Optimal Design of State Variable Filter using Partition-bound Particle Swarm Optimization

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ABSTRACT

Because of manufacturing constraints, designing analog active filters is highly challenging. Evolutionary computing is an effective method for automatically selecting the component values like resistors and capacitors. This work describes partition-bound particle swarm optimization (PB-PSO) for efficiently designing second-order active low-pass state variable filters (SVF), considering different manufacturing series. PB-PSO is responsible for efficiently picking components and minimizing total design error. The filter components are chosen to be compatible with the E12/ E24/ E96 series. Compared to earlier optimization strategies, the simulation findings show that PB-PSO reduces the overall design error.

Keywords: Analog active filter, SVF, Evolutionary technique, PSO, SPICE

1. INTRODUCTION

Filters are electronic circuits that play a crucial role in signal processing by allowing signals within a specific frequency range to pass through while attenuating those outside the designated range. This unique ability of filters to selectively permit certain frequencies is known as frequency selectivity. Filters are broadly classified into passive and active categories based on the components employed in their construction. Active filters, frequently employed in communication systems, leverage active components such as operational amplifiers to achieve their desired functionality.

Traditionally, filter design involves setting components to equal values, a practice that simplifies the design process but imposes constraints on flexibility. Components are often selected from standardized industrial series such as E12, E24, or E96 to enhance design flexibility. Existing literature explores various techniques for optimizing active analog filters. References [1-2] delve into utilizing genetic algorithms (GA) for components and topology optimization in filters. Specifically, these studies focus on second-order state variable filters (SVF) and employ design methods that incorporate both conventional approaches and evolutionary algorithms, such as GA [3], ABC [3], DE [4], HS [4], and PSO [5].

Within the realm of evolutionary techniques applied to filter design, references [6-8] explore different methodologies. This approach involves applying Particle Bound PSO (PB-PSO) to design second-order SVF using E12, E24, and E96 series. By combining the strengths of PSO and particle-based optimization, PB-PSO fine-tunes SVF parameters for optimal performance.

The structure of this article is organized as follows: Section II provides a brief overview of the PB-PSO algorithm. Subsequently, Section III illustrates the second-order state variable filter (SVF), and the article expounds on the cost function (CF) employed in the optimization process in the subsequent section. Section IV presents the simulation results, offering insights into the performance of the designed filters. Finally, Section V concludes the article, summarizing key findings and potentially suggesting avenues for future research in active analog filter optimization.

2. PARTITION BOUND PARTICLE SWARM OPTIMIZATION

This paper presents the PB-PSO algorithm. To modify particle velocities depending on iterations in an adaptive manner, two new parameters, ζ_1 and ζ_2, are utilized. The nonlinear convergence factor (α) and the iteration number determine the parameter $\zeta_1.\zeta_2$ divides iterations into two parts to facilitate local and global search.

2.1 Particle Swarm Optimization (PSO)

PSO [9-10] is a metaheuristic method that uses a swarm of particles to move through a search space. The particles are updated repeatedly, and their movements are impacted by their own prior experience as well as the experience of their swarm neighbor. In PSO, the velocity and position of particles are modified as:

$$\begin{aligned} V_i^{(k+1)} &= w \times V_i^{(k)} + C_1 \times r_1 \times \left(\text{pbest}_i^{(k)} - S_i^{(k)} \right) \\ &+ C_2 \times r_2 \times \left(\text{gbest}^{(k)} - S_i^{(k)} \right) S_i^{(k+1)} \\ &= S_i^{(k)} + V_i^{(k+1)} \end{aligned} \tag{1}$$

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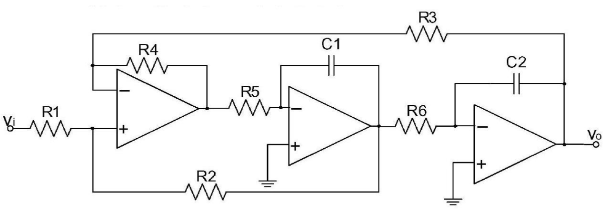

Fig. 1*: Second order state variable low pass filter.*

where $V_i^{(k)}$ denotes the i^{th} particle's velocity at iteration k, w represents the weighting function, the weighting factors are represented by C_1 and C_2, r_1 and r_2 are random numbers between 0 and 1, $S_i^{(k)}$ is the the i^{th} particle's position at iteration k, $pbest_i^{(k)}$ and $gbest^{(k)}$ are the personal best and the group best at iteration k.

