# A Neural Network Approach to the Adaptive Correction of Loudspeaker Nonlinearities

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# A NEURAL NETWORK APPROACH TO THE ADAPTIVE CORRECTION OF LOUDSPEAKER NONLINEARITIES

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***Abstract***

*An adaptive loudspeaker correction scheme for sub-woofers is presented that is based upon a four-layer neural network algorithm. Compensation for both dominant time-invariant non-linearities and time varying changes in cone mass and voice-coil resistance is achieved. Control data for the correction algorithm is derived using a novel method based upon the knowledge of the current and voltage monitored at the drive unit's terminals.*

## 0 INTRODUCTION

Digital recording systems together with certain types of music place a high demand upon the generation of low frequency signals using moving-coil technology. It has been shown by Fielder and Benjamin[1] that a bass extension to 20 Hz with sound levels up to 110 dB and distortion levels below 3% is desirable for realistic sound reproduction, where as an extreme case, Figures 1(a) and (b) show the musical content of a segment of the "1812 Overture" by Tschaikowsky[1].

Recognising the difficulty of achieving adequate bass performance within the context of modestly sized and cost-bounded loudspeakers, this paper explores techniques of compensation for non-linearities within low-frequency loudspeakers using digital signal processing. A range of distortion mechanisms are reviewed and a novel form of adaptive neural network introduced as a candidate for a correction strategy, where the performance of an example network is explored through computer simulation.

## 1 DOMINANT NON-LINEARITIES IN MOVING-COIL LOUDSPEAKERS

A moving-coil sub-woofer system employing a closed-box bass loading scheme may be driven from either a voltage source or a current source. Figures 2(a) and (b) contain the mechanical equivalent circuits of current and voltage drive closed-box sub-woofers. Most amplifiers provide a voltage source drive output to moving-coil loudspeakers, but specially constructed amplifiers (Mills and Hawksford[2]) can provide current drive to moving-coil loudspeakers. It is evident from comparisons made by Mills and Hawksford[2] and Klippel[3] that certain output non-linearities can be compensated for by employing current drive technology.

Figure 4 provides a detailed summary of moving-coil loudspeaker non-linearities. Current drive eliminates the effects of voice coil inductance change with cone excursion (whose contribution is anyway minor at bass frequencies) and the effects of $(bl)^2$ modulations contributing to non-linear electrodynamic damping. In addition, operating point variation caused by voice-coil current heating effects is very much reduced. Doppler distortion as reported in reference [1] may be neglected even at high acoustical outputs in the bass region. The positive features of current drive leave only the following non-linearities to be corrected for in a closed-box system:

a. Non-linear bl displacement factor,

b. Non-linear suspension spring force, and,

c. Non-linear box spring force.

## 2 OVERVIEW OF NON-LINEAR DISTORTION COMPENSATION

The incorporation of negative feedback and proper frequency alignment/equalisation has been the traditional approach (Mills and Hawksford[2]) used to reduce non-linear distortion in sub-woofers. Negative feedback and frequency alignment/equalisation entail the use of external sensors and special amplifiers, thereby subjecting the manufacturer to extra production costs and limited adjustment flexibilty. Recent advances in signal processing and computer technology have led to the incorporation of adaptive signal processing in the correction of non-linear loudspeaker distortion. Klippel[3] suggested the use of a mirror filter to provide a form of non-linear real-time inverse mapping function to linearise a loudspeaker's output at bass frequencies. A refinement in Klippel's technique [3], through the use of a neural network is proposed in this paper.

## 3 COMPUTER MODELLING AND SIMULATION

A computer model of a current-driven closed-box sub-woofer was constructed through the technique of Transient Analysis[4]. Neural network simulations are best observed in the time domain, as the effect of incremental change in the output gives a real-time indication of how the network is responding to an applied training algorithm. Therefore Transient Analysis is preferred to that of the Volterra Series [5] in modelling neural network loudspeaker correction systems. The input-output relationships amongst the output parameters of cone displacement, velocity and acceleration, and that of the driver's terminal voltage with that of the input parameter of drive current are illustrated in Figure 5. Integration and differentiation are carried out by numerical techniques (references [4] and [6]).

The non-linear differential equation describing the response of a closed-box current-drive low frequency loudspeaker is,

$$bl(x)i(t) = \mathrm{L}^{-1}\{ms^2+(Rms)s+k_0\}*x(t) + x(t)\{\Delta kmt(x)\} \tag{1}$$

where, $s = \sigma + j\omega$, the complex frequency,
$i(t)$ = the input drive current, and,
$x(t)$ is the resulting cone displacement output.

The term, $\Delta kmt(x)$, represents the total non-linear contributions of both the spring force and box spring force respectively. $k_0$ represents the total static box and suspension spring forces when the cone is at its rest position. The terms, $bl(x)$ and $kms(x)$ are modelled as polynomial expansions in powers of $x(t)$ as follows:

$$bl(x) = b_0 + b_1 x + \ldots\ldots + b_n x^n \tag{2}$$

$$kms(x) = ks_0 + ks_1 + \ldots\ldots + ks_n x^n \tag{3}$$

Following the suggestion of Kaiser[5], the box spring force, $kmb(x)$ may be expressed as,

$$kmb(x) = \gamma S^2 \frac{p_0}{V_0}\left\{1+\frac{Sx}{V_0}\right\}^{-(\gamma+1)} \tag{4}$$

where, $p_0$ = static air pressure of $1.01325 \times 10^5$ N/m$^2$,
$V_0$ = static volume of box enclosure,
$S$ = effective cone surface area of radiation, and,
$\gamma$ = adiabatic expansion constant of 1.4.

Figures 6(a) to 6(c) depict the variations of the $bl(x)$, $kms(x)$ and $kmb(x)$ with cone displacement $x(t)$. The plots of Figures 6(a) to 6(c) represent the characteristics of a typical medium-sized closed-box system which was used in this simulation.

## 4 CORRECTION STRATEGY

An inverse mapping function of the form,

$$i_{corr}(t) = N_{Bl}(x)\{i(t) + N_{kmt}(x)\} \tag{5}$$

where, $i_{corr}(t)$ = pre-distorted drive current,
$N_{Bl}(x)$ represents the non-linear correction factor for the bl displacement force, and,
$N_{kmt}(x)$ being the total correction for the suspension and box spring forces,

may be used to correct for the dominant non-linearities. Applying the inverse mapping equation (5) would result in the linearisation of *x(t)* as shown below:

$$x(t) = \mathrm{L}^{-1}\left\{\frac{bl(x)}{ms^2 + (Rms)s + kmt(x)}\right\} * i_{corr}(t) \qquad (6)$$

## 5 DESCRIPTION OF THE ARTIFICIAL NEURAL NETWORK CORRECTION SCHEME

The practical realisation of equation (6) may be obtained through the use of an adaptive correction scheme employing an artificial neural network. In addition to the correction of the dominant non-linearities, a neural network could adapt itself as the loudspeaker is in operation to time varying changes in cone mass and voice-coil resistance. Figure 7 contains a block diagram representation of the artificial neural network correction scheme. The correction strength of the network lies in its ability to make synaptic changes in the values of weights ***w*1** to ***w*8** in response to a change in the error between the output of the linear filter, which provides the reference or training signal and that of the derived cone displacement signal, which is representative of the actual cone displacement. Weight ***w*8** is normally set to 1.0, unless the output from the current sensor indicates a notable change in the voice-coil resistance due to heating. The correction of the dominant non-linearities and that of variations in the cone mass are effected by the synaptic strengths of the weights, ***w*1 *to w*7** respectively. The general equation representing the output at a summing junction may be expressed as:

$$N_{jk} = \sum_{i=1}^{n} w_{ij} N_{ij} \qquad (7)$$

$N_{jk}$ represents the network output of the kth layer which comprises of the total weighted strength of the jth layer network outputs represented by $N_{ij}$ and synaptically weighted by the jth layer weights, $w_{ij}$.

