Cognitive Insights into Metaheuristic Digital Twin based Health Monitoring of DC-DC Converters

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Keywords

Digital Twin, Genetic Algorithm (GA), Health Monitoring, Metaheuristic Optimization, Particle Swarm Optimization (PSO), Sensitivity Analysis.

Abstract

Reliability of components has always been a major concern to the performance and stability of DC-DC converters. After long-term operation, these passive components and switching devices start to degrade and become weak to withstand normal electrical and thermal stresses. An insightful digital interface to the physical layer known as Digital Twin (DT) can be a sustainable solution for ensuring reliability. This paper extends the DT concept to component level health monitoring in DC-DC converters. The proposed concept is noninvasive and does not require additional sensors. The working principle is to minimize the weighted least squared error between the digital twin output and the measured data of state variables through metaheuristic optimization. An application for Two-Phase Interleaved Boost Converter with reverse coupled inductor is considered and Hardware-in-the-loop (HIL) platform is used for sensitivity analysis for component degradation. Further, the optimization problem is solved using the following two popular metaheuristic optimization methods: Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Further, the performance of both methods for 20 executions in terms of computational time; convergence rate and dispersion are compared. It is evident from the results that GA outperforms PSO with 50 % less execution time and better accuracy > 95 %.

Introduction

In recent years, the use of DC-DC converters in various applications such as industrial, transportation and renewable energy has increased significantly. This poses a key concern for reliability of the converter as it determines the stability of the whole system. DC-DC converters comprise power semiconductors switches and energy storing elements such as inductor and capacitor. These components degrade over time due to environmental strains and switching action. [1]-[2]. For instance, the capacitance drops 10-20% [3] and R_{DSon} of the MOSFET increases 5-20% [4] due to aging.

Several methods have been proposed in literatures for health monitoring. Mostly, these methods rely on inserting extra sensors in the converter to sense a voltage or current signal primarily related to the health monitoring parameter [5], [6] or using averaged model with reduced sensitivity [7]. Further, the associated complexity such are additional DSPs and signal lines makes the whole design complex and vulnerable to errors.

Recently, the Digital Twin (DT) concept has been extended for health monitoring of DC-DC converters. The DT virtually replicates converter, which can be used to estimate the component values by matching the response of digital twin to that of the actual converter. A case for estimating parameters for buck converter using DT through average least square error minimization objective function f_{obj} through Particle Swarm Optimization (PSO) is proposed [8]. Although the proposed method is effective, it requires large memory for data acquisition and the accuracy for ESRs prediction is low.

This paper proposes an improved DT model for health monitoring of DC-DC converters. The proposed method is non-invasive and does not require need for additional sensors. It is based on minimizing the weighted least-squared error between response of the DT and the measured data over the health parameters, making it a multi-objective optimization problem. The efficacy of the proposed method is demonstrated on a higher order two-phase interleaved boost converter with coupled inductor with more parameters to estimate. For sensitivity analysis, Hardware-in-the-loop (HIL) testing is used for simulating component degradation. The optimization problem is solved using the following two metaheuristic methods: Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), along with performance comparison. Finally, health monitoring is performed on a hardware prototype and results are compared.

Digital Twin Modeling for Two-Phase Interleaved Boost Converter

Fig. 1 shows the schematic of a two-phase interleaved boost converter with reverse coupled inductor. iL_1, iL_2 and v_c represents the inductor currents and the output capacitor voltage. R_{L1}, R_{L2}, R_{DSon1}, R_{DSon2} and R_C are the parasitics resistances of the coupled inductor, switches, and output capacitor. Health monitoring involves estimating the following seven parameters: L, C, R_{L1}, R_{L2}, R_{DSon1}, R_{DSon2} and R_C. The coupling factor K_C of the converter can be assumed to be constant as it primarily depends on the physical layout of the winding, which does not change over time.

