the system identification methods. However it is not necessary in the capacitor time constant identification as presented in [54]. This is achieved by an adjustable RC filter added in parallel to the output capacitor. When the time constant of the RC filter matching the output capacitor's time constant, the zero crossing point of the filter resistance voltage is located in the middle of the switch off period. Using this principle, a binary search is performed on the filter resistance and the time constant of the RC filter is used to approximate the output capacitor's time constant with an error of less than 1.5% for the buck converter switching at 500 kHz.

Another identification method makes use of the limit cycle oscillation instead of the perturbations is presented in [55]. Limit cycle oscillation is a phenomenon in the digital controlled DC-DC converter with high resolution ADC and coarse PWM. The output voltage will exhibit a periodical oscillation with fixed amplitude and period. In [55] this oscillation is monitored and the measured oscillation period and amplitude is used for parameter estimation and online controller tuning. The identification methods mentioned above are summarized in Table 2.5

Table 2.5 Summary of Identification methods

System Identification Method	Limitations
Recursive subspace system identification for parametric fault detection in nonlinear systems [49]	Estimated and update the state space model of the system. Fault detection based on eigenvalue residue. No direct information on the fault size.
Estimation of physical parameters for dynamic processes with application to an industrial robot [50]	Requires to derive physical parameters from RLS estimation result. For some systems the physical parameters are not identifiable.
Active system identification of DC-DC converter using digital control [51, 52]	Only the closed loop and open loop characteristics are identified. Not useful for parameter fault detection and identification.
Active Online System Identification of Switch Mode DC–DC Power Converter [53]	Transfer function coefficient are estimated. Not useful for parameter fault detection and identification
Synchronized Zero-Crossing-Based Self-Tuning Capacitor Time-Constant Estimator for Low-Power Digitally Controlled DC–DC Converters [54]	Only capacitor time constant is estimated. Cannot isolate degradation in capacitance and ESR. Cannot detect inductor fault.
Limit-Cycle Oscillations Based Auto-Tuning System for Digitally Controlled DC–DC Power Supplies [55]	Does not consider parasitic effect of inductor ESR and capacitor ESR. Estimated parameters not isolated.

2.2.4 Life time estimation methods

Life time estimation can be used for failure prognosis of the degraded components. It is the most important application for online parameter estimation. In [56] the degradation model and model coefficients are estimated for the metallized film capacitor used in the electromagnetic launch system. The remaining life time is estimated with the same set of test results but different statistical models. Each of the statistical model is related to an assumption of the failure mechanism. The result shows that the estimated life time is essentially depending on the choice of the statistical model. The remaining life time of electrolytic capacitor is predicted based on the physical model of the degradation in [57]. The capacitance and ESR values of the 15 capacitors under thermal test are measured by the Electrochemical Impedance Spectroscopy and the result is show in Fig. 2.6.

Fig. 2.6 Capacitance time series for capacitor aging estimation. [57]

The capacitance value in the future is estimated with the Kalman filter method in [57]. This value is used for remaining life time estimation. The value of the Kalman

filter estimation is compared with experimental measurement. The result shows the degradation curve predicted fits well into the experimental result, and the capacitor degradation model was verified.

2.3 Summary

In this chapter, the failure mechanism and the state of art online failure identification methods are introduced. It is obvious from the summarized failure mechanisms in Table 2.1 to Table 2.4 that the electrical parameter degradation is important symptom for many of the component failures. Therefore it is reasonable to use the result of online parameter identification for fault identification and prognosis.

The previous online identification methods that are discussed in this chapter have been summarized in Table 2.6. The fault identification capability for these methods are evaluated by their parameter estimation accuracy.

Table 2.6 Summary of related research works

Methods	Sampling/ switching rate ratio	Identified components	Estimation Error in the experiment
Bond graph	10	R, C	-
Multi-model	-	Short circuit resistance	-
Ripple analysis	100	C, ESR	<5%
Kalman filter	16	C, ESR	$\pm 10\%$, $\pm 5\%$
Polynomial fitting	25	C, ESR	< 1.8 %, -
RLS on hybrid model	150	C, L, ESR	< 6 %
impulse response identification	1	a_1 , a_2 , b_1 , b_2	1%, 1%, 5%, 5%
RC filter matching	1	$\tau = (R * C)$	1.5 %
Limit cycle oscillation	1	$\omega = \sqrt{L * C}$	-

As shown in Table 2.6, none of the available online parameter estimation method is able to achieve full parameter estimation. Moreover, most of the parameter identification for fault detection requires a sampling frequency to be much higher than the switching frequency. However, the system identification method has lower requirement on the sampling frequency because these methods do not need very accurate model. The identified parameters are usually used for controller design.

CHAPTER 3

DC-DC Buck Converter Model Verification

As mentioned in Chapter 2, the sampling frequency used for the system identification is normally lower than the fault detection algorithm. This is because it uses a less accurate averaged model. In this chapter, the accuracy of the averaged model and the hybrid model used in the conventional fault identification methods is compared. The feasibility of using the averaged model for parameter fault detection will be evaluated.

There are a variety of ways to model the DC-DC converters. The hybrid model in [47] includes the switches ON/OFF status as one of its state variable. This unified modelling method is applicable for all the topologies of the power electronic circuit with switching component. Moreover, it is able to precisely describe the circuit behaviour at any time. However, the required sampling rate when applying this model to capture the states of the switch is much higher than the switching frequency. On the other hand, the averaged model technique has only been used for system identification so far. It offers the advantage that its sampling frequency can be lower than the switching frequency. Table 3.1 compares the pros and cons of the hybrid and averaged model of DC-DC converter.

Table 3.1 Comparison of hybrid and averaged model of DC-DC converter

Model type	Advantages	Disadvantages /assumptions
Hybrid model	<ul style="list-style-type: none"> • Highly accurate independent of switching symmetry and sampling instant. • Applicable for variable switching frequency applications. • Standard model for parameter estimation. 	<ul style="list-style-type: none"> • Alias occurs with sampling rate lower than 25 times of the switching frequency. • Different continuous model are applied during analysis • Assumes that the switching happen right after a sampling instant.
Averaged model	<ul style="list-style-type: none"> • Sampling rate lower than the switching frequency is achievable. • Only single continuous model is used. 	<ul style="list-style-type: none"> • Assumes that the discrete model's prediction always intersects with the averaged model's prediction at the sampling instant. • Not verified for parameter estimation in previous researches.

As shown in Table 3.1, the averaged model is only an approximate model and its accuracy is not guaranteed. In this chapter, it is shown that the approximation is accurate enough for parameter estimation under certain circumstances. The feasibility to use the averaged model for online monitoring of the DC-DC converter will be evaluated.

3.1 Averaged Model of the DC-DC Buck Converter

The average model and the small signal model derived from state averaging of the hybrid model have been used for controller design of the DC-DC converters. The state space averaging technique was proposed in [58] in 1976. The DC and small signal characteristics are represented in the derived model. In [59, 60], the PWM switch model is proposed, which is focused on the control-to-output behaviour

modelling. The modelling procedure is much simplified and the resulted model can be illustrated with a circuit diagram which will be discussed in details later.

The averaged model for DC-DC converter that was proposed in [58-60] is only an approximate model. The state variables in the averaged model represent the averaged circuit states over one switching period. Thus the circuit states need to be measured multiple times in one switching cycle. This defeat our objective of reducing the sampling frequency as mentioned in chapter 1. Therefore, a new sampling scheme needs to be investigated so that the sample taken at a particular time instance can represent the averaged value of the circuit states. Here, the sampling time is fixed at the end of the switching period. The question is whether the measurement taken using the chosen sampling scheme can describe the averaged model precisely. To answer this question, the prediction error is evaluated by comparing the state estimation of the averaged model with the result achieved with a hybrid model. This evaluation is first demonstrated based on an example of buck converter.

The synchronous buck converter and its averaged model derived with method in [59] is illustrated in Fig. 3.1.

(a)

Fig. 3.1 (a) Buck converter circuit. (b) Averaged model.

In Fig. 3.1, d is the input duty cycle. C, L, R, R_C, R_S are the capacitance, inductance, load resistance, capacitor equivalent series resistance (ESR) and serial loss resistance. The serial loss resistance R_S includes three losses in the circuit namely the inductor ESR loss, the MOSFET loss and the PCB trace loss. Another loss caused by the leakage current in the capacitor is not depicted in Fig. 3.1 to simplify the analysis. Since the inductor current is used for circuit parameter estimation instead of the output current, one can treat the resistor R here as a combination of the capacitor shunt resistance and the actual load's resistance. This will make the output resistance estimation biased. To fix this issue, output current i_o is measured in series with the load resistor. one can estimate the actual load resistance with Ohm's law, and the capacitor shunt resistance is also obtained as (3.1).

$$R_{shunt} = \frac{v_o * R}{v_o - R * i_o} \quad (3.1)$$

Another assumption is made in Fig. 3.1 in order to apply the averaged model: the load can be treated as linear and non-active constant resistance within the DC-DC converter's operating point during the data collection period. For nonlinear load, as the operating output voltage is fixed, a linearized approximation of the load can be obtained. For active load, high small signal impedance is expected. The purposed

fault detection method cannot work in this case as well as the zero load cases. However, if there are other non-active load connected to the converter's output, the active load can be ignored due to their high small signal impedance.

Define the measured output voltage v_o and inductor current i_L as the state vector $\mathbf{x} = [v_o \quad i_L]$. Moreover, let V_{in} represents the input voltage. Then the state space model for this system can be derived as

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{u}, \quad (3.2)$$

$$\text{where } \mathbf{A} = \begin{bmatrix} -\frac{L+CRR_C}{CL(R+R_C)} & \frac{R(L-R_CR_SC)}{CL(R+R_C)} \\ -\frac{1}{L} & -\frac{R_S}{L} \end{bmatrix}, \text{ and } \mathbf{u} = \begin{bmatrix} \frac{V_{in}dRR_C}{L(R+R_C)} \\ \frac{V_{in}d}{L} \end{bmatrix}$$

From (3.2) it is observed that the control input d only appears in $\mathbf{u}$. Therefore the corresponding transfer function of the buck converter can be determined as follows after some algebraic manipulations:

$$\frac{V_o(s)}{D(s)} = \frac{V_{in}(RR_C C s + R)}{(R+R_S) + (L+RR_C C + RR_S C + R_S R_C C)s + LC(R+R_C)s^2} \quad (3.3)$$

3.2 Prediction Accuracy of Averaged Model

The averaged model in (3.2) is well-known in the literatures. The uncertain part is the sampling scheme. Two types of digital PWM signals are generally used in the power converters. The first is the asymmetrical PWM which is generated by comparing a saw-tooth waveform with a threshold. The other is the symmetrical PWM, which is generated by comparing the triangular waveform with a threshold. The difference between the two PWM schemes is shown in Fig. 3.2.

(a)

(b)

Fig. 3.2 (a) Sampling scheme illustration in Symmetric PWM, (b) Sampling scheme illustration in Asymmetric PWM.

In Fig. 3.2 (a) and (b) the sample is taken at the end of every switching cycle as indicated by the red circle marker. The symmetric PWM signal for the high side

switch Q1 is plotted in green dashed line to indicate the sampling time. The blue triangle marker indicates the averaged output voltage described by the averaged model. It is observed in Fig. 3.2 (b) that the measurements are bumpier than the averaged data especially from 6.9 to 7.1 millisecond during which the duty cycle changes. Comparatively, the sampled curve is smoother and follows the trend of the averaged data closely in the symmetrical PWM case. The bias difference in Fig. 3.2 (a) is mainly caused by the phase shift due to the averaging. To study the average model error, the state estimations are firstly derived with the hybrid model. The hybrid model estimation result is independent from the PWM scheme, therefore the estimation is accurate in both cases. The averaged model estimation result in each case is then compared with the hybrid model estimations. Firstly, the symmetrical PWM case is considered. The analysis is shown in Fig. 3.3. The states $\mathbf{x} = [v_o, i_L]$ are predicted separately with hybrid model and the averaged model.

Fig. 3.3 Hybrid model (solid) and averaged model (dashed).

Suppose the initial state $\mathbf{x}(0)$ in Fig 3.3 is given, the averaged model predict the state at time T is

$$\mathbf{x}_{avg}(T) = e^{AT} \mathbf{x}(0) + (e^{AT} - I)A^{-1}\mathbf{u}d \quad (3.4)$$

Here we introduce a hybrid model which describes the converter circuit behavior with different state space equations in each switch status.

In the case when the switch is ON:

$$\dot{\mathbf{x}} = A \mathbf{x} + \mathbf{u}. \quad (3.5)$$

In the case when the switch is OFF:

$$\dot{\mathbf{x}} = A \mathbf{x}. \quad (3.6)$$

By solving the initial value problem consecutively with the hybrid model at time $\frac{T(1-d)}{2}$ and $\frac{T(1+d)}{2}$, the hybrid model to estimate the state at time T is

$$\mathbf{x}_{true}(T) = e^{AT} \mathbf{x}(0) + (e^{AT(1+d)/2} - e^{AT(1-d)/2})A^{-1}\mathbf{u} \quad (3.7)$$

The modelling error of the averaged model can be written in the Taylor expansion form by subtracting (3.7) from (3.4) as

$$err = (\sum_{n=1}^{\infty} (AT)^n (\frac{d}{n!} - \frac{(1+d)^n - (1-d)^n}{n!2^n})) A^{-1}\mathbf{u}. \quad (3.8)$$

It is observed in (3.8) that the modelling error is 0 when $d = 0$ or $d = 1$. Due to the time symmetry the zero to second order terms are all cancelled out. The modelling inaccuracies is only contributed by the higher order terms which can be ignored.

For the case that the asymmetrical PWM is used, the sampling needs to be configured at the middle of the switch on or switch off period in order to have the same time symmetric property. This means the sampling frequency is not a constant if the duty cycle varies. This method can also be implemented but both

the implementation and the data analysis becomes more complex due to the variations in the sampling frequency.

If the sampling frequency is fixed and the sampling still takes place at the end of every switching cycle as shown in Fig. 3.2 (b), then the hybrid model estimate the circuit state at time dT as:

$$\mathbf{x}_{true}(T) = e^{AT} \mathbf{x}(0) + e^{AT} (\mathbf{I} - e^{-AdT}) \mathbf{A}^{-1} \mathbf{u}. \quad (3.9)$$

The error can be obtained by subtracting (3.9) from (3.4):

$$err = (e^{A(1-d)T} - d\mathbf{I}) \mathbf{A}^{-1} \mathbf{u}. \quad (3.10)$$

Equation (3.10) shows the error terms cannot be cancelled out. Therefore the averaged model cannot estimate the next state accurately using this scheme.

3.3 Sensitivity Study of the Averaged Model

One aspect that affects the component estimation accuracy is the sensitivity of the modeled physical values against component value variations. Here the physical values are v_o and i_L states. If a small component value variation results in large difference in the state vector, then the model is considered sensitive to the specified component. Intuitively, the degradation on that component is more likely to be detected. The variation of state vector is also affected by the variation of the input duty cycle. The converter's output voltage stability affects the performance many other applications on the satellite bus such as attitude determination. 5% is the maximum perturbation level that these system can tolerate. For example, if the converter's nominal operating output voltage V_{ref} is 3.3V, the worst case output voltage ripple is 150 mV. The corresponding constrain on the duty cycle perturbation is obtained as:

$$\Delta d_{max} = \frac{V_{ref}}{V_{in}} * 5\% = 0.33 * 5\% = 0.0165 \quad (3.11)$$

To give some margin at both upper and lower side, the final duty cycle perturbation level is determined as ± 0.08 .

In the following simulation, the parameters in the buck converters are set as shown in Table 3.2.

Table 3.2 Simulation settings for RLS online parameter monitoring.