## 6 MEASUREMENT OF CONE DISPLACEMENT

In order that the synaptic strength of the neural weights ***w*1** to ***w*7** be changed in response to the input signal, a knowledge of the instantaneous cone displacement is required and this is obtained through a novel voltage feedback scheme. This scheme, unlike most servo-loop negative feedback systems, which obtain cone displacement information through the use of acoustical or mechanical sensors, only monitors the voltage across the driver's terminals. The terminal voltage is a representation of the instantaneous cone velocity, ***u(t)***, and thus by monitoring this voltage and then employing a suitable numerical integration technique, the instantaneous cone displacement, ***x(t)***, may be computed and fed back as an input signal, ***xfb(t)***, to the neural network. Figure 8(a) shows the scheme to obtain the derived cone displacement. If the circuit is operated in the digital domain, the derived displacement, ***xfb*[n]**, is thus,

$$xfb[\mathrm{n}] = \frac{\Delta}{2}\{2+\Delta\}\left\{\frac{v[n-1]-i_{corr}[\mathrm{n}-1]Re}{bl(xfb[\mathrm{n}-1])}\right\} + k\{xfb[\mathrm{n}-1]\} \qquad (8)$$

The term, $k$ is an integrator constant, to provide a levelling off of the integrator gain in order to ensure system stability. $\Delta$, the integration step size is numerically equated to the sampling interval of the digital system. $i_{corr}$ may be obtained without measurement through a knowledge of the network output $N5$. The use of equation (8) to obtain a sample of the instantaneous cone displacement is accurate and does not require laborious tuning and refinement unlike that of employing mechanical or acoustical sensors. A simulation run with an input current amplitude of 1 A and a frequency of 16 Hz produced the resultant outputs of Figure 8(b). The simulation result shows that the derived displacement obtained by the use of the novel scheme of equation (8) is in close agreement with the actual cone displacement.

## 7 TRAINING THE NEURAL NETWORK

In Figure 9, a flowchart illustrating the training and simulation strategy of the neural network correction scheme is presented. In order to simplify the actual training and implementation of the correction scheme, so as to reduce set-up and production times, the use of the ***generalised delta rule*** and ***back-propagation*** are adopted (Reference [7]). Weight changes are made following a simplified gradient descent procedure [8] where the error signal, $\varepsilon[\mathbf{n}]$, is computed as follows,

$$\varepsilon[\mathrm{n}] = x_{lin}[\mathrm{n}] - xfb[\mathrm{n}] \qquad (9)$$

The target signal, $x_{lin}[\mathbf{n}]$, is generated from the input drive current, $i[\mathbf{n}]$, from a linear filter, whose transfer function is the digital domain representation of the input-output relationship of the current-drive loudspeaker in the absence of non-linearities,

$$x_{lin}(t) = \mathrm{L}^{-1}\left\{\frac{b_0}{ms^2+(Rms)s+k_0}\right\} * i(t) \qquad (10)$$

Updating of the synaptic strength of the weights takes place first between the output layer and the hidden layer immediately behind it. This involves the update of $w7$. The new value of $w7$ is computed by this step,

$$w7[\mathrm{n}+1] = w7[\mathrm{n}] + \beta\varepsilon N5[\mathrm{n}] + \alpha\Delta w7[\mathrm{n}] \qquad (11)$$

$\beta$ represents the training factor which is allowed in the simulation runs to vary about an initial setting of 1.0, in accordance with the strength of the output $N5[\mathbf{n}]$. $N5[\mathbf{n}]$ is the digital representation of the actual pre-distorted drive current, $i_{corr}[\mathbf{n}]$. A momentum term, $\alpha$, is added to equation (11) to improve the rate of convergence. A value of 0.6 was found to be optimum, during simulation runs, as higher values of $\alpha$ resulted in overtraining and contributed more distortion to the cone displacement.

The weights $w1$ to $w6$ are embedded in the hidden layers of the neural network, and will bear no direct relationship with the output layer. Their synaptic strength may be updated by means of the backpropagation algorithm, where the updated value of $w7$, is propagated back together with the value of the error signal. So, for any weight in the hidden layers, $w_{ij}$,

$$w_{ij}[n+1] = w_{ij}[n] + \varepsilon x f b[n] w7[n+1] + \alpha \Delta w_{ij}[n] \qquad \textbf{(12)}$$

## 8 SELECTION OF THE TRAINING SET AND WEIGHT INITIALISATION

In the selection of a set of training signals, it is important that signals posess similar characteristics to that of actual music as well as have sufficient magnitude to drive the cone through its full displacement range. The training signals chosen for the simulation runs comprised of sine wave tones at an amplitude of 1A through a frequency range spanning 16 Hz to 120 Hz. It has been computed that a drive current of 1A in amplitude would produce maximum linear cone excursion amplitude of 7mm at resonance for the current drive model under study before the application of frequency alignment/equalisation. The training procedure involved simulation runs of one second duration with a sine wave tone set at a particular frequency commencing at 16 Hz. The training sequence continued at intervals of 4 Hz right through to 120 Hz. Weight changes in $w1$ to $w7$ are recorded at each frequency.

Kolen and Pollack[9], have reported that back propagation is sensitive to the initial synaptic strengths of the weights in a neural network at the commencement of a training cycle. A wrong choice of initial conditions may lead to network paralysis or the optimisation process being stuck at a local minimum. In order to avoid the training situations described above, the inital weight values are set either through the use of a look-up table or with some knowledge of the average correction to be applied to the dominant non-linearities over the span of the cone excursion.

$\boldsymbol{w8}$ is initialised to a value of 1.0 at the start of any training sesssion or when the loudspeaker correction system is in actual operation. A current sensor continually monitors the rms value of $i_{corr}(t)$ so that the change of the voice coil resistance due to heating effects could be compensated through the adjustment of the weight strength of $\boldsymbol{w8}$.

