CHAPTER 5 EXPERIMENTAL RESULTS

5.1 BIQUAD Filter Experiment

The most common BIQUAD circuit consists of three factors which are an operational amplifier circuit (OTA), the input current of each OTA and C connected to ground; the example circuit is shown in Figure 5.1. The design of the example is common and basic configuration. Especially, the BIQUAD-filter has enough equation to solve the problem:

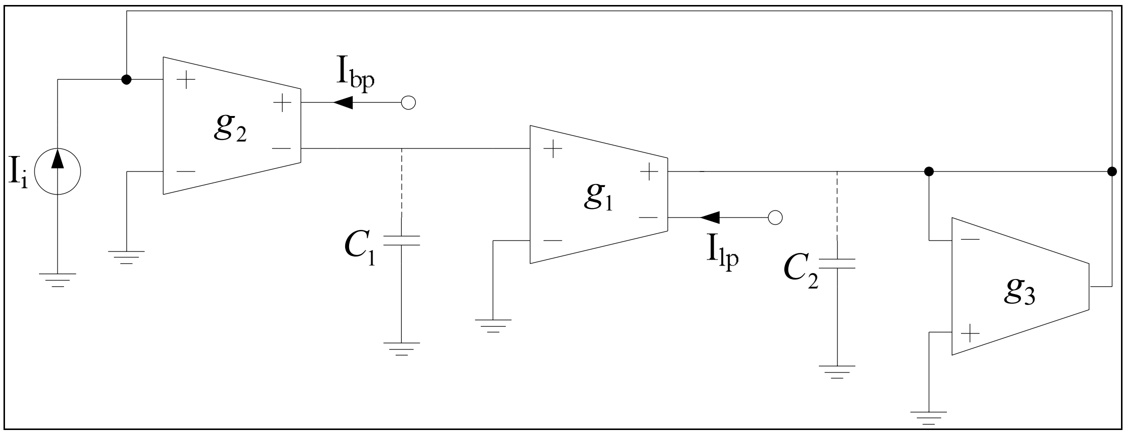

Figure 5.1 The experiment of BIQUAD circuit.

A current-mode BIQUAD [13], composed of an ideal and a lossy current integrators, is considered as a subject of experiment, which is modified by removing both capacitors as shown in Figure 5.1. The composed OTAs are a simple single-stage CMOS OTA [11]. The missing capacitors are replaced with parasitic capacitances of an OTA. Therefore, C_1 and C_2 virtually exist but cannot be controlled. Therefore, the controllable circuit's parameters are limited to the bias current of each OTA.

C_1 and C_2 are generated only at high frequency which includes the number of parasitic capacitances. Those parasitic capacitances can be adjusted by the bias current, and it is difficult to approximate the accurate values. Therefore, tuning of the bias current to generate the precise cut-off frequency or center frequency is required. The parasitic capacitances can be calculated as shown in Figure 5.2 below:

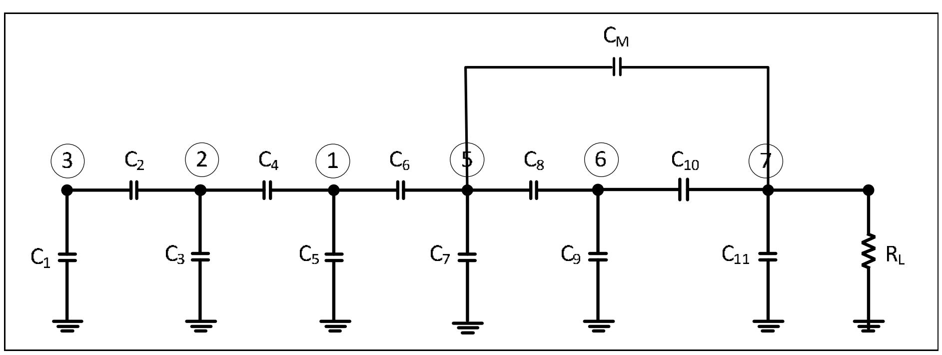

Figure 5.2 OTA simplifications with C-Miller

According to Figure 5.2, there is one C generated between nodes number 5 and 7 which is considered to be the Miller's theorem. Miller's capacitance can divided into input and output stages as shown in Figure 5.3.