Parameter	Symbol	Simulation Setting
Capacitance	C	330 (μ F)
Inductance	L	220 (μ H)
Capacitor ESR	R _C	0.025 (Ω)
Inductor ESR	R _L	0.075 (Ω)
Load resistance	R	1 (Ω)
Reference output voltage	V _{ref}	3.3 (V)
Input voltage	V _{in}	10 (V)

In the following test, it varies at least one component value slightly from the nominal values in Table 3.2. For each test, 300 samples of v_o and i_L are collected continuously. To study the sensitivity, the evaluation function can be derived as:

$$f = w_1 \sum_{i=1}^{300} (v_{oi} - v_{oi}')^2 + w_2 \sum_{i=1}^{300} (i_{Li} - i_{Li}')^2 \quad (3.12)$$

The v_{oi}' and i_{Li}' in (3.12) are calculated from (3.2) with the new component values different from the nominal values given in Table 3.2. In (3.12) the weightage w_1 and w_2 are set to one for the following study. Applying a different weightage will affect the sensitivity of the evaluation function to each component. Moreover, when there is colored measurement noise, the weightage will also affect the location of the

minimum optimization solution. In this research, the simplest weightage is chosen as this evaluation function are relatively sensitive to all the parameter changes, and the measurement noises in the later simulation and experiment are assumed to be white noise at the analogy-to-digital converter (ADC) output.

The sensitivity of the model against the capacitor parameters is illustrated in Fig 3.4.

Fig. 3.4 Sensitivity of the buck converter model against capacitor parameter variation

As shown in Fig. 3.4, the changes in v_o and i_L are not very sensitive with respect to change in capacitor ESR as a 50% change in R_C only results in 0.06 change in the evaluation function. It is also observed that the model is more sensitive to the capacitance as a 5% variation in the capacitance will increase the evaluation function by 0.08.

Fig. 3.5 Sensitivity of the buck converter model against inductor parameter variation

Fig. 3.5 shows that the buck converter model is comparatively more sensitive to the inductor parameters than the capacitor parameter. A 5% variation in the inductance will cause the evaluation function to increase by about 0.15, and a 5% variation of the inductor ESR is corresponding to 0.2 increase of the evaluation function.

Fig. 3.6 Sensitivity of the buck converter model against load variation

Fig. 3.6 shows that the converter model is very sensitive to the variation of the output resistance. A 0.1% change in the load resistance results in a change of the evaluation function by 0.2. Therefore its value is most easily detected.

3.4 Summary

In this chapter, the accuracy of the averaged model using two different PWM schemes has been studied. The analysis shows that the circuit state can be predicted with the averaged model more precisely under the symmetrical PWM scheme. The modeling errors in the asymmetric PWM case will introduce parameter estimation error which will be presented in Chapter 4. From the sensitivity analysis of the averaged model, component that is most sensitive is the most likely to be correctly estimated. The order for the sensitivities is $R > L > R_L > C > R_C$.

CHAPTER 4

Recursive Least Square Approach for Parameter Monitoring of DC-DC Converters

In Chapter 2, a literature review has been conducted on the available approaches for parameter monitoring of DC-DC converters. The results have been summarized in Table 2.5. It is clear that the current methods for online parameter estimation of DC-DC converter require a high sampling rate and cannot obtain the full parameter estimation. In Chapter 3 the accuracy of the averaged model has been studied. The result shows that the averaged model can be used for parameter monitoring. In this chapter, a new full parameter mapping estimation approach for DC-DC buck converter is introduced. Firstly the overall online monitoring system configuration is illustrated. Then the RLS with parameter mapping algorithm is introduced. The derivation of the parameter mapping equations will be illustrated in this chapter. These equations are able to convert the results of the RLS algorithm into the component parameters that are needed for degradation and fault monitoring.

4.1 System Configuration

The DC-DC converters that are used for power distribution need to provide low ripple voltage at its output. Fig. 4.1 shows the closed loop configuration.

Fig. 4.1 Online parameter monitoring block diagram.

As shown in Fig. 4.1, it consists of a PWM controlled DC-DC converter, a digital controller, and a parameter estimation system. During the identification process, a pseudo random binary sequence (PRBS) perturbation is applied. The parameter estimation algorithms can be run as a background routine on the satellite's on-board computer. The PWM duty cycle d from the digital controller and the output measurements from ADC are input to the parameter monitoring algorithm. In this thesis, the parameter monitoring is realized with two monitoring methods namely the RLS approach and the biogeography based optimization (BBO) approach. In this chapter, the RLS method is first presented.

4.2 System Identification with RLS method

The RLS algorithm has been used for various applications such as adaptive noise filtering [61] and adaptive control [53]. In this section, the acquisition of DC-DC buck converter's system coefficients from the RLS algorithm will be presented. The transfer function of the buck converter has been discussed in chapter 3. The output

voltage is measured and its sequence as well as the control signal sequence are gathered for processing. Let k be the time index for the sampling instant. Define $\boldsymbol{\varphi}(k)$ as the data vector as follows:

$$\boldsymbol{\varphi}(k) = [v_o(k-1), v_o(k-2), d(k-1), d(k-2)], \quad (4.1)$$

where v_o and d are the converter output voltage and duty cycle respectively. Let z^{-n} represents n step delay in the time domain. A second order discretized model can then be derived from (3.3) by:

$$G(z) = \frac{v_o(z)}{d(z)} = \frac{V_{in}(\theta_3 z^{-1} + \theta_4 z^{-2})}{1 + \theta_1 z^{-1} + \theta_2 z^{-2}}, \quad (4.2)$$

where $\boldsymbol{\theta}(k)^T = [\theta_1, \theta_2, \theta_3, \theta_4]$ is the parameter vector. (4.2) includes a zero order hold (ZOH) at the input of the converter system. Here zero order hold is the most accurate smoothing method in this case as the duty cycle is constant by nature between each sampling period. This is exactly the time response of a series of discrete input impulses followed by zero order hold. From the discretized model (4.2), the state prediction error can be determined as

$$\varepsilon(k) = v_o(k) - \boldsymbol{\varphi}(k)\hat{\boldsymbol{\theta}}(k). \quad (4.3)$$

where $\hat{\boldsymbol{\theta}}(k)$ is the estimated parameter vector. To solve for $\hat{\boldsymbol{\theta}}(k)$, the RLS algorithm is used to minimize $\sum_{k=1}^N \varepsilon(k)^2 \lambda^{N-k}$ through a series of recursive calculations. Here, N is the number of the available measurements and λ is the forgetting factor. The forgetting factor is added so that the RLS estimation could converge faster during the identification. The value of λ are normally set between 0.95 ~ 0.99. Low λ leads to fast convergence rate but the estimation results are more likely to be corrupted by noise. The λ value used in this research as well as the previous research [53] are set

to 0.98 to achieve accurate parameter estimation result in relatively short time. Table 4.1 shows the detail steps of the RLS algorithm.

Table 4.1 θ Value Estimation Based on RLS.

<p>Step 1: Initialization Set $P(1) = a * I$ and $\hat{\theta}(1) = \mathbf{0}$, where a is a large number, I is the identity matrix. repeat step 2 to step 4 :</p> <p>Step 2: Calculate the innovation gain γ</p> $\gamma(k) = \frac{P(k)\varphi(k)}{\varphi(k)'P(k)\varphi(k) + \lambda}$ <p>Step 3: Update the P matrix, so that the inverse of P is the weighted sum of the data covariance matrix $\Psi(k)'\Psi(k)$. Where $\Psi(k)^T = [\varphi(1)^T \varphi(2)^T \dots \varphi(k)^T]$</p> $P(k+1) = \frac{(I - \gamma(k)\varphi(k+1)')P(k)}{\lambda}$ <p>Step 4: Update the estimated parameter vector $\hat{\theta}$</p> $\hat{\theta}(k+1) = \hat{\theta}(k) + \gamma(k+1)(v_o(k) - \hat{\theta}(k)\varphi(k))$

From Table 4.1, it is observed that the algorithm continuously generates the estimation result $\hat{\theta}(k)$ to track the variations of the system on-line. When the algorithm converges the residue $\gamma(k)$ value approaches zero and $\hat{\theta}(k)$ value approaches the coefficients in (4.2).

4.2.1 Derivation of Parameter Mapping Equation

In order to retrieve the component values from $\hat{\theta}(k)$, the parameter mapping procedure shown in Fig. 4.2 is performed.

Fig. 4.2 Parameter mapping procedure.

The averaged model of the DC-DC buck converter in (3.2) can be expressed in a standard form by:

$$\frac{V_o(s)}{V_{inD}(s)} = \frac{\gamma\omega s + \beta(\alpha^2 \pm \omega^2)}{(s+\alpha)^2 \pm \omega^2}, \quad (4.4)$$

where $\alpha = \frac{L+RR_cC+RR_sC+R_cR_sC}{2L(R+R_c)C}$, $\alpha^2 \pm \omega^2 = \frac{R_c+R_s}{L(R+R_c)C}$, $\beta = \frac{R}{R+R_s}$, and $\gamma = \frac{RR_c}{L(R+R_c)\omega}$

As the control signal is the duty cycle which is hold as a constant in one sampling period, the overall sampled system transfer function could be represented by

$$G^*(s) = \frac{1-e^{-sT}}{s} \frac{\gamma\omega s + \beta(\alpha^2 \pm \omega^2)}{(s+\alpha)^2 \pm \omega^2}, \quad (4.5)$$

where $\frac{1-e^{-sT}}{s}$ is the transfer function of a zero-order hold. The corresponding z-domain transfer function can be derived as

$$G(z) = Z[\mathcal{L}^{-1}[G^*(s)]] = (1-z^{-1})Z\left[\mathcal{L}^{-1}\left[\frac{V_o(s)}{V_{inD}(s)}\right]\right] \quad (4.6)$$

where the symbol $\mathcal{L}^{-1}(\cdot)$ stands for the inverse Laplace transform which converts the system transfer function from the s-domain into the continuous time domain. The symbol $Z(\cdot)$ stands for the Z-transform which converts the system transfer function from continuous time domain into discrete z-domain. The discrete transfer function coefficients can then be represented by the RLS algorithm's estimation result. Depending on the actual conditions of the coefficients in the $\hat{\theta}$ vector achieved from RLS, the different discretization procedure is required. In the following discussions, the detailed derivation of the parameter mapping equations is presented for these two options.

- (a) For the case that $\theta_1^2 - 4\theta_2 < 0$

(4.4) can be written as $\frac{\gamma\omega s + \beta(\alpha^2 + \omega^2)}{(s + \alpha)^2 + \omega^2}$. By equating the parameters of z in (4.2)

and (4.6) the following results are derived:

$$\begin{cases} \theta_1 = -2e^{-\alpha T} \cos(\omega T) \\ \theta_2 = e^{-2\alpha T} \\ \theta_3 = \frac{(\beta - \beta e^{-\alpha T} \cos(\omega T) + e^{-\alpha T}(-\frac{\alpha\beta}{\omega} + \gamma) \sin(\omega T))}{V_{in}} \\ \theta_4 = \frac{e^{-\alpha T}(\beta e^{-\alpha T} - \beta \cos(\omega T) + (\frac{\alpha\beta}{\omega} - \gamma) \sin(\omega T))}{V_{in}} \end{cases} \quad (4.7)$$

From (4.7) the mapping to continuous transfer function coefficient is achieved as

$$\begin{cases} \alpha = -\frac{\ln(\theta_2)}{2T} \\ \omega = \sqrt{\frac{\arccos^2\left(\frac{-\theta_1}{2\sqrt{\theta_2}}\right)}{T^2}} \\ \beta = \frac{V_{in}(\theta_3 + \theta_4)}{1 + \theta_1 + \theta_2} \\ \gamma = \frac{V_{in}(\theta_3 - \theta_4) - \beta(1 - \sqrt{-(-4\theta_2 + \theta_1^2)}\frac{\alpha}{\omega} - \theta_2)}{\sqrt{-(-4\theta_2 + \theta_1^2)}} \end{cases} \quad (4.8)$$

By equating the coefficients of s in (3.2) to (4.4), the expressions of α , ω , β , γ can be derived as follows:

$$\begin{cases} \alpha = \frac{L + RR_c C + RR_s C + R_c R_s C}{2L(R + R_c)C} \\ \omega = \sqrt{\frac{R_c + R_s}{L(R + R_c)C} - \alpha^2} \\ \beta = \frac{R}{R + R_s} \\ \gamma = \frac{RR_c}{L(R + R_c)\omega} \end{cases} \quad (4.9)$$

From these relations, the component values can be estimated by the following equations:

$$\begin{cases} \hat{L} = -\frac{R(-2\alpha+\gamma\omega+\Delta)}{2\beta(\alpha^2+\omega^2)} \\ \hat{R}_C = \frac{R\gamma\omega(2\alpha\beta-2\gamma\omega+\beta\gamma\omega-\beta\Delta)}{2(\alpha^2\beta^2-2\alpha\beta\gamma\omega+(\beta^2+\gamma^2)\omega^2)} \\ \hat{C} = \frac{2\alpha\beta-2\gamma\omega+\beta\gamma\omega+\beta\Delta}{2R(-1+\beta)\beta(\alpha^2+\omega^2)} \\ \hat{R}_S = \left(-1 + \frac{1}{\beta}\right) R \end{cases} \quad (4.10)$$

where $\Delta = \pm\sqrt{4\alpha^2\beta - 4\alpha\gamma\omega + (-4 + 4\beta + \gamma^2)\omega^2}$

(b) For the case that $\theta_1^2 - 4\theta_2 \geq 0$,

(4.4) can be written as $\frac{\gamma\omega s + \beta(\alpha^2 - \omega^2)}{(s+\alpha)^2 - \omega^2}$. By equating the coefficient of z we

have

$$\begin{cases} \theta_1 = -2e^{-T\alpha} \cosh(\omega T) \\ \theta_2 = e^{-2\alpha T} \\ \theta_3 = \frac{\beta\left(-1 + \frac{\alpha}{\omega}e^{-T\alpha} \sinh(\omega T) + e^{-T\alpha} \cosh(\omega T)\right) - \gamma e^{-\alpha T} \sinh(\omega T)}{V_{in}} \\ \theta_4 = \frac{\beta\left(-e^{-2\alpha T} + e^{-T\alpha} \cosh(\omega T) - \frac{\alpha}{\omega}e^{-T\alpha} \sinh(\omega T)\right) + \gamma e^{-\alpha T} \sinh(\omega T)}{V_{in}} \end{cases} \quad (4.11)$$

The mapping to $\alpha, \omega, \beta, \gamma$ can be derived from (4.11) as:

$$\begin{cases} \alpha = -\frac{\ln(\theta_2)}{2T} \\ \omega = \sqrt{\frac{\text{arccosh}^2\left(-\frac{\theta_1}{2\sqrt{\theta_2}}\right)}{T^2}} \\ \beta = \frac{V_{in}(\theta_3 + \theta_4)}{1 + \theta_1 + \theta_2} \\ \gamma = \frac{V_{in}(\theta_3 - \theta_4) - \beta\left(1 - \frac{\alpha}{\omega}(2e^{-T(\alpha-\omega)} + \theta_1) - \theta_2\right)}{2e^{-T(\alpha-\omega)} + \theta_1} \end{cases} \quad (4.12)$$

By equating the coefficients of s in (3.2) to (4.4), the expressions of $\alpha, \omega,$

β, γ can be derived as follows:

$$\begin{cases} \alpha = \frac{L+RR_cC+RR_sC+R_cR_sC}{2L(R+R_c)C} \\ \omega = \sqrt{\alpha^2 - \frac{R_c+R_s}{L(R+R_c)C}} \\ \beta = \frac{R}{R+R_s} \\ \gamma = \frac{RR_c}{L(R+R_c)\omega} \end{cases} \quad (4.13)$$

The parameter mapping equations are derived from (4.13) as follows:

$$\begin{cases} \hat{L} = -\frac{R(2\alpha-\gamma\omega+\Delta)}{2\beta(\alpha^2-\omega^2)} \\ \hat{R}_c = \frac{-R\gamma\omega((2\alpha\beta+2\gamma\omega+\beta\gamma\omega)+\beta\Delta)}{2(\alpha^2\beta^2+2\alpha\beta\gamma\omega+(-\beta^2+\gamma^2)\omega^2)} \\ \hat{C} = \frac{2\alpha\beta+2\gamma\omega+\beta\gamma\omega-\beta\Delta}{2R\beta(1+\beta)(\alpha^2-\omega^2)} \\ \hat{R}_s = \frac{R(1+\beta)}{\beta} \end{cases}, \quad (4.14)$$

$$\text{where } \Delta = \pm\sqrt{-4\alpha^2\beta - 4\alpha\gamma\omega + (4 + 4\beta + \gamma^2)\omega^2}.$$

In (4.10) and (4.14), the parameter mapping gives two sets of analytical solutions depending on the sign of Δ . The inductor ESR value in the trivial solution and the real solution are the same. The trivial solution will change with different sampling rates or load settings while the real solution is independent from these variations. Therefore, the real solution can be identified by performing multiple estimations at different sampling rates or with different R . The trivial solution is resulted because only v_o is included in the objective function. To avoid the trivial solution, both v_o and i_L need to be included in the objective function. The procedure to achieve parameter estimation based on i_L is roughly the same as the procedure demonstrated on v_o . However, due to the limitation of the computing power on the satellite, this method was not carried out in this research to optimize the program size.

