VARYING DIMENSIONAL PARTICLE SWARM OPTIMIZERS FOR DESIGN OF SWITCHING SIGNALS

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Abstract: This paper presents varying dimensional particle swarm optimizers for design of switching signals in circuits and systems. The particle position and dimension correspond to the switching phase and the number of switches, respectively. The dimension can vary depending on an objective function in the search process, i.e., the number of switches is adjustable automatically. The algorithm is defined for a multi-objective problem described by the hybrid fitness consisting of analog functions and digital logic. The algorithm is defined in a general form and the performance is investigated in an example: design of a switching signal for single phase inverters with a two-objective problem corresponding to total harmonic distortion and power sufficiency.

1 INTRODUCTION

The particle swarm optimizer (PSO) is a populatiob-based optimization algorithm (Engelbrecht, 2005). The PSO is simple in concept, is easy to implement and is applicable to a variety of systems: image/signal processing (Wachowiak et al., 2004), artificial neural networks (Garro et al., 2009), power electronics (Ono and Saito, 2009), etc. The PSO has been improved in order to challenge various problems: multi-objective problems, multiple solutions, escape from a trap of local optima, variable swarm topology, etc. (Engelbrecht, 2005) (Parsopoulos and Vrahatis, 2004) (Miyagawa and Saito, 2009).

This paper presents a varying dimensional particle swarm optimizer (VDPSO) for application to design of switching signals in circuits and systems. The switching signals, which determine the on/off timing, are characterized by the switching phases. Design of such switching signals is a key in a variety of circuits and systems: digital communications (Maggio et al., 2001), switching power converters (Giral et al., 1999) (Sundareswaran et al., 2007), etc. In the VDPSO, the particle positions and their dimension correspond to the switching phases and the number of switches, respectively. The goal of the VDPSO is optimizing the objective function of the switching phases to realize a desired circuit operation. The particle dimension is adjustable automatically in the search process following the objective function: two switching phases can equalize (dimension reduction) and can separate (dimension recovery) if some conditions are fulfilled. Such dimension control is important because of several reasons including 1) The number of switchings affects performance of circuits and systems, however, the optimal number is unknown in many cases; 2) In optimization problems, the objective solution is often restricted in a lower dimensional subspace in the whole search space, however, automatic identification of the target subspace is hard. The VDPSO is defined in multi-objective problems (MOP) described by the hybrid fitness consisting of analog objective functions with criterion and digital logic (Ono and Saito, 2009). Some fitness component can increase below the criterion and this increase can help escape from a trapping solution.

After definition of the general form, the VDPSO performance is investigated in a two-objective problem of basic dc/ac inverters whose solution is known. The two-objective hybrid fitness function represents the total harmonic distortion and power sufficiency of the output waveform. Performing numerical experiments, we can confirm that the dimension varies suitably, the flexible search is realized and the particles approach to the solution. Note that we have used the basic problem whose solution is known because such a problem is convenient to investigate/evaluate the algorithm performance: this paper aims at proposal of a prototype of the VDPSO and investigation of the algorithm performance. The results provide ba-

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sic information to improve/establish the VDPSO and to realize effective applications in various circuits and systems. Preliminary results along these lines can be found in (Kawamura and Saito, 2010).

2 VARYING DIMENSIONAL PSO

Here we define the VDPSO for an optimization problem of switching signals $y(t)$ with period T:

$$y(t) = \begin{cases} 0 & \text{for } a_{l-1} \le t < a_l \\ 1 & \text{for } a_l \le t < a_{l+1} \end{cases} \quad y(t+T) = y(t) \quad (1)$$

where $l \in \{1,3,\cdots,N\}$, $a_0 \equiv 0 < a_1 \le \cdots \le a_N < a_{N+1} \equiv T$ and a_i denotes the switching phase as shown in Fig. 1 (a). $y = 1$ and $y = 0$ correspond to switch-on and -off, respectively. Let an objective problem be described by a set of functions of the switching phases a_i:

$$F_j(\vec{a}) \ge 0,\ \vec{a} \equiv (a_1,\cdots,a_N),\ j = 1 \sim N_f \quad (2)$$

where the minimum values are normalized as zero. Let the desired circuit operation corresponds to the minimum value of F_i for all i. The cases $N_f = 1$ and $N_f \ge 2$ correspond to the uni–objective problems and MOP, respectively. Since it is hard to find the exact minimum value of F_i for all i, we try to find an approximate solution $\vec{a}_s$ satisfying

$$0 \le F_i(\vec{a}_s) < C_i,\ \ i = 1 \sim N_f \quad (3)$$

where C_i is the criterion of the i-th component. Note that the problem has a margin $[0, C_1)$.

