The Use of Artificial Neural Networks to Predict Pure Tone Thresholds in Normal and Hearing- Impaired Ears with Distortion Product Otoacoustic Emissions

by

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Abstract

Title	:	The Use of Artificial Neural Networks to Predict Pure Tone Thresholds in Normal and Hearing- Impaired Ears with Distortion Product Otoacoustic Emissions
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In the evaluation of special populations, such as neonates, infants and malingerers, audiologist often have to rely heavily on objective measurements to assess hearing ability. Current objective audiological procedures such as tympanometry, the acoustic reflex, auditory brainstem response and transient evoked otoacoustic emissions, however, have certain limitations, contributing to the need of an objective, non-invasive, rapid, economic test of hearing that evaluate hearing ability in a wide range

of frequencies. The purpose of this study was to investigate distortion product otoacoustic emissions (DPOAEs) as an objective test of hearing. The main aim was to attempt to predict hearing ability at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz with DPOAEs and artificial neural networks (ANNs) in normal and hearing-impaired ears. Other studies that attempted to predict hearing ability with DPOAEs and conventional statistical methods were only able to distinguish between normal and impaired hearing.

Back propagation neural networks were trained with the pattern of all present and absent DPOAE responses of 11 DPOAE frequencies of eight DP Grams and pure tone thresholds at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz. The neural network used the learned correlation between these two data sets to predict hearing ability at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz. Hearing ability was not predicted as a decibel value, but into one of several categories spanning 10-15dB.

Results indicated that prediction accuracy of normal hearing was 92% at 500 Hz, 87% at 1000 Hz, 84% at 2000 Hz and 91% at 4000 Hz. The prediction of hearing-impaired categories was less satisfactory, due to insufficient data for the ANNs to train on. The variables age and gender were included in some of the neural network runs to determine their effect on the distortion product. Gender had only a minor positive effect on prediction accuracy, but age affected prediction accuracy considerably in a positive way. The effect of the amount of data that the neural network had to train on was also investigated. A prediction versus ear count correlation strongly suggested that the inaccurate predictions of hearing-impaired categories is not a result of an

inability of DPOAEs to predict pure tone thresholds in hearing impaired ears, but a result of insufficient data for the neural network to train on.

This research concluded that DPOAEs and ANNs can be used to accurately predict hearing ability within 10dB in normal and hearing-impaired ears from 500 Hz to 4000 Hz for hearing losses of up to 65dB HL.

Key words: otoacoustic emissions, distortion product otoacoustic emissions, artificial neural networks, prediction of hearing threshold, age and gender, objective hearing assessment.

Opsomming

Titel	:	Die Voorspelling van Suiwertoondrempels in Normale en Gehoorgestremde ore met behulp van Distorsie Produk Otoakoestiese Emissies en Kunsmatige Neurale Netwerke
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In die evaluasie van spesiale populasies, soos neonate, kleuters en persone wat gehoorverliese voorgee, moet oudioloë dikwels steun op objektiewe metings om gehoorvermoë te evalueer. Huidige objektiewe oudiologiese prosedures, soos timpanometrie, die akoestiese refleks, ouditiewe breinstam respons en transient-ontlokte otoakoestiese emissies, het egter soveel tekortkominge, dat daar steeds 'n behoefte bestaan vir 'n objektiewe, vinnige en ekonomiese toetsprosedure, wat

gehoorvermoë in 'n wye frekwensiegebied evalueer. Die doel van hierdie studie was, om distorsie produk otoakoestiese emissies (DPOAEs) te ondersoek as a moontlike nuwe objektiewe gehoortoets. Daar is gepoog om gehoordrempels by 500 Hz, 1000 Hz, 2000 Hz en 4000 Hz te voorspel met DPOAEs en kunsmatige neurale netwerke in normale en gehoorgestremde ore. Ander studies wat gepoog het om gehoorvermoë te voorspel met DPOAEs en konvensionele statistiese metodes, was slegs in staat om tussen normale en gehoorgstremde ore te onderskei.

Neurale netwerke is opgelei met die partoon van alle aanwesige en afwesige DPOAE response van 11 DPOAE frekwensies en agt DP Gramme, sowel as suiwertoondrempels by 500 Hz, 1000 Hz, 2000 Hz en 4000 Hz. Die neurale netwerk het die geleerde korrelasie tussen die twee data stelle toegepas om gehoorvermoë te voorspel by 500 Hz, 1000 Hz, 2000 Hz en 4000 Hz. Gehoorvermoë is nie as 'n desibel waarde voorspel nie, maar in 'n kategorie met 'n grootte van 10-15dB.

Resultate het gedui op voorspellingsakkuraatheid van normale gehoor van 92% by 500 Hz, 87% by 1000 Hz, 84% by 2000 Hz en 91% by 4000 Hz. Die voorspellings van kategorie waardes by gehoorgestremdheid was minder bevredigend weens onvoldoende data vir die opleiding van die neurale netwerk. Die veranderlikes ouderdom en geslag, is ook ingesluit in sommige van die neurale netwerke om die effek daarvan te bepaal op die distorsie produk. Geslag het slegs 'n minimale positiewe effek op voorspellingsakkuraatheid gehad, maar ouerdom het die voorspellingsakkuraatheid van die neurale netwerk aansienlik verbeter. Die uitwerking van die hoeveelheid data in elke kategorie wat beskikbaar was vir die neurale netwerk in die opleidingsfase op voorspellingsakkuraatheid, is ook ondersoek.

Die voorspellingsakkuraatheid versus die hoeveelheid ore in elke kategorie is met mekaar gekorreleer. Hierdie bevinding dui daarop dat die onvermoë om kategorië met gehoorverliese te voorspel, nie 'n tekortkoming van DPOAEs is nie, maar as gevolg van die onvoldoende data wat die neurale netwerk gehad het in die opleidingsfase.

Die gevolgtrekking van hierdie studie dui daarop dat DPOAEs en neurale netwerke gebruik kan word om gehoorvermoë binne 10dB akkuraatheid te voorspel in normale en gehoorgestremde ore, van 500 Hz tot 4000 Hz vir gehoorverliese tot en met 65dB.

Sleutelwoorde: otoakoestiese emissies, distorsie produk otoakoestiese emissies, neurale netwerke, voorspelling van gehoordrempels, ouderdom en geslag, objektiewe meting van gehoorvermoë.

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Abbreviations Used in this Study

ABLB	:	Alternate Binaural Loudness Balance
ABR	:	Auditory Brainstem Response
AEPs	:	Auditory Evoked Potentials
ANNs	:	Artificial Neural Networks
ANS	:	Artificial Neural System
dB	:	decibel
DP	:	Distortion Product
DP Gram	:	Distortion Product Audiogram
DPOAEs	:	Distortion Product Otoacoustic Emissions
EcochG	:	Electrocochleography
EEG	:	Electroencephalogram
EOAEs	:	Evoked Otoacoustic Emissions
GM	:	Geometric Mean
HL	:	Hearing Level
Hz	:	Hertz
I/O Function	:	Input/ Output Function
LLR	:	Long Latency Response
MLR	:	Middle Latency Response
OAEs	:	Otoacoustic Emissions
OHC	:	Outer Hair Cells
PTA	:	Pure Tone Average
PTT	:	Pure Tone Threshold
SFEs	:	Stimulus Frequency Emissions

SISI	:	Short Increment Sensitivity Index
SLRs	:	Short Latency Responses
SOAEs	:	Spontaneous Otoacoustic Emissions
SPAR	:	Sensitivity Prediction with the Acoustic Reflex
SPL	:	Sound Pressure Level
TEOAEs	:	Transient Evoked Otoacoustic Emissions

1 Introduction, Orientation, and Rationale

1.1 Introduction

Ever since Kemp (1978) first described otoacoustic emissions (OAEs), there has been an interest in the use of these measures to develop another diagnostic tool to predict hearing ability objectively, non-invasively, and rapidly. One might ask why the development of *another* objective diagnostic tool should be investigated if so many technologically advanced audiological tests already exist. The field of audiology exploded in the 1970s with electrophysiological test procedures such as tympanometry, acoustic reflex, auditory brainstem response, and otoacoustic emissions. All of these procedures were recently incorporated into audiological test batteries and are currently used routinely (Northern, 1991). These test batteries are used quite effectively in site of lesion testing and to determine hearing ability across a wide range of populations (Robinette, 1994). To better understand the need for another diagnostic tool to predict hearing ability objectively, a short overview of objective diagnostic procedures will be given.

1.2 Overview of Objective Diagnostic Procedures in Audiology

For many decades, diagnostic audiology relied on behavioral testing procedures in which hearing thresholds were determined by studying the listener's motor responses (Yantis, 1994). The first behavioral audiology test battery was developed in 1920 when bone conductors and speech channels became a standard feature included in an audiometer's capabilities (Brunt, 1994). For three decades, audiological tests were developed with only these basic features. Tests that were developed included the ABLB test for loudness growth to indicate cochlear pathology in the 1930s, the tone decay test to indicate retrocochlear pathology in the 1940s, and the SISI (Short Increment Sensitivity Index) for cochlear pathology in the 1950s (Brunt, 1994).

The first objective physiological procedure was developed in the 1970s. Progress in technology enabled audiologists to measure minimal changes in air pressure in the external meatus, which resulted in a completely new diagnostic tool, tympanometry. This allowed audiologists to obtain information not only about middle ear pressure and tympanic membrane movement but also about the stapedius reflex. This resulted in a variety of objective diagnostic functions, such as an indication of middle ear pathology, cochlear pathology when loudness recruitment is present, and retrocochlear pathology when reflex decay occurs. One application of the acoustic reflex, sensitivity prediction with the acoustic reflex (SPAR), was developed by Jerger in the 1970s to predict hearing ability (Northern & Gabbard, 1994). SPAR predicts hearing ability as normal, moderately impaired, or severely impaired. According to a study by Jerger in 1978 (cited in Northern & Gabbard, 1994), normal hearing ability was accurately predicted 100% of the time, severe hearing loss 85% of the time, and moderate hearing losses 54% of the time. However, SPAR is influenced by a number of variables, such as chronological age (children between 0 and 10 are most accurately predicted), minor middle ear abnormalities, and audiometric configuration. Even though prediction of moderate hearing levels is only slightly better than chance, in difficult-to-test populations SPAR can often offer a rapid, economical, and objective estimate of hearing sensitivity and is also useful in screening (Northern & Gabbard, 1994).

Tympanometry allowed audiologists to verify results obtained with behavioral audiometry objectively, for the first time. Today, pure tone air conduction and bone conduction, speech audiometry, and tympanometry still form the basis of every test battery (Robinette, 1994).

The second development toward objective audiological measurements also occurred in the 1970s, when audiologists began to measure the electric potentials of the nervous system with surface electrodes. Auditory evoked potentials (AEPs) occur in different time intervals after stimulation and provide information about the cochlea, auditory nerve, and brainstem. AEPs are usually classified by their "latency epoch," the time domain within which the response occurs after stimulus onset (Ferraro & Durrant, 1994). AEPs occurring in the first 10–15 milliseconds are known as short latency responses (SLRs). SLRs include the auditory brainstem response (ABR) and components preceding the ABR that are recorded via cochleography (ECoghG). EcochG is used for a variety of applications, such as the enhancement of wave I in ABR testing, when test conditions are less than optimal or when a hearing loss is present. EcochG is also used to monitor Meniere's disease and to monitor cochlear and nerve functioning during surgical procedures that might permanently damage those structures. SLRs arise from the periphery and brainstem (Ruth, 1994).

Middle latency responses (MLRs), which refer to components in the latency epoch of 10–50 milliseconds, are generated in structures beyond the inferior colliculus (Kraus, Kileny & McGee, 1994). MLRs are clinically used to objectively determine hearing ability in the lower frequencies. They are also used to assess the cochlear implant function and to localize auditory pathway lesions (Kraus et al., 1994). However, MLRs are affected by sleep and cannot be detected in certain phases of sleep. It is possible to monitor sleep phases with EEG measurements and to conduct MLR testing only in favorable sleep periods, but this requires much more expertise and expensive equipment. The fact that MLRs are affected by the subject's level of consciousness has limited their popularity as an objective diagnostic procedure (Ferraro & Durrant, 1994).

Components generated beyond 50–80 milliseconds post-stimulus onset are long latency responses (LLRs) and are cortically generated (Kraus et al., 1994). An example of an LLR measurement is the N_1-P_2 Complex, which was successfully used as an indicator of hearing sensitivity in difficult-to-test populations and also to detect lesions in the central auditory pathway (Ferraro & Durrant, 1994). Just like the MLR, the N_1-P_2 Complex is sensitive to the subject's state of consciousness. Another example of LLR is the P_{300}, whose most common uses include studies of aging, dementia, and attention disorders (Ferraro & Durrant, 1994).

Auditory evoked potentials (AEPs) did not enjoy widespread acceptance or clinical application until the discovery of the auditory brainstem response (ABR). Although Sohmer and Feinmesser (1967) are generally recognized as the first to report recording auditory evoked responses from the eighth nerve, it was Jewett and Williston (1971) who labeled the seven waves and set the basis for ABR testing (cited in Robinette, 1994).

The ABR dominated clinical attention to AEPs for about a decade and is still a very popular test of auditory function for difficult-to-test populations (Ferraro & Durrant, 1994). Behavioral evaluation of very young infants relies on spontaneous responses such as eye and head movements. Even with some kind of reinforcement, these responses cannot be elicited near the threshold value. Presentation of stimuli is via loudspeakers, which does not provide information about hearing ability in separate ears. All these limitations of behavioral hearing testing made ABR the preferred objective audiologic technique for infants younger than 6 months (Weber, 1994). With ABR, stimuli are presented via earphones, making it possible to test the hearing status of the individual ears. ABR enables the audiologist to obtain responses to low stimulus intensity levels from sleeping infants. As Robinette (1994) stated, the ABR is popular in the evaluation of hearing when traditional behavioral tests are precluded or their results are equivocal.

The ABR is, however, not without its own shortcomings. First, the frequency range in which hearing ability can be determined with ABR is limited. ABR testing with click stimuli provides only a one-point audiogram in the 2000–4000 Hz region. This is due to the type of stimuli needed to elicit an ABR—namely, abrupt onset acoustic clicks. The more abrupt the stimulus onset, the more neural fibers will respond in synchrony and the more clearly defined the ABR (Weber, 1994). The acoustic click has its greatest energy around 3000 Hz, therefore creating the stimulus range from 2000 to 4000 Hz.

Attempts to gain information about the low frequencies created a new set of problems. The use of low frequency tone bursts with abrupt stimulus onset resulted in high frequency contamination. (An abrupt stimulus onset might stimulate broad areas of the basilar membrane.) Investigators have used several alternative techniques in an attempt to gain reliable and frequency-specific low frequency information such as masking techniques and filtering. Weber (1994) wrote that "the quest continues for a sensitive and robust electrophysiologic measure of low frequency hearing status that can be used with the sleeping child" (p. 382).

The second shortcoming of ABR testing is the amount of time the test requires. It can take more than 30 minutes to obtain a single ABR threshold for each ear (Weber, 1994).

The third weakness is the possibility of sedation. When testing of hearing ability close to the threshold is performed, it can be affected by patient movement artifacts. The child should therefore be as still as possible, preferably asleep. When infants younger than 6 months are tested, it can be assumed that there will be periods of sleep long enough for ABR testing. For older infants, it is often necessary to ensure adequate test conditions by giving the child some form of sedative, usually administered orally (Weber, 1994).

Lastly, ABR requires highly trained personnel and is a relatively expensive procedure (Musiek, Borenstein, Hall III & Schwaber, 1994).

At the end of the 1970s, another objective way to evaluate hearing ability was discovered by David Kemp (1978), who called it otoacoustic emissions—that is, sounds generated from a normal cochlea either spontaneously or in the presence of acoustic stimulation. It appeared that normal cochleae emitted these responses, whereas ears with a hearing loss >35 dB HL did not.

Kemp's (1978) original reports were greeted rather skeptically, and much early research only replicated his study to confirm the presence of otoacoustic emissions. After two decades of intensive research, however, there is much excitement among researchers, since certain types of otoacoustic emissions prove to be highly applicable in the areas of hearing screening and even diagnostic audiology (Kummer, Janssen & Arnold, 1998; Martin, Probst & Lonsbury-Martin, 1990; Stach, Wolf & Bland, 1993; Stover, Gorga & Neely, 1996a). Many researchers hope that this relatively new field in audiology will prove to be the long-awaited objective, rapid, and accurate test of auditory function to aid in the assessment of difficult-to-test populations.

Otoacoustic measurement will certainly never replace pure tone audiometry, immittance, or ABR, but OAEs offer diagnostic information regarding the auditory system that is not available from any other test. This new objective procedure will be discussed below in more detail.

1.3 Otoacoustic Emissions

Otoacoustic emissions are low intensity acoustic signals generated by the outer hair cells (OHC) in the organ of Corti on the basilar membrane either spontaneously or in the presence of acoustic stimulation. Brownell (1990) describes the outer hair cell motility as a lengthening or shortening of the outer hair cells in response to acoustic stimulation. This active biological mechanism in the outer hair cells causes a vibration of the basilar membrane in an attempt to enhance the ear's sharpness and sensitivity (Attias, Furst, Furman, Haran, Horowitz & Breslof, 1995). The vibration of certain areas of the basilar membrane amplifies the basilar membrane's response to low level sound (Lonsbury-Martin, McCoy, Whitehead & Martin, 1992). This vibration, called an otoacoustic emission, can be recorded using a very sensitive microphone placed in the ear canal.

The primary value of otoacoustic emissions is that their presence indicates that the preneural cochlear mechanism (and middle ear as well) can respond to sound in a normal manner. A large area of the basilar membrane is stimulated, and the measured emissions are frequency-specific and frequency selective, so it is possible to gain information about different areas of the cochlea simultaneously. "No other clinical test," wrote Kemp, Ryan, and Bray (1990), "specifically tests cochlear biomechanisms or combines the operational speed, non-invasivity, objectivity, sensitivity, frequency selectivity, and noise immunity of otoacoustic emission testing" (p. 94).

Kemp (1978) described two main classes of otoacoustic emissions: spontaneous otoacoustic emissions (SOAEs) and evoked otoacoustic emissions (EOAEs), which will be described below.

<u>1.3.1 Spontaneous Otoacoustic Emissions (SOAEs)</u>

SOAEs are tonal or narrowband low level signals that can be recorded in the absence of any auditory stimulation in only 50% of all persons with hearing levels <20 dB HL and in 60% of persons with hearing levels <30 dB HL (Lonsbury-Martin, 1994). Because of this low incidence of SOAEs, they are not viewed as a suitable clinical indicator of the mechanical activity of the cochlea (Lonsbury-Martin, 1994; Norton & Stover, 1994). After Kemp (1978) reported the existence of SOAEs, many clinicians hoped that they would be the objective basis for tinnitus. It has been proved, however, that most people are unaware of their spontaneous otoacoustic emissions, and only a very small percentage of people with tinnitus have recordable SOAEs that can be linked to their tinnitus (Norton, Schmidt, & Stover, 1990). Spontaneous otoacoustic emissions can therefore only be used as a complementary technique for evoked otoacoustic emissions (Bonfils, Avan, Francois, Marie, Trotoux & Narcy, 1990).

Several types of evoked OAEs exist, depending on the type of stimulus used during the measurement. Evoked emission types include stimulus frequency emissions, transient evoked otoacoustic emissions, and distortion product otoacoustic emissions.

1.3.2 Stimulus Frequency Otoacoustic Emissions (SFEs)

A stimulus frequency otoacoustic emission (SFE) is the most frequency-specific of all emission types, but it is also probably the least clinically applicable (Norton & Stover, 1994). SFEs reflect the response of the cochlea at a certain pure tone, occurring simultaneously with and at the same frequency as the stimulus presented. When a tone is presented to the ear, the sound pressure measured in the ear canal is the sum of the sound pressure of the stimulus and the response. In the case of other evoked emission types, the stimulus sound pressure level is separated from the response either spectrally (as in the case of distortion product otoacoustic emissions) or temporally (as in the case of transient evoked otoacoustic emissions). Due to the lack of temporal or spectral separation techniques in measuring SFEs, more sophisticated equipment and processing of data are required, and therefore SFEs are not currently practical for clinical use (Lonsbury-Martin & Martin, 1990; Norton & Stover, 1994). Lonsbury-Martin, (1994) described this phenomenon quite effectively: "SFEs are technically difficult to measure, due to the complexities of separating the in-going acoustic stimulus from the out-going emitted response. Thus, to date, little information has accumulated concerning either their basic nature or their clinical utility" (p. 2).

1.3.3 Transient Evoked Otoacoustic Emissions (TEOAEs)

TEOAEs are responses that follow a brief acoustic stimulus such as a click or a tone burst. TEOAEs can be recorded in nearly all persons with normal hearing (hearing levels < 20 dB from 500 Hz to 4000 Hz) and are absent in all ears with a hearing loss 30–40 dB HL. (Hearing loss > 40 dB HL according to Glattke, Pafitis, Cummiskey, & Herer, 1995; hearing loss > 35dB according to Robinette, 1992; or hearing loss > 30 dB according to Kemp et al., 1990.)

In measuring a TEOAE, a probe is inserted into the ear canal, containing a miniature sound source for delivering the stimulus and a very sensitive microphone for detecting the response. TEOAEs are obtained by using synchronous time-domain averaging techniques. Responses to several stimuli (e.g., 500–2000 clicks) are averaged to improve the signal-to-noise ratio and make the response distinguishable from the noise floor (Glattke et al., 1995). The ear canal sound pressure is amplified, filtered, and then digitized, and the first 2.5 seconds of the response are eliminated to remove the stimulus (Norton & Stover, 1994). This process is presented schematically in Figure 1.1.

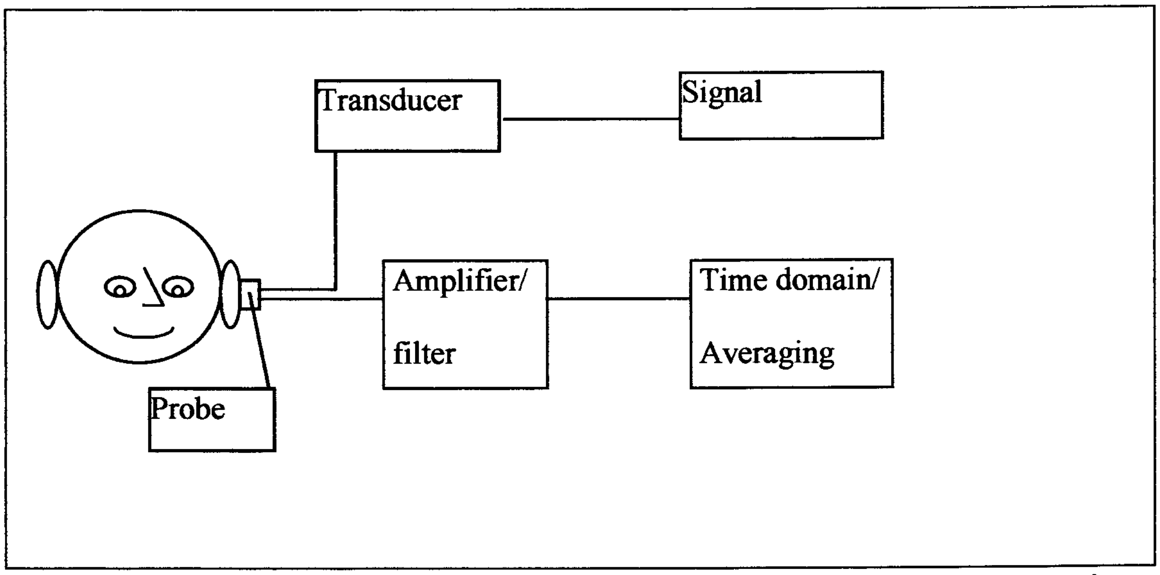


Figure 1.1: Schematic diagram of a representative system for measuring TEOAEs (Norton & Stover, 1994:450)

Another characteristic aspect of TEOAEs is that they are frequency dispersive: high frequencies coded basally on the basilar membrane have a shorter latency (4 ms for 5000 Hz) than low frequencies, coded apically on the basilar membrane (20 ms for 500 Hz). According to Kemp et al. (1990), this provides for temporal separation of the stimulus's and response's sound pressure level, both measured in the ear canal.

The frequency specificity of TEOAEs is determined by the bandwidth of the stimuli being used to elicit a response. Emissions can be evoked at most frequencies in the normal cochlea. The broader the stimulus spectrum, the broader the emission spectrum (Norton & Stover, 1994). Broadband clicks are usually used for measuring TEOAEs, which allows for simultaneous multifrequency testing (Kemp & Ryan, 1993). TEOAEs provide simultaneous information regarding the functioning of the outer hair cells on the basilar membrane for a very broad region of frequencies (Kemp et al., 1990; Norton & Stover, 1994). Some frequency-specific information can be gained by analyzing the spectral distribution. Kemp et al. (1990) successfully used TEOAEs to identify frequency ranges of normal hearing in pathological ears. In a case with a high frequency hearing loss, they obtained emissions up to the frequency of the hearing loss and no emissions for the pathological frequencies. It should be noted, however, that no information regarding the thresholds of the pathological frequencies could be obtained. Many other researchers have also had difficulty in making comparisons between frequency-specific audiometric thresholds and frequency information provided by TEOAEs (Bonfils et al., 1990; Lee, Kimberley & Brown, 1993; Lonsbury-Martin & Martin, 1990). The fact that no emissions can be obtained when the hearing loss exceeds 30–40 dB HL has proven TEOAEs to be more applicable in the area of hearing screening than diagnostic audiology (Harris & Probst, 1991; Lee et al., 1993).

TEOAEs were the first method to be tried and recommended for neonatal hearing screening and are currently the most widely used OAE method for screening (Kemp & Ryan, 1993). TEOAEs can be measured very effectively in newborns. Both ears can be screened in a sleeping infant in about 10 minutes, compared to about 20 minutes with screening ABR (Norton & Stover, 1994). Another advantage of TEOAEs is that a broader frequency spectrum is being evaluated than with ABR, they do not require highly trained personnel, and they are objective and non-invasive (Lonsbury-Martin et al., 1992; Stevens et al., 1990).

TEOAEs do, however, have limitations. The first is that they are only recordable in normal and near-normal ears (30–35 dB HL). TEOAE data cannot be translated into "threshold data." An ear with a hearing loss of 65 dB will have the same absent response as an ear with a hearing threshold of 40 dB (Kemp et al., 1990). Although TEOAEs function as a wonderful screening procedure (Stevens et al., 1990), no information regarding hearing status can be obtained once the emission is absent, as in the case of mild and moderate hearing losses.

Another weakness of TEOAEs is that even in cases where the TEOAE response is present, this test can still not predict frequency-specific hearing levels from the emission spectrum (Lee et al., 1993). Hurley and Musiek (1994) indicated that TEOAEs are affected by small changes in cochlear physiology that do not result in comparable changes in auditory threshold. In other words, they found considerable TEOAE variability among ears with similar hearing sensitivity. TEOAEs could only classify hearing levels as normal (<20 dB HL) or abnormal (>20 dB HL).

Finally, it seems that TEOAE amplitude and occurrence are negatively affected by increasing age. Norton and Widen (1990) reported a statistically significant decrease in TEOAE amplitude with increasing age even in a carefully screened sample. Kemp et al. (1990) also indicated stronger responses as well as responses at more frequencies for neonates than adults. It is still unclear whether the age-associated changes are due to normal developmental changes in the middle ear or to progressively impaired cochlear function.

All the emission types previously discussed—namely, SOAEs, SFEs, and TEOAEs—all have one limitation in common. None of these emission types can function as an objective test of hearing where pure tones can be predicted given only the otoacoustic emissions (Bonfils et al., 1990; Hurley & Musiek, 1994; Lee et al., 1993; Lonsbury-Martin, 1994). The requirement for an emission type to be able to potentially predict pure tone thresholds given only the otoacoustic emissions is that the emission type should be present in normal and hearing impaired ears (Kimberley, Hernadi, Lee & Brown, 1994). It should also be frequency-specific and easily compared to the frequencies of the behavioral thresholds (Lee et al., 1993). There is one emission type that might prove to be clinically applicable in the prediction of behavioral pure tone thresholds—namely, distortion product otoacoustic emissions (Lee et al., 1993; Lonsbury-Martin & Martin, 1990).

1.3.4 Distortion Product Otoacoustic Emissions (DPOAEs)

DPOAEs can be recorded in virtually all normal hearing ears (100% according to Lee et al., 1993; and 95% according to Kimberley et al., 1994). DPOAEs can also be measured in ears with a mild to moderate sensorineural hearing loss. The second advantage of DPOAE measurement over the measurement of TEOAEs is the frequency specificity of the stimuli used. With DPOAEs, pure tone stimuli are used. The location of stimulation on the basilar membrane can be pinpointed quite accurately. Very specific information regarding outer hair cell function at any chosen location on the basilar membrane can be obtained with DPOAEs (Lonsbury-Martin & Martin, 1990). The facts that specific input frequencies can be selected and that responses are measured at certain frequencies make it easier to make comparisons between DPOAE results and conventional pure tone thresholds. This feature of DPOAE measurement makes it the best-suited emission type to relate to behavioral thresholds (Lee et al., 1993). Lastly, DPOAEs are the only otoacoustic emission type that can be recorded in the presence of a hearing loss. TEOAEs can only classify a person's hearing as normal or abnormal (Bonfils, Piron, Uziel & Pujol, 1988). DPOAEs can classify hearing ability as normal, slightly impaired, mildly impaired, moderately impaired, or severely impaired (in cases where no emissions can be measured) (Durrant, 1992; Gaskill & Brown, 1990; Lee et al., 1993). This advantage of DPOAEs allows emission testing of a much larger population with varying hearing sensitivity, making this one of the best reasons to develop DPOAEs as an additional objective test of hearing.

The distortion product with all its characteristics and complexities will be discussed in detail in Chapter 2.

1.4 Rationale for This Study

This overview of the development of objective diagnostic procedures clearly indicates the profound improvement in the ability to measure hearing equity since the 1920s. Progress in modern technology enabled audiologists to measure the exact degree, configuration, and site of hearing loss and to confirm these findings with a series of objective electrophysiologic procedures, such as tympanometry, the acoustic reflex, ABR, and otoacoustic emissions. It is, however, evident that there are some weaknesses in current objective diagnostic procedures. In the evaluation of special populations such as neonates from birth to 6 months, the crucially ill, and malingerers, audiologists often have to rely heavily on the objective electrophysiological procedures to determine hearing ability. To determine hearing thresholds with electrophysiological procedures are often costly, require a large amount of time and highly trained and specialized personnel, and may require sedation. Above all, current objective physiologic procedures, such as ABR, have a limited frequency area in which hearing ability can be determined accurately. There is therefore a definite need for an objective, reliable, rapid, and economic test of hearing that evaluates hearing ability across a range of frequencies to aid in the assessment of difficult-to-test populations.

The rationale for this study is to investigate one type of emission, the distortion product otoacoustic emission (DPOAE), as a possible new objective test of hearing. Such a test will be an objective, rapid, non-invasive, inexpensive, and accurate measurement of hearing that will have a profound implication for the field of Audiology as we know it (Kimberley et al., 1994). First, the objectivity of the measurement will make it an ideal testing procedure for difficult-to-test populations such as newborns, infants, the crucially ill, foreign speakers, the multiply handicapped, and malingerers (Elberling, Parbo, Johnsen & Bagi, 1985; Lonsbury-Martin, 1994). When combined with other tests such as pure tone audiometry, speech audiometry, acoustic immittance, ABR, or electrocochleography, this new procedure will greatly improve the differential diagnosis of hearing pathology. The primary site of lesion will be determined accurately as sensory or neural, or as a central auditory dysfunction (Lonsbury-Martin, 1994; Robinette, 1992). This test will vastly improve the assessment of the peripheral ear.

Chapter 2 will discuss the distortion product in more detail.

2 Distortion Product Otoacoustic Emissions

2.1 Introduction to Distortion Product Otoacoustic Emissions

Distortion product otoacoustic emissions are different from the other emission types in a number of ways. First, DPOAEs are elicited by the simultaneous presentation of two pure tones and the emission is an internally produced frequency different from the two stimuli, in frequency and amplitude. Second, in contrast to other emission types such as TEOAEs, SOAEs and SFEs, the distortion product can very easily be measured in many common vertebrate laboratory animals (Mills, 1997). Research on laboratory animals allows experimental control of certain factors which contributes to a better understanding of the characteristics of distortion product emissions and OAEs in general (Zhang & Abbas, 1997). DPOAEs have even been measured in the ear of a grasshopper with a completely different morphology. The hearing organ of a grasshopper does not have any sensory hair cells, but the dendrites of the ciliated receptor cells are responsible for generation of distortion (Kossl & Boyan, 1998). Distortion product otoacoustic emissions have therefore been proven useful in both clinical and research settings. Third, DPOAEs can be measured in hearing impaired ears with elevated threshold levels of up to 65dB HL (Moulin, Bera & Collet, 1994). This feature enables DPOAEs to provide more than just hearing screening information.

These interesting differences between DPOAEs and other emission types led to an extensive investigation of DPOAEs to determine the clinical applicability of DPOAEs (Bonfils & Uziel, 1989). This clinical interest in DPOAEs is twofold. The first interest lies in the development of an objective test of auditory function. The second interest is to develop a test uniquely sensitive to the functioning of the outer hair cells, and therefore a useful tool in differential diagnostic testing (Durrant, 1992). This research project focuses on the first interest: To develop an objective, noninvasive test of auditory function with distortion product otoacoustic emissions.

To better understand the nature of the distortion product, its definition will now be discussed.

2.2 Definition of DPOAE

DPOAEs are elicited by the simultaneous presentation of two different pure tones, f1 and f2, where f1<f2. The distortion product response is a third tone of frequency, produced internally and in a frequency region different from the two primary frequencies. Responses can be expected at several different distortion product frequencies such as 2f1-f2, 3f1-2f2, 4f1-3f2, etcetera. Of all the distortion products, the cubic distortion product is the most prominent in humans and occurs at 2f1-f2 (Nielsen, Popelka, Rasmussen & Osterhammel, 1993).

The normal cubic distortion product is typically 60dB lower than the overall level of the primaries (Nielsen, et al., 1993). The relationship of the distortion product (2f1-f2) and the two primary frequencies (f1 and f2) can very clearly be seen in the spectrum of the ear canal sound pressure of normal hearing subjects undergoing DPOAE testing. This relationship is illustrated in Figure 2.1.

