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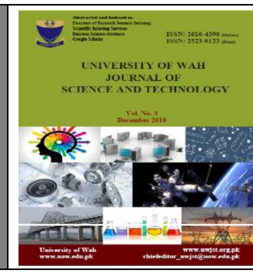

Optimization of Design Parameters of Low Pass Filter Using Genetic Algorithm

Abdul Shakoor, Shafqat Abbas and Zahid Abbas

***Abstract*—Analog filters are currently used for many purposes in most electronic circuits. For example, noise removal, digital signal conversion to analog, enhancing signals, etc. Filters play a significant role in the modern world, since the world is fundamentally analogous in nature. These filters can be designed with different approximations, since most of them are deterministic and sensitive to information about gradients. Numerical optimization techniques cannot offer ideal solutions. Meta heuristic algorithms can provide an opportunity to address these challenges. A Genetic Algorithm (GA) based optimization approach is presented in this paper for the optimization of the design parameters of 3rd order analog filters.**

***Index Terms*—Low pass filter, Genetic Algorithm, Sallen key filter**

I. Introduction

CONVENTIONAL design methods for the determination of active analog filter component values require that some of the component values be selected randomly. But it is not practicable as there are fewer mathematical expressions than the number of values of the component. Some of the passive parameters can be randomly chosen from easily accessible component values. But it is possible to determine other passive variables using well known mathematical expression. In addition, the calculated values may not match the steady values manufactured in the market that deteriorate the active filter's effectiveness. These results enhance demand for optimization algorithms to assess component values that are consistent with the components manufactured value.

Realization of the operational amplifier creates low output impedance, high input impedance, arbitrary and virtually gain excluding inductors that decreases the issues associated with the inductor. Discrete parts like resistors and condensers are available in the market as E12, E24, E48, E96 and E192 series. They are produced by a defined quantity of continuous values in approximate logarithmic multiples. To match market values carefully, the choice of component values must be optimized without infringing design requirements including filter gain, cut-off frequency and quality factor. The best way to optimize component values is through intelligent search techniques. A considerable numbers of mythologies are available for designing the 4th order Butterworth filter and Butterworth filter. Choice of component values needs to be optimized to carefully match market values without infringing design requirements including filter gain, quality factor and cut-off frequency.

Intelligent search techniques are the best way to optimize the component values. While implementing optimization algorithms and making the compatibility of the E-series, present literature [1-4] did not focus on the gain-restricted notion. Cascading other gain-regulated operating amplifier circuits offset the gain on such variable state filters. However, the gain value in the state variable filter depends on the quality factor, cutoff frequency and component values. If the optimization method is only implemented due to the cutoff frequency and quality factor, it will affect the gain value. Other operational amplifier cascade for gain compensation raises the noise element induced by the integrated semiconductors and resistors thereby affecting stability. Efforts were made to limit the state variable filter gain while implementing the optimization algorithms and maintaining them in line with the E-series [1-4]. The method of finite elements and Particle Swarm Optimization (PSO) were used to optimally model the filter [5]. The digital recurrent 2D filter has been designed using the Genetic Algorithm (GA) [6]. In literature, digital filter design was optimized by using PSO and Artificial Bee Colony (ABC) algorithms [7]. Passive filter element values are selected using tree representation methods based on GA and Genetic Programming (GP) [8] respectively.

The parallel tabu search algorithm (TSA) was studied in order to design active filter component values compatible with the E12 series in [9]. In addition to the optimum filter circuit design, an improved ABC algorithm has been added [10]. An extensive comparative research with different

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evolution methodologies on analog passive filter design is given in [11]. An automated framework was studied for passive analog circuit synthesis using GA [12]. An analog filter design [13] with unconstrained and limited low-pass LCR filter design has been discussed.

