APPENDIX

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Feasibility Analysis and ANN-Based Tuning of a Capacitorless Bandpass Biquad

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Abstract — A capacitorless all-OTA bandpass biquad is tuned by utilizing an artificial neural network (ANN) with updated training sets. The training set contains a few tens samples which is varying in experiment. The training set is selected from predefine bias points that are closing to the desired biquad requirement. A second-order bandpass requirement, centered at 406.2 MHz, is successfully tuned as a sample. Feasibility can be easily indicated by observing maximum error of the worst record in the initial training set. Experiments indicate the unnecessary of training set that contains over 10 records. In addition, feasibility is effectively estimated by threshold of 10% maximum error of the worst record in the training set as this value almost yields no type-I and type-II errors no matter how large the training set is.

I. Introduction

Though the processing of signal in digital domain is certainly powerful, most signals of practical interest are analog [1]. Therefore, to gain the advantages of digital signal processing, an analog-to-digital converter (ADC) is first required. However, the ADC only operates on bandlimited signals which are usually in form of passband especially in digital communications. Therefore, a continuous-time (CT) bandpass filter is often utilized as an anti-aliasing filter (AAF).

Regularly, CT active filters are implemented based on biquad circuit or simply biquad, which are the second-order circuits providing operations of CT filters such as lowpass, bandpass, highpass, etc. However, most biquad structures require passive resistors and capacitors which are not favorable to be embedded in an integrated circuit (IC) as they are poorly tolerance and large area are needed.

Recently, there are literatures [2 – 3] introducing the possibility of utilizing a capacitorless bandpass biquad which is actually an OTA-C biquad without dominant capacitors. The transfer functions are usually managed by parasitic capacitance, which virtually renders the manual tuning impossible. Therefore, biquad tuning is conducted via the genetic algorithm (GA) [2] and the artificial neural network (ANN) [3]. The tuning via the GA is quite inefficient of response evaluation which is the slowest task are usually required. Therefore, quite long tuning time per a biquad's specification is observed [2]. Contrastingly, the ANN tuning scheme requires very little tuning time because the circuit's parameters are simply extracted as an output of the trained ANN. However, to train the ANN for fitting all predefined bias points is quite impossible especially in training with validation and test. Therefore, training without validation is utilized, which requires extremely long and impractical training time. In addition, this training method degrades the generalization of the ANN [4]. Therefore, the trained ANN hardly provides solutions that precisely match the biquad specifications [3].

This paper shows the ANN is sequentially trained with updated small training set consists of a few tens bias points which are closed to the specified biquad parameters. The update of this set is occurred if and only if the trained ANN provides solution that is not satisfied but better than the worst bias point in the present training set. Through several updating and training, the ANN is supposed to provide an acceptable solution. By limiting size of training set, the complexity of an ANN is significantly reduced and the training time is greatly decreased. Though there may be several response generations and evaluations, its amount is far less than the minimum required by the GA. Based on experiments, the proposed process is far better than the GA-based tuning [1] and the characterizing ANN [2] that are previously introduced.

Refer to the experiment; the size of training set is first varied to perceive its effects on tuning performance. The analysis of variance (ANOVA) is utilized to indicate whether the difference is significant or not. If it is not, there is no point in using large training set as the process can be accomplished by less effort. In addition, feasibility analysis is examined based on 100 random biquad requirements with three sizes of training set.

II. Tuning Process

A. Definition of biquad experiment

A current-mode biquad [2-3], composed of an ideal and a lossy current integrators, is considered as a subject of experiment, which is modified by removing all capacitors. The composed OTAs are a simple single-stage CMOS OTA [5]. The missing all capacitors are replaced with parasitic capacitances of an OTA. Therefore, the capacitors are virtually existed but cannot be controlled. Therefore, the controllable circuit's parameters are limited to the bias current of each OTA.

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B. Concept of applied Artificial Neural Network

The general form of a bandpass biquad is composed of three main parameters, which are the gain (K), pole frequency (ω_p), and Q-factor (Q_p) [6]. According to the experiment biquad, there are three bias current (I_1, I_2, and I_3) to be adjusted. The associate ANN, applied to utilize the studied biquad, is operating in opposite to the actual circuit as the biquad's parameters are taken as input, which is employed to estimate the corresponding bias currents. Therefore, the operation of the trained ANN is functionalized:

$$\begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = \mathbf{F}_{ANN}\left(\begin{bmatrix} K \\ \omega_p \\ Q_p \end{bmatrix}\right) \quad (1)$$

where F_{ANN} is a virtual function representing the transferring of biquad's requirements to actual circuit's parameters based on the trained ANN. The training process treats a requirement vector as an input and recognizes the vector of the corresponding circuit's parameters as an output.