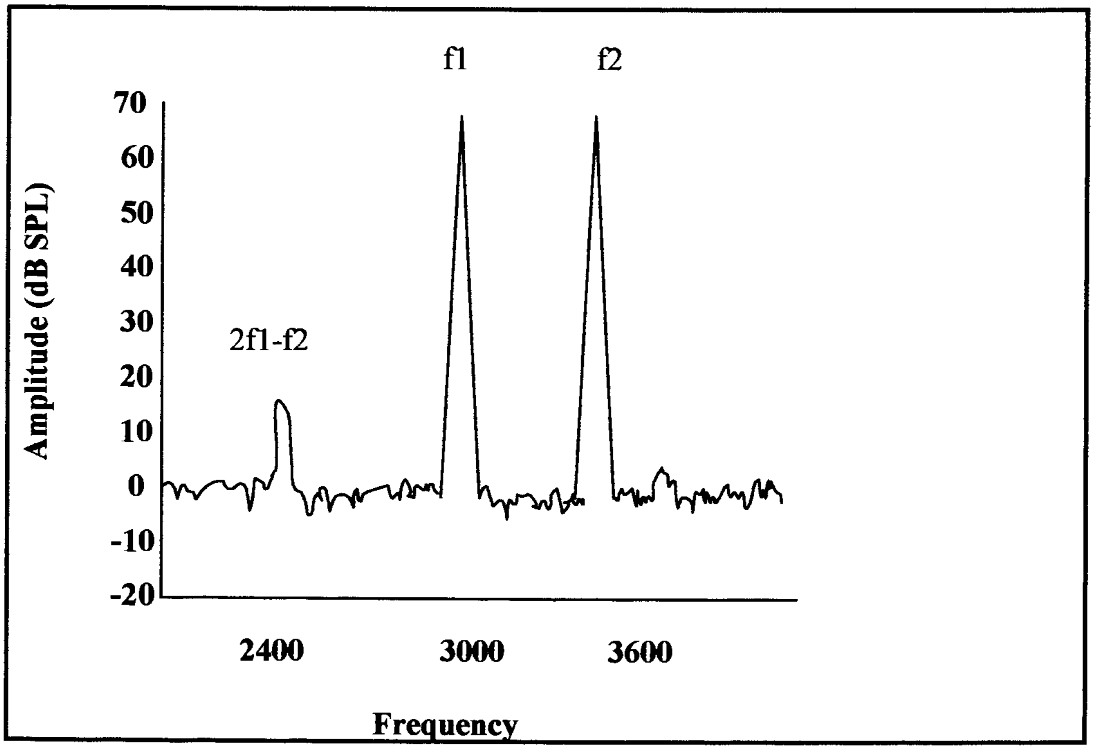


Figure 2.1: The spectrum of the ear canal sound pressure of a normal hearing adult undergoing DPOAE testing. f1 and f2 are the stimuli and 2f1-f2 is the response (from Norton & Stover, 1994:457).

The acoustic distortion product can be measured in the ear canals of animals and humans. The next section will discuss the measurement procedures and instrumentation necessary to elicit a distortion product otoacoustic emission.

2.3 Measurement Procedures and Instrumentation for DPOAEs.

For the measurement of a distortion product otoacoustic emission, two separate channels for stimulus generation and attenuation are necessary. These two channels should be electrically isolated to prevent distortion. The signals are presented to the ear canal via a probe microphone assembly with two delivery ports. Probe microphone systems for DPOAEs consist of a miniature sound source and a very sensitive microphone built into a unit small enough to fit snugly into a human ear canal (Siegel, 1995). Figure 2.2 represents such a probe microphone system schematically.

After the two signals are presented to the ear canal, the ear canal sound pressure is averaged to reduce the noise floor and then spectrally analyzed for the levels of the primaries (f1 and f2) and the response (2f1-f2). Figure 2.1 shows the spectrum of the sound pressure measured in the ear canal, depicting the two primary stimuli f1 and f2, as well as the response, 2f1-f2.

A complete DPOAE system is presented schematically in Figure 2.3.

There are several different stimulus parameters that influence the emission amplitude or threshold (lowest level where an emission can be elicited above the noise floor). These stimulus parameters will be discussed in the following section.

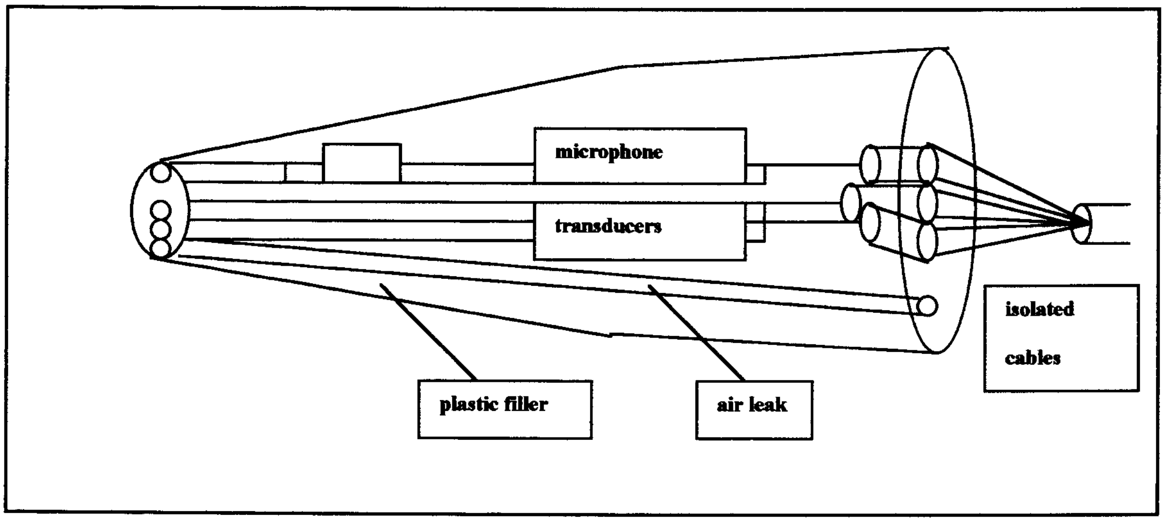


Figure 2.2: Probe microphone system for distortion product otoacoustic emissions (Kemp, Ryan & Bray, 1990).

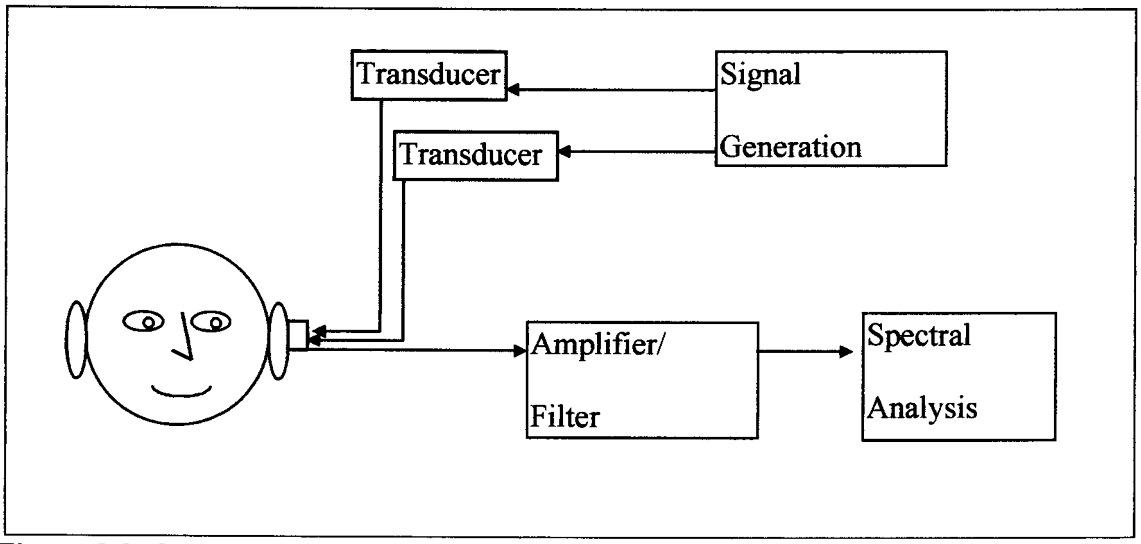


Figure 2.3: Schematic representation of a system used to measure distortion product otoacoustic emissions (Norton & Stover, 1994:456).

2.4 Stimulus Parameters of DPOAEs

There are a number of critical factors or variables involved in the generation of the stimuli necessary to elicit a DPOAE. The distortion product 2f1-f2 is highly influenced by the primary frequencies f1 and f2, the intensities of both stimuli, L1 and L2, the frequency ratio of the primary frequencies (f2/f1) and the loudness ratio of f1 and f2 (L1/L2). David Mills (1997:414) rightly commented on this four-dimensional space over which cochlear space can be explored: "In practice, this aspect may have led to more confusion than understanding." Either the frequencies are changed and the loudness level kept constant (this is sometimes referred to as a "distortion product audiogram") or the frequencies are being kept constant while the loudness level is changed (an input/output function is obtained). It should be noted that the "distortion product audiogram" does not include the concept of threshold, as does the conventional audiogram in this case.

A study by Harris, Lonsbury-Martin, Stagner, Coats and Martin (1989) investigated which f2/f1 ratio yielded the maximal DPOAE amplitude. They used stimulus frequencies and level ranges that were representative of clinical audiograms and found that on the average, a ratio of 1.22 elicited the largest acoustic distortion products for emissions between 1kHz and 4kHz.

Nielsen et al. (1993) measured the cubic distortion product at six probe tone frequency ratios varying between 1.15 and 1.40 using equilevel primaries of 75dB SPL. The results showed that a frequency ratio between 1.20 and 1.25 optimizes the amplitude of the distortion product and is also most applicable to the standard frequencies used in pure tone audiometry.

Other studies that described the optimum frequency ratio included f1/f2 = 1.225 (Gaskill & Brown, 1990), f1/f2 = 1.23 (Avan & Bonfils, 1993) and f1/f2 = 1.3 (Stover, Gorga & Neely, 1996a).

It would therefore seem that a frequency ratio of f1/f2 = 1.2 to 1.3 yields the best DPOAE amplitudes (Avan & Bonfils, 1993; Gaskill & Brown, 1990; Harris et al., 1989, Nielsen, et al., 1993; Stover et al., 1996a).

Another factor that influences DPOAE amplitude, apart from the frequency ratio, is the loudness level ratio of the primaries, namely L1 and L2.

Mills (1997) studied the effect of the loudness levels of the primaries on the distortion product. The author concluded that the cubic distortion emission amplitude is not symmetric, so that given the same L1, higher emission amplitudes can occur for L2 > L1 compared to L1 = L2. Authors such as Stover et al., (1996a) found maximal DPOAE amplitudes when L2 > L1 by 10dB and Gorga, Neely, Bergman and Beauchaine, (1993) found maximal DPOAE amplitudes when L2 > L1 by 15 dB.

"Recently, there has been emerging consensus on recommendations for using L1/L2 ratios in the range of 10-15dB" (Mills, 1997:414).

It is very important to choose the right frequency and loudness level ratios that yield maximum DPOAE amplitudes. These variables should be chosen in such a manner that the stimulus levels and frequency ranges are representative of clinical audiograms, to enable comparisons between the DPOAEs and pure tone thresholds (Moulin, et al., 1994). Once the optimal parameters are determined, experiments can be conducted to study DPOAEs in persons with normal or impaired hearing (Harris et al., 1989).

Apart from all the parameters that should be specified, there are also two different ways to construct DPOAE testing, namely, to obtain a distortion product audiogram (DP Gram) or an input/output function (I/O function). The differences between these two options will be reviewed in the next section.

2.5 DP Gram versus I/O Function

The distortion product can be measured and displayed in two forms.

2.5.1 The DP Gram

The first form, namely the DP Gram, depicts DPOAE amplitude as a function of stimulus frequency at a fixed loudness level (Lonsbury-Martin & Martin, 1990). In other words, the loudness level is kept constant and the frequencies are changed. In this manner, a test cochlea can be evaluated over a large frequency range by comparing the evoked DPOAE amplitudes to average amplitudes determined from a population of normal hearing individuals (Lonsbury-Martin, 1994). Figure 2.4

represents a DP Gram of a normal hearing person. The DP Gram is analyzed by comparing DPOAE amplitudes with average amplitudes obtained from normal hearing persons. It does not obtain "threshold" information, as does the conventional pure tone audiogram.

2.5.2 The I/O Function

The second form of DPOAE measurement, namely the I/O function, can be used to determine the dynamic range of the distortion generation process (Lonsbury-Martin & Martin, 1990). This procedure described the growth of DPOAE amplitude at a constant frequency (Lonsbury-Martin, 1994). An I/O function can be obtained when the frequencies of the primaries are kept constant and the loudness levels are being changed (Norton & Stover, 1994).

The threshold of a DPOAE depends almost entirely on the noise floor and the sensitivity of the measuring equipment whereas the DPOAE amplitude is greatly influenced by the frequency ratio and decibel ratio of the primaries (Martin et al., 1990b; Norton & Stover, 1994).

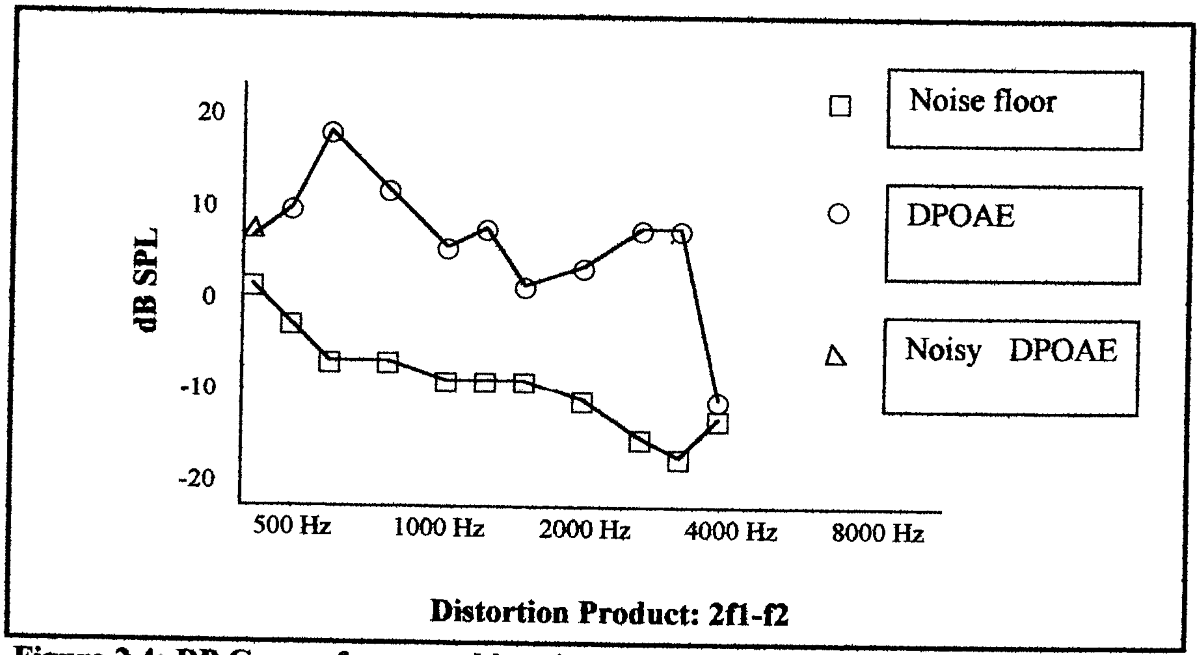


Figure 2.4: DP Gram of a normal hearing adult's right ear at a loudness level of L1=65 dB SPL, L2=55 dB SPL, in the frequency region of 2f1-f2 from 406 Hz to 4031 Hz.

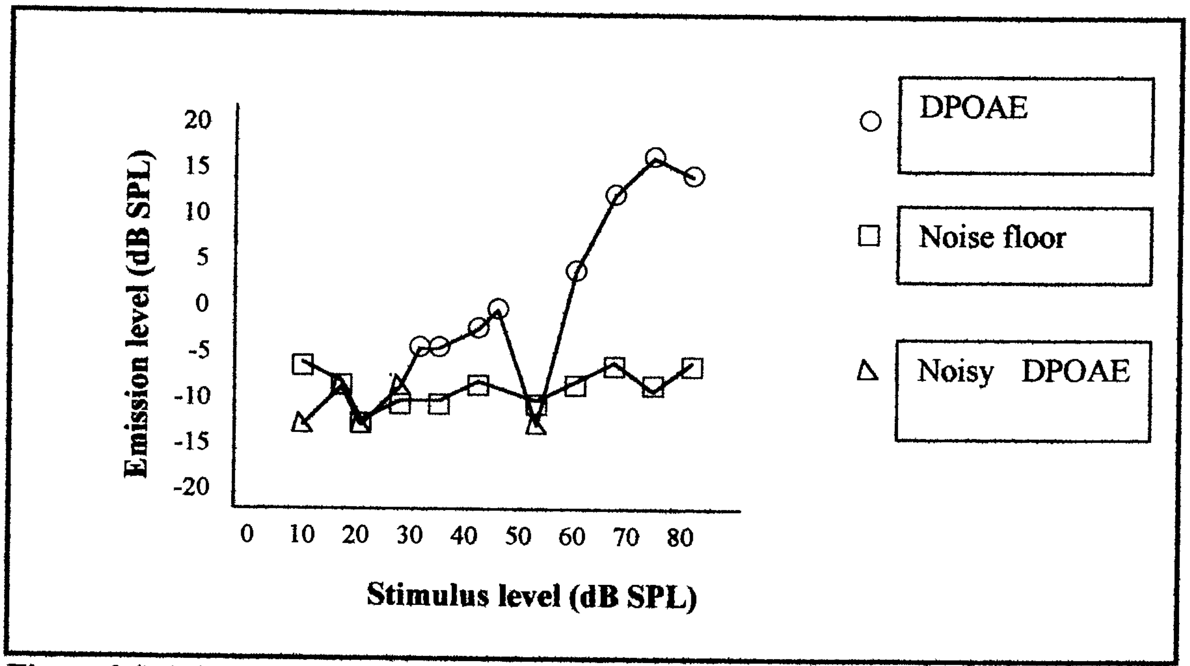


Figure 2.5: I/O function of a normal hearing adult. The fixed frequencies are f1= 1660Hz, f2= 2000 Hz and the loudness levels vary from 10 dB to 80dB SPL (Norton & Stover, 1994:457).

To determine the normalcy of an I/O function, the detection threshold (i.e. the stimulus level where the DPOAE reaches a pre-determined criterion level, for example 3 dB, above the noise floor) is compared to average detection thresholds of normal hearing individuals (Lonsbury-Martin & Martin, 1990). Figure 2.5 illustrates an I/O function for a normal hearing adult. The DPOAE threshold should not be confused with the pure tone audiogram threshold, and can not be directly compared (Norton & Stover, 1994).

There is not yet clear consensus on the best testing procedure to identify normal and impaired ears. Gorga, Stover, Neely and Montoya (1996) conducted a study to determine critical values and levels of confidence for clinical DPOAE measurement and used only I/O functions where DPOAE thresholds were determined. Gorga, et al. (1993), on the other hand, used only DP Grams to investigate DPOAE responses in normal hearing and hearing impaired subjects.

Most researchers, however, use a combination of the two procedures or perform both procedures separately. Martin, Ohlms, Franklin, Harris and Lonsbury-Martin (1990), Spektor et al., (1991) and Smurzynski, Leonard, Kim, Lafreniere, Marjorie and Jung, (1990) performed both procedures in their studies separately, while Moulin et al. (1994), and Kimberley and Nelson (1989) combined the two procedures in an interesting way. Moulin et al. (1994), conducted several DP Grams but at different loudness levels in 10 dB steps, therefore gaining almost the same information as performing both procedures. Kimberley and Nelson (1989), on the other hand, measured several I/O functions but at eight different frequencies.

"Thus it remains unclear which test protocol is more diagnostically effective and whether DPOAE amplitude or DPOAE threshold is the better indicator of cochlear status" (Stover et al., 1996a: 957). Not knowing which procedure is currently the most applicable in the areas of diagnostic effectivity, it seems plausible to gain as much information as possible by combining the two procedures or performing both separately (Kimberley & Nelson, 1989; Martin, et al., 1990a; Smurzynski et al., 1990).

Now that the distortion product with all its complex parameters, instrumentation and measurement procedures is fully understood, other issues such as prevalence, age and gender effects, frequency specificity and their relation to auditory sensitivity can be discussed.

2.6 Prevalence of DPOAEs in Normal Hearing and Hearing Impaired Populations

Many studies provided comprehensive descriptions of the prevalence of DPOAEs in normal hearing and hearing impaired subjects. There is growing evidence that DPOAEs can be measured in essentially all normal hearing subjects (Gorga et al., 1996; Kimberley & Nelson, 1989; Kimberley et al., 1994; Lonsbury-Martin et al., 1990; Smurzynski et al., 1990; Spektor, et al., 1991). However, optimal stimulus parameters are required for optimal measuring procedures. Gorga, et al. (1993) for example, indicated the prevalence of DPOAEs in normal hearing subjects to be 95%, but used equilevel primary frequencies of 75 dB SPL. When primary frequencies with a frequency ratio of 1.22 and loudness levels of L1>L2 by 10-15 dB are used, it can be expected to measure recordable DPOAE responses in 99-100% of normal hearing subjects with pure tone levels 0-10 dB HL (Martin et al., 1990b; Moulin et al., 1994; Vinck, Vel, Xu & Van Cauwenberge, 1995).

Popelka, Karzon and Arjmand (1995) investigated prevalence of DPOAEs for low level stimuli in premature normal hearing neonates and concluded that DPOAE I/O functions for low level stimuli produced the same results as those reported for adults. These results have important implications for developing the use of DPOAEs to accurately estimate cochlear function in this population.

In humans, DPOAE levels typically vary from –20 dB SPL to +20 dB SPL and are typically 40-60 dB below the level of the eliciting stimuli (Kimberley & Nelson, 1989). Probst and Hauser (1990) found DPOAE levels to be 60-70 dB below the level of the stimuli but used only one high level of input stimuli namely L1 = 73 dB and L2 = 67 dB. Kimberley and Nelson (1989), on the other hand, tested DPOAEs over a range of 50 dB from 30 dB to 80 dB and therefore could elicit DPOAEs at lower levels.

In some cases, the DPOAE level may be only 10-20 dB less than the primaries. This interesting phenomenon can be observed when the DPOAE frequency corresponds with a spontaneous otoacoustic emission (Moulin et al., 1994). When a normal hearing ear exhibits a spontaneous otoacoustic emission and DPOAEs are measured in that ear close to the SOAE (within 50 Hz), the distortion product may be enhanced (Probst & Hauser, 1990).

In contrast to other emission types, the distortion product is the only emission type that has been measured in hearing impaired ears (Lee et al., 1993). In human pathology, however, considerable variation in DPOAE prevalence has been found. This variation is partly due to the numerous different stimulus parameters used in many of the studies, making a comparison between studies somewhat difficult (Gorga et al., 1996). When low intensity primaries are used, the distortion product can be measured in ears with a hearing loss of up to 30 dB (Avan & Bonfils, 1993). With high level intensities of the primaries (>60 dB), DPOAEs have been measured in ears with a hearing loss of up to 65 dB HL (Moulin et al., 1994). Many researchers agree that the distortion product can be measured in hearing impaired ears with pure tone thresholds between 50-60 dB HL (Lonsbury-Martin & Martin, 1990; Moulin et al., 1994; Ohlms, Lonsbury-Martin & Martin, 1990; Spektor, et al., 1991).

It should be noted that this hearing impairment should be of a sensorineural nature (Zhang & Abbas, 1997). The distortion product depends on optimal transmission through the middle ear (Osterhammel, Nielsen & Rasmussen, 1993). DPOAEs have to perform a "twofold pass" through the middle ear. This means that the stimulus sound coming to the cochlea is highly dependent on the forward transfer function of the middle ear mechanism. Middle ear functioning also influences the cochlear response that is transferred back through the middle ear system (Hall III, Baer, Chase & Schwaber, 1993). It is therefore very important to determine the status of the middle ear before any interpretation of DPOAE findings can be attempted (Kemp et al., 1990).

Moulin et al. (1994) attempted to explain some of the reasons why DPOAEs can be measured in hearing impaired ears while all the other emission types are absent. The first explanation discusses the nature of the stimulus needed to elicit a response. The energy carried by a short transient stimulus (as in the case of TEOAEs) cannot be compared to the continuous stimulus of two pure tones, used to elicit a DPOAE. The continuous stimulus used to generate a DPOAE carries more energy at specific places in the cochlea, whereas the transient stimulus used to elicit a TEOAE is a short duration click and the energy is spread out across the whole cochlea. According to Moulin et al. (1994), this difference in stimulus type may account for the differences of OAE occurrence in ears with a hearing loss.

Another hypothesis described by Moulin et al. (1994) implies that in some ears with hearing loss, there might be residual functioning outer hair cells that are able to generate a distortion product at a specific cochlear region. The amount of residual outer hair cells is however insufficient to elicit TEOAEs on broad regions of the basilar membrane.

Lastly, the third hypothesis speculates that DPOAEs elicited with high level stimuli might depend on a different generation mechanism than low level stimuli. It seems possible that DPOAEs recorded with low levels are more dependent on the outer hair cells than DPOAEs recorded with high level stimuli. The recording of TEOAEs is entirely dependent on the state of the outer hair cells (Martin et al., 1990a; Moulin et al., 1994).

Prevalence of DPOAEs might also be affected by other factors than hearing loss. The effect of age and gender on the prevalence of DPOAEs will be discussed next.

2.7 The Effect of Age and Gender on DPOAEs

Subject age and gender influence many aspects of auditory function (Hall III et al., 1993). Within the first decade after the discovery of auditory brainstem response (ABR), many studies were conducted to investigate the influence of age and gender. Significant differences were found between different age and gender groups. Ever since then, these two factors have been routinely taken into consideration in the interpretation of ABR results (Weber, 1994).

There is some debate about the effect of age on distortion product otoacoustic emissions. Some authors found statistically significant decreases in amplitudes of other emission types such as TEOAEs with increasing age (Norton & Widen, 1990). In the case of DPOAEs, it seems possible that age related differences could be attributed to sensitivity changes related with aging, rather than aging itself (He & Schmiedt, 1996).

Lonsbury-Martin et al. (1990) indicated that in the presence of normal hearing (pure tone thresholds lower than 10 dB HL), DPOAE amplitudes and thresholds, especially those associated with high frequency primary tones, were significantly correlated with the subject's age. The subjects ranged from 21-30 years of age. It should be noted however, that the authors described the audiograms of the 30 year old subjects as "exhibiting a high frequency hearing loss pattern" (Lonsbury-Martin et al. 1990:10) with hearing thresholds around 10dB HL. The younger subjects had pure tone thresholds of 0-5 dB HL. The lower DPOAE amplitudes and thresholds found in the results of the 30-year-old subjects can therefore be partly explained by higher pure tone thresholds and not solely by the subject's age.

A more recent study by Karzon, Garcia, Peterein and Gates (1994) investigated DPOAEs in the elderly to determine the age effect on DPOAEs. DPOAE results of 71 elderly volunteers, ranging from 56-93 years were compared to DPOAE results of normal hearing young adults, age 19-26 years. The authors found that the amplitudes of DPOAEs did not increase significantly with age, when adjusted for pure tone levels. "Although DPOAEs are reduced with age, this effect is largely mediated by age-related loss of hearing sensitivity." (Karzon et al., 1994:604). Avan and Bonfils (1993) confirmed this viewpoint and stated that many of the age related effects were due to high frequency hearing losses even when subjects were "normal" within their age category. He and Schmiedt (1996) also stated that when pure tone thresholds are controlled, there is not a significant aging effect on DPOAE amplitudes.

It would therefore seem that many authors agree that the negative correlation between DPOAE levels and age is due to changes in hearing threshold associated with aging rather than age itself (Avan & Bonfils, 1993; He & Schmiedt, 1996; Karzon et al., 1994; Kimberley et al., 1994; Nieschalk, Hustert & Stoll, 1998).

Another potentially relevant factor may be the influence of gender on the prevalence of distortion product otoacoustic emissions.

Gender differences have been reported in other emission types. Cacace, McClelland, Weiner and McFarland (1996) reported spontaneous otoacoustic emissions to be more prevalent in females than males and higher incidence of SOAEs in right ears than left ears. Hall III et al. (1993) indicated that TEOAE amplitudes are significantly larger for females than males.

Lonsbury-Martin et al. (1990) conducted a study to investigate basic properties of the distortion product including the effect of gender on the prevalence of DPOAEs. A comparison of DPOAE amplitudes and thresholds failed to reveal any significant differences except at 4 kHz. Women revealed significantly lower DPOAE thresholds at 4 kHz (about 10 dB lower). The pure tone audiometry thresholds for men and women at 4 kHz were the same. Gaskill and Brown (1990) and Cacace et al. (1996) reported that DPOAEs were significantly larger in female than male subjects tested in the frequency range of 1000- 5000Hz. Both studies however, indicated that the female subjects in their studies had more sensitive auditory thresholds than the males (an average of 2.4 dB better). The differences found between the two groups could therefore not be explained by gender only.

Cacace et al. (1996) attempted to explain some of the reasons why the females had higher amplitudes than the males in the higher frequencies. One reason is the existence of a spontaneous otoacoustic emission (SOAE) in conjunction with DPOAE measurement. Several authors described the effect that a SOAE could have on a DPOAE (Kulawiec & Orlando, 1995; Moulin et al., 1994; Probst & Hauser 1990). If a spontaneous emission exists within 50 Hz of the primary frequencies used to elicit a DPOAE, the spontaneous emission could enhance the DPOAEs amplitude significantly under certain experimental conditions (Kulawiec & Orlando, 1995; Probst & Hauser, 1990). Spontaneous emissions are more prevalent in females than in males and could therefore possibly explain the higher DPOAE amplitudes in females.

This amplitude amplification effect that SOAEs have on DPOAEs can not always clearly be seen. Cacace et al. (1996) reported that no systematic peaks or notches could be observed in DPOAE responses in the presence of a spontaneous otoacoustic emission in any of the subjects they tested. The mere presence of a SOAE in a frequency region close to the primaries can not be taken as evidence of amplitude amplification. It is however so, that this gender effect is greatly reduced when only subjects with no SOAEs are considered.

Gender effects on DPOAEs are apparently limited to minor differences in DPOAE amplitudes and thresholds.

The fact that the distortion product is present in normal and hearing impaired ears and has only minimal age and gender effects makes it the emission type that has great potential as a new test of auditory function. In any test of auditory function, one very important factor to consider is the frequency specificity with which measurements can be made. The distortion product's frequency specificity warrants some discussion.

2.8 Frequency Specificity of DPOAE Measurements

Many authors reported DPOAE measurement to be the most frequency-specific type of otoacoustic emission currently available (Durrant, 1992; Lee et al., 1993; Nielsen, et al., 1993; Probst & Hauser, 1990; Rasmussen, Popelka, Osterhammel & Nielsen, 1993; Spektor, et al., 1991).

The explanation for this frequency specificity lies with the stimuli used to elicit different types of otoacoustic emissions. The stimulus used to elicit a TEOAE, such as a click or tone burst, has broad spectral qualities and stimulates broad regions of the basilar membrane simultaneously (Lee et al., 1993). The stimuli used to elicit DPOAEs are two pure tones that stimulate the basilar membrane at two discrete locations. DPOAEs can therefore be elicited at almost any selected frequency since it depends on the frequencies of the primaries (Lonsbury-Martin et al., 1990; Probst & Hauser, 1990). The measurement of otoacoustic emissions at the lower frequencies are always more difficult due to interference of low frequency noise such as breathing and swallowing. According to Stover et al. (1996a), the distortion product can differentiate normal from impaired ears for frequencies as low as 707 Hz (or 725 Hz according to Bonfils, Avan, Londero, Trotoux & Narcy, 1991).

One very interesting study by de Boer (1983) (cited in Avan & Bonfils, 1993), investigated frequency specificity of DPOAEs by measuring the number of outer hair cells (OHC) contributing to a DPOAE on the basilar membrane of a guinea-pig cochlea. The author concluded that about 1mm on the basilar membrane (which represents about a third octave in the guinea-pig cochlea) contributed to a single DPOAE. The number of outer hair cells (OHC) involved is of course depending on the level of stimuli used to elicit the DPOAE. For loudness levels over 60 dB SPL, broader regions of outer hair cells are involved in the distortion product emission. Mills, (1997) refers to this phenomenon as "active" and "passive" emissions. In the case of high stimulus levels, broader areas of the basilar membrane are stimulated. With high intensity stimuli, phase relationships between travelling waves that generated emissions evoke a different type of emissions, namely a "passive" emission. A passive emission is less frequency-specific and has less correspondence to auditory sensitivity. When low intensity primaries are used, it seems that only a very small number of OHC contribute to the distortion product emission. The fact that such a small number of OHC contributes to the generation of a DPOAE evoked at low intensities is in itself an indication of the frequency specificity with which measurements can be made.

There is, however, not clear consensus on which frequency variable of the DPOAE correlates best with the region on the basilar membrane that is responsible for the measured distortion product. In other words, does a DPOAE indicate the state of the OHC on the basilar membrane in the region of the f1 frequency, the f2 frequency, the geometric mean of the two primary frequencies (GM) or at the 2f1-f2 frequency? Many authors also disagree on which frequency variable of the DPOAE should be compared to the pure tone threshold (PTT).

According to research conducted by Kimberley et al., (1994) and Harris et al., 1989, the features that best correlate with pure tone thresholds (PTTs) are those associated with f2 values close to the pure tone threshold frequency. The distortion product, according to these authors, is generated very close to the f2 cochlear place.

Other studies support the notion that the generation of the distortion product correlates best with the cochlear place near the geometric mean (GM) of the primaries (Bonfils et al., 1991; Lonsbury-Martin & Martin, 1990; Martin et al., 1990b). These authors concluded that the acoustic distortion product at 2f1-f2 should be correlated with PTTs near the GM of the primaries.

According to Moulin et al. (1994) no attempt has been made to compare the correlations between DPOAEs and PTTs measured at the GM frequency with the correlations between DPOAEs and PTTs measured at the f2 frequency, because the GM and f2 frequencies are too close.

Avan and Bonfils (1993) discussed factors that contribute to the difficulty of determining which frequency region of the basilar membrane corresponds with the distortion product. First, the presence of a simple correlation between a DPOAE parameter and a PTT at some frequency does not mean that the DPOAE is a valid predictor of hearing loss at that frequency. It would only be valid if auditory thresholds were independent variables, which is not true in typical sensorineural hearing losses (Avan & Bonfils, 1993; Moulin et al., 1994). Second, DPOAEs may be generated at any place where nonlinear interactions between travelling waves f1 and f2 are possible and that basal spreading of such places is not precisely known, especially for high intensity stimuli (Avan & Bonfils, 1993). It seems that high level stimuli causes a spread of energy along the basilar membrane and causes a lack of frequency specificity (Bonfils et al., 1991; Harris & Probst, 1991; Moulin et al., 1994).

It is therefore not clear, whether it is in fact f1, f2, the GM frequency or 2f1-f2 frequency that is actually being stimulated on the basilar membrane. Most authors agree that DPOAEs appear to be generated in the region stimulated between the primary frequencies, rather than the frequency at the distortion product (Harris et al., 1989; Kimberley et al., 1994; Martin et al., 1990b; Moulin et al., 1994; Smurzynski et al., 1990). To illustrate this concept: if f1 = 1000 Hz and f2 = 1187 Hz (the frequency ratio 1.2), then the GM = 1093 Hz and the 2f1-f2 distortion product 812 Hz. According to all the above authors, the basilar membrane region that is being stimulated in this case, is between f1 = 1000 Hz and f2 = 1187 Hz. Although the question of precise frequency stimulation on the basilar membrane is still not solved, it is clear that the narrow region that is being stimulated on the basilar membrane is quite frequency specific.

"Compared to other classes of otoacoustic emissions, distortion product emissions are highly frequency-specific in a manner easily controllable by stimulus conditions. Therefore, they are of clinical interest as a means by which cochlear activity at specific sites along the basilar membrane may be monitored in a simple non-invasive manner." (Rasmussen et al., 1993:22).

Another very important aspect of DPOAEs that received much attention in the literature is the relationship of the distortion product to auditory sensitivity. This is probably the single most important factor in the development of DPOAEs as an objective test of auditory function and warrants a detailed discussion.

2.9 Relation of the Distortion Product to Auditory Sensitivity

Otoacoustic emissions reflect the status of the outer hair cells on the basilar membrane. Pure tone behavioral thresholds not only reflect the physiology of the auditory system at numerous parts, but also involve auditory perception (Lee et al., 1993). Despite these fundamental differences, many studies that attempted to describe the relationship of the distortion product to auditory sensitivity came to the same conclusion. It seems that there is a positive relationship between DPOAEs and hearing thresholds. DPOAEs are elevated in subjects with mild hearing losses and are absent when hearing sensitivity is moderately or significantly impaired (Avan & Bonfils, 1993; Durrant, 1992; Gorga, et al., 1993). It is very important to understand the exact relationship between DPOAEs and pure tone thresholds. "An understanding of that relationship is essential if DPOAE measurements is to gain acceptance as an objective diagnostic test in audiologic and otologic settings" (Lee et al., 1993:18).