2.2 Partition Bound Particle Swarm Optimization (PB-PSO) Algorithm

This paper suggests employing error-dependent coefficients to accelerate convergence. The coefficients, represented by ζ_1 and ζ_2, enhance the learning rate by accelerating particle velocity in the direction of the minimum error, as demonstrated by equation (3) [11].

$$\begin{aligned} V_i^{(k+1)} &= \zeta_1 \times w \times V_i^{(k)} + ... \\ ... &+ \zeta_2 \times C_1 \times r_1 \times \left(pbest_i^{(k)} - S_i^{(k)}\right) + ... \\ ... &+ \left(1-\zeta_2\right) \times C_2 \times r_2 \times \left(gbest^{(k)} - S_i^{(k)}\right) \end{aligned} \tag{2}$$

In this case, the variable parameters ζ_1 and ζ_2 change according to the iteration number (k). Variation in ζ_1 is represented as

$$\zeta_1(k) = \left(1 - \frac{k}{N}\right)^{2\alpha} \tag{3}$$

where α is a non-linear convergence factor, N is the maximum number of iterations.

The value of α is affected by the complexity of the circuit and the design variables. As the design variables increase, more iterations are required to obtain an optimal solution. When design complexity increases, α must decrease to provide more iterations. The trade-off between a better convergence and lower CF yields $\alpha = 4$.

ζ_2 is a random number within $(0, 1)$. The variation of ζ_2 is divided into two cases. ζ_2 is a random number within $(0, 0.5)$ upto N_1 th iteration cycle. This controls the global search in (3). When the iteration count exceeds N_1, ζ_2 is generated randomly within $(0.5, 1)$. This dominates the local search over the global search in (3). The value of N_1 is set to be N/2.

$$\begin{aligned} \zeta_2(k) &= \mathrm{rand}(0, 0.5);\ \text{where } k \le N_1 \\ &= \mathrm{rand}(0.5, 1);\ \text{where } k > N_1 \end{aligned} \tag{4}$$

The pseudo-code of PB-PSO is shown below. P is the swarm size, D is the dimension of the optimization problem, N is the maximum number of iterations.

Algorithm 1 Pseudo code of PB-PSO algorithm

```
Input: P, D, N, w, C1, C2
Output: gbest
iteration ← 1
Initialize particles with random positions and velocities
Initialize personal best positions (pbest) for each particle as their initial positions
Initialize global best position (gbest) among all particles
while iteration < N do
    for each particle in the swarm do
        Evaluate each particle's cost function (CF)
        if CF < pbest then
            Update particle's pbest to current position
        end if
        if CF < gbest then
            Update gbest to the current position
        end if
    end for
    for each particle in the swarm do
        Update particle velocity using equation (3)
        Update particle position using equation (2)
    end for
    iteration ← iteration + 1
end while
Return gbest as the optimized solution
```

3. ACTIVE LOW PASS FILTER DESIGN

3.1 SVF Design

The SVF is given in Fig. 1 [12]. The transfer function is expressed as:

$$H(s) = \frac{\dfrac{R_2(R_3+R_4)}{R_3(R_1+R_2)R_5R_6C_1C_2}}{s^2 + \dfrac{R_1(R_3+R_4)}{R_3(R_1+R_2)R_5C_1}s + \dfrac{R_4}{R_3R_5R_6C_1C_2}} \tag{5}$$

The cut-off frequency and quality factor are expressed as follows:

$$\begin{aligned} \omega_{SVF} &= \sqrt{\left(\frac{R_4}{R_3}\right)\left(\frac{1}{C_1C_2R_5R_6}\right)} \\ Q_{SVF} &= \frac{R_3(R_1+R_2)}{R_1(R_3+R_4)}\sqrt{\frac{C_1R_4R_5}{C_2R_3R_6}} \end{aligned} \tag{6}$$