## 9 LOOK-UP TABLE WEIGHT INITIALISATION

Figures 10(a) to 10(g) show the correction values for the dominant non-linearities to be initially applied as weight values. $w7$ provides compensation for the bl factor non-linearity. $\boldsymbol{w1}$ to $\boldsymbol{w4}$ compensate for the non-linearity of the suspension spring force, while $\boldsymbol{w5}$ and $\boldsymbol{w6}$ compensate for the non-linearity in the box spring force. As the training cycle progresses for a particular frequency, the value of the derived displacement is used to compute the index, N of the look-up table as illustrated in Figure 11. Once the individual weight values in a particular indexed row are identified, they will be used as initial weight values for that particular sample of time. The weight updates then continue with gradient descent and back propagation and the updated values of $\boldsymbol{w1}$ to $w7$ are recorded in a data file indexed to Nth row. Once the network has been trained over the full complement of signals in the training set, the average individual value of a particular weight in an indexed row N becomes,

$$\overline{w}_{ij,f}[\mathrm{N}] = \frac{1}{\mathrm{K}}\sum_{f=1}^{\mathrm{K}} w_{ij,f}[\mathrm{N}] \qquad (13)$$

$f$ in equation (13) refers to a particular frequency of the input and **N**, index number of the Nth row. It has been observed during simulation that the number of steps in the look-up table affects the rapidness of convergence and hence the accuracy of compensation. A 4096 step look-up table with equal incremental steps spanned over the ±7 mm cone excursion range of the model yielded good results. **K** represents the total number of frequencies in the training set.

## 10 FIXED WEIGHT INITIALISATION

An alternative to look-up table initialisation, would be that of fixed weight initialisation. This method reduces the memory overhead needed to store a huge 4096 x 7 array of weight values. In fixed weight initialisation, a weight value $w_{ij}$***(inital)***, is initialised by taking the mean of all the correction values that span over the cone excursion range,

$$w_{ij}(\textbf{\textit{initial}}) = \frac{1}{\mathrm{S}}\sum_{\mathrm{N}=1}^{\mathrm{S}} w_{ij}[\mathrm{N}] \qquad (14)$$

where, S = number of steps in look-up table, and,
N = step index.

It is evident that fixed initialisation requires a total storage of only seven weight values at any one time during either training or operation of the system.

## 11 EVALUATION OF NETWORK PERFORMANCE

The performance of the neural network is compared against that of a frequency equalised/aligned and that of an unequalised/unaligned current drive model with the same parameter values. Evaluation of performance in the areas of second and third harmonic distortion levels, cone compression and sensitivity to cone mass variations revealed the good correction ability of the neural network compensation scheme. Look-up table weight initialisation were used in these tests.

Reference to Figure 12(a) reveals the superior performance of the neural network in the correction of second harmonic distortion, especially in the region between 20 Hz to 45 Hz. In the area of third harmonic distortion output, the neural network provides superior performance in the frequency range between 48 Hz to 92 Hz when compared with the other two systems.

Figures 13(a) to (c) show the simulation results of the performance of the three above systems in the area of intermodulation distortion. The two test tones chosen were 16 Hz and 64 Hz, both with an equal amplitude of 0.5 A. This would simulate a reasonably accurate real world situation where a 16 Hz organ pedal note may be modulated with a 64 Hz note from a double bass or a contra-bassoon. (Richard Strauss' opening bars of the Also Sprach Zarathrustra tone poem recorded in the Telarc CD of reference [1] is one typical musical example). The neural network system showed reduced intermodulation distortion output at 32 Hz, 48 Hz and 80 Hz in comparison with the aligned/equalised system. The intermodulation products at frequencies beyond 200 Hz are at least 60 dB below the two test tones, indicating that the neural network scheme would produce very little upper bass and lower mid-range energy which interfere with the output of low bass frequencies.

The neural network system also showed good adaptation to parameter variations from design specifications. Simulation runs were conducted where the cone mass was first reduced by 20% and then increased by 20% of the design value. The percentage change (relative to that of the output with design specified cone mass) in cone excursion amplitude is observed at intervals of 4 Hz for the frequency range between 20 Hz to 120 Hz. In the frequency range between 20 Hz to 110 Hz (typical sub-woofer operation range), the neural network system exhibited no more than ± 25% variation in excursion amplitude when the mass is reduced by 20%. An increase in cone mass by 20% from that of the design specified value resulted in a fluctuation of excursion amplitude of no greater than ± 32%. The amplitude fluctuations produced by the other two systems under test over the frequency range of 20 Hz to 110Hz are more extreme as indicated in Figures 14(a) and (b) when compared against the neural network scheme.

## 12 NETWORK PERFORMANCE COMPARISON - FIXED VS LOOK-UP TABLE WEIGHT INITIALISATION

It is interesting to make observations of network performance under fixed and look-up table weight initialisation strategies. A simulation run with a 16 Hz, 1 A sine wave tone was conducted with both weight initialisation schemes and the results were compared against the equalised/aligned model. Fixed weight initialisation produced the least compression but showed inferior second and third harmonic distortion reduction when compared against look-up table weight initialisation. Figures 15(a) and (b) summarise these results. Simulation runs conducted at higher frequencies indicated poorer overall performance for the fixed weight initialisation scheme, thereby confirming the observation of Kolen and Pollack[9], regarding the sensitivity of network performance to the initial synaptic values of the neural weights.

## 13 CONCLUSIONS

Evaluation of the main performance areas of the neural network correction scheme has indicated that the scheme holds promise of good performance especially in the areas of reduced cone compression and second harmonic distortion output in the low bass region between 20 Hz to 45 Hz where cone excursion is substantial. In the reduction of intermodulation and third harmonic distortion output, the neural network system performed equally well if not better than the other two systems in the comparison tests (the unaligned/unequalised and frequency aligned/equalised systems respectively). In the area of adaption to parameter variations such as changes in voice-coil resistance and cone mass variations, the neural network scheme is superior to the other two systems under test, thereby indicating the network's tolerance to time-varying parametric changes. This paper merely represents the "tip of the iceberg" in the exploitation of neural network theory to loudspeaker non-linearity correction. Further investigations into more advanced strategies (references [10] to [15]) will certainly lead to the conceivement of more powerful and efficient correction schemes. The corrective properties of neural networks are rich in scope and variety, and are very well suited to use in a non-linear control problem such as loudspeaker non-linearity correction.