The derivations of (4.10) and (4.14) are all based on the assumption that V_{in} and R are constant during the identification process. R composites of load

resistance R_{Load} in parallel with the capacitor's shunt resistance R_{shunt} . However, normally shunt resistance is ignored and R is simply replaced by R_{Load} . The estimation bias of R can be derived as

$$R_{bias} = R - R_{Load} = \frac{R_{Load} * R_{shunt}}{R_{Load} + R_{shunt}} - R_{Load} \quad (4.15)$$

Thus, the effect of R_{shunt} on the estimation bias of all the other component can be derived from (4.10) and (4.14).

It is also assumed that the θ_2 estimated from the RLS algorithm is positive since it appears in (4.8) and (4.12) under the square root. If this assumption is not satisfied, the component parameters cannot be solved from the RLS estimation. In the actual experiment, θ_2 is sometimes estimated to be negative value due to the measurement noise. In this case, the parameter mapping equations cannot be applied and a default zero value is assigned to each component estimation result. The overall RLS online parameter estimation process is illustrated in Fig. 4.3.

Fig. 4.3 Parameter mapping procedure.

4.2.2 Simulation Study for RLS Method

MATLAB simulation has been conducted to verify the RLS method as well as the mapping equations. The Simulink model has been implemented following the system configuration in Fig. 4.1 as shown in Fig. 4.4 (a). The details of the parameter monitoring block in Fig. 4.1 is shown in Fig. 4.4 (b).

(a)

(b)

Fig. 4.4 (a) Simulink blocks for overall parameter estimation. (b) Simulink block for RLS parameter estimation.

Fig. 4.4 (a) illustrated the buck converter circuit which is controlled by a digital PI controller. The ZOH and quantizer blocks are added to emulate the ADC. The highlighted parameter estimation block takes input from the sampled data and estimated circuit parameters in 'RLC' and 'RLC1' block according to (4.10) and (4.14). The configuration of the parameter estimation block is shown in Fig. 4.4 (b), the RLS algorithm is written in 'ERLS' MATLAB function block, the estimated θ values from the RLS are averaged before the parameter mapping. This is to reduce

the ripples in θ estimations which are caused by the perturbation and measurement noises.

The MOSFET switching noise and ADC white noise are the major noise sources that are included in the proposed parameter estimation approach. The MOSFET switching noise is ignored in the simulation because measurements are taken in the middle of a switching period. The switching noise should be stabilized at this time. The white Gaussian noise is therefore the only source that are considered in this case, which is inserted at the location of the ADC. The converter parameters and control parameters for the simulation are shown in Table 4.2.

Table 4.2 Simulation settings for RLS online parameter monitoring.

Parameter	Symbol	Simulation Setting
Capacitance	C	330 (μ F)
Inductance	L	220 (μ H)
Capacitor ESR	R_C	0.025 (Ω)
Inductor ESR	R_L	0.075 (Ω)
v_o measurement Noise invariance	σ^2	10^{-6} (V^2)
Reference output voltage	V_{ref}	3.3 (V)
Input voltage	V_{in}	10 (V)
Switch frequency	f_{sw}	20 (kHz)
Sampling frequency	f_s	5 (kHz)
Resistive Load	R	1 (Ω)
PID block proportional gain	Kp	0.0076
PID block integral gain	Ki	50

As shown in Table 4.2, the sampling and the switching rates are different. The use of a lower sampling rate has been applied typically in the PWM converter system to allow for the use of a low cost processor for the controller and reduce the power

consumption [62, 63]. The ratio between them is termed as the Sampling Switch Ratio (SSR). Here the SSR is set to 4, which corresponding to shortest holding period to achieve high estimation accuracy at the specified measurement noise level. The relationship between the SSR and the noise level is explained in details in the discussions later. The RLS estimated θ values are depicted against the simulation time in Fig. 4.5.

Fig. 4.5 (a) Simulation data shows the enable point of the PRBS signal.

(b) θ estimated by RLS algorithm.

Fig. 4.5 (a) shows the time response of v_o and i_L of the buck converter. The buck converter is controlled by a PID controller. It is observed that the output voltage reached the reference voltage of 3.3 V after 0.01s. The PRBS is enabled at 0.02 s after the steady state is achieved. This is to ensure that the provided perturbation is large enough for the identification process avoiding the system dynamics at start-up. Small ripples within acceptable range ($\pm 5\%$) is observed at v_o due to the

perturbation. Fig. 4.5 (b) shows that the estimated parameters converged to their theoretical values after 0.15 s. These results can be mapped into the component values using (4.7) and (4.14). The corresponding results are shown in Fig. 4.6.

Fig. 4.6 Estimated circuit parameters of the buck converter circuit.

In Fig. 4.6 the estimation errors are initially large but the results converged to the simulation settings in Table 4.2 after 0.15s.

The previous simulation results are based on the assumption of nearly ideal measurements. To investigate the noise rejection performance of the proposed method, the simulation at the non-ideal measurement case is conducted. In this simulation the same settings in Table 4.2 is used, and the deviation of the measurement noise is set to 8 mV. To generate a stable estimation result, the SSR is increased to 8. The simulation results are depicted in Fig. 4.7

Fig. 4.7 Estimation results with 7 mV noise deviation. (a) Simulation data shows the enable point of the PRBS signal. (b) θ estimated by RLS algorithm. (c)

Estimated circuit parameters for the buck converter circuit.

Fig. 4.7 shows that the proposed parameter mapping method is able to generate accurate parameter estimation result when the deviation of the measurement noise

is increased from 1mV to 7 mV in the simulation. However the estimation results are not very stable as compared with the result achieved in Fig. 4.6.

The normalized root mean square error is used to evaluate the parameter estimation result. The Normalized Root Mean Square Error (NRMSE) of the estimation $\hat{X}$ is evaluated as:

$$E_{\hat{X}} = \frac{1}{K \cdot X} \sqrt{\sum_{i=1}^K (X - \hat{X}_i)^2} \quad (4.16)$$

where K is the number of estimation samples taken in the evaluation. The NRMSE of the estimation results achieved in Fig. 4.6 and Fig. 4.7 between 0.2 s ~ 0.3 s are calculated and summarized in Table 4.3. The averaged estimation errors that have been achieved by other research groups [8, 32] are also illustrated for comparison.

Table 4.3 Average estimation error for the online parameter estimation methods.

NRMSE	C	L	R_C	R_L
Proposed RLS method (noise deviation = 1 mV)	1.04%	1.46%	5.38%	1.83%
Proposed RLS method (noise deviation = 7 mV)	7.85%	7.09%	73.24%	3.45%
Ripple method [8]	N.A	N.A	0.3%	N.A
Kalman Filter [32]	2.7%	N.A	2.2%	N.A

From Table 4.3, it is observed that the simulation result of the proposed RLS method is in agreement with the results achieved in [32] and [8]. However, the proposed RLS approach is achieved at a much lower sampling rate of 5kHz instead of 80kHz in [32] and 2MHz in [8]. Moreover, full parameter estimation is achieved with the proposed method.

To evaluate the performance of the RLS online parameter estimation method at different noise levels, the simulation study is repeated for different noise levels. The ADC measurement noise normally include three parts. One is related to the analogy signal that is being measured and the digitization level, which is called the quantization noise. The quantization noise amplitude is limited to the least significant bit of the ADC and this is modelled by a quantizer block in MATLAB Simulink. Another one is clock jitter which means the sampling is not taken at the expected sampling time. This is not a problem in our study since the ADC clock frequency is generally much faster than the converter's switching frequency. The last part is thermal noise which is generated by the random thermal motion of the electrons. The ADC noises are usually modelled with Gaussian noise in the previous studies [32, 64]. Therefore, the measurement noise is assumed to be Gaussian white noise. The noise variation σ^2 is increased from 1 mV² to 151 mV² in a step size of 30 mV². The normalized root mean squared parameter estimation error is depicted against the SSR and noise level. The root mean square error is calculated for each point in this figure from 100 estimations at the specified noise level and SSR.

Fig. 4.8 Estimated circuit parameters at different noise levels.

Fig. 4.8 shows that the parameter estimation error is below 20% of the nominal component values at the noise variation of 151 mV² if higher SSR is applied. It also shows that the estimation error is very large when SSR is one even at the lowest noise level. Therefore the effect of the measurement noise on the estimation result can be reduced by an increase in SSR. The simulation result shown in Fig. 4.6 and Fig. 4.7 are marked at their corresponding positions in Fig. 4.8.

The results that have been shown are obtained for the RLS online parameter estimation performance with symmetrical PWM. For the asymmetrical PWM, it was mentioned in Chapter 3 that it will not fit into the average model and the fixed sampling rate. This can be verified through a simulation. The RLS estimation result in the asymmetrical PWM case is shown in Fig. 4.9. The simulation settings is identical with the previous setting in Table 4.2.

(a)

(b)

Fig. 4.9 (a) v_o , i_L state measurements and duty cycle with asymmetric PWM

(b) RLS parameter estimation result with asymmetric PWM

By comparing the result achieved in Fig. 4.5, large estimation errors on θ_3 and θ_4 are observed in Fig. 4.9 (b) due to the asymmetric PWM. This verifies the discussion that the average model is not accurate enough to describe the circuit behaviour if asymmetric PWM is used.

4.2.3 Experimental Evaluation of RLS method

The proposed approach has been realized using a digital signal processor (DSP) TMS320F28335. The experimental setup is illustrated in Fig. 4.10. The PWM switching frequency of this DC-DC buck converter is set to 20 kHz.

Fig. 4.10 Experimental setup.

The input and output voltages of the converter are 10V and 3.3V respectively. The output is connected to a 2Ω load resistor. Therefore the output power in this setup is 5.4W, and the maximum power for this converter circuit is 19.8W. The PRBS sequence is injected when the start identification command is initiated. 1000 samples of v_o and i_L are collected at a sampling rate of 2.5 kHz and the data is stored in the on-chip memory. The sampling count is determined by the RLS convergence rate. Large sampling count is normally required in case of noisy measurement in the experiment. During the sampling period the load is assumed to be constant and linear. In case that the nonlinear load is applied and the operating point is changed during the sampling period, the accuracy of the estimation result will be affected. Fortunately the output voltage is regulated and therefore the operation point will not vary much even with large sampling counts. The perturbation is disabled after 0.4s and the data is transferred to a personal computer through a serial port. The output voltage is also captured by the oscilloscope in order to calibrate the ADC sensors in the DSP board. The calibration process is completed before the identification

process. v_o is measured with the ADC port of the DSP through a voltage divider and i_L is measured with a high slew rate current sensor (e.g. INA193AIDBVT) which is shunt to a 20 m Ω low ESL sensing resistor. The error of the current sensor is 3% in the worst scenario. The sensor noise is also measured before identification starts. The derivation of the noise in the output voltage at steady state is 7mV. The oscilloscope waveform before and after enabling the identification is displayed in Fig. 4.11.

Fig. 4.11 Output voltage waveform shows oscillation after PRBS injection

In Fig. 4.11, the waveforms from the oscilloscope were captured during the execution of the RLS identification program. Channel 1 measured the output voltage. Channel 2 measured the output signal from the inductor current sensor. The current sensor gain is given by

$$G = \frac{1}{R_{sense} * 20} \approx 2.5 \quad (4.17)$$

Although the inductor current i_L is not needed for the RLS algorithm directly, the averaged i_L is useful for load resistance R estimation. It is observed in Fig. 4.11 that the output voltage oscillation stops when the PRBS is disabled. The measurement and the estimation results of the RLS method are depicted in Fig. 4.12.

(a)

(b)

(c)

Fig. 4.12 (a) v_o , i_L and d waveforms. (b) The estimation result of the discrete transfer function parameter θ . (c) The estimation result for L, C, R_C, R_S after parameter mapping.

Fig. 4.12 (a) shows the measurement waveforms of v_o and i_L . In Fig. 4.12 (b), the transfer function coefficients are estimated. The RLS algorithm has converged after 0.15 second. This is in agreement with the simulation result. The parameter estimation result in Fig. 4.12 (c) is unstable and some coupling are observed in the estimations of the capacitance and inductance values. It is observed that there is no estimation result for all the four parameters between 0.2s and 0.23s, and similar scenarios happens frequently in the Fig. 4.12 (c). This is due to the fact that the parameter mapping equations do not have a feasible solution when θ_2 is estimated as a negative number. When this happens, each estimated variable will be assigned as zero. Among the available results where the mapping solutions are achievable, the estimated capacitance and inductance are also varying from time to time. The NRMSE of the estimations from 0.15 to 0.4 second in Fig. 4.12 (c) are summarized in Table 4.4. Due to the coupling between the inductance and capacitance estimation in Fig. 4.12(c), the samples are not included in the results obtained in Table 4.4 if the estimated capacitance is less than the inductance. The estimation error is achieved by comparing with a truth value which is measured with a LCR meter at 10 kHz frequency.

Table 4.4 NRMSE of the estimation result in the simulation and experiment.

	C Error	L Error	R_c Error	R_s Error
LCR meter Reading	0.335	0.223	0.124	0.163 (R_L)
experiment	11.2%	24.3%	8.85%	N.A

Comparing the results obtained in Table 4.3 and Table 4.4, the RLS method is able to estimate the circuit component values in a buck converter in the simulation when the noise level is low. However the estimation result achieved for the capacitance and inductance in the experiment are not as stable as the simulation results.

4.3 Generalization of RLS method on other converter topologies

The transfer function of the buck converter can be derived without linearization. However, this may not be the case for other PWM converters. For the DC-DC converter topologies such as the boost converter, the control to output transfer function can only be obtained after linearization. In this case, the measurement accuracy of the operating point will also affect the parameter estimation result. The averaged boost converter model is illustrated in Fig. 4.13

Fig. 4.13 Boost converter averaged circuit

The variables in Fig. 4.13 are defined similarly to the synchronous buck converter case. The only difference is that the diode voltage drop V_D is introduced. The state

space equation is derived from the Kirchhoff's current law (KCL) and Kirchhoff's Voltage Law (KVL) relationships as follows:

$$\begin{bmatrix} \dot{v}_c \\ \dot{i}_L \end{bmatrix} = \begin{bmatrix} -\frac{1}{C(R+R_c)} & \frac{R\bar{d}}{C(R+R_c)} \\ -\frac{\bar{d}R}{L(R+R_c)} & -\frac{1}{L}(R_s + \frac{\bar{d}RR_c}{(R+R_c)}) \end{bmatrix} \begin{bmatrix} v_c \\ i_L \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{V_{in} - \bar{d}V_D}{L} \end{bmatrix} \quad (4.18)$$

$$v_o = \begin{bmatrix} \frac{R}{(R+R_c)} & \frac{RR_c\bar{d}}{(R+R_c)} \end{bmatrix} \begin{bmatrix} v_c \\ i_L \end{bmatrix}$$

where $\bar{d} = 1 - d$ in (4.15). Linearization of (4.18) at the particular operating point (V_c, I_L) can be derived as

$$\Delta \dot{\mathbf{x}} = \mathbf{A} \Delta \mathbf{x} + \mathbf{b} \Delta \bar{d} \quad (4.19)$$

$$\mathbf{A}_l = \begin{bmatrix} \frac{-1}{C(R+R_c)} & \frac{\bar{D}R}{C(R+R_c)} \\ \frac{-\bar{D}R}{L(R+R_c)} & \frac{-R_cR_s - \bar{D}RR_c - RR_s}{L(R+R_c)} \end{bmatrix},$$

$$\mathbf{b}_l = \begin{bmatrix} \frac{RI_L}{C(R+R_c)} \\ \frac{R_cRI_L}{L(R+R_c)} - \frac{V_cR}{L(R+R_c)} - \frac{V_D}{L} \end{bmatrix},$$

$$\mathbf{c}_l = \begin{bmatrix} \frac{R}{(R+R_c)} & \frac{RR_c\bar{D}}{(R+R_c)} \end{bmatrix}$$

where $\bar{D}$, V_c and I_L represent the nominal value of the complementary duty cycle, capacitor voltage and inductor current respectively.