Let a swarm contain N_p pieces of N-dimensional particles. The i-th particle at a discrete time n is characterized by its position $\vec{a}_i(n) \equiv (a_{i1},\cdots,a_{iN})$ and velocity $\vec{v}_i(n) \equiv (v_{i1},\cdots,v_{iN})$ where $i = 1 \sim N_p$ is the index of the particles. The positions correspond to the switching phases $\vec{a} \equiv (a_1,\cdots,a_N)$ and the velocity controls their movement. Each particle tries to approach a solution using two key pieces of information: the personal best particle $\vec{a}_{p_i}$ (*pbest*$_i$) that has the best evaluation in the past history, and the global best particle $\vec{a}_g$ (*gbest*) that is the best of the *pbest*$_i$ for all i. The $\vec{a}_g$ is the occasional solution at time n. The search space is the one period of time axis and is divided into N subintervals as illustrated in Fig. 1 (b):

$$I_k \equiv [(k-1)d, (k+1)d),\ d = T/N,\ k = 1 \sim N \quad (4)$$

Note that two successive subintervals overlap $I_k \cup I_{k+1} = [kd, (k+1)d]$. This overlapping plays an important role in the dimension control in the algorithm. The algorithm is defined in the following 6 steps.

Step 1. Let $n = 0$. As illustrated in Fig. 1: the k-th element of the ith particle position is assigned randomly

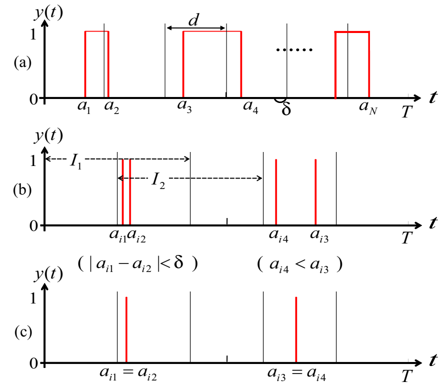

Figure 1: Particles assignment and dimension control.

in I_k: $a_{ik} \in I_k$, $k = 1 \sim N$. Note that if I_k consists of N_l lattice points then the possible number of $\vec{a}_i$ is N_l^N. The brute force search becomes hard as N increases. Other variables are also initialized: velocity $\vec{v}_i(n) = \vec{0}$, personal best $\vec{a}_{p_i} = \vec{a}_i(n)$ and global best $\vec{a}_g = \vec{a}_1(n)$.

Step 2. If Eq. (5) is satisfied for all i then the algorithm is terminated, otherwise go to Step 3.

$$0 \le F_i(\vec{a}_g) < C_i,\ \ i = 1 \sim N_f \quad (5)$$

Step 3 (Renewal of velocity and position)**.**

$$\begin{aligned} &\vec{v}_i(n+1) = w_i\vec{v}_i(n) + \rho_1(\vec{a}_{p_i} - \vec{a}_i(n)) + \rho_2(\vec{a}_g - \vec{a}_i(n)) \\ &\vec{a}_i(n+1) = \vec{a}_i(n) + \vec{v}_i(n+1),\ i = 1 \sim N \end{aligned} \quad (6)$$

where w, ρ_1 and ρ_2 are deterministic parameters, not random parameters as standard PSOs. In order to avoid overflow, speeding and stagnation; we apply

If $a_{ik}(n) \notin I_k$ then $a_{ik}(n)$ = RND(I_k)
If $v_i(n) \notin [-V_L, V_L]$ then $v_{ik}(n)$ = RND($[-V_L, V_L]$)
If $|v_i(n)| < \varepsilon$ then $v_{ik}(n) = qv_{ik}(n)$

where q, ε and V_L are control parameters. RND(I_k) means a random number on the k-th subinterval I_k.

