Genetically Evolved Fdnr And Leap-Frog Active Filters Using Preferred Component Values

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GENETICALLY EVOLVED FDNR AND LEAP-FROG ACTIVE FILTERS USING PREFERRED COMPONENT VALUES

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***Abstract* - The use of Genetic Algorithms to design both FDNR and Leap-Frog Active Filters is described, where resistor and capacitor values are constrained to be chosen from a set of preferred values. It is found that the Leap-Frog configuration generally produces more successful designs and this is explained.**

I. INTRODUCTION

In the realisation of discrete-component analogue electronic circuits it is common practice, because of costs, to specify component values from a set preferred of values. For the design of Integrated Circuits it can also be desirable to use a standard set of passive component values. For example, to obtain accurate ratio matching of integrated resistors and capacitors by stacking identical unit valued components [1].

The usual design approaches produce circuits in which the permitted component values are assumed to be unrestricted. The circuit is then converted to a practical circuit by simple rounding of the exact component values to the nearest value in the permitted set. Of course, in general the circuit performance realised will differ from the ideal. It may then be necessary to repeat the design with a more stringent specification or to use a more closely spaced set of permitted values, both of which can have cost implications. However if other combinations of permitted values are considered, a better circuit performance may potentially be achieved than that obtained by simple rounding. The difficulty is that in all but trivially simple circuits the space of all feasible combinations to be searched is huge.

We have shown in [6] and [7] that Genetic Algorithms (GAs) can be used to search that space for passive and active filter circuits. A feature of this approach is that the design is carried out as a single stage directly on the response template, rather than the two stages of the conventional approach of polynomial approximation stage followed by a second stage of approximation as preferred values are allocated to the components.

For the realisation of higher order active filter structures on LC ladder prototypes are often used because of low component tolerance. There are various methods to do this, and two of the most commonly used are FDNR [2] and Leap-Frog [3] structures. Because they are based on the same prototype, these methods lead to similar sensitivity properties to component tolerances. A relevant question is, does this similarity also apply when GAs are used to the component design circuits using preferred values, or in general does one type of structure yield better designs that better fit the specifications? This question is considered here. It is shown that one structure does in general produce better designs and the reason for this is explained.

The next section gives an overview of GAs, followed by a description of its implementation for this application. Results then are given for both the FDNR and the Leap-Frog structures and a comparison is made. Two specification templates are used to justify the performance of the circuits. The first is specified by 1 dB pass band ripple with a pass band edge of 10^5 rad/sec and a stop band edge attenuation of -170 dB at a stop band edge of 10^6 rad/sec, The second template is the same as the first but with a more constrained stop band attenuation of -175 dB at the same stop band edge of 10^6 rad/sec.

II. GENETIC ALGORITHMS

GAs are search algorithms which are based on the evolutionary improvement in populations based on selection and reproduction based on fitness that is found in nature. Detailed descriptions of GAs can be found in the literature, such as Goldberg [4] and Davis [5]. There are many proposed variants and the topic is the subject of much current research.

The parameter values to be optimised are represented as a string of bits, called a *gene*. A *fitness* function is defined which is used to measure the goodness of each gene. An initial *population* of randomly chosen genes is created. From this a new population of genes is generated by randomly choosing pairs of genes, and based on their joint fitness, probabilistic decisions are made to breed child genes for the new population. Breeding is performed by splitting both parent genes at two randomly chosen points and crossing over the corresponding gene sections. This is *two-point cross-over*. In addition, a *mutation* operation is randomly applied to each bit with a pre-defined probability.

III. IMPLEMENTATION

In implementing the standard GA mentioned above we used two mutation strategies. The first applies mutation to all bits in the chromosome with a mutation rate of 0.02. This has the effect of identifying some good local regions in the solution space. When it is detected by the GA that one or more solutions meet the specifications, the second mutation strategy is used to refine the solutions within this local region. Here the mutation is applied only to the least significant bit of each component representation, with the same mutation rate of 0.02. This change of strategy is done in order to conserve the locality of the identified good solutions. This compound strategy was found to be more effective than if just one strategy was used throughout.