The cut-off frequency (ω_0) is targeted as 10krad/s and the quality factor (Q_t) is targeted as 0.707 [3-4]. The cutoff frequency deviation $(\Delta\omega_0)$ and the quality factor deviation (ΔQ_t) are expressed as:

$$\begin{aligned} \Delta\omega_0 &= \frac{|\omega_{SVF} - \omega_0|}{\omega_0} \\ \Delta Q_t &= \frac{|Q_{SVF} - Q_t|}{Q_t} \\ \Delta\omega_0 &= \frac{\left|\sqrt{\left(\frac{R_4}{R_3}\right)\left(\frac{1}{C_1C_2R_5R_6}\right)} - \omega_0\right|}{\omega_0} \\ \Delta Q_t &= \frac{\left|\frac{R_3(R_1+R_2)}{R_1(R_3+R_4)}\sqrt{\frac{C_1R_4R_5}{C_2R_3R_6}} - Q_t\right|}{Q_t} \end{aligned} \tag{7}$$

***Table 1**: Component values.*

E series	Tolerance	Number of values in each decade	Values
E12	ś10%	12	1.0, 1.2, 1.5, 1.8, 2.2, 2.7, 3.3, 3.9, 4.7, 5.6, 6.8, 8.2
E24	ś5%	24	1.0, 1.1, 1.2, 1.3, 1.5, 1.6, 1.8, 2.0, 2.2, 2.4, 2.7, 3.0, 3.3, 3.6, 3.9, 4.3, 4.7, 5.1, 5.6, 6.2, 6.8, 7.5, 8.2, 9.1
E96	ś1%	96	1.00, 1.02, 1.05, 1.07, 1.10, 1.13, 1.15, 1.18, 1.21, 1.24, 1.27, 1.30, 1.33, 1.37,1.40, 1.43, 1.47, 1.50, 1.54, 1,58, 1.62, 1.65, 1.69, 1.74, 1.78, 1.82, 1.87,1.91, 1.96, 2.00, 2.05, 2.10, 2.16, 2.21, 2.26, 2.32, 2.37, 2.43, 2.49, 2.55,2.61, 2.67, 2.74, 2.80, 2.87, 2.94, 3.01, 3.09, 3.16, 3.24, 3.32, 3.40, 3.48,3.57, 3.65, 3.74, 3.83, 3.92, 4.02, 4.12, 4.22, 4.32, 4.42, 4.53, 4.64, 4.75, 4.87, 4.99, 5.11, 5.23, 5.36, 5.49, 5.62, 5.76, 5.90, 6.04, 6.19, 6.34, 6.49, 6.65, 6,81, 6.98, 7.15, 7.32, 7.50, 7.68, 7.87, 8.06, 8.25, 8.45, 8.66, 8.87, 9.09, 9.31, 9.53, 9.76

***Table 2**: Constraints for each series.*

Components	Constraints
E12	$0.1 \le p,q,r,s,t,u,v,w \le 0.82$ and $2 \le a,b,c,d,e,f,g,h \le 4$.
E24	$0.1 \le p,q,r,s,t,u,v,w \le 0.91$ and $2 \le a,b,c,d,e,f,g,h \le 4$
E96	$0.1 \le p,q,r,s,t,u,v,w \le 0.976$ and $2 \le a,b,c,d,e,f,g,h \le 4$

***Table 3**: Control parameters of PB-PSO.*

Parameters	PB-PSO
Population size	10
Iteration cycles	1000

***Table 4**: Component values and performance of PB-PSO for State variable filter design (E12 series).*

Components	CRPSO [6]	PB-PSO
R1(kΩ)	100	82
R2(kΩ)	4.7	20
R3(kΩ)	4.7	47
R4(kΩ)	1	17.2
R5(kΩ)	82	11.5
R6(kΩ)	5.6	10
C1(nF)	1	6.8
C2(nF)	4.7	4.7
Cut-off frequency deviation ($\Delta\omega_0$)	0.0071	0.0022
Quality factor deviation (ΔQ_t)	0.0058	0.0050
Total design error (CF_{SVF})	0.0065	0.0036
Iteration cycle required	757	361
Execution Time (second)	29.14	15.021

The total cost function is written as:

$$CF_{\mathrm{SVF}} = \left(0.5\Delta\omega_0 + 0.5\Delta Q_t\right) \tag{8}$$

The PB-PSO will minimize the CF_{SVF}.