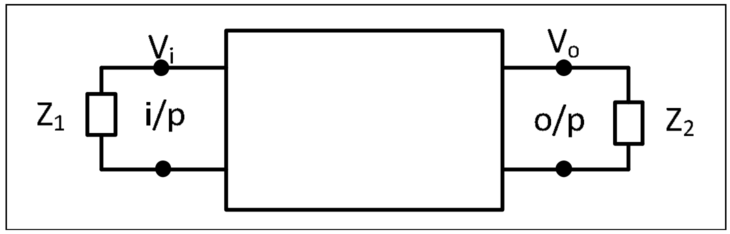

Figure 5.3 Miller's theorem divided capacitors

From Figure 5.3, Z_1 and Z_2 can be calculated as the capacitances (C_1 and C_2) which are presented in the equations 5.4 and 5.8 respectively.

$$Z_1 = \frac{Z'}{1-K} \tag{5.1}$$

$$\frac{1}{sC_1} = \frac{\frac{1}{sC'}}{1-K} \tag{5.2}$$

$$\frac{1}{sC_1} = \frac{1}{sC'(1-K)} \tag{5.3}$$

$$C_1 = C'(1-K) \tag{5.4}$$

$$Z_2 = \frac{Z'K}{K-1} \tag{5.5}$$

$$\frac{1}{sC_2} = \frac{\frac{1}{sC'}K}{K-1} \tag{5.6}$$

$$\frac{1}{sC_2} = \frac{1}{sC'\left(\frac{K-1}{K}\right)} \tag{5.7}$$

$$C_2 = C'\left(\frac{K-1}{K}\right) \tag{5.8}$$

The constant value of K can be calculated by $K = R_L g_m$, where $g_m \approx 100\mu S$ and $R_L \approx 1k\Omega$ Therefore, the constant value of K is $K \approx 0.1$.

According to the BIQUAD filter in the experiment, each OTA can be simplified as shown in Figure 5.4.

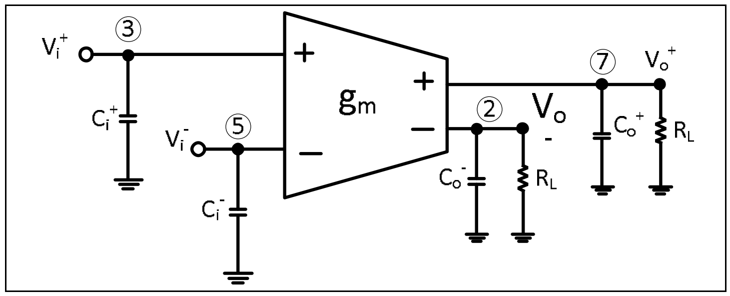

Figure 5.4 OTA-C selections from circuit experiment

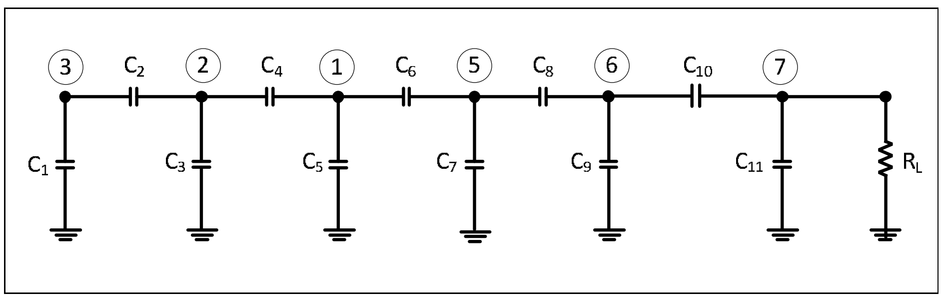

Figure 5.5 OTA simplifications without C-Miller

Figure 5.5 presents the final OTA simplification; we are able to approximate the typical value of C_1 and C_2 of the experimental BIQUAD by following the equation. To simplify C_i^+, the result can be expressed by equation 5.11.

