Application of Independent-minded Particle Swarm Optimization for Design of Class-E Amplifiers

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Abstract—The class-E amplifier is one of the switching amplifiers, which satisfies the class-E switching conditions. It is, however, difficult to determine the values of the passive elements included in the circuit for achieving the class-E switching conditions. Recently, the Newton type algorithm is proposed to determine the passive elements. However, this method requires a good initial estimation. In this paper, an algorithm using Independent-minded Particle Swarm Optimization (IPSO) is introduced to estimate the initial conditions. To find it efficiently, the MOSFET in the class-E amplifier is replaced with an ideal switch and the objective function for the optimization is efficiently evaluated. Unfortunately, the objective function has multimodal characteristics and a robust optimization method is required. Then, the optimum solution is found by using IPSO which shows good performances for multimodal cases. Therefore, the initial estimation for the Newton type algorithm is easily obtained and a good design of the class-E amplifier becomes available.

I. INTRODUCTION

The class-E switching-mode circuits have become increasingly valuable components in many applications, e.g., radio transmitters, switching mode-dc power supplies, devices of medical applications, and so on. Since the class-E switching, namely, both zero voltage switching (ZVS) and zero derivative switching (ZDS), the class-E switching circuits can achieve high power conversion efficiency at high frequencies. However, the design of the class-E amplifier is quite difficult because two switching conditions should be satisfied simultaneously on the steady-state of the circuits.

Since the invention of the class-E amplifier, many analytical descriptions of this circuit have been presented [1]-[7]. Early designs assumed an ideal switch, infinite output network Q, and an RF choke in the dc supply [1], [2]. Later work allowed the finite output Q [3], [4], [5], drain current fall time [5], and nonlinear parasitic capacitance on the active device [6], [7]. Although these treatments give useful guidance for designs of the class-E amplifiers, it is impossible for these design methods to consider all the effects of passive/active elements including in these circuits.

A design procedure for the generalized class-E amplifiers was given by using SPICE [9]. In this method, the designs of the class-E amplifier are regarded as the simultaneous determinations of steady-state waveforms and parameters for obtaining the class-E ZVS/ZDS conditions. The fundamental concept of the method in [9] is based on the time-domain shooting method for finding the steady-state responses. The design variables of the class-E switching circuits and steady-state responses are simultaneously determined by using the Newton method [8]. This method allows us to consider all the physical effects of devices within the mathematical model of circuit simulator. The Newton type algorithm requires a good initial estimation to ensure the convergence. Therefore, the implementation using SPICE is not necessarily robust. Instead of the Newton method, Particle Swarm Optimization (PSO) was introduced for design of the class-E amplifier [10]. PSO is a population based stochastic optimization technique inspired by the social behavior of bird flock algorithm [11]. This algorithm is a computationally simple and robust. In this method, the steady-state solution is found by the time-domain shooting method in a circuit simulator. PSO is a stochastic method which essentially requires many evaluations of the objective function. The steady-state analysis of the nonlinear circuits needs a lot of computational time. Hence, even though a parallel operational library as OpenMP is introduced to evaluate the objective function, the PSO for designing the class-E amplifiers is still computationally expensive [10].

In this paper, an algorithm using Independent-minded PSO (IPSO) [12], [13] is applied to finding a good initial estimation for the Newton method [9]. First, the MOSFET of the class-E amplifiers is replaced with an ideal switch, and the steady-state responses are expressed in a closed form. Next, the objective function is defined in order to evaluate whether the circuit satisfies the ZVS and ZDS conditions. However, since the objective function has multi-modal features, a robust algorithm is required. Generally, stochastic algorithms are powerful for solving this kind of problems. As a robust method, we apply IPSO to finding the optimum solution. In the algorithm of PSO, multiple potential solutions called “particles” coexist, and each particle moves toward the best position in the swarm and the personal best position. The most important feature of IPSO is that in contrast to the standard PSO whose particles are always influenced by the swarm, it is decided stochastically whether each particle depends on the best position in the swarm or is isolated from the swarm at every step. In other words, the particles of IPSO are not always connected each other, and they act with self-reliance. It has been confirmed that IPSO is effective for complex problems with numerous local optima [14]. Hence, the IPSO is suitable for finding the initial estimation for the Newton method, since there exist many local minimums in the parameter region of the objective
function for the optimization of class-E switching circuits. This paper confirms that IPSO can obtain better results with high success rate. Furthermore, by investigating the relationship between the success rate and the important parameter of IPSO, we confirm that the parameter-dependence of IPSO is weak and IPSO is more effective than the standard PSO.