Step 4 (Dimension Control)**.** As illustrated in Fig. 1 (b) and (c), the particle position is equalized if two successive particles are sufficiently close or the order of particles are inversed:

$$\begin{aligned} &a_{ik} = a_{i(k+1)} = \frac{a_{ik} + a_{i(k+1)}}{2} \ \text{ if} \\ &|a_{ik} - a_{i(k+1)}| \le \delta \ \text{ or } \ a_{i(k+1)} < a_{ik} \end{aligned} \quad (7)$$

where $k = 1 \sim M - 1$. This equalization $a_{ik} = a_{i(k+1)}$ means dimension reduction of $\vec{a}$ in principle. If Eq. (7) is not satisfied in the future, then a_{ik} can be separated from $a_{i(k+1)}$ and the dimension can be recovered in Steps 3 and 4. If "the maximum dimension" N is large then the particle can express very wide-band switching signals.

Step 5 (Hybrid Fitness)**.** The ith personal best, $i = 1 \sim N_p$, is renewed if some fitness component(s) is improved and other component(s) satisfies the criterion:

$$\begin{aligned}
&\vec{a}_{p_i} = \vec{a}_i(n+1) \text{ if either (A) or (B) is satisfied} \\
&\text{(A) } C_j < F_j(\vec{a}_i(n+1)) < F_j(\vec{a}_{p_i}) \text{ for all } j = 1 \sim N_f \\
&\text{(B) } F_j(\vec{a}_i(n+1)) < C_j \text{ for some } j \text{ and} \\
&C_k < F_k(\vec{a}_i(n+1)) < F_k(\vec{a}_{p_i}) \text{ for } k \neq j
\end{aligned} \quad (8)$$

Since Eq. (8) is constructed by analog function F_i and digital logic, we refer it to as hybrid fitness. The *gbest* is renewed as the best of all the personal bests.

Step 6. $n = n+1$, go to Step 2 and repeat until the maximum time limit n_{max}.

Note that the dimension control in Step 4 can find the suitble number (dimension) of switchings automatically. Note also that some fitness F_j can increase below the criterion C_j before Eq. (5) is fulfilled. This flexibility can help to search for a suitable solution. Existing algorithms often use a weighted sum of the objectives for the MOPs, however, it is difficult to get the best weight values (Engelbrecht, 2005).

3 NUMERICAL EXPERIMENTS

In order to investigate the basic performance, we consider the two-objective problem for switching signal of the dc/ac inverter. Figure 2 shows an output waveform $y(t)$. Since this is odd-symmetric, it is sufficient to consider in the first quarter:

$$y(t) = \begin{cases} 0 & \text{for } a_{l-1} \le t < a_l \\ 1 & \text{for } a_l \le t < a_{l+1} \end{cases} \quad (9)$$

where the period is normalized as 2π, $a_0 \equiv 0 < a_1 \le \cdots \le a_{N_s} < a_{N_s+1} \equiv \pi/2$, $l \in \{1,3,\cdots,N_s\}$ and N_s is the number of the switches. Let $\vec{a} \equiv (a_1,\cdots,a_{N_s})$. Let us define two positive definite objective functions.

$$F_1(\vec{a}) = 1 - \frac{b_1^2}{2P(\vec{a})},\; F_2(\vec{a}) = \left|1 - \frac{P(\vec{a})}{P_d}\right| \quad (10)$$

$$y(t) = \sum_m^{\infty} b_m \sin mt,\; P(\vec{a}) = \frac{1}{2\pi}\int_0^{2\pi} y(t)^2 dt.$$

