Implementation of a Decoupled Optimization Technique for Design of Switching Regulators Using Genetic Algorithms

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Abstract—This paper presents an implementation of a decoupled optimization technique for design of switching regulators using genetic algorithms (GAs). The optimization process entails the selection of component values in a switching regulator, in order to meet the static and dynamic requirements. Although the proposed method inherits characteristics of evolutionary computations that involve randomness, recombination, and survival of the fittest, it does not perform a whole-circuit optimization. Thus, intensive computations that are usually found in stochastic optimization techniques can be avoided. Similar to many design approaches for power electronics circuits, a regulator is decoupled into two components, namely the power conversion stage (PCS) and the feedback network (FN). The PCS is optimized with the required static characteristics, whilst the FN is optimized with the required static and dynamic behaviors of the whole system. Systematic optimization procedures will be described and the technique is illustrated with the design of a buck regulator with overcurrent protection. The predicted results are compared with the published results available in the literature and are verified with experimental measurements.

Index Terms—Circuit optimization, circuit simulation, computer-aided design, genetic algorithms, power electronics.

I. INTRODUCTION

I N THE last two decades, small-signal models have been widely used in the design of switching regulators. Among various approaches, the state-space averaging and its variant [1]–[4] are the most common ones. By recognizing that a converter has an output filter cutoff frequency much lower than the switching frequency, linear time-invariant models can be derived to approximate the time-variant power electronics circuits (PECs) at the operating point. After performing a Bode plot of the converter characteristics and applying the classical control theories, circuit components in the feedback compensation network can be designed. Although the procedures are simple and elegant, they are usually applicable for specific circuits and control scheme [3], [4] that require comprehensive knowledge on the circuit operation. In addition, as the circuit has been converted into a mathematical model and its state variables have

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been averaged, no detailed information about the exact waveforms and the response profiles can be obtained. Circuit designers would sometimes find it difficult to predict precisely the circuit responses under large-signal conditions [2].

As power electronics technology continues to develop, there is a growing need for automated synthesis that starts with a high-level statement of the desired behavior and optimizes the circuit component values for satisfying required specifications. About two decades ago techniques for analog circuit design automation began to emerge. These methods incorporated heuristics [5], knowledge bases [6], simulated annealing [7], and other algorithms for circuit optimization. Classical optimization techniques such as the gradient methods and Hill-Climbing techniques have been applied [8], [9]. However some methods might subject to becoming trapped into local minima, leading to suboptimal parameter values, and thus, having a limitation of operating in large, multimodal, and noisy spaces.

Recently, modern stochastic optimization techniques involving evolutionary computation such as genetic algorithms (GAs) [10] have been shown to be an effective way to find solutions close to the global optimum and are less dependent upon the initial guess [11]–[15]. GAs belong to the class of probabilistic algorithms, yet they are very different from random algorithms as they combine elements of directed and stochastic search. Because of this, GAs are also more robust than existing directed search methods. Another important property of such genetic based search methods is that they maintain a population of potential solutions—all other methods process a single point of the search space [15].

Many GA-based design schemes for analog circuits, like voltage reference circuit [12], transconductance amplifier [13], and analog circuit synthesis [14], have been proposed. Circuit behaviors are described by well-defined mathematical functions with unknown optimal coefficients. A set of guided stochastic searching procedures that are based loosely on the principles of genetics is formulated. The procedures are flexible, allowing mixed type, bounded decision variables, and complex multifaceted goals. Although GAs are appropriate for solving off-line design problem, the searching process is usually computationally intensive with all components included in the optimization and design.

This paper presents an implementation of a GA-based, decoupled optimization technique for design of switching regulators. It entails selection of the component values to satisfy the static and dynamic requirements. Although the proposed

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and

Fig. 1. Block diagram of power electronics circuits.

approach inherits characteristics of evolutionary computations, it does not perform a whole-circuit optimization as in classical method and thus intensive computations can be lessened. Similar to many design approaches for PECs [2], a regulator is decoupled into two components namely the power conversion stage (PCS) and the feedback network (FN). The components in the PCS are optimized with the required static characteristics such as the input voltage and output load range. The components in the FN are optimized with the required static behaviors of the whole regulator and the dynamic responses during the input and output disturbances. Design of a buck regulator with overcurrent protection is illustrated. A prototype using the GA-optimized component values has been built. Simulated results are compared with the ones in the literature available and experimental measurements.