$$C_x = \frac{\left(\frac{C_{11}C_{10}}{C_{11}+C_{10}} + C_9\right)C_8}{\left(\frac{C_{11}C_{10}}{C_{11}+C_{10}} + C_9 + C_8\right)} + C_7 \tag{5.9}$$

$$C_y = \frac{\left(\frac{C_x C_6}{C_x + C_6} + C_5\right)C_4}{\left(\frac{C_x C_6}{C_x + C_6} + C_5 + C_4\right)} + C_3 \tag{5.10}$$

$$C_i^+ = \left(\frac{C_y C_2}{C_y + C_2}\right) + C_1 \tag{5.11}$$

According to the related above equations, C_o^- can be expressed as equation 5.14.

$$C_{yy} = \frac{C_1 C_2}{C_1 + C_2} \tag{5.12}$$

$$C_{xx} = \frac{\left(\frac{C_x C_6}{C_x + C_6} + C_5\right) C_4}{\left(\frac{C_x C_6}{C_x + C_6} + C_5 + C_4\right)} + C_3 \tag{5.13}$$

$$C_o^- = \frac{C_{xx} C_3}{C_{xx} + C_3} + C_{yy} \tag{5.14}$$

Therefore, C_i^- can be expressed in the form of equation 5.18.

$$C_A = \frac{\left(\frac{C_{11} C_{10}}{C_{11} + C_{10}} + C_9\right) C_8}{\left(\frac{C_{11} C_{10}}{C_{11} + C_{10}} + C_9 + C_8\right)} \tag{5.15}$$

$$C_B = \frac{\left(\frac{C_1 C_2}{C_1 + C_2} + C_3\right) C_4}{\left(\frac{C_1 C_2}{C_1 + C_2} + C_3 + C_4\right)} + C_5 \tag{5.16}$$

$$C_C = \frac{C_B C_6}{C_B + C_6} \tag{5.17}$$

$$C_i^- = \left(\frac{C_A C_7}{C_A + C_7}\right) + C_C \tag{5.18}$$

Therefore, C_o^+ can be expressed in the form of equation 5.20.

$$C_{zz} = \frac{\left(\frac{C_B C_6}{C_B + C_6} + C_7\right) C_8}{\left(\frac{C_B C_6}{C_B + C_6} + C_7 + C_8\right)} + C_9 \tag{5.19}$$

$$C_o^{\ +} = \left(\frac{C_{zz} C_{10}}{C_{zz} + C_{10}} \right) + C_{11} \tag{5.20}$$

Finally, we can approximate C1 and C2 by equations 5.21 and 5.22 respectively.

$$C_1 = C_{o1}^{\ -} + C_{i2}^{\ +} \tag{5.21}$$

$$C_1 = C_{o2}^{\ +} + C_{i3}^{\ -} \tag{5.22}$$

If the capacitances are given by 1 pF, the typical value of C_1 will approximately be 2.49 and C_2 will be 2.6.

This biquadratic equation can also be expressed in terms of the parameters K, ω_p, Q_z and Q_p as follows:

$$\varpi_p = \sqrt{\frac{g_1 g_2}{C_1 C_2}} \tag{5.23}$$

$$Q_p = \frac{1}{g_3} \sqrt{\frac{g_1 g_2 C_2}{C_1}} \tag{5.24}$$

5.2 Setting Experiment Parameters

There are three different functions of composed transistors: active-loaded, differential-pair, and current source. Based on the AMS's 0.35µ CMOS process, dimensions of the composed transistors are presented in Table 5.1.

Table 5.1 Transistor dimensions.

Function	Width (µm)	Length (µm)
Active-loaded	7	0.35
Differential-pair	12	0.35
Current source	25	0.35

The range of the bias current is stimulatingly estimated to 11 µA – 1.1 mA, which is approximately over 2 decades. However, this wide range only guarantees the saturated operation of all transistors. Therefore, to estimate the range of the bias current reasonably, the transconductance at DC (g_{m0}), opened loop bandwidth (f_b) of transconductance, and output resistance (R_o) is examined and summarized in Table 5.2.