The fitness value of a certain chromosome must reflect the ability of the corresponding filter to meet the desired specifications. In this application, the fitness function is defined from the total amplitude response error. The total error is calculated as the sum squared of amounts in dB by which the amplitude response falls outside the template specification. For this a linear grid of one hundred frequencies is chosen in the pass band together with the frequency of the stop band edge. Errors in the pass band are given twice the weighting of errors at the stop band edge [8]. The fitness is then defined as the reciprocal of the error value, except if the error is zero in which case a large positive value is given for the fitness.

A population size of fifty gave satisfactory performance. With these control parameters the population was usually found to have stabilised by around two hundreds generations.

IV. THE FDNR CONFIGURATION

For the FDNR circuit configuration Figure 2(a) and 2(b), the component values are represented in a chromosome by contiguous groups of six bits to specify each component from the menu of preferred values. This allows components to be selected by the GA from a range of sixty-four permitted values. This range is narrower than the range of preferred values commonly used for discrete components, which span many decades, and assumed in the examples studied here. However this was not a restriction since in practice the solutions obtained were bunched and suitable initial range scaling was easily chosen to centre the component values produced within a range of sixty-four values within the full range of preferred values spanning many decades.

For the example considered here of a seventh order all-pole low pass filter, the chromosome consists of 150 bits representing 25 deferent component. Four groups of five components each make the four required Bruton's FDNR configuration [2] according to equation (1).

$$D = \frac{c_a \cdot c_e \cdot r_b \cdot r_d}{r_c} \tag{1}$$

V. THE LEAP-FROG CONFIGURATION

In the Leap-Frog configuration Figure(3), the same chromosome representation method is used. The chromosome length in this case is 120 bits long only representing 20 deferent component. The main deference here is that not only the capacitances were replaced by an active model, but also the inductances as in equations (2) and (3). The circuit obtained [3] consists of integrators that simulate the operation of inductors and capacitors, and summers that simulate the Kirchhoff loop and node equations of the LC-Ladder.

$$C_i = \frac{c_n \cdot r_m \cdot c_{n+1} \cdot r_{m+1}}{L_{i-1}} \tag{2}$$

$$L_{i+1} = \frac{c_{n+1} \cdot r_{m+2} \cdot c_{n+2} \cdot r_{m+3}}{C_i} \tag{3}$$

VI. RESULTS

In this investigation resistors and capacitors were chosen from two sets of preferred values. The twelve series of preferred values, 10, 12, 15, 18, 22, 27, 33, 39, 47, 56, 68, 82, 100,... was used first and designs were produced for the two template cases, for each of the FDNR and Leap-Frog structures.

For the -170 dB stop band template, five successful designs were obtained by the GA for the FDNR configuration and eight successful designs for the Leap-Frog configuration. A selection of their responses is plotted in figures 4(a) and (b). For the more constrained template of -175 dB stop band attenuation, the number of successful designs were three and six respectively for the FDNR and the Leap-Frog configurations. Some of their responses are plotted in figures 4(c) and (d).

These designs were repeated with components selected from a six-series of preferred values, 10, 12, 22, 27, 56, 68, 100, ... For the -170 dB stop band template, only two successful design was obtained by the FDNR configuration, and 5 successful designs for the Leap-Frog Configuration. For the -175 dB stop band attenuation it was found that the FDNR design was not capable of finding any design that satisfy the template while three deferent designs were obtained in the case of Leap-Frog configuration.

VII. DISCUSSION AND CONCLUSION

The above results indicate that when component values are selected from a set of preferred values, the number of designs obtained that satisfy the specification is likely to be more in the case of the Leap-Frog then for the FDNR configuration.