II. DECOUPLED REGULATOR CONFIGURATION

The basic block diagram of a power electronics circuit including the PCS and FN is shown in Fig. 1. The PCS is supplied from the source v_{in} to the load R_L . The PCS consists of I_P resistors (R), J_P inductors (L), and K_P capacitors (C). The FN consists of I_F resistors, J_F inductors, and K_F capacitors. The signal conditioner H_o converts the PCS output voltage v_o into a suitable form (i.e., v'_o) for comparing with a reference voltage v_{ref} . Their difference v_d is then sent to an error amplifier (EA). The EA output v_e is combined with the feedback signals W_p , derived from the PCS parameters, such as the inductor current and input voltage, to give an output control voltage v_{con} after performing a mathematical function $g(v_e, W_p)$. v_{con} is then modulated by a pulse-width modulator to derive the required gate signals for driving the switches in the PCS. All passive components in the PCS and the FN can be represented with the use of two vectors Θ_{PCS} and Θ_{FN} , respectively. They are defined as follows.

$$\Theta_{PCS} = \begin{bmatrix} \overline{R}_P & \overline{L}_P & \overline{C}_P \end{bmatrix}$$
$$\Theta_{FN} = \begin{bmatrix} \overline{R}_F & \overline{L}_F & \overline{C}_F \end{bmatrix}$$
(1)

where $\overline{R}_P = [R_1 \ R_2 \ \cdots \ R_{I_P}], \overline{L}_P = [L_1 \ L_2 \ \cdots \ L_{J_P}],$ $\overline{C}_P = [C_1 \ C_2 \ \cdots \ C_{K_P}], \overline{R}_F = [R_1 \ R_2 \ \cdots \ R_{I_F}], \overline{L}_F = [L_1 \ L_2 \ \cdots \ L_{J_F}],$ and $\overline{C}_F = [C_1 \ C_2 \ \cdots \ C_{K_F}].$

Apart from satisfying the static and dynamic responses, the components might also be optimized for other factors such as the physical size and the total cost of the components. Conventional techniques usually perform a whole- circuit optimization, in which all components are optimized together. Such approach will be computationally intensive since it involves considerable searching dimensions. In this paper, Θ_{PCS} and Θ_{FN} are optimized separately with the GA by decoupling the PCS and FN. Θ_{PCS} is optimized for the steady-state operating requirements of the PCS, including the input and output load range, steady state error, and output ripple voltage. With the determined Θ_{PCS} , Θ_{FN} is optimized for the whole-system steady state and dynamic characteristics.

III. CHROMOSOME STRUCTURES AND THE FITNESS FUNCTIONS

A. Optimization Mechanism of GA

GA, differing from conventional search techniques, start with an initial set of random solutions called population. In other words, population is a group of potential solutions for the design. Each individual in the population is called a chromosome, representing a solution to the problem at hand. Θ_{PCS} and Θ_{FN} in (1) are grouped in a chromosome-like structure. Each chromosome comprises a number of individual structures called genes. Each gene encodes the value of a particular component [i.e., the resistor, inductor, and capacitor values in (1)]. An index of merit (fitness value) is assigned to each chromosome, according to a defined fitness function. A new generation is evolved by a selection technique, in which there is a larger probability of the fittest individuals being chosen. Pairs of chosen chromosomes are used as the parents in the construction of the next generation. A new generation is produced as a result of reproduction operators applied on parents, namely mutation and crossover. New generations are repeatedly produced until a predefined convergence level is reached.

B. Chromosome and Population Structures

The formats of the chromosome CP for the PCS and the chromosome CF for the FN in a population are as follows:

$$CP = [R_1 R_2 \cdots R_{I_P} | L_1 L_2 \cdots L_{J_P} |$$

$$C_1 C_2 \cdots C_{K_P}]$$

$$CF = [R_1 R_2 \cdots R_{I_F} | L_1 L_2 \cdots L_{J_F} |$$

$$C_1 C_2 \cdots C_{K_F}].$$
(2)

CP and CF are coded as vectors of floating point numbers of the same length as the solution vector. Each parameter in CPand CF is forced to be within the desired range. The precision of such an approach depends on the underlying machine, but is generally much better than that of the binary representation in conventional GA-training [15]. Same chromosome structure is defined in C-language for CP and CF in the respective population. The searching space of each component value is bounded within a predefined range.

C. Fitness Functions

An index (fitness value) is assigned to each chromosome in the population according to a predefined fitness function. The fitness value shows the degree of attainment of the chromosome on the optimization objectives. In this paper, a multi-objective optimization for optimizing PCS and FN is adopted. Two types of fitness functions, including type-one and type-two fitness functions, are used and are discussed as follows.