Early studies of the relationship between otoacoustic emissions and hearing thresholds investigated the relationship of TEOAEs to pure tone thresholds. These studies found only a categorical relationship, that is, ears with pure tone thresholds < 30 – 40 dB HL generated emissions and ears with greater hearing losses did not (Bonfils, Uziel & Pujol, 1988; Collet, Gartner, Moulin, Kauffmann, Disant, Morgon, 1989; Kemp, 1978).

An early study by Kimberley and Nelson (1989) investigated the correlation between distortion product otoacoustic emissions and hearing threshold. Subjects were selected without regard to age, sex, and etiology of hearing loss or pattern of hearing loss. The frequency ratio of the primaries (f2/f1) was 1.2. Distortion product otoacoustic emissions were measured over a stimulus range from 30 dB SPL to 80 dB SPL in 6 dB steps. DPOAE I/O functions were measured covering the frequency range from 700 Hz to 6000 Hz. Kimberley and Nelson (1989) then plotted emission thresholds and auditory thresholds of 21 ears on a scattergram. (Emission thresholds represent the stimulus level required to just raise the emission above the noise floor.) Kimberley and Nelson's (1989) scattergram can be viewed in Figure 2.6. The linear fit shown with the data points has a slope of 1.0 and a correlation coefficient of .86.

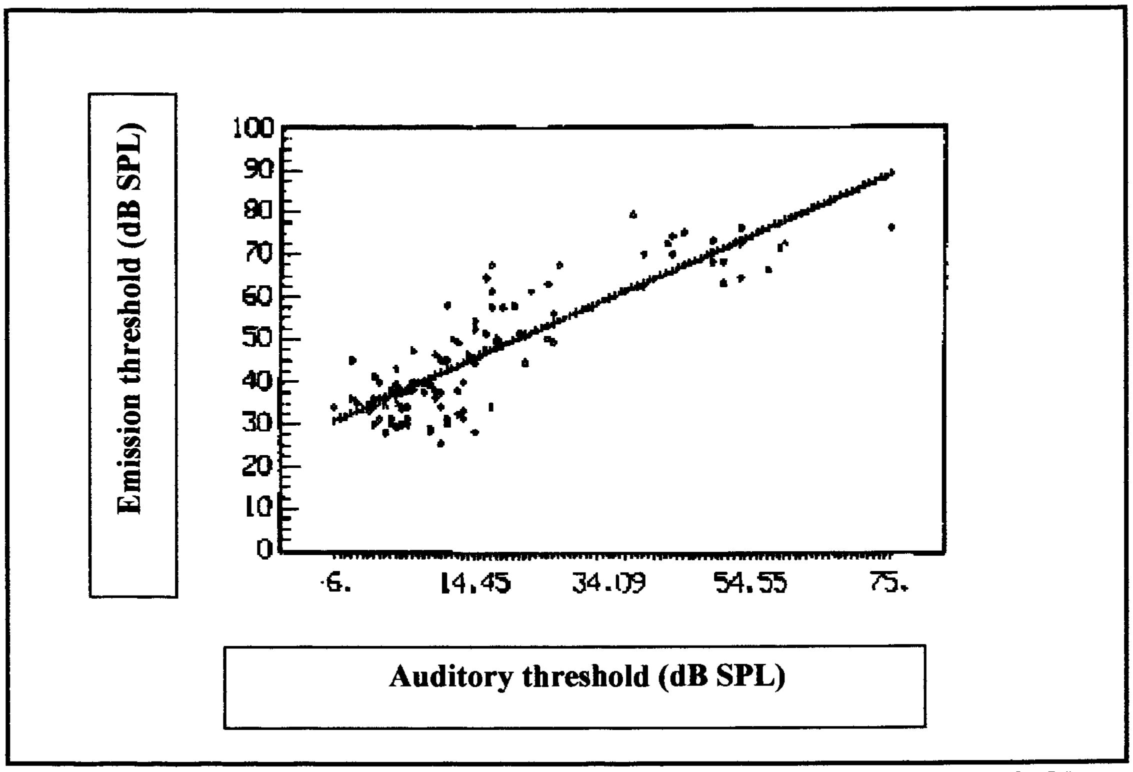


Figure 2.6: Scattergram of emission threshold versus auditory threshold as measured by Kimberley and Nelson, (1989:368).

The results displayed in this scattergram in Figure 2.6 suggest that DPOAE measurements can predict auditory thresholds within 10 dB over a range from 0 dB

SPL to 60 dB SPL. The authors claim that this was the first report of such a precise correlation.

Studies that are more recent continued to investigate the correlation between DPOAE responses and pure tone thresholds. The primary goal of these investigations was to develop another objective tool for the evaluation of "difficult-to-test" populations or mass hearing screening (Gorga, et al., 1993; Kimberley et al., 1994; Moulin et al., 1994; Stach, Wolf & Bland, 1993). A few of these studies would be reviewed.

Gaskill and Brown (1990) investigated the behavior of the acoustic product in humans and its relation to auditory sensitivity. They concluded that with certain optimal stimulus parameters (stimulus levels below 60 dB SPL; L1>L2 by 15 dB; f1/f2 = 1.225), half of the subjects showed a statistically significant correlation between DPOAE results and auditory sensitivity at the corresponding f1 stimulus. According to Gaskill and Brown (1990), there are probably differences in the mechanisms responsible for producing DPOAEs using high versus low-level stimuli. High level DPOAEs may not correspond well to hearing sensitivity. DPOAEs generated with low intensity stimuli approximate hearing thresholds more closely (Bonfils et al., 1991; Gaskill & Brown, 1991; Harris & Probst, 1991).

Avan and Bonfils (1993) confirmed these findings. The authors conducted a study on DPOAEs in 25 normal hearing and 50 hearing impaired ears. Their results indicated that the DPOAEs evoked by low intensity primary tones (below 62 dB SPL) were strongly correlated with the auditory threshold at the mean frequency of f1 and f2 and that DPOAEs disappear for hearing losses larger than about 30dB. This research also suggests that when low intensity primaries are used, DPOAEs provide frequency-specific information on the local cochlear state of the primaries.

Gorga, et al. (1993) measured DPOAEs in normal hearing and hearing-impaired human subjects. They investigated the extent to which DPOAEs can be used to correctly distinguish between normal and impaired hearing. DPOAE amplitude was able to distinguish between normal and impaired subjects at 4000 Hz, 8000 Hz and to a lesser extent at 2000 Hz. At 500 Hz, performance was no better than chance, due to high biological noise levels such as breathing and swallowing. They concluded that DPOAE measurement could successfully be implemented to identify high frequency hearing loss, but that it was not an accurate predictor of hearing loss in the lower frequencies.

A study by Bonfils et al. (1991) on low frequency audiometry by distortion product otoacoustic emissions revealed interesting findings. Two different experiments were conducted. In the first experiment, the frequency ratios varied from 1.06 to 1.38 by steps of 0.02 to determine the most suitable frequency ratio for low frequency testing. Equilevel stimuli ranging from 84 dB SPL to 30 dB SPL were delivered in 6 dB steps to determine the most suitable loudness level for low frequency testing. In the second experiment, the frequency ratio was fixed at 1.22 and equilevel primaries ranging from 84 dB SPL to 30 dB SPL were delivered over a geometric mean frequency range of 485 Hz to 1000 Hz. Two important points were derived from this study. First, I/O functions tested with low level primaries (intensities below 60 dB SPL) and frequency ratios around 1.2 showed saturated growth. When primary intensities exceeded 66 dB SPL or when frequency ratios were greater than 1.3 or lower than 1.14, the input output functions became linear without any clear saturating plateau. The authors concluded that DPOAEs generated by primary intensities below 60 dB SPL probably have their origin in the outer hair cells. With high level stimuli however, it is probable that only passive properties of the cochlea contribute to the emission. The high level versus low level testing is therefore just as important in low frequency testing. The second important factor derived from this study is variations of DPOAE properties as a function of DPOAE frequency. It seems that for primary intensities below 60 dB SPL, DPOAEs at frequencies lower than 725 Hz (DPOAE frequency of 512.5 Hz) were absent or had no saturating portion. "As the saturating behavior of DPOAE input-output functions probably has its origin in the properties of the outer hair cells, these results suggest that active mechanisms are absent below 725 Hz in the human cochlea." Bonfils et al., (1991:1171). It seems that DPOAEs at frequencies lower than 725 Hz are generated by passive components in the cochlea. This could explain the absence of SOAEs and other evoked otoacoustic emissions below 725 Hz.

A study conducted by Stover et al., (1996a) examined the effect of the primary stimulus levels on the ability of DPOAE measurements to separate normal hearing from hearing impaired ears. Clinical decision theory was used to assess both DPOAE threshold and DPOAE amplitude as diagnostic indicators of hearing status. This research suggests that DPOAE threshold and DPOAE amplitude perform equally well in distinguishing normal from impaired hearing but DPOAE amplitude is more suited as a screening method due to shorter testing times.

Probst and Hauser (1990) performed similar research in 1990 and concluded that the measurement of DPOAE amplitude alone might fail to detect a mild hearing loss. To determine hearing ability more accurately, more detailed measurements such as I/O functions with DPOAE thresholds should be performed.

Kimberley et al. (1994), tried to predict hearing status in normal and hearing impaired ears with distortion product otoacoustic emissions at 6 frequencies ranging from 1025 Hz-5712 Hz. They used a statistical technique known as discriminant analysis which attempts to determine which attributes (variables) such as DPOAE levels, age and gender are most significant in defining normal versus abnormal pure tone thresholds. After these discriminant functions were determined, they were applied to a new set of unfamiliar data to determine their predictive accuracy at each frequency. They found that the more attributes they included as being significant in the prediction of the data, the more the prediction of the data worsened. By including only 5-10 of the "best" variables, the prediction was at its best. Classification accuracy varied from 71% correct classification of normal hearing at 1025 Hz to 92% correct classification of normal hearing at 2050Hz. The lowest frequency evaluated was 1025 Hz where the worst performance was observed. Kimberley et al., (1994) concluded that DPOAE measures can reliably categorize pure tone thresholds as being normal or impaired in a population with varied cochlear hearing status.

A few other studies indicated positive relationships between DPOAEs and pure tone thresholds. Spektor, Leonard, Kim, Jung and Smurzynski (1991) reported a positive qualitative relationship between pure tone thresholds and DPOAE thresholds in 19 children (although these authors did not quantitatively correlate DPOAE thresholds with pure tone thresholds). It seemed that the configuration of the hearing loss correlated well with the frequency pattern of the DPOAEs. Lonsbury-Martin and

Martin, (1990) assessed DPOAEs in subjects with noise induced hearing loss. They found that DPOAE thresholds provide reasonably good estimates of hearing loss in cases where primary damage to the outer hair cells can be assumed (such as noise induced hearing losses). The authors found a relatively strong correlation between DPOAE thresholds and magnitude of hearing loss. In the subjects they examined, for every 1dB increase in DPOAE threshold, hearing level increased by 1dB. When DPOAE threshold was > 63 dB SPL, the accompanying hearing level was > 20 dB HL. Such a strong correlation between DPOAEs and pure tones in subjects with OHC pathology proves it as an efficient measurement of cochlear functioning. DPOAEs could potentially be successfully applied to other cochlear pathologies such as Meniere's disease and ototoxicity.

Conclusion: It seems that a certain set of stimulus parameters and conditions are needed to elicit DPOAEs that are comparable to pure tone thresholds. First, the frequency ratio should be close to 1.2 (Bonfils et al., 1991; Gaskill & Brown, 1991; Harris et al., 1989). Second, the loudness levels should preferably be 10-15 dB apart, with L1>L2 (Gaskill & Brown, 1991; Mills, 1997). Third, the loudness levels of the primaries seem to be a very important factor in DPOAE measurement and should not exceed 65 dB SPL (Bonfils et al., 1991; Gaskill & Brown, 1991; Mills, 1997). When primary intensities exceed 65 dB SPL, measurements are less frequency-specific and might not indicate true outer hair cell functioning but rather some passive reaction of the basilar membrane to the stimuli. Another aspect to keep in mind is the limited range in which low frequency DPOAEs can be elicited. According to Stover et al., (1996a) the lowest frequency to be tested with DPOAEs is 707 Hz or 725 Hz (Bonfils et al., 1991). Lastly, it seems that DPOAE amplitude is more suitable for screening purposes (Gorga, et al., 1993; Stover, Neely & Gorga, 1996b) whereas information obtained from DPOAE I/O functions compare better with pure tone thresholds (Gorga et al., 1996; Kimberley & Nelson, 1989; Probst & Hauser, 1990).

There is therefore consistent qualitative and quantitative evidence that there is a relationship between behavioral pure tone thresholds and DPOAE thresholds (Lee, et al., 1993). "Although DPOAE output is not a direct measure of hearing sensitivity and may not follow the audiogram perfectly, it does demonstrate impressively good quantitative correlation with degree of hearing loss and good qualitative correspondence with configuration of hearing loss, at least for mild to moderate losses" (Durrant, 1992:43).

If DPOAEs were proven to be highly frequency specific, strongly correlated with pure tone thresholds and only slightly influenced by aspects such as age and gender, then why is there still so much controversy on its effectiveness to predict hearing ability accurately? These issues are discussed in the next section.

2.10 Limitations of Previous Studies Investigating Possible Correlation between DPOAEs and Pure Tone Audiometry

"While several investigators have studied the relationship between DPOAEs and pure tone thresholds, there have been no reports of a general rule that accurately predicts pure tone threshold on the basis of DPOAEs or any other features in large populations of ears with varying cochlear hearing losses. Defining such a predictive relationship, if one exists, could be of great clinical significance. A strong correlation between

DPOAEs and pure tone thresholds could provide important insights into how frequency-specific cochlear function relates to behavioral measures of auditory function (pure tone threshold)." (Kimberley et al., 1994:199).

Statistical methods used to date, such as multivariate (discriminant) analysis in the case of the study of Kimberley et al., (1994), but also in all the other studies previously discussed, indicated a correlation between DPOAE measurements and behavioral pure tones. These studies however, could not predict the actual pure tone thresholds given only the distortion product responses. "However, at the present time, there are no quantitative studies identifying a precise mathematical relationship such that behavioral thresholds may be accurately predicted. Additional research in this area is needed in order to predict behavioral thresholds from DPOAE threshold values." (Lee, et al., 1993:19).

To define such a relationship between two sets of data (DPOAE measurements and pure tone thresholds), a mathematical tool is needed that has excellent correlation finding capabilities, even in the case of a possible non-linear correlation. This mathematical technique should also be able to predict pure tone thresholds given only the distortion product responses. One such a mathematical tool, that has excellent correlation finding and prediction abilities, is a relatively new method of computational analysis called artificial neural networks. This new information processing technique is discussed in Chapter 3.

2.11 Summary

Distortion product otoacoustic emissions can be evoked by the simultaneous presentation of two pure tones. The emission is a third tone of frequency, produced internally and by the outer hair cells on the basilar membrane. The distortion product is affected by a large number of stimulus parameters including the frequencies and loudness levels of the primaries as well as frequency and loudness level ratios. DPOAEs can be recorded in virtually all normal hearing ears. The prevalence of DPOAEs are impaired in subjects demonstrating hearing loss and can be recorded in ears with a hearing loss of up to 65dB HL. The distortion product is relatively unaffected by age and gender effects. Many studies examining DPOAEs in hearing-impaired subjects concluded that DPOAEs correlate well with degree of hearing loss as well as configuration of hearing loss. The distortion product was also found to be highly frequency-specific and recordable in broad frequency areas as low as 707 Hz (Stover et al., 1996a). All those aspects indicated that DPOAEs might be the revolutionary new objective, non-invasive, rapid and accurate test of hearing that has been so long awaited. Many researchers studied the distortion product with the prime objective to develop a new diagnostic procedure for special populations such as neonates, infants and malingerers. Although most of the studies found a strong positive correlation between pure tones and DPOAEs, none of these studies could formulate the precise mathematical relationship between these two measurements with conventional statistical methods. It seems that in order to predict pure tone thresholds with DPOAEs a special mathematical model with excellent correlation finding and prediction capabilities is needed. One such mathematical model that might prove to be able to solve this complex problem is an artificial neural network.

3 Artificial Neural Networks

3.1 Introduction

The mystery of the human brain's capability to solve complex problems has fascinated scientists for many centuries. Studies revealed that the human brain uses a web of highly interconnected neurons or processing elements to process complex data. Each neuron is independent and can function without any synchronization to other events taking place. (Rao & Rao, 1995). Some scientists tried to reconstruct or simulate the way the brain works by using binary valued information processing units, which are abstracted versions of their biological counterparts. "Much of this surge of attention results, not from interest in neural networks as models of the brain, but rather from their promise to provide solutions to technical problems of "artificial intelligence" that the traditional, logic based approach did not yield." (Muller & Reinhardt, 1990:preface.)

Artificial neural networks are a promising new field. Not only does it yield a better understanding of how the brain's complex information processing abilities work, but it also solves difficult problems too complex for conventional information processing techniques such as statistics.

3.2 Overview of History and Development of Artificial Neural Networks

The study of the human brain goes back a long way. Nelson and Illingworth (1991) mention the work described in the Edward Smith Papyrus. It is a medical paper about the sensory and motor locations in the brain, written around 3000 B.C, almost five millennia back. It was only until this century that researchers tried to simulate the actual functioning of a human brain.

The first person to use the human brain as a computing paradigm was Alan Turing in 1936 (Nelson & Illingworth, 1991). In 1943, McCulloch and Pitts (cited in Nelson & Illingworth, 1991) wrote the first paper about the theory of how the nervous system might work and also simulated a simple neural network with electrical circuits. Researchers began to imitate the biological model to create intelligent machines. Donald Hebb made the connection between psychology and physiology and pointed out that a neural pathway is reinforced every time it is used. He formulated his learning rule, still referred to as the Hebb rule of learning in 1949 (Nelson & Illingworth, 1991). This rule states that changes in connections between neurons are proportional to the activation of the neurons. This was the formal basis for the creation of neural networks that have the ability to learn.

Research expanded and neural network terminology started to appear in the 1950s. In 1957 Rosenblatt expanded on the theory of Hebbian learning and incorporated it into a two layer network, calling the result a "perceptron" (Blum, 1992). Rosenblatt formulated his own learning rule "the perceptron convergence theorem". This rule describes the weights adjusted in proportion to the error between output neurons and target outputs. Many neural networks still use this method of adjusting weights until the desired set of weights is achieved to learn and predict outcomes (Blum, 1992).

A very important turning point in the development of ANNs was at the Dartmouth Summer Research Project of Artificial Intelligence (AI) in 1956. This project provided the momentum for many different projects in the 1950s and 1960s such as MADELINE (Multiple ADAptive LInear Element), the first neural network to be applied to a real word problem. This application consists of adaptive filters to eliminate echoes on telephone lines. MADELINE has been in commercial use for several decades (Blum, 1992). The 1960s were also a period where the potential of neural networks were blown out of proportion. "Some observers were disappointed as promises were left unfulfilled. Others felt threatened by the thought of "intelligent machines"" (Nelson & Illingworth 1991:29).

Neural network development came almost to a standstill in the 1970s but research continued in Japan and Europe. Interest in neural networks renewed in 1982 when John Hopfield presented his neural network paper to the National Academy of Sciences. The emphasis was on practicality. He showed how these networks worked and what it could do (Nelson & Illingworth, 1991).

Various disciplines became interested in the use of ANNs to address complex problems in the last two decades, ranging from cognitive psychology, physiology, medicine, computer science, electrical engineering, economy and even philosophy. ANNs have barely reached its late infancy stage. "Hopefully the rich blend of intellects and backgrounds and divergent objectives will continue the quest" (Nelson & Illingworth, 1991:34).

3.3 Definition of Artificial Neural Networks

Artificial neural networks (ANNs) are a new information processing technique that attempts to simulate or mimic the processing characteristics of the human brain (Medsker, Turban & Trippi, 1993). An artificial neural network is an algorithm for a cognitive task, such as leaning or optimization, recognition of a pattern or retrieval of large amounts of data (Muller & Reinhardt, 1990). ANNs were inspired by studies of the central nervous system and the brain (Medsker et al., 1993; Klimasauskas, 1993) and therefore share much of the terminology and concepts with its biological counterpart. This biological analogy will be discussed in the next section.

3.4 "Anatomy" and "Physiology" of Artificial Neural Networks: A Discussion of Concepts and Terms

Neural networks were initially developed to gain a better understanding of how the brain works. It resulted in computational units, called neural networks, that work in ways similar to how we think the neurons in the human brain work. Several human characteristics such as "learning, forgetting, reacting or generalizing" and also the biological aspects of networks consisting of neurons, dendrites, axons and synapses were ascribed to these artificial neural networks in order to promote understanding of these abstract terms (Nelson & Illingworth, 1991). Some of the terminology of neural networks will be reviewed briefly.

3.4.1 Biological Neural Networks

The human brain is composed of cells called neurons. Estimates of the number of neurons in the human brain range up to 100 billion (Medsker, et al., 1993). Neurons function in groups called networks. Each network contains several thousand highly interconnected neurons where each neuron can interact directly with up to 20 000 other neurons (Nelson & Illingworth, 1991). This architecture can be described as parallel distributed processing, where the neurons can function simultaneously (Muller & Reinhardt, 1990). In contrast with conventional computers which process information serially, or one thing at a time, the human brain's parallel processing ability enables it to outperform supercomputers in some areas regarding complexity and speed of problem solving such as pattern recognition (Blum, 1992).

A typical biological neuron (Figure 3.1) consists of a cell body containing a **nucleus, dendrites** which provides input to the cell and an **axon**, which carries the output signal from the nucleus (Hawley, Johnson & Raina, 1993). Very often, the axon of one neuron merges with the dendrites of a second neuron. Signals are transmitted through synapses. A synapse is able to increase or decrease the strength of the connection and causes inhibition or excitation of a subsequent neuron (Nelson & Illingworth, 1991). Although there are many different neurons, this typical neuron serves as a functional basis to make further analogies to artificial neural networks.

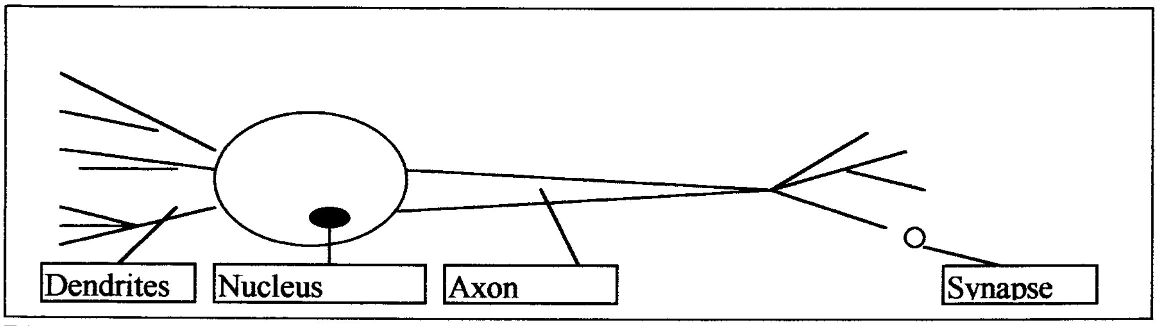


Figure 3.1: A biological neuron (Medsker, et al., 1993:5)

"Artificial neural networks are based only loosely on biology. We don't understand how the brain works or what intelligence really is." (Nelson & Illingworth, 1991: 41) ANNs are an attempt to create a technique to process information in the same fascinating and highly successful way the human mind does. It borrows features from the biological system, to enable scientists to form compact representations of complex problems such as image recognition and forecasting or prediction.

3.4.2 Artificial Neural Networks (ANNs):

The building blocks of an artificial neural network is also referred to as a neuron, or sometimes as a node, a perceptron or processing element. These artificial neurons (Figure 3.2) bear only a modest resemblance to biological neurons in the sense that they can perform approximately three of the processes we know neurons perform. (Biological neurons perform about 150 processes in the human brain) (Nelson & Illingworth, 1991). An artificial neuron receives an incoming stimulus **(input)** analogous to the impulses that the dendrites of biological neurons receive. The second function is to **calculate** a total for the combined input signals and compare it to some threshold level. Finally, it determines the **output** and sends it out just like a biological neuron sends out an output through its axon (Muller & Reinhardt, 1990).

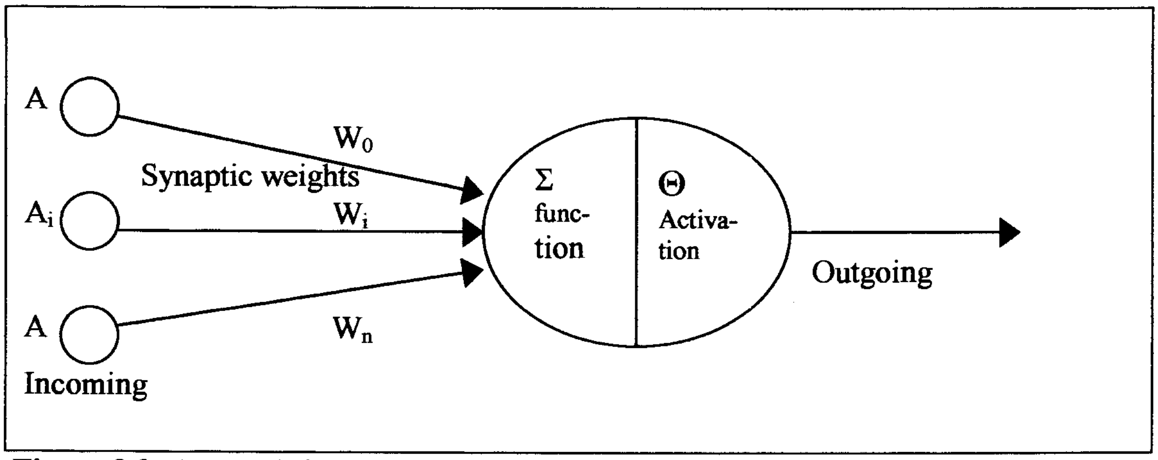


Figure 3.2: An artificial neuron (Blum, 1992: 37).

Several of these artificial neurons or nodes can be combined to make a **layer** of nodes as illustrated in Figure 3.3.

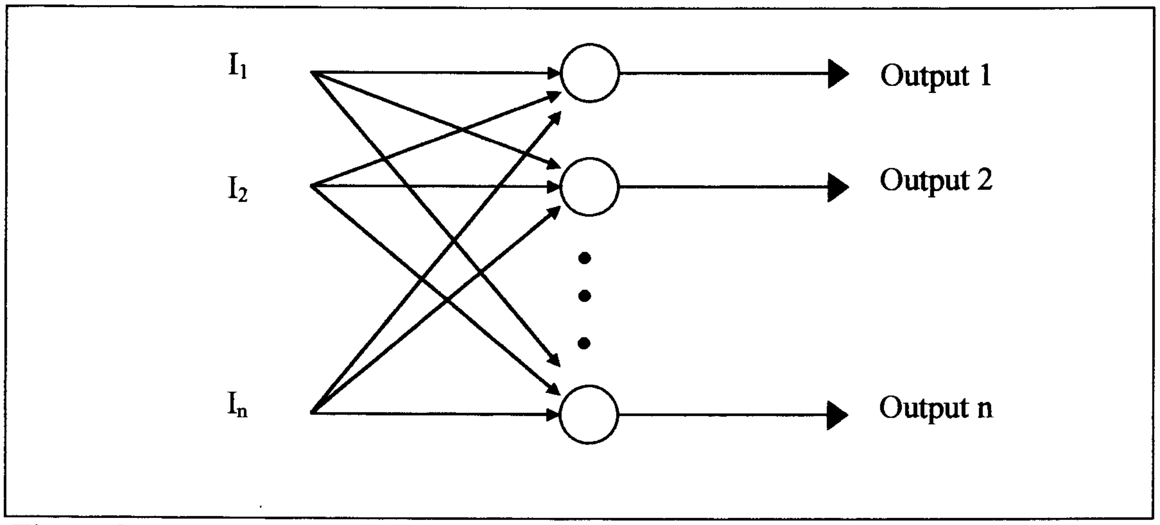


Figure 3.3: Inputs to several nodes to form a layer (Nelson & Illingworth, 1991: 49).

To form an artificial neural network (Figure 3.4), several layers are connected to each other.

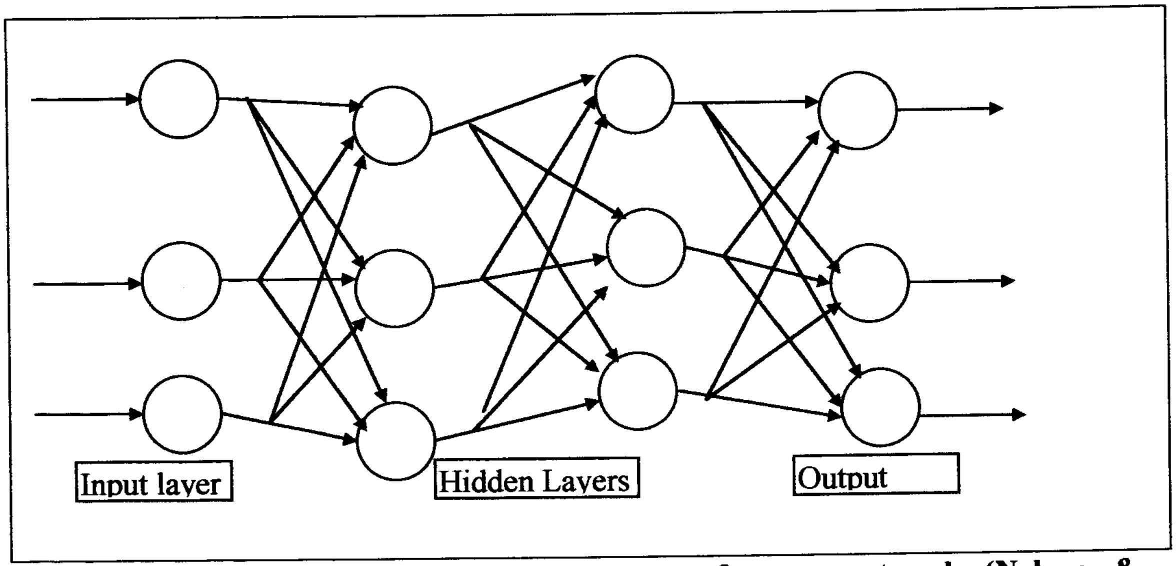


Figure 3.4: Connection of several layers to form a network (Nelson & Illingworth, 1991:50).

The first layer that receives the incoming stimuli is referred to as the **input layer.** The network's outputs are generated from the **output layer** and all the layers in between are called the **hidden layers** or **middle layers.**

The "anatomy" of artificial neural networks has just been reviewed. The terminology used in the "physiology" of an artificial neural network will be discussed next.

The first layer of neurons, called the input layer, receives the incoming stimulus. The next step is to calculate a total for the combined incoming stimuli. In the calculation of the total of the input signals, there are certain weighting factors: Every input is given a relative **weight** (or mathematical value) which affects the impact or importance of that input. This can be compared to the varying synaptic strengths of the biological neurons. Each input value is multiplied with its weight value and then all the products are added up for a weighted sum. If the sum of all the inputs is greater than the threshold, the neuron generates a signal (output). If the sum of the inputs is less than the threshold, no signal (or some inhibitory signal) is generated. Both types of signals are significant (Blum, 1992; Nelson & Illingworth, 1991). These weights can change in response to various inputs and according to the network's own rules for modification. This is a very important concept because it is through repeated adjustments of weights that the network "learns" (Medsker, et al., 1993).

Medsker, Turban and Trippi (1993:10) summarized the crucial steps of the **learning** process of an artificial neural network very effectively:

"An artificial neural network learns from its mistakes. The usual process of learning or training involves three tasks:

1) Compute outputs.
2) Compare outputs with desired answers.
3) Adjust the weight and repeat the process."

The learning process usually starts by setting the weights randomly. The difference between the actual output and the desired output is called Δ. The objective is to minimize Δ, or even better, eliminate Δ to zero. The reduction of Δ is done by comparing the actual output with the desired output and by incrementally changing the weights every time the process is repeated until the desired output is obtained.

Hawley, et al. (1993) compared the learning process of an artificial neural system (ANS) with the training of a pet: "An animal can be trained by rewarding desired responses and punishing undesired responses. The ANS training process can also be thought of as involving rewards and punishments. When the system responds correctly to an input, the "reward" consists of a strengthening of the current matrix of nodal weights. This makes it more likely that a similar response will be produced by similar inputs in the future. When the system responds incorrectly, the "punishment" calls for the adjustment of the nodal weights based on the particular learning algorithm employed, so that the system will respond differently when it encounters similar inputs again. Desirable actions are thus progressively reinforced, while undesirable actions are progressively inhibited." (Hawley, et al. (1993:33)

The learning of a neural network takes place in its **training** process. Every neural net has two sets of data, a **training set** and a **test set**. The training phase of a neural network consists of presenting the training data set to the neural network. It is in this training process, that the network adjusts the weights to produce the desired output for every input. The process is repeated until a *consistent* set of weights is established, that work for all the training data. The weights are then "frozen" and no further learning will occur. After the training is complete, the data in the test set is presented to the neural network. The set of weights as calculated by the training set is then applied to the test set. The presentation of the test set is the final stage in the neural network where the answer is given whether it is to predict an outcome, find a correlation, or recognize a pattern (Blum, 1992; Medsker, et al., 1993; Nelson & Illingworth, 1991). This type of learning, where a training set of actual data is used to train the neural net, is also referred to as **supervised learning** (Nelson & Illingworth, 1991). Some neural nets learn through **unsupervised learning** where there are no data available to train on. Such a network looks for regularities or trends in the input signals and makes adaptations according to the function of the network. "At the present state of the art, unsupervised learning is not well understood and is still the subject of much research." (Nelson & Illingworth, 1991:133).

Another term that justifies some explaining is the **programming of a neural network**. "Artificial neural networks are basically software applications that need to be programmed" (Medsker, et al., 1993:22). A great deal of the programming is about the training algorithms, transfer functions and summation functions. According to Medsker, et al. (1993) it makes sense to use standard neural network software where computations are preprogrammed. Several of these preprogrammed neural networks are available on the market. Every person using an artificial neural network however, has certain additional programming that needs to be done. It might be necessary to program the layout of the database, to separate the data into two sets, namely, a training set and a test set, and lastly to transfer the data to files suitable for input into the standard artificial neural network.

The basic components of a general neural network have been discussed. The next section will review different types of neural networks.

3.5 Different Types of Artificial Neural Networks

There are different types of neural networks, categorized by their topology (the number of layers in the network). To provide just a limited overview of the basic types of neural networks, the single layer network, the two layer network and multi layer networks will be discussed briefly (Rao & Rao, 1995).

3.5.1 Single Layer Networks

The single layer network has only one layer of neurons and can be used for pattern recognition. The specific type of pattern recognition in this case is called autoassociation, where a pattern is associated with itself. When there is some slight deformation of the pattern, the network is able to relate it to the correct pattern.

3.5.2 Two Layer Networks

Some models have only two layers of neurons, directly mapping the input patterns to the outputs. Two layer models can be used when there is good similarity of input to output patterns. When the two patterns are too different, hidden layers are necessary to create further internal representation of the input signals. Two layer networks are capable of heteroassociation where the network can make associations between two slightly different patterns (Blum, 1992; Nelson & Illingworth, 1991).