Table 5.2 Performances of the OTA at specified bias current.

I_0 (µA)	g_{m0} (µS)	f_b (MHz)	R_o (kΩ)
11	120	212.5	988
55	381	502	278
110	557	694	163
550	1040	1350	41.7
1100	1180	1770	10.6

The ratio of g_{m0}/I_0 indicates the efficiency of an OTA; a high ratio means the efficient utilization of the bias current and dissipated power. In addition, very low output resistance seriously deteriorates the performance of applications. As shown in Table 5.2, the bias current should not be over a few hundred µA to maintain the significant R_o and efficiency. Therefore, the maximum bias current of 300 µA is specified.

5.3 Sample Tuning

The sample bandpass specification in Table 5.3 is compiled by the Chevyshev approximation, which results in the desired BIQUAD parameters (K, ω_p and Q_p) that are fed to the implemented tuning scheme. At the 5th iteration or in 37 seconds, the tuning process successfully estimates I_1 = 99.57 µA, I_2 = 63.95 µA, and I_3 = 211.11 µA. The test BIQUAD is then simulated based on these bias currents, which gives the bandpass response shown in Figure 5.6. The key specifications are measured and presented in the last column of Table 5.3 alongside the desired specification. Comparing the BIQUAD's parameters, a very low percentage error is obtained, which leads to a well satisfaction of filter's requirements.

Table 5.3 Specification of bandpass response.

Requirement	**Desired Spec.**	**Obtained Spec.**
Filter type	Bandpass	Bandpass
Passband ripple	≤ 3 dB	≤ 3 dB
Stopband attenuation	≥ 20 dB	≥ 20 dB
Passband	300MHz – 550 MHz	300 MHz – 551 MHz
Stopband	≤ 50 MHz, ≥ 3 GHz	≤ 77 MHz, ≥ 1.68 GHz
BIQUAD parameters	**Desired Spec.**	**Obtained Spec.**
K	1	0.997
ω_p	2.55×109 rad/s	2.56×109 rad/s
f_p	406.2 MHz	407.4 MHz
Q_p	1.621	1.62

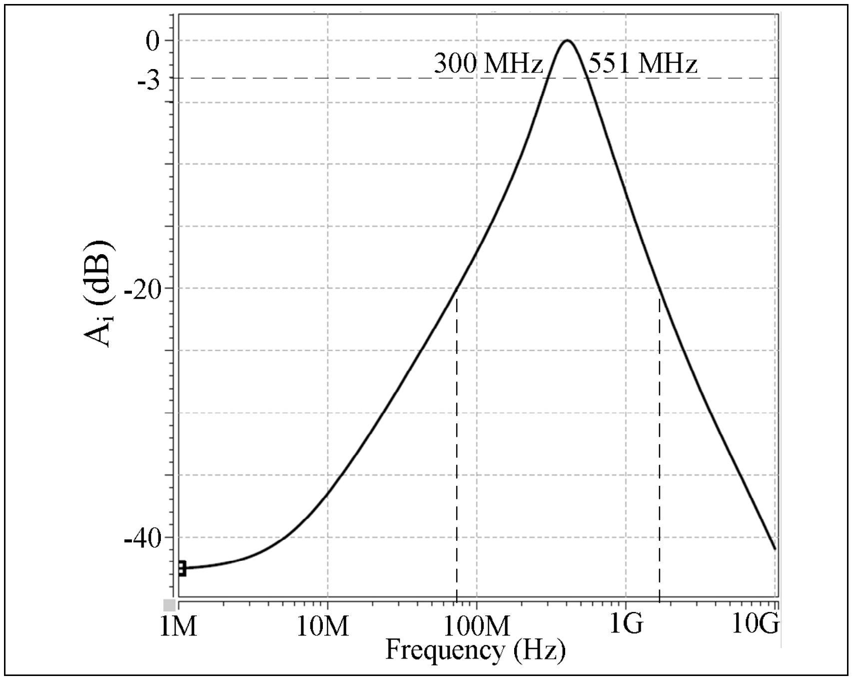

Figure 5.6 The response of bandpass obtained from sequentially tuned ANN.