1) Type-One Fitness Functions: This one is suitable for those that should be as small as possible, such as the steady-state error. The fitness function has the maximum attainable value of K. For example, a candidate chromosome gives a steady-state error of E_S during the searching process and a linear fitness function f is defined as follows:

$$f = K(1 - mE_S) \tag{3}$$

where m is the slope of the linear fitness function. As illustrated in Fig. 2(a), f decreases as E_S increases and $m = m_1$. At the beginning of the searching process, most candidates do not perform satisfactorily and their steady-state errors are much greater than zero. In order to cope with a wide distribution of E_S , min (3) has to be small. However, after several generations, many



Fig. 2. Different types of fitness functions.

candidates in the population have attained some acceptable level of the fitness value (i.e., their E_S are close to zero). In order to differentiate the merit of each candidate effectively in this stage, m should be large [Fig. 2(b)] and $m = m_2$. One possible implementation scheme is to formulate an adaptive fitness function. However, this approach involves the adaptive tuning of fitness function slope.

A more simple solution is to use a piecewise fitness function shown in Fig. 2(c). $m(=m_2)$ is large when E_S is near zero. Conversely, $m(=m_1)$ is small when E_S is far away from zero. In this paper, instead of using this piecewise linear fitness function for f, an exponential function [Fig. 2(d)] is used to perform similar function as in Fig. 2(c). Mathematically

$$f = K e^{-E_s/\tau} \tag{4}$$

where τ is rate of decay of the function. It is equivalent to adjust the slopes of the two linear functions in Fig. 2(c). Method of determining τ is based on considering the expected fitness value at $E_S = E_M$. For example, it is required to make f decay to ε when $E_S = E_M$. Hence, τ is obtained by (4) that

$$\varepsilon = K e^{-E_M/\tau} \Rightarrow \tau = \frac{E_M}{-\ln(\varepsilon/K)}.$$
 (5)

The major advantages of the exponential function lie on its simplicity and its well-defined characteristics in practical implementation.

2) Type-Two Fitness Function: Another form of the fitness function f_2 is based on the sigmoid function of

$$f_2 = \frac{K}{1 + e^{(T_S - T_S^*)/\tau}}.$$
(6)

Apart from constituting the two-slope characteristics as in (4), f_2 will clip to a value of K when $T_S \ll T_S^*$. Equation (6) is suitable for specifications, like the settling time, maximum overshoot and undershoot.

3) Fitness Function for the PCS: The fitness function Φ_P for evaluating each chromosome in PCS population is based on the following considerations, including

- 1) the steady state error of v_o within the required input voltage range $v_{in} \in [V_{in, \min}, V_{in, \max}]$ and output load range $R_L \in [R_{L, \min}, R_{L, \max}]$,
- the operation constraints on circuit components, such as the maximum voltage and current stresses, ripple voltage and ripple current,
- 3) the steady state ripple voltage on v_o , and
- the intrinsic factors concerning with the components in the selected chromosome, such as the total cost, physical size, etc.

Hence, Φ_P measures the attainment of a generic chromosome CP for the above four objectives in the static operating conditions. Each objective is expressed by an objective function (OF_x) . For the *n*th chromosome in the population, Φ_P is expressed in the form of

$$\Phi_P(CP_n) = \sum_{R_L=R_L, \min, \delta R_L}^{R_L, \max} \sum_{\substack{v_{in}=V_{in, \min}, \delta v_{in}}}^{V_{in, \max}} \sum_{\substack{(OF_1(R_L, v_{in}, CP_n) + OF_2(R_L, v_{in}, CP_n) + OF_3(R_L, v_{in}, CP_n) + OF_4(R_L, v_{in}, CP_n)]} + OF_3(R_L, v_{in}, CP_n) + OF_4(R_L, v_{in}, CP_n)]$$
(7)

where δR_L and δv_{in} are the steps in varying R_L and v_{in} , respectively, for evaluating Φ_P . The definitions of all OFs in (4) are defined as follows.