In order to test the performance of the RLS parameter estimation performance, MATLAB simulation is configured for the boost converter with the settings shown in

Table 4.5.

Table 4.5 Simulation setting for boost converter RLS parameter monitoring

Parameter	Symbol	Simulation Setting
Capacitance	C	330 (μF)
Inductance	L	220 (μH)
Capacitor ESR	R_C	0.025 (Ω)
Inductor ESR	R_L	0.075 (Ω)
v_o measurement Noise invariance	σ^2	10^{-6} (V^2)
Reference output voltage	V_{ref}	10 (V)
Input voltage	V_{in}	3.3 (V)
Switch frequency	f_{sw}	20 (kHz)
Sampling frequency	f_s	5 (kHz)
Resistive Load	R	5 (Ω)
PID block proportional gain	K_p	0.005
PID block integral gain	K_i	15
Nominal complementary duty cycle	$\bar{D}$	0.2688
Nominal capacitor voltage	V_C	10.0506 (V)
Nominal inductor current	I_L	7.4782 (A)

The nominal values at this operating point is obtained through averaging 1000 sampled data in the steady state. With this parameter setting the theoretical discrete transfer function should be estimated by the RLS algorithm as

$$G(z) = \frac{v_o(z)}{\bar{d}(z)} = \frac{3.4472z^{-1} - 4.4969z^{-2}}{1 - 1.7792z^{-1} + 0.8229z^{-2}} \quad (4.20)$$

The RLS method is able to identify these coefficients as shown in Fig. 4.14.

Fig. 4.14 Boost converter RLS system identification

Fig. 4.14 shows the transfer function coefficients estimated by the RLS method as well as their theoretical value in (4.20) as indicated by the black dotted line. The estimation result for θ_3 and θ_4 are not as stable as the result obtained in Fig. 4.5 although the two simulations have the same measurement noise level. This is due to the operating point changes caused by the duty cycle perturbation. As the theoretical coefficients are different at each operating point during perturbation, the ripples in the estimation result are therefore expected. The parameter mapping for boost converter can also be derived with the similar approach as shown in the buck converter.

4.4 Summary

In this chapter, a low sampling rate online parameter estimation approach for a DC-DC converter has been developed with parameter mapping of the transfer function coefficients. The simulation and experimental studies have been conducted to verify

the proposed method. The simulation performance is comparable with the previous research works. The averaged estimation error for the capacitance, capacitor ESR, inductance and inductor ESR are 1.04%, 5.38%, 1.46%, and 1.83% respectively. Due to the measurement noise and the imperfections in the circuit, the experimental performance is not as good as the simulation result as shown in Table 4.4. The measurement circuit needs to be refined to reduce the noise deviation from 7 mV to 2-3 mV in order to generate stable and acceptable result according to the simulation. Moreover, generalizing the RLS to other converter topologies will have the additional error introduced by the linearization approximations. To overcome these shortcomings, another online monitoring method based on state estimation error optimization is proposed. This will be presented in the next chapter.

CHAPTER 5

Parameter Monitoring for DC-DC Converters Using Biogeography Based Optimization

In Chapter 4 the results from the RLS system identification have been used for online parameter estimation. The advantage of the RLS method is its recursive nature making it easier for real-time implementation. However, the derivation of the parameter mapping equation is system dependent. Therefore it is not a general solution for the fault detection problems for all the power converters. Besides, the system identification result is sensitive to the measurement noise. The required noise level for good performance is difficult to achieve in the switching circuit due to the Electro-Magnetic Interference (EMI). In this chapter, a new method based on biogeography base optimization (BBO) is proposed. The BBO method is normally applied to optimize the multi-variable objective functions. In the proposed method, the variable values are taken as the final result when the objective function reaches the expected level. The noise rejection ability of the proposed BBO method can be improved as more measurements can be included in the objective function. Moreover, this method uses a general state space model to formulate its objective function. Therefore the error introduced in the linearization procedure in RLS can be avoided.

5.1 Introduction to Biogeography Base Optimization

Method

BBO method is an evolutionary algorithm that was first proposed in [65]. It is inspired by the biogeographical immigration of the species among different habitats. The fitness for a solution is defined as its suitability index in the biogeography context. When the habitat suitability index (HSI) is low, the species will immigrate to another habitat with a higher HSI. The variables that determine the HSI are called the suitability index variables (SIV). This relationship is demonstrated in the biogeography immigration curve in Fig. 5.1.

Fig. 5.1 Biogeography immigration curve.

In Fig. 5.1 v_k and μ_k are the immigration rate and emigration rate. S_0 and S_{max} are the numbers of species at equilibrium and maximum number of species in the habitat respectively. When the HSI for a habitat (solution) increases the immigration rate decreases and the emigration rate increases. As a result the number of species in this habitat will increase. In this way the best individual in the population will gradually converge at the optimum solution. The overall procedure are illustrated briefly in the flowchart in Fig. 5.2.

Fig. 5.2 Flowchart of Biogeography Based Optimization Procedure

The SIV variables in Fig. 5.2 are 5-tuples. The element in the SIV corresponding to the circuit parameters in the DC-DC converter: L, C, R_S, R_C and R .

BBO is a relatively new evolutionary algorithm and it can provide competitive results as compared to other optimization algorithms including Genetic Algorithms (GA) [66, 67] and Particle Swarm Optimization (PSO) [68, 69]. These evolutionary methods aim to improve the solution of a multi-variable optimization problem by sharing the information among the randomly initiated individuals iteratively. In GA, the unselected individuals with poor fitness are discarded directly. Due to the lack of search range diversity, GA tends to converge prematurely. In PSO,

the best feature in a particle is stored and perturbed with a random solution in each iteration disregard of its fitness. As a result, the dimension of the innovation in PSO is wide. The BBO provides an alternative selection scheme besides GA and PSO. A solution with poor fitness in BBO is given a lower chance to affect others. This is similar to GA. However that solution in BBO is also given a higher chance to move to other solutions. As the components in a circuit normally degrade slowly, the population in the previous estimation could be added into the initial population in a new estimation to accelerate the convergence. For this reason, the BBO is preferred than other population-based optimization algorithms in this study.

5.2 Improved BBO Methods

The original BBO algorithm has been improved in different aspects recently to refine the tuning parameters in the algorithm [70-73] and also to adapt to different application requirements [74-78]. For example, it is found that when the SIVs in the problem are strongly interactive, the original BBO convergent rate slows down significantly. This is because the original BBO only changes the solutions along one dimension at a time. This creates a rotational variance among the interactive variables[79]. As a result the BBO algorithm has poorer performance for problems with non-separable objective functions [80].

Two approaches to improve the BBO performance in solving non-separable problems were introduced in the study [79] using the Linearized Biogeographical Based Optimization with local search (LBBO). One is to make the problem objective function more dimensional independent through linearization. However the perfect dimensional independence is usually not achievable. The second approach is to take

advantage of the available gradient search method. The gradient search with the interior-point algorithm is typically used in LBBO. The local search based on this algorithm is performed with the few best solutions in the population as the initial guess and fast convergence can be achieved. However, this calculation involves Hessian matrix inversion. It becomes inefficient as the problem dimension increases. For the more complicated DC-DC converter systems such as the interleaved converters, the problem dimension increases as more components and measurements are added into the system. To simplify the calculation for the purpose of online implementation, the cooperative co-evolution BBO (CBBO) algorithm was proposed in [81] for solving multi-variable optimization problem. In CBBO, the populations are divided into fixed groups and all the groups are identically treated as a subpopulation. The fitness of each individual in a subpopulation is determined by evaluating the fitness of the context vector (CONVER) it constructed with the best individuals from other subpopulations. However, this method often leads to convergence at the local optima due to the lack of population diversity. To overcome this issue, [81] also proposed to construct the context vector by randomly select individuals from each subpopulation. However, this could slow down the convergence rate significantly depending on the properties of the objective function. The problem with the context vector is that the function evaluation process is only performed on part of the variables effectively at a time, the other variables that do not belong to the currently evaluating group will be dumped even though it might have great contribution to the evaluation result. This fixed grouped implementations of the cooperative co-evolutions is similar to the approach in [82]. Studies have shown that the fixed group method often fails in the non-separable problems in which the variables are tightly interactive. Therefore, the random grouping is

proposed and it has been successfully implemented with different evolution algorithms [80, 83-86] but it has not been implemented with BBO yet.

In summary, the BBO method with local search (LBBO) [79] is the most efficient algorithm for small dimension optimizing problems. For example, the online parameter estimation of a buck converter which will be discussed in sequel in this chapter has only five parameters to be estimated. Thus the LBBO is investigated in the following discussions. When the problem dimension increases, the efficiency of the local search method decreases. The CBBO for large scaled problem [81] cannot improve the efficiency when optimizing non-separable problems with tightly interactive variables. In this case, a new modified BBO algorithm is required and this will be presented in chapter 6.

5.3 Formulation of the LBBO for a Buck Converter

In the remaining of this chapter, the buck converter will be considered. As there is only five variables in a buck converter circuit, the local search BBO method is considered.

The objective function is derived based on the state space model in the sequel. Given the initial states $\mathbf{x}_0$ and d sequence, the subsequent states can be estimated as a function of the component values by solving an initial value problem using the state space model (3.1). Firstly, the eigenvectors and eigenvalues for matrix A in (3.1) are obtained as $\mathbf{v}_i$ and λ_i . The system state at time t is estimated as

$$\hat{\mathbf{x}}(t) = \sum_{i=1}^2 c_i \mathbf{v}_i e^{\lambda_i^* t} + \mathbf{x}_p, \quad (5.1)$$

where c_i are constant coefficients of the eigenvectors and $\mathbf{x}_p$ is the particular solution of (3.1). In the case that the imaginary eigenvalues are $\lambda = a \pm bi$ and the corresponding eigenvectors are $\mathbf{v} = \begin{bmatrix} w_{11} \\ w_{12} \end{bmatrix} \pm \begin{bmatrix} w_{21} \\ w_{22} \end{bmatrix} i$, where $\begin{bmatrix} w_{11} \\ w_{12} \end{bmatrix} = \mathbf{w}_1$, and $\begin{bmatrix} w_{21} \\ w_{22} \end{bmatrix} = \mathbf{w}_2$, the state estimations can be determined as

$$\hat{\mathbf{x}}(t) = \sum_{i=1}^2 c_i e^{at} (\mathbf{w}_1 \cos(bt) + (-1)^i \mathbf{w}_2 \sin(bt)) + \mathbf{x}_p \quad (5.2)$$

c_i and $\mathbf{x}_p$ in (5.1) and (5.2) can be obtained from the initial condition $\mathbf{x}_0$ as:

$$\mathbf{x}_p = -A^{-1}\mathbf{u}, \quad (5.3)$$

$$\mathbf{c} = Q^{-1}(\mathbf{x}_0 - \mathbf{x}_p),$$

where Q is $[\mathbf{v}_1 \ \mathbf{v}_2]$ in the case of real eigenvectors and $[\mathbf{w}_1 \ \mathbf{w}_2]$ in the case of imaginary eigenvectors respectively. The objective function of the BBO algorithm is defined as the sum of squared state estimation error as:

$$J = \sum_{k=1}^N \|(\mathbf{x}(k) - \hat{\mathbf{x}}(k))\|_2 \quad (5.4)$$

where the estimated state $\hat{\mathbf{x}}(k)$ is obtained from (5.1) and (5.2) by substitute t with the sampling period T and $\mathbf{x}_0$ with the last step measurement. A total number of N samples are included in the objective function (5.4). The value of N is a design parameter and its selection will be discussed later.

It is observed that the BBO method solves a minimum squared error problem. On the other hand, the RLS estimation can only reach the minimum squared error solution with the forget factor $\lambda = 1$ in the steady state. The selection of the forget factor λ in the RLS method is a trade-off between noise rejection and convergence rate [87]. To reduce the total sampling and perturbation time, it is typical to choose $\lambda = 0.98$ [53]. Therefore, the RLS method cannot match the performance of BBO

method especially when the noise level is high. The detail procedures for the proposed algorithm are given in Table 5.1.

Table 5.1 BBO algorithm.

Step 1: Initialization

Generate a population of n_{pop} individuals $\chi = [\hat{C}, \hat{L}, \hat{R}_c, \hat{R}_s, \hat{R}]$. Each of χ contains a random estimation of the parameters within the given boundary. Assign suitable values to the following BBO constants:

Problem dimension $D = 5$,
Population size $n_{pop} = 10D$,
Maximum function evaluation $FE_{max} = 150000$,
Threshold of objective function value J_{th} ,
Mutation rate $\xi = 0.01$,
Local search criteria $N_{ls} = 10$,
Number of solutions in local search $n_{ls} = 2$,
Re-initialization criteria $N_{ri} = 10$.
Set $counter = 0$.

While the number of function evaluations $FE \leq FE_{max}$ or $J > J_{th}$ repeat step 2 to step 7 for each generation.

Step 2: counter++

Step 3: Check the habitat suitability index HSI for each individual

The HSI for the k^{th} individual χ_k is defined as:

$$HSI(\chi_k) = \frac{1}{J_k},$$

where J_k is obtained from (5.4). The emigration rate μ_k and immigration rate ν_k are defined as:

$$\mu_k = rank(HSI(\chi_k)) / (n_{pop} + 1),$$

$$\nu_k = 1 - \mu_k,$$

where the function $rank(\cdot)$ gives the rank of the individual's HSI value in an increasing order. The best individual is stored as χ_{best}

Step 4: Habitat modification and mutation

for $k=1; k \leq n_{pop}; k++ \{$

for $i=1; i \leq 4; i++ \{$

if $rand_1 > \mu_k$

Select another individual l using Roulette wheel selection so that the chance of each individual being selected is proportional to its immigration rate ν . Update the k^{th} individual with the step size proportional to ν_l .

$$\chi_k(i) = \chi_k(i) + \nu_l(\chi_l(i) - \chi_k(i))$$

if $rand_2 > \xi$

Reinitialize $\chi_k(i)$ with random number

}}

Step 5: Elite ranking

Rank the HSI again, replace the worst individual with previous χ_{best}
Calculate $\Delta \chi_{best}$ and update χ_{best} .
Update FE

Step 6:

Local search with **fmincon** function in MATLAB Optimization Toolbox. The default parameter tuning of this function is used. E.g. the maximum iterations **MaxIter** = 1000.

if $\Delta \chi_{best} < N_{ls} * J_{th}$

Apply gradient decent search. The initial guess to be the n_{ls} best solutions in the population, replace the solutions with the local searched result.

Step 7: Re-initialization

if $counter \% N_{ri} == 0$

Add n_{pop} randomly generated individuals into the population.

Evaluate their HSI for each individual with (5.4)

Select the best n_{pop} from the population of $2n_{pop}$ individuals as the new population.

Update FE

In Table 5.1, the four component parameters of the buck converter are estimated with the BBO method. The HSI is evaluated as the inverse of the state estimation error. The immigration rate and emigration rate are then calculated and the best few solutions in each generation are used for local search. Most of the BBO parameters such as FE_{max} , N_{ls} , n_{ls} and N_{ri} are determined using the nominal values as in other research works [79, 88]. The population size n_{pop} is usually set as 10 times of the problem's dimension so that the search space is explored more often. The studies in [84] show that BBO is relatively robust to different mutation schemes and the mutation rate is typically selected as 0.01. The expected threshold J_{th} in Table 5.1 can be estimated from the noise level in the measurement by the definition of the deviation as:

$$J_{th} = (1 + \Delta)N(\sigma_v^2 + \sigma_i^2), \quad (5.5)$$

where σ_v and σ_i are the standard deviations of the v_o and i_L measurements respectively. For a reasonably large sample size N (e.g. $N \geq 50$), the margin $\Delta = 0.3$ is adopted to guarantee the convergence. The computation cost of RLS parameter estimation has been discussed in [53] in the worst case scenario. The parameter mapping process requires only a few more elementary operations as shown in chapter 4. Comparatively the computational load for BBO method is analysed as well and the results are shown in Table 5.2.