3.5.3 Multi Layer Networks

Several types of multi layer networks exist. The most common multi layer network is the back propagation network. According to Rao & Rao (1995), over 80% of all neural network projects in development use back propagation. "Back propagation is the most popular, effective, and easy-to-learn model for complex, multi layered networks." (Nelson & Illingworth, 1991:121). Most back propagation networks consist of three layers, an input layer, an output layer and a hidden or middle layer (Figure 3.5). The connections between the layers are forward and are from each neuron in one layer to every neuron in the next layer.

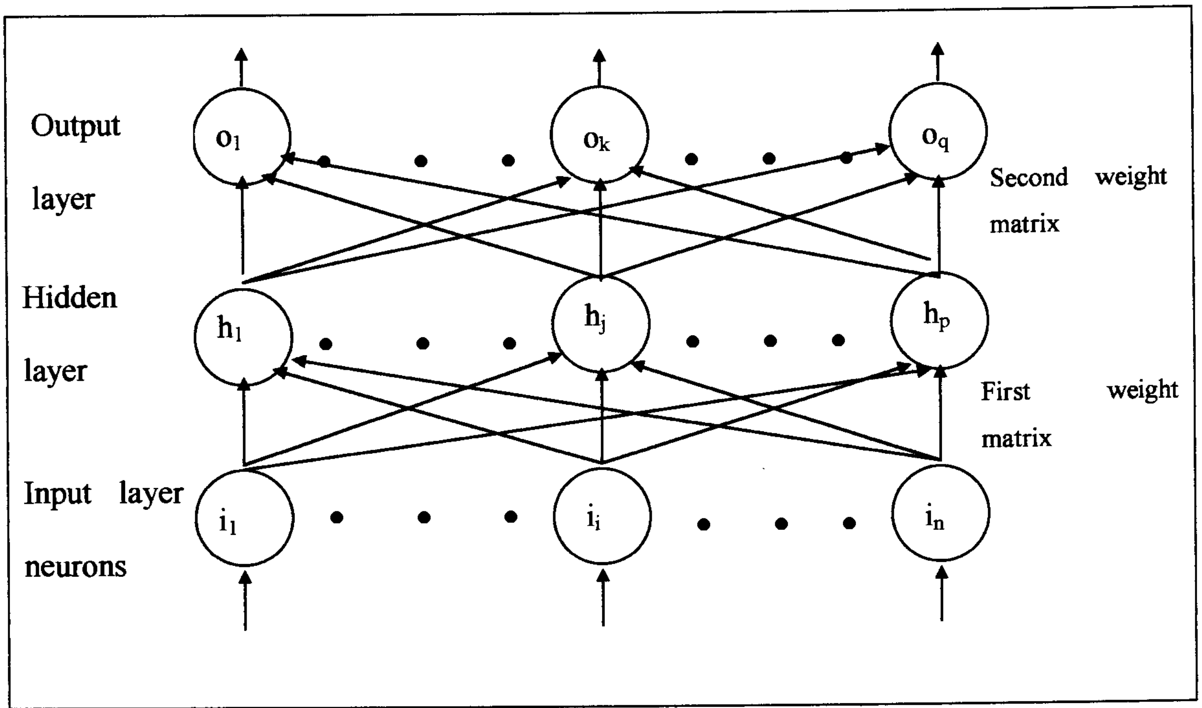


Figure 3.5: Diagram of a back propagation neural network (Blum, 1992: 56).

There are two phases in the learning process of a back propagation neural network, and it works the same as the learning process described earlier. The first stage propagates the input signal through the network in a forward manner (from the input layer, to the hidden layer, to the output layer). The second stage is to calculate the difference between the actual output and the desired output and to adapt the output, by changing the weights in the network in a backward manner (from the output layer, to the hidden layer, to the input layer). The error signals of the output are propagated back into the network for each cycle. At each back propagation, the hidden layer neurons adjust the weights of connections and reduce the error in each cycle until it is finally minimized (Blum, 1992). This process was summarized by Nelson and Illingworth, (1991: 122): "The whole sequence involves two passes: a forward pass to estimate the error, then a backward pass to modify weights so that the error is decreased." Back propagation networks require supervised learning where the network is trained with a set of data (training set) similar to the test set.

3.6 Current Applications of Artificial Neural Networks

Current applications of artificial neural networks include forecasting, image recognition, text processing and optimization (Blum, 1992).

3.6.1 Forecasting or Prediction

Intelligent forecasting is predicting future events based on historical data. A set of "historical" data can be chosen for a neural net to form a set of pattern associations. Once a neural network is trained with the pattern associations of input and output factors of the historical data, the net will "recall" output patterns when presented with input patterns. When a new set of data is presented to the trained neural net, the network can predict future events by applying the trained pattern associations to the new set of inputs (Blum, 1992).

An example of the prediction ability of neural networks is the "Airline Marketing Tactician" (AMT) from a company called BehavHeuristicts, Inc. in Silversprings, Maryland. This system is trained to monitor patterns on seat bookings on airplanes, pricing, no-show rates of passengers, etcetera, to maximize profit and minimize overbooking. The system predicts demand and no-show rates and advises a user to raise or lower the number of seats for each fare (Nelson & Illingworth, 1991). The prediction ability of neural networks is also very commonly used in the financial markets. "Financial applications that require pattern matching, classification, and prediction such as corporate bond rating, credit evaluation, and underwriting have been proven to be excellent candidates for this new technology "(Salchenberger, Cinar & Lash, 1993:230).

Blum (1992) specifically referred to the excellent forecasting and prediction abilities of back propagation neural networks. Several other investigators also proved back propagation neural networks to be highly applicable in the prediction of bankruptcy (Odom & Shara, 1993; Raghupathi, Schkade & Raju, 1993; Rahimian, Singh, Thammachote & Virmani, 1993). Odom and Shara (1993) specifically compared the predictive ability of a neural network and multivariate discriminant analysis model in bankruptcy prediction. The authors concluded that the neural network performed better on both the original set of data and the holdout sample (training set and test set). Salchenberger et al. (1993) confirmed the findings that back propagation neural networks predicted more accurately than any other method originally used. These research findings show promise in using back propagation neural networks for prediction purposes.

3.6.2 Image Recognition

An example of the image recognition ability of neural networks is the project of Paul Gorman of Bendix Aerospace (cited in Nelson & Illingworth, 1991). He trained a neural network to recognize underwater targets by sonar and to tell the difference between a mine and a rock shaped like a mine. The neural network performed better than trained human listeners or the traditional technique called nearest neighbor classifier and could recognize 90% of the mines correctly.

The area of image recognition also include recognition of handwriting, recognition of human speech (Blum, 1992) and even to estimate speech intelligibility of hearing impaired speakers (Metz, Schiavetti & Knight, 1992). In this last study, a back propagation neural network was used to predict the intelligibility of hearing-impaired speakers from acoustic speech parameters. The study attempted to classify hearing impaired persons into 4 groups of varying speech intelligibility. The network very successfully classified hearing impaired persons into the first and last group (most and least intelligible) but the neural network experienced difficulty classifying middle categories probably due to the variable chosen to separate the different classes. This experiment is currently being expanded to improve network performance.

3.6.3 Text Processing

An example of a neural network's text processing abilities is a simple spell checker, designed by Jagota and Jung of SUNY, Buffalo (cited in Blum, 1992). Text processors can also be combined with speech recognition systems. Some types of neural networks are bi-directional and can perform both functions where inputs and outputs can be reversed to achieve the desired function. If such a bi-directional system is given a word, it can return the pronunciation or the corrected spelling or both, depending on the specified output and input (Blum, 1992).

3.6.4 Optimization

Neural networks can also be used to solve difficult optimization problems such as cost minimization where numerous factors can influence a manufacturing process (Blum, 1992). An example of such an application is used in the GTE Laboratories fluorescent bulb manufacturing plant (cited in Nelson & Illingworth, 1991). A neural network was trained to monitor the production line and keep track of all the variables that influence production such as heat, pressure and the chemicals used to make the bulbs. The neural network determines and monitors optimum manufacturing conditions and can shut down the plant in emergency situations.

3.7 Advantages of Artificial Neural Networks over Conventional Statistical Methods

"One could argue that in many cases it would be *possible* to formulate a statistical approach to the same problem. For example in the image recognition applications, the program could make probabilistic guesses about what character is being viewed based on the results of a statistical model. There are several problems in this approach, however, which is why progress in the fields of pattern recognition and handwriting recognition was so slow prior to the advent of applied neural networks" (Blum, 1992:7). Some of the advantages of artificial neural networks as described by Blum, (1992) will be reviewed briefly.

3.7.1 Less Need to Determine Relevant Factors A Priori

To formulate a statistical model, one should know what factors one wish to correlate. With neural networks, irrelevant data has such low connection strength that it has no effect on the outcome. Neural networks excel at determining what data is relevant.

3.7.2 Sophistication of the Model

When hundreds of factors are at play, even if some only have a very small effect, neural network models are much more likely to be more accurate for difficult problems than any statistical model.

3.7.3 Directness of the Model

A statistical method is a more indirect way of learning correlations, where artificial neural networks model a problem directly. The example the Blum (1992) describes is to map pixelated images to alphabet letters. A neural network would simply connect the objects (all pixels of the image are neurons and are connected through a hidden layer to the output neurons that guess the letter). If a statistical method were used, the first step would have been to determine factors that are likely to influence the guess of the character. The next step to formulate a statistical model, run the model, analyze the results and then to build a system that incorporates the results. If the character can still not be identified correctly, the whole process should be repeated with other factors that are likely to influence the guess. Although it is possible to solve a problem like this with a statistical model, it requires much more time, planning and trial and error guesses.

3.7.4 Fault Tolerance

Neural networks are extremely fault tolerant and can learn from and make decisions based on incomplete data (Nelson & Illingworth, 1991). Even if some of the hardware fails, the neural network system will not be considerably changed. Blum (1992) even suggests to train on noisy data to possibly enhance post training performance.

3.7.5 Inherent Parallelism

ANNs simulate the human brain's parallelism where neurons are highly interconnected and function independently and in parallel. There are no time dependencies among synapses of the same layer all of them can work in parallel and simultaneously. Although digital computers have to simulate this parallelism, true neural network hardware really perform operations in parallel. This feature makes very fast decisions possible and the solving of very complex problems (Blum, 1992, Nelson & Illingworth, 1991).

3.8 Limitations of Neural Networks

"There is still a tendency to portray neural networks as magical, a sort of black box that does magical things" (Nelson & Illingworth, 1991:263). ANNs however, have a number of limitations that should be reviewed (Nelson & Illingworth, 1991).

Neural networks do not excel in precise exact answers. It can for example, not be used to do finances. Neural networks have the tendency to generalize.

Neural networks can not count. Counting has to take place in a sequential mode and neural networks function in parallel.

Designing a neural network is somewhat of a mysterious process. The learning process of a neural network is a tedious and painstaking trial-and-error effort. There are no standards for learning algorithms for ANNs. Another factor of importance influencing the learning process is the quality of the material that is used to train on.

Scaling is another problem. The networks may perform very well on the training and test set in the laboratory but less well as soon as it is implemented as a commercial model.

Another limitation is that ANNs can sometimes generalize or guess incorrectly. These mistakes are hard to undo since it spreads out through the network. Back propagation algorithms address this issue by extensive training on a set of data before any generalizations or guesses are made.

"In general, a neural network can not justify its answers. There is no facility to match the "how" or "why" found in expert systems. There is no way to stop it and say, "What are you doing now?" It is as if the network were instead saying, "Trust me, trust me." (Nelson & Illingworth, 1991:75). There are current efforts to build "knowledge extraction tools" for neural networks also called "justification systems" to verify the learned relationships directly (Blum, 1992).

3.9 Summary

DPOAE measurements are potentially a fantastic new objective, rapid, non-invasive, inexpensive and accurate test of auditory sensitivity. Conventional statistical methods however, could not yet provide a general rule to predict pure tone thresholds given DPOAE results.

Artificial neural networks are a new information processing technique proved to be highly applicable in the areas of prediction and correlation finding. The application of neural networks to the field of audiology, specifically, DPOAEs to predict pure tone thresholds, could result in an ideal objective testing procedure for special populations. It would have a profound positive effect on current screening procedures, as well as the differential diagnosis of sensorineural hearing losses, in the assessment of the peripheral ear.

4 Research Methodology

4.1 Introduction

Leedy (1993) gave one very interesting viewpoint on the essence of research methodology. "The process of research, then, is largely circular in configuration: It begins with a problem; it ends with that problem solved. Between crude prehistoric attempts to resolve problems and the refinements of modern research methodology the road has not always been smooth, nor has the researcher's zeal remained unimpeded." (Leedy, 1993:9).

The problem inspiring this research project has already been elaborately stated in Chapter 1. In short, the need for an objective, non-invasive and rapid test of auditory functioning has led to numerous previous studies attempting to develop such a procedure. Shortcomings in conventional statistical methods prevented accurate predictions of hearing ability with distortion product otoacoustic emissions. A new form of information processing called artificial neural networks might prove useful in the solving of this problem.

4.2 Aims of Research

The aims of this research project are:

4.2.1 Main Aim

The main aim is to predict hearing ability at 500 Hz, 1000 Hz, 2000 Hz, and 4000 Hz with distortion product otoacoustic emission (DPOAE) responses in normal and hearing-impaired ears with the use of artificial neural networks.

4.2.2 Sub Aims

The first sub aim is to determine optimal neural network topology to ensure accurate predictions of hearing ability at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz. The number of input nodes and number of output neurons are determined by the number of input- and output data. The number of middle layer neurons however, should be determined by trial and error until the required accuracy of prediction in the training stage is reached.

The second sub aim is to train a neural network with sufficient data to predict pure tone thresholds with DPOAE results. Sufficient data implies enough data from different categories of hearing loss to ensure accurate training and prediction of various hearing abilities.

The third sub aim is to determine the possible effects of age and gender on the distortion product.

4.3 Research Design

For this research project, the chosen research design was a multivariable correlational study (Leedy, 1993). The correlation between selected variables of DPOAE and selected variables of pure tone thresholds was studied by the use of artificial neural networks.

The selected variables for DPOAE measurements are:

1. The frequency of f1.
2. The frequency of f2.
3. The loudness level of f1 (L1).
4. The loudness level of f2 (L2).
5. The pattern of present and absent DPOAE responses of 8 DP Grams.
6. The age and gender variables.

The selected variables for pure tones are:

1. The frequency of the pure tone.
2. The lowest dB level where a response can be measured 50% of the time.

4.4 Subjects

For this study, data obtained from 70 subjects (120 ears, in some cases only one ear fell within subject selection specification) were used to train a neural network to predict pure tone thresholds given only the distortion product responses. Subjects were recruited from a private audiology practice as well as a school for hard of hearing children. The subjects included 28 males and 42 females, ranging from 8 to 82 years old.

4.4.1 Criteria for the Selection of Subjects

The following criteria were chosen for the selection of subjects.

4.4.1.1 Hearing Ability

In order to train a neural network with sufficient data to make an accurate prediction of hearing ability, data across all groups of hearing impairment were needed. For this study, subjects were chosen that had varying hearing ability, ranging from normal to moderate severely sensorineural hearing impaired. To obtain an equal amount of data in different areas of hearing impairment, data in three different categories of hearing impairment were included, namely normal hearing ability, mild hearing losses and moderately severe hearing losses.

There are two general classification systems to classify hearing level as being normal or impaired (Yantis, 1994). The first method converts hearing levels into a rating scale based on percentage. A Pure tone threshold average (PTA) for the frequencies 500 Hz, 1000 Hz, 2000 Hz and 3000 Hz is calculated, 25dB is subtracted (which is assumed to be the normal range) and the answer is multiplied by 1.5 to find percentage of impairment for each ear.

The second approach to describe normal ranges and hearing impairment also uses monaural PTA in the speech frequencies but adds additional descriptors to the different levels. Clark 1981 (cited in Yantis, 1994) modified Goodman's recommendations from 1965 into the following categories:

-10 to 15dB	Normal hearing
16 to 25dB	Slight hearing loss
26 to 40dB	Mild hearing loss
41 to 55dB	Moderately severe hearing loss
56 to 70dB	Severe hearing loss
91dB plus	Profound hearing loss

For this study, the second approach to classification of hearing impairment (as used by Clark, 1981 in Yantis, 1994) was used. Subjects with normal hearing, slight hearing loss, mild hearing loss and moderately severe sensorineural hearing loss were included in the study. To divide the subjects into three groups of 40 ears each, the group with normal hearing ranged from 0 dB to 15 dB. The group with slight and mild hearing loss ranged from 16 to 35dB and the moderately severe hearing-impaired group had PTAs in the range of 36 - 65dB. It should be noted that according to Clark's (1981) (cited in Yantis, 1994) specification the moderate hearing loss group only includes hearing losses of up to 55 dB, whereas the severely hearing impaired group extends to 70 dB. DPOAEs has been reported in ears that have a hearing threshold as high as 65dB HL (Moulin, et al., 1994) at the frequencies close to the primaries. It was therefore decided to combine the category of moderate and severe hearing impairment to form the category moderately severe hearing impairment ranging from 36 to 65 dB HL. The data was divided into three groups merely to ensure that an equal amount of data was obtained in each category. Another modification to Clark's classification system has been made. In addition to the frequencies used by Clark (1981) (cited in Yantis, 1994) to determine the PTA, namely 500 Hz, 1000 Hz, 2000 Hz and 3000 Hz, for this study 4000 Hz was also taken in consideration in the classification of hearing impairment. The reason for this modification is that DPOAE measurements are required at 4 kHz to predict the pure tone threshold at 4 kHz.

4.4.1.2 Middle Ear Functioning

The second selection criterion was normal middle ear functioning. Otoacoustic emissions can only be recorded in subjects with normal middle ear function. Only a very small amount of energy is released by the cochlea and is transmitted back through the oval window and ossicular chain to vibrate the tympanic membrane. Normal middle ear function is crucial to this transmission process (Norton, 1993; Osterhammel, Nielsen & Rasmussen, 1993; Zhang & Abbas, 1997).

Normal middle ear functioning was determined by otoscopic examination and tympanometry.

4.4.1.2.1 Otoscopic Examination

Otoscopic examination was performed to determine the amount of wax in the ear canal, for excessive wax may block the otoacoustic emission microphone and prevent the reading of a response. The second aspect that was investigated was the light reflection on the tympanic membrane, indicative of a healthy tympanic membrane (Hall III & Chandler, 1994).

4.4.1.2.2 Tympanometry

A subject's tympanometry results must have been within the following specifications to be included in the study:

A normal type A tympanogram was one of the criteria for normal middle ear functioning. A type A tympanogram has a peak (or point of maximum admittance) of 0 to -100 daPa. The peak may even be slightly positive, for example +25daPa (Block & Wiley, 1994). A type A tympanogram's static immittance when measured at 226 Hz ranges from about 0.3 cm^3 to 1.6 cm^3 (Block & Wiley, 1994). Subjects demonstrating type A tympanograms within these specifications were accepted for the study.

4.4.1.3 Attention Span

Only persons that were able to cooperate for approximately an hour were included in the study. Subjects had to be able to follow instructions and sit quietly and still in one position for about forty minutes for DPOAE testing. Subjects demonstrating inadequate ability to follow instructions or cooperate during pure tone audiometry, tympanometry or DPOAE testing were not included in the study. Some of the reasons subjects were excluded from the study in this regard include very young age, ill health and hyperactivity.

4.4.1.4 Criteria Regarding subject Age and Gender

There is some debate regarding the effect of age on distortion product otoacoustic emissions. In a study by Lonsbury-Martinet al. (1991), a negative correlation between DPOAE measurements and age for subjects 20-60 years was reported. In their report however, it is suggested that this negative correlation is due to changes in hearing threshold associated with aging. A study by Stover and Norton (1993) (cited in He & Schmiedt, 1996) also indicated that the difference in DPOAEs between younger and older subjects can be attributed to the sensitivity changes, rather than the aging itself. According to He and Schmiedt (1996) a 60-year-old person with normal hearing (PTA < 15dB) will therefore have the same DPOAEs as a 12-year-old with the same pure tone threshold levels.

There was therefore no selection criteria regarding age. The only population that was excluded in this study is the pediatric population, due to differences in middle ear properties such as canal length, canal volume and middle ear reverse transmission efficiency that may cause differences in DPOAE amplitudes (Lasky, 1998a; Lasky, 1998b; Lee, Kimberley & Brown, 1993).

There was also no selection criteria regarding gender. Gaskill and Brown (1990) and Cacace et al. (1996) reported that DPOAEs were significantly larger in female than male subjects tested in the frequency range of 1000- 5000Hz. Both studies however, indicated that the female subjects in their studies had more sensitive auditory thresholds than the males (an average of 2.4 dB better). The differences found between the two groups could therefore not be explained by gender only.

Lonsbury-Martin et al. (1990) conducted a study to investigate basic properties of the distortion product including the effect of gender on the prevalence of DPOAEs. A comparison of DPOAE amplitudes and thresholds failed to reveal any significant differences except a minor difference at 4 kHz.

Gender effects on DPOAEs are apparently limited to minor differences in DPOAE amplitudes and thresholds and therefore gender was not one of the selection criteria for this study.

4.4.2 Subject Selection Procedures

The procedure in which subjects were selected started with a brief interview, following an otoscopic examination of the external meatus, tympanometry and pure tone audiometry.

4.4.2.1 Case History and Personal Information

A short interview was performed to obtain a limited case history and some personal information. The research project was also discussed with the subject in a very brief manner and any questions answered. The purpose of the case history was to obtain enough personal information to open a new subject file and obtain the subject's age and gender for later studies of these effects on DPOAEs. Second, information regarding hearing status such as any complaints of tinnitus and vertigo, the amount of noise exposure and complaints of middle ear problems was obtained. In the analysis of data, some subjects may exhibit abnormal DPOAEs in conjunction with normal pure tone thresholds. In a study by Attias, Furst, Furman, Horowitz and Bresloff (1995), it was found that in some cases, subjects with normal pure tone thresholds of 0 dB exhibited abnormal otoacoustic emissions, due to noise exposure. The effects of noise exposure can clearly be seen long before the actual hearing loss occurs. This is also true for ototoxic medication (Danhauer, 1997). By obtaining this background information, possible reasons for abnormal DPOAEs may be formulated. Appendix A reviews the aspects which were addressed in the short interview. This short interview lasted approximately 10 minutes.

4.4.2.2 Otoscopic Examination

Otoscopic examination of both ears was performed, with special attention to the light reflection of the eardrum and excessive wax in the ear canal. The duration of the otoscopic examination was about 3-5 minutes.

4.4.2.3 Tympanometry

The next step in the subject selection procedure was to obtain a tympanogram to determine middle ear functioning. The subject was instructed to sit in front of the tympanometer and not to speak or swallow. Tympanometry was performed in both ears and the duration of the procedure was about 5 minutes.

4.4.2.4 Traditional Audiogram

If the subject had normal middle ear functioning, the subject selection procedure continued. A traditional audiogram was obtained from the subject. The frequencies that were tested during pure tone air conduction was 125 Hz, 500 Hz, 1000 Hz, 2000 Hz, 4000 Hz and 8000 Hz. If a hearing loss was present, or if any of the frequencies except 8000 Hz had a threshold >15 dB, then pure tone bone conduction was also performed. If sensorineural hearing losses varied with more than 15 dB between adjacent frequencies, in between frequencies such as 3000 Hz or 750 Hz were also tested. Only subjects with sensorineural hearing losses (no gap between air conduction and bone conduction) were accepted for the study. Threshold determination was in 5dB steps and a threshold was defined as 50% accurate responses at a specific dB level (Yantis, 1994).

Audiograms from subjects were then analyzed. All audiograms indicating normal hearing (500 Hz, 1000 Hz, 2000 Hz, 3000 Hz and 4000 Hz below 15 dB) were included in the first group. Audiograms indicating hearing loss were analyzed in terms of the degree and configuration of the hearing loss. Mild hearing loss, indicating a hearing loss between 16-35 dB in the frequency region 500-4000 Hz were categorized in the second group, namely mild hearing loss. Audiograms indicating hearing loss of 36-65 dB in the frequency region of 500-4000 Hz were categorized in the third group, namely moderately severe hearing loss. In each category, 40 audiograms were included.

The duration of pure tone audiometry was approximately 15-20 minutes.

If a subject demonstrated normal middle ear functioning and a pure tone audiogram that could be categorized into one of the three groups, DPOAE measurements were performed within the next hour. This procedure will be discussed in data collection procedures.

4.5 Apparatus

The apparatus for the different sections of research were as follows:

4.5.1 Subject Selection Apparatus

- For otoscopic examination of the external meatus and tympanic membrane an otoscope was used, specifically the Welch Allyn pocketscope model 211.

- For tympanometric measurements the GSI 28 A middle ear analyzer, calibrated April 1997 was used (Testing was performed in January 1998).

- For determination of auditory pure tone thresholds, the GSI 60 Audiometer, calibrated April 1997 was used. The model of the earphones on the audiometer was 296 D 200-2. Pure tone thresholds were measured in a sound proof booth.

4.5.2 Data Collection Apparatus

- The measurement of Distortion Product Otoacoustic Emissions were conducted with a Welch Allyn GSI 60 DPOAE system and the probe was calibrated for a quiet room in January, 1998. All measurements were made in a quiet room.

4.5.3 Data Preparation Apparatus

- For the preparation of data files, a Pentium 200 MMX computer was used. The software included Excel for Windows 1998.

4.5.4 Data Analysis Apparatus

- For the training of the neural network, the back propagation neural network from the software by Rao and Rao, 1995 (in addition to the book) was be used. The neural network was trained on a Pentium 200 MMX.

- Further analysis of data was performed in Excel for Windows 1998 and with custom software.

4.5.5 Preliminary Study

The reason for the preliminary study was twofold: First, to determine which persons may participate as subjects and second, which stimulus parameters to use in the measurements of DPOAEs.

4.5.5.1 Determination of Subject Selection Criteria

A very large part of the determination of subject selection criteria was based on an extensive overview of related literature. The researcher did however conduct a series of DPOAE measurements on subjects with various categories of hearing ability to confirm current subject selection criteria. Just a few of the interesting finds during DPOAE measurement of the preliminary study will be discussed briefly.

To confirm the studies of the importance of normal middle ear functioning by researchers such as Zhang and Abbas, (1997); Osterhammel et al., (1993); Hall III et al., (1993) and Kemp et al., (1990), a few DPOAE measurements were performed on subjects that displayed acceptable hearing ability for this study but small variations in tympanometric results. One subject had perfect hearing (pure tone hearing thresholds of 0 dB HL at all frequencies) but no airtight seal could be obtained as a result of grommets in the tympanic membrane. This subject displayed very high levels of low frequency background noise during DPOAE testing and it was difficult to distinguish the DPOAE responses from the noise floor at most of the low and mid frequencies. Another subject had a mild sensorineural hearing loss but the tympanogram's compliance was just below 0.3cc. This subject also demonstrated very high levels of low and mid frequency noise with indistinguishable DPOAE responses above the noise floor. A normal type A tympanogram with static compliance of 0.3-1.75cc was therefore set as one of the subject selection criteria.

A few measurements were also made in the ears of severely hearing impaired subjects and varying levels of stimuli was used. Another aspect that became apparent after a few tests were conducted was the absence of DPOAEs in persons with hearing losses greater than 65dB HL. This confirmed studies by Moulin et al., (1994) and Spektor et al., (1991) which found that when stimuli lower than 65dB SPL are used, DPOAEs can not be measured in ears with a hearing loss exceeding 65dB HL. Therefore, for this study, only subjects were included with sensorineural hearing losses of up to 65 dB HL.

These same tests also revealed that when very high intensity primaries were used (such as 70- 80dB SPL), in some instances one could observe "passive" emissions from the ears of these severely hearing impaired subjects. The reason for passive emissions, according to Mills, (1997) is that very high level stimuli can stimulate broad areas of the basilar membrane and phase relations between travelling waves can cause these "passive" emissions that do not correspond well to hearing sensitivity or frequency specificity. In this preliminary study, passive emissions were only observed when stimuli levels were higher than 70dB. It was therefore decided not to use stimuli levels higher than 70dB.

A second series of tests were conducted to determine optimal stimulus parameters.

4.5.5.2 Determination of Optimal Stimulus Parameters

Most of the stimulus parameters for this study were derived from an in depth literature study. Parameters such as the frequency ratios between the primaries, the loudness levels of L1 and L2 and whether to measure DP Grams or I/O functions were selected on recommendation of other previous studies. There are however a few stimulus parameters that requires some experimenting in order to determine applicability and practicality for a certain research project. One such example is the configuration setup, or specifically, the number of frames of data that will be collected in each measurement. The GSI-60 DPOAE system offers two possibilities, a screening option and a diagnostic option.

The screening option collects a maximum of 400 frames before stopping each primary tone presentation. Not every test runs up to 400 frames, if a very clear response is measured, the measurement can be made in as little as 10 frames. Test acceptance conditions for the screening configuration are a cumulative noise level of at least –6dB SPL and either a DPOAE response amplitude that is 10 dB above the noise floor or a cumulative noise level of at least –18 dB SPL (GSI-60 manual, p2-44). A maximum of 400 frames are measured, and if no clear response was present, the results are labeled "timed out."

The diagnostic option runs up to 2000 frames for each primary tone presentation. The minimum number of accepted frames is 128. Test acceptance conditions are that the distortion product minus the average noise floor should be at least 17 dB.

After a few measurements in both configurations it became clear that the diagnostic option requires much more testing time. Testing time of one single DP Gram measured at low level stimuli in the diagnostic configuration could increase testing time up to 12 minutes. Even though the general noise floor was slightly lower during the diagnostic option, it was not practical to conduct 8 DP Grams in each ear with tests lasting 6-12 minutes each. It would take between an hour and one and three quarters of an hour to measure one ear alone with DPOAEs. It was therefore not practical to evaluate 120 ears with the diagnostic option. The screening option with a testing time of up to 2 minutes per DP Gram was selected for this study. One ear could be evaluated in about 15 minutes with DPOAEs and the screening procedure yielded very much the same information.

Lastly, the stimulus parameter that required some experimenting was the selection of the frequencies of the primary tone pairs. The GSI-60 DPOAE system has a "Custom DP" function where the examiner can choose any primary frequencies for DPOAE measurement. After a few tests it became clear that care should be taken when selecting primary tones. Not only should the frequency ratio of the primaries preferably be 1.2, but the frequency values from one tone pair to the next should be at least one octave apart to avoid interaction between stimuli (GSI-60 manual, p2-39). The GSI-60 measures the noise floor from the first primary tone pair per group, and if frequency pairs are selected too close to each other, very high levels of noise are being measured. So after a lot of changes in primary tone pairs were made to avoid interaction between stimuli, the researcher ended up with stimuli very similar to the default stimuli of the GSI-60. It was therefore decided to use the default primary frequencies of the GSI-60 for this study by activating all four octaves. (It seems that those stimuli are set as default for a very obvious reason.)

Just for practicality, a few test runs that incorporated the whole data collection procedure were conducted to determine the amount of time required testing each subject. This was determined in order to schedule appointments. As seen in Table I, the whole data collection procedure lasted about an hour. In some cases, especially in the case of subjects with a hearing loss, more time was required for bone conduction but on the average, one hour was sufficient to test one subject.

Table I: Time required testing one subject

Subject history	5 minutes
Audiometry	15 minutes
Otoscopic examination	5 minutes
Tympanometry	5 minutes
DPOAE measurements left ear	15 minutes
DPOAE measurements right ear	15 minutes
Total testing time	**60 minutes**

4.6 Data Collection Procedures

The following procedure was conducted in the various stages of the research project.

4.6.1 Data Collection Procedures in the Selection of Subjects

In the selection of subjects, the procedure included a short interview, an otoscopic examination, tympanometry and pure tone audiometry. Data that was collected during the interview, the otoscopic examination and tympanometry was used for subject selection only. Data that was collected during pure tone audiometry was not only used in the selection of subjects, but also in the main purpose of the study, namely to train a neural network to predict pure tone thresholds given the distortion product responses. These procedures were discussed in **4.4.2 Subject Selection Procedures**.

4.6.2 Data Collection Procedures Conducted During Research

In order to train a neural network to predict pure tone thresholds given only the distortion product responses, two sets of data should be collected namely each subject's pure tone thresholds and each subject's DPOAEs.

4.6.2.1 Data Obtained From Pure Tone Audiometry

The necessary pure tone audiometry data has already been obtained during subject selection and the collection procedure for this set of data has been described in the section **4.4.2.4. Traditional Audiogram**.

4.6.2.2 Data Obtained from DPOAE Measurements

The second set of data that was collected was each subject's DPOAE responses. The procedure for the collection of this set of data is quite complex, due to the number of stimulus parameters that should be specified. There is a four dimensional space in which the stimulus parameters for DPOAE measurement should be specified (Mills, 1997). The frequencies of the two primary stimulus tones f1 and f2 (f1>f2), the frequency ratio of f2/f1 (how many octaves apart the two frequencies are), the loudness level of f1 (which is L1) and the loudness level of f2 (which is L2). Furthermore, the difference in loudness level between L1 and L2 should also be specified.

4.6.2.2.1 Specification of Stimulus Parameters for DPOAE Measurements

The specification of stimulus parameters will be reviewed shortly.

4.6.2.2.1.1 The Selection of the Frequencies

In the case of the GSI-60 Distortion Product otoacoustic emissions system, the number of octaves that should be tested can be specified as well as the amount of data points to plot between octaves. The octaves available are 0.5 - 1 kHz; 1-2 kHz; 2-4 kHz and 4 -8 kHz. All of these octaves was selected for DPOAE testing because information regarding all these frequencies was required to make comparisons with the audiogram in the frequency range 500 - 4000 Hz. The amount of data points between frequencies could be any number between 1 and 20. The more data points per octave, the longer the required test time since more frequency pairs are tested between frequencies. The GSI-60 manual suggests three data points per octave to be adequate, not increasing the test time too much but yielding enough information regarding DPOAE prevalence between frequencies. In the case of the pure tone audiogram, in-between frequencies were only tested when hearing losses between frequencies varied more than 15 dB (to measure the slope of the hearing loss) and only one or in extreme cases two in-between frequencies were evaluated. The selection of three data points between octaves in the case of DPOAE measurement should therefore be adequate.

The frequencies tested by the GSI-60 when all four octaves are activated and three data points per octave is specified amount to 11 frequency pairs. The 11 frequency pairs are presented in Table II.

f1 and f2 are always presented simultaneously as a pair, f1>f2 and the f2/f1 ratio is ~1.2.

Table II: The 11 frequency pairs tested by the GSI-60 DPOAE system when all four octaves are activated.

PAIR	1	2	3	4	5	6	7	8	9	10	11
f1 Hz	500	625	781	1000	1250	1593	2000	2531	3187	4000	5031
f2 Hz	593	750	937	1187	1500	1906	2406	3031	3812	4812	6031

4.6.2.2.1.2 The Selection of the Frequency Ratio of the Primary Frequencies (f2/f1)

Several studies investigated the effect of the frequency ratio on the occurrence of DPOAEs (Cacace et al., 1996; Popelka, Karzon & Arjmand, 1995; Avan & Bonfils, 1993; He & Schmiedt, 1997).

It appears that the frequency ratio of 1.2 - 1.22 is most applicable to a wide range of clinical test frequencies (0.5-8kHz) and a wide range of stimulus loudness levels. A stimulus ratio of f2/f1 = 1.2 was therefore selected for this study.

4.6.2.2.1.3 The Selection of the Loudness Levels of the Primaries, L1 and L2.

As mentioned in the introduction, there are two ways of eliciting a DPOAE response. Either the frequencies are changed and the loudness level kept constant, this is sometimes referred to as a "distortion product audiogram" (DP Gram), or the frequencies are being kept constant while the loudness level is changed (an input/output function (I/O) is obtained). In this case, several DP audiograms were obtained. All the frequencies selected for all four octaves were presented to the subjects at different loudness levels, starting with maximum loudness levels at L1= 70 dB; L2 =60 dB. Loudness levels were decreased in 5 dB steps until DP "thresholds" (lowest intensities where DP responses can be distinguished from the noise floor) for all the frequencies were obtained. The lowest loudness level for the primaries that was tested was L1= 35 dB; L2= 25dB. Eight loudness levels were therefore evaluated resulting in eight DP "audiograms" for each ear.