3.2 Descript of setting of components

Each component is selected to have a resistance value between 10^3 and $10^6\Omega$ and a capacitance value between

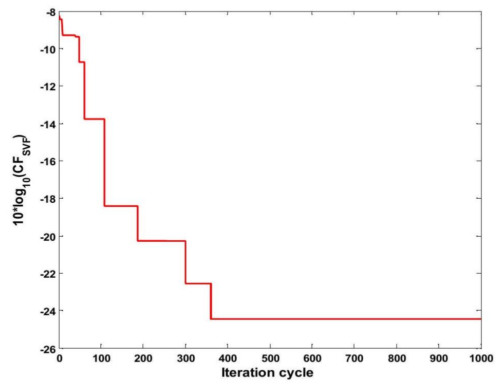

***Fig. 2**: Convergence profile for E12 series.*

10^{-9} and 10^{-6} F. Any row vector is determined as:

$[p\ a\ q\ b\ r\ c\ s\ d\ t\ e\ u\ f\ v\ g\ w\ h]$

If the values of the resistors and capacitors lie outside this range, then they must be discarded. Since the probable values vary from three-decade ranges, a coding scheme is used, as shown in Table 1.

The design constraints for each series are given in Table 2.

For E12 series, the design constraints are given as follows: $0.1 \le p,q,r,s,t,u,v,w \le 0.82$ and $2 \le a,b,c,d,e,f,g,h \le 4$.

For E24 series, the design constraints are given as follows: $0.1 \le p,q,r,s,t,u,v,w \le 0.91$ and $2 \le a,b,c,d,e,f,g,h \le 4$.

For E96 series, the design constraints are given as follows:

$0.1 \le p,q,r,s,t,u,v,w \le 0.976$ and $2 \le a,b,c,d,e,f,g,h \le 4$

***Table 5**: Component values and performance of previous methods versus PB-PSO for State variable filter design (E24 series)*

Components	GA [3]	PSO[3, 5]	ABC[3]	DE[4]	HS[4]	PB-PSO
R_1(kΩ)	43	10	62	560	43	11.8
R_2(kΩ)	5.6	1.65	1	1.6	8.2	391
R_3(kΩ)	24	30.11	91	30	33	11
R_4(kΩ)	280	212	4.3	750	7.5	47
R_5(kΩ)	4.4	1.04	27	4.7	27	1.2
R_6(kΩ)	9.2	3.9	1.8	62	13	143
C_1(nF)	180	470	2.7	390	2.7	9.1
C_2(nF)	16	37	3.6	2.2	2.4	27.36
Cut-off frequency deviation ($\Delta\omega_0$)	3.613×10^{-4}	4.082×10^{-4}	1.434×10^{-4}	NA	NA	3.5×10^{-5}
Quality factor deviation (ΔQ_t)	0.734×10^{-4}	3.239×10^{-4}	6.176×10^{-4}	NA	NA	2.1712×10^{-5}
Total design error (CF_{SVF})	2.174×10^{-4}	3.661×10^{-4}	3.801×10^{-4}	3.2×10^{-5}	1.9×10^{-4}	2.8356×10^{-5}
Iteration cycle required	1541	110	2219	34,652	232,138	661
Execution Time (second)	312	270	3.4	36.7	79.8	37.321

***Table 6**: Component values and performance of previous methods versus PB-PSO for State variable filter low pass design (E96 series)*

Components	GA [3]	PSO[3,5]	ABC[3]	DE[4]	HS[4]	PB-PSO
R_1(kΩ)	69	10.2	59	953	95.3	105
R_2(kΩ)	2.55	8.66	88.7	4.64	6.34	127.28
R_3(kΩ)	65.3	14.7	54.9	7.87	4.42	23.7
R_4(kΩ)	237	187	90.9	442	57.6	133
R_5(kΩ)	2.87	1.13	10	4.22	97.6	18.7
R_6(kΩ)	1.43	2.94	51.1	2.94	42.2	15.261
C_1(nF)	110	464	7.5	953	9.53	11.3
C_2(nF)	80.4	82.5	4.32	47.5	3.32	17.402
Cut-off frequency deviation ($\Delta\omega_0$)	3.627×10^{-5}	1.457×10^{-4}	0.295×10^{-4}	NA	NA	1.5×10^{-6}
Quality factor deviation (ΔQ_t)	1.045×10^{-4}	4.759×10^{-4}	0.047×10^{-4}	NA	NA	6.7716×10^{-6}
Total design error (CF_{SVF})	1.045×10^{-4}	3.108×10^{-4}	0.171×10^{-4}	1.9×10^{-5}	1.6×10^{-5}	4.1358×10^{-6}
Iteration cycle required	4441	1028	175	47,169	298,725	721
Execution Time (second)	444	336	2.6	50	102.7	43.089