## 14 ACKNOWLEDGEMENTS

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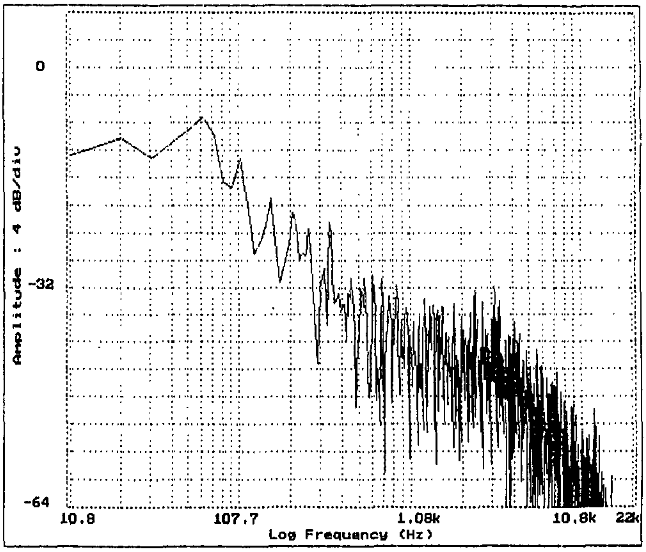



*Figure 1(a) - Frequency Spectrum of a Segment of the "1812 Overture" by Tschaikowsky*

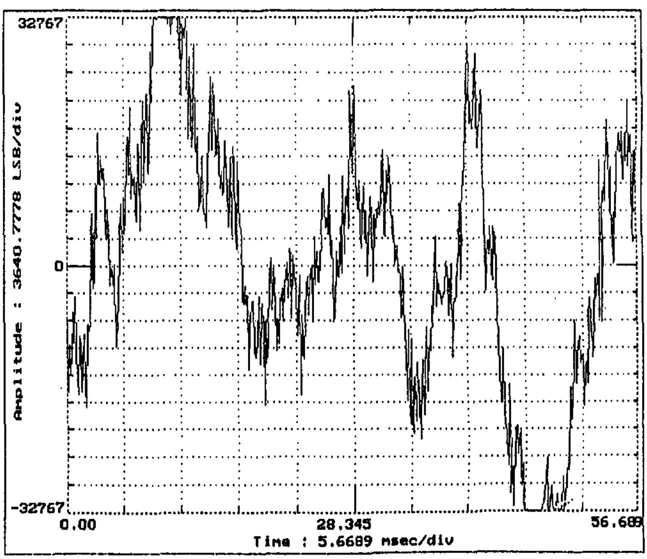



*Figure 1(b) - Time Domain Representation of a Segment of the "1812 Overture" by Tschaikowsky*

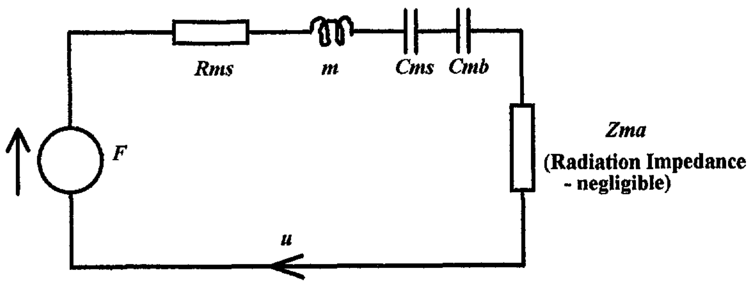
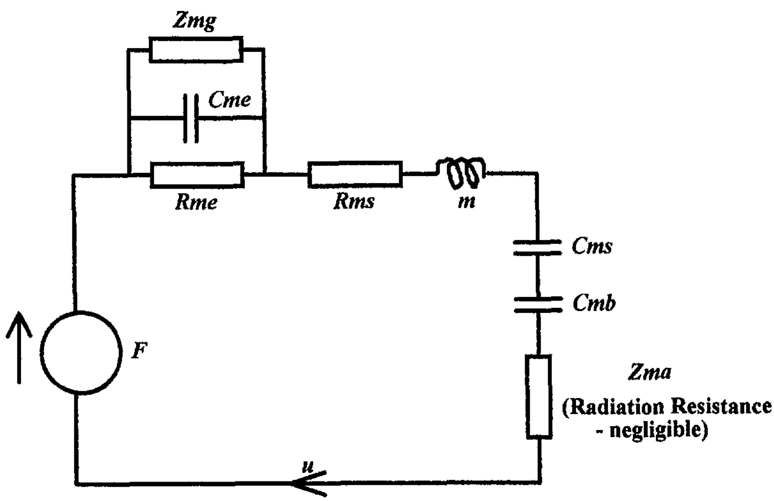



*Figure 2(a) - Mechanical Model of a Current Drive Moving-Coil Loudspeaker System*




**(b)**

*Figure 2(b) - Mechanical Model of a Voltage Driven Moving-Coil Loudspeaker. Effects of $(bl)^2$ modulations are reflected from electrical input circuit and manifestedin the parameters of Zmg, Cme and Rme respectively.*

| *PARAMETER/DRIVE UNIT* | *ELECTRICAL MODEL* | *MECHANICAL MODEL* |
| --- | --- | --- |
| **Voice Coil Resistance** | $Re$ Ω | $Rme = \frac{(bl)^2}{Re}$ kg/s |
| **Voice Coil Inductance** | $Le^*$ H | $Cme^* = \frac{Le}{(bl)^2}$ m/N |
| **Enclosure Compliance/ Box Spring Force** | $Lmb^* = Cmb(bl)^2$ H | $Cmb^* = \frac{1}{kmb}$ m/N |
| **Suspension Compliance/ Restoration Spring Force** | $Lms^* = Cms(bl)^2$ H | $Cms^* = \frac{1}{kms}$ m/N |
| **Moving Cone Mass/ Suspension Mass** | $Cmcs = \frac{m}{(bl)^2}$ F | $m$ kg |
| **Mechanical Resistive Losses** | $Res = \frac{(bl)^2}{Rms}$ Ω | $Rms$ kg/s |
| **Source Impedance** | $Zg$(assume zero) Ω | $Zmg = \frac{(bl)^2}{Zg}$ kg/s |
| **Voltage/Force (Drive Units)** | $V$ (voltage) V | $F$ (force) N |
| **Current/Velocity (Drive Units)** | $I$ (current) A | $u$ (cone velocity) m/s |
| **Other Mechanical Units** | | $x$ (cone displacement) m<br>$a$ (cone acceleration) m/s² |
| **Electromagnetic Conversion Parameter/Force Factor** | $bl^*$ N/A | |

*** Indicates non-linear parameter dependent on cone displacement, $x$.**

***Figure 3 - Tabular Summary of Main Modelling Parameters in Transient Analysis***

## MAIN NON-LINEARITIES IN MOVING-COIL LOUDSPEAKERS

*A. NON-LINEARITIES IN THE MOTOR COIL AND MOTOR/MAGNET SYSTEM*

1. Variation of bl force factor with cone displacement*
2. $(bl)^2$ variations producing non-linear electro-dynamic damping of cone motion
3. Variation of the voice coil inductance with cone excursion
4. Variation of the voice coil induced emf with cone excursion
5. Changes in the operating point of the permanent magnet system due to a variation of voice coil current (heating effects)