The proposed health monitoring approach is based on minimizing the least-squared error between response of the DT and the measured data. This requires DT to model both the transient and steady-state responses. The transient response is sensitive to the values of the passive components such as L, C. To cater this, the actual state space model $\dot{x} = Ax + B$, is considered instead of the averaged state space model. The state space $\dot{x} = Ax + B$ with state variables iL_1, iL_2 and v_c and output voltage v_{out} for four possible switching states S_1-D_2, D_1-D_2, S_2-D_1 and S_1-S_2 are given in (1)-(4) respectively. The quantity d represents the instantaneous duty cycle of the converter. The differential equations in state-space representation in (1)-(4) are in continuous time domain. However, the data from the converter is in discrete time, sampled at sampling frequency f_s. This requires discretization of the differential equations with adequate accuracy. Among, the popular discretization methods such as 4th Order Runge-Kutta (RK), Trapezoidal, Backward and Forward Euler, RK is chosen as it provides better accuracy. Further, although RK's computational time is larger than the other methods, it is not a concern as degradation is not time sensitive. The discretized expressions using 4th Order RK with time step T_s, for iL_1, iL_2 and v_c are given in (5)-(7). The parameters k_{a1}-k_{a4}, k_{b1}-k_{b4} and k_{c1}-k_{c4} are implicit auxiliary variables of RK method. From v_c^{n+1}, v_{out}^{n+1} can be computed by using the respective expression for each switching state in (1)-(4).

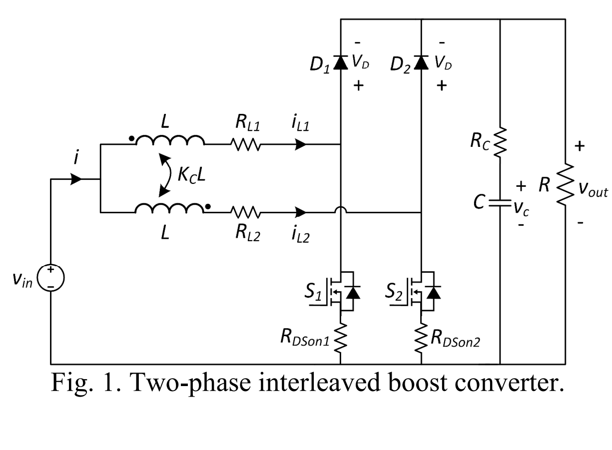


Fig. 1. Two-phase interleaved boost converter.

$$
\begin{cases}
A = \begin{bmatrix} -L(R_{L1}+R_{DSon1}) & -K_C L R_{L2} + \frac{-K_C L R R_C}{R_C+R} & \frac{-K_C L R}{R_C+R} \\ -K_C L(R_{L1}+R_{DSon1}) & -L R_{L2} - \frac{L R R_C}{R_C+R} & -\frac{LR}{R_C+R} \\ 0 & \frac{R}{C(R+R_C)} & -\frac{1}{C(R_C+R)} \end{bmatrix} \\
B = \begin{bmatrix} -K_C L V_D + L(1+K_c)v_{in} \\ -L V_D + L(1+K_c)v_{in} \\ 0 \end{bmatrix} \\
v_{out} = \frac{R R_C}{R_C+R} i_{L2} + \frac{R v_c}{R_C+R}
\end{cases} \tag{1}
$$

$$
\begin{cases}
A = \begin{bmatrix} -L R_{L1} & -K_C L R_{L2} & 0 \\ -K_C L R_{L1} & -L R_{L2} & 0 \\ \frac{R}{C(R+R_C)} & \frac{R}{C(R+R_C)} & -\frac{1}{C(R_C+R)} \end{bmatrix} \\
B = \begin{bmatrix} L(1+K_c)(-d v_{in}/(1-d)+V_D) \\ L(1+K_c)(-d v_{in}/(1-d)+V_D) \\ 0 \end{bmatrix} \\
v_{out} = \frac{R R_C}{R_C+R}(i_{L1}+i_{L2}) + \frac{R v_c}{R_C+R}
\end{cases} \tag{2}
$$