3.3 Multi-parameter sensitivity analysis

Let $f_i(X)$ is an objective function, where $X = [x_1, \ldots .x_n]^T$. The single parameter sensitivity [13-14] is defined as

$$S_{x_j}^{f_i} \approx \frac{x_j}{f_i}\frac{\partial f_i}{\partial x_j} \tag{9}$$

The multi-parameter sensitivity is as follows [14]:

$$S^{f_j} = \sqrt{\sum_{i=1}^{n} \left|S_{x_i}^{f_j}\right|^2 \cdot \sigma_{x_i}^2} \tag{10}$$

where σ_{x_i} is a variability parameter of x_i.

The multi-parameter sensitivity for the CF_{SVF} is expressed as:

$$S^{CF_{SVF}} = \sqrt{\left(\sum_{i=1}^{6} \left|S_{R_i}^{CF_{SVF}}\right|^2 \cdot \sigma_{R_i}^2 + K\right)} \qquad K = \sum_{i=1}^{2} \left|S_{C_i}^{CF_{SVF}}\right|^2 \cdot \sigma_{C_i}^2 \tag{11}$$

where x_i is substituted by R_i or C_i.

4. SIMULATION RESULTS AND DISCUSSIONS

The components of the SVF using E12/E24/E96 series are obtained using the PB-PSO algorithm. The algorithm was implemented in MATLAB 7.5 on the core (TM) 2 duo processor, 3.00 GHz with 2 GB RAM, and the maximum number of iterations was 1000. The control parameters for the PB-PSO are shown in Table 3.

4.1 Results for the designed SVF

The components of the SVF are chosen from the E12 series. The E series, also known as the preferred number series, refers to a set of standardized values used for various components in engineering and manufacturing. These series are designed to provide a convenient selection of values that follow a logarithmic scale, making it easier to choose appropriate values for components such as resistors, capacitors, and other electronic parts.