*B. MECHANICAL NON-LINEARITIES*

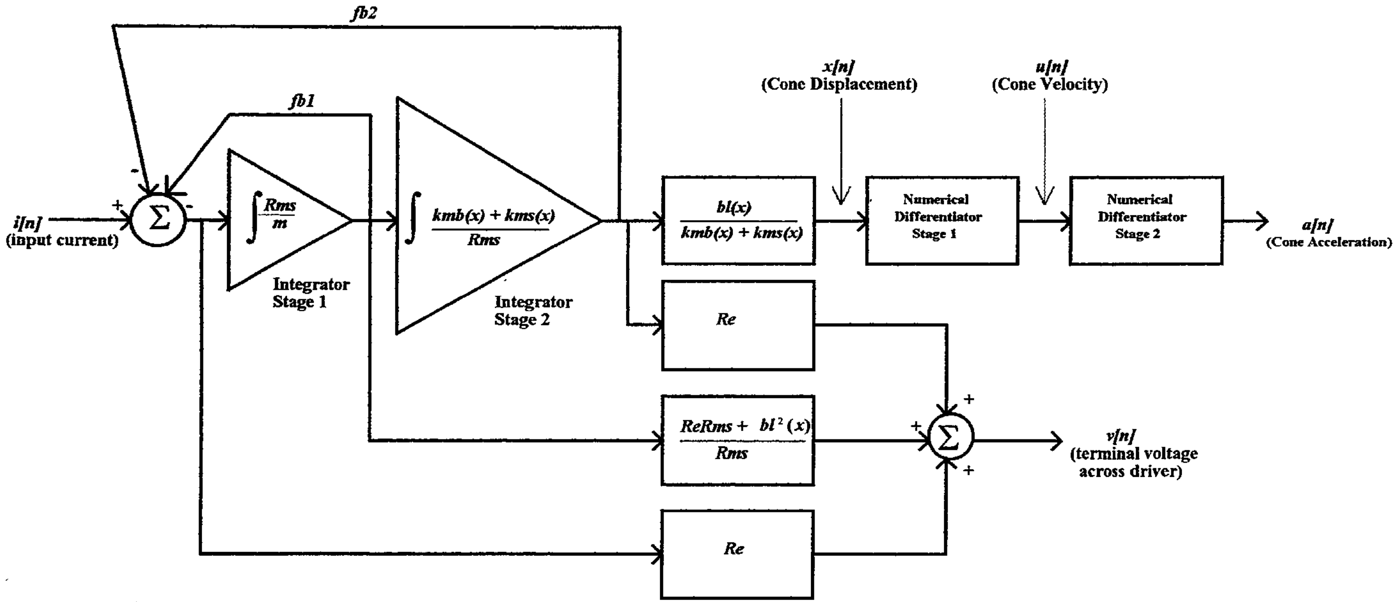
1. Non-linear suspension stiffness (or compliance) of the loudspeaker spider and outer rim with cone excursion*
2. Mechanical clipping and compression * of the voice coil
3. Hysteresis effect of the displacement or driving force of the voice coil
4. Generation of sub-harmonics (or rocking) due to cone material non-linearities at extreme drive levels
5. Adiabatic compression of enclosed air in closed-box systems* (box compliance or box spring force)

*C. NON-LINEARITIES IN RADIATED SOUND*

1. Doppler Distortion
2. Contributions of non-ideal room acoustical conditions

*** Included in current drive model.**

***Figure 4***




Legend: *fb1, fb2 - Non-linear Feedback*
*Re - Voice Coil Resistance*
*Rms - Mechanical Resistive Losses*
*bl(x) - Non-linear Force Factor*
*kmb(x) - Non-linear Box Spring Force*
*kms(x) - Non-linear Suspension Spring Force*
*m - Moving Cone Mass*