C. Data Collection

To create a set of predefined bias points, the range of bias current is quantized based on a desired quantizing resolution (Δ_D), which is resulted in the minimum quantizing level (L_Q).

$$L_Q = \left\lceil \frac{I_{\max} - I_{\min}}{\Delta_D} \right\rceil + 1 \quad (2)$$

Based on full combination of all bias currents, the total amount of predefined records (T_R) are simply:

$$T_R = L_Q^n \quad (3)$$

where n is the number of circuit's parameters. Finally, the actual quantizing resolution is:

$$\Delta_A = \frac{I_{\max} - I_{\min}}{L_Q - 1} \quad (4)$$

According to eq. (2) and (4), the actual resolution is always lower than or equal to the desire resolution.

D. Initialize the Training Set

Fig. 1 presents the organized distribution of bias points which usually generate the chaotic biquad points displayed in fig. 2. To select an appropriate initial training set, the gathering cube is centered at the specific point representing the biquad specification as displayed in fig. 2. To initialize the training set, the volume of the gathering cube can be increased or decreased until the amont of biquad points inside the cube is equal to the size of training set.

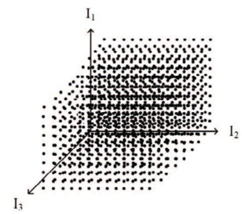

Fig. 1. Predefined bias point

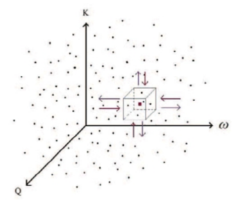

Fig. 2. Predefined biquad point with gathering cube

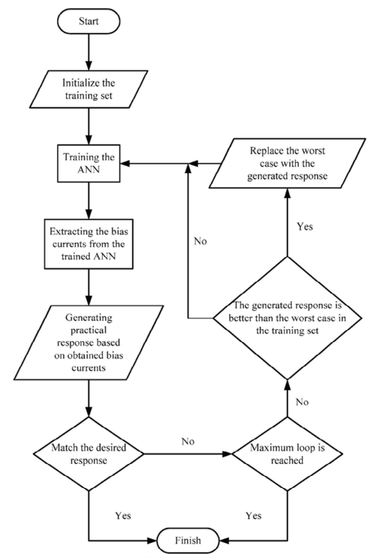

Fig. 3. Sequential Training

E. Sequential Training and Utilization

As the training set is small and contains only samples that are closed to the desired biquad, there is no division of data. Therefore, the training of the deployed ANN is conducted without validation and test. If there is significant training error, it will be relieved through the sequential training process presented by the flowchart in fig. 3.

Firstly, the ANN is trained with the initial training set. Once the ANN is completely trained, it is utilized to estimate the bias currents which are exploited to generate the practical response based on the HSPICE simulation. If the deviation in biquad's parameters of generated response is considered insignificant, the process is finished. If not, the training set is updated if the recently generated response is better than the worst member in the present training set. Then, the ANN is trained again. These tasks can be looped forever if there is no second terminating criterion which is the reaching of maximum loop that strongly indicates the failure of tuning.

III. Tuning a Sample of Biquad

A. *Implementation of Tuning Scheme*

We use a single-stage CMOS OTA [2-3] which support the AMS's 0.35μ CMOS process. The range of bias current is stimulatingly estimated to 11 μA – 1.1 mA and the ratio of g_{m0}/I_0 indicates the efficiency of an OTA; high ratio means the efficient utilization of bias current and dissipated power. 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.

The key characteristics of the proposed process are the less complex ANN which is sequentially trained with very small training set. Therefore, the predefined bias point must be collected with quite small resolution of bias current to cover most of the operational region. Key parameters concerning the implementation of tuning scheme are listed in table 2.

