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Designing Tuneable Narrowband Bandpass Filter Utilizing Neural Network

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Abstract: In this study we aim at adjusting the singleband and dualband bandpass filter designed in a ED02AH technology. The quality factor and center frequency of the filter will change by varactor diodes. Here, we use a neural network to acquire the proper biasing voltages of varactor diodes in order to obtain specific gain and quality factor.

Key words: bandpass filter, neural network, ED02AH.

INTRODUCTION

Tuneable filters have several advantages. They can reduce the complexity of a system avoiding the introduction of filter banks. Multi band telecommunication systems, radiometers, and wideband radar systems are some of applications of these filters. Previous tuning methods include adjusting the cavity dimensions of the resonators or altering the resonant frequency of a ferromagnetic yttrium-iron-garnet element. New approaches are based on solid state varactor diodes (Musoll-Anguiano, *et al.*, 2009; Brown, *et al.*, 1999).

In this study, we applied neural network to adjust the gain and quality factor of narrowband filter, because of its ability to represent RF and microwave component behaviors. Once trained to model the electrical behavior of passive and active components/circuits (Fang, *et al.*, 2000; Xu, *et al.*, 2002), They often referred to as neural-network models, can then be used in high-level simulation and design, providing fast answers to the task they have learned (Gupta, 1998; Devabhaktuni, *et al*., 2001). Moreover, they are efficient alternatives to conventional methods such as numerical modeling methods, which could be computationally expensive, or analytical methods, which could be difficult to obtain for new devices, or empirical models. This paper organized as follows:

First, we adjust the two-stage bandpass filter. Then, training of neural network will be discussed. Afterwards, tuning the dual band bandpass filter using desired neural network will be addressed.

Tuning Two-Stage Bandpass Filter by Neural Network:

Alternatively, a narrowband bandpass filter (BPF) can be constructed by two low-pass filters in a negative feedback loop (Alahyari, *et al*., 2011). The overall structure of a two-stage dualband filter is shown in Fig.1a. It is important to notice that, in a single band filter there are only two varactor diodes in the second stage (V_{a2} and V_{f2}) whose biasing voltages can control the center frequency as well as quality factor. Frequency displacement is illustrated in Fig.1b. It is prominent that the gain is constant

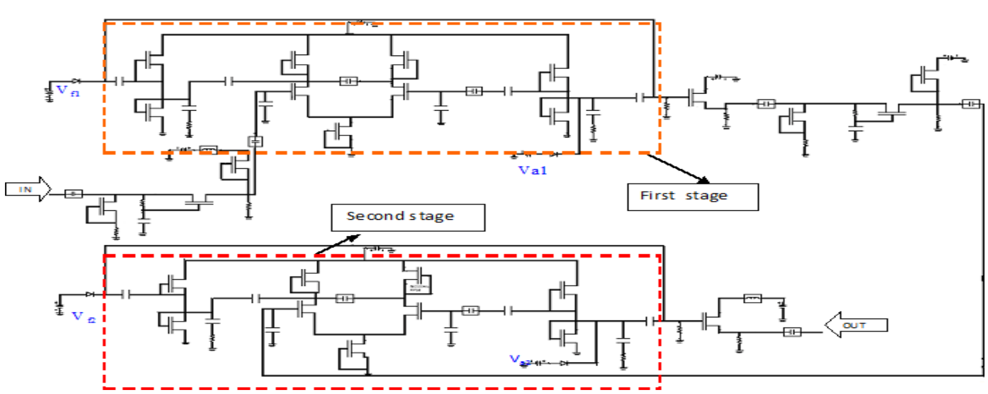

Fig. 1a: The circuit of dual band bandpass filter.

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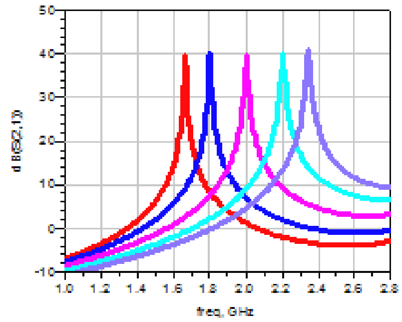

Fig. 1b: Frequency displacement in Two-stage filter.