$$
\begin{cases}
A = \begin{bmatrix} -L R_{L1} - \frac{X R R_C}{R_C+R} & -K_C L(R_{L2}+R_{DSon2}) & \frac{-LR}{R_C+R} \\ -K_C L R_{L1} + \frac{Y R R_C}{R_C+R} & -L(R_{L2}+R_{DSon2}) & \frac{K_C L R}{R_C+R} \\ \frac{R}{C(R+R_C)} & 0 & -\frac{1}{C(R_C+R)} \end{bmatrix} \\
B = \begin{bmatrix} -L V_D + L(1+K_c)v_{in} \\ -K_C L V_D + L(1+K_c)v_{in} \\ 0 \end{bmatrix} \\
v_{out} = \frac{R R_C}{R_C+R} i_{L1} + \frac{R v_c}{R_C+R}
\end{cases} \tag{3}
$$

$$
\begin{cases}
A = \begin{bmatrix} -L(R_{L1}+R_{DSon1}) & -K_C L(R_{L1}+R_{DSon1}) & 0 \\ -K_C L(R_{L1}+R_{DSon1}) & -L(R_{L1}+R_{DSon1}) & 0 \\ 0 & 0 & -\frac{1}{C(R_C+R)} \end{bmatrix} \\
B = \begin{bmatrix} L(1+K_c)v_{in} \\ L(1+K_c)v_{in} \\ 0 \end{bmatrix} \\
v_{out} = \frac{R v_c}{R_C+R}
\end{cases} \tag{4}
$$

$$iL_1^{n+1} = iL_1^n + \frac{T_s}{6}(k_{a1} + 2k_{a2} + 2k_{a3} + k_{a4}) \tag{5}$$

$$iL_2^{n+1} = iL_2^n + \frac{T_s}{6}(k_{b1} + 2k_{b2} + 2k_{b3} + k_{b4}) \tag{6}$$

$$v_c^{n+1} = v_c^n + \frac{T_s}{6}(k_{c1} + 2k_{c2} + 2_{c3} + k_{c4}) \tag{7}$$

Health Monitoring Through Metaheuristic Optimization

Health monitoring can be performed by matching the response of DT with that of the actual converter by minimizing the sum of squared error for N data points, like multivariate regression, between the measured and the DT values for iL_1, iL_2 and v_{out}. This becomes a multi-objective optimization problem with the following objective functions:

$$f_{obj1}(x) = \sum_{k=1}^{N} \left(i_{L1,m}^k - i_{L1,d}^k\right)^2 \tag{8}$$

$$f_{obj2}(x) = \sum_{k=1}^{N} \left(i_{L2,m}^{k} - i_{L2,d}^{k}\right)^2 \quad (9)$$

$$f_{obj3}(x) = \sum_{k=1}^{N} \left(v_{out,m}^{k} - v_{out,d}^{k}\right)^2 \quad (10)$$

defined on $x = (L,\ C,\ R_{L1},\ R_{L2},\ R_{DSon1},\ R_{DSon2}, R_C)$, with inequality constraints only. The inequality constraints cater the component tolerances as well as degradation. The subscripts m and d corresponds to measured and DT values. The multi-objective optimization problem can be converted into single objective f_{obj} by using weighted sum method [10], given by (11).

$$\underset{(L,\ C,\ R_{L1},\ R_{L2},\ R_{DSon1},\ R_{DSon2},\ R_C)}{\text{minimize}} \quad \begin{array}{c} f_{obj} = \alpha f_{obj1} + \beta f_{obj2} + \gamma f_{obj3} \\ L_{min} \le L \le L_{max1} \\ C_{min} \le C \le C_{max} \\ R_{L1\_min} \le R_{L1} \le R_{L1\_max} \\ R_{L2\_min} \le R_{L2} \le R_{L2\_max} \\ R_{DSon1\_min} \le R_{DSon1} \le R_{DSon1\_max} \\ R_{DSon2\_min} \le R_{DSon2} \le R_{DSon2\_max} \\ R_{C\_min} \le R_C \le R_{C\_max} \end{array} \quad (11)$$