where b_m is the Fourier sine coefficient, $0 < P(\vec{a}) < 1$ is the normalized average power of $y(t)$ and $0 < P_d < 1$ is a desired average power. F_1 relates to the total harmonic distortion (THD) and $F_1 = 0$ means pure sinusoidal waveform. F_2 describes the power sufficiency and $F_2(\vec{a}) = 0$ gives the desired power. If both F_1 and F_2 are minimized, we can obtain the output having desired power with low distortion. It is suitable for continuous control of the ac power. Substituting $N = N_s$ and $N_f = 2$ into the algorithm, we can implement the VDPSO for this problem. The goal is described by $F_1(\vec{a}_g) \le C_1$ and $F_2(\vec{a}_g) \le C_2$. If $P(\vec{a})$ in F_2 is given, the optimal solution is $a_1 = \cdots = a_{N_s} = \pi(1 - P(\vec{a})/2$. That is, the optimal dimension is one. We investigate how the algorithm reduces the dimension automatically. We note again that our purpose is investigation of basic performance of the algorithm and the search process. For the numerical experiments, we select C_1, C_2 and P_d as control parameters and the other 10 parameters are fixed after trial-and-errors: $N_p = 20$, $N_s = 17$, $w = 0.8$, $\rho_1 = \rho_2 = 2$, $V_L = 0.2$, $\varepsilon = 10^{-15}$, $q = 0.1$, $\delta = 0.01$ and $n_{max} = 400$. Fig. 3 shows a typical result: as n increases, the number of the switching phases decreases by the dimension control in Step 4 and the criterion is attained. Fig. 3 (b) shows position transition of the *gbest* particle where the number of the switches changes from 20 to 1 by repeating dimension control. Fig. 4 shows the search process. As n increases, F_2 decreases and reaches the criterion C_2 rapidly. Below the criterion C_2, the F_2 can increase and this increase helps decrease of F_1 and attainment of the criterion C_1. That is, the VDPSO can adjust the number of switches automatically and can give the desired solution. Table 1 summarizes results of 50 trials for various parameter values and initial conditions. We have used the three measures: SR (The successful

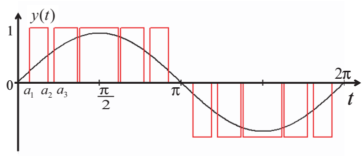

Figure 2: PWM control signal of dc/ac inverters.

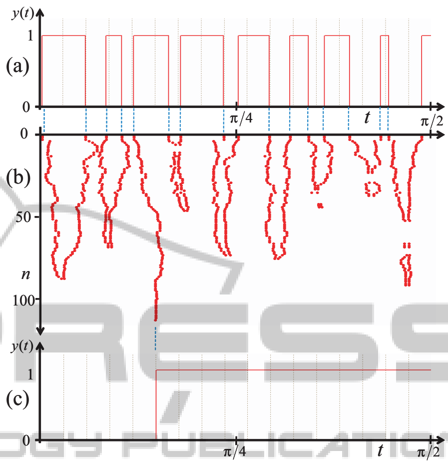

Figure 3: Search process for $P_d = 0.7$, $C_1 = 8\times10^{-2}$ and $C_2 = 8\times10^{-3}$. (a) initial waveform at $n = 0$, (b) position transition of the *gbest* particle, (c) waveform of the criterion attainment at $n = 112$: (F_1, F_2) = (7.99×10^{-2}, 7.40×10^{-3}).

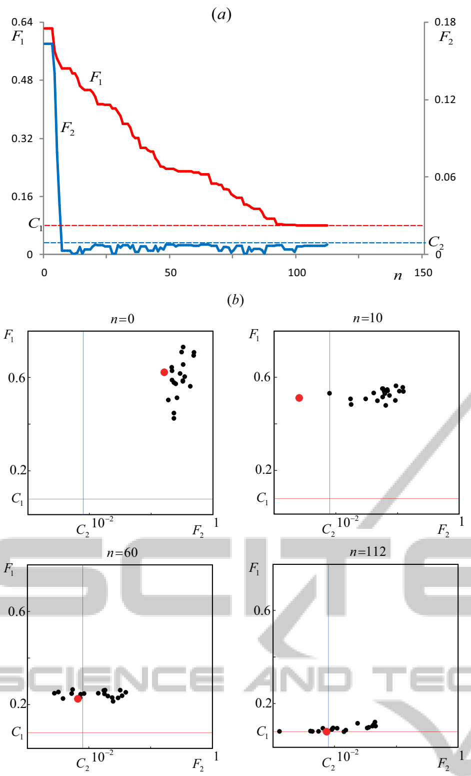

Figure 4: Search process for $C_1 = 8\times10^{-2}$ and $C_2 = 8\times10^{-3}$. (a) Time evolution of the two fitness functions. (b) Behavior of particles. The red point is the global best.

rate of the criterion attainment within the time limit), #ITL (The average number of iterations to attain the criterion for successful run) and #SW (The average number of switches at the criterion attainment in successful runs).