Table 5.2 Worst case computational complexity of RLS and BBO in Each Iteration.

Method	Multiplications	Additions	Others
RLS	$14 + M_n + M_{map}$	$14 + A_n + A_{map}$	Elementary functions
BBO	$(2n_{pop} + n_{ls}\mathbf{MaxIter})$ $(2N + M_{eig})$ $+ n_{pop}D$	$(2n_{pop} + n_{ls}\mathbf{MaxIter})$ $(2N + A_{eig})$ $+ 2n_{pop}D$	Sorting; Roulette wheel selections

In each BBO iteration, $2n_{pop} + n_{ls}\mathbf{MaxIter}$ function evaluations, $n_{pop}D$ habitat modifications, and two round of sorting with n_{pop} elements are involved. In each function evaluation, the number of addition and multiplication operation is given by $2N + A_{eig}$ and $2N + M_{eig}$, where A_{eig} and M_{eig} are the number of operations required to obtain the eigenvalues and eigenvectors from the BBO generated circuit parameters. The RLS and BBO algorithms have been tested with the MATLAB scripts running on a desktop computer with Intel i7-3700 3.4 GHz processor. On average, the RLS takes 0.0086 seconds and the parameter mapping process takes 0.0103 seconds. The total time to obtain the component parameters in one iteration with RLS method is less than 0.02 seconds. For the BBO algorithm,

each function evaluation takes 0.0074 seconds and the process time for one iteration takes about 0.55 seconds ($N = 300$) on average.

5.4 Simulation Results

The objective function of the BBO algorithm is constructed according to (5.4). The search range of BBO for the five parameters in the buck converter is defined to cover all possible values. Their values are listed in Table 5.3. The R load estimation is normally ignored in the discussion of the results because this estimation is trivial, and the comparison is not provided in the benchmark since it is not included in RLS estimation results.

Table 5.3 BBO Search Range for Buck Converter Component.

	C (mF)	L (mH)	R_c (Ω)	R_s (Ω)	R (Ω)
Model	0.33	0.22	0.025	0.075	1
BBO range	$[\epsilon, 1000]$	$[\epsilon, 1000]$	$[\epsilon, 1]$	$[\epsilon, 1]$	$[\epsilon, 10]$

To investigate the suitable sample size for the construction of the BBO objective function, the sample size N in (5.4) is varied from 50 to 500 with a step size of 50 in simulation. The circuit parameter settings for this simulation are identical to the settings in

Table 4.5.

Fig. 5.3 BBO estimation accuracy at different sample size.

Fig. 5.3 shows the parameter estimation error at different sample sizes. The averaged Normalized Root Mean Square Error (NRMSE) of the estimated $\hat{C}, \hat{L}, \hat{R}_C, \hat{R}_S$ are evaluated as:

$$\text{NRMSE} = \frac{1}{4} (E_{\hat{C}} + E_{\hat{L}} + E_{\hat{R}_C} + E_{\hat{R}_S}) \quad (5.6)$$

where $E_{\hat{X}} = \frac{1}{K \times X} \sqrt{\sum_{i=1}^K (X - \hat{X}_i)^2}$, K is the number of simulation execution.

In (5.6), X can be any one of the parameters C, L, R_C, R_S . For each sample size, the BBO algorithm is executed for $K = 100$ times with different measured data to form the objective function (5.4). From Fig. 5.3, it is observed that the estimation error decreases as more samples are used in the objective function. At the same time, the difference between the maximum and minimum estimation error is reduced. However large sample size requires more computational power. After trade-off, a sample size of $N = 300$ is selected for all the subsequent BBO estimations.

Fig. 5.4 Evolution of BBO estimation error and.

Fig. 5.4 illustrates the evolution process in the BBO estimation. The local search feature in the BBO algorithm allows all the five parameters to be updated simultaneously. The results show that all the five parameters of the buck converter are estimated close to their settings. The final estimation is a stabilized solution because the cost function J converged to about 0.0012 which is expected according to (5.5) at a noise deviation of 1mV. The average estimation error from 100 repeated tests with different measurement samples are listed in Table 5.4.

Table 5.4 Average estimation error of different components

	C (mF)	L (mH)	R_c (Ω)	R_L (Ω)
Simulation settings	0.330	0.220	0.025	0.075
Estimation result in Fig. 5.4	0.317	0.233	0.024	0.071
NRMSE estimation error	0.95%	1.31%	5.17%	1.61%

As shown in Table 5.4 the estimation error for R_c is the largest among these parameters. This is due to the output sensitivity for capacitor ESR is low as shown in the sensitivity study in Chapter 3.

5.4.1 Estimation Accuracy of BBO and RLS

To compare the performance of RLS and BBO algorithms, similar tests with different parameter settings have been conducted. In the first set of test, the loading scenario have been varied from 30% to 130% of the nominal load of 10.89 W. The v_o , i_L and d for BBO estimation and the RLS results are all collected in the same time interval [0.4s 0.5s] with the SSR varied from 1 to 10. The BBO is repeated for $K = 10$ times with different samples in this interval. These 10 estimations are then used for the NRMSE evaluation for BBO method at each point. The noise deviation for the simulation is set to 1 mV and the result is show in Fig. 5.5.

(a)

(b)

Fig. 5.5 Estimation accuracy under load variation for (a) BBO (b) RLS.

Fig. 5.5 shows that the accuracy of BBO is better than RLS method. It is also observed that the performances of both algorithms are improved by increasing the SSR moderately. This is expected since the correlation between the duty cycle and the state variables increases when the duty cycle is hold for a longer period. Moreover, the imperfections in the duty cycle due to the switching noise are smoothed over multiple switching cycles. When the SSR is 1, which is the case in [53], the parameter estimation error is much greater than 30% due to the measurement noise.

To study the effectiveness of the proposed approach under noisy environment, the noise variation of the output voltage and inductor current measurements are increased in step of 30 mV^2 starting from $\sigma^2 = 1$. The result is shown in Fig. 5.6.

Fig. 5.6 Estimation accuracy under different measurement noise level for (a) BBO (b) RLS.

Fig. 5.6 shows that the performance for both RLS and BBO estimations have improved with larger SSR under noisy environment.

The simulation result in Fig. 5.5 and Fig. 5.6 shows that the BBO algorithm outperforms the RLS algorithm under different load and noise levels. However, the contribution may come from the additional i_L measurement that is introduced in the BBO objective function. To compare the estimation performance of the BBO and

RLS algorithm with the same measurement, the BBO objective function is derived directly from the discrete transfer function (4.2).

$$J(C, L, R_s, R_C) = \sum_{k=1}^N \|v_o(k) - \hat{v}_o(k)\|_2 \quad (5.7)$$

where k is the sampling step, N is the total sample size for this estimation. v_o is measured from the circuit. In this implementation, the measurement that is used in the objective function is the same as the RLS method. In this implementation the inductor current measurement is not used.

In (5.7), the value of $\hat{v}_o(k)$ can be estimated from (4.2) as

$$\hat{v}_o(k) = \boldsymbol{\varphi}(k) \cdot \boldsymbol{\theta}(C, L, R_s, R_C) \quad (5.8)$$

As compared with the RLS method, the deriving of parameter mapping equation is not required and the implementation is simple. The objective function (5.7) is used in the following comparison. The BBO algorithm is executed under a noise variance of 31 mV² and the SSR is varied from 1 to 10. The result is depicted in Fig. 5.7 together with the results obtained for BBO and RLS in the noise level test.

Fig. 5.7 Comparison of RLS method and BBO method with only the output

It is observed in Fig. 5.7 that the BBO result is more accurate than the RLS method regardless of the number of measured states. However, the BBO algorithm has better performance with full state estimation. These behaviours are expected as the RLS method needs to balance between the convergence speed and noise rejection by tuning the forgetting factor λ . When $\lambda < 1$ the contribution of the previous estimation errors decrease with time and therefore the effective samples that can affect the current estimation is less than the number of samples taken in (5.7). The BBO with i_L measurement performs better than the BBO without i_L measurement also for the same reason.

5.4.2 Monitoring of Multiple Parameter Variations

The performance of a DC-DC buck converter is dependent on the normal operation of each component in the circuit. When there are more than one component degrade, the proposed method is able to detect and fully isolate them. To illustrate this capability, the simulation is repeated with different C and R_S parameter settings. The capacitance is varied in the range of $\pm 50\%$ with a step of 10%. At the same time, R_S is varied from 0.04Ω to 0.44Ω in step of 0.04Ω . The BBO estimation result is depicted in Fig. 5.8. The normalized estimation error of the varied components and the estimated value of the normal components are evaluated in this test.

Fig. 5.8 (a) R_S estimation error under parameter C, R_S variation. (b) R_C estimation under parameter C, R_S variation. (c) C estimation error under parameter C, R_S variation. (d) L estimation under parameter C, R_S variation.

Fig. 5.8 (a) shows that when C is large, the $\hat{R}_s$ estimation accuracy is independent from the variation in capacitance. It is observed that the estimation error increased to 10% with 50% reduction in capacitance due to the model inaccuracy. Fig. 5.8 (b), (c) and (d) show that the variations in the capacitance and inductor ESR will not affect the estimation of the other three components as the surfaces of the estimation results are almost flat.

5.4.3 Performance with Non-resistive Loading

The previous simulations are based on the assumption that the converter is connected with a pure resistive load. In actual circuit, the load might be passive or active. In the active load scenario, the output current and voltage relation for the supplying converter is depending on the load converter's switching states. In this case the averaged system model is no longer valid. In the passive load scenario, the load capacitor must be connected in parallel with the output capacitor of the converter. The equivalent output capacitance is the sum of them. The following simulation aims to investigate the effect of the load inductance on the parameter estimation accuracy.

In this simulation, the load inductance L_o is varied from 10^{-5} mH to 1 mH which is connected in series with the load resistance R . The noise deviation is set to 1 mV for the voltage measurement and 1 mA for the current measurement. The other simulation parameter settings are unchanged. The averaged estimation error is calculated with (5.6) and depicted in Fig. 5.9, which shows that the estimation accuracy is not affected by the load inductance.

Fig. 5.9 Estimation accuracy under load variation.

Due to the limitation of the MATLAB Simulink the nonlinear load scenario cannot be simulated. However, the nonlinear load can be viewed as linear when the terminal voltage is regulated at a fixed point. In the worst case scenario, the variation of the load resistance due to the terminal voltage variation can be added independently in the simulation. This study is carried out in the following simulation.

5.4.4 Performance with Load Perturbation

The study of the sensitivity of BBO and RLS has been carried out through simulation with small perturbation on the load. For example the load can be the satellite's attitude control system (ACS) which consist of actuators such as reaction wheels and magnetorquers. The load profile is a square waveform with the original load R_0 and the perturbation ΔR as indicated in Fig. 5.10. The DC part of the load profile comes from the magnetorquers which draw constant current in certain period, and the squared waveform comes from the DC motors to accelerate the reaction wheel. Usually the reaction wheels are also regulated using the PWM signal.

Fig. 5.10 Load profile for unknown load dynamics sensitivity testing.

The period of the square waveform is T_R . The noise deviation is set to 1 mV and 1 mA so that the difference in the performance is mostly caused by the sensitivity of the different algorithms rather than the measurement noise. The switching frequency is set at 20 kHz and the sampling frequency is fixed at 5 kHz in this simulation. The sample size N in (5.4) is 300, and R_0 is set to 1 Ω . The test is run for 20 times with different measured data and the NRMSE of the estimation results are depicted in Fig. 5.11 to illustrate the influence of the load dynamics on the estimation result.

Fig. 5.11 Sensitivity tests at different ΔR with $T_R = T$.

Fig. 5.12 Sensitivity tests at different T_R with $\Delta R = 0.05R_0$.

The result in Fig. 5.11 shows that both BBO and RLS algorithms can tolerate the unknown dynamics of the load and BBO is less sensitive. In Fig. 5.12, when $T_R \leq T$ the estimation error is small. When $T < T_R < 2NT$ the estimation accuracy will be affected by the load perturbation. When $T_R > 2NT$ the perturbation of the load will not affect the accuracy of the estimation. In the actual scenario, both SSR and sample size N can be adjusted to eliminate the load perturbation effect if the period of the perturbation is known.

5.5 Experimental Results

The same experimental setup of RLS method in Fig. 4.1 is used in this study. The data sequence of v_o , i_L and d are measured in the RLS estimation, and the same data set is used for the BBO estimation. The evolution process of the proposed BBO approach is illustrated in Fig. 5.13.

Fig. 5.13 BBO evolution process with the experimental data.

Fig. 5.13 shows that the BBO's estimation converges at 21st generation and the cost function has decreased to 0.016 which is expected according to (5.5) at a noise deviation of 7 mV. The BBO parameter estimation is repeated with different data sequences for 100 times with SSR varied from 7 to 10. The averaged results are summarized in Table 5.5, and the standard deviation is plotted in Fig. 5.14. Using the measured values from a LCR meter as reference, the NRMSE is calculated excluding the R_s estimation due to the unmeasurable series losses.

Table 5.5 Model Parameters for Boost Converter Example.

	C (mF)	L (mH)	R_c (Ω)	R_s (Ω)	NRMSE %
LCR meter	0.335	0.223	0.124	0.163 (R_L)	-
SSR = 7	0.3972	0.2108	0.1105	0.3501	10.75
SSR = 8	0.3399	0.2358	0.1116	0.3308	8.27
SSR = 9	0.3523	0.2398	0.1235	0.3364	6.48
SSR = 10	0.3461	0.2443	0.1213	0.3396	9.55

Fig. 5.14 Estimated circuit component values and the standard deviation (3σ) with varies SSR.

The estimation accuracy achieved in the experiment is in good agreement with the simulation result in Fig. 5.6 at the specified noise level. As shown in Fig. 5.6, better performance is expected for lower noise level. It is also observed from Table 5.5 that the estimation results of the parameters are consistent regardless of the SSR settings. It should be noted that the averaged circuit model becomes inaccurate with increased sampling time as discussed in chapter 3. Therefore the performance did not improve when the SSR was increased from 9 to 10. The trade-off between the model accuracy and noise rejection should be considered in the actual applications. For example, the best performance of the proposed method is achieved with the sampling frequency of 2.22 kHz for the noise level at 7 mV deviation.

5.6 Capacitor Ageing Simulation and Lifetime Estimation

As an extension of the research work on parameter monitoring, the lifetime estimation of the capacitor is presented in this section using the proposed BBO parameter estimation method. The degradation of a capacitor causes its capacitance

to reduce linearly with respect to time [57, 89]. In some applications with pulsed charging and discharging cycles the capacitance loss may increase unexpectedly at certain pulses [56]. In the capacitor endurance test, a 5% drop of the capacitance can be considered a failure. In this case, the lifetime can be much shorten by the sudden capacitance loss. To estimate the lifetime correctly, the degradation model is updated after online parameter estimation with BBO. The degradation model of capacitor is given by

$$C(t) = C_0 + \xi t \quad (5.9)$$

where ξ is the time coefficient and C_0 is the initial capacitance. Without sudden loss, the capacitor lifetime is estimated according to the degradation model as

$$\hat{t}_C = \frac{\Delta C}{\xi} = \frac{0.05C_0}{\bar{\xi}} \quad (5.10)$$

The degradation model parameters can be extracted from the interpolated data of the thermal stress test result [57]. Through offline measurements the average degradation rate of the 15 capacitors at 105 °C is determined as $\bar{\xi} = 0.05(\text{uF/h})$. This feature is used to estimate the life time for each capacitor when online parameter monitoring is not available.

The capacitance value estimated at each monitoring session is shown in Fig. 5.15. The degradation data for capacitor 13 in [57] is chosen as an example and used for simulation. The capacitor's ESR and other parameters are assumed to be remained constant as in Table 4.2 in the simulation.

Fig. 5.15 Online monitoring of capacitor degradation detection.