*Figure 5 - Transient Analysis Model of a Current Drive Loudspeaker System.*

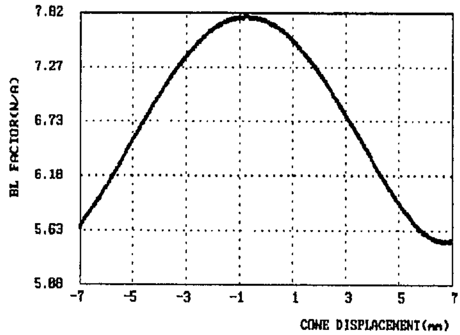



*Figure 6(a) - Plot of bl factor variation with cone displacement*

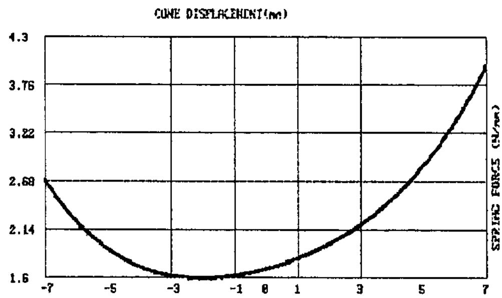



*Figure 6(b) - Plot of suspension spring force variation with cone displacement*

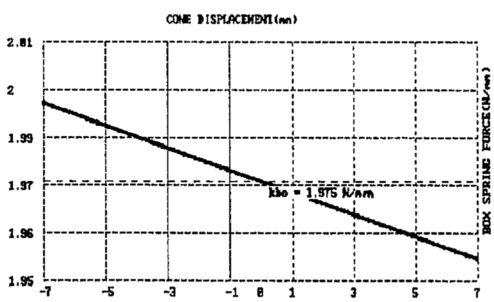



*Figure 6(c) - Plot of Box Spring Force variation with Cone Displacement*

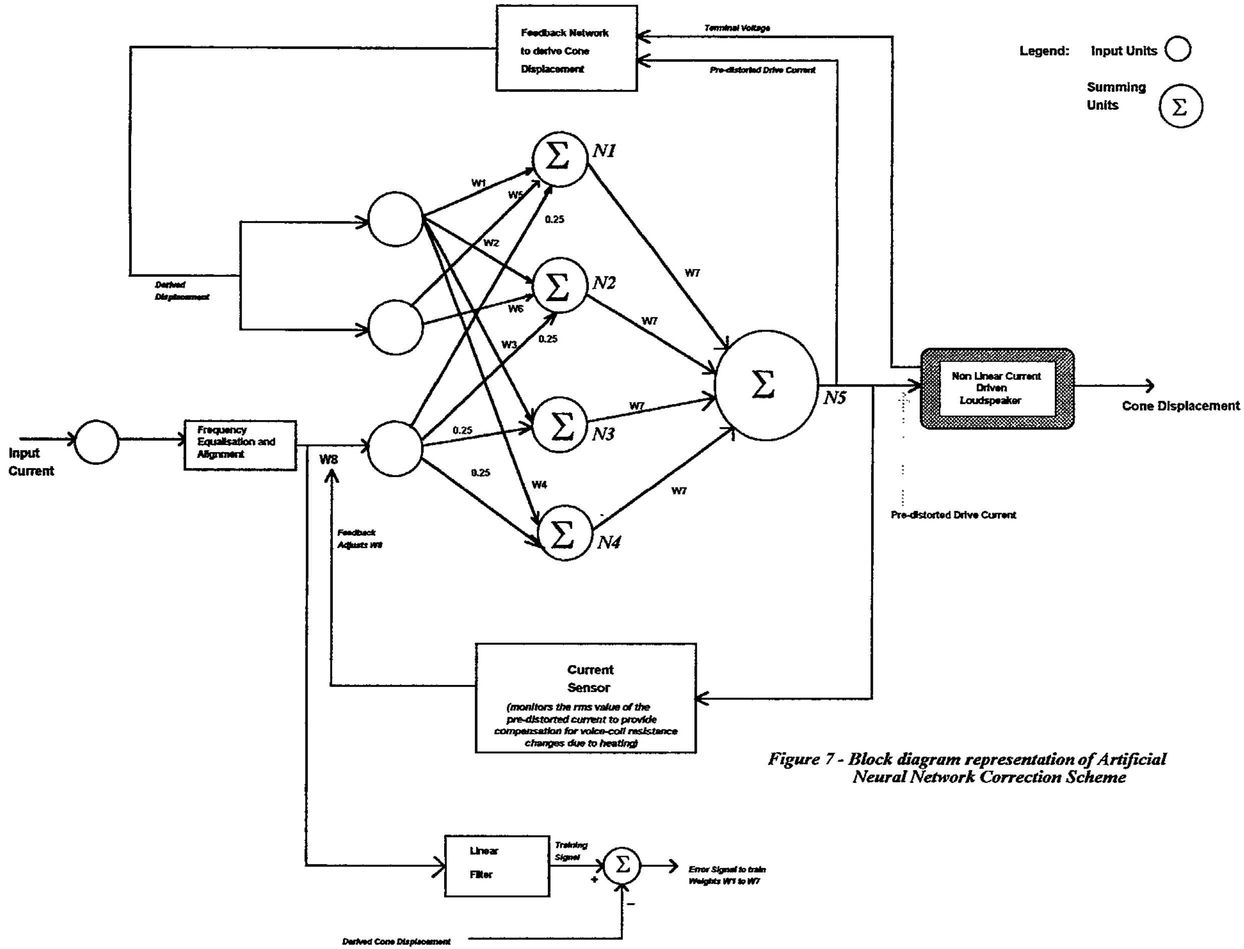
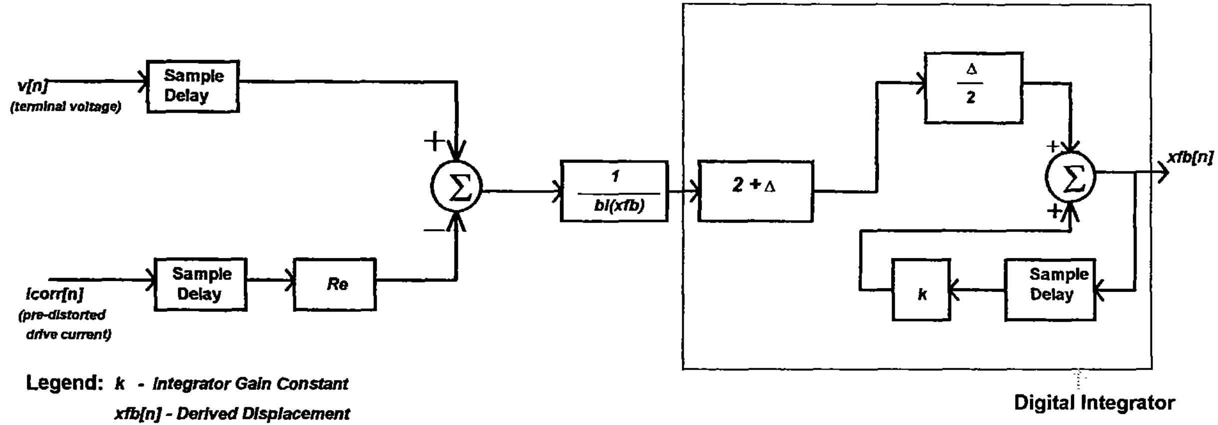



*Figure 7 - Block diagram representation of Artificial Neural Network Correction Scheme*




**Legend:** *k - Integrator Gain Constant*

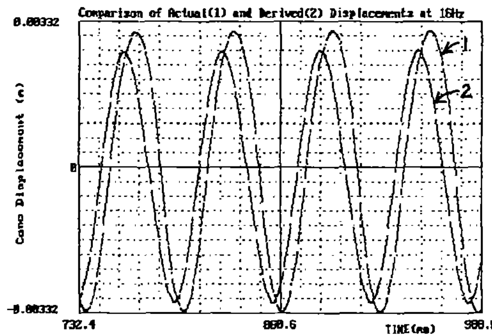
*xfb[n] - Derived Displacement*

*Re - Voice Coil Resistance*

*Δ – Incremental Step Size*

*Figure 8(a) - Terminal Voltage feedback scheme to derive the instantaneous cone displacement of a current drive loudspeaker.*

*Figure 8(b) - Time domain plots of the actual(1) and derive(2) cone displacement of a current drive loudspeaker at 16 Hz. Notice that the derived displacement obtained from the voltage feedback scheme follows the actual displacement with good accuracy.*



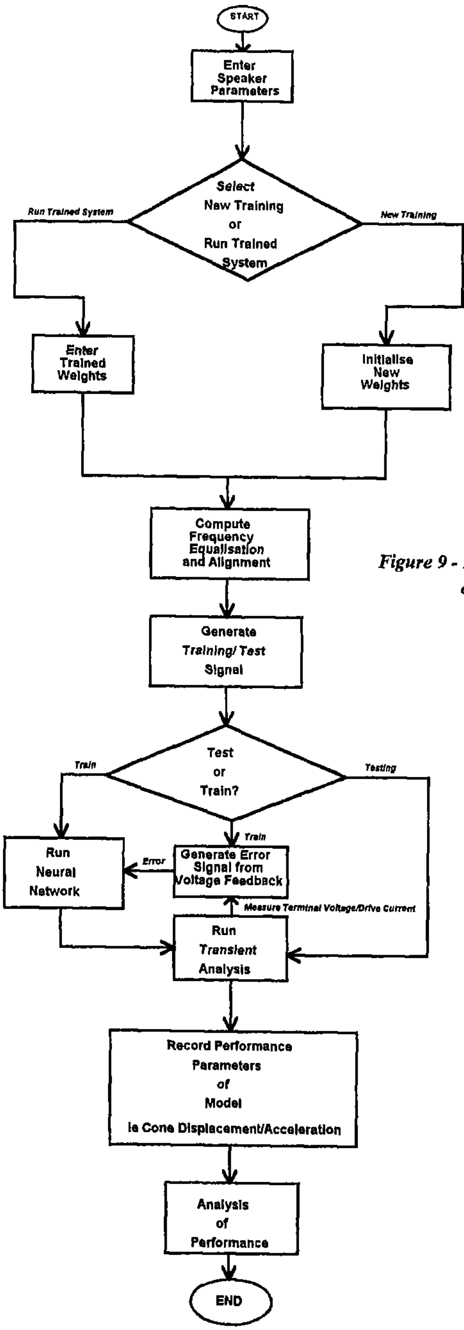



*Figure 9 - Flowchart Description of Simulation Strategy*

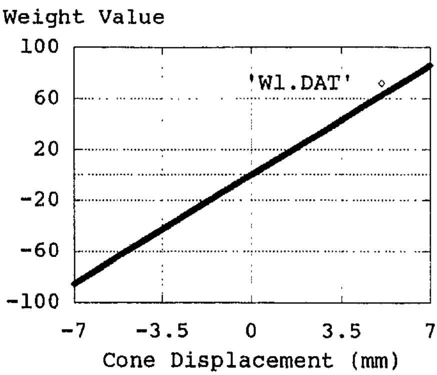



*Figure 10(a) - Initial Values of weight w1 which compensate for the first order non-linearity of the suspension spring force.*