a) OF_1 for objective (1): The steady state v_o is used to determine the suitability of Θ_{PCS} in the population. The implied goal is to find whether there exists a value of v_{con} in Fig. 1 such that the value of v_o after the signal conditioning of H_o [i.e., v'_o] is same as v_{ref} . An iterative Secant method [16] is applied to determine the steady state waveforms. An integral square error function $E_2^{(r)}$ is defined in the *r*th iteration to estimate the closeness of v'_o with v_{ref} in N_s simulated values

$$\mathbf{E}_{2}^{(r)} = \sum_{m=1}^{N_{s}} \left[v_{o}^{\prime(r)}(m) - v_{ref} \right]^{2}$$
(8)

 v'_o is obtained by performing a time-domain simulation using the method in [16] for a given value of v_{con} and the initial state vector x(0) of a switching period in the PCS with the FN excluded. If E₂ is less than a tolerance ε , it is assumed that the system is in the steady state conditions. Otherwise, another guess of $v_{con}^{(r+1)}$ and $x^{(r+1)}(0)$ will be iterated by

$$\tilde{x}^{(r+1)} = \tilde{x}^{(r)} - \frac{\tilde{x}^{(r)} - \tilde{x}^{(r-1)}}{\mathbf{E}_2^{(r)} - \mathbf{E}_2^{(r-1)}} \mathbf{E}_2^{(r)}$$
(9)

where $\tilde{x}^{(r)} = [v_{con}^{(r)} x^{(r)} (0)]$. $x^{(r)}$ is the initial state vector in the *r*th iteration [17].

 $\tilde{x}^{(r+1)}$ will be used in the next iteration until a steady state solution is determined. The iteration will also be terminated when r is larger than a preset number N_r . Formulation of OF_1 is based on E₂. If no steady state solution can be found, OF_1 will be small. Otherwise, OF_1 will be large. OF_1 is based on (4) and defined as follows:

$$OF_1 = K_1 e^{-E_2/K_2} \tag{10}$$

where K_1 is the maximum attainable value of OF_1 and K_2 adjusts the sensitivity of OF_1 with respect to E_2 .

b) OF_2 for objective (2): Under the steady state condition, there are constraints controlling the operating limits of some waveforms. For example, if $\lambda_{C,m}$ is the limit of a considered quantity q_m in the *m*th constraint, the fitness function OF_2 will be based on (6) and is defined as

$$OF_2 = \sum_{m=1}^{N_C} \frac{K_{3,m}}{1 + e^{(q_m - \lambda_{C,m})/K_{4,m}}}$$
(11)

where N_C is the number of constraints, $K_{3,m}$ is the maximum value of the *m*th constraint, and $K_{4,m}$ determines the sensitivity of the considered quantity. For example, if λ_C represents the maximum voltage rating of a switch and *q* is the actual voltage stress, OF_2 is large when *q* is much smaller than λ_C .

c) OF_3 for objective (3): The ripple voltage on v_o has to lie within a limit of $\pm \Delta v_o$ around the expected output $v_{o, exp}$. A measure of the attainment of the chromosome CP_n in this objective is to count the area of v_o outside $v_{o, exp} \pm \Delta v_o$ in N_s simulated samples. OF_3 is based on (4) and is defined as

$$OF_3 = K_5 e^{-A_1/K_6} \tag{12}$$

where K_5 is the maximum attainable value for this objective, K_6 is the decay constant, and A_1 is the ripple area outside the tolerance band. Similar to OF_1 , OF_3 decreases as A_1 increases.

d) OF_4 for objective (4): Apart from the electrical performance of the PCS, some intrinsic factors relating to the components are considered in this objective function. Factors such as the cost, physical size, lifetime of the components can be included. Thus, OF_4 is based on (6) can be expressed as

$$OF_4 = \sum_{i=1}^{I_P} \phi_R(R_i) + \sum_{j=1}^{J_P} \phi_L(L_j) + \sum_{k=1}^{K_P} \phi_C(C_k) \quad (13)$$

where ϕ_R , ϕ_L , and ϕ_C are the objective functions for measuring individual component type. They are defined as follows:

$$\phi_R(R_j) = \frac{K_{7,i}}{1 + e^{(R_i - R_{i,\max})/\tau_R}}$$

$$\phi_L(L_j) = \frac{K_{8,j}}{1 + e^{(L_j - L_{j,\max})/\tau_L}},$$

$$\phi_C(C_k) = \frac{K_{9,k}}{1 + e^{(C_k - C_{k,\max})/\tau_C}}$$
(14)

where $K_{7, i}$, $K_{8, j}$, and $K_{9, k}$ are the maximum attainable values of ϕ_R , ϕ_L , and ϕ_C , respectively. $R_{i, \max}$, $L_{j, \max}$, and $C_{k, \max}$ are the maximum values for R_i , L_j , and C_k , respectively.