Fig. 5.15 shows the measured capacitance and the estimated capacitance in the simulation. Without online parameter monitoring, the lifetime of the capacitor is estimated as $\hat{t}_C = 1930 \text{ h}$. However the 5% limit is exceeded at time $t_F = 1580 \text{ h}$. The proposed online monitoring method is able to identify the capacitance at each time instant accurately and therefore it can determine the end of life time of the capacitor correctly.

5.7 Application of Online Parameter Monitoring on Lossless Current Sensing

Digital controlled DC-DC converters and inverter have been widely employed in different power management systems. In order to achieve some special control requirements such as load sharing and overcurrent protection, the inductor current is measured as a control parameter [90-94]. However, direct measurement

of the inductor current with a shunt resistor causes additional power loss and reduces the power efficiency [95]. To improve the efficiency of the converters, various lossless current sensing techniques have been proposed [90-94, 96, 97]. The matched complementary filter (MCF) method [90] is easy to implement, but the accuracy is highly dependent on the operating environment. For example, the inductor ESR can be increased by 30% as the temperature varies from 25 to 100 °C. Works have been published to compensate this variation in [91] but the sensing error after compensation is still significant. Table 5.6 summarizes various lossless current sensing methods.

Table 5.6 Lossless sensing techniques.

Method	Description	Drawbacks
Current Transformer	Sense a fraction of the current in a mutual inductor with a series resistor	Large physical size
PCB trace resistance	Sense the voltage drop across PCB trace	Thermal drifts
MOSFET R_{on} [92]	Sense the voltage drop across MOSFET when it is turned ON	Half cycle missing
SenseFet [93]	MOSFET with build in well matched current sensing mirror	Hard to manufacture
MCF [90, 91]	Filter inductor voltage using RC filter with a matched time constant	Thermal drifts
Gm-C Filter [94]	Use Gm-C filter to replace the RC filter in MCF	Extra switches

In this study, a new online calibration approach for MCF base lossless current sensing is proposed in [98]. The proposed approach makes use of the BBO online parameter monitoring to tune the MCF current sensor. In the proposed method, a variable resistance controlled by a microcontroller is employed as the filter resistance. The time constant of the RC filter is adjusted based on the online parameter estimation result. The result shows that the method is able to achieve 5%

Fig. 5.16 setup for proposed calibration method.

As shown in Fig. 5.16, the test setup consist of three blocks, the hardware circuit, the DSP and the PC. The circuit is consist of a buck converter, a RC filter and a differential amplifier. The controller and filter tuning algorithm is running on DSP and the parameter monitoring algorithm is running on MATLAB program. The buck converter is controlled by a digital controller with a DPWM duty cycle $\mathbf{d}$. Two measurements are taken from the analog to digital converter (ADC) which are $\mathbf{v_o}$, $\mathbf{v_{cf}}$. These measured values are then passed to a DSP for parameter estimation. The estimated inductance is then used to determine the desired variable resistance to achieve a matched $\mathbf{RC}$ filter. The filter capacitor $\mathbf{C_f}$ and the filter resistance $\mathbf{R_f}$ are shunt with the inductor. The series loss resistance, inductor ESR, inductance, capacitance, capacitor ESR and the load resistance are indicated in Fig. 5.16 as $\mathbf{R_s, R_L, L, C, R_c, R}$ respectively. Their estimated values are denoted as $\mathbf{R_s'}$ and $\mathbf{R_L'}$ etc.

The proposed method consists of two steps. Firstly the inductor ESR value is estimated based on the steady state voltage across the filtering capacitor and the output voltage. In the second step the online identification is performed to estimate the inductance. The inductor current is then calculated based on these two estimations.

To estimate the inductor ESR, a RC filter is first connected in parallel with the inductor in order to measure its ESR. The inductor circuit can be analyzed with KVL to yield

$$L \frac{di_L}{dt} + i_L R_L = R_f C_f \frac{dv_{cf}}{dt} + v_{cf}. \quad (5.11)$$

Taking Laplace transform of (5.11) and rearrange it yields

$$V_{cf}(s) = \frac{(R_L + Ls)}{1 + C_f R_f s} I_L(s) + \frac{C_f R_f v_{cf}(0) - i_L(0)}{1 + C_f R_f s}. \quad (5.12)$$

The last term in (5.12) will decay to zero in the steady state. Therefore its value can be neglected. Hence, the ideal matched filter is achieved when

$$C_f R_f = L/R_L. \quad (5.13)$$

When the condition (5.13) is satisfied, it is observed from (5.12) that the inductor current can be obtained simply by amplifying the v_{cf} signal with a constant gain $1/R_L$. It is also observed that the DC components in the v_{cf} and i_L can be determined by

$$V_{cf}(0) = R_L I_L(0). \quad (5.14)$$

$V_{cf}(0)$ can be obtained by averaging v_{cf} over a period and $I_L(0)$ is approximated by the output current v_{out}/R . Finally, the inductor ESR value is estimated as

$$\hat{R}_L = \frac{V_{ef}(0)}{I_L(0)}. \quad (5.15)$$

The expression in (5.14) is independent on the filter physical parameters R_f , C_f and L . Therefore, the inductor ESR can be correctly estimated without calibrating the sensing resistor.

Using the ESR estimated in (5.15) and the inductance estimated with the proposed BBO parameter estimation method, the filter resistance can be calibrated as

$$R_f = L/(C_f * R_L). \quad (5.16)$$

To test the performance of the online calibration method under the parameter deviations, the simulation is setup follows the settings in Fig. 5.16. Table 5.7 shows the simulation settings.

Table 5.7 Simulation Parameter Settings.

		R_L (Ω)	L (mH)
Case 1	Before variation	0.1	0.22
	After variation	0.1	0.15
Case 2	Before variation	0.1	0.22
	After variation	0.13	0.15

As shown in Table 5.7, there are two cases studied in this simulation. In each of the two cases the result is shown in the time sequence. Initially the circuit parameters are maintained at constant. At time 0.05s the parameters are varied according to the settings shown in Table 5.7. These variations are identified shortly by the proposed method. Finally at time 0.1s the filter resistance value is adjusted according to the estimation result. The MCF lossless current sensing is applied

throughout the simulation period. The parameter estimation results of $\hat{R}_L$ and $\hat{L}$ for the different cases are shown in Fig. 5.17 and Fig. 5.18.

Fig. 5.17 Case 1 lossless current sensing before and after calibration

Fig. 5.18 Case 2 lossless current sensing before and after calibration

From Fig. 5.17 and Fig. 5.18, it can be observed that the dynamics of the inductor current are caused by the PRBS perturbation. In both cases, the MCF current sensing becomes inaccurate immediately after the parameter variation due to the mismatch filter time constant before the parameter identification. The variations of L lead to attenuation error and the variations of R_L lead to a bias error.

It is also observed that the RLS method requires about 0.04 seconds to converge. The average values of $\hat{\mathbf{R}}_L$ and $\hat{\mathbf{L}}$ during 0.09s to 0.1s are then used to tune the filter resistance $\mathbf{R}_f$. After the calibration is completed, the current sensing becomes accurate again.

To verify the proposed calibration method, an experimental system has been setup using a digital controlled PWM buck converter. The experimental setup is shown in Fig. 5.19. The circuit is constructed according to Fig. 5.16.

Fig. 5.19 Experimental setup for lossless current sensing test.

As shown in Fig. 5.19, the output voltage and duty cycle sequence are measured from the circuit and transmitted to the PC through the I2C interface. These data are then used for parameter estimation.

The exact values of capacitor and inductor are measured with a TTI LRC400 meter at 10 kHz. The parameter estimated with the BBO algorithm is compared with

the meter readings in Table 5.8. All the readings are taken at room temperature. The BBO estimation is repeated for 100 times and $SSR = 10$ is used in this experiment.

Table 5.8 Parameter Estimation result

		$\hat{C}$ (mF)	$\hat{L}$ (mH)	$\hat{R}_c$ (Ω)	$\hat{R}_s$ (Ω)
reference		0.335	0.223	0.124	0.139 (RL)
System Identification	Max	0.431	0.265	0.158	0.239
	Min	0.345	0.216	0.114	0.237
	Average	0.415	0.225	0.129	0.237

From the results of RLS estimation, it can be concluded that the estimation error of the averaged estimations of $\hat{L}$ is less than 1%. For the estimate of the inductor's ESR based on the v_{cf} measurement, the experimental results are illustrated in Fig. 5.20.

Fig. 5.20 v_{ADC} (Channel F1) and i_L (Channel C3) waveform before tuning.

In Fig. 5.20, the filter resistance R_f is arbitrarily selected as 820Ω . The inductor's ESR $\hat{R}_L$ is estimated as

$$\hat{R}_L = \frac{R_1 R^* v_{ADC}}{R_2 v_{out}} = \frac{100k \cdot 2.1 \cdot 0.409}{200k \cdot 3.3} \Omega = 0.130 \Omega \quad (5.18)$$

The filter resistance is then calculated based on the result of parameter estimation using (5.15) as

$$R_f = \frac{\hat{L}}{C_f \hat{R}_L} = \frac{225 \mu}{1 \mu \cdot 0.130} = 1.73 \text{ k}\Omega \quad (5.19)$$

Fig. 5.21 shows the measurement curve after the online tuning using the proposed approach. The filter resistance R_f is adjusted to 1.73 k Ω with the variable resistor.

Fig. 5.21 v_{ADC} (Channel F1) and i_L (Channel C3) waveform after tuning.

As observed in Fig. 5.20 and Fig. 5.21, the mean value of v_{ADC} is the same regardless of the filter resistance variations. It is also observed that the peak to peak inductor current is close to 550 mA for both tests. In Fig. 5.21, the peak to peak inductor current is estimated as:

$$i_{Lpkpk} = \frac{v_{cf}}{\hat{R}_L} = \frac{(458.1 - 307.3)/2}{0.130} = 580 \text{ mA} \quad (5.20)$$

This error is less than 5% as compared with the current probe reading. In conclusion, the proposed method is able to calibrate the MCF current sensor with online parameter estimation. When the thermal conditions are changed in the circuit, the parameter estimation will recalculate the proper filter resistance, and the DSP will adjust the variable resistor to adapt to the changes in the inductor's time constant.

5.8 Summary

In this chapter, a low sampling rate online parameter estimation of a DC-DC buck converter is realised with BBO method. Simulation study at different loads and noise levels has been conducted to benchmark with the RLS method. The simulation results show that the BBO method outperforms the RLS method in terms of estimation accuracy especially when the measurement noise level is high. The BBO algorithm has also been verified under the non-resistive load scenario and load perturbation scenario. The averaged estimation error for the capacitance, capacitor ESR, inductance and inductor ESR are 0.95%, 1.31%, 5.17%, 1.61% respectively, and the averaged experimental error for the capacitance, capacitor ESR, and inductance are 5.2%, 0.4%, and 7.5% respectively. The extended applications of the proposed BBO methods have been presented with simulation and experimental results on capacitance lifetime estimation and the online calibration of a lossless inductor current sensor. 5% error has been achieved after the calibration with the proposed method. This error is significantly reduced as compared with the 30% error in the uncalibrated case [90].

CHAPTER 6

Fault Detection of Interleaved Boost Converters

In previous chapters, the identification of the component degradations for a single buck or boost converter has been presented. The reconfiguration of the system after a failure detection requires redundant hardware in the circuit. They can be configured as hot redundancy or cold redundancy as illustrated in Fig. 6.1.

Fig. 6.1 Hot and cold redundancy reconfiguration.

The red blocks in Fig. 6.1 is powered on while the green blocks are powered off. The hot redundancy configuration ensures that a continuous power is supplied to the subsystems when a reconfiguration is performed. In the normal operation, the hot redundancy can also distribute the electrical stress on each component to achieve longer lifetime. The interleaved converter is an example of hot redundancy in which multiple phases of inductors and MOSFET switches are connected in parallel. In this chapter, the online parameter identification of the circuit components is performed

on the interleaved boost converter. A typical interleaved boost converter schematic is shown in Fig. 6.2.

Fig. 6.2 Schematic of DC-DC interleaved boost converter.

As shown in Fig. 6.2, the input voltage, inductor, MOSFET, diode, Capacitor and load are indicated as V_{in} , L_n , S_n , D_n , C and R respectively. Interleaved converter has been widely used in the industries to achieve scalable high voltage gain and better reliability [99, 100]. The averaged model of the interleaved boost converter system is developed in this chapter for online parameter monitoring. In chapter 5 the BBO method was introduced and the performance of BBO with local search is evaluated on a buck converter parameter identification problem. However, the local search algorithm involves inverse matrix calculation. As the parameter identification problem of the interleaved converter has more unknowns in the objective function, the original BBO method would become inefficient. Therefore, the BBO algorithm is modified to accommodate the extra unknowns and measurements introduced to the system. Apart from the passive component value monitoring demonstrated in chapter 5, the MOSFET ON-state resistance of each phase will be monitored under different thermal conditions.

6.1 Interleaved converter system setup

Fig. 6.3 Interleaved DC-DC boost converter monitoring setup

The setup for the online parameter monitoring system of the interleaved boost converter is shown in Fig. 6.3. The measurements are taken from the circuit, namely the inductor current for each phase i_{Li} , the input voltage v_{in} , and the output voltage v_o . The measurement noise is assumed to be Gaussian with a standard deviation σ . The output voltage is regulated at the reference voltage V_{ref} with the cascaded PI controllers. The cascaded PI control scheme is adopted due to the non-minimum phase nature of the boost converter. For brevity, the controller design is not included. The independent PRBS perturbation signals are added into the duty cycles of the different phases for identification. The amplitude of the perturbations are set as $\pm 2.5\%$ of the nominal value of duty cycle in that phase. The duty cycle at the degraded phases can be disabled by the controller, and the converter can still function normally with the remaining phases.

6.2 Modelling of the Interleaved Boost Converter

6.2.1 Converter modelling

A general state space model for an n -phase interleaved DC-DC boost converter has not been reported in the literature. To derive the state space model, it is assumed that the symmetrical PWM switching is used. The averaged model for interleaved boost converter is shown in Fig. 6.4.

Fig. 6.4 Interleaved DC-DC boost converter monitoring setup

As shown in Fig. 6.4, the inductor current for each phase is measured as i_{Li} and the output voltage is measured as v_o . The converter's behaviour can be described using the KCL and KVL by

$$\begin{bmatrix} V_{in} - V_{D1}(1 - d_1) \\ V_{in} - V_{D2}(1 - d_2) \\ \dots \\ V_{in} - V_{Dn}(1 - d_n) \\ \sum_{i=1}^n i_{Li} \end{bmatrix} = \begin{bmatrix} L_1 \frac{d1}{dt} + i_{L1}R_{S1} - \frac{d_1 R v_c}{R + R_c} + v_c + R_c C \frac{dv_c}{dt} \\ L_2 \frac{d2}{dt} + i_{L2}R_{S2} - \frac{d_2 R v_c}{R + R_c} + v_c + R_c C \frac{dv_c}{dt} \\ \dots \\ L_n \frac{dn}{dt} + i_{Ln}R_{Sn} - \frac{d_n R v_c}{R + R_c} + v_c + R_c C \frac{dv_c}{dt} \\ C \frac{dv_c}{dt} + (v_c + R_c C \frac{dv_c}{dt})/R \end{bmatrix} \quad (6.1)$$

where L_i and R_{Si} represent the inductance and serial loss resistance in the i^{th} branch respectively. The serial loss resistance is the sum of the inductor ESR loss, PCB

trace loss and the MOSFET conduction and switching loss. n is the number of phases. C , R_c and R represent the output capacitance, capacitor ESR and the load resistance respectively. V_{in} is the constant input voltage and d_i is the duty cycle of the i^{th} branch. Let $\mathbf{x} = [v_c, i_{L1}, i_{L2}, \dots, i_{Ln}]^T$ be the state vector, then the state space model of the interleaved boost converter system can be derived from (6.1) by

$$\dot{\mathbf{x}} = A\mathbf{x} + B \quad (6.2)$$

where $A =$

$$\begin{bmatrix} R_c C & L_1 & 0 & \dots & 0 \\ R_c C & 0 & L_2 & \dots & 0 \\ \dots & \dots & \dots & \dots & 0 \\ R_c C & 0 & \dots & \dots & L_n \\ \frac{C(R_c+R)}{R} & 0 & \dots & \dots & 0 \end{bmatrix}^{-1} \begin{bmatrix} \frac{d_1 R}{R+R_c} - 1 & -R_{S1} + \frac{d_1 R R_c}{R+R_c} & 0 & \dots & 0 \\ \frac{d_2 R}{R+R_c} - 1 & 0 & -R_{S2} + \frac{d_1 R R_c}{R+R_c} & \dots & 0 \\ \dots & \dots & \dots & \dots & 0 \\ \frac{d_n R}{R+R_c} - 1 & 0 & \dots & \dots & -R_{Sn} + \frac{d_n R R_c}{R+R_c} \\ -\frac{1}{R} & 1 - d_1 & \dots & \dots & 1 - d_n \end{bmatrix}$$

$$B = [0, -(V_{in} - V_{D1}(1 - d_1))/L_1, \dots, -(V_{in} - V_{DN}(1 - d_n))/L_n]^T$$

Different from the MOSFET used in the synchronous converter, the diode in the boost converter introduces a voltage drop which cannot be ignored in the estimation. Therefore, the diode voltage drop V_{Di} is modelled as an ideal voltage source and the value is adjusted by the duty cycle as the voltage drop only occurs when the switch is turned off. This voltage source is added in series with each phase. All the parameters in matrix A and B in (6.2) will be estimated by the proposed BBO method except for V_{in} and d_i . The details will be discussed later.