TABLE II
KEY PARAMETER OF SAMPLED TUNING SCHEME

Parameter	Value
Resolution	10μA
Minimum bias current	10μA
Maximum bias current	300μA
Size of predefined bias point	24,389 records
Final iteration of sequential training	20^{th}
ANN type	Cascade-forward (CF)
Number of hidden layer	1
Size of each layer except the output	10
Size of output layer	3
Training goal	0.1
Size of training set	20

B. *Tuning Example*

The sample bandpass specification in table 3 is compiled by the Chevyshev approximation, which is resulted in the desired biquad parameters (K, ω_p and Q_P) that are fed to the implemented tuning scheme. At the 5^{th} 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 4. The key specifications are measured and presented in the last column of table 4 alongside the desired specification. Comparing biquad's parameters, very low percentage error is obtained, which leads to a well satisfaction of filter's requirements.

TABLE III
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	2.55×10^9 rad/s	2.56×10^9 rad/s
f_p	406.2 MHz	407.4 MHz
Q_p	1.621	1.62

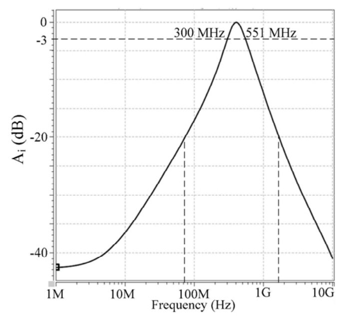

Fig. 4 Bandpass response obtained from sequential tuned ANN

IV. Performance Analysis

A. *Size of Training Set and Its effects*

The sample bandpass specification is tuned via the varied size of training set, ten times per each size. Average errors are recorded in table 4 which is fed to the analysis of variance (ANOVA) to indicate the significance of varied sizes.

The result of ANOVA is shown in table 5. There is no indication of significant difference between varied sizes of training set as the p-value is very large and larger than the test α of 0.05. Therefore, the size of training set is not significant as long as it is greater than 10 records.

TABLE IV
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
7	0.420530	0.227604	0.415627

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No.	The average error of training set		
	10	20	30
8	0.302668	0.603579	0.469140
9	0.436234	0.419670	0.264486
10	0.279890	0.313035	0.445083

TABLE V
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			

B. *Feasibility analysis*

As there are some biquad specifications that may not possible to 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 error. The type-I error is occurred when the infeasible requirement can be successfully tuned. If the process fails to tune a feasible requirement, then the type-II error is happened.

In this case, the threshold to indicate the feasibility is 10% and the successfully tuned responses must not deviate over 1%. According to the based OTA and its reasonable bias range, 100 random biquad requirements are generated in the following range; $0.8 \leq K \leq 2$, $300\text{ MHz} \leq f_p \leq 500\text{ MHz}$, and $0.8 \leq Q_P \leq 2$. Figure 5 shows tuning results of vary training set at 100 trails which are sorted by maximum initial error of initial training set. Each trial is numbered and its corresponded maximum initial and tuned errors are presented.

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

The second case which 20 size of training set also indicates no α and β as same as the first case but the number of feasible and infeasible requirements is difference

In proportion to the last case which the size of 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 6 summarizes performances of feasibility analysis by threshold equal to 10%. Interestingly, varying the training set is virtually not affecting the α and β. Thus, the threshold of 10% is proved most suitable to indicate the feasibility.

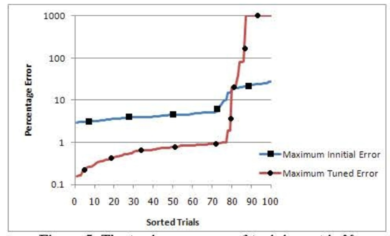

Figure 5. The tuning response of training set is 30

TABLE VI
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

V. CONCLUSIONS

A capacitorless all-OTA bandpass biquad is tuned via the sequential trained ANN. A training set of a few tens samples is selected from predefine bias points that are closing to the biquad specification. With this selection scheme, the deployed ANN can be less complex, which consequently requires little tuning time. The feasibility of biquad requirements is indicated by examining the maximum error of the training set. A second-order bandpass requirement is picked as a sample which is successfully tuned within a minute. Experiments on varied size of training set indicate the insignificance of training set larger than 10 records. In addition, threshold of 10% is recommended as there is virtually no difference in α and β while varied the size of training set.