5.4 Massive Tuning

5.4.1 Effect of the Sizes of Training Set

The sample band-pass specification shown in Table 5.3 is tuned via the varied sizes of the training set, ten times per each size. Average errors are recorded in Table 5.4 which is fed to the analysis of variance (ANOVA) to indicate the significance of the varied sizes.

Table 5.4 The response of varying the training set

No.	The average error of training set		
	10	20	30
1	0.529242	0.213770	0.515820
2	0.225351	0.276198	0.586067
3	0.282924	0.386446	0.315664
4	0.413365	0.429341	0.392547
5	0.511378	0.532021	0.484542
6	0.621450	0.499951	0.369264

Table 5.4 The response of varying the training set (Cont.)

No.	**The average error of training set**		
	10	**20**	**30**
7	0.420530	0.227604	0.415627
8	0.302668	0.603579	0.469140
9	0.436234	0.419670	0.264486
10	0.279890	0.313035	0.445083
Average error	**0.4023032**	**0.3901615**	**0.425824**

The result of ANOVA is shown in Table 5.5. There is no indication of significant difference between the varied sizes of the training set as the p-value is very large and larger than the test α of 0.05. Therefore, the size of the training set is not significant as long as it is greater than 10 records.

Table 5.5 One-way ANOVA: Average error versus size

Source	**DF**	**SS**	**MS**	**F**	**P**
Size	2	0.0066	0.0033	0.23	0.796
Error	27	0.3868	0.0143		
Total	29	0.3934			

5.4.2 Feasibility Analysis

As there are some BIQUAD specifications that may not be possible to be generated, the feasibility of the BIQUAD's requirement can be simply indicated by observing the initial training set. A BIQUAD specification is feasible if and only if the maximum percentage deviation in BIQUAD parameters observed from all records is less than or equal to the threshold.

The performance of the proposed tuning scheme is expressed in terms of type-I and type-II errors. The type-I error occurs when the infeasible requirement can be successfully tuned. If the process fails to tune a feasible requirement, then the type-II error happens.

In this case, the threshold to indicate the feasibility is 10% and the successfully tuned responses must not be deviated over 1%. According to the based OTA and its reasonable bias range, 100 random BIQUAD requirements are generated in the following ranges; $0.8 \leq K \leq 2$, 300 MHz $\leq f_p \leq$ 500 MHz, and $0.8 \leq Q_P \leq 2$. Figures 5.7 – 5.9 show tuning results of the varied training set of 100 trails which are sorted by a maximum initial error of the initial training set. Each trial is numbered and its corresponding maximum initial and tuned errors are presented.

According to the first case, there are 66 random requirements which suffer a maximum initial error of less than 10%, which are all successfully tuned as their maximum tuned error of less than 1%. The rest 34 random requirements are initiated with a maximum error greater than 10%, which consequently causes all associated tuning processes to fail as their maximum tuned errors are all greater than 1%. Therefore, no wrong indication occurs, and this makes the probability of type-I (α) and type-II (β) errors zero.