The SR is good around $P_d = 0.7$ and decreases as P_d is apart from it. Note that #SW=2.2 for $p_d = 0.7$ and $C_1 = 0.08$ means that the criterion can be attained even in the case of 3 switchings. As C_1 decreases for $P_d = 0.7$, #SW approaches 1. As C_1 increases, the #ITE and #SW tend to increase: the criteria are attained before the #SW is optimized. These results suggest that the VDPSO is efficient if the desired power P_d is in some range, however, several improvements are required for finding solution in a wider range of P_d. We have also confirmed that the desired operation is hard to be given if the dimension control or/and hybrid fitness is not used.

4 CONCLUSIONS

The VDPSO has been studied and its performances have been investigated in a simple example. It is confirmed that the dimension control can work effectively together with the hybrid fitness function. However, this paper provides a first step to develop an efficient optimization algorithm with dimension control. Future problems are many, including analysis of search process, role of key algorithm parameters, comparison with other kinds of PSOs and application to switching signals in various circuits and systems.

Table 1: Basic performances ($N_s = 17$, $C_2 = 8\times10^{-3}$).

P_d	C_1	SR	#ITE	#SW
0.9	0.08	n/a	n/a	n/a
	0.12	74	157	1.0
	0.15	100	46	4.6
	0.19	100	37	5.9
0.7	0.08	100	97	2.2
	0.12	100	65	5.4
	0.15	100	52	7.4
	0.19	100	43	9.6
0.5	0.15	n/a	n/a	n/a
	0.19	92	175	1.0

REFERENCES

Engelbrecht, A. P. (2005). *Fundamentals of computational swarm intelligence*. Willey.

Garro, B. A., Sossa, H., and Vazquez, R. A. (2009). Design of artificial neural networks using a modified particle swarm optimization algorithm. In *Proc. IEEE-INNS Joint Conf. Neural Netw.*, pages 938–945.

Giral, R., Martinez-Salamero, L., and Singer, S. (1999). Interleaved converters operation based on cmc. *IEEE Trans. Power Electron.*, 14(4):643–652.

Kawamura, K. and Saito, T. (2010). Design of switching circuits based on particle swarm optimizer and hybrid fitness function. In *Proc. Annual Conf. IEEE Ind. Electron. Soc.*, pages 1099–1103.

Maggio, G. M., Rulkov, N., and Reggiani, L. (2001). Pseudo-chaotic time hopping for uwb impulse radio. *IEEE Trans. Circuits Syst. I*, 48(12):1424–1435.

Miyagawa, E. and Saito, T. (2009). Particle swarm optimizers with growing tree topology. *IEICE Trans. Fundamentals*, E92-A:2275–2282.

Ono, K. and Saito, T. (2009). Application of particle swarm optimizers to two-objective problems in design of switching inverters. In *Proc. IEEE-INNS Joint Conf. Neural Netw.*, pages 2353–2357.

Parsopoulos, K. E. and Vrahatis, M. N. (2004). On the computation of all global minimizers through particle swarm optimization. *IEEE Trans. Evol. Comput.*, 8(3):211–224.

Sundareswaran, K., Jayant, K., and Shanavas, T. N. (2007). Inverter harmonic elimination through a colony of continuously exploring ants. *IEEE Trans. Ind. Electron.*, 54(5):2558–2565.

Wachowiak, M. P., Smolikova, R., Zheng, Y., and Zurada, J. M. (2004). An approach to multimodal biomedical image registration utilizing particle swarm optimization. *IEEE Trans. Evol. Comput.*, 8(3):289–301.