Genetic Algorithm for Optimization of Design Variables in 4th Order Sallen Key High Pass Filter

Kwang Shenq Eu and Siew Chin Neoh
School of Microelectronic Engineering, Universiti Malaysia Perlis (UniMAP), Pauh Putra Campus 02600 Pauh Perlis, Malaysia
E-mail: scneoh@unimap.edu.my

Abstract—**Filter design is complicated especially when advance or higher order circuits are involved. Complex circuit parameters interaction may lead to nonlinearities that require tedious mathematical and theoretical calculations for achieving the design specifications. Thus, expertise is required to study the filter behaviour. This paper suggests a stochastic Genetic Algorithm (GA)-based model to optimize the 4th Order Sallen Key High Pass Filter. The optimization aims to achieve specified range of output gain, cut-off frequency and pass band ripple. The circuit is simulated with LTspice, while the algorithm is developed in Matlab. The results shows that GA has fulfill both input and output requirements of the filter.**

Index Terms—**Genetic Algorithm, Circuit Optimization, High Pass filter**

I. Introduction

Filter passes certain frequency band signal and attenuates other. As different applications require different filter specifications, the suitable combination of input components plays important roles to achieve the required filter performance. The determination of appropriate input components often depends on the expertise in filter characteristics and it is time consuming to fresh designers. Interactions among various input parameters always involve the non-linear and complicated trade-off [1] relationship to obtain the desired output specifications. In advance filter design, the combination of Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filter increase the complexity of circuit and results a higher threshold for the fresh designer. Thus, many resources are required to study the filter in each case.

Instead of professional filter knowledge, Evolution Algorithm (EA) proposed an impressive filter design optimization with better efficiency. It can be implemented as a black-box algorithm for optimization problems in which subjective expertise can be replaced by information on parameters specifications and constraints. EA is inspired from the biological evolution [2] where individuals adapt themselves to survive in the environment. The survivors pass their trait to the offspring and over the time, the weak trait is lost, while the strong trait is remained and become the dominant in the population [3].

In addition, EA is a global optimization technique that search through a wide range of space, emphasizing more on exploration rather than exploitation. With its parallel searching capability, the solution is accelerated to the optimum in a short time.

EA has its weakness on detail searching or exploitation of space. This is curbed with hybrid of local searching technique, such as Hill-Climbing, Simulated Annealing [4] and Tabu search. The local searching becomes important when the problem has a complicated and sensitive landscape profile. Every optimization algorithm signified a designated compromise [5]. Hence, the hybrid of global and local search algorithm is able to capture the overall picture, and search more thoroughly in the most promising region.

In this paper, the challenge is to optimize a 4th Order Sallen Key High Pass Filter for achieving the desired gain, cut-off frequency and pass band ripple. The Genetic Algorithm (GA) which is a subsidiary of EA is employed as the optimization model in this research.

II. Concept of GA

GA is a stochastic optimization method. It shares much similarity with Particle Swamp Optimization (PSO) [6]. The GA's search mechanism is dependent on the solution encoding, fitness evaluation function, population initialization, selection operator and reproduction operator.

In the beginning, the possible candidate solutions are randomly generated in a population. Each candidate solution is encoded in a string-liked chromosome. The chromosome consists of genes that represent each particular input parameter. After initialization, fitness evaluation is then carried out to all candidate solutions for fitness assignment.

The GA process continues to the selection operation after fitness assignment. The higher fitness individuals are most likely to be selected to undergo crossover and mutation operations. Crossover and mutations are genetic operators for offspring reproduction. The crossover

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operation swaps the genes between individuals to search for a space, while mutation jumps the searching out from a static configuration [7]. This reproduction process is terminated once the specified targets are met.

III. Filter

The high pass filter is used to boost the signal above the cut-off frequency and attenuate the signal below the cut-off frequency. The filter design specifications often involve gain, cut-off frequency and passband ripple.