The purpose of the Butterworth 4th order filter design is to use Grey Wolf Optimizer (GWO) and PSO to minimize and generate the E12 series compliant Gain Sensitivity Product (GSP) [14]. One of the biggest benefits of using EAs is that they can be comfortably linked to current models of simulation and integrated models of assessment. This can be accomplished in a straightforward way, requiring only two methods of integrating the optimization algorithm with the (current) simulation model. This makes it easier to compare alternatives produced by informal optimization with Expert Advisor (EA) optimization alternatives that can assist the users to trust the outcomes of optimization [15]. Algorithm values were acquired as part of informal optimization procedures using personal domain expertise, understanding and intuition with the assistance of developmental operators in the EA-based system, and these improvements in decision variable values are automatically acquired from one iteration to the next. Another advantage of EAs is that they usually operate with discrete and continuous variables of choice as opposed to most traditional techniques of optimization requiring ongoing mathematical methods to optimize variables of decision [16]. It benefits a large number of applications in the real world where there are either numerical decision variables or where practical considerations restrict continuous variables.

Generally, EAs are suitable for parallel computing environment implementation. In order to accelerate the search, individual alternatives in the population can be assessed on various processors in parallel at each generation. This can lead in important time savings compared to most traditional techniques of optimization. As EAs operate with populations, they generate a quantity of near-perfect alternatives that can be comparable in objective function space, but in decision variable space quite distinct. This allows the final optimal solution to be selected to consider factors other than those captured in the optimization issue's mathematical formulation. Decision-makers therefore have higher control over the use of their judgment and intuition to select the final solution from the optimization algorithm based on a number of suggested exceptional solutions [17]. While EAs have several benefits over numerical algorithms of optimization as they also pose a number of extra difficulties, particularly associated to computational effectiveness and search behavior adjustment.

There are some computational effectiveness challenges with EAs because they work with alternative populations and generally create better alternatives over dozens or hundreds of iterations. The number of opportunities to calculate objective function and limit values is the result of population size and number of iterations. Applying EAs to complex problems in the real world can be of particular interest model in the order of minutes or even hours of runtime and search regions can be extremely large and require larger spaces. Considering uncertainties such as performance measures such as hazard, resilience, reliability, or robustness, computational difficulties are exacerbated [18].

Meta-heuristic optimization algorithms are becoming more common in many fields due to a straightforward population-based notion, including engineering to minimize cost functions. Furthermore, these are easy to enforce, with the least likelihood of falling into perfect local information and thus not requiring gradient information. It can be categorized as methods based on evolution, physics and swarm. Most common optimization algorithms are Big Bang Big Crunch, GSA, System Search Charged, etc. The swarm based methods are the social behaviors inspired by nature of living beings. Some of examples of these methods are PSO, Monkey Search, ACO, Cuckoo Search, etc. [19].

II. THEORETICAL BACKGROUND

A. *Genetic Algorithm*

Genetic algorithm is an intelligent optimization method based on natural evolution theory, a powerful global search capability in which the organism produces many offspring through random changes and crossover, but the offspring of each heritage property may be different from GA. The basic system is specifically designed to imitate the development process in the natural system for those who first follow Charles Darwin's principle of best practice. The survival probability is based on the wellbeing of the individual in which healthier individual is highly probable to survive [20]. The GA is used only when insensitive, extremely nonlinear, static or unmodified derivatives are the objective function. GA can provide alternatives to highly complicated search locations and perform well on all types of issues. The basic operators of GA are reproduction, crossover and mutation. GA's solution to an optimization problem begins with a population of population vector compromise of random strings. In general, the population size in GAs is fixed. To find its fitness value, each string is evaluated. To produce a new population, the population is operated by the reproduction, crossover and mutation of three operators. In order to find the fitness values, the new population is further evaluated and examined for process convergence.

A cycle of evaluation of reproduction, crossover, mutation and fitness is known in GAs as generations. If the convergence criterion is not met, iteratively the three operators will operate the population and evaluate the fitness values of new generations. The method continues through various generations until the convergence criterion is met and the process is completed. The following steps of the GA can solve a optimization problem as discussed in [21] and also shown in *Fig. 1*.

- Initialization: Generally speaking, GAs begin with an original population that is randomly generated using distinctive techniques to produce greater original population quality. Consequently, an approach is intended to give the GA a healthy beginning and accelerate the process of evolution.