In this section we consider the center frequency, quality factor, and desired gain as the neural network inputs. The network output specifies the voltages that are appropriate to adjust above parameters. The structure of neural network includes three inputs and two outputs. F_0, Q, and A, are perceived as inputs. Network outputs are V_a and V_f such that the center frequency and quality factor can be controlled simultaneously using them (Fig. 2).

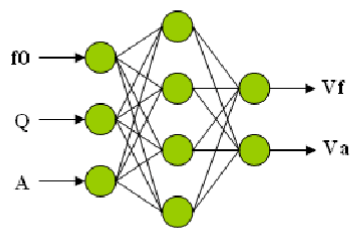

Fig. 2: Neural Network structure.

Network Training:

Several samples (from circuit of the filter) are obtained by ADS software in order to design and train the neural network. In fact, These samples are the values of center frequencies and quality factors and gain as a function of V_a and V_f. That means, we applied V_f and V_a (the number of voltages is the number of samples used to neural network training) to the circuit and we measured the center frequency and quality factor generated by the filter. This sample is used to neural network training via levenberg marquardt algorithm. Three layers of the network include; sigmoid function in the first and second layer and hyperbolic tangent in the third layer. After training the' b 'and 'w' factors will be determined using levenberg marquardt algorithm.

In order to verify the network performance, some data is applied as a test data. We choose ten numbers of V_f and V_a as the real values to design the specified filter. The data in the First group in Table. 1 shows them. Then, we applied these random data to ADS and new values for center frequency, quality factor, and gain are achieved (second group). These values are different from those utilized to network training.

Now in order to test a network, the values of center frequencies and quality factors obtained in previous step are entered as inputs. The output of this network determines the V_f and V_a (third group) and verifies that they are close to the first group. The diagrams of V_f and V_a as a result of ten samples of center frequency and quality factor are illustrated in Fig.3a and Fig.3b.

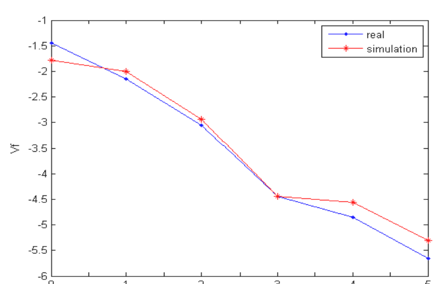

Fig. 3a: Compassion diagram of real V_f and network output V_f.

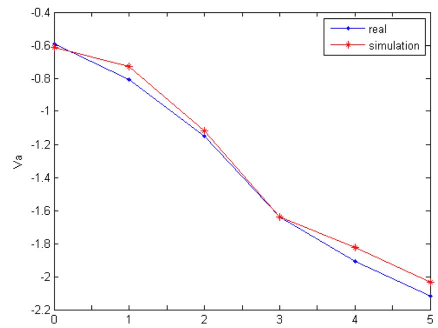

Fig. 3b: Compassion diagram of real V_a and network output V_a.

Table 1: Real data and obtained data from neural network.

First group		Second group			Third group		Fourth group		
V_f	V_a	f_0	Q	A	V_f	V_a	f_0	Q	A
-1.45	-0.59	2.09	70	38.95	-1.7844	-0.6129	2.11	75	44.74
-2.15	-0.81	2.145	72	41.73	-2.0032	-0.7302	2.13	72	43.67
-3.05	-1.15	2.206	75	40.30	-2.9437	-1.1180	2.22	78	41.6
-4.45	-1.64	2.280	72	41.21	-4.4487	-1.6409	2.28	70	41.29
-4.85	-1.91	2.300	70	39.60	-4.5587	-1.8248	2.29	68	38.75
-5.65	-2.12	2.325	70	40.30	-5.3071	-2.0343	2.32	72	41.12

As a case of comparison, we apply one real voltage (first group) and obtained voltage from neural network (third group) to desired filter. Simulation results depict that two filters are similar to each other (Fig. 4)

Line color	V_f	V_a	f_0	Q	A
	-3.05	-1.15	2.206	75	40.30
	-2.9437	-1.1180	2.22	78	41.6