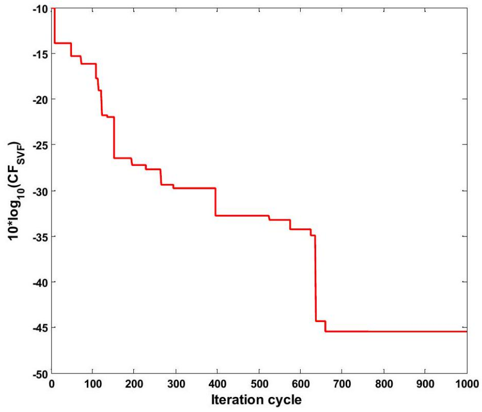

***Fig. 3**: Convergence profile for E24 series.*

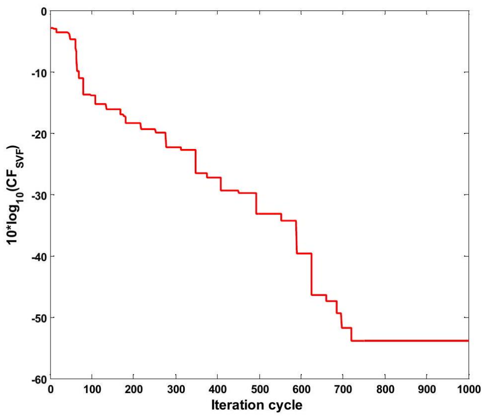

***Fig. 4**: Convergence profile for E96 series.*

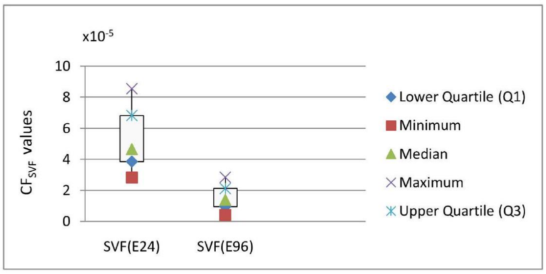

***Fig. 6**: Box and whisker plots for E24 and E96 series over 50 trials for each series.*

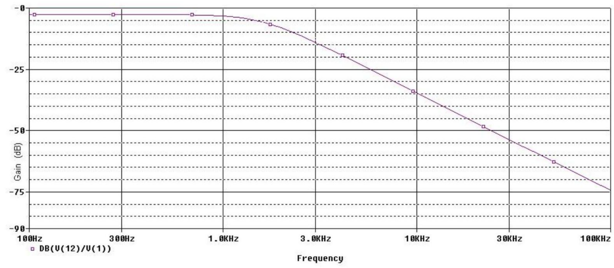

***Fig. 7**: Amplitude response for E12 series.*

The "E" stands for "exponential" or "decadic". Every subsequent resistor or capacitor in the E12 series is within -10% to +10% of the preceding value. There are further E24 and E96 series for components with tighter tolerance, with 24 and 96 distinct values within each decade, respectively. These E series are standardized by organizations such as the International Electrotechnical Commission (IEC) and the Electronic Industries Alliance (EIA). They help streamline the selection and use of components in various industries, ensuring compatibility, availability, and ease of design. The target CF_{SVF} is smaller than 0.0057. The CF_{SVF} value achieved is 0.0036 for PB-PSO-based SVF filter design. At iteration 361, PB-PSO achieved the target CF_{SVF} in 15.021 seconds. PB-PSO-based results are shown in Table 4. The E12 series contains five components.

For E24 series, the target CF_{SVF} is smaller than 3.2×10^{-5} [4]. The CF_{SVF} obtained is 2.8356×10^{-5} for PB-PSO-based SVF filter design. At iteration 661, PB-PSO achieved the target CF_{SVF} in 37.321 seconds. PB-PSO-based results are given in Table 5. Four components of SVF belong to E24 series.

For E96 series, the target CF_{SVF} is smaller than 1.6×10^{-5}[4]. The CF_{SVF} attained is 4.1358×10^{-6} for PB-PSO-based SVF filter design. At iteration 721, PB-PSO obtained the target CF_{SVF} in 43.089 seconds. PB-PSO-based results are given in Table 6. Five components of SVF belong to the E96 series.

Figs. 2-4 demonstrate the plots of $10 \log_{10} \left(CF_{SVF}\right)$ vs iteration cycle for E12, E24 and E96 series, respectively. Parameters of state variable low pass filters for different series are given in Table 7.

Figs. 5 and 6 demonstrate the box and whisker plots of PB-PSO based SVF design for each series over 50 runs. The minimal range of variance in CF_{SVF} indicates that the designs are stable and robust. The SVFs are constructed utilizing the LM741 model in the SPICE [3, 5]