Gain is defined as the ratio of output to input. With higher gain, the filter output signal is boosted with respect to input signal. On the other hand, the cut-off frequency is to determine the passband and stopband frequency. The sought signal is located in passband and unwanted signal is located in stopband. Signal is amplified according to the gain in passband and attenuated in stopband. Passband ripple is the indication of the filter ability to maintain a flat gain level. The fluctuation of ripple results a variation in output signal. Hence, the ripple should be keep as minimum to zero.

Sallen Key Filter is a famous active filter topology with two poles. It has the characteristic of simplicity, non-inverting amplifier (positive gain) and replication of element. This provides flexibility in cascading the Sallen Key Filter to form a higher order filter.

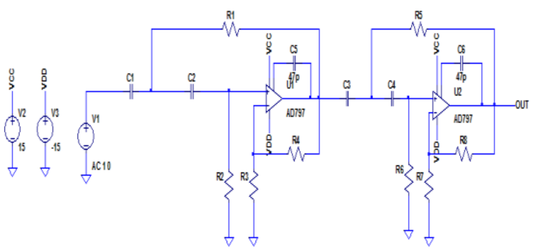

Figure 1. 4th Order sallen key high pass filter

TABLE I. Input Parameter Constraints

Component	Minimum	Maximum
R1(ohm)	10K	100K
R2(ohm)	10K	100K
R3(ohm)	1K	50K
R4(ohm)	1K	50K
R5(ohm)	10K	100K
R6(ohm)	10K	100K
R7(ohm)	1K	50K
R8(ohm)	1K	50K
C1(F)	100p	500p
C2(F)	500p	1000p
C3(F)	100p	500p
C4(F)	10n	100n

A 4th Order Sallen Key High Pass Filter is constructed from the cascade of two 2nd Order Sallen Key High Pass Filters. Fig. 1 shows a 4th Order Sallen Key High Pass Filter with the 12 input design variables. The constraint boundary for input design variables are depicted in Table I whereas the target output specifications are shown in Table II. Our aim is to improve the result to acceptable range and eventually optimize it to the optimum value.

TABLE II. 4TH Order Sallen Key High Pass Filter output Specifications

Output	Min	Max	Optimization
Gain (dB)	13	15	Maximize
Cutoff Frequency(Hz)	13000	14000	Minimize
Passband Ripple(dB)	0	0.4	Maximize

IV. Flow of GA

The GA main mechanisms are selection and recombination. The good quality individual is selected to perform recombination with crossover and mutation operation. This imply the survival of the fittest [8]. The GA operations are briefly explained as follow [9]:

1) Initialize the population with random solution.

Repeat

2) Fitness computation of each proposed solution.
3) Selection of individual for reproduction to bring new population.
4) Select individuals to undergo crossover and mutation.
5) Recombination to form offspring

Until terminate criterion

In this research, GA is employed to optimize the design variables for filter. The flow of GA-based filter optimization is illustrated in Fig. 2.