α , β and γ represents the weights for the objective functions. The optimization problem is complex to be solved through derivative-based methods such as geometric programming or convex optimization; the response of the state variables is based on piecewise differential equations. The resultant solutions of the differential equations are continuous at the boundary but not differentiable. As a result, meta-heuristic-based optimization methods are best suited for this problem. Two popular metaheuristic methods: PSO [11] and GA [12] are selected to solve the optimization problem in (11). The algorithms have been proven to be effective in solving highly non-linear optimization problems in the power electronics domain [13]-[14]. Compared with deterministic methods, these methods are derivative free and search for optimal solution through concept of biological evolution and collaborative behavior of biological populations. PSO is inspired by the ability of bird flocks to adapt to new environment through information sharing. GA on the other hand is inspired by Charles Darwin's theory of natural evolution to arrive to an optimum solution through concept of chromosomal crossover and mutation. Although the searching process for both methods lead to longer computational time, it is not critical for health monitoring as degradation happens slowly.

Health Monitoring Validation

To validate the performance of the proposed DT, a 60 V to 100 V 2.5 kW two-phase interleaved boost converter, switching at f = 50 kHz, is simulated in Typhoon HIL 402 with gating signals generated from Texas Instrument LAUNCHXL-F28379D DSP (Fig. 2). HIL platform is chosen as it gives flexibility in varying the component values dynamically. The data for 5 switching cycles, as opposed to 80 cycles in [8], is sampled and passed to PSO and GA based optimization program for health monitoring with $\alpha = \beta = 2\gamma = 1/length(data)$ in (11). $length(data)$ refers to the number of data points used for computation, which in turn depends on the sampling frequency and the number of switching cycles considered. For instance, with 1 MHz sampling, the weight $1/length(data)$ comes out to be 0.01. The lower and upper bounds of the inequality constraints are set to ± 30 % of their nominal value. Table I tabulates the nominal values of the health monitoring parameters. The coupling factor K_C is fixed to 0.8 throughout the analysis, as coupling factor depends on the orientations and placement of windings on the core, which do not change with degradation.

The learning factors r_a and r_b for particle best P_{Best} and global best G_{Best} value for computation of particle new position (pos^{i+1}) for PSO in (12) are both set to 2.05. Further, the inertia weight ω for velocity V is initialized with a large value and then reduced dynamically in each iteration to ensure better convergence [11].

$$pos^{i+1} = \omega V^i + 2r_a\left(P_{Best} - P^i\right) + 2r_b\left(G_{Best} - G^i\right) \tag{12}$$

Table I: Converter Parameters

Parameter	Nominal Value
L	100 µH
C	47 µF
R_{L1}	50 mΩ
R_{L2}	50 mΩ
R_{DSon1}	10 mΩ
R_{DSon2}	10 mΩ
R_C	3 mΩ

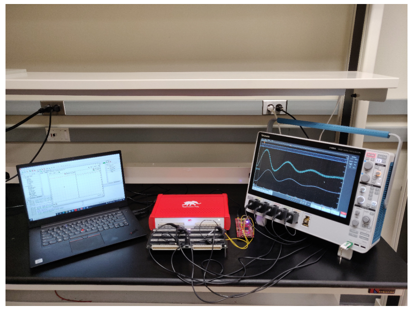


Fig. 2. HIL validation test setup.

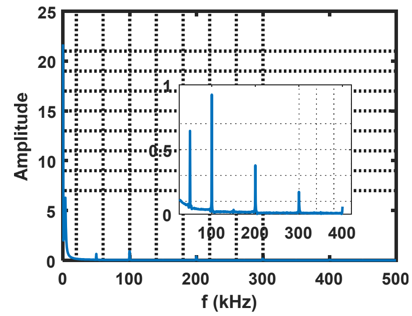


Fig. 3. FFT of i_{L1}.

For GA, roulette wheel selection method with Boltzmann probability distribution is chosen [12]. For performance comparison, the swarm size in PSO and number of chromosomes in GA are both set to 200; the number of iterations during a single execution is set 80. Moreover, the sampling frequency has a huge influence on the convergence and correct estimation of health parameters. The channel currents i_{L1} and i_{L2} for the boost converter in Fig. 1 contain fourth order harmonic of the switching frequency f (Fig. 3). To avoid aliasing, sampling frequency f_s is set to 1 MHz ($2.5 \times 4f$). The effect of aliasing is shown in Fig. 4 for i_{L1}, where the DT is not able to follow the measured data if $f_s < 2 \times 4f$.