4.6.2.2.1.4 The Relative Loudness Levels of the Primaries (L1 and L2)

An overview of several studies indicated the following loudness level ratios to be most suitable for the detection of DPOAEs: L1>L2 by 10dB (Stover et al., 1996a), L1>L2 by 15 dB (Gorga et al., 1993) and L1>L2 by 10-15 dB (Norton & Stover, 1994). A study by Mills (1997) indicated that more DPOAEs were recorded when L1>L2 than L1 = L2.

A loudness level ratio of L1>L2 by 10 dB was chosen for this study.

4.6.2.2.1.5 The Criteria for DPOAE Threshold

The detection threshold for a distortion product otoacoustic emission depends almost entirely on the noise floor and the sensitivity of the measuring equipment (Martin et al., 1990b). A distortion product with an amplitude less than the noise floor can not be detected (Kimberley & Nelson, 1989; Lonsbury-Martin et al., 1990). Most researchers specify a DP response to be present if the DP response is 3-5 dB above the noise floor. Harris and Probst (1991:402) specified a DP response as "the first response curve where the amplitude of 2f1-f2 is ≥ 5 dB above the level of the noise floor." Lonsbury-Martin et al., (1990) reported detection thresholds for DPOAE measurements 3 dB above the noise floor. Lonsbury-Martin (1994) set the criterion level for a DPOAE threshold at ≥ 3 dB.

For this study, a detection threshold for a DPOAE response will be defined as the first response where the distortion product (2f1-f2) is 3 dB above the noise floor.

4.6.2.2.2 DPOAE Testing Procedure

DPOAE measurements were performed directly after the subject selection procedure. Subjects were instructed to sit next to the GSI 60 DPOAE system, not to talk and to remain as still as possible. Subjects were allowed to read as long as they kept their heads as still as possible. First, a new file was opened for the subject. Then the DPOAE probe tip was inserted into the external meatus in such a manner that an airtight seal was obtained.

Eight tests or DP Grams were performed in each ear. Every DP Gram consisted of eleven frequency pairs. Every frequency pair consisted of two pure tones, f1 and f2 presented to the ear simultaneously (see Table II for the 11 frequency pairs). The eleven frequency pairs were presented to the ear in a sweep, one at a time starting with the low frequencies, ending with the high frequencies.

The first DP Gram was conducted on the loudness levels F1 = 70dB SPL, F2 = 60dB SPL. The second DP Gram was conducted 5 dB lower at F1 = 65 dB SPL, F2 = 55 dB SPL. The third DP Gram was conducted 5 dB lower than the second, namely F1 = 60 dB SPL, F2 = 50 dB SPL. A total of eight DP Grams were conducted, each one 5 dB lower than the previous one. The lowest intensity DP Gram that was performed was F1 = 35 dB SPL, F2 = 25 dB SPL.

The procedure was repeated for both ears if both ears fell within selection criteria. The duration of DPOAE testing of eight DP Grams for one ear was between 15-20 minutes. If a subject was tested binaurally, the duration of DPOAE testing was approximately 30-40 minutes.

4.7 Data Preparation Procedures

The first step in the data preparation procedures is to organize all raw data in files.

4.7.1 Creation of a Data File for Each Ear

Each ear has its own file. A file is merely a row of numbers, depicting the test results in a certain order. The first column represents the subject or file number, the second number the DP Gram number, then the ear that has been tested (left or right) and so the numbers continue until all data relating to the DPOAE testing procedure and pure tone testing results have been depicted. Table III represents a data file for one DP Gram. 8 DP Grams for each ear were conducted. The complete data file for one ear would therefore have 88 rows of data under each column number. The column numbers in the top row is explained to indicate which measurement that column represents in the section following the Table III.

Table III: Example of a data file for one DP Gram

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1	R	500	70	593	60	406	8	0	N	0	0	5	0	0	0	24	F
1	1	R	625	70	750	60	500	9	-1	T/O	0	0	5	0	0	0	24	F
1	1	R	781	70	937	60	625	14	-6	A	0	0	5	0	0	0	24	F
1	1	R	1000	70	1187	60	812	3	-2	N	0	0	5	0	0	0	24	F
1	1	R	1250	70	1500	60	1000	12	-6	A	0	0	5	0	0	0	24	F
1	1	R	1593	70	1906	60	1281	-1	-9	A	0	0	5	0	0	0	24	F
1	1	R	2000	70	2406	60	1593	13	-7	A	0	0	5	0	0	0	24	F
1	1	R	2531	70	3031	60	2031	5	-8	A	0	0	5	0	0	0	24	F
1	1	R	3187	70	3812	60	2562	7	-9	A	0	0	5	0	0	0	24	F
1	1	R	4000	70	4812	60	3187	8	-6	A	0	0	5	0	0	0	24	F
1	1	R	5031	70	6031	60	4031	5	-6	A	0	0	5	0	0	0	24	F

Explanation of column numbers for Table III:

1 Subject number.

2 Number of DP Gram.

3 Ear that is being tested (right or left).

4 Frequency of f1 in Hz.

5 Loudness level of L1 in dB SPL.

6 Frequency of f2 in Hz.

7 Loudness level of L2 in dB SPL.

8 Distortion product frequency in Hz.

9 Distortion product amplitude in dB SPL.

10 Loudness level of noise floor in dB SPL.

11 Test status (A= accepted, N= noisy, T/O= timed out response).

12 Pure tone threshold of 250 Hz in dB HL.

13 Pure tone threshold of 500 Hz in dB HL.

14 Pure tone threshold of 1000 Hz in dB HL.

15 Pure tone threshold of 2000 Hz in dB HL.

16 Pure tone threshold of 4000 Hz in dB HL.

17 Pure tone threshold of 8000 Hz in dB HL.

18 Subject age.

19 Subject gender.

The next step in the preparation of data was to select the type of neural network needed for this study and also the topology of the neural network.

4.7.2 Selection of the Type of Neural Network

A back propagation network was chosen for this study for two reasons: **1)** A possible nonlinear correlation is suspected between DPOAE thresholds and traditional pure tone thresholds. Metz, et al., 1992 reported the back propagation neural network to be very successful in dealing with nonlinearities that potentially occur in complex data sets. According to Blum, 1992, the back propagation neural network is capable of nonlinear mappings and able to generalize well. **2)** The purpose of this study is to predict pure tone thresholds with distortion product thresholds with the use of neural networks. According to Blum, (1992), the back propagation neural network is highly applicable in the areas of forecasting and prediction. Tam and Kiang, (1993) indicated a back propagation neural network to be very effective in the prediction of bank failure. Salchenberger, et al. (1993) also chose a back propagation neural network for their prediction study where thrift institution failures were predicted and obtained predictions better than any other method originally used.

To summarize, back propagation networks are applicable in the areas of *prediction* and can be used where a possible *nonlinear correlation* is sought between two sets of data.

4.7.2.1 Selection of the Topology of the Neural Network

Aspects that determine the topology of a neural network are:

4.7.2.1.1 Number of Layers in the Neural Network

"A neural network has its neurons divided into subgroups, or fields, and elements in each subgroup are placed in a row, or column, in the diagram depicting the network." (Rao & Rao, 1995:81).

For this back propagation neural network a three-layer structure was chosen: The first layer is an input layer only. The third layer is the output layer and the second layer, also referred to as the hidden layer, categorizes the input pattern and serves as a connection between the first and third layer.

4.7.2.1.2 Number of Nodes in the Input Layer

The number of input data sets that the neural network is trained with determines the number of nodes in the input layer. For example, if one threshold value at each of the 11 distortion product frequencies is used to train the neural network, the input layer will consist of 11 nodes. If two values at each of the 11 distortion product frequencies are used, such as the threshold value and the amplitude value, then the number of nodes in the input layer will be 22.

Several experiments were conducted to find the optimal number of input nodes for this study. These “trial runs” to determine the optimal topology of the neural network are described in **4.7.2.1.5: Trial Runs to Determine Neural Network Topology**.

4.7.2.1.3 Number of Neurons in the Output Layer

In the case of the output and hidden layers, the components are being referred to as neurons because of the two layers of connectivity (an input and an output) which gives it the similar structure as a neuron with a synapse on each side.

The number of aspects that is being predicted determines the number of neurons in the output layer. For example, if the neural network has to predict hearing thresholds at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz, then the number of output neurons will be four. If the neural network has to predict only one frequency, then only one output neuron in needed. Even though the aim of this study was to predict hearing ability at all four these frequencies, one network does not necessarily have to do it simultaneously, the same results can be achieved by four different networks, trained to predict only one of the frequencies. The trial runs that were conducted to determine the optimal number of output neurons for this study are also discussed in **4.7.2.1.5: Trial Runs to Determine Neural Network Topology**.

4.7.2.1.4 Number of Neurons in the Middle- or Hidden Layer

The number of neurons in the hidden or middle layer cannot be determined merely by the amount of input or output data but is a function of the diversity of the data (Blum, 1992). The number of middle layer neurons determines the accuracy of prediction during the training period. With an insufficient number of middle neurons, the network is unable to form adequate midway representations or to extract significant features of the input data (Nelson & Illingworth, 1991). With too many middle neurons the network has difficulty to make generalizations (Rao & Rao, 1995; Nelson & Illingworth, 1991). The number of middle layer neurons was determined by trial and error, based on the accuracy of the prediction during the training period. All these trial runs are discussed in the following section.

4.7.2.1.5 Trial Runs to Determine Neural Network Topology

The **first scenario** encompassed all the data from all 120 ears. DPOAE thresholds were determined for all 120 ears at all 11 DPOAE frequencies (in other words, the lowest L1 value that still yielded a DPOAE response). The criteria for a DPOAE threshold was that the lowest L1 DPOAE response had to be 3 dB above the noise floor and that the test status had to be "accepted".

All the lowest L1 values where a DPOAE response was measured were used as input data for the neural network. There were however some of the hearing impaired subjects that did not have any DPOAE responses at certain frequencies, and no DPOAE threshold values were available to use as input data. All these absent DPOAE thresholds were depicted with a "zero".

The input level of this neural network therefore had 11 nodes and each represented the L1 dB SPL value where the DPOAE threshold was measured. The neural network had to predict hearing ability at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz in dB SPL. There were therefore 4 output neurons in this network. The number of middle level neurons were set at 20 and the acceptable prediction error during the training period at 5 dB for this test run. After a few hours it became clear that the neural network was unable to converge during the training period and that no accurate predictions could be made. For the next few trial runs, middle level neurons were increased up to 100 or the acceptable prediction error during the training period were decreased to 1 dB. All these changes did not improve convergence or prediction ability. It became clear that the absence of DPOAE thresholds in the hearing impaired population (about 66% of the subjects) called for a different data preparation method.

In the **second scenario**, an attempt was made to determine necessary neural network topology and acceptable prediction error with only those subjects that had DPOAE responses at all 11 frequencies. There were 20 ears with DPOAE thresholds at all 11 DPOAE frequencies, and naturally, almost all (19) had normal hearing (pure tone thresholds < 15 dB HL). Many different trial runs were conducted to determine the effects of the number of middle level neurons and acceptable error during training on the prediction abilities of the neural network. The general tendency revealed that more accurate predictions were made with higher numbers of middle level neurons (around 100) but that the acceptable error during training did not have a great influence on the accuracy of the prediction. An acceptable error of 5 dB in the training stage did not worsen prediction abilities compared to a training error of 1dB. It was actually found in some instances that the network had a better ability to generalize with the larger training error of 5dB. Just for general interest, one example of the second scenario trail runs will be discussed briefly.

All ears with DPOAE responses at all 11 frequencies were selected. (There were 20 ears, 19 had normal hearing (0-15 dB HL) and one had a mild hearing loss (25dB HL). For input data, only the eight highest DPOAE frequencies were used. The 3 low DPOAE frequencies were omitted because of high levels of low frequency noise. This time DPOAE amplitudes were used instead of DPOAE thresholds. The DPOAE amplitudes at L1 = 65, L2 = 55 were used as input values for the eight high frequencies. The neural network was programmed to predict only one high frequency, namely 2000 Hz. The number of middle neurons was set at 20 and the acceptable error during training at 0.5dB. The network converged fairly quickly and predictions turned out to be extremely accurate. 2000 Hz could be accurately predicted within 10 dB 100% of the time and within 5 dB 83% of the time. Although this seems like a cause for celebration, one should ask oneself what the relevance of such a prediction is. If all the ears in the training set are normal ears, and the network predicts all the ears as normal, would it necessarily know an ear with a hearing loss if it encountered one? All that could be derived from this trial run was that it was time to try a new data preparation method to incorporate all data from hearing impaired subjects as well. Accurate predictions of hearing ability across different categories of hearing impairment can only be made if a neural network is trained with sufficient data to recognize all the different categories.

Scenario three required drastic changes in the way the data is presented to the neural network. Up to now, input data consisted of decibel sound pressure level (SPL) quantities, depicting either a DPOAE threshold at a certain L1 value or DPOAE amplitude. Output data also predicted hearing thresholds in decibel sound pressure level (dB SPL) values. For scenario three, a whole new approach was used. All data was rewritten in a binary format. The presence of a DPOAE response was depicted with a "1" whereas the absence of a DPOAE response was depicted with a "0".

The criteria for the presence of a DPOAE response was that the DPOAE response had to be 3 dB above the noise floor and that the test status had to be "accepted". All responses less than 3 dB above the noise floor or with a test status that was "noisy" or "timed out" were regarded as absent responses. (It should be noted that Kemp (1990) warned that in order to determine if a response is 3 dB above the noise floor, one could not merely subtract the noise floor from the DPOAE amplitude in its decibel form. The two values should be converted back to their pressure value (Watt/m^2), then subtracted.)

Responses from each of the eight DP Grams in each of the 120 ears were rewritten in this binary format. In the end, each ear had a row of 88 numbers ("ones" and "zeros") and every number depicted the presence or absence of a DPOAE response at one of the 11 DPOAE frequencies and one of the 8 loudness levels. These 88 numbers served at input information in the neural network (the network therefore had 88 input nodes). The only information available to the neural network in this trail run was therefore the pattern of absent and present responses at all eight loudness levels.

Another drastic change was made in the way the pure tone audiogram was depicted. As a first level approach every audiogram was graded into seven categories of average hearing ability. Each category spanned 10 dB, category one ranged from 0-10dB, category two from 11-20 dB, three from 21-30 dB and so forth. The seven categories can be seen in Table IV. Each category of hearing ability was determined by taking the average of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz. Each ear had one number in the end, depicting its average hearing ability according to one of the seven categories. The network had only binary input information, not dB SPL values, and only had to guess a category, not a decibel value. The decibel hearing level categories of the audiogram were therefore used in its hearing level (HL) form.

To present average hearing ability according to one of the seven categories in a binary fashion, each ear had seven number places (or columns). Column one represented hearing ability in category one, column two represented hearing ability in category two and so forth. To indicate average hearing ability, the column that represented that specific hearing ability was given a "one" and the rest "zeros". For example, an ear with an average hearing ability of 29 dB HL would fall in category 3. This ear would be written: [0 0 1 0 0 0 0]. An ear with an average hearing ability of 5 dB HL would be written as [1 0 0 0 0 0 0], therefore depicting category one.

Table IV : Seven categories of hearing ability for scenario three and four

Category 1	0 -10 dB
Category 2	11-20 dB
Category 3	21-30 dB
Category 4	31-40 dB
Category 5	41-50 dB
Category 6	51-60 dB
Category 7	61-70 dB

The neural network was trained with the 88 input nodes depicting the pattern of present and absent DPOAE responses at all 11 DPOAE frequencies and all 8 loudness levels as well as the average hearing ability in one of the seven categories. The number of middle level neurons was set at 140 and the prediction error at 5%.

The results of scenario three is presented in Chapter 5.

This binary approach offered the first solution to the problem of absent DPOAE results. For the first time all the data could be used and the neural network could be trained with data across all categories of hearing impairment. Scenario three however, predicted only average hearing abilities across the whole audiogram. The main aim of this study is to predict hearing ability at the frequencies 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz. It was decided to take the binary approach one step further, by predicting hearing ability at a specific frequency, one at a time.

4.7.2.1.6 Prediction of Hearing Ability at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz

Prediction of hearing abilities at specific frequencies was conducted in scenario four.

Scenario four used the same DPOAE input information as scenario three, which was the 88 columns of binary information, depicting present and absent DPOAE responses at all the DP Grams and DPOAE frequencies. Scenario four also used the seven categories of hearing ability to write output information in a binary format. Instead of using the average hearing ability of a subject as output information, only the pure tone frequency to be predicted was used. Four different neural networks were used to predict 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz, one at a time. For each neural network, the number of middle neurons was set at 140 and the acceptable error during training at 5%. The neural network took about 4 days non-stop to predict one frequency of all 120 subjects.

After completion of neural network prediction it became clear that in some instances, certain categories had very little hearing-impaired data. In the case of 500 Hz for example, many of the subjects with hearing losses had normal hearing at 500 Hz (such as subjects demonstrating ski slopes). Category 7 in the case of the 500 Hz prediction had only data for one ear. Category 6 had only data for six ears and category 5 only data for five ears. It could be possible that the neural network did not have sufficient data in every category to train on and this aspect might influence the accuracy of the prediction. It was decided to enlarge the categories depicting hearing impairment to 15 dB, in order to attempt to include more hearing-impaired data in every category. In **scenario five**, hearing ability was divided in five categories. Categories that depicted normal hearing spanned 10 dB whereas categories that depicted hearing impairment spanned 15 dB. The five categories are presented in Table V.

Table V. The five categories of hearing ability for scenario five.

Category 1	0 – 10 dB HL
Category 2	11 – 20 dB HL
Category 3	21 – 35 dB HL
Category 4	36 – 50 dB HL
Category 5	51 – 65 dB HL

The network was trained with the binary written DPOAE responses and hearing abilities in the five categories. The number of middle level neurons was set at 140 and the acceptable training error at 5%. The network was trained with the data of 119 ears and predicted one ear. This process was repeated 120 times to predict every ear once.

The prediction of hearing ability at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz as well as the prediction of average hearing ability were performed in both seven categories (as in scenario 4) and in five categories (as in scenario 5). The differences in results between these two scenarios will be discussed in Chapter 5 and Chapter 6.

<u>4.7.2.1.7 The Inclusion of the Age and Gender Variables</u>

To determine the effects of age and gender on the distortion product, it was decided to include these variables into the neural network as input information. The variables age and gender were included in the network run where the network had to predict average hearing ability.

The variables age and gender also had to be presented to the neural network in a binary format. For the network run that included the gender variable, it was very easy to depict the new variable in a binary mode. The one gender was given a zero and the other gender a one. The one extra input did not influence the complexity of the neural network topology to such an extent that it was necessary to include more middle neurons in the hidden layer. This neural network therefore had 89 input nodes, 140 middle layer neurons and seven output neurons, one for every 10dB category. The prediction error during training was set at 5%. The neural network was exactly the same as for the prediction of average hearing ability, except for the extra input variable, gender. The neural network had to predict average hearing as being in one of the seven 10dB categories of scenario four.

The age variable was also incorporated in a neural network run to predict average hearing ability in the seven 10dB categories of scenario four to determine its effect on the distortion product. To represent the age variable to the neural network in a binary format required much more input neurons. Subject age ranges from 8 to 82 years old. To present this to the neural network in a binary mode, nine categories of different ages were created, every category spanning 10 years. It was written in a binary format in the same way that hearing ability categories were. For example, a subject with an age of 12 would fall in the second 10-year category and would be written binary as [0 1 0 0 0 0 0 0]. A subject with an age of 82 would fall in the ninth 10-year category and would be binary written as [0 0 0 0 0 0 0 0 1]. The network that was presented with subject age had therefore nine more input neurons, amounting to a total of 97 input neurons. (The network had 88 regular input nodes to represent all absent and present DPOAE responses at the 8 DP Grams of all 11 DPOAE frequencies plus 9 input nodes to represent the age category). The middle level neurons were kept at 140 and the network had seven output neurons, one for every 10dB category.

To determine the combined effects of gender and age, one neural network was run to include both variables at the same time. The network therefore had 98 input nodes, 140 middle level neurons and seven output neurons for the seven 10dB categories of scenario four. Prediction accuracy during training was set at 5%.

4.8 Data analysis procedures

After the completion of a neural network run, the results were given in a table format, with 120 rows (each ear had one row) and 15 columns of numbers (as in the case of scenario four). The first column number depicted the ear number, the other 14 the actual hearing category and predicted hearing category, written in a binary format. To illustrate this concept, an example of a neural network's output for the data of 10 ears is presented in Table VI. The predicted frequency was 1000 Hz.

Ear 1 had an actual hearing threshold of 5 dB at 1000 Hz, therefore a category one. The category was depicted binary by the "1" in the "actual" (A) column of Category 1. All the other "actual" (A) columns of the other categories for ear one is therefore "0". The neural network investigated the pattern of the input information and made more than one prediction for possible categories of hearing ability for this ear.

The category where the most energy is concentrated, is taken as the prediction of the neural network, and in the case of ear 1, it is in category 1. This ear's hearing ability was therefore correctly predicted as a category 1.

Table VI: Example of the results of the neural network's prediction of 1000 Hz for 10 ears, (scenario four). A= Actual hearing category, P= Predicted hearing category.

EAR #	CATEGORY 1		CATEGORY 2		CATEGORY 3		CATEGORY 4		CATEGORY 5		CATEGORY 6		CATEGORY 7	
	A	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**
1	1	1	0	0.4	0	0	0	0	0	0.03	0	0.1	0	0
2	0	0.3	1	0.9	0	0.3	0	0.01	0	0.01	0	0.1	0	0.01
3	0	0.2	0	0	0	0.01	0	0.3	0	0.01	1	0.4	0	0.9
4	0	0	0	0	1	1	0	0	0	0	0	0	0	0
5	1	1	0	0	0	0.3	0	0.02	0	0.03	0	0.4	0	0.02
6	0	0.05	1	1	0	0.44	0	0.14	0	0.05	0	0.01	0	0
7	0	0.01	0	0.03	0	1	0	0.8	1	0.6	0	0.4	0	0.02
8	0	0.01	1	1	0	0.3	0	0.21	0	0.12	0	0.02	0	0.01
9	1	1	0	0.2	0	0.15	0	0.11	0	0.02	0	0.01	0	0
10	0	0	0	0	0	0	0	0	0	0.02	0	0.3	1	0.7

In the case of ear 3, the actual hearing threshold of the specific frequency fell in Category 6. After analysis of this ear's pattern of present and absent DPOAE responses the neural network predicted hearing ability to be most probably in Category 7. It should be noted that some energy was also predicted in other categories. The category where the most energy is predicted is taken as the predicted category. Another ear in this example that was wrongly predicted is ear 7, predicted as a Category 3, instead of a Category 5. All the other ears were predicted correctly.

The data analysis therefore consisted of analyzing the actual and predicted values of all 120 ears and to determine how many were predicted accurately, how many within one class and how many were predicted incorrectly.

Another aspect that was determined for every frequency was the percentage accurate prediction of normal hearing for every frequency. This was determined in terms of false positive responses (how many subjects with normal hearing were predicted as hearing impaired) and false negative responses (how many subjects with hearing impairment were predicted as having normal hearing ability) at every frequency.

4.9 Summary

The need for an objective non-invasive and accurate test of auditory functioning inspired this research project. The aim of this research project was to predict hearing ability at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz, with DPOAEs and artificial neural networks. Data obtained from DPOAE results and pure tone thresholds of 120 ears were used to train the neural network. Subject selection criteria included varying degrees of sensorineural hearing loss and normal middle ear functioning. Subjects ranged from 8 to 82 years old and included 28 males and 42 females.

The distortion product otoacoustic emission has numerous variables that influence the effectivity in which measurements can be made. For this research project, eight DP Grams at 5dB intervals ranging from L1=70dB SPL to L1=35dB SPL were measured. A frequency ratio of 1.2 was selected for the two primaries and the loudness level ratio of the two primaries was L1>L2 by 10dB. The frequency range of F1= 500 to F1= 5031 was tested.

The neural network that was chosen for the prediction of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz was a back propagation neural network. The network had 140 middle neurons, 88 input nodes and seven output neurons in scenario four, five output neurons in scenario five. The network's acceptable prediction error during training was set at 5%. All data that was used for neural network training was rewritten in a binary format.

Hearing ability was predicted in two scenarios. In scenario four, hearing ability was predicted into one of seven 10dB categories (Table V). In scenario five, the network had to predict hearing ability into one of five categories, the first two spanned 10dB and the rest 15dB. The neural network was not trained with the precise decibel values of a hearing threshold but with the categorical value. Four different networks were trained for the four prediction frequencies 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz. Data analysis consisted of analyzing the actual and predicted values of all 120 ears and to determine how many were predicted accurately, how many within one class and how many were predicted incorrectly.

There are numerous variables that influenced the outcome of this research project. It is quite possible that different DPOAE settings such as other frequency ratios or different loudness levels could yield different results (Cacace et al., 1996). It is also possible that a different type of neural network or a network with a different topology could affect the results significantly (Nelson & Illingworth, 1991). It was attempted to specify all the stimulus variables that could have an effect on the outcome of this research project in great detail in the preceding Chapters.

5 Results

5.1 Introduction

Many studies succeeded to find a correlation between distortion product otoacoustic emissions and pure tone thresholds (Durrant, 1992, Avan & Bonfils, 1993; Gaskill & Brown, 1990). Other researchers attempted to predict hearing status in normal hearing and hearing-impaired populations as being normal or impaired with DPOAEs (Gorga et al., 1993; Kimberley et al., 1994; Moulin et al., 1994). To the author's knowledge, there has not been a report of the prediction of specific decibel values for pure tone thresholds for normal hearing and hearing-impaired subjects with DPOAEs to date. All studies attempting to predict hearing ability with DPOAEs classified hearing as being normal or abnormal but once a hearing loss was identified, no attempts were made to speculate what the exact degree of hearing loss was at that frequency. This study attempted to predict the pure tone thresholds of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz within 10dB categories of hearing loss.

Scenario three was the first scenario where the neural network was able to predict hearing ability for normal and hearing impaired ears. This was partly due to the fact that the presentation of input data to the neural network was in a new binary format, allowing the network to use present and absent responses as input data.

5.2 Scenario Three: Prediction of Average Hearing Ability

For scenario three, every audiogram was graded into seven categories of average hearing ability. Each category spanned 10 dB, category one ranged from 0-10dB, category two from 11-20 dB, three from 21-30 dB and so forth. The seven categories can be seen in Table IV. Each category of hearing ability was determined by taking the average of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz. Each ear had one number in the end, depicting its average hearing ability according to one of the seven categories. The neural network had to predict this average hearing ability.

Before the actual results of the prediction are given, it is deemed necessary to comment on the first two categories depicting the normal range of hearing. Description of hearing impairment is based on definitions of "normal hearing" that have been recommended in the medical profession. The American Academy of Otolaryngology and the American Council of Otolaryngology (AAO-ACO) recommended in 1979 that impaired hearing function begin at an average hearing level of 25dB HL (cited in Yantis, 1994). Goodman (1965) (cited in Yantis, 1994) also recommended normal hearing to include hearing ability up to 25dB HL but Clark (1981) (cited in Yantis, 1994) recommended normal hearing from –10dB to 15dB. In this study, the first category spans 0-10dB and the second 11-20dB. For this study, it was decided to describe results that were in the first two categories (0-20dB) as an indication of normal hearing. The first category (0-10dB) is sometimes referred to as very good hearing ability at a specific frequency. Other researchers have also used 0-20dB as the criteria for normal hearing (Probst & Hauser, 1990; Stover et al, 1996a).

5.2.1 The Prediction of Average Hearing Ability in the Seven 10dB Categories

The results of the neural network's prediction of average hearing ability is discussed below.

The overall prediction of the neural network across all seven categories were completely accurate (predicted in the same category as the actual hearing average) 40% of the time. The network predicted average hearing ability as being in an adjacent 10dB class 30% of the time. The network predicted average hearing ability as completely wrong 30% of the time. This overall prediction ability of the neural network does not seem to be very good, but when the prediction of some of the categories is investigated separately, the picture changes considerably. The neural network was able to predict very good average hearing ability (0-10dB) correctly 91% of the time. In this first category (0-10dB), the network predicted average hearing as being in the adjacent 10dB class (11-20dB) 9% of the time. Very good average hearing (0-10dB) were therefore predicted as "normal" (0-20dB) 100% of the time. The results for all the categories are presented in Table VII.

Table VII: Results of the neural network's prediction accuracy for average hearing ability for the seven 10dB categories.

Categories	1 (0-10dB)	2 (11-20dB)	3 (21-30dB)	4 (31-40dB)	5 (41-50dB)	6 (51-60dB)	7 (61-70dB)
100% correct	91%	11%	23%	0%	27%	25%	0%
one class out	9%	58%	54%	31%	20%	31%	100%
completely wrong	0%	31%	23%	69%	53%	44%	0%
0-10dB predicted as <20dB	100%	-	-	-	-	-	-
0-20dB predicted as 0-20dB	87%	-	-	-	-	-	-

One aspect that should be kept in mind is the sensitivity and specificity of any procedure that might potentially be used as a hearing screening or diagnostic procedure. The sensitivity of a test refers to the test's ability to correctly identify subjects with a hearing loss whereas the specificity refers to the test's ability to correctly identify normal hearing (Konkle & Jacobson, 1991). Sensitivity and specificity is tied directly with the predictive value of a test. The more sensitive a test, the better it's negative predictive value, and the more specific a test, the better it's positive predictive value (Schwartz & Schwartz, 1991). The number of false negative responses therefore affects the sensitivity of a test. (A false negative response is when a subject with a hearing loss is predicted as having normal hearing.) Specificity on the other hand, is affected by the number of false positive responses. (False positive responses refer to the number of subjects with normal hearing that has been identified as having a hearing loss.)

The number of false positive and false negative responses for the prediction of average hearing ability is presented in Tale 5.2.

Table VIII: False positive and false negative responses for the prediction of average hearing at the seven 10dB categories.

False negative responses		False positive responses				
Category 1 (0-10dB)	Category 2 (11-20dB)	Category 3 (21-30dB)	Category 4 (31-40dB)	Category 5 (41-50dB)	Category 6 (51-60dB)	Category 7 (61-70dB)
7%	9%	1%	1%	2%	3%	0%

One aspect that could possibly affect he prediction ability of the neural network, is the amount of data it has to train on. Table IX indicates the number of ears in every one of the seven categories of scenario four for the prediction of average hearing ability.

Table IX: Number of ears in the seven categories of scenario four for prediction of average hearing ability.

Category	1 (0-10dB)	2 (11-20dB)	3 (21-30dB)	4 (31-40dB)	5 (41-50dB)	6 (51-60dB)	7 (61-70dB)
Ears	43	19	13	13	15	16	1

Category seven had only one ear. The fact that there was only one ear in category 7 could possibly have a negative effect on the neural network's capabilities to predict that category accurately, since there were so little data to train on. It was therefore decided to try a new approach on the size of the categories, to attempt to include more ears in the hearing loss categories. Average hearing ability was divided into five categories, the first two spanning 10dB and the hearing loss categories 15dB each. These five categories were presented in Table V. Neural networks that were trained to predict hearing into one of these five categories are referred to as scenario five.

5.2.2 The Prediction of Average Hearing Ability in the Five Categories

The enlargement of categories depicting hearing loss had the desirable effect that more ears were included in the hearing loss categories. The number of ears in every one of the five categories is presented in Table X.

Table X: Number of ears in the five categories of scenario five for the prediction of average hearing ability.

Category	1 (0-10dB)	2 (11-20dB)	3 (21-35dB)	4 (36-50dB)	5 (51-65dB)
Number of Ears	43	19	18	23	17

Even though the categories depicting normal hearing (category one and two) still had the greatest number of ears, the other categories had a better representation and the neural network had more data to train on.

The results for the prediction of average hearing in the five categories of scenario five will be discussed next:

Overall prediction ability of the neural network improved to 52% correct predictions (predicted in the correct category). Predictions into an adjacent category were made 28% of the time. Predictions were completely wrong (more than one category wrong) 20% of the time. The neural network was able to predict certain categories much better, especially the two categories depicting normal hearing. Very good hearing (0-10dB) was predicted as such 93% of the time, very good hearing (0-10dB) was predicted as normal (0-20dB) 98% of the time. Normal hearing (0-20dB) was predicted as normal 85% of the time. The results for the predictions of every one of the five categories are presented in Table XI.

Table XI: Results of the neural network's prediction accuracy for prediction of average hearing ability for the five categories of scenario five.

Categories	1 (0-10dB)	2 (11-20dB)	3 (21-35dB)	4 (36-50dB)	5 (51-65dB)
100% correct	93%	5%	55.5%	35%	24%
one class out	5%	58%	28%	35%	53%
completely wrong	2%	37%	16.5%	30%	23%
0-10dB predicted as <20dB	98%	-	-	-	-
0-20dB predicted as 0-20dB	85%	-	-	-	-

False positive and false negative predictions for the prediction of average hearing ability are presented in Table XII.

Table XII: False positive and false negative responses for average hearing ability at the five categories of scenario five.

False negative responses		False positive responses		
Category 1 (0-10dB)	**Category 2 (11-20dB)**	**Category 3 (21-30dB)**	**Category 4 (31-40dB)**	**Category 5 (41-50dB)**
4%	7%	1%	5%	2%

By including more data in every category to enable the neural network to have more data to train on even the specificity of the test improved (less false negative responses).

The main aim of this study is to predict hearing ability at the frequencies 500, 1000, 2000 and 4000 Hz. It was decided to take the binary approach one step further, by predicting hearing ability at a specific frequency, one at a time.

5.3 Prediction of 500 Hz

500 Hz were predicted in two scenarios. Scenario four had seven 10dB categories (described in Table IV) and scenario five had five categories (as described Table V).

5.3.1 The Prediction of 500 Hz in Scenario Four.

The results of scenario four where the neural network had to predict 500 Hz within the seven 10dB categories as in Table IV were as follows:

The neural network could predict hearing ability in all seven categories correctly 53.3% of the time. The neural network predicted hearing ability in an adjacent category (the next 10dB span) 23.3% of the time. The network predicted hearing completely wrong (in a category more than one 10dB span away) 23.3% of the time. It was very clear that the neural network could predict certain categories better than others could. It was also interesting to see that the larger the hearing impairment at 500 Hz was, the less accurate the neural network could predict hearing ability. Most accurate predictions were made when hearing ability was perfect (pure tone thresholds (PTTs) 0-10dB) or normal (PTTs 0-20dB). Perfect hearing ability (PTTs 0-10dB) were predicted as perfect (0-10dB) 82% of the time. Perfect hearing ability (PTTs 0-10dB) were predicted as normal (0-20dB) 97% of the time. Normal hearing ability (PTTs 0-20dB) were predicted as normal (0-20dB) 87% of the time. As the hearing loss at 500 Hz increased, the accuracy of the neural network's prediction at 500 Hz decreased. Table XIII presents the results for the prediction accuracy for the seven categories of hearing impairment. Note how the accuracy of the prediction worsens as the hearing loss of 500 Hz increases.

Another aspect that should be noted is the number of false negative responses in Category one and two. Category one (0-10dB) had 12% false negative responses, in other words, subjects with hearing losses were predicted as having perfect hearing 12% of the time. Category two had 8% false negative responses. If the two categories are combined to represent normal hearing (0-20dB), the false negative rate is 20%. This aspect raises questions regarding the sensitivity of this procedure.

Table XIII: Results of the neural network's prediction accuracy at 500 Hz for the seven 10dB categories of scenario four.