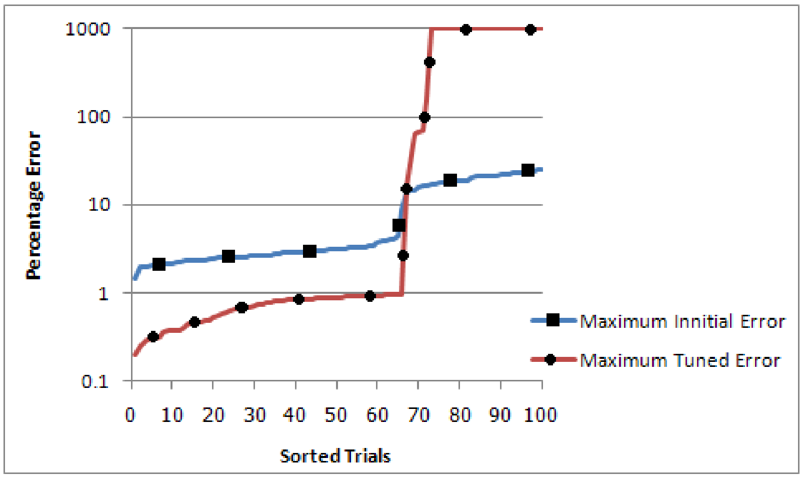

Figure 5.7 The responded tuning of training set is 10

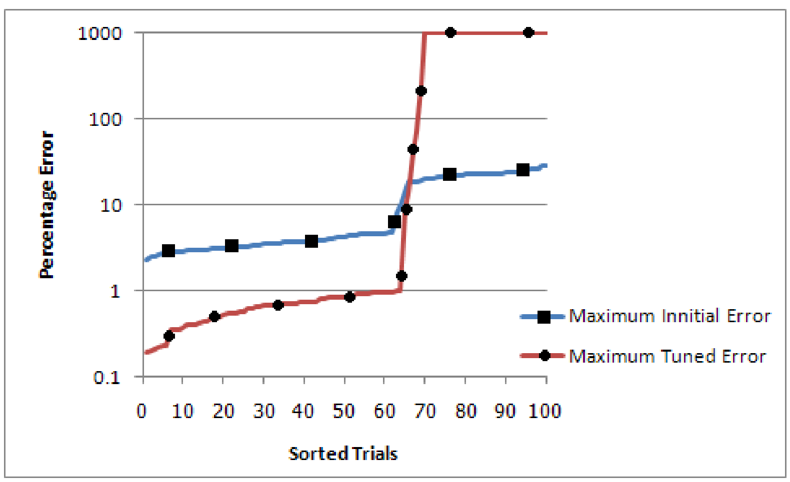

Figure 5.8 The responded tuning of training set is 20

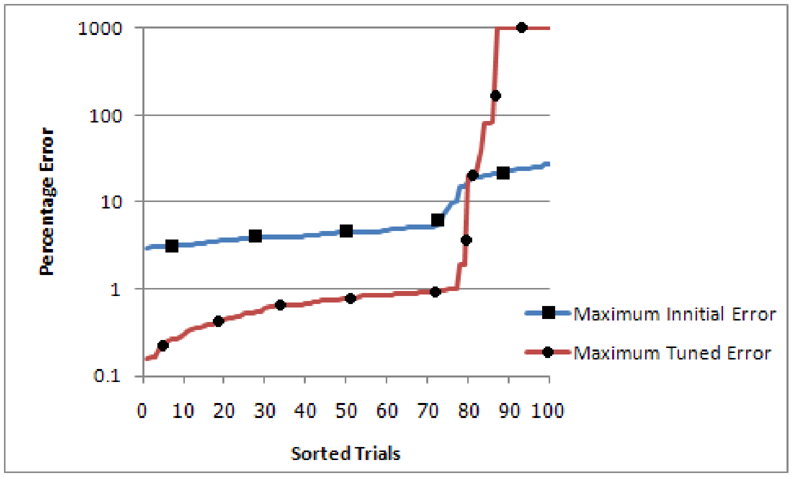

Figure 5.9 The responded tuning of training set is 30

The second case also indicates no α and β in the same way as the first case but the number of feasible and infeasible requirements is different.

Table 5.6 Summation of performance on threshold = 10%

Size of training set	Feasible Requirements		Infeasible Requirements	
	Error ≤ 1%	Error > 1%	Error ≤ 1%	Error > 1%
10	66	0	0	34
20	64	0	0	36
30	76	0	1	23

In the last case which the size of the training set is 30, there is no wrong indication of feasible requirements but there is only one false indication of infeasible requirements. Therefore, the α is only 0.013 with no β. Table 5.6 summarizes performances of feasibility analysis when a threshold is equal to 10%. Interestingly, varying the training set does virtually not affect the α and β. Thus, the threshold of 10% is proved most suitable to indicate the feasibility.