- Selection: Depending on their fitness, it selects the two parent chromosome from a population, better the fitness then greater the chance to be selected.
- Reproduction: It chooses the two chromosomes and crossover on them and gets one or two off springs, maybe apply mutation as well and insert the outcome back into that population, according to the present selection method.
- Crossover: With a crossover probability, the parent will generate new offspring.
- Mutation: This operator will be performed after a crossover. Mutation is a genetic operator used for maintaining genetic diversity from one generation of a chromosome population to the next.
- Replacement: For a further run of algorithms, use new created population to further operate algorithms.

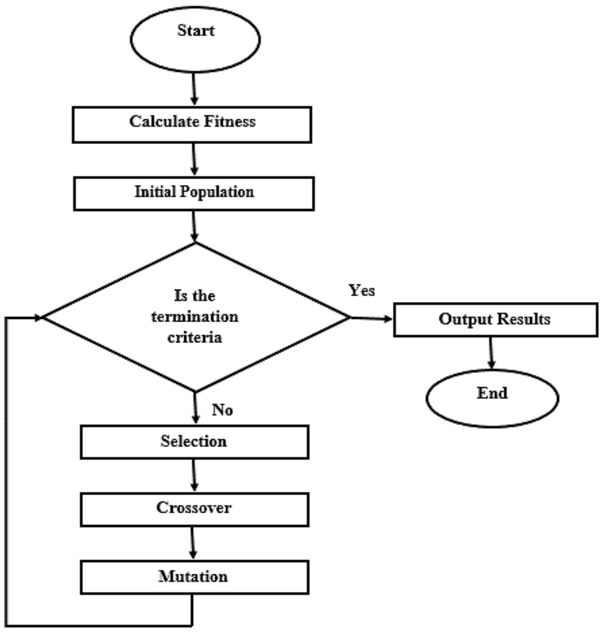

Fig. 1. Flow chart of Genetic Algorithm (GA).

B. Active Low Pass Filter

In the circuit, active filter uses operational amplifier or transistor that takes power from the external power supply and boosts or amplifies the output signal. Amplification is the major distinction between the passive and active filter. In contrast to a passive high-pass filter with constant high-frequency response in practice, an efficient filter's maximum frequency reaction is limited to the gain - bandwidth product (or open loop gain) of the operational amplifier. In specific, active filters are much easier to design than passive filters, creating exceptional performance characteristics, very excellent accuracy when used with a good circuit layout with steep roll-off and low noise. While this setup offers excellent stability for the filter, its primary drawback is that there is no above-one voltage gain.

1) Active Low Pass Filter With Unity Gain

It is discovered that in the passive low pass filter, output signal amplitude never exceeds the input signal gain. Active filter utilizes the circuit working amplifier or transistor that requires external power supply energy and boosts or amplifies the output signal as shown in *Fig. 2*. Amplification is the major distinction between the active passive filter and the active filter. In reality, contrary to a passive high-pass filter with an infinite high-frequency response, the peak frequency response of an effective filter is restricted to the operational amplifier's gain - bandwidth product (or open loop gain). Specifically, when used with a good circuit layout with steep roll-off and low noise, active filters are much simpler to design than passive filters, producing great quality characteristics, very nice accuracy, while this setup gives excellent stability to the filter, its primary drawback is that there is no increase in voltage above one.

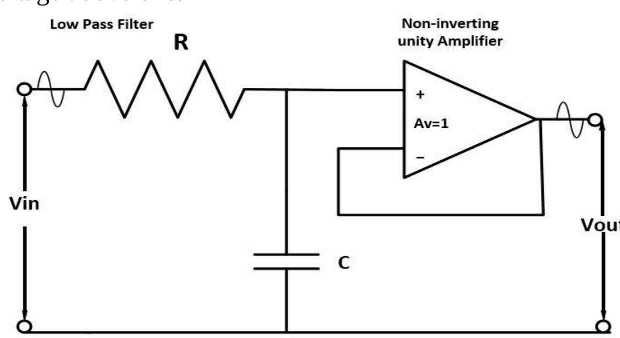

Fig. 2. Active low pass filter circuit diagram.

2) Active Low Pass Filter With Amplification

The circuit's frequency response will be the same as the passive RC filter as shown in *Fig. 3*, except that by raising the amplifier's pass band [22], the output amplitude will be improved.