Categories	1 (0-10dB)	2 (11-20dB)	3 (21-30dB)	4 (31-40dB)	5 (41-50dB)	6 (51-60dB)	7 (61-70dB)
100% correct	82%	19%	0%	22%	0%	0%	0%
one class out	15%	50%	75%	11%	20%	0%	0%
completely wrong	3%	31%	25%	67%	80%	100%	100%
0-10dB predicted as <20dB	97%	-	-	-	-	-	-
0-20dB predicted as 0-20dB	87%	-	-	-	-	-	-

The false positive rate for category 3 (21-30dB) was 1%, category 4 (31-40dB) was 3%, category 5 (41-50dB) was 2%, category 6 (51-60dB) was 3% and category 7 (61-70dB) was 0%. The false positive rate refers to how many subjects with normal pure tone thresholds at 500 Hz were predicted as having a hearing loss.

The false positive and false negative responses for all seven categories are listed in Table XIV.

Table XIV: False positive and false negative responses for 500 Hz at the seven categories of scenario four.

False negative responses		False positive responses				
Category 1 (0-10dB)	Category 2 (11-20dB)	Category 3 (21-30dB)	Category 4 (31-40dB)	Category 5 (41-50dB)	Category 6 (51-60dB)	Category 7 (61-70dB)
12%	8%	1%	3%	2%	3%	0%

The sensitivity and specificity of scenario four will be discusses in more detail in Chapter 6.

Subjects were initially selected in such a way that their average hearing ability fell into one of three categories (40 ears with average hearing ability in the 0-15dB range, 40 ears in the 16-35dB range and 40 ears in the 36-65 dB range). There were however not an equal number of ears in every one of the seven categories at 500 Hz in scenario four due to the fact that many subjects with hearing losses had normal pure tone thresholds (PTTs) at 500 Hz. The number of ears in every one of the seven categories is presented in Table XV.

Table XV: Number of ears in the seven categories of scenario four for 500 Hz.

Category	1 (0-10dB)	2 (11-20dB)	3 (21-30dB)	4 (31-40dB)	5 (41-50dB)	6 (51-60dB)	7 (61-70dB)
Ears	60	26	4	18	5	6	1

Category 1 had the highest number of ears with normal PTTs at 500 Hz, followed by category 2 and category 4. In category 7 (PTTs for 500 Hz between 61-70dB) there were only one ear. This is partly due to the fact that very few people had flat enough audiograms to have a pure tone threshold of >61dB at 500 Hz and still be submitted to the study with a subject selection criteria of average hearing ability of <65dB. (Average hearing ability was determined by calculating the average for 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz). There were only five ears in category 5, only 6 ears in category six and only one ear in category seven. The fact that the neural network had only a few ears to train on in these categories possibly affected the prediction accuracy (no accurate predictions in either one of the three categories were made). It was decided to attempt to predict hearing ability at the categories depicting hearing loss more accurately by including a larger number of ears in each category. The categories depicting hearing loss were therefore enlarged to span 15dB.

5.3.2 Prediction of 500 Hz in Scenario Five.

Scenario five had more ears in every category that presented subjects with hearing loss. The number of ears in every one of the five categories of scenario five is presented in Table XVI. Even though there were still more ears in the normal hearing categories, the neural network had more ears in hearing loss categories to train on.

Table XVI: Number of ears in the five categories of scenario five for 500 Hz.

Category	**1 (0-10dB)**	**2 (11-20dB)**	**3 (21-35dB)**	**4 (36-50dB)**	**5 (51-65dB)**
Number of Ears	60	26	15	12	7

In scenario five, the neural network could predict hearing ability in all five categories correctly 51% of the time. The neural network predicted hearing ability in an adjacent category (the next 10dB span) 33% of the time. The network predicted hearing completely wrong (more than one category away) 16% of the time. It was again very clear that the neural network could predict certain categories better than others could. Just as in scenario four, the larger the hearing impairment at 500 Hz was, the less accurate the neural network could predict hearing ability. Most accurate predictions were made when hearing ability was very good (PTTs 0-10dB) or normal (PTTs 0-20dB). Very good hearing ability (PTTs 0-10dB) were predicted as such 80% of the time. Very good hearing ability (PTTs 0-10dB) were predicted as normal (0-20dB) 93% of the time. Normal hearing ability (PTTs 0-20dB) were predicted as normal (0-20dB) 92% of the time. Again the accuracy of the neural network's prediction at 500 Hz decreased as the hearing loss at 500 Hz increased. Table XVII presents the results for the prediction accuracy for the five categories of hearing impairment at 500 Hz for scenario five.

Table XVII: Results of the neural network's prediction accuracy at 500 Hz for the five categories of scenario five.

Categories	1 (0-10dB)	2 (11-20dB)	3 (21-35dB)	4 (36-50dB)	5 (51-65dB)
100% correct	80%	31%	13%	25%	0%
one class out	13%	65%	47%	33%	14%
completely wrong	7%	4%	40%	42%	86%
0-10dB predicted as <20dB	93%	-	-	-	-
0-20dB predicted as 0-20dB	92%	-	-	-	-

There were 11% false negative responses for the first category (0-10dB) and 7% false negative responses for the second category (11-20dB) for the prediction of 500 Hz, scenario five. False positive responses for category 3 were 3%, category 4 had 3% and category five had 0%. These results are summarized in Table XVIII.

Table XVIII: False positive and false negative responses for 500 Hz at the five categories of scenario five.

False negative responses		False positive responses		
Category 1 (0-10dB)	**Category 2 (11-20dB)**	**Category 3 (21-30dB)**	**Category 4 (31-40dB)**	**Category 5 (41-50dB)**
11%	7%	3%	3%	0%

Scenario four made better predictions for normal hearing ability but scenario five were able to make slightly better predictions in areas of severe hearing loss. If category 6 and 7 of scenario four is combined, it spans the same degree of hearing loss (51-70dB) as category five of scenario five. In scenario four, no accurate predictions could be made when subjects demonstrated PTTs >51dB, not even predictions that were one class out. Scenario five could make predictions that were one class out 14 % of the time. It seems that by increasing the number of ears in each category, the neural network had a better prediction ability. It is however very evident that hearing loss at 500 Hz affects the prediction accuracy of the neural network negatively, and that prediction of normal hearing is far better than prediction of hearing loss. The implications for the accuracy of the prediction of 500 Hz will be discussed in Chapter 6.

5.4 Prediction of 1000 Hz

The results of scenario four where the neural network had to predict 1000 Hz within the seven 10dB categories as in Table IV were as follows:

5.4.1 Prediction of 1000 Hz in Scenario Four.

The neural network could predict hearing ability in all seven categories correctly 54% of the time. The neural network predicted hearing ability in an adjacent category (the next 10dB span) 14% of the time. The network predicted hearing completely wrong (in a category more than one 10dB span away) 32% of the time. Just as in the case of 500 Hz, the neural network was able to predict the categories representing normal hearing ability better than those representing hearing impairment. Most accurate predictions were made when hearing ability was perfect (pure tone thresholds (PTTs) 0-10dB) or normal (PTTs 0-20dB). Perfect hearing ability (PTTs 0-10dB) were predicted as perfect (0-10dB) 92% of the time. Perfect hearing ability (PTTs 0-10dB) were predicted as normal (0-20dB) 95% of the time. Normal hearing ability (PTTs 0-20dB) was predicted as normal (0-20dB) 84% of the time. Table XIX presents the results for the prediction accuracy for the seven categories of hearing impairment for the prediction of 1000 Hz.

Table XIX: Results of the neural network's prediction accuracy at 1000 Hz for the seven categories of scenario four.

Categories	1 (0-10dB)	2 (11-20dB)	3 (21-30dB)	4 (31-40dB)	5 (41-50dB)	6 (51-60dB)	7 (61-70dB)
100% correct	92%	23%	0%	0%	31%	12.5%	14%
one class out	3%	44%	33%	67%	13%	25%	0%
completely wrong	5%	33%	67%	33%	56%	62.5%	86%
0-10dB predicted as <20dB	95%	-	-	-	-	-	-
0-20dB predicted as 0-20dB	84%	-	-	-	-	-	-

False negative responses for category 1 (0-10dB) was 8% and category 2 had 12% false negative responses. Category 3 had 3% false positive responses, category 4 had 1%, category 5 had 4%, category 6 had 0% and category 7 had 2% false positive responses. The summary of false positive and false negative responses is given in Table XX.

Table XX: False positive and false negative responses for 1000 Hz at the seven categories of scenario four.

False negative responses		**False positive responses**				
Category 1 (0-10dB)	**Category 2 (11-20dB)**	**Category 3 (21-30dB)**	**Category 4 (31-40dB)**	**Category 5 (41-50dB)**	**Category 6 (51-60dB)**	**Category 7 (61-70dB)**
8%	12%	3%	1%	4%	0%	2%

The number of ears in every one of the seven categories is presented in Table XXI.

Table XXI: Number of ears in the seven categories of scenario four for 1000 Hz.

Category	**1 (0-10dB)**	**2 (11-20dB)**	**3 (21-30dB)**	**4 (31-40dB)**	**5 (41-50dB)**	**6 (51-60dB)**	**7 (61-70dB)**
Ears	59	18	9	3	16	8	7

1000 Hz had a slightly better representation of data in the categories representing hearing loss than 500 Hz. It was however decided to enlarge the categories of 1000

Hz as well to attempt to achieve more accurate predictions of categories representing hearing loss.

5.4.2 Prediction of 1000 Hz in Scenario Five.

The number of ears in every one of the five categories of scenario five for the prediction of 1000 Hz is presented in Table XXII.

Table XXII: Number of ears in the five categories of scenario five for 1000 Hz.

Category	1 (0-10dB)	2 (11-20dB)	3 (21-35dB)	4 (36-50dB)	5 (51-65dB)
Number of Ears	59	18	9	19	15

The results of the prediction of 1000 Hz in the five categories of scenario five are:

Normal hearing (0-20dB) could be predicted as normal (0-20dB) 87% of the time. Very good hearing (0-10dB) was predicted as normal (0-20dB) 98% of the time. The neural network's overall prediction accuracy of all five categories was 58% correct (within the same category) and 17% within one category. The network predicted 1000 Hz completely wrong 33% of the time. The results for every separate category's prediction accuracy are presented in Table XXIII.

Table XXIII: Results of the neural network's prediction accuracy at 1000 Hz for the five categories of scenario five.

Categories	1 (0-10dB)	2 (11-20dB)	3 (21-35dB)	4 (36-50dB)	5 (51-65dB)
100% correct	93%	22%	0%	37%	27%
one class out	5%	39%	67%	5%	20%
completely wrong	2%	39%	33%	58%	53%
0-10dB predicted as <20dB	98%	-	-	-	-
0-20dB predicted as 0-20dB	87%	-	-	-	-

There were 9% false negative responses for the first category (0-10dB) and 9% false negative responses for the second category (11-20dB) for the prediction of 1000 Hz, scenario five. False positive responses for category 3 were 2%, category 4 had 3% and category five had 3%. These results are summarized in Table XXIV.

Table XXIV: False positive and false negative responses for 1000 Hz at the five categories of scenario five.

False negative responses			**False positive responses**	
Category 1 (0-10dB)	**Category 2 (11-20dB)**	**Category 3 (21-30dB)**	**Category 4 (31-40dB)**	**Category 5 (41-50dB)**
9%	9%	2%	3%	3%

The prediction of 1000 Hz was influenced by the degree of hearing loss as well as the number of ears in every category. These aspects as well as the number of false positive and false negative responses will be discussed in Chapter 6.

5.5 Prediction of 2000 Hz

The results where the neural network had to predict 2000 Hz in the seven categories of scenario four were as follows:

5.5.1 Prediction of 2000 Hz in Scenario Four.

The neural network had an average accurate prediction ability (all seven categories) of 43%. The neural network predicted hearing as being in an adjacent category 25% of the time, and completely wrong (more than one category wrong) 32% of the time. The neural network predicted very good hearing (0-10dB) as such 88% of the time, and normal hearing (0-20dB) as normal (0-20dB) 82% of the time. The network predicted very good hearing ability (0-10dB) as normal (0-20dB) 94% of the time. The results for the separate categories are presented in Table XXV.

False negative responses for category 1 (0-10dB) was only 6% and false negative responses for category 2 (11-20dB) was 15%. False positive responses for category 3 (21-30dB) was 3%, category 4 (31-40dB) 1%, category 5 (41-50dB) 3%, category 6 (51-60dB) 3% and category 7 (61-70dB) 1%. These results are presented in Table XXVI.

Table XXV: Results of the neural network's prediction accuracy at 2000 Hz for the seven categories of scenario four.

Categories	1 (0-10dB)	2 (11-20dB)	3 (21-30dB)	4 (31-40dB)	5 (41-50dB)	6 (51-60dB)	7 (61-70dB)
100% correct	88%	15%	0%	0%	24%	19%	0%
one class out	6%	55%	29%	11%	29%	37%	33%
completely wrong	56	30%	71%	89%	47%	44%	67%
0-10dB predicted as <20dB	94%	-	-	-	-	-	-
0-20dB predicted as 0-20dB	82%	-	-	-	-	-	-

Table XXVI: False positive and false negative responses for 2000 Hz at the seven categories of scenario four.

False negative responses		False positive responses				
Category 1 (0-10dB)	Category 2 (11-20dB)	Category 3 (21-30dB)	Category 4 (31-40dB)	Category 5 (41-50dB)	Category 6 (51-60dB)	Category 7 (61-70dB)
6%	15%	3%	1%	3%	3%	1%

The number of ears in every category for the prediction of 2000 Hz in the seven categories of scenario four is presented in Table XXVII.

Table XXVII: Number of ears in the seven categories of scenario four for 2000 Hz.

Category	1 (0-10dB)	2 (11-20dB)	3 (21-30dB)	4 (31-40dB)	5 (41-50dB)	6 (51-60dB)	7 (61-70dB)
Ears	48	20	7	9	17	16	3

2000 Hz had a better representation of data in the categories depicting hearing loss. This is due to the configuration of hearing loss of many of the subjects. Most of the subjects with a hearing loss had better hearing at the lower frequencies and higher degrees of impairment at the higher frequencies. This is a very typical aspect of sensorineural hearing loss (Yantis, 1994). The data of Kimberley et al. (1994) also indicated that the lower frequencies had more available data in the normal hearing areas and a lesser amount of hearing-impaired data. This aspect influenced the accuracy with which the discriminant analysis of these authors could train on, just as it is influencing the training and prediction of this neural network. Even though 2000 Hz had the best representation of data in hearing-impaired categories so far, it was decided to attempt to get an even more accurate prediction of categories depicting hearing-impairment by dividing the data in larger categories. 2000 Hz was therefore also predicted in scenario five.

5.5.2 Prediction of 2000 Hz in Scenario Five.

The number of ears in every one of the five categories of scenario five is presented in Table XXVIII. Category 4 and category 5 have the greatest number of ears in any one of the tests so far.

Table XXVIII: Number of ears in the five categories of scenario five for 2000 Hz.

Category	1 (0-10dB)	2 (11-20dB)	3 (21-35dB)	4 (36-50dB)	5 (51-65dB)
Number of Ears	48	20	12	21	19

The results of the prediction of 2000 Hz in the five categories of scenario five were:

The overall prediction capabilities of the network for all five categories was correct 48% of the time, within one class 33% of the time and completely wrong only 19% of the time. Very good hearing (0-10) was predicted as being normal (0-20dB) 96% of the time. Normal hearing (0-20dB) was predicted as normal 84% of the time. The results of every category are presented in Table XXIX. Note that the accuracy of the prediction in category five (51-65dB) was 37% and in the adjacent 15dB category 47% of the time which is considerably better than the results at 500 Hz and 1000 Hz.

Table XXIX: Results of the neural network's prediction accuracy at 2000 Hz for the five categories of scenario five.

Categories	1 (0-10dB)	2 (11-20dB)	3 (21-35dB)	4 (36-50dB)	5 (51-65dB)
100% correct	88%	15%	8%	24%	37%
one class out	8%	45%	67%	48%	47%
completely wrong	4%	40%	25%	28%	16%
0-10dB predicted as <20dB	96%	-	-	-	-
0-20dB predicted as 0-20dB	95%	-	-	-	-

There were only 4% false negative responses for the first category (0-10dB) and 8% false negative responses for the second category (11-20dB) for the prediction of 2000 Hz, scenario five. False positive responses for category 3 were 1%, category 4 had 5% and category five had 3%. These results are summarized in Table XXX.

Table XXX: False positive and false negative responses for 2000 Hz at the five categories of scenario five.

False negative responses		**False positive responses**		
Category 1 (0-10dB)	**Category 2 (11-20dB)**	**Category 3 (21-30dB)**	**Category 4 (31-40dB)**	**Category 5 (41-50dB)**
4%	8%	1%	5%	3%

If the number of false positive responses in the first two categories for 500 Hz, 1000 Hz and 2000 Hz are compared, 2000 Hz had the lowest numbers of false negative responses for category one and two so far.

The last frequency that was predicted was 4000 Hz.

5.6 Prediction of 4000 Hz

The prediction of 4000 Hz was also conducted in two scenarios, scenario four with seven 10dB categories, and scenario five with only five categories.

5.6.1 Prediction of 4000 Hz in Scenario Four.

The results of the prediction of 4000 Hz in scenario four are:

The overall average prediction ability of the neural network across all seven 10dB categories was completely accurate 49% of the time, within one 10dB category 23% of the time and completely wrong (more than one 10dB category wrong) 28% of the time. Very good hearing (0-10dB) was predicted as normal (0-20dB) 94% of the time. Normal hearing (0-20dB) was predicted as normal 89% of the time. The results for every separate category are presented in Table XXXI.

Table XXXI: Results of the neural network's prediction accuracy at 4000 Hz for the seven categories of scenario four.

Categories	1 (0-10dB)	2 (11-20dB)	3 (21-30dB)	4 (31-40dB)	5 (41-50dB)	6 (51-60dB)	7 (61-70dB)
100% correct	94%	0%	13%	0%	25%	41%	26%
one class out	0%	71%	0%	11%	50%	41%	37%
completely wrong	6%	29%	87%	89%	25%	18%	37%
0-10dB predicted as <20dB	94%	-	-	-	-	-	-
0-20dB predicted as 0-20dB	89%	-	-	-	-	-	-

Category 6 (51-60dB) and category 7 (61-70dB) were predicted most accurately for 4000 Hz, for the seven 10dB categories of scenario four. This might be due to the good representation of hearing impaired data for these categories. The neural network had quite a number of ears to train on in scenario 6 and 7. The numbers of ears for every one of the seven categories are presented in Table XXXII.

Table XXXII: Number of ears in the seven categories of scenario four for 4000 Hz.

Category	1 (0-10dB)	2 (11-20dB)	3 (21-30dB)	4 (31-40dB)	5 (41-50dB)	6 (51-60dB)	7 (61-70dB)
Ears	47	7	8	9	8	22	19

The false positive and false negative responses for the seven categories of scenario four is presented in Table XXXIII. This is the lowest incidence of false negative responses for scenario four at the frequencies 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz.

Table XXXIII: False positive and false negative responses for 4000 Hz at the seven categories of scenario four.

False negative responses		False positive responses				
Category 1 (0-10dB)	Category 2 (11-20dB)	Category 3 (21-30dB)	Category 4 (31-40dB)	Category 5 (41-50dB)	Category 6 (51-60dB)	Category 7 (61-70dB)
6%	3%	2%	1%	0%	0%	3%

5.6.2 Prediction of 4000 Hz in Scenario Five.

For the prediction of 4000 Hz in scenario five, the number of ears in every category is presented in Table XXXIV.

Table XXXIV: Number of ears in the five categories of scenario five for 4000Hz.

Category	1 (0-10dB)	2 (11-20dB)	3 (21-35dB)	4 (36-50dB)	5 (51-65dB)
Number of Ears	47	7	12	13	41

The results of the prediction of 4000 Hz in the five categories of scenario five were as follows:

The overall prediction capabilities of the network for all five categories was correct 63% of the time, within one class 21% of the time and completely wrong only 16% of the time. Very good hearing (0-10) was predicted as being normal (0-20dB) 94% of the time. Normal hearing (0-20dB) was predicted as normal 91% of the time. The results of every category are presented in Table XXXV. Note that the accuracy of the prediction in category five (51-65dB) was 68%. Category four (36-50dB) was predicted within one class all the time and had no complete wrong predictions. This was the best accurate prediction of moderately severe haring loss so far.

Table XXXV: Results of the neural network's prediction accuracy at 4000 Hz for the five categories of scenario five.

Categories	1 (0-10dB)	2 (11-20dB)	3 (21-35dB)	4 (36-50dB)	5 (51-65dB)
100% correct	92%	14%	17%	15%	68%
one class out	2%	57%	25%	85%	15%
completely wrong	6%	29%	58%	0%	17%
0-10dB predicted as <20dB	94%	-	-	-	-
0-20dB predicted as 0-20dB	91%	-	-	-	-

There were 7% false negative responses for the first category (0-10dB) and 3% false negative responses for the second category (11-20dB) for the prediction of 2000 Hz, scenario five. False positive responses for category 3 were 1%, category 4 had 1% and category five had 3%. These results are summarized in Table XXXVI.

Table XXXVI: False positive and false negative responses for 4000 Hz at the five categories of scenario five.

False negative responses		False positive responses		
Category 1 (0-10dB)	Category 2 (11-20dB)	Category 3 (21-30dB)	Category 4 (31-40dB)	Category 5 (41-50dB)
7%	3%	1%	1%	3%

This concludes the prediction of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz. In order to visualize all this information, a summary of results will be given in the next section.

5.7 Summary of Results at 500, 1000, 2000 and 4000 Hz

The results of the prediction of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz are have been reported over a number of pages. To better visualize these results, it will be attempted to include all the results for the four frequencies of every scenario into one encompassing table. The results for scenario four for all four frequencies is presented in Table XXXVII. (The symbol (✓) refers to correct predictions, the symbol (✗) refers to wrong predictions and "1out" to predictions in an adjacent category.)

The summary of results for the prediction of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz for scenario five is presented in Table XXXVIII.

Table XXXVII: Summary of the results for 500, 1000, 2000 and 4000 Hz for scenario four.

	500 Hz			1000 Hz			2000 Hz			4000 Hz		
	% ✓	% 1out	% ✗	% ✓	% 1out	% ✗	% ✓	% 1out	% ✗	% ✓	% 1out	% ✗
Category 1 (0-10dB)	82	15	3	92	3	5	88	6	56	94	0	6
Category 2 (11-20dB)	19	50	31	23	44	33	15	55	30	0	71	29
Category 3 (21-30dB)	0	75	25	0	33	67	0	29	71	13	0	87
Category 4 (31-40dB)	22	11	67	0	67	33	0	11	89	0	11	89
Category 5 (41-50dB)	0	20	80	31	13	56	24	29	47	25	50	25
Category 6 (51-60dB)	0	0	100	12.5	25	62.5	19	37	44	41	41	18
Category 7 (61-70dB)	0	0	100	14	0	86	0	33	67	26	37	37
False negative (0-10dB)	12%			8%			6%			6%		
False negative (11-20dB)	8%			12%			15%			3%		
False positive (21-30dB)	1%			3%			3%			2%		
False positive (31-40dB)	3%			1%			1%			1%		
False positive (41-50dB)	2%			4%			3%			0%		
False positive (51-60dB)	3%			0%			3%			0%		
False positive (61-70dB)	0%			2%			1%			3%		
Overall prediction accuracy	53.3%			54%			43%			49%		
Overall one category out	23.3%			14%			25%			23%		
Overall wrong	23.3%			32%			32%			28%		
0-10dB as normal (0-20dB)	97%			95%			94%			94%		
0-20dB as normal (0-20dB)	87%			84%			82%			89%		

Table XXXVIII: Summary of the results for 500, 1000, 2000 and 4000 Hz for scenario five.

	500 Hz			1000 Hz			2000 Hz			4000 Hz		
	% ✓	% 1out	% ✗	% ✓	% 1out	% ✗	% ✓	% 1out	% ✗	% ✓	% 1out	% ✗
Category 1 (0-10dB)	80	13	7	93	5	2	88	8	4	92	2	6
Category 2 (11-20dB)	31	65	4	22	39	39	15	45	40	14	57	29
Category 3 (21-35dB)	13	47	40	0	67	33	8	67	25	17	25	58
Category 4 (36-50dB)	25	33	42	37	5	58	24	48	28	15	85	0
Category 5 (51-65dB)	0	14	86	27	20	53	37	47	16	68	15	17
False negative (0-10dB)	11%			9%			4%			7%		
False negative (11-20dB)	7%			9%			8%			3%		
False positive (21-35dB)	3%			2%			1%			1%		
False positive (36-50dB)	3%			3%			5%			1%		
False positive (51-65dB)	0%			3%			3%			3%		
Overall prediction accuracy	51%			58%			48%			63%		
Overall one category out	33%			17%			33%			21%		
Overall wrong	16%			33%			19%			16%		
0-10dB as normal (0-20dB)	93%			98%			96%			94%		
0-20dB as normal (0-20dB)	92%			87%			84%			91%		

To better visualize the results of the prediction of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz in scenario four, it is presented schematically in the form of a histogram in Figure 5.1. The zero (0) domain value on the histogram represents the number of correct predictions (within the same category). The minus one domain value (-1) on the histogram represents the number of predictions that were made in one adjacent category, depicting better hearing than the subject's actual hearing. The minus two (-

2) domain value depicts predictions two categories to the less hearing-impaired side, and so forth. The positive one (1) domain value on the histogram represents the number of predictions that were made in one adjacent category depicting greater hearing impairment. The positive two (2) domain value represents predictions that were made two categories to the more hearing- impaired side, and so forth. The green area represents the standard deviation.

The histogram representing the results for the prediction of 500 Hz, 1000 Hz, 2000 H and 4000 Hz, scenario five, is illustrated in Figure 5.2.

The histogram for the prediction of average hearing ability is illustrated in Figure 5.3.

5.8 The Effects of Age and Gender on the Distortion Product

To determine the possible effect of age and gender on the distortion product, it was decided to include these factors as input stimuli in the neural network. The variables age and gender were included in a neural network run of scenario four where the network had to predict average hearing ability. (Average hearing ability refers to the average of 500Hz 1000 Hz, 2000 Hz and 4000 Hz, as described Chapter 4.) The influence of age and gender were therefore not tested for each individual frequency, but on the prediction of average hearing to determine its effect on the distortion product.

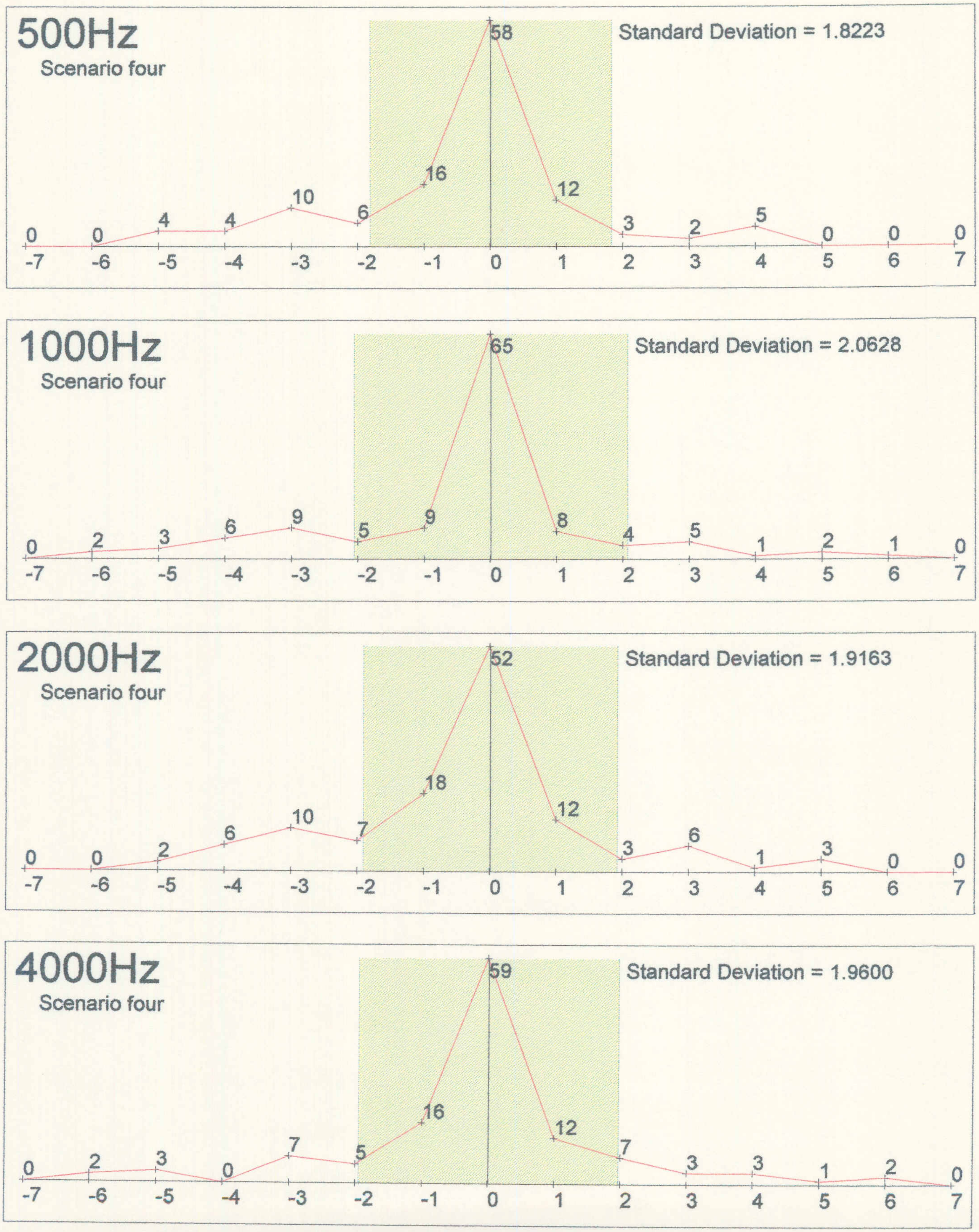


Figure 5.1: Accuracy of the neural network prediction at 500Hz, 1000Hz, 2000Hz and 4000Hz, scenario four.

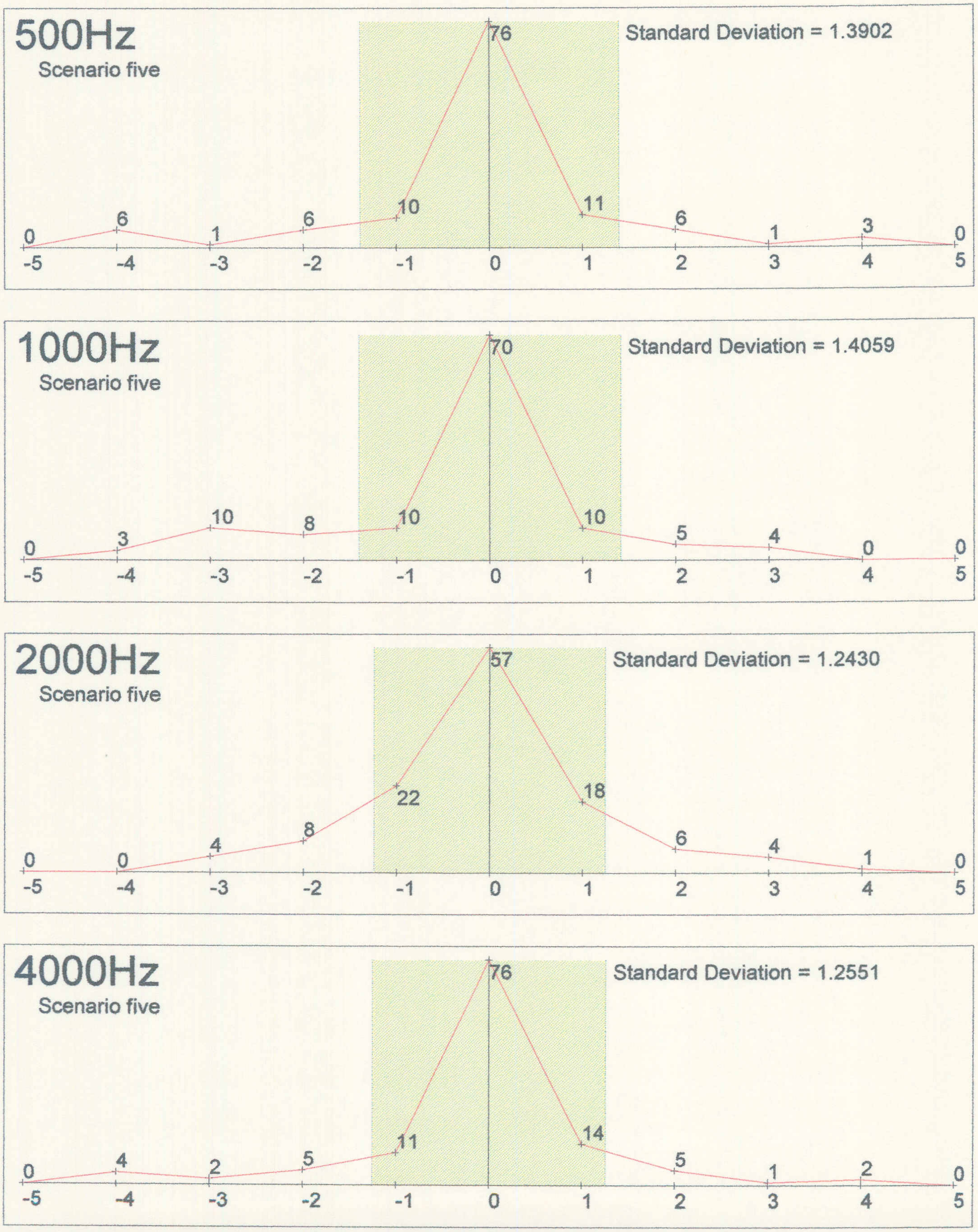


Figure 5.2: Accuracy of the neural network prediction at 500Hz, 1000Hz, 2000Hz and 4000Hz, scenario five.

5.8.1 The Effect of Gender

Gender had a slight positive effect on the prediction abilities of the neural network. The prediction of average hearing with the age variable included resulted in slightly more accurate prediction. The results for the overall prediction accuracy for the seven 10dB categories are presented in Table XXXIX.

Table XXXIX: Prediction of average hearing ability with DPOAEs and gender.

	Average hearing without gender	Average hearing with gender
Right (in same category)	40%	44%
In an adjacent 10dB category	30%	29%
Completely wrong	30%	27%

When the gender variable was included in the neural network, prediction accuracy for predictions in the same 10dB class (correct predictions) improved from 40% to 44%. The number of predictions in the adjacent 10dB class worsened from 30% to 29%. When correct predictions and predictions in adjacent categories are combined, results for the two neural network runs differ with only 3%. With the gender variable, predictions for correct or adjacent categories were 73% and without the gender variable it was 70%.

The gender variable influenced prediction accuracy in all seven 10dB categories. It seems that the gender variable improved the prediction of hearing ability in categories 2 and 4 and had a lower incidence of false negative predictions in category one. All these results are summarized in Table XLIII.

5.8.2 The Effect of Age

Age affected the prediction of average pure tones with DPOAEs positively. Markedly better predictions were made when the age variable was included. Prediction accuracy for correct predictions (in the same 10dB category) improved from 40% (without age effect) to 50%. Predictions in an adjacent 10dB category worsened from 30% to 24%. These results are presented in Table XL.

Table XL: Prediction of average hearing ability with DPOAEs and age.

	Average hearing without age	Average hearing with age
Right (in same category)	40%	50%
In an adjacent 10dB category	30%	24%
Completely wrong	30%	26%

The effect of age on the prediction of the seven 10dB categories is clearly seen in the improvement of predictions across five of the seven categories (2 categories, namely 6 and 7 remained the same). These results are presented in Table XLIII.