5.5 Comparison Experiments

To satisfy the experiments, some similar cases are used to compare results which are the generally trained ANN [6] and Particle Swarm Optimization (PSO) [10].

5.5.1 Sequentially Trained ANN versus the Generally Trained ANN [6]

According to the previous literature [6], the ANN is generally trained which requires little tuning time because the circuit's parameters are simply extracted as an output of the trained ANN but it is quite impossible in training with validation and test. Therefore, the trained ANN hardly provides solutions that precisely match the BIQUAD specifications. The ANN is sequentially trained with an updated small training set and is used to improve this problem, and the training set is close to the specified BIQUAD parameters. The performance of both trained ANNs is compared in Table 5.7 which is tested at the same twenty BIQUAD specifications.

Table 5.7 The percentage deviations of the Sequentially Trained ANN versus the Generally Trained ANN with the same random BIQUAD specifications

No.	Desired BIQUAD			Generally Trained Error	Sequentially Trained Error
	K	ω_p	Q_p		
1	0.8	2.3	1.4	17.98976	0.661758
2	0.8	2.4	1.5	32.63592	0.122447
3	0.8	2.7	1.6	23.13746	0.319451
4	0.8	2.4	1.8	7.576389	0.311027
5	0.9	2.3	1.6	69.64149	0.422467
6	1.1	2.3	1.5	3.974655	0.544301
7	1.1	2.5	1.6	28.5206	0.51097
8	0.9	2.5	1.8	42.92956	0.54595
9	1.2	2.7	1.4	9.501137	0.500463
10	0.9	2.4	1.5	8.31236	0.366637
11	1.1	2.4	1.7	14.24014	0.33402
12	1.2	2.4	1.7	22.24305	0.158827
13	1.2	2.4	1.4	3.469744	0.512314
14	1	2.3	1.7	72.71483	0.405249
15	0.9	2.4	1.6	36.71957	0.153991
16	1.2	2.4	1.4	3.59438	0.629239
17	1.1	2.5	1.4	6.024301	0.556684
18	0.8	2.4	1.7	48.48321	0.272138
19	0.9	2.7	1.7	15.23539	0.513762
20	1.2	2.7	1.5	5.546565	0.345121
			Aver Err	**23.62453**	**0.409341**

Table 5.8 summarizes the performances of the generally trained model and sequentially trained model with the same random desired specifications. The results are very clear that the tuning parameters are quite the same but the percentage deviation of the sequentially trained model is close to goal than the generally trained model. It means that the sequentially trained model can provide more precise solutions than the generally trained model with the same specifications.

Table 5.8 The compared performances between the generally trained model and the sequentially trained model of ANN

BIQUAD Parameters	**Desired Specification**	**Generally Trained ANN**	**Sequentially Trained ANN**
Gain (K)	1	0.9963	0.997
Pole Frequency(ω_p)	2.55×10^9 rad/s	2.56×10^9 rad/s	2.56×10^9 rad/s
Frequency (f_p)	406.2 MHz	407.4 MHz	407.4 MHz
Quality Factor (Q_p)	1.621	1.6205	1.62
% deviation	0	23.62453	0.409341

5.5.2 Sequentially Trained ANN versus the PSO based on a very small swarm

Previously, there is the method which tunes a capacitorless all-OTA bandpass BIQUAD and its tuning by ANN, Particle Swarm Optimization (PSO). It finds the optimal part of swarm to optimize the BIQUAD specifications. Along the experiments which are compared with the same BIQUAD specifications, the results are shown in Table 5.9.

Table 5.9 The compared performances between the Sequentially Trained ANN and PSO

BIQUAD Parameters	**Desired specification**	**Sequentially Trained ANN**	**PSO**
Gain (K)	1	0.997	0.996
Pole Frequency (ω_p)	2.55×10^9 rad/s	2.56×10^9 rad/s	2.56×10^9 rad/s
Frequency (f_p)	406.2 MHz	407.4 MHz	407.38 MHz
Quality Factor (Q_p)	1.621	1.62	1.6187