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Tuning of a Capacitorless Bandpass Biquad through Sequentially Trained ANN

Montira Moonngam * , Roungsan Chaisricharoen, and Boonruk Chipipop

Abstract — *The sequential trained artificial neural network (ANN) based on updated training sets is successfully deployed to tune a capacitorless all-OTA bandpass biquad. The training set contains less than a few tens samples which are selected from predefine bias points that are closed to the desired biquad requirement. To limit training time, the less complex ANN is recommended. Feasibility of a biquad requirement is easily indicated by observing the maximum error of the worst element in an initial training set. A second-order bandpass requirement, centered at 406.2 MHz, is successfully tuned as a sample. The proposed feasibility analysis and tuning process are tested with one hundred random bandpass requirements. As there is no indication of type-I and type-II errors, the proposed process is considered very efficient*[1].

Index Terms — capacitorless, ANN, bandpass biquad

I. INTRODUCTION

Though the processing of signal in digital domain is certainly powerful, most signals of practical interest are analog [1]. Therefore, to gain the advantages of digital signal processing as an analog-to-digital converter (ADC) is first required. However, the ADC only operates on bandlimited signals which are usually in form of passband especially in digital communications. Therefore, a continuous-time (CT) bandpass filter is often utilized as an anti-aliasing filter (AAF).

Regularly, CT active filters are implemented based on biquad circuit or simply biquad, which are the second-order circuits providing operations of CT filters such as lowpass, bandpass, highpass, etc. However, most biquad structures require passive resistors and capacitors which are not favorable to be embedded in an integrated circuit (IC) as they are poorly tolerance and large area are needed.

Recently, there are literatures [2 – 3] introducing the possibility of utilizing a capacitorless bandpass biquad which is actually an OTA-C biquad without dominant capacitors. The transfer functions are usually managed by parasitic capacitance, which virtually renders the manual tuning impossible. Therefore, biquad tuning is conducted via the genetic algorithm (GA) [2] and the artificial neural network (ANN) [3]. The tuning via the GA is quite inefficient as several thousands of response generation and evaluation which very slowly task are usually required. Therefore, quite long tuning time per a biquad's specification is observed [2]. Contrastingly, the ANN tuning scheme requires very little tuning time because the circuit's parameters are simply extracted as an output of the trained ANN. However, to train the ANN for fitting all predefined bias points is quite impossible especially in training with validation and test. Therefore, training without validation is utilized, which requires extremely long and impractical training time. In addition, this training method typically degraded the generalization of the ANN [4]. Therefore, the trained ANN hardly provides solutions that precisely match the biquad specifications [3].

In this paper, the ANN is sequentially trained with updated small training set consists of a few tens bias points which are closed to the specified biquad parameters. The update of this set is occurred if and only if the trained ANN provides solution that is not satisfied but better than the worst bias point in the present training set. Through several updating and training, the ANN is supposed to provide an acceptable solution. By limiting size of training set, the complexity of an ANN is significantly reduced and the training time is greatly decreased. Though there may be several response generations and evaluations, its amount is far less than the minimum required by the GA. Based on experiments, the proposed process is far better than the GA-based tuning [2] and the characterizing ANN [3] that are previously introduced.

II. CIRCUIT DESCRIPTION

This section covers the details regarding the experiment circuit in both network and transistor levels.

A. Definition of Experiment Biquad

A current-mode biquad [5], 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 fig. 1. However, the missing capacitors are replaced with parasitic capacitances of an OTA. Therefore, C_1 and C_2 are virtually existed but cannot be controlled. Therefore, the controllable circuit's parameters are limited to the bias current of each OTA.

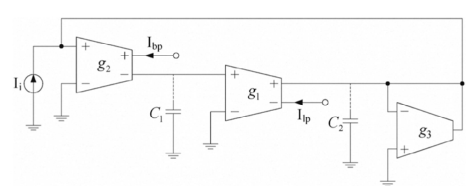

Fig. 1. Biquad in experiment.

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B. Design and Evaluation of the Fundamental OTA

A simple active-loaded differential-pair can be configured as single-stage OTA [6] of both plus and minus outputs as displayed in fig. 2.

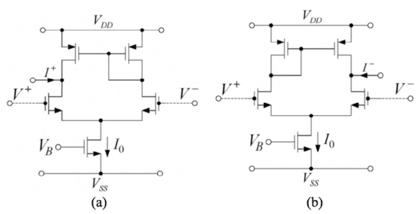

Fig. 2. Single-Stage OTA with plus (a) and minus (b) outputs

The balanced-output OTA, required in biquad, is simply implemented by piling up both structures in fig. 2 and sharing the same input. To generate bias voltage from external current source, only one additional NMOS transistor is required. Therefore, if n outputs are need, the number of required transistors (N_T) is:

$$N_T = 5n + 1 \tag{1}$$

The determination of channel width/length is quite simple as there are only three different functions of composed transistors: active-loaded, differential-pair, and current source. Based on the AMS's 0.35μ CMOS process, dimension of composed transistors are presented in table 1.