II. CLASS-E AMPLIFIER

A circuit topology of the class-E amplifier is shown in Fig. 1(a). The class-E amplifier consists of dc-supply voltage $V_D$, dc-feed inductor $L_C$, n-channel MOSFET $S$, shunt capacitor $C_S$, and series resonant circuit composed of inductor $L_0$, capacitor $C_0$, and output resistor $R$. For achieving high power conversion efficiency, it is effective that the zero voltage switching (ZVS) and zero derivative switching (ZDS) are achieved simultaneously at the turn-on instant of switch. These conditions are called the class-E ZVS/ZDS conditions which are written by

\[
v_s(T) = 0, \quad \left. \frac{dv_s}{dt} \right|_{t = T} = 0, \tag{1}
\]

where $T$ is the switching period and we define that the switch turns on at $t = kT$ for an integer $k$. Figure 2 shows a typical waveform of the switch voltage $v_s$ when the class-E switching conditions are satisfied. The voltage $v_s$ switches smoothly at $T$ and $2T$ without switching losses. In order to satisfy the conditions (1) and (2), design parameters such as values of the passive elements and device parameters of the MOSFET $S$ should be adjusted optimally. Moreover, the class-E switching conditions should be satisfied on the steady-state of the circuit, which make design of the class-E amplifier difficult.

The resonant filters in the class-E amplifiers usually have a high $Q$ value, which means that the transition time is long until it reaches the steady-state and the transient analysis of the class-E amplifier requires a large computational cost. It is uncertain how many cycles of input voltage $D_r$ shown in Fig. 2 is necessary for obtaining the steady-state waveform. Therefore, a method for finding the steady-state solution directly should be used for analyzing the class-E amplifiers. By using a simulator as HSPICERF, we can know the steady-state response. However, the computational cost is still large for the optimization purpose. Therefore, we express approximately the steady-state responses in a closed form, where the MOSFET is replaced with an ideal switch as shown in Fig. 1(b).

Since the circuit equation of Fig. 1(b) is classified into the ‘on’ and ‘off’ states of the ideal switch $S$. The circuit equation at the on state is written by

\[
\frac{dx_{on}}{dt} = \alpha_1 x_{on} + \beta, \quad (0 \leq t \leq T/2) \tag{3}
\]

where $x_{on}(t) = \{i_C(t), v_S(t), i_O(t), v(t)\}_{on}$ is the state vector at the on state. $\alpha_1$ and $\beta$ are coefficient matrix and a constant vector related with DC voltage supply, respectively. As (3), the circuit equation at the off state is expressed by

\[
\frac{dx_{off}}{dt} = \alpha_2 x_{off} + \beta, \quad (T/2 \leq t \leq T) \tag{4}
\]

where $x_{off}(t) = \{i_C(t), v_S(t), i_O(t), v(t)\}_{off}$ is the state vector at the off state.

Equations (3) and (4) are both linear and time invariant. Thus, the solutions are expressed via the eigen decomposition of the coefficient matrix $\alpha$: $\alpha S = S \text{diag} \{\lambda_1, \ldots, \lambda_4\}$, where $\lambda_1, \ldots, \lambda_4$ are the eigen values. The solutions are then written by

\[
x_{on}(t) = \gamma_1 x(0) + \phi_1, \tag{5}
\]

\[
x_{off}(t) = \gamma_2 x(T/2) + \phi_2, \tag{6}
\]

where

\[
\gamma_1 = S \text{diag} \{e^{\lambda_1 t}, \ldots, e^{\lambda_4 t}\} S^{-1},
\]

\[
\phi_1 = S \text{diag} \{e^{\lambda_1 t} - 1, \ldots, e^{\lambda_4 t} - 1\} S^{-1} \beta.
\]

$\gamma_2$ and $\phi_2$ can be written similarly to $\gamma_1$ and $\phi_1$. From the steady-state condition, $x_{on}(0) = x_{off}(T)$, the initial conditions which give the steady-state responses are obtained from

\[
x(0) = (I - \gamma_2 \gamma_1)^{-1} (\gamma_2 \phi_1 + \phi_2) \beta, \tag{7}
\]

where $I$ is the identity matrix.