D. Fitness Function for FN

Similar to the PCS, the fitness function Φ_F for evaluating each chromosome in FN population is based on the following considerations:

- 1) the steady state error of v_o within the required input voltage range $v_{\text{in}} \in [V_{\text{in},\min}, V_{\text{in},\max}]$ and output load range $R_L \in [R_{L,\min}, R_{L,\max}]$,
- 2) the maximum overshoot and undershoot, and the settling time of v_o (or v_d) during the startup,
- 3) the steady state ripple voltage on v_o , and
- 4) the dynamic behaviors as in 2) during the input voltage and output load disturbances.



Fig. 3. Typical transient response of v_d .

 Φ_F measures the attainment of CF for the above four objectives. Mathematically, for the *h*th chromosome in the population, Φ_F is expressed as

$$\Phi_F(CF_h) = \left[\sum_{R_L=R_L, \min, \delta R_L}^{R_{L, \max}} \sum_{v_{\text{in}}=V_{\text{in}, \min}, \delta v_{\text{in}}}^{V_{\text{in}, \max}} OF_5(R_L, v_{\text{in}}, CF_h) + OF_6(R_L, v_{\text{in}}, CF_h) + OF_7(R_L, v_{\text{in}}, CF_h)\right] + OF_8(CF_h).$$
(15)

a) OF_5 for objective (1): With a defined set of component values in the PCS, the steady state condition of the whole system is determined by the dual loop iteration method in [16]. As this objective is similar to OF_1 , formulation of OF_5 is also based on (10) and is defined as

$$OF_5 = OF_1 = K_1 e^{-E_2/K_2}.$$
 (16)

b) OF_6 and OF_8 for objective (2) and objective (4): During the startup or external disturbances, a transient response appears at v_d , where

$$v_d = v_{ref} - v'_o. \tag{17}$$

A typical response of v_d is shown in Fig. 3. OF_6 and OF_8 are used to measure the transient response of v_d , including 1) the maximum overshoot, 2) the maximum undershoot, and 3) the settling time of the response, during the startup and disturbances, respectively. The general form of OF_6 and OF_8 can be expressed as

$$OF_6 = OV(R_L, v_{\rm in}, CF_h) + UV(R_L, v_{\rm in}, CF_h) + ST(R_L, v_{\rm in}, CF_h)$$
(18a)

$$OF_8 = \sum_{i=1}^{N_T} OV(R_{L,i}, v_{\text{in},i}, CF_h) + UV(R_{L,i}, v_{\text{in},i}, CF_h) + ST(R_{L,i}, v_{\text{in},i}, CF_h)$$
(18b)

where N_T is the number of the input and load disturbances in the performance test.

In the above expressions, OV, UV, and ST are the objective functions for minimizing the maximum overshoot, maximum undershoot, and settling time of v_d . Thus, (6) is applied and the functions in (18) are defined as follows:

$$OV = \frac{K_{10}}{1 + e^{(M_p - M_{p0})/K_{11}}}$$
(19)

where K_{10} is the maximum attainable value of this objective function, M_{p0} is the maximum overshoot, M_p is the actual overshoot, and K_{11} is the passband constant

$$UV = \frac{K_{12}}{1 + e^{(M_v - M_{v0})/K_{13}}}$$
(20)

where K_{12} is the maximum attainable value of this objective function, M_{v0} is the desired maximum undershoot, M_v is the actual undershoot, and K_{13} is the passband constant.

$$ST = \frac{K_{14}}{1 + e^{(T_S - T_{S0})/K_{15}}}$$
(21)

where K_{14} is the maximum attainable value of the objective function, T_{s0} is a constant, T_s is the actual settling time, and K_{15} adjusts the sensitivity. T_S is defined as the settling time of v_d that falls within a $\pm \sigma$ % band. That is

$$|v_d(t)| \le 0.01\sigma, \qquad t \ge T_S. \tag{22}$$

c) OF_7 of objective (3): OF_7 is same as the criteria in the PCS optimization. The number of samples that are outside the tolerance band of v_o (i.e., $\pm \Delta v_o$) are calculated. OF_7 is then same as (12). That is

$$OF_7 = OF_3 = K_5 e^{-A_1/K_6}.$$
 (23)

IV. STEPS OF OPTIMIZATION

The optimization procedures for the PCS and FN are similar. Their major differences are on the definitions of the fitness functions and population. Thus, with the aid of the flowchart in Fig. 4, only the steps of optimizing the PCS in one generation are illustrated.