It is suggested that this can be explained by the differing resolutions of the effective achievable component values for the inductors and capacitors in the LC prototype from which the active filter structures are transformed. For the Leap-Frog configuration, as equations (2) and (3) show, the equivalent inductances and capacitances are given by the product of four preferred values. Because of the large number of combinations, the number of achievable values is therefore high for both inductors and capacitors. For the FDNR configuration, the shunt capacitors in the LC prototype are replaced by FDNR elements which are given by the product and division of five preferred value components, see equation (1). Although this leads to higher resolution for the capacitors, the inductors on the other side are replaced by a single preferred value resistor and therefore have low resolution. Since, as is well known, the sensitivity to component value deviations for inductors and capacitors is broadly similar in LC ladder circuits, it follows that it can be expected that relatively fewer successful designs can be achieved for the FDNR case.

In general therefore, active circuit configurations based on LC prototypes and using component values chosen from a restricted set are more likely to result in successful designs if the resolution between achievable equivalent LC values is evenly balanced.

GAs are useful tools for searching the very large discrete solution space. They have the useful feature that designs are obtained directly from the response template without the need for an intermediate step of obtaining a polynomial transfer function approximation. A further feature is that rather than a single solution, a group of satisfactory designs are obtained.

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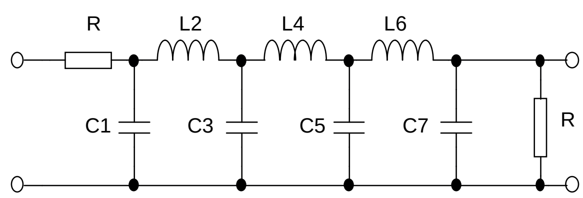

Fig. 1 Low-pass all-pole LC structure

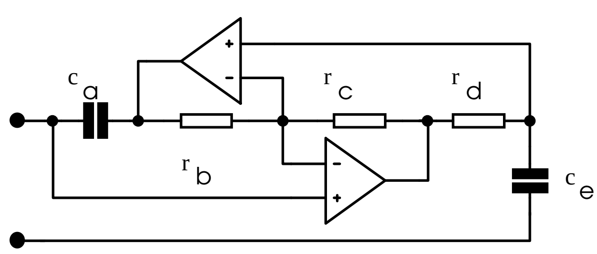

Fig. 2(a) Generalised Impedance Converter FDNR

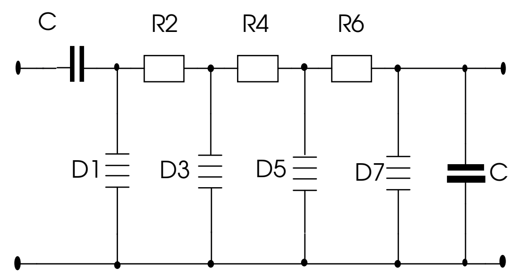

Fig.2(b) Low pass all-pole FDNR structure.

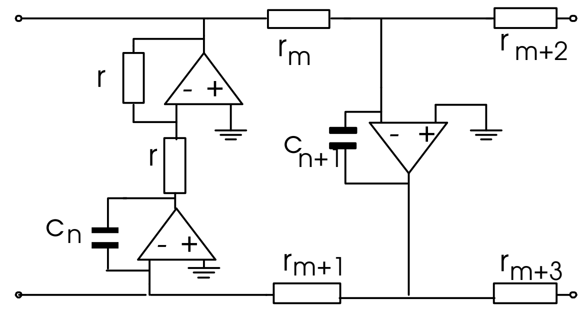

Fig.3 A section in a Leap-Frog all-pole structure.