The fact that there were more input neurons increased the complexity of the neural network slightly. To investigate if this increased complexity had a negative effect on the prediction accuracy of the neural network, another network run was conducted with more middle level neurons. The number of middle level neurons was increased from 140 to 165. Prediction error during training was kept at 5%. The network therefore had 97 input nodes, 165 middle neurons and seven output neurons (one for every 10dB category). Average hearing without any extra variables, as well as the influence of age on the prediction of average hearing was predicted with this increased set of middle neurons. Results indicated that the increased number of middle level neurons did not improve the predictions. It was therefore decided to keep the middle level neurons at 140, not to add another variable that might influence the data.

5.8.3 The Effect of Age and Gender Combined

Results indicated slightly less accurate predictions compared to that of the prediction with the age variable alone. Predictions were correct 48% of the time, within one category 23% of the time and completely wrong 29% of the time. These results are presented in Table XLI.

Table XLI: Prediction of average hearing ability with the combined effects of gender and age.

	Average hearing without age	**Combined effects of age and gender**
Correct (in same category)	40%	48%
In an adjacent 10dB category	30%	23%
Completely wrong	30%	29%

To summarize the results of the influence of age and gender on the overall prediction accuracy of the neural network the results are presented in Table XLII.

Table XLII: Summary of the prediction of average hearing ability and the effects of age and gender on prediction accuracy:

	Average hearing alone	Average hearing with gender	Average hearing with age and gender	Average hearing with age
Correct (in the same category)	40%	44%	48%	50%
In adjacent 10dB category	30%	29%	23%	24%
Wrong (more than one category out)	30%	27%	29%	26%

Even though the age variable alone had the best overall prediction accuracy, the combined effects of age and gender had the most accurate predictions of very good hearing (0-10dB). The combined effects of age and gender also predicted normal hearing (0-20dB) as normal most accurately (90% of the time). The gender variable alone only improved the number of false negative responses in category 1 but did not have drastic positive effect on the prediction accuracy of the neural network in any of the other categories, only a slight positive effect in category 2). In some of the categories it had a slight negative effect (category 3 and 5). The age variable alone had a drastic improvement in prediction accuracy in most of the categories. The summary of the influence of all these variables on every one of the seven 10dB categories is presented in Table XLIII.

To illustrate the differences in neural network predictions with the inclusion of age and gender, these results are presented in a histogram in Figure 5.3. Again, the zero (0) domain value on the histogram represents the number of correct predictions (within the same category). The minus one domain value (-1) on the histogram represents the number of predictions that were made in one adjacent category, depicting better hearing than the subject's actual hearing. The minus two (-2) domain value depicts predictions two categories to the less hearing-impaired side, and so forth. The positive one (1) domain value on the histogram represents the number of predictions that were made in one adjacent category depicting greater hearing impairment. The positive two (2) domain value represents predictions that were made two categories to the more hearing- impaired side, and so forth. The green area represents the standard deviation.

Table XLIII: Summary of the effects of age and gender on the seven 10dB categories of scenario four

	Average hearing alone			**Average hearing with gender**			**Average hearing with age and gender**			**Average hearing with age**		
	% ✓	**% 1out**	**% ✗**	**% ✓**	**% 1out**	**% ✗**	**% ✓**	**% 1out**	**% ✗**	**% ✓**	**% 1out**	**% ✗**
Category 1 (0-10dB)	**91**	9	0	**91**	7	2	**98**	2	0	**93**	7	0
Category 2 (11-20dB)	**11**	58	31	**16**	63	21	**21**	63	16	**26**	48	26
Category 3 (21-30dB)	**23**	54	23	**15**	46	39	**23**	31	46	**31**	38	31
Category 4 (31-40dB)	**0**	31	69	**0**	62	38	**8**	31	61	**8**	38	54
Category 5 (41-50dB)	**27**	20	53	**20**	33	47	**27**	40	33	**40**	27	33
Category 6 (51-60dB)	**25**	31	44	**25**	37.5	37.5	**25**	12	63	**25**	19	56
Category 7 (61-70dB)	**0**	100	0	**0**	0	100	**0**	100	0	**0**	100	0
False negative (0-10dB)	7			3			2			3		
False negative (11-20dB)	9			9			11			10		
False positive (21-30dB)	1			3			3			2		
False positive (31-40dB)	1			1			1			1		
False positive (41-50dB)	2			2			1			3		
False positive (51-60dB)	3			2			1			0		
False positive (61-70dB)	0			0			0			0		
0-10dB as normal (0-20dB)	100			98			100			100		
0-20dB as normal (0-20dB)	87			87			90			89		

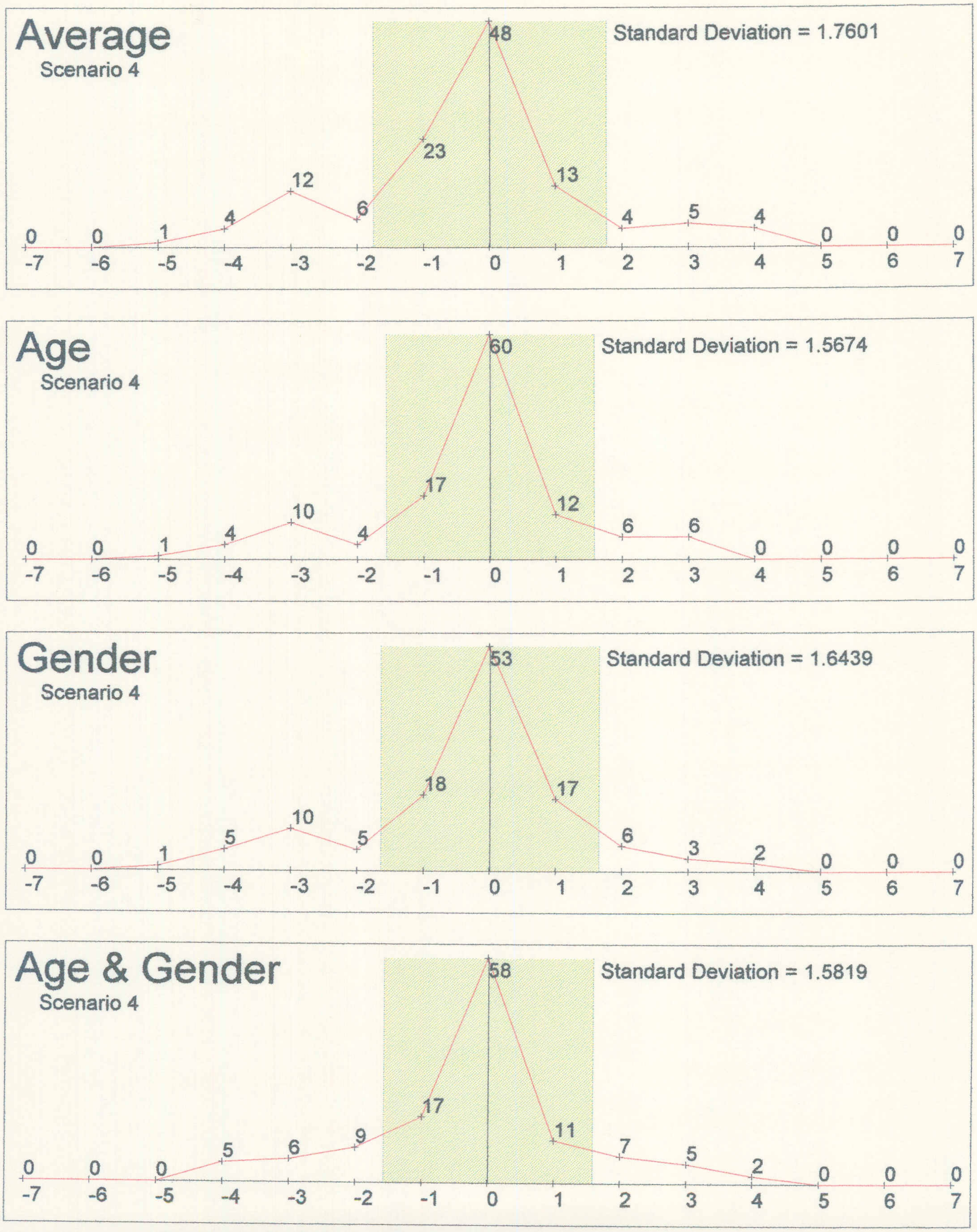


Figure 5.3: Prediction accuracy of average hearing ability when the age and gender variables are included.

5.9 Summary of Results

ANNs were used to predict hearing ability given only DPOAEs. Hearing ability was predicted at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz as well as average hearing ability at these four frequencies. Neural networks were also used to investigate the effect of age and gender on the prediction accuracy of a neural network given distortion product otoacoustic emissions.

There are different ways to interpret the results obtained from these neural networks. The overall prediction accuracy of a neural network across all the categories can be determined or categories can be analyzed separately. When overall prediction accuracy across all categories are determined, results do not seem very impressive. Best overall prediction capabilities were measured at 4000 Hz (scenario five), which was 63% and second best prediction at 1000 Hz (scenario five), which was 58%. The worst overall prediction capabilities were measured at 2000 Hz (scenario four), namely 43%. The largest completely wrong predictions (more than one category out) were also measured at 1000 Hz (scenario five) which was 33% while 500 Hz and 4000 Hz (both at scenario five) had the least completely wrong predictions, 16%.

When categories are analyzed separately, results improve substantially for some of the categories. Categories one and two, depicting normal hearing (0-20dB) revealed the best results. Best prediction of normal hearing were measured at 500 Hz (scenario five) where the neural network correctly predicted normal hearing as normal 92% of the time. Worst prediction of normal hearing was 82% measured at 2000 Hz (scenario four).

The inclusion of the age and gender variables yielded interesting results. With the inclusion of the combination of age and gender, the prediction of very good average hearing (0-10dB) was phenomenal, namely 98% and it had a very low false negative rate of 2%. The inclusion of age yielded better overall prediction across all the categories and also lowered false negative responses in category one.

Specific predictions of decibel values for pure tone thresholds that indicated hearing impairment were rather disappointing. With closer analysis it is evident that there is a negative correlation between prediction of pure tone thresholds and hearing loss. The larger the hearing impairment, the less accurate the prediction of hearing ability. Another aspect that influenced prediction accuracy considerably was the number of ears in every category and the amount of data the neural network had to train on. The greater number of ears included in a category, the better the ability of the neural network to predict that category correctly.

The technique that was used in this study namely to use the pattern of all present and absent DPOAE responses for 8 DP Grams yielded very interesting and rewarding results nevertheless. The neural network was able to predict normal hearing very accurately, even in the case of 500 Hz. This is an exiting improvement in the prediction of hearing ability, especially the prediction of frequencies lower than 1000 Hz, which did not yield satisfactory results in the past (Gorga et al., 1996; Gorga et al., 1993; Kimberley et al., 1994). The differences in results between previous studies and this study will be discussed in Chapter 6.

6 Discussion of Results

6.1 Introduction

The development of objective procedures in audiology came a long way since the 1920s. With the aid of modern technology, audiologists can measure the exact degree, configuration, and site of hearing loss and confirm these findings with a series of objective electrophysiologic procedures, such as tympanometry, the acoustic reflex, ABR, and otoacoustic emissions (Northern, 1991). From the overview of the development of objective procedures in audiology in Chapter 1, however, it is evident that there are some weaknesses in current objective diagnostic procedures. In the evaluation of special populations such as neonates from birth to 6 months, the crucially ill, and malingerers, audiologists often have to rely heavily on the objective electrophysiologic procedures to determine hearing ability. To determine hearing thresholds with electrophysiologic procedures is often costly, requires a large amount of time and highly trained and specialized personnel, and may require sedation. Above all, current objective physiologic procedures, such as ABR, have a limited frequency area in which hearing ability can be determined accurately. There is therefore a definite need for an objective, reliable, rapid, and economic test of hearing that evaluates hearing ability across a range of frequencies to aid in the assessment of difficult-to-test populations.

The distortion product otoacoustic emission was investigated as a possible new test of hearing. It was attempted to predict pure tone thresholds at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz with the use of artificial neural networks. Very interesting and promising results were obtained. The following Chapter will attempt to discuss the implications of the present study's findings.

6.2 Indication of a Correlation between DPOAE Measurements and Pure Tone Thresholds

Many other studies used statistical techniques to determine the correlation between DPOAEs and pure tone thresholds or described case studies that demonstrated a close relationship between DPOAEs and pure tone thresholds (Gaskill & Brown, 1990; Gorga et al., 1993; Kummer et al., 1998; Lee et al., 1993; Vinck et al., 1996). In the case of statistical methods, a correlation coefficient can be determined and that serves as an indication of the correlation found and its significance. In this study, however, artificial neural networks were used to predict pure tone thresholds. The network extracts necessary information from input stimuli and then forms an internal representation of relations between different data sets by adjustment of the weights of the middle neurons. The neural network then uses the learned representations to make predictions. As stated in Chapter 3, one of the limitations of a neural network is that it cannot justify the learned relationships and specify exact correlations in terms of strength or significance. By analyzing the accuracy of the predictions, one can make assumptions about the correlation between DPOAEs and pure tone thresholds, but one cannot dissect a neural network to find precise reasons for accurate predictions. With this aspect in mind, the implied correlation between DPOAEs and pure tone thresholds will be discussed briefly.

If there were no correlation between DPOAEs and pure tone thresholds (PTTs), then the neural network would not have been able to make accurate predictions of hearing ability with more than 50% accuracy. Correct predictions of hearing ability would have been mere chance or at random. If a histogram was drawn to illustrate the prediction accuracy of a set of data that is not correlated with the other set at all, one can expect to see an equal number of predictions in every one of the domain values. This would result in a "flat" histogram or a histogram representing random predictions at the various domain values. It would definitely not result in a histogram depicting a normal distribution curve.

The prediction accuracy of this neural network is illustrated in the histograms in Figure 5.1, Figure 5.2 and Figure 5.3. At first glance the presence of a normal distribution curve can be seen in all these histograms. Most ears were predicted accurately within the same class (these ears are indicated at the zero (0) place on the histogram) or within one category of hearing impairment. This is clearly an indication that the neural network found a correlation between DPOAEs and PTTs and used that correlation to make the predictions.

This study therefore confirms the results of many other researchers that the distortion product is strongly correlated with pure tone thresholds in normal hearing and hearing-impaired ears (Gaskill & Brown, 1990; Gorga et al., 1993; Kimberley et al., 1994; Kummer et al., 1998; Lee et al., 1993; Moulin et al., 1994; Vinck et al., 1996).

6.3 Prediction of Average Hearing Ability

Some studies attempting to predict hearing ability as normal or abnormal with DPOAEs have used the amplitude of the distortion product (Gorga et al., 1993). Other studies used DPOAE threshold information (the single response that could be elicited with the lowest primary stimuli, still measurable above the noise floor) (Gorga et al. 1996). Most studies use both amplitude and threshold information by combining these procedures or by performing both separately (Kimberley & Nelson, 1989; Moulin et al., 1994). This study did not use amplitude or threshold data as neural network input, but a complete new approach. For this study, the pattern of all present and absent distortion product otoacoustic emissions in the frequency range f1 = 500 Hz to f1 = 5031Hz over a 35dB span of L2 = 65dB SPL to L2 = 25dB SPL were used. The mere presence or absence of an emission and the pattern thereof across 8 DP Grams and 11 DPOAE frequencies were used as input information for the training of the neural network.

As a first level approach, the average hearing ability of every subject was determined by taking the average of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz. The neural network was trained with the DPOAE responses of all frequencies and loudness levels and average hearing ability. The network had to predict average hearing into one of the seven 10dB categories of scenario four and also into one of the five categories of scenario five.

Predictions were overall better in scenario five for the prediction of average hearing ability. The overall prediction accuracy of the network (average of all the categories) improved from 40% accurate in scenario four to 52% accurate in scenario five. This improvement is due to the fact that there were more ears in the hearing loss categories of scenario five, than in the hearing loss categories of scenario four. The neural network had more data to train on and could make better representations of what a hearing impaired subject's DPOAE pattern look like. It could be speculated that an increase in hearing-impaired subjects included in this study would improve the accuracy of the prediction, for the network would have more data to train on.

It was clear that the network was able to make more accurate predictions in certain categories. Categories depicting normal hearing, especially category 1 (0-10dB) was always predicted most accurately. There are two possible reasons for this. First, category 1 always had the largest number of ears for the neural network to train on. The network therefore had a better representation of the qualities and pattern distributions of a subject with normal average hearing. Second, it is also likely that subjects with normal average hearing exhibited the best DPOAE responses. It is possible that once the average hearing becomes impaired, there is a decrease in DPOAE responses, resulting in more absent than present responses, making it difficult for the neural network to distinguish between different classes of hearing impairment.

Average hearing in category 1(0-10dB) could be accurately predicted 93% of the time in scenario five, and as normal (into the next 10dB category, 11-20dB) 5% of the time. Prediction of very good average hearing was therefore completely wrong (more than one category out) just 2% of the time. Category 2 (11-20dB) however, could be accurately predicted only 5% of the time, into and adjacent category 58% of the time and was completely wrong 37% of the time. This poor prediction for the upper half of normal hearing ability contributes to the fact that normal hearing (0-20dB) could only be predicted accurately, 85% of the time in scenario five and 87% of the time in scenario four. Ears demonstrating a hearing loss was falsely predicted as normal 16% of the time in scenario four and 11% of the time in scenario five. These high values of false negative responses raise questions regarding the sensitivity of this procedure. A procedure demonstrating such a high false negative rate can not make accurate and reliable predictions regarding average hearing ability.

6.4 Prediction of 500 Hz

The prediction of 500 Hz with distortion product otoacoustic emissions has been problematic for many authors (Gorga et al., 1993; Moulin et al., 1994; Probst & Hauser, 1990; Stover et al. 1996a). Regardless of the loudness level of the primaries, the chosen frequency ratios, loudness level ratios or any other variables that could influence the study, the rising noise floor below 1000 Hz limited the measurement of clear responses at f2 = 500 Hz (Durrant, 1992). Probst and Hauser (1990) attempted to predict hearing ability as normal or impaired in the geometric mean frequency range of 500 Hz to 8000 Hz. Their findings indicated that the majority of normal and near-normal ears had no or small DPOAE amplitudes at 500 Hz and 8000 Hz. No correlations with hearing threshold could be established at these two frequencies. In a study by Stover et al. (1996a), the noise floor for lower frequencies (500 Hz and 707 Hz) was so high, that data at these two frequencies were interpreted as unknown or absent and coded as missing for data analysis. At 500 Hz, the prediction of normal hearing was no better than chance. Gorga et al. (1993) and Moulin et al. (1994)

experienced similar problems with very high noise measurements at low frequencies and could also not predict normal hearing at 500 Hz.

The prediction accuracy for hearing ability at 500 Hz for this study yielded promising and interesting results. Normal hearing (0-20dB HL) at 500 Hz was predicted as normal 92% of the time in scenario five. The improvement in prediction ability of low frequencies in this study can be attributed to two reasons. The first reason includes the different data processing procedure, an artificial neural network with excellent correlation finding and prediction capabilities. The second reason, pure tone thresholds were not predicted with DPOAE amplitude or threshold at a single DPOAE measurement, but with a pattern of all present and absent DPOAE responses across all 11 DPOAE frequencies and all eight DP Grams. Previous studies attempted to correlate the pure tone threshold with either the threshold (or amplitude) of the f2 frequency (Harris et al., 1989; Kimberley et al., 1994), the geometric mean frequency (Bonfils et al., 1991; Lonsbury-Martin & Martin, 1990) or the distortion product frequency (Smurzynski et al., 1990). This study did not use a single point DPOAE measurement to predict a single point pure tone threshold, but used the whole spectrum of emissions to predict a single pure tone threshold. The artificial neural network was able to gain enough information from the whole spectrum of absent and present responses to predict normal hearing ability at 500 Hz correctly 92% of the time in scenario five.

The purpose of this study however, was to predict pure tone thresholds in hearing impaired categories as well. Hearing ability was divided into categories, and the neural network had to predict the most probable category of hearing ability. 500 Hz was predicted in two scenarios, scenario four, with seven 10dB categories and scenario five, with five categories of different decibel intervals. The differences in results between these two scenarios will be discussed next.

The prediction of 500 Hz was usually better in scenario five than in scenario four, with the exception of a few categories. In scenario four, the accurate prediction of normal hearing at 500 Hz was 87%. The reason for the improved prediction accuracy in scenario five was due to the fact that the neural network had more ears in every category depicting hearing loss to train on. The number of ears in a category had a definite effect on the prediction accuracy of the neural network. This aspect is discussed as one of the variables influencing the outcome of this study, in **6.10.2.2 Amount of Data Available to Train on in Every Category**.

The prediction of hearing ability into specific categories for 500 Hz was rather disappointing. In scenario five, category 3 (21-35dB) could be accurately predicted only 13% of the time and into an adjacent category 47% of the time. The categories depicting hearing impairment of scenario five spanned 15dB, so even if hearing ability was predicted into an adjacent category, it could still be as far as 30dB wrong. Category 4 (36-50dB) was predicted accurately only 25% of the time and category 5 (51-65dB) was never predicted accurately. A possible reason for the poor prediction of categories depicting hearing loss, is the distribution of the number of ears in every category. Although subjects were initially selected in such a manner that their average hearing ability fell into one of three categories, normal, mild, and moderately severe hearing loss, category one and two (depicting normal hearing) had a total of 86 ears (out of 120). This is due to the typical pattern of sensorineural hearing losses, usually involving the higher frequencies (Yantis, 1994). Most of the subjects therefore had normal hearing at 500 Hz even though they might have had a hearing loss at higher frequencies. The neural network therefore did not have a good representation of the characteristics of a DPOAE pattern of a subject with a hearing loss at 500 Hz. Prediction accuracy in categories depicting hearing impairment improved from scenario four to scenario five. This is most likely due to the fact that the number of ears in the hearing loss categories increased and that the neural network had more data to train on. It is very possible, that results would improve even more, if more subjects were included in the study. Another possibility for the poor prediction in hearing impairment categories is that hearing impairment at 500 Hz might result in absent or diminished DPOAE results in the low frequencies. This aspect would make it difficult for the neural network to extract enough data from the pattern of absent and present responses to make a prediction.

Another aspect of the prediction of hearing ability at 500 Hz that should be investigated, is the number of false positive and false negative predictions the neural network made in scenario five. Category one (0-10dB) had 12% false negative responses, in other words, subjects with hearing losses were predicted as having perfect hearing (0-10dB) 12% of the time. Category two had 8% false negative responses. If the two categories are combined to represent normal hearing (0-20dB), the false negative rate is 20%. Even though these values are lower than reported elsewhere (Gorga et al., 1993; Moulin et al., 1994; Probst & Hauser, 1990; Stover et al. 1996a), the high incidence false negative responses raises questions regarding the sensitivity of this procedure. A false negative value of 20% is too high for a reliable prediction.

As far as the test's specificity is concerned, false positive rates were lower than false negative rates. Normal ears were predicted as hearing impaired only 6% of the time in scenario five.

Bonfils et al. (1991) investigated objective low-frequency audiometry by distortion product otoacoustic emissions and found that active emissions could be measured as low as 2f1-f2 = 512 Hz. The authors concluded that DPOAEs could be used as an objective low-frequency test of auditory functioning. This study confirms the results of Bonfils et al. (1991). DPOAEs can accurately categorize hearing ability at 500 Hz as normal, 92% of the time.

6.5 Prediction of 1000 Hz

Researchers attempting to predict normal hearing at 1000 Hz with DPOAEs performed better than at 500 Hz, but still found considerable influence of low frequency noise interfering with test measurements (Gorga et al., 1993; Kimberley et al. 1994; Moulin et al., 1994; Probst & Hauser, 1990). In a study by Kimberley et al. (1994), hearing ability at 1000 Hz could be accurately predicted as normal 71% of the time. Kimberley et al. (1994) did not state the false negative rate for 1000 Hz specifically, but an average false negative rate (where hearing-impaired ears were predicted as normal) across the frequency range f2 = 1025 Hz to 5712 Hz of 22%. Moulin et al. (1994) accurately predicted normal hearing at 1000 Hz 73% of the time. False negative responses in this study varied between 12% and 17% with an average of 15%. In the study by Gorga et al. (1993), false negative rates ranged from about 25% to over 60% depending on the hit rate that was selected. From the previous results and can be seen that many researchers experienced difficulty with the prediction of normal hearing ability at 1000 Hz.

In this study, 1000 Hz could be accurately predicted as normal 87% of the time in scenario five and 84% of the time in scenario four. Again, predictions improved in scenario five when hearing loss categories were enlarged to present the neural network with more data to train on. Very good hearing ability (0-10dB) was predicted most accurately. Very good hearing ability (0-10dB) could be accurately predicted 93% of the time with a false negative rate of 9% in scenario five. Very good hearing ability was predicted into the adjacent 10dB category (11-20dB) 5% of the time, and predicted completely wrong only 2% of the time. Category 2 (11-20dB), however, had less accurate predictions in scenario five. Category 2 (11-20dB) could only be accurately predicted 22% of the time and had a false negative rate of 9%. This poor prediction of the upper half of the normal hearing range affected the prediction of normal hearing ability considerably, bringing it down to 87% in scenario five with the combined false negative rate of 18%. Even though the predictions in this study for 1000 Hz were more accurate than stated elsewhere (Gorga et al., 1993; Kimberley et al. 1994; Moulin et al., 1994; Probst & Hauser, 1990), the high incidence of false negative responses influences the sensitivity of this procedure. Such a high incidence of false negative responses lessen the clinical applicability of this neural network run as a possible screening procedure.

The prediction of specific categories of hearing ability at 1000 Hz was again somewhat disappointing. By enlarging the categories in scenario five and including more ears in every category depicting hearing loss, results improved somewhat and overall prediction accuracy across all categories improved from 54% to 58%. The improvement, however, was not enough to allow for prediction of pure tone threshold of hearing impaired categories at 1000 Hz. In category 3 (21-35dB) scenario five, for example, hearing ability could never be predicted accurately. Hearing ability was predicted into an adjacent category 67% of the time. In scenario five, to predict hearing ability into an adjacent category of category 3 (21-35dB), it means that it was either in category 2 (11-20dB) or in category 4 (36-50). If the neural network predicted hearing ability in category 2 (11-20dB), it means the results could be as far as 24dB out (somewhere between 11dB and 35dB). If the network predicted hearing ability in category 4 (36-50dB), it means the prediction can be as much as 29dB out (between 21dB and 50dB). Category two to four spans from 11dB to 50dB. This is a very broad region of hearing ability, not yielding specific results regarding the hearing ability of 1000 Hz at all. It is therefore very important to attempt to have as many accurate predictions (within the same class) as possible. The 10dB categories of scenario four therefore provide more frequency-specific information regarding predictions into an adjacent class, but in the case of scenario four, less accurate predictions were made because of the shortage of data in some of the categories. It could be speculated that the prediction of 1000 Hz might be better if more subjects with hearing impairment is included in the study, and the neural network is trained with 10dB categories only. Although the prediction of specific regions of hearing impairment was rather disappointing, the results obtained from the prediction of very good hearing ability (0-10dB) and normal hearing ability (0-20dB) were more promising.

6.6 Prediction of 2000 Hz

The prediction of normal hearing at 2000 Hz in other studies yielded far more promising results than the predictions at 500 Hz and 1000 Hz. Kimberley et al. (1994) predicted normal hearing at 2050 Hz with 92% accuracy. Mean false negative responses for f2 = 1025 Hz to 5712 Hz was 22%. Moulin et al. (1994) predicted the DPOAE frequency of 1413 Hz (closest to the GM frequency of 2000 Hz) correctly 76% of the time with an average false negative response of 15%. Even though predictions of normal hearing were more accurately at 2000 Hz, the false negative rate was still unacceptably high.

The predictions of 2000 Hz for this study yielded the poorest predictions of all four of the frequencies. Normal hearing at 2000 Hz could be predicted accurately only 84% of the time. False negative rates were 12%, which was lower than in the other two studies (Moulin et al., 1994; Kimberley et al., 1994). In scenario four, prediction of normal hearing at 2000 Hz was only 82% and had a false negative rate of 19%. The prediction of very good hearing (0-10dB) was once again more satisfactory. Very good hearing could be accurately predicted at 2000 Hz 96% of the time in scenario five with a false negative rate of only 4%. If the objective is to identify very good hearing at 2000 Hz in the range of 0-10dB, this would be quite a sensitive and specific screening procedure.

It is interesting that normal hearing at 500 Hz and 1000 Hz could be predicted more accurately in this study than at 2000 Hz. Some studies that measured DPOAE amplitudes, reported a “trough” or a dip in DPOAE amplitude in the 2000 Hz region

(Gaskill & Brown, 1990; Gorga et al., 1993; Lonsbury-Martin et al., 1990; Spektor et al. 1991). Although the reason for this drop in DPOAE amplitude is still unknown, Lonsbury-Martin et al., (1990) suggested that it could be as a result of individual differences in middle and inner ear resonance. This study did not use DPOAE amplitude as an input stimulus, but the whole spectrum of present and absent responses. It could be argued however, that a decrease in DPOAE amplitude at 2000 Hz might influence the level where the distortion product vanishes into the noise floor. If this hypothesis is true, it could result in less present responses and more absent ones and that could account for the differences in prediction accuracy.

The comparison of the prediction abilities of scenario four and five for 2000 Hz indicates that scenario five predicted severe hearing loss much more accurately. For example, when the two categories that represents severe hearing loss in scenario four is combined, the result is a category that spans 51-70dB. This category overlaps with category five of scenario five (51-65dB) if one consider that only persons with pure tone thresholds > 65dB HL were selected for this study. The average accuracy of prediction of the two categories in scenario four was 10% and in scenario five it improved to 37%. The average prediction within one 10dB class in scenario four was 35% and it improved to 47% within one category in scenario five. Average prediction of the two classes of scenario four was more than one 10dB class wrong 56% of the time. Scenario five had only 16% completely wrong. The differences in category size between scenario four and five makes it difficult to make comparisons of prediction accuracy when predictions are one or more categories out, but the improvement of prediction accuracy within the same category can clearly be seen in scenario five. This improvement is probably also due to the fact that the neural network had more data to train on. Improvements in scenario five, however, was not enough to make accurate predictions regarding hearing status at 2000 Hz when a hearing loss is present.

6.7 Prediction of 4000 Hz

The prediction of normal hearing at 4000 Hz has been a strong point for some of the previous studies (Gorga et al., 1993; Moulin et al., 1994). In the study by Gorga et al. (1993), normal hearing could be accurately predicted 90% of the time with a false alarm rate of only 5%. Moulin et al., (1994) successfully predicted the DPOAE frequency of 4000 Hz (primary frequencies are between 5000 Hz and 6000 Hz) as normal 79% of the time. These authors predicted the DPOAE frequency of 2826 Hz (primary frequencies between 3500 Hz and 4500 Hz) as normal 82% of the time, with an average false negative rate of 15%.

The prediction of normal hearing at 4000 Hz with the use of DPOAEs and neural networks revealed that normal hearing could be predicted accurately 91% of the time in scenario five. The false negative rate for this prediction was 10%. Very good hearing ability (0-10dB) at 4000 Hz was accurately predicted 92% of the time with a false negative rate of 7%.

Prediction of specific classes of hearing impairment at 4000 Hz was once more not satisfactory. Even category 2(11-20dB) in scenario four, depicting the upper half of normal hearing, was not predicted accurately once. Category 3(1-30dB) was predicted accurately only 13% of the time and category 4(31-40dB) was never accurately predicted.

The comparison of prediction accuracy for scenario four and five revealed significant improvement of the prediction of moderately severe hearing losses and overall prediction accuracy across all categories. In scenario five, the prediction of category 5(51-65dB), which represents the moderately severe hearing losses were accurately predicted 68% of the time, one category out 15% of the time and completely wrong 17% of the time. This is a great improvement for the prediction accuracy of moderately severe hearing losses in scenario four, where the average accurate prediction was 34%, the average one category out prediction was 38% and the average wrong prediction was 28%. The moderately severe hearing category had its best prediction at 4000 Hz, scenario five by far. One reason for this improvement in prediction accuracy was because the neural network had so many ears in that category to train on. Category 5 (51-65dB), scenario five had 41 ears and category 1 (0-10dB) had 47. This large number of ears in the moderately severe hearing loss category can be attributed to the general pattern of sensorineural hearing losses, often involving the higher frequencies to a greater extent (Yantis, 1994). The poor accurate prediction of the second category (11-20dB), correct only 14% of the time, can be attributed to the lack of data in that category. There were only seven ears that had a hearing loss of 11dB to 20dB at 4000 Hz and apparently it was not enough data for the neural network to train on. It could be speculated that prediction accuracy for all categories could be greatly improved if there were more subjects included in every one of the categories.

To integrate results obtained from the prediction of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz, a few case studies will be investigated where the neural network accurately predicted hearing ability in all four frequencies. A few case studies will also be investigated where the neural network made false predictions and possible reasons for inaccurate predictions. These results are discussed below.

6.8 Case Studies where the Audiogram was Predicted Accurately

The network predicted hearing ability into one of seven 10dB categories in scenario four or into one of five categories in scenario five. Examples of correct predictions are from scenario four and can be seen in Figure 6.1. Subjects that demonstrated very good hearing ability (0-10dB) at all four frequencies were usually predicted accurately. Figure 6.1. A is the audiogram and predicted categories for ear 35, an ear with normal hearing that was predicted accurately. Figure 6.1. B is the audiogram and prediction of ear 85, an ear with a hearing loss predicted accurately except for 4000 Hz that was 10dB out. The third example, Figure 6.1. C is from ear 107, an ear of an 80-year-old person, predicted accurately except for 500 Hz that was 10dB out. Subject information, such as age, gender, and complaints of tinnitus or vertigo is presented in Table XLIV.

Figure 6.1: Case studies where the audiogram was predicted accurately (prediction in green).

Table XLIV: Subject information of cases predicted accurately

	Ear 35	Ear 85	Ear 107
Subject age	61	72	80
Subject gender	Female	Male	Female
Tinnitus	No	No	High frequency
Vertigo	No	No	No
Medication	None	None	None
Noise exposure	None	None	None

6.9 Case Studies where the Audiogram was Predicted Inaccurately

Subjects demonstrating hearing loss were sometimes predicted inaccurately. All examples are from scenario four. Six examples of inaccurate predictions will be given. Audiograms and predictions can be seen in Figure 6.2. The subject information of these six ears is presented in Table XLV.

Table XLV: Subject information of cases predicted inaccurately

	Ear 19	Ear 33	Ear 71	Ear 73	Ear 74	Ear 91
Subject age	31	35	16	39	39	43
Gender	Female	Female	Male	Male	Male	Male
Tinnitus	No	High Frequency	No	No	No	No
Vertigo	No	No	No	No	No	No
Medication	None	None	None	None	None	None
Noise exposure	None	None	None	20 years	20 years	15 years

6.9.1 Interesting Phenomena in Cases Predicted Inaccurately

With closer analysis of the cases that were predicted inaccurately, it became evident that there were a few circumstances in which the neural network could almost never predict hearing ability correctly. Some of these instances included noise exposure, very mild hearing losses, and possible retrocochlear hearing losses. These cases will be discussed below. It is however, also the case that in some instances, the neural network predicted hearing ability inaccurately for no apparent reason.

6.9.1.1 Subjects Demonstrating Hearing Loss Due to Noise Exposure

Subjects with a large amount of noise exposure revealed poor correspondence between pure tone audiograms and DPOAE measurements. The DPOAE measurements indicated a much larger hearing loss than the pure tone audiograms when DPOAE measurements were compared to the normal range. This confirms the research by Durrant (1992) that indicated that damage in outer hair cells could be measured before the actual hearing loss occurs. Even though these subjects already had noise-induced hearing loss, damage to these subject's outer hair cells indicated a far greater hearing loss than their pure tone audiograms. The neural network therefore predicted hearing ability inaccurately as much more hearing-impaired in most of the cases demonstrating noise-induced hearing loss, such as in the cases of ears 73, 74 and 91.