1) Step 1—Initialization: The population size (N_p) , the maximum number of generations (G_{\max}) , the probability of crossover operation (p_x) , the probability of mutation operation (p_m) , and the generation counter (gen) are initialized. All chromosomes are initialized with random numbers, which lie within the design limits. By using (7) [or (15) for FN optimization], the fitness values of all chromosomes are calculated. The best chromosome in the initial generation $CP_B(0)$ having the highest fitness value {i.e., $\Phi[CP_B(0)] = \max{\Phi[CP_n(0)], n = 1, \ldots, N_p}$, is then selected as reference for the next generation.

 p_x and p_m are two vital parameters that affect the searching process. Types of adaptation can be classified into static, dynamic deterministic, dynamic adaptive and dynamic self-adaptive [18]. In this paper, static approach is applied. p_x and p_m

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Fig. 4. Flowchart of the optimization steps for the PCS.

are fixed throughout the evolution. As discussed in [19], values of $p_x \in [0.75, 0.95]$ and $p_m \in [0.005, 0.01]$ are recommended. Recent studies have impressively clarified, however, that much larger mutation rates, decreasing over the course of evolution, are often helpful with respect to the convergence reliability and velocity of a GA. On the other hand, selection of N_p is depen-

dent on the searching dimension. It is suggested in [20] that $N_p \in [20, 100]$. In this paper, $N_p = 30$, $p_x = 0.85$, and $p_m = 0.25$ are used.

2) Step 2—Selection of Chromosomes: A selection process, which is based on applying the roulette wheel rule, is performed. It starts with the calculation of the fitness value $\Phi_p[CP_n(gen)]$,



Fig. 5. Reproduction process. (a) Crossover operation. (b) Mutation operation.



Fig. 6. Buck regulator with overcurrent protection.

the relative fitness value $\Phi_{p,r}[CP_n(gen)]$ and the cumulative fitness value $\Phi_{p,c}[CP_n(gen)]$ for the $CP_n(gen)$:

$$\Phi_{p,r} [CP_n(gen)] = \frac{\Phi_p [CP_n(gen)]}{\sum_{z=1}^{N_p} \Phi_p [CP_z(gen)]}$$

and

$$\Phi_{p,c}[CP_n(gen)] = \sum_{z=1}^{n} \Phi_{p,r}[CP_z(gen)].$$
(24)

A random number $p \in [0, 1]$ is generated and is compared with $\Phi_{p,c}[CP_n(gen)]$ for $n = 1 \cdots N_p$. If $\Phi_{p,c}[CP_{z-1}(gen)] , <math>CP_z$ is selected to be a member of the new population. This selection process is repeated until N_p members have been selected for the new population. Chromosomes with higher fitness values will have

TABLE I PARAMETERS USED IN THE OPTIMIZATION

Power Conversion Stage (PCS)		Feedback Network (FN)	
Parameter	Value	Parameter	Value
P _x	0.85	P _x	0.85
P _m	0.25	p_m	0.25
G _{max}	500	G _{max}	500
N _p	30	N _p	30
Ns	15000	Ns	15000
N _T	6	N _T	6
<i>K</i> ₁	2	K ₁₀	2
K ₂	400	<i>K</i> ₁₁	0.455
K5	2	K ₁₂	2
K ₆	32	K ₁₃	0.455
<i>K</i> ₈	2	K ₁₄	2
K9	2	K ₁₅	2.28 x 10 ⁻³
τ_L	4.55 x 10 ⁻³		
τ_C	2.14 x 10 ⁻³		
δv_{in}	20V		
δR_L	3Ω		

TABLE II

(a) Initial Values of L and C and the Results After 500 Generations. (b) Initial Component Values for the Controller and the Results After 500 Generations

Component	Initial Value	Optimized value after 500 generations
L	200µН	194µH
С	1000µF	1054µF
		(a)

Component	Initial Value	Optimal Value after 500 generations
<i>R</i> _{C3}	4.7kΩ	3.5 kΩ
<i>C</i> ₂	2µF	5.9 μF
<i>C</i> ₃	3.3µF	0.46 μF
<i>R</i> ₂	300kΩ	767 kΩ
<i>C</i> ₄	1.8µF	1.1 μF
R ₄	1kΩ	6.5 kΩ
<i>R</i> ₁	0.6kΩ	1.1 kΩ
	L	(b)

higher probability to survive and might appear repeatedly in the new population.