In order to satisfy the class-E ZVS/ZDS conditions (1) and (2), the design of the class-E amplifier is defined as an optimization problem. The objective function is given by

\[
f(\xi_1, \ldots, \xi_n) = \sqrt{v_S(T)^2 + i_S(T)^2}, \tag{8}
\]

where $\xi_1, \ldots, \xi_n$ are design parameters. $v_S(T)$ and $i_S$ are respectively the voltage of the shunt capacitor $C_S$ and current flowing through it on the steady-state which are calculated by (7). It should be noted that the capacitance $C_S$ is used as a scaling factor of the time derivative $dv_S/dt|_{t = T}$ of (2).
III. INDEPENDENT-MINDED PARTICLE SWARM OPTIMIZATION (IPSO)

In the algorithm of PSO, multiple potential solutions called “particles” coexist. At each time step, each particle flies toward its own past best position (pbest) and the best position among all particles (gbest). Namely, they always influence each other. In this study, we propose the novel concept of the complex network; the Independent-minded PSO (IPSO). The particles of IPSO have independence, thus, it is decided stochastically whether they are connected to others at every step. In other words, they are not always affected by gbest and their pbest does not always affect the swarm.

Each particle has two kinds of information: position and velocity. The position vector of each particle i and its velocity are represented by \( \mathbf{X}_i = (x_{i1}, \ldots, x_{id}, \ldots, x_{iD}) \) and \( \mathbf{V}_i = (v_{i1}, \ldots, v_{id}, \ldots, v_{iD}) \), respectively, where \( d = 1, 2, \ldots, D \), \( i = 1, 2, \ldots, M \).

(Step1) (Initialization) Let a generation step \( t \) be 0. Initialize the particle position \( \mathbf{X}_i \) \( (x_{id} \in [x_{\text{min}}, x_{\text{max}}]) \) randomly, its velocity \( \mathbf{V}_i \) to zero, and \( \mathbf{P}_i = (p_{i1}, p_{i2}, \ldots, p_{iD}) \) with a copy of \( \mathbf{X}_i \). Evaluate the objective function \( f(\mathbf{X}_i) \) for each particle \( i \) and find \( \mathbf{P}_g = (p_{g1}, p_{g2}, \ldots, p_{gD}) \) with the best function value among all the particles.

(Step2) Decide whether each particle \( i \) is connected to the others according to \( \mathbf{r}_{3i} = (r_{3i1}, r_{3i2}, \ldots, r_{3iD}) \) which is a \( D \)-dimensional random vector \( (\in (0, 1)) \) for \( i \). If a component \( r_{3id} \) satisfies \( r_{3id} \leq K \), the particle \( i \) is connected to other particles; \( i \in S_c \), where \( S_c \) is a set of particles connected to the swarm. If not, the particle \( i \) is isolated from the swarm, then, the particle \( i \) and the others does not interact. \( K \) is a constant cooperative coefficient which is the independent probability of the particles, and a value \( \in [0.01, 0.1] \) can be used for most problems [13].

(Step3) Evaluate the fitness \( f(\mathbf{X}_i) \) for each particle \( i \). Update the personal best position (pbest) as \( \mathbf{P}_i = \mathbf{X}_i \) if \( f(\mathbf{X}_i) < f(\mathbf{P}_i) \).

(Step4) Let \( \mathbf{P}_l \) represents the best position lbest with the best pbest among particles being connected to others. Update lbest \( \mathbf{P}_l = (p_{l1}, p_{l2}, \ldots, p_{lD}) \) according to

\[
    l = \arg \min_i f(\mathbf{P}_i), \quad i \in S_c.
\]

(Step5) Update \( \mathbf{V}_i \) and \( \mathbf{X}_i \) of each particle \( i \) according to

\[
    v_{id}(t + 1) = \begin{cases} 
    wv_{id}(t) + c_1r_1(p_{id} - x_{id}(t)) + c_2r_2(p_{lg} - x_{id}(t)), & r_{3id} \leq K \\
    wv_{id}(t) + c_1r_1(p_{id} - x_{id}(t)), & r_{3id} > K 
    \end{cases}
\]

\[
    x_{id}(t + 1) = x_{id}(t) + v_{id}(t + 1),
\]

where \( w \) is the inertia weight determining how much of the previous velocity of the particle is preserved. \( c_1 \) and \( c_2 \) are two positive acceleration coefficients, generally \( c_1 = c_2 = r_1 \) and \( r_2 \) are uniform random numbers \( U(0, 1) \). These equations mean that whether each particle is affected by lbest or not is decided at random with the cooperativeness \( K \). When \( K = 0 \), all the particles move depending only on pbest, and when \( K = 1 \), the algorithm is completely the same as the standard PSO.