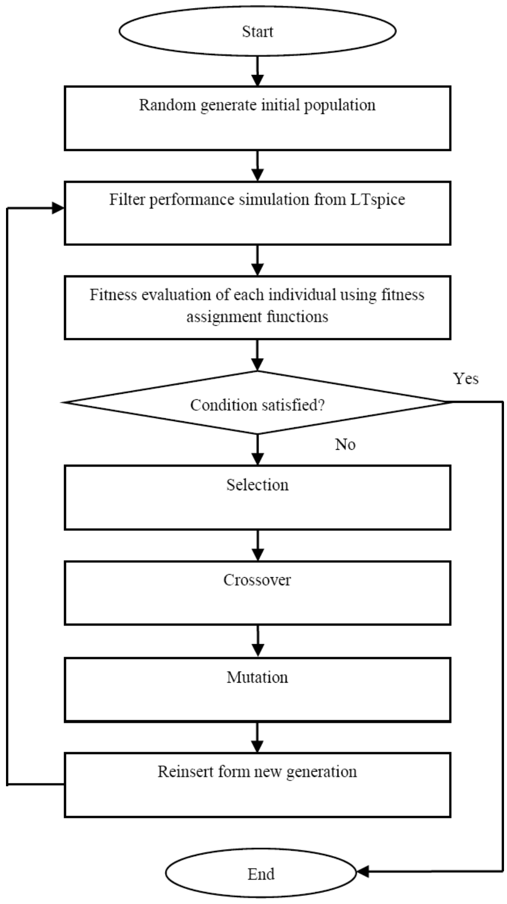

Figure 2. The flow of genetic algorithm

A. Initialization

The initial population is generated randomly to introduce wide range of diversity for candidate solutions [10] so as to avoid significant skew of population. Each gene in the individual (candidate solution) represents a design variable element. The genes are generated according to the constraint boundary and the values of gene are formulated as follow (1):

$$\text{Gene}_i = \text{Min}_i + \text{Rand}^* (\text{Max}_i - \text{Min}_i) \tag{1}$$

where,

Min_i = The i^{th} min value of the input parameter

Max_i = The i^{th} max value of the input parameter

Rand = Random number between 0 and 1

B. Fitness Evaluation

The circuit is simulated through LTspice to observe the filter performance. The proximity of filter outputs to the required performance specifications is calculated using fitness assignment function. A merit value is assigned to each individual to indicate the distance from the target [11].

Equations (2-4) show the fitness assignment function of F_1, F_2 and F_3, which indicates the fitness of gain, cut-off frequency and passband ripple. In this function, the lower the value of fitness, the fitter the solution is. From the equations, is introduced as a penalty value for low fit individual that do not satisfy the required range of specifications. Although is included to contribute to the fitness evaluation, the value should be logically introduced to prevent too much bias on overall fitness.

$$F_1= \begin{cases} \alpha + (12\text{-gain}), \text{ if gain}<12 \\ (15\text{-gain}) \quad , \text{ if } 13\leq \text{gain} \leq 15 \\ \alpha + (\text{gain-}15), \text{ if gain}>15 \end{cases} \tag{2}$$

$$F_2= \begin{cases} \alpha + (13K\text{-cutoff}) \ , \text{ if gain}<13K \\ (14K\text{-cutoff}), \text{ if } 13K\leq \text{gain} \leq 14K \\ \alpha + (\text{cutoff -}14K), \text{ if cutoff}>14K \end{cases} \tag{3}$$

$$F_3= \begin{cases} \alpha + (0\text{-ripple}), \text{ if ripple}<0 \\ (0.4\text{-ripple}), \text{ if } 0<\text{ripple}<0.4 \\ \alpha + (\text{ripple-o.4}), \text{ if ripple}>0.4 \end{cases} \tag{4}$$

$$F_{total} =\sum (F_1/F_{1average} + F_2/F_{2\ average}+ F_3/F_{3\ average}) \tag{5}$$

Comparing to single objective, multi-objective optimization problem usually face a more tricky fitness landscape and conflicting object function issue. For special non-critical conflict case, weighted-sum approach is acceptable for multi-objective optimization. It adds up all objectives into a single and parameterized objective through a linear combination of the objective. Sometime, weight is applied based on cost function [12].

In this paper, three objectives (gain, cut-off frequency and passband ripple) are involved. Fitness function results great influence on selection, crossover and mutation. Based on F_1, $F_2$and F_3, an overall fitness value is obtained using the weighted sum approach in (5). This value represents the overall performance of an individual. The better the fitness value, the higher the chance to be selected for crossover and mutation.

C. Stopping Condition

Stopping condition is the situation for the GA to end the search. After the LTspice simulation, the filter gain, cut-off frequency and passband ripple are evaluated based on Table II to check whether the targets are achieved. If the criteria are not fulfilled, GA will continue to search for the optimum solution until convergence. Termination based on convergence and achievement of specification is described as follow:

- Terminate when no enhancement in solution for a number of consecutive generations.
- Terminate when almost all candidate is similar.
- Terminate when objective function slope is nearly zero.
- Terminate when the target is achieved.