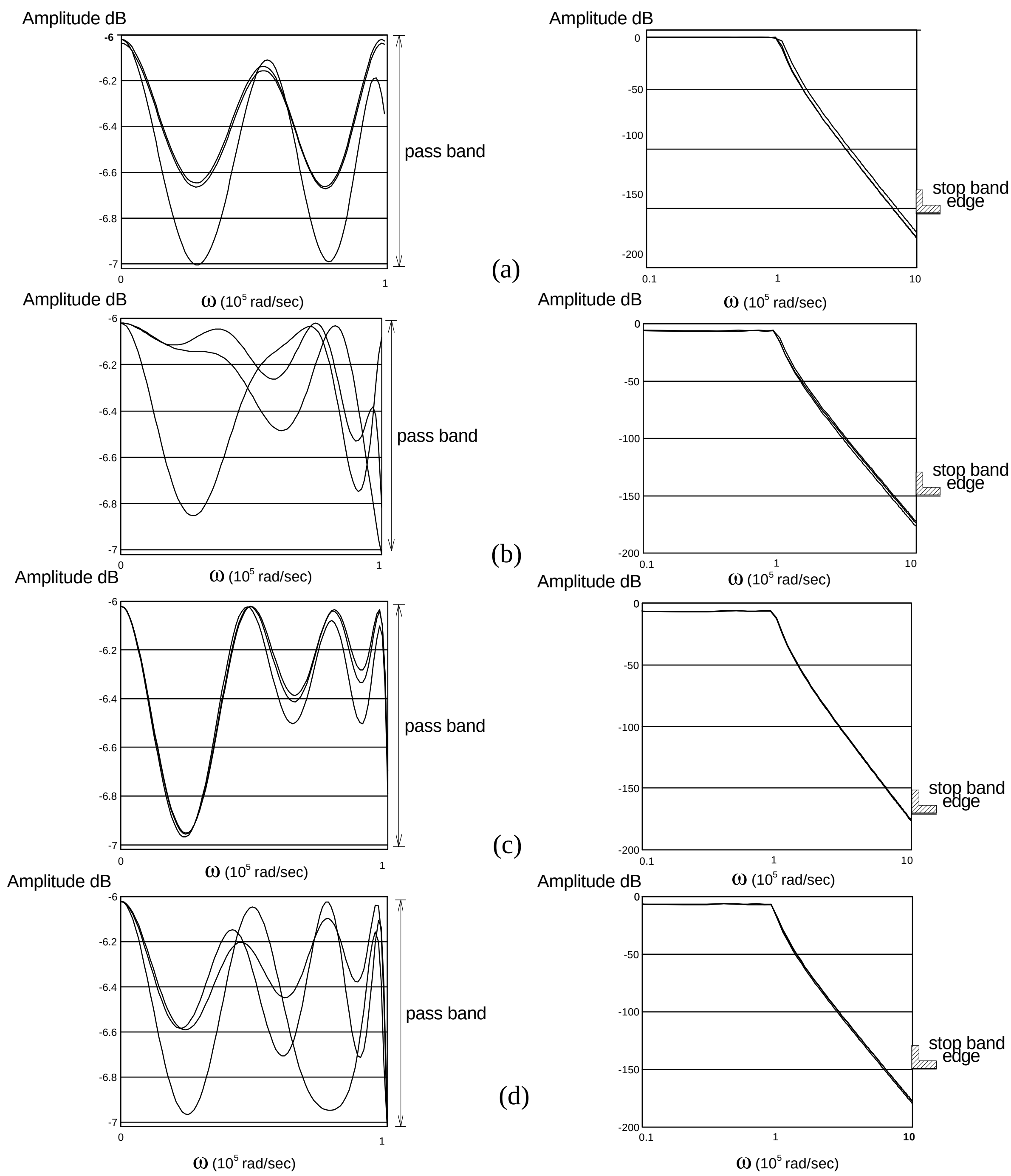

Fig.4 (a) Responce of FDNR and (b) Leap-Frog active filters with a 12-series and stop band attenuation of -170dB
(c) Responce of FDNR and (d) Leap-Frog active filters with a 12-series and stop bend attenuation of -175 dB