C. Sallen-Key Low Pass Filter

The passive component and operating amplifier's particular structure is known as the sallen-key filter, also known as the voltage control current source (VCCS). Sallen Key Filter design is often an active second order filter topology that can be used as the basic building blocks to perform high-order filter circuits such as low-pass (LPF), high-pass (HPF) and band-pass (BPF) filter circuits. It is the configuration that is most frequently used. One reason for this popularity is that from the filter output it demonstrates the least reliance on the op amp output. Unlike the integrator, the op-amp is regarded as the amplifier, which minimizes the need for bandwidth product to be achieved by the op amps. This enables us to create a higher frequency filter for designated op amps with other topologies that do not limit the effectiveness of the filter as it would be configured as an integrator by the op amps gain bandwidth product.

Another benefit of Sallen-Key low pass filter is that the low value (component spread) is the proportion of the biggest resistor to the lowest resistor proportion and the ratio of the biggest condenser to the smallest. The Q term and frequency are somewhat autonomous, but both are extremely susceptible to the gain parameter. Using Sallen-Key Filter designs has the benefit of being simple to execute and understand. Sallen-Key Topology is an active filter design based on a single operating amplifier and two resistors, creating a voltage-controlled voltage source (VCVS) design with filter characteristics, high input impedance, low output impedance and good stability, allowing the cascading of individual Sallen-Key filter sections to produce much higher order.

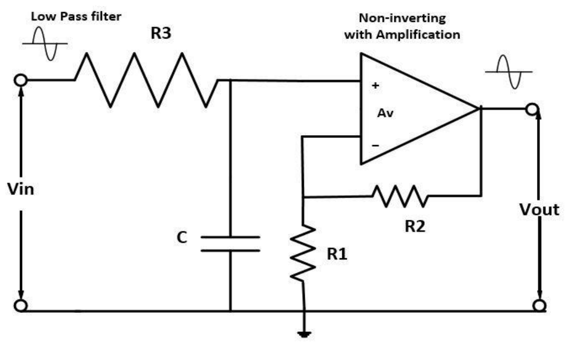

Fig. 3. Active low Pass filter with amplification.

III. Results and Analysis

A. Modelling of 3rd Order Sallen-Key Filter

In this research paper genetic optimization algorithm is used to optimize the Sallen key 3rd order low pass active filter. Which is considered an optimization problem as shown in *Fig. 4*. It is developed by cascading the low-pass filter of the first order with the low-pass filter of the second order.

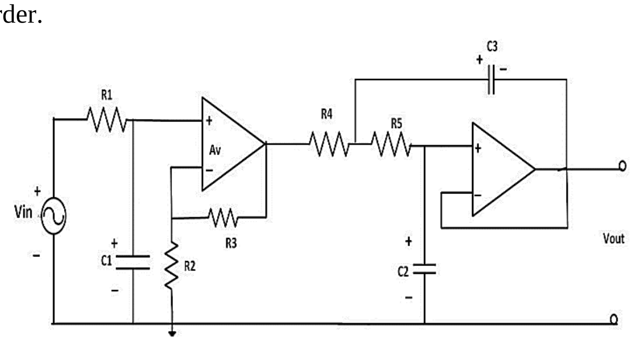

Fig. 4. Sallen key 3rd order low pass active filter.

The transfer function of the first order low pass filter is given by the equation (1),

$$\frac{V_2}{V_{in}} = \left(\frac{1}{sR_1C_1+1}\right)\left(1+\frac{R_3}{R_2}\right) \tag{1}$$

Similarly the transfer function of the 2nd order Sallen key filter is given by the equation (2),

$$\frac{V_{out}}{V_{in}} = \frac{\left(\frac{1}{R_2C_2R_5C_5}\right)}{s^2+s\left(\frac{1}{R_3C_2}+\frac{1}{R_4C_2}\right)+\frac{1}{R_4C_2R_5C_3}} \tag{2}$$

So the overall transfer function is multiplication of the two functions as given by the equation (3),

$$\frac{V_{out}}{V_{in}} = \frac{V_{out}}{V_2} \times \frac{V_2}{V_{in}} \tag{3}$$

B. Optimization of the Parameters of 3rd Order Sallen Key Filter

The above discussed cascaded Sallen key low pass filter is optimized using GA. Optimization algorithm selects the parameters of the filter in such a way that objective function is optimized. As problem is multi objective optimization, so there are two objective functions. One is related with gain and other is linked with cut off frequency, f_c.