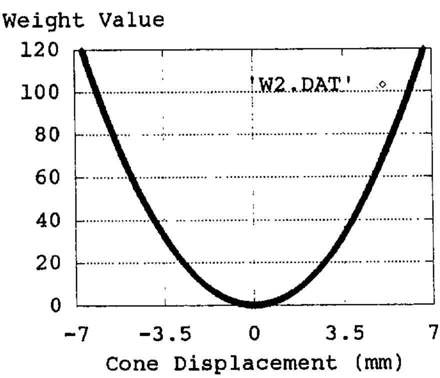



*Figure 10(b) - Initial Values of weight w2 which compensate for the second order non-linearity of the suspension spring force.*

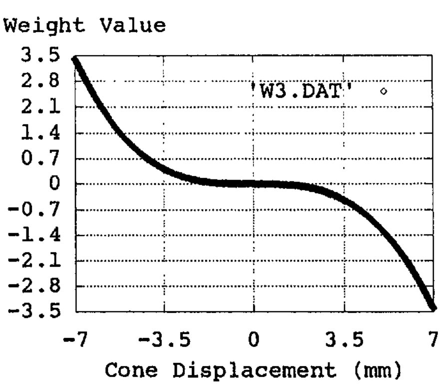



*Figure 10(c) - Initial Values of weight w3 which compensate for the third order non-linearity of the suspension spring force.*

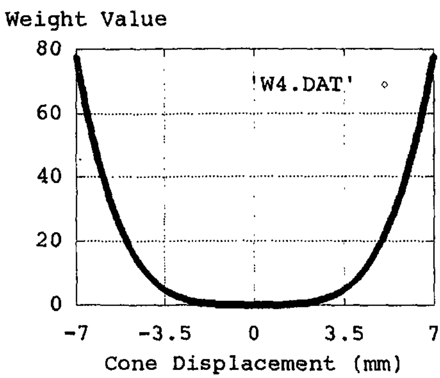



***Figure 10(d) - Initial Values of weight w4 which compensate for the fourth order non-linearity of the suspension spring force.***

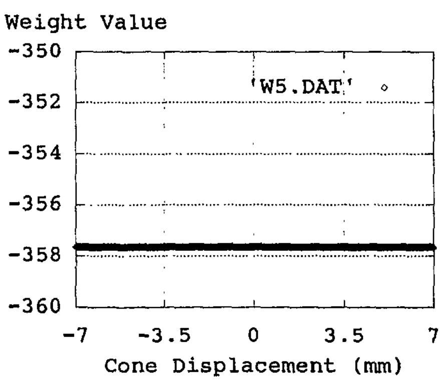



***Figure 10(e) - Initial Values of weight w5 which provides first order compensation for the box spring force.***

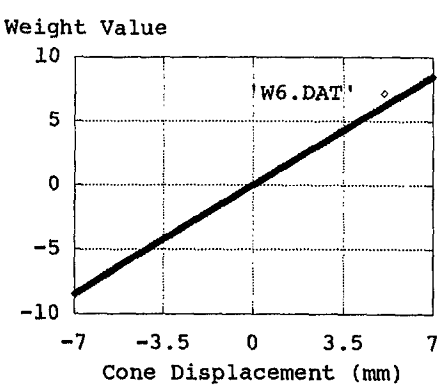



***Figure 10(f) - Initial Values of weight w6 which compensates for the second order non-linearity in the box spring force.***

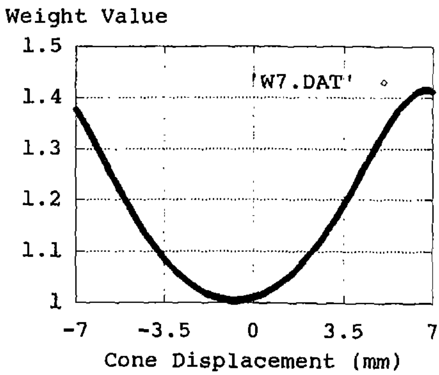



*Figure 10(g) - Initial Values of weight w7 which provide correction for the bl force non-linearity.*

| STEP | *xfb[n]* | W1 | W2 | W3 | W4 | W5 | W6 | W7 |
|---|---|---|---|---|---|---|---|---|
| 1 | -7.0 | -85.67 | 131.172 | 3.4213 | 77.947 | -357.6557 | -8.512 | 1.3773 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 2037 | -0.041 | -0.502 | 0.004503 | 1.0e-6 | 0.0 | -357.6557 | -0.0499 | 1.00902 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 4096 | 6.997 | 85.628 | 131.044 | -3.4162 | 77.794 | -357.7557 | 8.508 | 1.4125 |
| | | Weight Values that are varied during training | | | | | | |

Nth Step

Derived Cone Displacement in mm

***Figure 11 - Structural Layout of Look-Up Table used in the look-up table weight initialisation scheme. The synaptic strengths of weights w1 to w7 in a certain row are varied if indexed by the step number N which is computed from a knowledge of the derived cone displacement.***

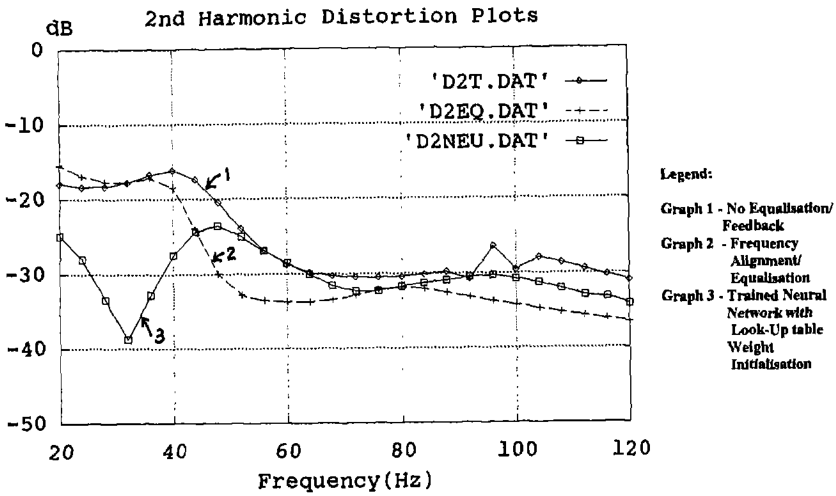



*Figure 12(a) - 2nd Harmonic Distortion Comparison Plots of three different current drive loudspeaker models.*