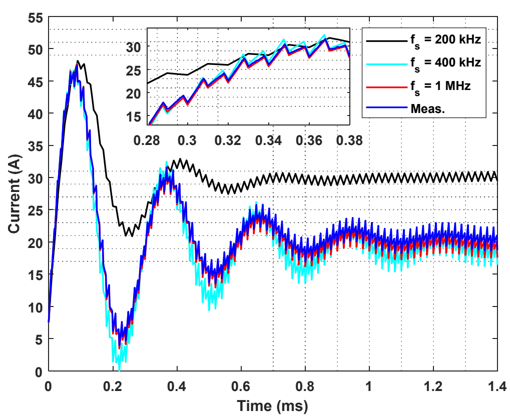


Fig. 4. Impact of sampling frequency f_s.

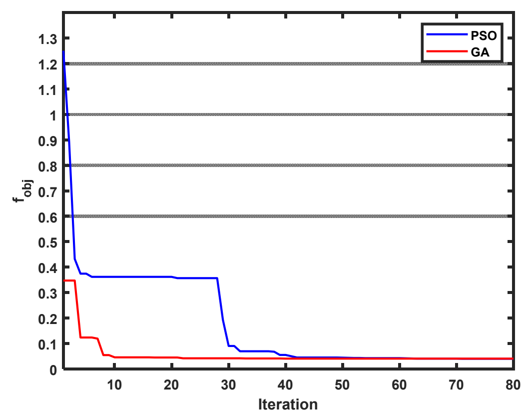
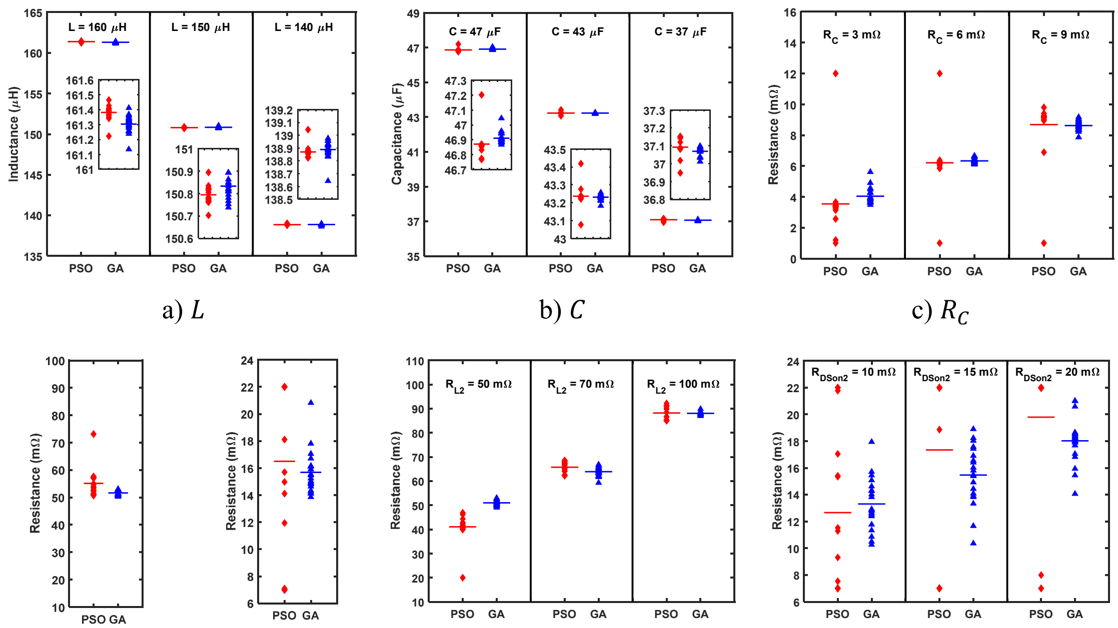


Fig. 5. PSO and GA f_{obj} descent comparison.