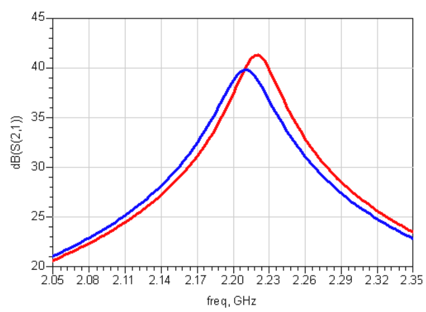

Fig. 4: Compassion result of a real filter and its counterpart achieved by neural network.

Tuning two-stage dual band bandpass filter by neural network:

The structure of a dualband bandpass filter is introduced above (see Fig.1). It includes two varactor diodes in the first and second stage respectively. As mentioned before, biasing voltages variation is applied to adjust f_0 and Q. Frequency displacement is depicted in Fig. 5.

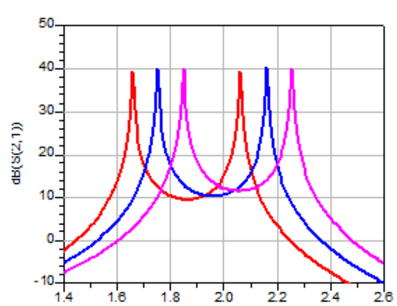

Fig. 5: Frequency displacement in dual band bandpass filte

Since each stage works separately and biasing voltage variation in one stage does not affect on the second, the neural network for each stage is designed independently. Similar structure is employed as discussed in two-stage filter. In this case, we train the neural network using achieved samples from ADS and finally we will test the network with seven new data. Fig.6a and Fig.6b show the behavior of the first stage dual band filter. Values of V_a and V_f from network output; seven samples of center frequency, quality factor and gain used as testing input; are compared with real V_a and V_f.

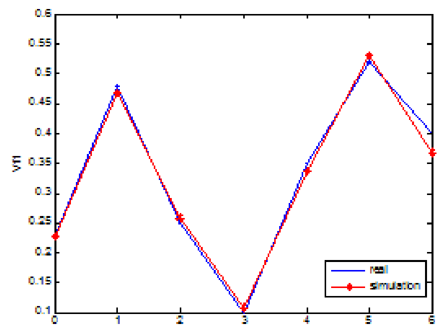

Fig. 6 a: Diagram of V_{f1} of the first stage dual band filter.

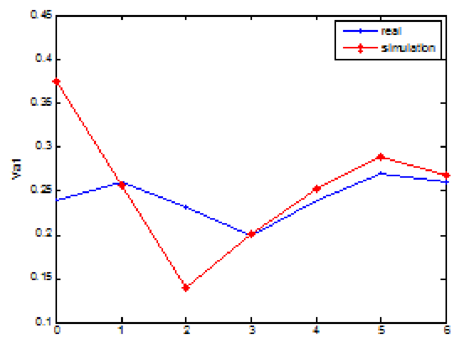

Fig. 6 b: Diagram of V_{a1} of the first stage dual band filter.

Table.2: Real data and obtained data from neural network

First group		Second group			Third group		Fourth group		
V_{f1}	V_{a1}	f_1	Q_1	A_1	V_{f1}	V_{a1}	f_1	Q_1	A_1
0.23	0.24	1.780	95	50.19	0.2258	0.3757	1.755	60	28.95
0.48	0.26	1.7	85	40.00	0.4687	0.2563	1.69	80	42.00
0.25	0.23	1.775	80	44.24	0.2585	0.1391	1.795	65	33.45
0.10	0.20	1.820	90	63.41	0.1073	0.2003	1.820	90	63.56
0.35	0.24	1.745	85	42.06	0.3358	0.2529	1.750	90	46.38
0.52	0.27	1.665	80	41.12	0.5308	0.2885	1.675	80	39.96
0.40	0.26	1.720	90	45.31	0.3686	0.2688	1.735	110	54.40

The same test method is exerted on the second stage of a dualband filter. Fig.7a and 7b illustrate the comparison results.