In order to maximize both gain and cut off frequency, GA algorithm selects the input parameters in such a way that final objective function is optimized. The developed optimization algorithm chooses the seven input parameters Resistors: R_1, R_2, R_3, R_4, R_5 and capacitors: C_1, C_2. All these parameters are selected by optimization algorithm, whereas Gain and cut-off frequency is calculated from transfer function of the filter.

Objective of the research work is to optimize the overall fitness of the filter. There are three fitness functions: gain, cut-off frequency and overall fitness function. The fitness function of the gain is calculated as given by equation (4)

$$F_1 = \begin{Bmatrix} 5+(\text{gain}-12); \text{gain} > 12 \\ 5+(8-\text{gain}); \text{gain} < 8 \\ (12-\text{gain}); 8 < \text{gain} < 12 \end{Bmatrix} \tag{4}$$

Similarly fitness function of the cutoff frequency is given by equation (5).

$$F_2 = \begin{Bmatrix} 40+(f_C-1800); f_C > 1800 \\ 40+(1500-f_C); f_C < 1500 \\ (1800-f_C); 1500 < f_C < 1800 \end{Bmatrix} \tag{5}$$

The overall fitness function is weighted sum of the F_1 and F_2 given by the equation (6).

$$F = \frac{F_1}{F_{1avg}} + \frac{F_2}{F_{2avg}} \tag{6}$$

Where,

F_{1avg} is the average value of F_1 which is nearly round about 4 and similarly F_{2avg} is the average value of F_2, which is nearly round about 50.

The GA is used to optimize the cascaded low pass active filter, whereas GA toolbox of MATLAB™ is used for optimization. Main code for optimization using GA toolbox is given below:

$$fun = @GA\_analysis;$$

$$N_{var} = 7;$$

$$L_b = \begin{bmatrix} 10e^3 & 800 & 1e^3 & 1e^3 & 1e^3 & 5e^{-9} & 100e^{-9} \end{bmatrix}$$

$$U_b = \begin{bmatrix} 50e^3 & 2e^3 & 2e^3 & 10e^3 & 3e^3 & 50e^9 & 500e^{-9} \end{bmatrix}$$

$$A = [\ ]$$

$$B = [\ ]$$

$$A_{eq} = [\ ]$$

$$B_{eq} = [\ ]$$

$$X = ga(fun, 7, A, B, A_{eq}, B_{eq}, L_b, U_b)$$

where: "fun" is points toward the objective function.

The objective function is calculated in the "GA_analysis" function. "N_{var}" indicates the dimension of the input variables. Optimization problem stated in the research work is 7D problem, because there are 7 selection parameters: 5 resistors and 2 capacitors. L_b and U_b indicate the lower and upper bounds of the input parameters respectively listed in Table I. As there is no equality and non-equality constraints, hence constrained parameters are declared as null.

TABLE I
UPPER AND LOWER BOUND OF DESIGNED PARAMETERS

Parameters	Min. value	Max. value
R_1	10 KΩ	50 KΩ
R_2	800 Ω	2 KΩ
R_3	1 KΩ	2 KΩ
R_3	1 KΩ	10 KΩ
R_5	1 KΩ	3 KΩ
C_1	5 nF	50 nF
C_2	50 nF	500 nF

C. *Pseudo Code of Moga for 3rd Order Low Pass Filter Design*

- Initialization of different parameters of MOGA and Low Pass Filter.
- Generation of initial population randomly in search space.
- Run MATLAB simulation to evaluate the fitness of initial population.
- Design Point Update: The design points of 3rd order low pass filter are being updated in the new population.
- Fitness evaluation for each chromosome and Convergence validation
  Yes: Final selection/Best solution
  No: Optimization not converged, the process continues to the next (Crossover and Mutation).
- Stop Criteria Validation: If the optimization has not converged, it will be validated to satisfy the stop criteria.
  Yes: Stop Criteria Met The process is stopped without convergence when the maximum number of iterations criteria is met.
  No: Stop Criteria Not met unless the stop criteria have been met, the MOGA will again be used to generate a new population (return).