6.2.2 MOSFET On-state failure isolation

In (6.2), the degradation of R_{Si} can be deduced by the inductor ESR degradation or the MOSFET On-state resistance degradation. Moreover, it is desired that the

inductor ESR is estimated individually such that fault isolation can be achieved. To achieve this, a RC filter is connected in parallel with the inductor in order to measure its ESR. The overall inductor circuit is shown in Fig. 6.5.

Fig. 6.5 Inductor ESR estimation with RC filter.

As shown in Fig. 6.5, the filter capacitor C_f and the filter resistance R_f is shunt with the inductor. Although additional components are added into the converter circuit, the reliability of the overall circuit will not be affected if large filter resistance R_f is used. The inductor ESR can be estimated with (5.15) as introduced in Chapter 5 and it can be subtracted from the serial loss resistance. The MOSFET On-state resistance is proportionally related to the remaining serial loss resistance. Therefore the degradation of R_{on} in MOSFET can be detected and isolated.

6.2.3 Formulation of the Objective Function for BBO Parameter Monitoring

To detect the degradation of circuit parameters of the interleaved converter, the BBO approach presented in Chapter 5 is extended in this Chapter with some modifications. These changes are introduced to overcome the low convergence rate issue due to the additional variables added in the optimization problem. These

variables are highly internal related as can be observed during the formulation of the objective function.

The objective function can be formulated similar to (5.4) but with more measurements and unknowns included. To estimate all the circuit parameters in (6.2), the state estimation error is used as the objective function of the BBO algorithm.

Given the initial states $\mathbf{x}_0$ and d sequence in the state space model (6.2), the subsequent states can be estimated as a function of the component values by solving an initial value problem. Firstly, the eigenvectors and eigenvalues for matrix A in (6.2) are obtained as $\mathbf{v}_i$ and λ_i . The system state at time t is estimated as

$$\hat{\mathbf{x}}(t) = \sum_{i=1}^{\Lambda} c_i \mathbf{v}_i e^{\lambda_i^* t} + \mathbf{x}_p \quad (6.3)$$

where Λ is the number of the states in the state vector $\mathbf{x}$. c_i are constant coefficients of the eigenvectors and $\mathbf{x}_p$ is the particular solution of (6.2). In the case that a pair of imaginary eigenvalues are obtained as $\lambda_i = a \pm bi$ and the corresponding eigenvectors are $\mathbf{v}_i = \begin{bmatrix} w_{i11} \\ w_{i12} \end{bmatrix} \pm \begin{bmatrix} w_{i21} \\ w_{i22} \end{bmatrix} i$, where $\begin{bmatrix} w_{i11} \\ w_{i12} \end{bmatrix} = \mathbf{w}_{i1}$, and $\begin{bmatrix} w_{i21} \\ w_{i22} \end{bmatrix} = \mathbf{w}_{i2}$, the corresponding terms in (6.3) can be replaced with the expression in the real form as

$$\sum_{i=1}^{\Lambda} c_i e^{at} (\mathbf{w}_{i1} \cos(bt) + (-1)^i \mathbf{w}_{i2} \sin(bt)) \quad (6.4)$$

In (6.3) and (6.4), c_i and $\mathbf{x}_p$ can be obtained from the initial condition $\mathbf{x}_0$ as

$$\mathbf{x}_p = -A^{-1}\mathbf{u}, \quad (6.5)$$

$$\mathbf{c} = Q^{-1}(\mathbf{x}_0 - \mathbf{x}_p),$$

where $Q = [\mathbf{q}_1 \ \dots \ \mathbf{q}_\Lambda]$, $\mathbf{q}_i = \mathbf{v}_i$ for the real eigenvectors and $\mathbf{q}_i = [\mathbf{w}_{i1} \ \mathbf{w}_{i2}]$ for the imaginary eigenvectors. The objective function of the BBO algorithm is defined as the total squared state estimation error

$$J = \sum_{k=1}^N \|(\mathbf{x}(k) - \hat{\mathbf{x}}(k))\|_2 \quad (6.6)$$

where k is the sampling sequence, and the estimated state $\hat{\mathbf{x}}(k)$ is obtained from (6.3) by substitute t with the sampling period T and $\mathbf{x}_0$ with $\hat{\mathbf{x}}(k - 1)$. A total number of N samples are included in the objective function (6.6). If all the parameters in (6.2) are accurate and the averaged model is accurate, the value of (6.3) should reach its theoretical value which is determined by the deviation of the measurement noise σ_x in the measurement $\mathbf{x}$. Hence it is reasonable to set the stopping criteria as

$$J_{th} = (1 + \Delta)N(\sigma_v^2 + \sum_{i=1}^n \sigma_{i_{Li}}^2), \quad (6.7)$$

where $\Delta = 0.3$ is the margin added to the threshold so that the convergence could still be achieved even if there are small model inaccuracies. σ_v^2 and $\sigma_{i_{Li}}^2$ are the measurement noise variance for the output voltage and the inductor current in the i^{th} phase.

6.3 BBO with Grouped Immigration

As mentioned in Chapter 5, the modified BBO for large scale problem [81] cannot improve the efficiency when optimizing non-separable problems with tightly interactive variables. By applying pairwise check [80] on each variable in (6.6) to form the additively separable groups, it is found that the variables are non-separable.

The random grouping method has been adopted by many cooperative coevolution algorithms [85, 101] to improve the convergence rate for non-separable problems. The similar approach is considered in this research for the BBO. Table 6.1 shows the pseudo code for the proposed BBO with grouped immigration (BBOGI) method.

Table 6.1 Proposed BBO with Grouped Immigration Method.

Step 1: Initialize algorithm parameters.

Initialize n_{pop} individuals χ of dimension D randomly. Each of χ contains a random estimation of the parameters within the given boundary.

Initialize a group χ^{sub} with $D/2$ members selected randomly from the D . The group members are repeatable, therefore the actual group size $D_{gp} \leq D/2$.

Initialize *counter*.

While the number of function evaluations $FE \leq FE_{max}$ or $J > J_{th}$ repeat step 2 to step 6 for each generation.

Step 2: Check the habitat suitability index (HSI) for each individual with the objective function hence calculate their emigration rate μ_j and immigration rate ν_j . The best individual with the highest HSI is stored as χ_{best} . Update the $FE = FE + n_{pop}$

Step 3: Group Habitat modification and mutation. $rand_{1,2,3}$ are generated randomly in the range [0,1].

for $j = 1; j < n_{pop}; j++$

for $m = 1; m < D; m++$

if $m \in \chi^{sub} \& (rand_1 > \mu_m/D_{gp})$,

{

Select another individual l with Roulette wheel selection method based on ν_l .

$$\chi_j^{sub} = \chi_j^{sub} + \nu_l (\chi_l^{sub} - \chi_j^{sub})$$

if $rand_2 > \xi/D_{gp}$, for each member m in the group χ_j^{sub} , use Gaussian mutation operator.

$$\chi_j^{sub'}(m) = \chi_j^{sub}(m) + N(0, \delta^2)$$

```

    }
    else if ( $rand_1 > \mu_m$ ),
    {
        Select another individual  $l$  with Roulette wheel selection method
        based on  $v_l$ .

         $\chi_k(m) = \chi_k(m) + \lambda(\chi_l(m) - \chi_k(m))$ ,
        where  $\lambda$  is the immigration step size.

        if  $rand_2 > \xi$ , perform normal mutation.

         $\chi_j'(m) = \chi_{low}(m) + (\chi_{up}(m) - \chi_{low}(m)) * rand_3$ 

    }
end
end

```

Step 4: Elite. Evaluate the HSI for each individual again. Update the $FE = FE + n_{pop}$. Replace the worst solution with the previous χ_{best} .

Step 5: If χ_{best} has not been updated for more than g_{lim} times, then reform the group randomly with $D/2$ members.

Step 6: $counter++$

In summary, two improvements have been made to improve the BBO convergence rate in Table 6.1. Firstly, the Gaussian mutation operator and the conventional random mutation operator are applied separately for the interactive variables and non-interactive variables. Secondly, the interactive variables migrate as a group to keep their relative positions. Gaussian operator is adopted because the improvement of the strongly interactive variables are more likely to be found locally. The proposed method is different from the RCBBO method [72], in which the Gaussian operator is applied on all the variables. In the following discussions, the

convergence rate of the proposed method will be evaluated together with the conventional BBO method and the RCBBO method.

6.4 Validation of BBOGI Algorithm

To evaluate the performance of different BBO algorithms, the interleaved converter model based on MATLAB Simulink has been developed. In order to have a good reference for estimation accuracy evaluations (e.g. for serial loss resistance R_s), the ON-state resistance of MOSFET and diode are set to zero. Also as the quantization error in the 12-bit ADC is less than 1 mV, here we assume the measurement noise deviation is 3 mV and 3 mA for the voltage and current measurement considering the voltage divider ratio. The simulation setup is illustrated in Fig. 6.3. The default simulation settings are summarized in Table 6.2.

Table 6.2 Simulation settings for different BBO algorithms

Method	δ	g_{lim}	Other BBO parameters	Simulation parameters
BBO	-	-	$FE_{max} = 200,000;$ $N = 300;$ $n_{pop} = 50;$ $\xi = 0.1;$ $margin = 0.5.$ $\lambda = 0.95$	$R_{L1} = 0.175 \Omega;$ $R_{L2} = 0.21 \Omega;$ $R_C = 0.075 \Omega;$ $L_1 = 0.22 mH;$ $L_2 = 0.176 mH;$ $C = 0.3 mF;$ $R = 5 \Omega;$ $\sigma = 3 mV(mA);$ $V_{in} = 5 V;$ $V_{ref} = 10 V$
RCBBO	0.05	-		
BBOGI	0.05	1		

The typical evolution curve of different optimization algorithms are depicted in Fig. 6.6 with the parameter settings in Table 6.2.

Fig. 6.6 Evolution curve for the proposed BBOGI method and other BBO methods.

As shown in Fig. 6.6, the proposed BBOGI method is able to converge faster than the conventional BBO method and the RCBBO method. This can be achieved through the parameter tuning of the additional parameters δ and g_{lim} introduced to the BBOGI algorithm.

The tuning of δ and g_{lim} would affect the BBOGI algorithm performance. The generations taken for the algorithm to converge is used to evaluate the convergence rate. The simulation is repeated 100 times with the parameters in Table 6.2 and using different data samples collected from the simulation. The number of generation before convergence is recorded. The number of times that the convergence generation falls within a range of 2000 are counted, and histogram for the convergence generations are illustrated in Fig. 6.7 and Fig. 6.8 for δ and g_{lim} tunings accordingly.

Fig. 6.7 Parameter tuning of δ with $g_{lim} = 1$.

As shown in Fig. 6.7, most of the test runs require longer convergence time as δ increases. When δ is 0.02, 12k iterations are required to let 80% of the trials to converge. When δ is 0.05, the number of iterations required is reduced to 8k, and when δ is further increased to 0.1, the number of iterations required is increased to 14k. Therefore the value $\delta = 0.05$ is chosen for the mutation operator.

Fig. 6.8 Parameter tuning of g_{lim} with $\delta = 0.05$.

Fig. 6.8 shows the distributions of generations to convergence with different g_{lim} . When $g_{lim} = 1$, the algorithm switches to a new group configuration immediately if the solution stops to improve. This means that the algorithm can try more group configurations in the given FE limit. However, it also tends to discard the old suitable group configurations and starts to search for new configuration. In general it still performs better than the case with $g_{lim} = 5$ as it takes only 8k generations for 80% of the trials to converge. These two tests have also shown that the majority of the tests are able to converge in the first few thousand generations.

To compare the convergence rate of the proposed BBOGI method with the conventional BBO methods, the trends of their convergence along each generation are illustrated in Fig. 6.9. In this test the converter component values are estimated with conventional BBO, BBO with Gaussian mutation operator (RCBBO), and the proposed BBO with grouped immigration (BBOGI).

(b)

(c)

Fig. 6.9 Trend of convergence of (a) BBO (b) RCBBO, and (c) BBOGI.

In Fig. 6.9, the BBOGI method converged faster and reached the stop criteria before reaching the function evaluation limit. The Gaussian mutation operator slows down the convergence as the search range is centralized at the local solutions as compared with the normal BBO in which the mutation range is distributed evenly in the search space. The average and the deviation of the estimation errors using BBOGI are calculated from the data collected in the 20 estimation results shown in Fig. 6.9 (c).

(a)

(b)

(c)

Fig. 6.10 The estimation error of the (a) BBO (b) RCBBO (C) BBOGI algorithm.

Fig. 6.10 show the estimation error and the standard deviation of the result achieved at the last generation in the evolutions shown in Fig. 6.9. Fig. 6.10 (c) shows that the proposed method is able to generate stable and accurate estimation result when the algorithm stops after the stopping criteria $J \leq J_{th}$ is met. Due to the FE limit, the conventional BBO method and the BBO with Gaussian mutation operator sometimes fail to converge to the optimum point when the algorithm stops and large estimation errors are generated as shown in Fig. 6.10 (a) and (b) .

The estimation error for the seven components which are shown in Fig. 6.10 are studied at the measurement noise level varying from 1~121 mV^2 (mA^2). The errors are averaged according to (5.6) and the results are depicted in Fig. 6.11. As the BBOGI method used the same objective function as BBO, it only improves the convergence rate. The purpose of this study is mainly to show the performance of the parameter monitoring algorithm at different noise levels.

Fig. 6.11 Interleaved boost converter parameter estimation at different noise level and SSR using BBOGI algorithm.

Fig. 6.11 shows that the proposed parameter monitoring method is able to estimate the parameter values in the interleaved boost converter with small estimation error (<5%) even when the noise level is high.

In all the conducted simulations, the MOSFET is set as an ideal component so that the serial loss resistance R_S is equivalent to the inductor ESR and the estimation accuracies in Fig. 6.10 can be evaluated. To test the fault tolerant performance of the proposed method in the MOSFET failure scenario, the non-ideal MOSFET and diode are introduced to the simulation setup in Fig. 6.1. Among all the component failures, the MOSFET failure is most likely to occur, but it is difficult to predict. In this test, the On-state resistance for the MOSFET in the second phase is increased in 0.01Ω step size from the nominal value of 0.01Ω until 0.1Ω to emulate the degradation process. The RC filter is used to estimate the inductor ESR with a $0.1 \mu\text{F}$ capacitor and a $10 \text{ k}\Omega$ resistor. The simulation noise is 1 mV and the sampling switching period ratio (SSR) is 4. $N=300$ samples of v_o, i_{L1}, i_{L2} and v_{cf} are taken for each test. The simulation settings are listed in Table 6.3.