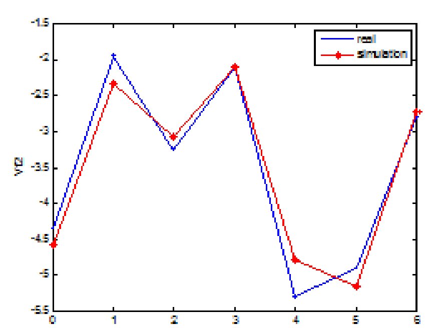

Fig. 7a: Diagram of V_{f2} of the second stage dual band filter

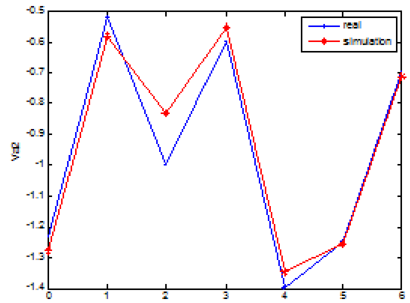

Fig. 7b: Diagram of V_{a2} of the second stage dual band filter

Table 3: Real value and neural network output value

First group		Second group			Third group		Fourth group		
V_{f2}	V_{a2}	f_2	Q_2	A_2	V_{f2}	V_{a2}	f_2	Q_2	A_2
-4.35	-1.23	2.21	60	32.02	-4.5737	-1.2786	2.215	65	32.30
-1.95	-0.52	2.095	90	49.80	-2.3407	-0.5803	2.075	110	47.50
-3.25	1.00	2.145	110	54.23	-3.0726	-0.8318	2.145	85	42.60
-2.10	-0.60	2.09	85	43.33	-2.0864	-0.5517	2.085	85	45.95
-5.30	-1.40	2.23	85	43.90	-4.7897	-1.3455	2.225	65	33.20
-4.90	-1.25	2.22	75	39.22	-5.1536	-1.2578	2.225	75	38.88
-2.80	-0.70	2.125	85	44.01	-2.7244	-0.7112	2.120	85	42.34

In the following of this study, two samples of both Table 2 and Table 3 are applied to the filter. One real voltage value (first group) and one value obtained from neural network (third group). As Fig.8a and Fig.8b imply, the diagrams are adjacent to each other.

	V_{a1}	V_{f1}	V_{a2}	V_{f2}
Real value	0.26	0.48	-0.52	-1.95
Network output	0.2563	0.4687	-0.58	-2.34

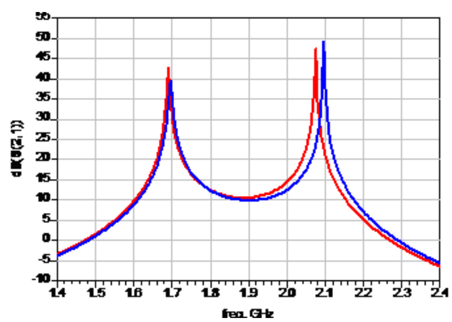

Fig. 8a: Comparison of real filter and obtained filter from neural network (data of Table 2).

	V_{a1}	V_{f1}	V_{a2}	V_{f2}
Real value	0.27	0.52	-1.25	-4.90
Network output	0.2885	0.5308	-1.2578	-5.1536

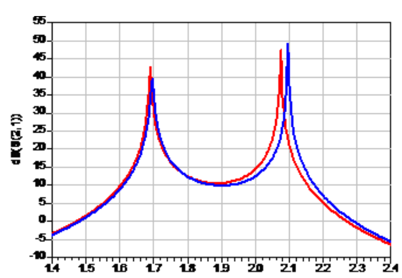

Fig. 8b: Comparison of real filter and obtained filter from neural network(data of Table 3).

Conclusion:

As depicted in this study, using biasing voltages of varactor diodes we could control the center frequency as well as quality factor. The filter behaviour obtained from neural network output is very similar to a real filter. In further works, we can do similar estimation utilizing fuzzy systems and comparing the results with neural network. We used ED02AH technology in this paper. We aim to achieve filters with wider bandwidth while applying other technologies such as BICMOS or RFCMOS in the same structure.

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