D. Selection, Crossover and Mutation

Stochastic Universal Sampling is applied in this study to perform selection for reproduction. Compare to Roulette Wheel Selection, Stochastic Universal Sampling suffer less issues of bias and enjoy better diversity. The selected individuals are more appropriately reflected according to the proportional fitness distribution.

The crossover operation swaps the portion of a string. Exchange of information allows the GA to explore in a new search space [13]-[14]. In this study, a single point crossover is adopted. Individuals are selected to perform the crossover based on a probability of 0.8 whereby the crossover point is randomly selected.

In contrast to crossover, mutation operation pioneers new searching space in a population. This genetic operator decelerates the premature convergence issue to local optimal [15]. Usually, the mutation occurs probability is much lower than the crossover. Too high mutation rate prompt the GA to lose the searching direction. In this paper, a mutation probability of 0.2 is used and the gene to be mutated is randomly selected.

V. Results and Discussion

From the result, the best found combination of design variables is shown in Table III with its specification performance depicted in Table IV. Thegain, cut-off frequency and passband ripple obtained is 15dB, 13891Hz and 0.087dB respectively. The gain and ripple reach the optimum, while the cut-off frequency is very close to the optimum with a proximity distance less than 1% only. Overall, the result fulfills the filter requirement in Table II. Fig. 3 illustrates the minimum overall objective or best found overall fitness value in each GA generation. It is observed that convergence is detected before termination.

TABLE III. GA OPTIMIZED DESIGN VARIABLES

component	Values	Unit
R1	98	kΩ
R2	68	kΩ
R3	25	kΩ
R4	23	kΩ
R5	46	kΩ
R6	84	kΩ
R7	5	kΩ
R8	8	kΩ
C1	169	pF
C2	695	pF
C3	367	pF
C4	82	nF

TABLE IV. GA OPTIMIZED OUTPUT SPECIFICATION

Gain (dB)	15
Cut-off frequency (HZ)	13891
Ripple (dB)	0.087

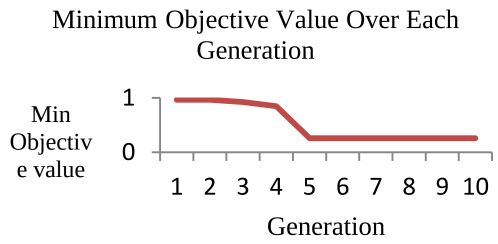

Figure 3. Minimum objective value in each generation

VI. CONCLUSION

The GA is robust and can be applied in many situations with minimum variation adjustment to algorithm. With the combination of LTspice simulation and GA, the optimized 4th Order Sallen Key High Pass Filter design has successfully achieved the target constraints and required specifications. Instead of using random trial and error method for design variable tuning, GA optimizer offers a more systematic and logical way to search for optimum solution. By representing circuit parameters as genes in chromosomes, the evolution of GA is able to optimize the circuit towards the desired performance. Future study will be carried out based on the hybrid model of GA and other heuristic search algorithms.

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Kwang Shenq Eu, was born in Taiping, Malaysia on August 4, 1988. He is currently pursuing hisB.Engdegree (Electronic Engineering) in the Schoolof Microelectronic Engineering at Universiti Malaysia Perlis (UniMAP). In 2006, he had participated in the Natural Disaster Youth Summit 2006, organized by International Education and Resource Network (iEARN) Taiwan to discuss the natural disaster. Besides, he was elected as member of student representative council (MPP 2010/2011) in UniMAP. Along the serving, he has been the program committee of many UniMAP activities. In 2012, he has completed his internship in Plexus Manufacturing Sdn. Bhd. where he was assigned to support the production line.His research interests include genetic algorithm, multi-objective optimization and simulated annealing.

S. C. Neoh received her B. Tech. degree in quality control and instrumentation from the School of Industrial Technology, UniversitiSains Malaysia (USM) in 2003 and Ph.D. degree in the School of Electrical and Electronic Engineering, USM, NibongTebal in 2009. Her research interests include evolutionary computing, circuit design optimization, production planning, intelligent manufacturing systems, operations management, and decision support systems.