Table 6.3 Simulation of MOSFET degradation failure detection

Ron2	R_{S1} (Ω)	R_{S2} (Ω)	R_C (Ω)	L_1 (mH)	L_2 (mH)	C (mF)	R (Ω)	V_{D1} (V)	V_{D2} (V)	R_{L1} (Ω)	R_{L2} (Ω)
Setting	-	-	0.075	0.22	0.176	0.30	5	0.3	0.3	0.175	0.21
0.01	0.273	0.316	0.073	0.228	0.180	0.299	4.853	0.295	0.245	0.177	0.212
0.02	0.274	0.325	0.073	0.228	0.180	0.300	4.79	0.295	0.224	0.175	0.211
0.03	0.274	0.332	0.074	0.228	0.181	0.299	4.862	0.292	0.219	0.174	0.210
0.04	0.275	0.339	0.074	0.227	0.181	0.298	4.865	0.288	0.214	0.177	0.212
0.05	0.276	0.344	0.073	0.227	0.182	0.299	4.868	0.283	0.222	0.174	0.212
0.06	0.275	0.350	0.075	0.228	0.182	0.298	4.869	0.293	0.220	0.174	0.210
0.07	0.274	0.359	0.075	0.228	0.183	0.298	4.871	0.294	0.207	0.175	0.209
0.08	0.277	0.364	0.074	0.227	0.183	0.299	4.873	0.276	0.208	0.175	0.211
0.09	0.277	0.371	0.075	0.228	0.183	0.298	4.875	0.280	0.202	0.174	0.210
0.10	0.278	0.378	0.075	0.227	0.184	0.298	4.877	0.274	0.198	0.174	0.211

The results in Table 6.3 show that as the R_{on2} increases the estimated R_{S2} also increases and other parameters including R_{L2} are almost unaffected. Therefore the MOSFET degradation can be identified.

The time response of the capacitor filter voltage and the L_1 current are depicted in Fig. 6.12. The R_{L1} value for the first case in Table 6.3 is derived from these measurements. The inductor ESR values in other simulation cases are estimated similarly from their time responses.

Fig. 6.12 Simulation result for inductor ESR estimation.

It is observed in Fig. 6.12 that the inductor ESR can be estimated according to (5.15) as 0.177Ω .

6.5 Experimental Results

Two experimental results are presented in this section. The modelled parameters such as the capacitance and inductance are firstly estimated, and then the MOSFET on-state resistance degradation isolation is tested.

Small amount of thermal disturbances are injected to verify the stability of the proposed method in the first experiment. The heat is injected through the thermal plate of the MOSFET to emulate the heat trapped in the switch in space. Due to the vacuum environment in space, the temperature of the MOSFET switch can be quite high as there is no convection. The thermal characteristics of the IRFZ48N MOSFET specified in the datasheet is shown in Fig. 6.13. The On-state resistance is increased by 40% when the junction temperature is increased from 30 °C to 80 °C. The nominal on-state resistance is less than 14 mΩ. According to the simulation results in Table 6.3, the small variation in the on-state resistance of MOSFET will not affect the other parameters' estimation.

Fig. 6.13 On state resistance vs. temperature in IRFZ48N datasheet.

To heat up the MOSFET a heater is placed at the thermal plate behind one of the switching MOSFETs as shown in the test setup in Fig. 6.14.

Fig. 6.14 Test setup and heater location

The heater is connected to a 24V power supply. The resistance of the heater is $137\ \Omega$. It is controlled by a PWM signal with duty cycle increased from 0 ~ 100%. A thermal coupler is used to measure the temperature for the MOSFET and inductors of both phases and the temperature is logged with the NI-SCXI1600 Data Acquisition (DAQ) equipment. The temperature measured from the 4 components are plotted in Fig. 6.15.

Fig. 6.15 Temperature of the related components during the testing process.

As shown in Fig. 6.15 the MOSFET of second phase is heated up to 80 °C while the other components remain at the normal operating temperature. The rated temperature of the MOSFET IRFZ48N is 175 °C. The waveforms of the output voltage, and the two inductors' current sensor output during the identification process are shown in Fig. 6.16.

Fig. 6.16 Experiment waveforms before and after the PRBS is disabled.

Fig. 6.16 shows the output voltage waveform in channel 1, inductor 1 current sensor output in channel 2 and inductor 2 current sensor output in channel 4. The same current sensor as introduced in Chapter 4 is used.

The parameters estimated during the heat injection are shown in Table 6.4. The nominal values of the components are measured with the TTI LRC400 component meter at room temperature.

Table 6.4 Experimental Result with MOSFET Heat Injection

Q_2 Temp(°C)	R_{S1} (Ω)	R_{S2} (Ω)	R_C (Ω)	L_1 (mH)	L_2 (mH)	C (mF)	R (Ω)	V_{D1} (V)	V_{D2} (V)
Reference	0.22 (R_{L1})	0.22 (R_{L2})	0.166	0.229	0.220	0.333	10.2	0.24	0.25
29.22	0.6221	0.6011	0.1774	0.2440	0.2127	0.3401	9.7957	0.0532	0.0755
30.63	0.6255	0.6018	0.1834	0.2479	0.2140	0.3422	9.8063	0.0493	0.0751
35.12	0.6262	0.6127	0.1726	0.2458	0.2129	0.3512	9.7714	0.0454	0.0511
39.17	0.6282	0.6040	0.1810	0.2478	0.2177	0.3399	9.7847	0.0427	0.0629
45.34	0.6216	0.6083	0.1717	0.2450	0.2158	0.3449	9.7795	0.0524	0.0530
47.40	0.6330	0.6107	0.1771	0.2472	0.2155	0.3395	9.7706	0.0318	0.0459
52.98	0.6250	0.6049	0.1706	0.2449	0.2134	0.3455	9.7622	0.0458	0.0531
56.12	0.6213	0.5991	0.1680	0.2485	0.2184	0.3459	9.7725	0.0555	0.0659
61.83	0.6322	0.6054	0.1801	0.2464	0.2166	0.3521	9.7701	0.0410	0.0555
66.64	0.6359	0.6200	0.1797	0.2465	0.2135	0.3473	9.7715	0.0333	0.0261
72.09	0.6309	0.6095	0.1845	0.2478	0.2171	0.3456	9.7702	0.0352	0.0453
74.86	0.6311	0.6103	0.1805	0.2496	0.2178	0.3476	9.7636	0.0252	0.0405
79.56	0.6314	0.6146	0.1778	0.2471	0.2139	0.3530	9.7638	0.0411	0.0313
NRMS Error%	-	-	7.39	7.80	2.30	4.04	4.16	-	-

The result in Table 6.4 shows that the estimation is quite stable except for the R_{S1} and R_{S2} estimation. The resistance increased by 0.01 Ω due to the conducted heat on the PCB trace.

The next experiment is designed to study the performance of the proposed algorithm when the on-state resistance of MOSFET is increased. In order to emulate the MOSFET on-state resistance failure, a resistance R_{fault} of 10 m Ω , 20 m Ω and 30 m Ω are connected in series with the MOSFET drain and the proposed parameter estimation algorithm is carried out on the modified circuit. The results are summarized in Table 6.5.

Table 6.5 Experimental Result

R_{fault}	RS1 (Ω)	RS2 (Ω)	RC (Ω)	L1 (mH)	L2 (mH)	C (mF)	R (Ω)	RL1 (Ω)	RL2 (Ω)
RLC meter	-	-	0.16	0.22	0.22	0.32	10.2	0.23	0.24
0 m	0.6297	0.6128	0.1814	0.2506	0.2384	0.3171	9.7804	0.22	0.22

10 mΩ	0.6295	0.6159	0.1807	0.2499	0.2374	0.3188	9.7811	0.22	0.22
20 mΩ	0.6298	0.6186	0.1842	0.2504	0.2367	0.3188	9.7794	0.22	0.22
30 mΩ	0.6294	0.6221	0.1809	0.2510	0.2358	0.3191	9.7779	0.22	0.22

Table 6.5 shows that as the fault resistance increases the series loss resistance estimated by the BBO algorithm is increased while the estimated inductor ESR remains unchanged. Therefore, the fault isolation of the inductor ESR and the MOSFET on-state resistance can be achieved with the proposed method. The measured waveform of the voltage across the L_1 filter capacitor as well as the inductor current sensor output are illustrated in the Fig. 6.17. This measurement is taken with $R_{fault} = 0$.

Fig. 6.17 Inductor ESR estimation for L_1 .

The measured waveform of the voltage across the L_1 filter capacitor as well as the inductor current sensor output are illustrated in Fig. 6.17. The gain of the current sensor for the first channel is 1.54, and the inductor ESR is estimated with (5.15) as

$$R_{L1} = \frac{V_{cf1}}{I_{L1}} = \frac{179.92}{525.49 \times 1.54} = 0.22 \Omega \quad (6.13)$$

The second phase inductor ESR is estimated with the same method with a current sensor gain of 1.97. The inductor ESR for the second phase is estimated as

$$R_{L2} = \frac{V_{cf2}}{I_{L2}} = \frac{170.57}{392.33 \times 1.97} = 0.22 \Omega \quad (6.14)$$

Fig. 6.18 Inductor ESR estimation for L_2 with $R_{fault} = 0 \text{ m}\Omega$.

With a fault resistance of $30 \text{ m}\Omega$ added into the circuit, the inductor ESR of the second phase is estimated again and the waveform is shown in Fig. 6.19.

Fig. 6.19 Inductor ESR estimation for L_2 with $R_{fault} = 30 \text{ m}\Omega$.

It is verified from Fig. 6.18 and Fig. 6.19 that the inductor ESR of the second phase is not affected by the fault resistor. The ESR of the second phase remains as

$$R_{L2} = \frac{V_{cf2}}{I_{L2}} = \frac{168.45}{389.60 \times 1.97} = 0.22 \Omega \quad (6.15)$$

The waveforms in Fig. 6.17, Fig. 6.18 and Fig. 6.19 are in agreement with the simulation result in Fig. 6.12.

6.6 Summary

In this chapter, the online parameter monitoring of the interleaved boost converter has been studied. A general state space equation of the interleaved boost converter has been derived. Comparing with the previous model that was developed in chapter 3, the interleaved model involves more measurements and unknown parameters to be identified. In this chapter the BBO algorithm has been modified by adding the

group immigration and Gaussian mutation features. By adaptively changing the members in the immigration group, the proposed method has improved the nominal convergence rate so that accurate and stable boost converter parameter estimations can be achieved in 200,000 function evaluations. With this improvement, more variables can be added into the BBO algorithm and thus the method is applicable for interleaved converter with more phases. The simulation results show that the averaged estimation error for the capacitance, inductance, capacitor ESR and inductor ESR are 0.46%, 1.2%, 3.3%, 4.5% respectively. The experimental estimation errors for the capacitance, capacitor ESR, inductance L_1 , and inductance L_2 are 7.39%, 7.80%, 2.30%, 4.04% respectively. The inductor ESR estimation results are identical with the RLC meter readings for both the inductors. The MOSFET on-State resistance deviation is detected in addition to the modelled circuit parameters discussed in the previous work. The error isolation is achieved through an independent inductor ESR estimation method using the filtering technique.

CHAPTER 7

Conclusion and Future Work

In this research, a low sampling rate online monitoring method for a DC-DC converter circuit has been proposed and verified with both simulation and experimental results. Comparing with the conventional methods which require a sampling frequency to be at least 25 times of the switching frequency, the proposed method lower this ratio to 0.1 ~ 1. Therefore a low cost DSP could be used for online monitoring and the switching frequency requirement is satisfied at the same time. The averaged model for the DC-DC converter is proved to be accurate for parameter estimation when the symmetrical PWM switching is used. The proposed use of the averaged model for the general interleaved DC-DC boost converter has been derived using the state space model. The averaged estimation errors for the different components in the circuit are summarized in Table 7. 1. All the simulation results have been conducted with a simulated ADC noise of 1 mV deviation.

Table 7. 1 Online parameter estimation accuracy

		C	L	R_c	R_L
Buck Converter	Simulation RLS	1.04%	1.46%	5.38%	1.83%
	Experiment RLS	N.A	N.A	N.A	N.A
	Simulation BBO	0.95%	1.31%	5.17%	1.61%
	Experiment BBO	5.2%	7.5%	0.4%	N.A
Interleave Boost Converter	Simulation BBOGI	0.46%	3.30%	1.20%	4.5%
	Experiment BBOGI	7.39%	7.80% 2.30%	4.04%	N.A

As shown in Table 7.1, the full parameter estimation of the DC-DC converter has been achieved using the proposed method. The estimation accuracy is comparable with other reported research works that could only perform partial parameter estimation. At the same time, the sampling frequency of the proposed method has significantly been reduced. According to the survey result shown in Fig 1.2, the proposed converter parameter monitoring covers 53.45% of the possible failures consists of 17.85% of capacitor failure, 31% of switches failure and 4.6% of inductor failures.

For the online parameter monitoring of the DC-DC converters, the BBO approach has been introduced. Moreover, the grouped immigration and mutation features have been introduced in this research into the BBO method. Unlike the conventional BBO method, the proposed BBOGI algorithm has a dynamic mutation and immigration process. They can improve the convergence rate significantly and the estimation error in the fixed 200,000 function evaluation time is reduced to less than 10% for all the parameters under estimation.

The proposed method have demonstrated its advantages in online monitoring of DC-DC power converters at low sampling rate. However, there are still some limitations of this method as it is designed for the voltage regulation converters. In this case, minimum output voltage disturbance is favorable. This characteristic of the voltage regulation converters also simplifies the model of nonlinear load to a constant load as the operation point is fixed. However, there are also some other applications, in which the DC-DC converters are used to extract power from the nonlinear sources. In these applications, the load can also be connected to a battery

which can sink arbitrary amount of current in the ideal case. The proposed method is also not applicable in this case as the voltage perturbation that is applied is not high enough to change the battery's terminal voltage. In this case the state in the averaged model need to be changed and the complete problem will need to be redefined. For the future work in the satellite power electronics fault detection, the online parameter monitoring could be considered for the DC-DC converters used for the maximum power point tracking (MPPT) from the solar panel. This limitations of the proposed method could possibly be relieved with a suitable model of the solar panel and extra accurate measurements. The new measurement will be required on light intensity and the solar panel temperature which affect the boost converter model as shown in [102].

Moreover, this research is focused on the power converters with MOSFET switches but not BJTs and IGBTs. BJTs are seldom used for controlling high switching frequency converters as they are controlled by current. MOSFETs have higher power efficiency than IGBTs for low voltage and high frequency applications. If the IGBT switches are used, the converter models in this research need to be improved to include the constant voltage drop across the switches. The voltage drop is not dependent on the current and the value is too large to be ignored in the low voltage applications. Si-C MOSFET is a good choice for high voltage and high frequency power switching. As Si-C MOSFETs also possess low on state resistance characteristics that can fit into the averaged models, the results in this work should be applicable to Si-C MOSFET driven converters too.

The fault detection of satellite power system includes many aspects. In this research only the parameter fault in the DC-DC converters are considered. The sensor fault detection using analytical redundancy has been proposed in [103, 104].

Some attempts have been made by the author starting from the basic DC circuit using the L1 norm optimization method in [105] and the result shows that the method is efficient and could be analysed with the standard tools in statistics. Due to time constrain this research remains in the initial phase. The sensor fault and the component fault are essentially related as shown in [104]. Therefore the future satellite power system fault detection should consider both of the failures and evaluate them simultaneously. Table 7. 2 shows the summary of future works in the satellite power electronics fault detection.

Table 7. 2 Future works of satellite power electronics fault detection

Future works
<ul style="list-style-type: none"> • Introduce new models of power generation circuit components (such as solar panels and battery) into the converter's fault detection.
<ul style="list-style-type: none"> • Introduce sensor fault detection and inference algorithms.

LIST OF AUTHOR'S PUBLICATIONS

1. B.X. Li, and K.S. Low, "Low Sampling Rate Online Parameters Monitoring of DC-DC Converters for Predictive-Maintenance Using Biogeography-Based Optimization", *IEEE Transactions on Power Electronics*, vol. 31, no. 4, pp. 2870-2879, Apr. 2016.
2. B.X. Li, K.S. Low, B.Y. Kang, "Modeling and Online Health Monitoring of Interleaved DC-DC Converters Using Biogeographical Based Optimization with Grouped Immigration", in *IEEE Transactions on Aerospace and Electronic Systems* (submitted) .
3. B.X. Li, K.S. Low, "Fault Detection of Nano-satellite Power Management System", in *The 29th International Symposium on Space Technology and Science (ISTS)*, 2013.
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