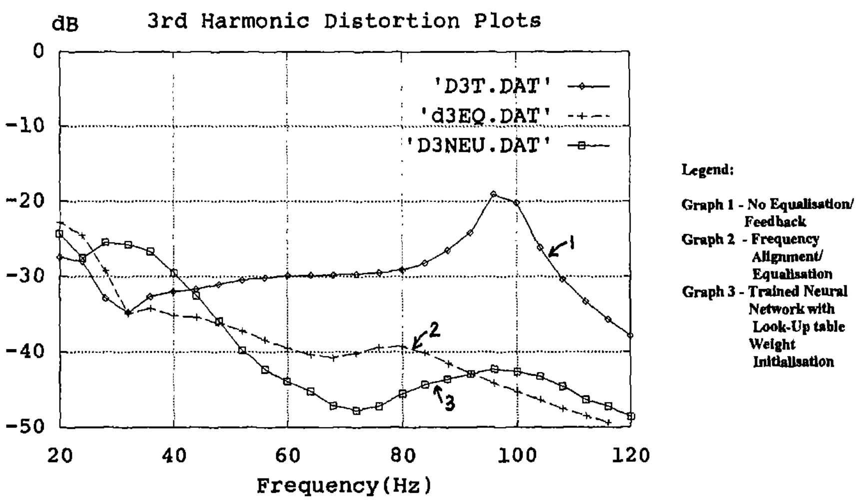



*Figure 12(b) - 3rd Harmonic Distortion Plots of three different current drive loudspeaker models*

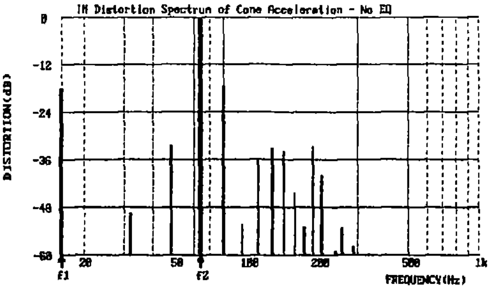



***Figure 13(a) - Intermodulation Distortion Plot of an curent drive loudspeaker model without alignment and equalisation.***

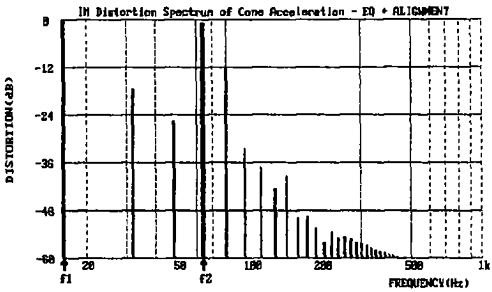



***Figure 13(b) - Intermodulation Distortion Plot of a Frequency Aligned/Equalised current drive loudspeaker model.***

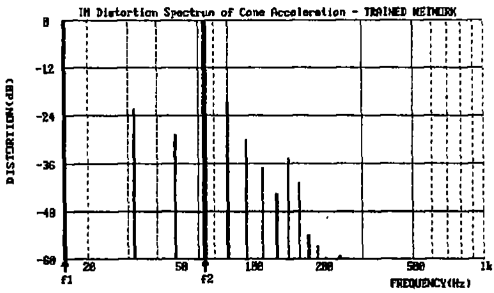



***Figure 13(c) - Intermodulation Distortion Plot of a trained artificial neural network compensated current drive loudspeaker model which uses a look-up table weight initialisation scheme.***

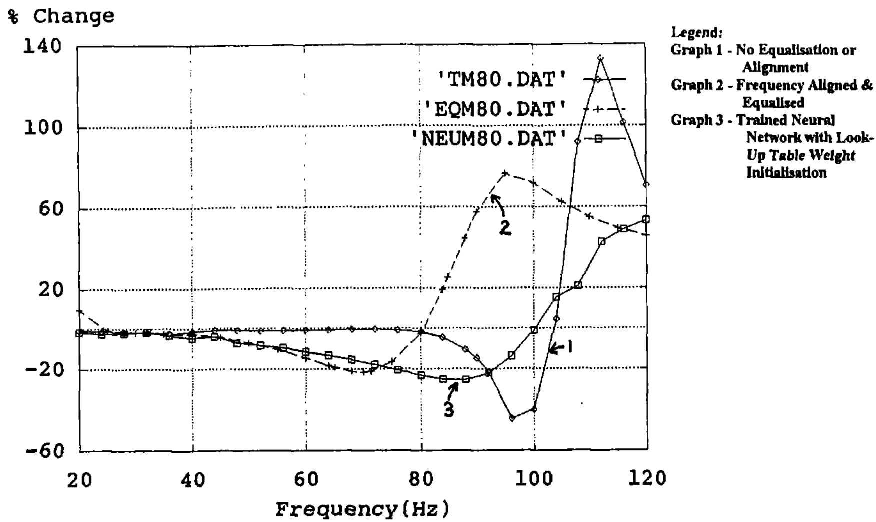



*Figure 14(a) - Comparisons of sensitivity to cone mass variations for three different current drive models. The cone mass is reduced by 20% from that of the design value. The y-axis records the percentage change in cone displacement at different frequencies referenced against the cone displacement obtained when the mass is of the correct design value.*

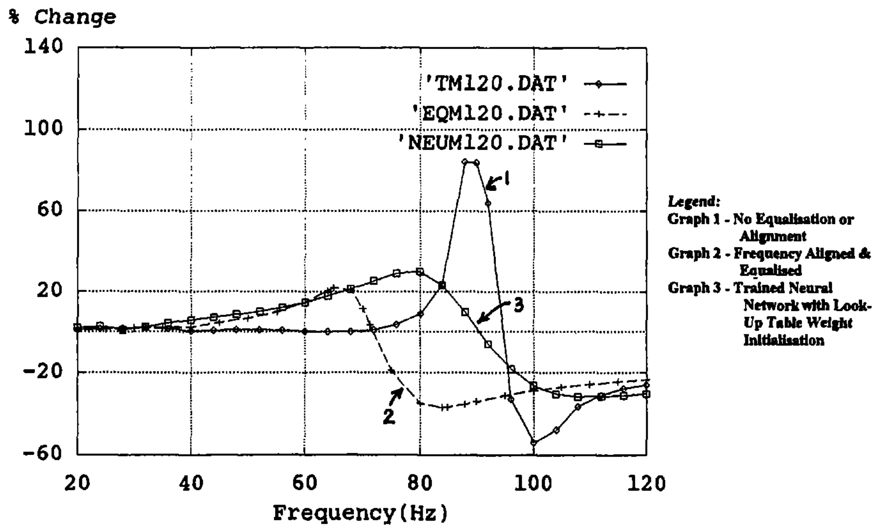



*Figure 14(b) - In this figure, the cone mass is increased by 20% and the percentage change in cone displacement is plotted against frequency for three different current drive models.*