(Step6) Let \( t = t + 1 \) and go back to (Step2).

IV. RESULTS

For the design of the class-E amplifier, design specifications are given as \( f = 1 \text{MHz}, V_D = 5 \text{V}, R = 5 \Omega, L_C = 7.96 \mu \text{H}, \) and \( L_0 = 7.96 \mu \text{H} \). Thus, \( C_S \) and \( C_0 \) are selected as the design parameters. In other words, these parameters correspond to the particle’s position in PSOs, namely, \( \mathbf{X} \equiv (x_1, x_2) \equiv (C_S, C_0) \), thus \( D = 2 \).

For both the standard PSO and IPSO, the parameters are set as follows; the population size \( M = 24 \), the inertia weight \( w = 0.7 \) and the acceleration coefficients \( c_1 = c_2 = 1.6 \). The cooperative coefficient \( K \) of IPSO is set at 0.01 by trial and error. The maximum generation of each simulation is 1000, and the results are evaluated in a success rate over 100 trials.

If the simulation result \( \mathbf{P}_g = (p_{g1}, p_{g2}) \) satisfied

\[
    5.8 \times 10^{-9} \leq p_{g1} \leq 6.8 \times 10^{-9}
\]

and

\[
    3.1 \times 10^{-9} \leq p_{g2} \leq 4.1 \times 10^{-9},
\]

it is defined as the trial was successful.
Fig. 3. Obtained results \( \mathbf{P}_g \equiv (C_S, C_0) \) over 100 trials. (a) X-axis is \( C_S \) and Y-axis is \( C_0 \). Success area are shown in yellow. (b) Magnified figure of (a). (c) Obtained fitness values \( f(\mathbf{P}_g) \) according to \( (C_S, C_0) \).

| TABLE I |
|----------------|----------------|
| Comparison results of PSO and IPSO over 100 trials. |

<table>
<thead>
<tr>
<th></th>
<th>Success rate[%]</th>
<th>Mean ( f(\mathbf{P}_g) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>40</td>
<td>0.0184</td>
</tr>
<tr>
<td>IPSO</td>
<td>99</td>
<td>0.0070</td>
</tr>
</tbody>
</table>

A. Optimization Results

The success rates and mean fitness values of \( \text{gbest} \) over 100 trials are summarized in Table I. We can confirm that the success rate is significantly improved by using IPSO. In addition, the obtained fitness values of IPSO were also better than the standard PSO.

Figure 3(a) shows respective positions of \( (C_S, C_0) \) obtained by 100 trials. We can see that the standard PSO obtained the results which are either close to the optimum value or far from the optimum value. On the other hand, IPSO converged to around the optimum value with extraordinary frequency. In just one failed case, IPSO converged to near the success area shown as Fig. 3(b) which is a magnified figure of Fig. 3(a).

The fitness values according to obtained \( (C_S, C_0) \) over 100 simulations are shown in Fig. 3(c). It is rare for IPSO to fall into the local optima, while, the convergence speed is slower than the standard PSO. It is highly possible that the results of IPSO converge to the global optima by increasing the learning steps.

Figure 4 shows the success rate over 100 runs in different cooperativeness \( K \). Note that the standard PSO used \( K = 1.0 \) for all the trials, namely, IPSO with \( K = 1.0 \) is corresponding to the standard PSO. It should be noted that IPSO with \( K = 0.005-0.7 \) obtained better results than when it was fully-connected \( (K = 1.0) \). From this result, we can understand that this optimization problem is the multimodal problem [12] and the parameter-dependence of IPSO is weak because IPSO kept better results than the standard PSO in a wide range of \( K \). Furthermore, this result mean for this optimization, that the particle diversity is more important than the quick communication, and the particles of IPSO is more diverse than the standard PSO.

From these results, we can conclude that IPSO is effective
not only for the optimization benchmarks but also for designing of the class-E amplifier which is a real-world optimization problem.

V. CONCLUSIONS

IPSO is applied to the design of the class-E amplifiers in this paper, where the algorithm is used to find a good initial estimation for the Newton type algorithm [15]. To extract the initial estimation efficiently, the responses of the class-E amplifier are expressed in a closed form. However, the objective function of the optimization problem is so complicated that the standard PSO is incapable of solving it. Hence, we use the IPSO which is suggested as quit powerful for multimodal cases [14]. Combing the IPSO with the Newton method, we can efficiently determine the design parameters which satisfy the class-E ZVS and ZDS conditions considering all the effects of nonlinear device within the circuit simulation level.

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