TABLE I
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 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 2.

TABLE II
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; high ratio means the efficient utilization of bias current and dissipated power. In addition, very low output resistance seriously deteriorates the performance of applications. As shown in table 2, 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.

III. TUNING PROCESS

A. Concept of applied Artificial Neural Network

The general form of a bandpass biquad is composed of three main parameters, which are the gain (K), pole frequency (ω_p), and Q-factor (Q_p) [7]. According to the experiment biquad, there are three bias current (I_1, I_2, and I_3) to be adjusted. The associate ANN, applied to utilize the studied biquad, is operating in opposite to the actual circuit as the biquad's parameters are taken as input, which is employed to estimate the corresponding bias currents. Therefore, the operation of the trained ANN can be functionalized:

$$\begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = \mathbf{F}_{ANN}\left(\begin{bmatrix} K \\ \omega_p \\ Q_p \end{bmatrix}\right) \tag{2}$$

where $\mathbf{F}_{ANN}$ is a virtual function representing the transferring of biquad's requirements to actual circuit's parameters based on the trained ANN. The training process treats a requirement vector as an input and recognizes the vector of the corresponding circuit's parameters as an output.

B. Data Collection and Selection of Initial Training Set

To create a set of predefined bias points, the range of bias current is quantized based on a desired quantizing resolution (Δ_D), which is resulted in the minimum quantizing level (L_Q).

$$L_Q = \left\lceil \frac{I_{\max} - I_{\min}}{\Delta_D} \right\rceil + 1 \tag{3}$$

Based on full combination of all bias currents, the total amount of predefined records (T_R) are simply:

$$T_R = L_Q^n \tag{4}$$

where n is the number of circuit's parameters. Finally, the actual quantizing resolution is:

$$\Delta_A = \frac{I_{\max} - I_{\min}}{L_Q - 1} \tag{5}$$

According to eq. (3) and (5), the actual resolution is always lower than or equal to the desire resolution. Fig. 3 presents the organized distribution of bias points which are usually generating the chaotic biquad points displayed in fig. 4. To select an appropriate initial training set, the gathering cube centered at the specific point representing the biquad specification which placed as displayed in fig. 4. To initialize the training set, the volume of the gathering cube can be increased or decreased until the amount of biquad points inside the cube is equal to the size of training set.

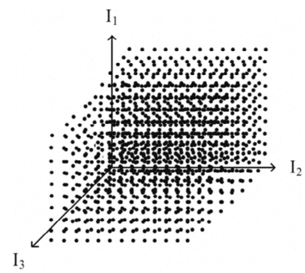

Fig. 3. Predefined bias points

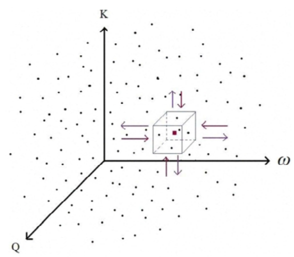

Fig. 4. Predefined biquad points with gathering cube

C. *Feasibility Analysis*

As there are some biquad specifications that may not possible to 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.

D. *Sequential Training and Utilization*

As the training set is small and contains only samples that are closed to the desired biquad, there is no division of data. Therefore, the training of the deployed ANN is conducted without validation and test. If there is significant training error, it will be relieved through the sequential training process presented by the flowchart in fig. 5.

Firstly, the ANN is trained with the initial training set. Once the ANN is completely trained, it is utilized to estimate the bias currents which are exploited to generate the practical based on the HSPICE simulation. If the deviation in biquad's parameters to generated response is considered insignificant, the process is finished. If not, the training set is updated if the recently generated response is better than the worst in the present training set. Then, the ANN is trained again. These tasks can be looped forever if there is no second terminating criterion which is the reaching of maximum loop that strongly indicates the failure of tuning.