From step 2 to 5 are repeated sequentially until optimization converges or the criteria for stopping are met as shown in *Fig. 5*.

D. *Results*

The problem is optimized by using the given bounds and transfer function of the "Low pass filter". Simulation shows that Gain and cut-off frequency are optimized to 12 dB and 1800 Hz respectively. The value of input parameters, which optimized the solution, are given in the Table II. The bode plot of the transfer function is plotted with above given optimized parameters as shown in Fig. 6. The bode plot shows the 3-dB cut-off frequency of 1.8K and gain of 12 dB.

TABLE II
OPTIMAL PARAMETERS

Parameters	Optimal value
R_1	13.32 KΩ
R_2	1.84 KΩ
R_3	1.51 KΩ
R_3	8.75 KΩ
R_5	2.7 KΩ
C_1	16.8 nF
C_2	495 nF

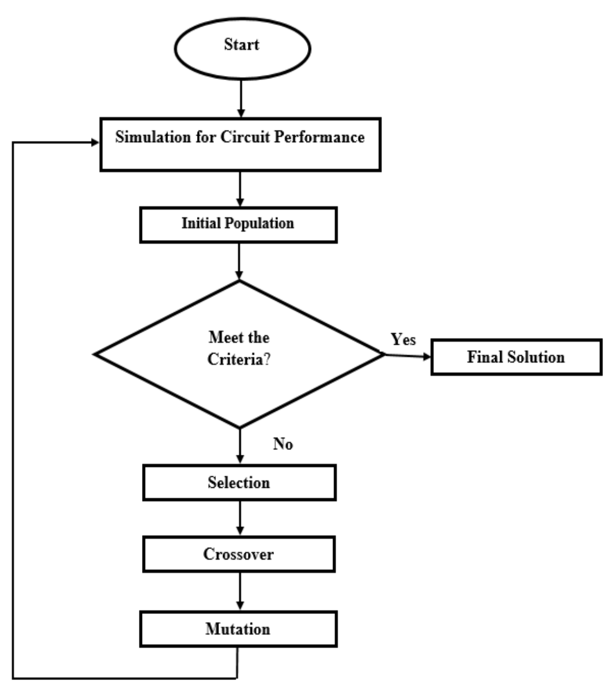

Fig. 5. Illustration of MOGA for 3rd order low pass filter design.

IV. Conclusion

Sallen-key type 3rd order low pass active filter is optimized using GA. Transfer function is used to find the gain and cut-off frequency, which are optimized using GA toolbox in MATLAB™ by designing the seven (7) selection parameters: five (5) resistors and two (2) capacitors. Gain and cut-off frequency are optimized to 12dB and 1800 Hz respectively. Results shows that presented optimization procedure can be used to design any type of active filters and can optimize multi-objective function by implementing different constraints.

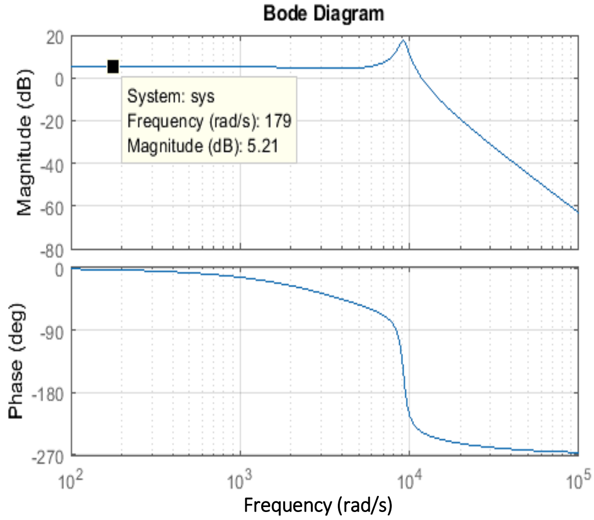

Fig. 6. Bode of the low pass filter.

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