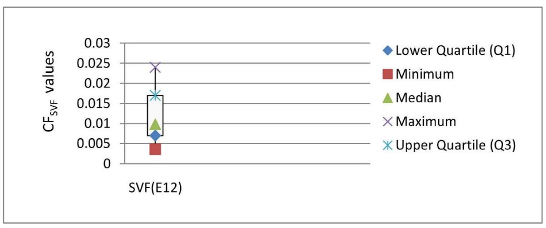

***Fig. 5**: Box and whisker plots for E12 series over 50 runs.*

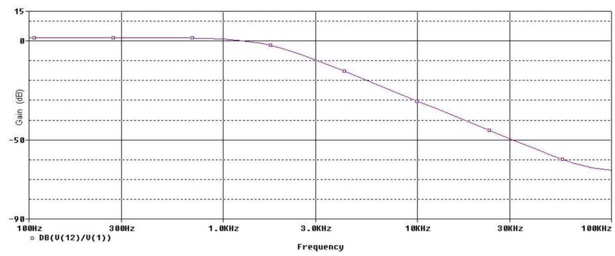

***Fig. 8**: Amplitude response for E24 series.*

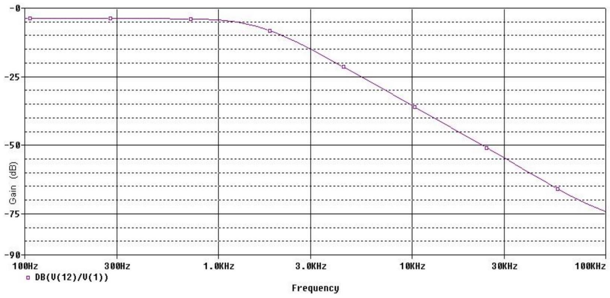

***Fig. 9**: Amplitude response for E96 series.*

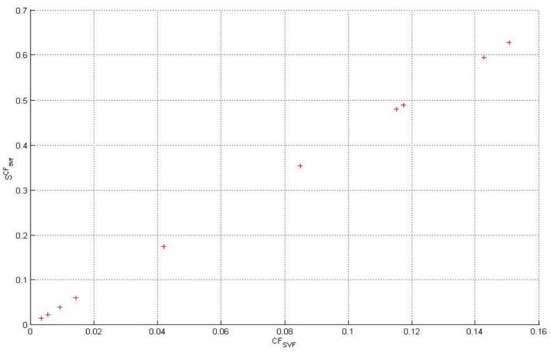

***Fig. 10**: Multi-parameter sensitivity of CF_{SVF} for E12 series.*

to verify the outcomes of PB-PSO optimization.

The amplitude responses of the SVFs are shown in Figs. 7-9, respectively. In these figures, the X-axis denotes the frequency, and the Y-axis is the amplitude response in decibels (Gain (dB)). V (1) and V (12) illustrate the input and output voltages of the SVF for SPICE simulation. The suggested optimization strategy offers a maximum flat response and a cut-off frequency of 10.038 krad/s, 10.038 krad/s, and 9.993 krad/s, respectively for E12, E24 and E96 series.

Figs. 10-12 exhibit the multi-parameter sensitivity of CF_{SVF} computed by (16), with $\sigma = 1\%$ for the SVFs having components compatible with E12, E24 and E96 series, respectively. Figs. 10-12 demonstrate that the low

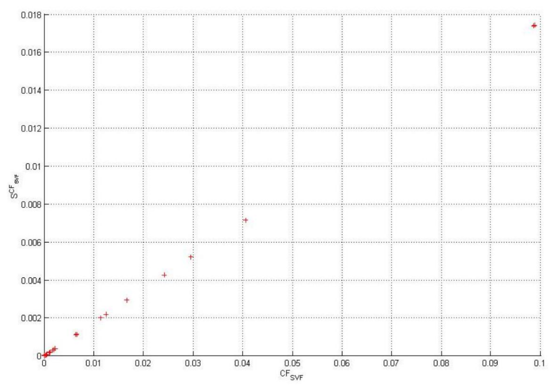

***Fig. 11**: Multi-parameter sensitivity of CF_{SVF} for E24 series.*

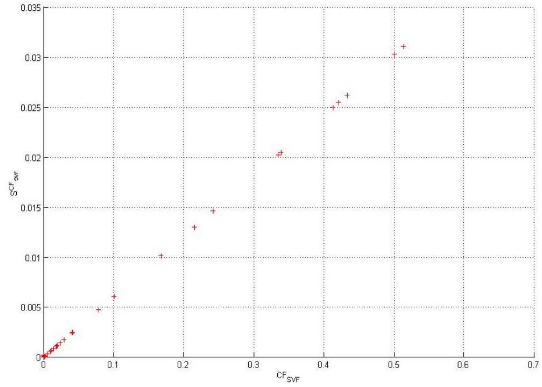

***Fig. 12**: Multi-parameter sensitivity of CF_{SVF} for E96 series.*

***Table 7**: Parameters of State variable low pass filter for different series.*

Series	E12	E24	E96
Cut-off frequency (ω_0(krad/s))	10.022	10.00035	10.000015
Quality factor (Q_t)	0.710	0.707015	0.7070047
Gain in Pass Band (dB)	-2.711	1.5683	-3.8

CF_{SVF} indicates lower multi-parameter sensitivity.

5. CONCLUSIONS

In this paper, PB-PSO is utilized for SVF design. Components are selected from different manufactured series for SVF. For SVF design with E24 and E96 series, PB-PSO attains lower CF compared to the previous techniques. SPICE results demonstrate that PB-PSO-based filters offer flat response in the pass band. Thus, PBPSO establishes itself as a useful optimization method for analog filter design.

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