3) Step 3—Reproduction Operations: New chromosome will be reproduced with the crossover and mutation operations. The crossover operation is illustrated in Fig. 5(a). Two chromosomes are selected from the population. In order to determine whether a chromosome will undergo a crossover operation, a random selection test (RST) is performed. The RST is based



Fig. 7. Φ_P and Φ_F versus the number of generation gen. (a) Φ_P versus gen. (b) Φ_F versus gen.

on generating a random number $p \in [0, 1]$. If p is smaller than an assigned crossover probability p_x , the chromosome will be selected. Another chromosome will be chosen with the similar procedure. [In Fig. 5(a), CP_1 and CP_2 are illustrated.] A crossover point is selected randomly with equal probability from 1 to the total number of components in the chromosomes. The genes after the crossover point will be exchanged to create two new chromosomes (i.e., CP'_1 and CP'_2). The operations are repeated until all members in the population have been considered.

The mutation operation [Fig. 5(b)] also starts with a RST for each chromosome. If a generated random number $p \in [0, 1]$ for a chromosome is larger than an assigned mutation probability p_m , the chromosome will undergo mutation. In Fig. 5(b), CP_1 is illustrated. A random number will be generated for the chosen component with a value lie within the component limits. The procedures will be repeated until all members have been considered.

4) Step 4—Elitist Function: After finishing the reproduction operation and the calculation of the fitness value of each chromosome, the best member $CP_B(gen)$ that has the largest fitness



Fig. 8. Simulated startup transients when v_{in} is 20 V and R_L is 5 Ω . (a) v_o and v_{con} . (b) i_L .

value and the worst member $CP_w(gen)$ that has the smallest fitness value will be identified. $CP_B(gen)$ will be compared with the best one in the last generation [i.e., $CP_B(gen - 1)$]. If the fitness value of $CP_B(gen)$ is smaller than the one of $CP_B(gen-1)$, the chromosome content of $CP_B(gen-1)$ will replace the content of $CP_B(gen)$. Afterwards, the chromosome content of $CP_B(gen-1)$ will be substituted into $CP_w(gen)$ and the next GA cycle will be started from step 2).

V. DESIGN EXAMPLE

The above method is illustrated with the design of a buck regulator with overcurrent protection [21]. The schematic is shown in Fig. 6. It consists of a buck converter and a proportional-plusintegral (PI) controller. The required specifications are as follows.

1)	Input voltage range:	$40 V \pm 20 V$
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2) Output load range:	$5 \Omega - 10 \Omega$
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- 3) Nominal output voltage: $5 V \pm 1\%$
- 4) Switching frequency: 20 kHz
- 5) Maximum settling time: 20 ms.

 v_{ramp} and v_{ref} in Fig. 1 are $0.2V/\mu s$ and 5 V, respectively. For the PCS, L and C are the design parameters and R_L , r_C ,



Fig. 9. Experimental startup transients when v_{in} is 20 V and R_L is 5 Ω . (a) v_o (1 V/div) and v_{con} (1 V/div) (Timebase: 5 ms/div) (b) i_L (0.5 A/div) (Timebase: 2 ms/div).

and r_E are assumed to be known *a priori*. For the FN, all components are the design parameters. All fitness functions except OF_2 in Section III are used in the optimization. OF_2 is not considered because no special constraints are imposed on the buck converter's waveforms. The maximum attainable value of each fitness function is chosen to be two, which is arbitrary. Thus, K_1 , K_5 , K_8 , K_9 , K_{10} , K_{12} , and K_{14} equal two. Other coefficients are determined as follows.

1) OF_1 and OF_5 : As these two objective functions govern the steady state output, this requirement should be tight. OF_1 and OF_2 are made equal 0.2 (i.e., 10% of the maximum value) if the steady-state value of the N_s samples in (8) has 5% deviation from the expected output (i.e., 5 V). N_s is equal to 15 000. Thus, based on (5), $K_2 = 400$.

2) OF_3 and OF_7 : This objective function is to ensure that the output voltage is within the $\pm 1\%$ tolerance band. A very tight arrangement is that OF_3 becomes 0.2 if the total output voltage samples has 0.1% outside the tolerance band. Thus, based on (5), $K_6 = 32$.



Fig. 10. Simulated transient responses when v_{in} is changed from 20 V into 40 V. (a) v_o and v_{con} . (b) i_L .

3) OF_4 : Only ϕ_L and ϕ_C have to be considered in this objective function. $L_{j, \max}$ and $C_{k, \max}$ are chosen to be 5 mH and 4700 μ F. ϕ_L equals 0.2 if L_j is five times larger than $L_{j, \max}$. ϕ_C equals 0.2 if C_k is twice $C_{k, \max}$. Thus, $\tau_L = 4.55 \times 10^{-3}$ and $\tau_C = 2.14 \times 10^{-3}$ in (14).