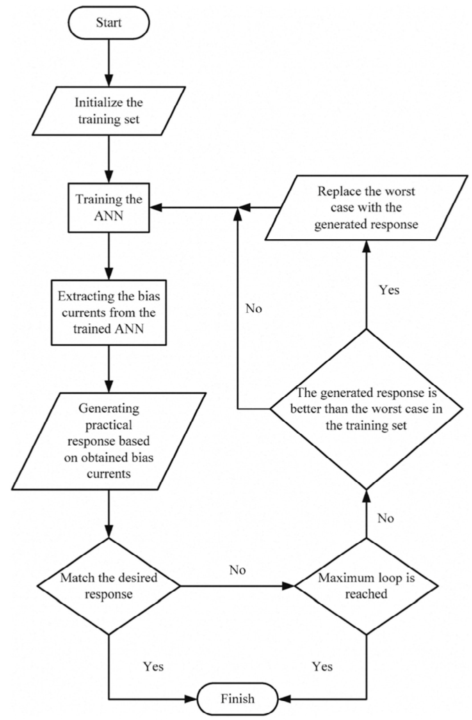

Fig. 5. Sequential training

IV. EXPERIMENTS

A. *Implementation of Tuning Scheme*

The key characteristics of the proposed process are the less complex ANN which is sequentially trained with very small training set. Therefore, the predefined bias point must be collected with quite small resolution of bias current to cover most of the operational region to tuned biquad. Key parameters concerning the implementation of tuning scheme are listed in table 3.

TABLE III
KEY PARAMETER OF SAMPLED TUNING SCHEME

Parameter	Value
Resolution	10μA
Minimum bias current	10μA
Maximum bias current	300μA
Size of predefined bias point	24,389 records
Final iteration of sequential training	20^{th}
ANN type	Cascade-forward (CF)
Number of hidden layer	1
Size of each layer except the output	10
Size of output layer	3
Training goal	0.1
Size of training set	20

B. *Tuning Example*

The sample bandpass specification in table 4 is compiled by the Chevyshev approximation, which is resulted 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 fig. 6. The key specifications are measured and presented in the last column of table 4 alongside the desired specification. Comparing biquad's parameters, very low percentage error is obtained, which leads to a well satisfaction of filter's requirements.

TABLE IV
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	2.55×10^9 rad/s	2.56×10^9 rad/s
f_p	406.2 MHz	407.4 MHz
Q_p	1.621	1.62

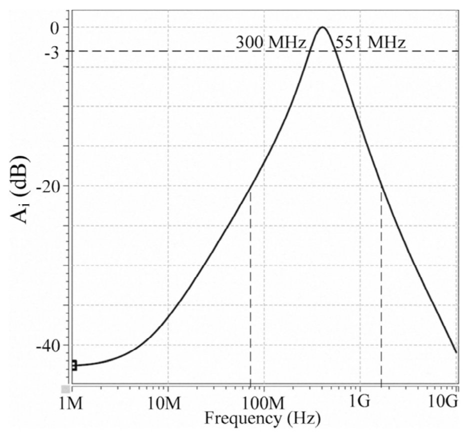

Fig. 6. Bandpass response obtained from sequential tuned ANN

C. *Performance Analysis*

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

In this case, the threshold to indicate the feasibility is 10% and the successfully tuned responses must not deviate over 1%. According to the based OTA and its reasonable bias range, 100 random biquad requirements are generated in the following range; $0.8 \leq K \leq 2$, 300 MHz $\leq f_p \leq$ 500 MHz, and $0.8 \leq Q_p \leq 2$. In table 5, the tuning results tunings are cumulatively grouped by feasibility indications.

TABLE V
PERFORMANCE SUMMATION

Feasible Requirements		Infeasible Requirements	
Error ≤ 1%	Error > 1%	Error ≤ 1%	Error > 1%
73	0	0	27

As there is no wrong indication, the probability of type-I (α) and type-II (β) errors are zero. Therefore, this tuning scheme and the related feasibility analysis are considered very effective.

V. CONCLUSION

A capacitorless all-OTA bandpass biquad is tuned via the sequential trained ANN. A training set of a few tens samples is selected from predefine bias points that are closing to the biquad specification. With this selection scheme, the deployed ANN can be less complex, which consequently requires little tuning time. The feasibility of biquad requirements is indicated by examining the maximum error of the training set. A second-order bandpass requirement is picked as a sample which is successfully tuned within a minute. Based on one hundred tunings of random biquad requirements, the proposed process is considered very efficient as there is no indication of type-I and type-II errors.

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