Fig. 5 compares the descending process of f_{obj} using PSO and GA. The f_{obj} value after first iteration using GA is 3.7 times lower than PSO. Also, GA minimizes f_{obj} in a smaller number of iterations. The average execution times observed for PSO and GA are 25.5 s and 13.2 s respectively. Both algorithms can minimize the f_{obj} to 0.005. The results for nominal (Table I) and sensitivity analysis are compared and summarized in Fig. 6 for both optimization methods. The horizontal line represents the average value for 20 independent executions. It is evident from the results that both PSO and GA are able to estimate L, C within 3 % tolerance. However, the estimated values for ESRs (R_{L1}, R_{L2}, R_{DSon1}, R_{DSon2}, R_c), using PSO have more dispersion around the set/average value compared with GA. Table II compares the standard deviations σ_{PSO} and σ_{GA}, observed for the estimated results of ESRs in Fig 6. Based on the results, it can be concluded that GA is best suited for the DT-based health monitoring with better accuracy.



a) L b) C c) R_C

d) R_{L1} e) R_{DSon1} f) R_{L2} g) R_{DSon2}

Fig. 6. Estimated parameters using PSO and GA for nominal and perturbed cases.

Table II: Estimated ESRs Standard Deviation Comparison

Parameter	R_{L1}	R_{L2}			R_{DSon1}	R_{DSon2}			R_C		
Case (mΩ)	50	50	70	100	10	10	15	20	3	6	9
σ_{PSO} **(mΩ)**	4.9	5.3	2.3	2.7	6.3	6.2	6.8	5.2	2.1	1.7	1.8
σ_{GA} **(mΩ)**	0.8	1.1	1.8	0.6	1.5	1.9	2.1	1.7	0.5	0.2	0.3

Hardware Prototype Validation

A 20 to 36 V low-voltage hardware prototype (Fig. 7), switching at 50 kHz, is built, and tested to validate the effectiveness of the proposed concept. The switches are realized using two CREE KIT-CRD-8FF65P modules, based on CREE C3M0060065J, 650 V 65 mΩ MOSFETs. Based on the results from the previous section, an optimization is run using GA, owing to its better accuracy. The nominal measured values and the estimated values of the health parameters are tabulated in Table III. The estimated values are in line with the nominal values, justifying the efficacy of the method. The maximum percentage error observed is 2 % for L and C and 7 % for the ESRs.

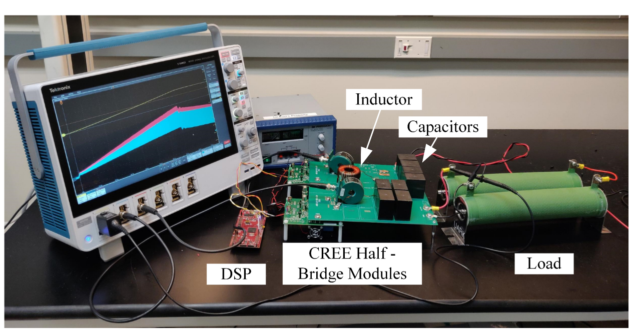


Fig. 7. Test setup.

Table III: Nominal and estimated parameters

Parameter	**Nominal Value**	**Estimated Value**
L	662.3 μH	657.3 μH
C	120.0 μF	124.1 μF
R_{L1}	169.4 mΩ	182.7 mΩ
R_{L2}	142.8 mΩ	126.3 mΩ
R_{DSon1}	65.0 mΩ	72.3 mΩ
R_{DSon2}	65.0 mΩ	67.7 mΩ
R_C	9.2 mΩ	11.5 mΩ

Conclusion

Health monitoring of DC-DC converter components is essential for ensuring peak efficiency and reliability in the long run. An improved metaheuristic DT concept is proposed for determining the health parameters of passive components and the power devices of complex DC-DC converters. The proposed concept is validated using PSO and GA optimization techniques. Based on the results, GA has better accuracy with less dispersion and executes faster than PSO, while utilizing less memory resources.

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