4) OF_6 and OF_8 : OV and UV are determined in the same manner. M_{po} and M_{vo} are chosen to be 4 V during disturbances. OV and UV will be less than 0.2 if M_p and M_v are larger than 5 V. Thus, $K_{11} = K_{13} = 0.455$. ST becomes 0.2 if T_s is 30 ms. T_{s0} is taken to be (20 + 30)/2 ms = 25 ms. Thus, $K_{15} = 2.28$ ms.

All coefficients are tabulated in Table I. The computer program continuously monitors the fitness value and stops when the fitness value has close to a relatively constant value. In this example, it was found that the fitness value has been steady after 500 generations. Table II(a) shows the initial values of L and C and the results after 500 generations. The optimized values of the inductor and capacitor in the buck converter were found to be 194 μ H and 1054 μ F, respectively. These two values are close to the ones in [21]. This means that the original L and C have shown satisfactory performance within the requirements. In the actual implementation, an inductor of 200 μ H and a capacitor of 1000 μ F are used. The PI controller is then optimized after the PCS optimization. Table II(b) shows the initial component



Fig. 11. Experimental transient responses when v_{in} is changed from 20 V into 40 V. (a) v_o (2 V/div) and v_{con} (2 V/div) (Timebase: 2 ms/div) (b) i_L (1 A/div) (Timebase: 2 ms/div).

values for the controller and the optimized results after 500 generations. Those values are much different from the ones in [21], even if the components of the PCS are similar. Fig. 7 shows the fitness values of Φ_P and Φ_F versus the number of generation. The fitness values have come to a satisfactory level after 500 generations. It was found that our proposed methods required five hours for the whole optimization starting from entering the specifications whilst the original method (i.e., the decoupled optimization method was not applied) required eight hours. The computer was a Pentium III 500 MHz machine.

The simulated startup transients when the input voltage is 20 V and the output load is 5 Ω are shown in Fig. 8. Compared with the original component values used in [21], the GA-optimized component values have better performance, giving smaller overshoot in the inductor current and faster settling time, even if the optimized values of the PCS are similar to the ones in [21]. Moreover, the steady state error is zero and the output ripple voltage is less than 1%. Fig. 9 shows the experimental results, which are all in close agreement with the predicted waveforms.



Fig. 12. Simulated transient responses when R_L is changed from 5 Ω into 10 Ω and v_{in} is 40 V. (a) v_o and v_{con} . (b) i_L .

The settling time is less than 20 ms. Experimental results also show that the performance of the converter is within the specification throughout the input voltage range. This confirms that the regulator with the GA-optimized component values give satisfactory results in the startup transients.

A similar large-signal disturbance test as [21] is performed. When the input voltage is 20 V and the regulator is in steady state, the input voltage is suddenly changed into 40 V. The transients are shown in Fig. 10. The experimental results are shown in Fig. 11. Compared with [21], when the voltage is changed into 40 V, the system will become unstable and is in sub-harmonic oscillation. With the optimized component values, the system is still stable.

Similar tests on load disturbances are studied with v_{in} equal 40 V. Under the steady state condition, R_L is changed from 5 Ω into 10 Ω . The simulated and experimental transients are shown in Figs. 12 and 13, respectively.

The experimental results agree well with the predicted ones. The static and the dynamic responses are well within the designed specifications, confirming the proposed optimization approach. It can also be seen that the technique is independent on the operating mode of the PCS. During the transient periods in the startup and large-signal disturbances, the converter may operate between continuous and discontinuous mode. It is



Fig. 13. Experimental transient responses when R_L is changed from 5 Ω into 10 Ω and v_{in} is 40 V. (a) v_o (1 V/div) and v_{con} (1 V/div) (Timebase: 2 ms/div) (b) i_L (0.5 A/div) (Timebase: 2 ms/div).

because the optimization is based on the actual time-domain performance, without assuming any pre-determined operating mode.

It can also be observed that the optimization scheme is general and is particularly suitable for designing PECs with complex structure and with many circuit components, such as resonant converters. In addition, apart from the PI controllers as in the illustration, it is applicable for optimizing complex controllers, like fuzzy logic controllers in [22]–[24].

VI. CONCLUSIONS

This paper presents a systematic GA-based, decoupled optimization technique for design of switching regulators. The process entails the selection of the component values in the power conversion stage and the feedback network. No complicated mathematical analysis of the whole system is needed. The algorithm automatically determines the values of the components to meet the specifications, independent on the circuit structure and control schemes. An example of the design of a buck regulator is illustrated. The predicted results are compared to the published results in the literature available and are verified with experimental measurements.

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