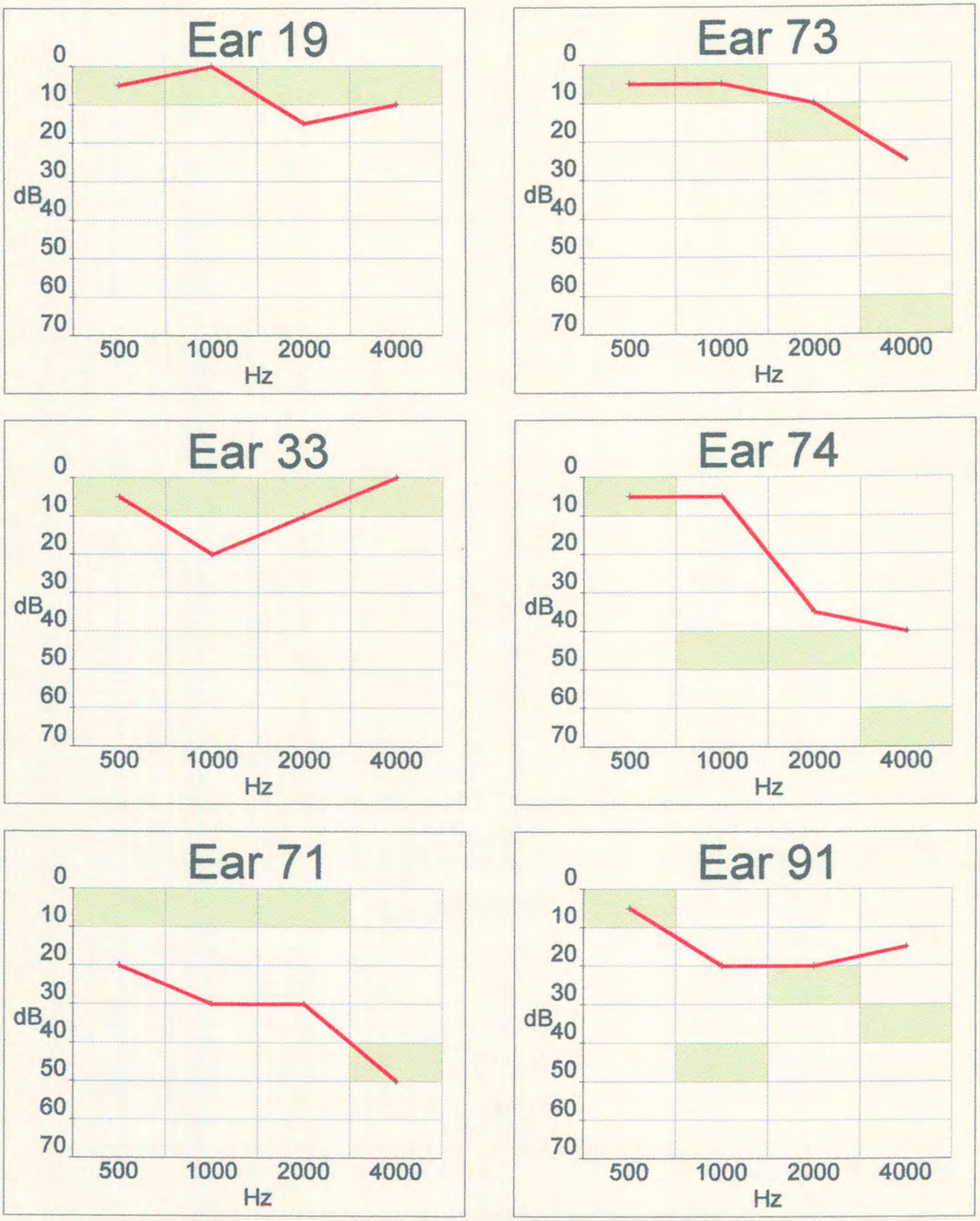


Figure 6.2: Case studies where the audiogram was predicted inaccurately (prediction in green).

6.9.1.2 Subjects Demonstrating Very Mild Hearing Loss

Subjects demonstrating very mild hearing loss, especially if only some of the frequencies were hearing impaired, were often predicted as normal. Smurzynski et al. (1990) also referred to a subject with a very mild hearing loss that had normal DPOAEs. Probst and Hauser (1990) and Gorga et al. (1996) found that a mild hearing loss is sometimes not detected with DPOAE measurement. If the DPOAE measurements of a specific ear are within the normal range, the neural network will predict that ear as normal. For this study, all eleven DPOAE frequencies were used for input information. If most of the DPOAE responses were normal, it often happened that the neural network predicted all the frequencies as normal, as in the case of ear 19 and ear 33.

6.9.1.3 A Subject Demonstrating A Possible Retrocochlear Hearing Loss

Another example of poor correspondence between DPOAE results and the pure tone audiogram was that in a few instances, DPOAE results appeared much better than the hearing ability depicted in the audiogram. This could possibly be one of the small percentage of subjects that could be classified as having a retrocochlear pathology based on otoacoustic emission results (Robinette, 1992). In the case of ear 71, the neural network predicted hearing ability as normal at 500 Hz, 1000 Hz and 2000 Hz, but ear 71 demonstrated a mild hearing loss (the audiogram and predictions of ear 71 can be seen in Figure 6.2.). The DPOAE measurements, when compared with the normal range of DPOAE measurements, also indicated that DPOAEs were much better than would be expected from an ear with a mild hearing loss. Even though other site-of-lesion tests were not performed on this ear, the fact that the DPOAE measurements and neural network predictions were so much better than expected could be as a result of retrocochlear pathology. The outer hair cells on the basilar membrane in the cochlea could therefore be normal and capable of normal DPOAEs.

The next section discusses all the variables that possible influenced the outcome of this study.

6.10 Variables that Influenced the Outcome of this Study

Numerous variables influenced the outcome of this study. The variables will be divided into variables of the distortion product otoacoustic emission, variables of the neural network, and variables of the subject.

6.10.1 Variables of the Distortion Product Otoacoustic Emission

Variables of the distortion product can be divided into technical parameters of DPOAE measurements and variables concerning the data analysis. Different aspects of the distortion product can be used to predict hearing threshold and these aspects are referred to as DPOAE analysis variables. These variables will be discussed in the following section.

6.10.1.1 Technical Parameters of DPOAE Measurements

In every research project that measures DPOAEs, there are a large number of stimulus variables that should be specified before results can be interpreted. Different frequencies, loudness levels, frequency ratios and loudness level ratios can influence the outcome of the results. The fact that every research project has a different technical setup makes it very difficult to compare the results. The stimulus parameters for this study were chosen with great care, based on the recommendations of many other researchers (Avan & Bonfils, 1990; Gaskill & Brown, 1990; Gorga et al., 1993; Harris et al., 1989; Kimberley et al., 1994; Mills, 1997; Moulin et al., 1994; Nielsen et al., 1993; Stover et al., 1996a).

The stimuli that were used for this study were specified in detail in Chapter 2. To summarize the stimulus parameters briefly, 11 pure tone frequencies spanning f1 = 500 Hz to f1 = 5031 Hz were used. The primary frequency ratio of f1/f2 was 1.2. Loudness levels for the primaries ranged from L2 = 65dB SPL to L2 = 25dB SPL. The loudness level ratio for L1/L2 was L1>L2 by 10dB.

6.10.1.2 DPOAE Analysis Variables

There are different aspects of the distortion product that can be used in the analysis of data. Information regarding the threshold or the amplitude of a distortion product can be used to attempt to predict hearing thresholds, or a combination of both.

There is not yet clear consensus on the best analysis procedure to identify normal and impaired ears (Stover et al., 1996a). Some authors used only I/O functions where DPOAE thresholds were determined (Gorga et al.,1996) where others used only DP Grams or DPOAE amplitudes to investigate DPOAE responses in normal hearing and hearing impaired subjects (Gorga et al., 1993).

Most researchers, however, use a combination of the two procedures or perform both procedures separately. Martin et al. (1990a), Spektor et al. (1991), and Smurzynski, et al. (1990), performed both procedures in their studies separately, while Moulin et al. (1994), and Kimberley and Nelson (1989), combined the two procedures in an interesting way. Moulin et al., (1994) conducted several DP Grams but at different loudness levels in 10 dB steps, therefore gaining almost the same information as performing both procedures. Kimberley and Nelson (1989) on the other hand, measured several I/O functions but at eight different frequencies.

Not knowing which procedure is currently the most applicable in the areas of diagnostic effectivity, it seems plausible to gain as much information as possible by combining the two procedures or performing both separately (Kimberley & Nelson, 1989; Martin, et al., 1990a; Smurzynski et al., 1990). Thus far, researchers used amplitude or threshold measurements to predict hearing ability. Even though these authors combined these procedures, they used only the lowest measurable responses and not every measured response, as in the case of this study. This study did not analyze the amplitude or the threshold of the distortion product, but the pattern of all present and absent responses from eight DP Grams. The mere presence of a DPOAE and its position in the pattern of emissions served as input information for the neural network.

The second aspect of DPOAEs that has been used for data analysis in the past is the frequency of the emission that should be correlated with the frequency of the distortion product. In other words, does a DPOAE indicate the state of the OHC on the basilar membrane in the region of the f1 frequency, the f2 frequency, the geometric mean of the two primary frequencies (GM) or at the distortion product itself (the 2f1-f2 frequency). Many authors also disagree on which frequency variable of the DPOAE should be compared to the pure tone threshold (PTT). Some authors suggest that it is the f2 value of the DPOAE that best correlate with pure tone thresholds (PTTs) (Harris et al., 1989; Kimberley et al., 1994). Other studies support the notion that the generation of the distortion product correlates best with the cochlear place near the geometric mean (GM) of the primaries (Bonfils et al., 1991; Harris et al., 1989; Kimberley et al., 1994; Lonsbury-Martin & Martin, 1990; Martin et al., 1990b; Moulin et al., 1994; Smurzynski et al., 1990).

For this study, the pattern of present and absent responses of all 11 DPOAE frequencies was used, and not only DPOAE information at one frequency, such as the f2 place or the geometric mean or the 2f1-f2 place. This aspect is possibly the reason why 500 Hz could be predicted so accurately. Other researchers attempting to predict normal hearing at 500 Hz, used DPOAE information around 500 Hz and experienced a lot of background noise and absent responses. In this study, the neural network could gain enough information from surrounding frequencies to predict the status of 500 Hz accurately 92% of the time.

The next set of variables that influenced this study, are variables of the neural network.

6.10.2 Variables of the Neural Network

Variables of the neural network can be divided in neural network topology and the amount of data available to train on. These variables are discussed below.

6.10.2.1 Neural Network Topology

Neural network topology can be divided into the size of the hidden layer and the accuracy of the prediction during training.

6.10.2.1.1 The Size of the Hidden Layer

As was stated in Chapter 4, the size of the hidden layer is function of the diversity of the data (Blum, 1992). The number of middle layer neurons determines the accuracy of prediction during the training period. With an insufficient number of middle neurons, the network is unable to form adequate midway representations or to extract significant features of the input data (Nelson & Illingworth, 1991). With too many middle neurons the network has difficulty to make generalizations (Nelson & Illingworth, 1991; Rao & Rao, 1995). The number of middle layer neurons was determined by trial and error, based on the accuracy of the prediction during the training period. If the neural network was unable to converge during training, the number of middle level neurons was increased and the prediction attempted again.

Various network runs were conducted with varying numbers of hidden layer neurons, ranging from 20 to 180. With a number of hidden layer neurons below 100, the network was unable to extract significant features from the input data and sometimes would not converge during training. A number of hidden layer neurons more than 160 resulted in poor generalization ability. For this study, a number of 140 hidden layer neurons were found to yield optimal results.

6.10.2.1.2 Accuracy of the Prediction During Training

Another neural network variable, is the acceptable error during training. As stated in Chapter 3, a neural network learns from its mistakes. The first step in the learning process is to compute the outputs, the second step to compare the outputs with the desired answers and the last step to adjust the set of weights to enable a better prediction the next time. The second step, namely the comparing of outputs with desired answers, can be made in various levels of accuracy. The neural network can be required to make predictions within 5dB, 10db, 1dB or within any decibel amount during the training stage. The normal assumption would be that 1dB accuracy during training would yield the most accurate predictions. It was actually found in this study that if the neural network were trained with 1dB accuracy during training, the network had limited generalization abilities and made poorer predictions when presented with unfamiliar data. Blum (1992) also stated that it sometimes help to train on slightly "noisy" data to enhance generalization ability during the prediction of unfamiliar data.

By setting the acceptable error during the training period to 5dB, most accurate predictions of unfamiliar data was obtained in this study.

6.10.2.2 Amount of Data Available to Train on in Every Category

This variable influenced the prediction accuracy of the neural network considerably. It was very evident that categories with large numbers of ears were predicted more accurately than categories with only a few ears. The prediction of 4000 Hz, scenario five for example, revealed 68% prediction accuracy for moderately severe hearing losses, due to the large number of ears in that category to train on (41 ears) but only 14% prediction accuracy for category 2 (11-20dB) with only seven ears. To investigate the effect that this variable had on prediction accuracy, the number of ears in every category were correlated with the percentage of accurate predictions. The prediction accuracy versus number of ears in every category for scenario four is illustrated in Figure 6.3. Scenario five is illustrated in Figure 6.4. The scattergrams in Figure 6.3 and Figure 6.4 indicate a very strong correlation between the number of ears in every category and the accuracy of the prediction. The linear fit shown with the data points in Figure 6.3 has a slope of 1.703 and Figure 6.4 has a slope of 1.714. The correlation coefficient for Figure 6.3 (scenario four) is 0.94 and for Figure 6.4 (scenario five) is 0.92.

Two conclusions can be derived from these scattergrams. First, there is a very strong correlation between the number of ears in every category that the neural network had to train on, and the accuracy of the prediction that was made. The more data the network had to train on, the more accurate the predictions. Second, derived

Figure 6.3: Prediction Accuracy and Ear Count Correlation
- Scenario 4 -

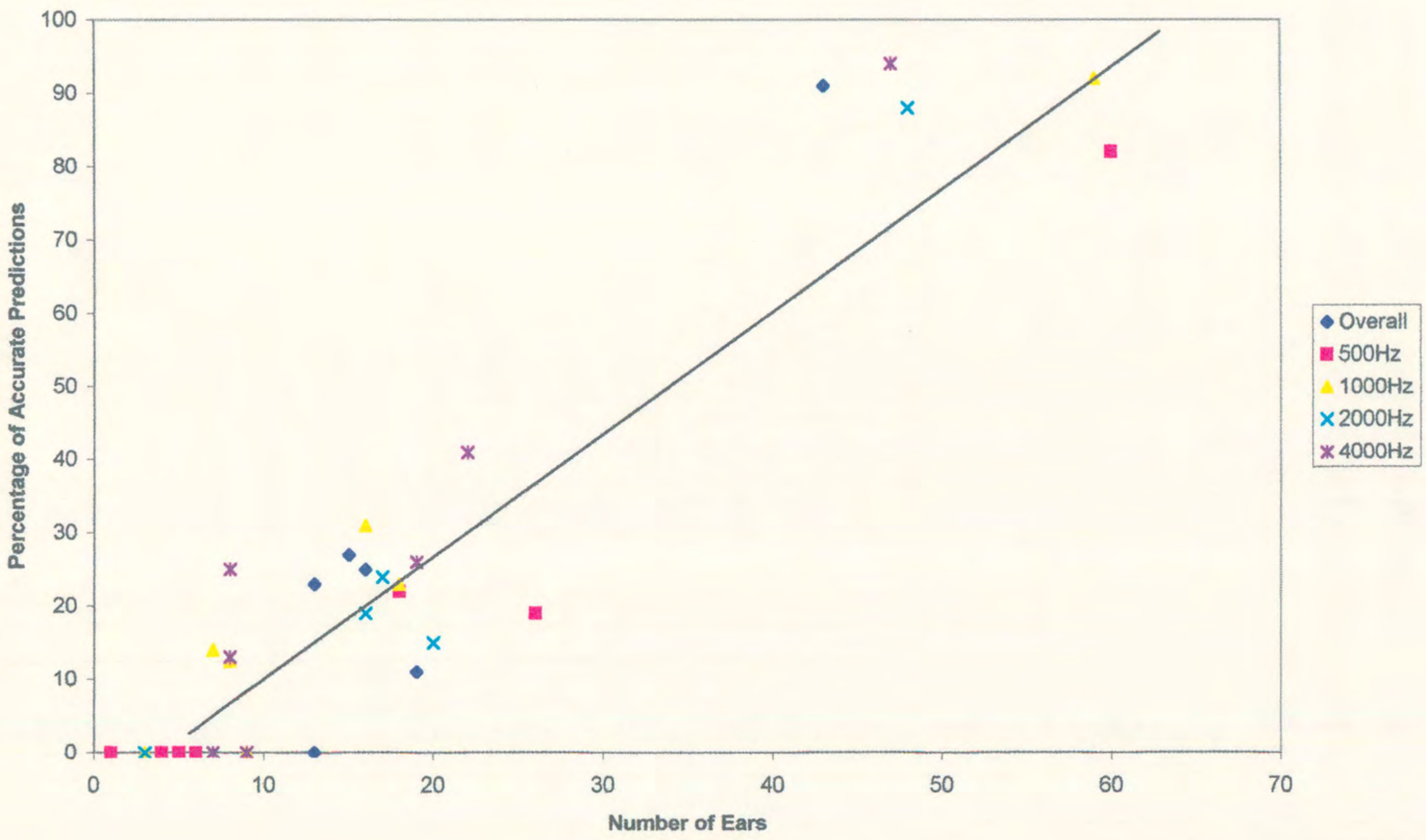
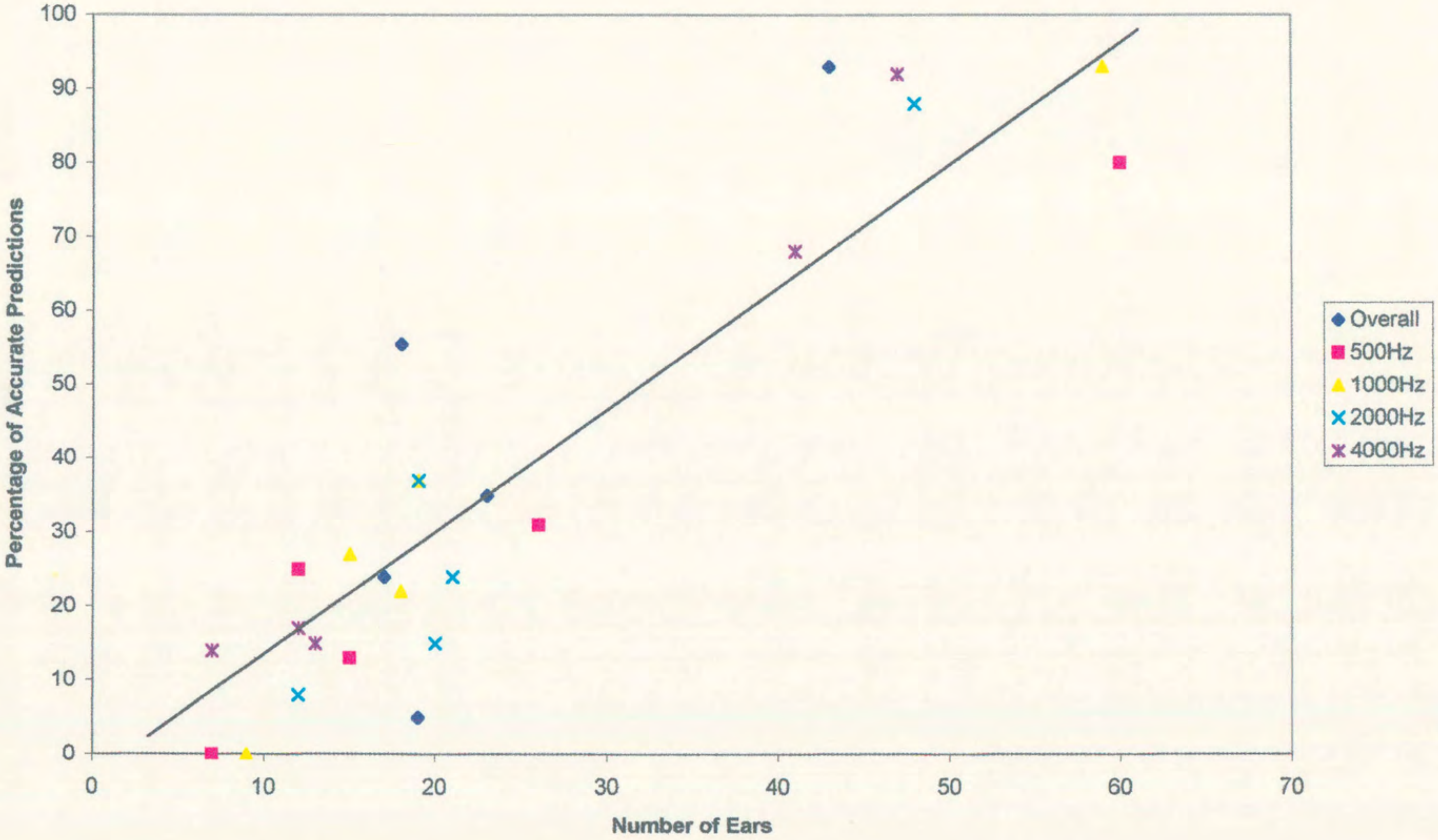


Figure 6.4: Prediction Accuracy and Ear Count Correlation
- Scenario 5 -



from the linear fit of the data points, one can expect to find a saturation level in prediction accuracy when the number of ears reach more or less 65. For example, a study with 1000 ears in every 10dB category would not yield significantly better predictions than a study with 70 ears in every 10dB category.

This strong correlation between number of ears to train on and prediction accuracy indicates a very good possibility that pure tone thresholds can be predicted in normal hearing and hearing-impaired ears with DPOAEs and neural networks. If more ears are included in the training of a neural network, accurate predictions of all categories of hearing impairment seems possible. To predict hearing ability within 10dB in normal hearing and hearing-impaired ears objectively, non-invasively and accurately in the frequency range of 500Hz to 4000 Hz (and even in higher frequencies), would improve diagnostic hearing assessment of difficult-to-test populations greatly. Such a test would change and improve the field of pediatric audiology, as we know it, dramatically.

Other variables that influenced the outcome of this study will be discussed next.

6.10.3 Subject Variables

Subject variables that influenced the outcome of this study include age, gender and the combination of age and gender. Another subject variable is the presence of a spontaneous otoacoustic emission close to a DPOAE frequency. These variables are discussed in the following section.

6.10.3.1 The Age Variable

It seems that the investigation of the influence of age on the distortion product has been problematic for many authors (Avan & Bonfils, 1993; He & Schmiedt, 1996; Karzon et al. 1994; Nieschalk et al., 1989). The reason for this is, that it is very difficult to determine how much of the differences in the distortion product observed in elderly subjects are due to age, and how much is due to sensitivity changes associated with aging. It seems that these authors agree that the negative correlation between DPOAE levels and age is due to changes in hearing threshold associated with aging rather than age itself. However, when the age variable was included as a neural network input, prediction of average hearing ability improved from 40% overall accuracy to 50% overall accuracy. It is quite remarkable that one more input variable could provide enough information to the neural network to enhance prediction abilities so drastically. One can not help but wonder if the negative correlation between age and DPOAEs is really just a reflection of sensitivity changes related to aging, or if there is perhaps more to the influence of the age variable on the distortion product. Based on the improvement in prediction ability when the age variable is included in the neural network, it is suggested that future neural network runs should include this variable in the prediction of hearing ability at different frequencies.

6.10.3.2 The Gender Variable

The gender variable did not have a remarkable effect on the prediction accuracy of the neural network. Prediction accuracy improved from 40% overall prediction accuracy to 44% overall prediction accuracy. Some of the categories showed no improvement and prediction accuracy in some of the categories was even affected negatively. These results confirm the studies of Lonsbury-Martin et al. (1990), Gaskill and Brown (1990) and Cacace et al. (1996) that gender effects on DPOAEs are apparently limited to minor differences in DPOAE amplitudes and thresholds. It is not recommended that the gender variable should be included in the neural network's input alone, but it could be included as a variable in conjunction with the age variable.

6.10.3.3 The Combination of the Age and Gender Variables

The combination of the age variable and gender had an interesting effect on the prediction accuracy of the neural network for average hearing ability. Even though overall prediction accuracy for the neural network was slightly poorer than with the age alone, (48% with age and gender, 40% without any extra variables, 50% with age alone, 44% with gender alone, see Table XLII), the prediction accuracy of very good hearing (0-10dB) improved to 98% (Table XLIII). Very good average hearing (0-10dB) was predicted as normal (0-20dB) 100% of the time. The age variable alone predicted all categories, except the first one, better than the combination of age and gender did. It is therefore recommended that for the development of DPOAEs and neural networks for screening purposes, the age and gender variables should both be included, to ensure optimal prediction of the normal hearing ability categories. For prediction of hearing ability for diagnostic purposes however, (the prediction of specific categories of hearing ability) it seems that the age variable should be included alone as neural network input.

The last variable that could possibly have affected the outcome of this study is the presence of a spontaneous emission close to the distortion product.

6.10.3.4 The Presence of a Spontaneous Otoacoustic Emission Close to the Distortion Product

It was mentioned in Chapter 2 that a spontaneous otoacoustic emission within 50Hz of the primaries of a distortion product otoacoustic emission could enhance the amplitude of a DPOAE significantly under certain experimental conditions (Kulawiec & Orlando, 1995; Probst & Hauser, 1990). It could be argued that SOAEs were never measured in the data collection procedure and that it could have influenced the outcome of this study.

The presence of SOAEs close to the primaries did not influence this study significantly for the following reasons. First, SOAEs are recordable only in 50% of subjects with normal hearing and is completely absent in subjects demonstrating a hearing loss of more than 30dB HL (Lonsbury-Martin, 1994). Even if some of the subjects with normal hearing demonstrated spontaneous emissions close to the primary frequencies of the distortion product, the neural network would still have predicted their enhanced DPOAE amplitudes as normal. The only possible difference in the prediction accuracy of the neural network if a normal hearing subject demonstrated a SOAE, is that a category two (11-20dB) could possibly be predicted as a category one (0-10dB). It would however not have any effect on the prediction of normal hearing (0-20dB) as normal. Second, SOAEs are only present in normal hearing subjects and could therefore not have affected the neural network's prediction of hearing impaired categories. Studies investigating the normal characteristics of the distortion product should however be aware of this phenomenon and measure SOAEs in their data collection procedures.

6.11 DPOAE Measurements as a Diagnostic or Hearing Screening Procedure

In Chapter 1, current objective physiologic hearing assessment procedures were discussed as well as their shortcomings in the assessment of difficult-to-test populations. ABR is currently the most popular and widely used objective test of hearing for special populations (Weber, 1994), but ABR has a series of shortcomings limiting its effectiveness as a diagnostic procedure. Some of these limitations include that ABR measurement is often costly, it provides only limited frequency information, requires a large amount of time and highly trained and specialized personnel, and may require sedation.

The need for an objective, rapid, non-invasive, inexpensive, and accurate measurement of hearing was identified in Chapter 1. In the following chapter, one type of emission, the distortion product otoacoustic emission (DPOAE) was investigated as a possible new test of hearing and Chapter 2 concluded that DPOAEs have the necessary characteristics to be developed as a new objective test of hearing.

Otoacoustic emissions have been applied for a number of clinical applications in audiology. Applications include (a) screening of neonates and infants; (b) differential diagnosis of cochlear versus retrocochlear hearing losses; (c) monitoring of the effects of noise exposure or ototoxic drugs on the outer hair cells; and (d) to monitor fluctuating hearing loss in persons with Meniere's disease (Lonsbury-Martin et al., 1992; Norton & Stover, 1994; Norton & Widen, 1990; Robinette, 1992).

The distortion product has been proven as an acceptable screening procedure. It is present in all normal hearing ears and even though it is measurable in ears with a hearing loss of up to 65dB HL, amplitude and threshold information indicate different qualities, revealing hearing impairment (Moulin et al., 1994; Smurzynski et al., 1990). It can be measured non-invasively, objectively and rapidly (Norton & Stover, 1994). It is not significantly affected by gender (Cacace et al. 1996; Lonsbury-Martin et al., 1990) and has good test-retest stability (Cacace et al., 1996). Furthermore, it can be measured over a wide range of frequencies (Bonfils et al., 1991). DPOAEs are not affected by state of consciousness and do not require sedation (Norton & Stover, 1994). Lastly, it is an economic test that yield ear specific information. Many researchers used these attributes to correctly identify normal hearing in populations with varying degrees of hearing ability successfully (Gorga et al., 1993; Kimberley et al., 1994; Moulin et al., 1994). The only limitation of DPOAEs as a screening procedure is the lack of sensitivity sometimes prevalent in some of the studies. Sensitivity of a screening procedure is affected negatively by a high incidence of false negative responses. False negative responses refer to hearing-impaired ears that are predicted as normal (Schwartz & Schwartz, 1991). Some studies, including the present one, revealed an incidence of false negative responses too high for clinical acceptability (Kimberley et al. 1994; Moulin et al., 1994). According to Brass and Kemp (1994), it is very important to have a very high sensitivity for a first pass screening procedure (low incidence of false negative responses), as close as 100% sensitive as possible. The specificity of a screening procedure (affected by the number of false positive responses), on the other hand, is less important and is quite acceptable even if the test is only moderately specific (such as a specificity of 75%). Brass and Kemp (1994) compared test effectiveness and efficiency quite effectively: "In terms of screening effectiveness, the final number of false negatives is very important as this is the group of those for whom we were screening but missed. In terms of screening efficiency, the final number of false positives is important as this increase the number passed on to and hence the cost of the next stage of screening." (Brass & Kemp, 1994: 386).

It would therefore seem that the number of false negatives in this study is too high for an acceptable screening procedure, even though it is better than reported elsewhere (Gorga et al., 1993; Moulin et al., 1994; Probst & Hauser, 1990; Stover et al. 1996a).

Otoacoustic emissions however, have never been used as a diagnostic test of hearing where specific thresholds for frequencies were determined (Kimberley et al., 1994; Lee et al., 1993). Many researchers mentioned the increasing role that otoacoustic emissions have in diagnostic audiology (Kemp et al. 1990; Martin et al., 1990) and described the possibility of DPOAEs as a diagnostic audiologic test (Durrant, 1992; Kimberley et al., 1994; Lee et al., 1993). These authors also stated that additional research is necessary before otoacoustic emissions can be implemented as a diagnostic test of hearing.

The aim of this research project was, as stated in Chapter 4, to predict hearing ability at 500 Hz, 1000 Hz, 2000 Hz, and 4000 Hz with DPOAEs in normal and hearing impaired ears with the use of artificial neural networks. It was attempted to predict specific hearing levels within 10-15dB for normal and hearing-impaired ears. Even though this study could correctly identify normal hearing quite accurately, the specific predictions of hearing levels at various frequencies were rather disappointing. One possible reason for the poor prediction of categories depicting hearing loss is the number of ears in every category that the neural network had to train on. Chapter 3 explained the learning and training of a neural network, and that every category should have enough data for the neural network to train on, to form adequate representations and to make accurate predictions. To investigate this possibility, the accuracy of the prediction was correlated with the amount of data that the neural network had to train on. Results indicated that these two aspects are strongly correlated. The correlation coefficient was 0.94 for scenario four and 0.92 for scenario five. Every prediction was presented by a point on a scattergram, indicating the number of ears in a category and the accuracy of that prediction. These results confirm the speculation that categories depicting hearing impairment can be predicted accurately, if there is enough data in every category for the neural network to train on. If all the parameters of this research project were kept exactly the same with just one alteration of research design namely, the increase of subjects, hearing ability could be accurately predicted within 10dB from 500 Hz to 4000 Hz, for hearing levels up to 65dB HL.

This find is definitely a great contribution to the development of DPOAEs as a diagnostic test of hearing. The research in this study should be viewed as a stepping stone for further research to develop the distortion product as a new objective diagnostic test of hearing.

6.12 The Effectiveness of the Application of Neural Networks to the Field of Audiology

Artificial neural networks (ANNs) have been applied to the field of Speech Pathology quite effectively in the past. One such an example is the study by Metz et al., 1992, who used artificial neural networks to estimate speech intelligibility of hearing-impaired subjects from acoustic variables. These authors were also confronted by complex data sets with potential nonlinear relationships between acoustic speech parameters and speech intelligibility. Metz et al. (1992) also used a back propagation neural network, but with two hidden layers that had between 4- 20 hidden layer neurons. The neural network was capable of dealing with the systematic nonlinearities in their complex data sets. The network very successfully classified hearing impaired persons into the first and last group (most and least intelligible) but the neural network experienced difficulty classifying intermediate categories probably due to the criterion chosen to separate the different classes. This experiment is currently being expanded to improve network performance.

The application ANNs to the field of audiology in this study revealed promising results. For the first time, normal hearing (PTTs < 20dB HL) could be predicted at 500 Hz with DPOAEs with 92% accuracy. This has never been possible with conventional statistical methods. The prediction of normal hearing at 1000 Hz was also improved considerably, from 73% accuracy (Moulin et al. 1994) to 87% accuracy in this study with ANNs. Results obtained at higher frequencies in this study were similar or slightly poorer than the predictions of normal hearing at the higher frequencies in other studies.

Another aspect that the results in this study revealed, it that is there is a very good possibility that pure tone thresholds can be accurately predicted (within 10dB) with artificial neural networks, given that there is enough subject data for the neural net to train on.

The application of neural networks to the field of audiology was therefore very successful. The neural network extracted significant information from the input data and identified a correlation between pure tone thresholds and DPOAEs. The network then used this learned correlation to make predictions of pure tone thresholds effectively. If all categories of hearing ability had sufficient data for the neural network to train on, hearing ability would have been predicted accurately in all categories. Even with a shortage of data in some of the categories, the neural network was still able to distinguish normal from impaired hearing ability effectively and accurately.

6.13 Summary

In the investigation of DPOAEs as a possible new hearing screening or diagnostic procedure, many authors used conventional statistical methods to find a correlation between DPOAEs and pure tone thresholds (Gaskill & Brown, 1990; Gorga et al., 1993; Kummer et al., 1998; Lee et al., 1993; Vinck et al., 1996). Some researchers used statistics to predict hearing ability as normal or hearing-impaired at various frequencies, with more success in the high frequencies (Kimberley et al., 1994; Moulin et al., 1994).

The aim of this research project was to predict hearing ability at 500 Hz, 1000 Hz, 2000 Hz, and 4000 Hz with DPOAEs in normal and hearing-impaired ears with the use of artificial neural networks.

Even though this study could correctly identify normal hearing quite accurately, even at 500 Hz, the specific predictions of hearing levels at various frequencies were rather disappointing. One possible reason for the poor prediction of categories depicting hearing loss is the limited number of ears in every category that the neural network had to train on. With closer analysis of the correlation between prediction accuracy and data quantities, it became clear that the neural network would perform much better with more data to train on. This finding serves as a strong recommendation for future research in hearing prediction with artificial neural networks and DPOAEs.

7 Summary, Evaluation of the Study and Conclusion

7.1 Summary

Ever since Kemp (1978) first described otoacoustic emissions, there has been an interest in these measurements to develop another diagnostic tool to evaluate hearing ability objectively, non-invasively and accurately. An overview of current objective diagnostic procedures revealed that many technological advanced procedures exist for the successful evaluation of hearing ability and site of lesion testing in adults. It is in the evaluation of difficult-to-test populations however, that limitations in current objective diagnostic procedures were identified. It seemed that, despite all the strengths and positive attributes of ABR, tympanometry, MLR, and LLR, a few weaknesses in these procedures made it difficult to measure exact hearing ability and site of lesion in populations such as neonates, infants, malingerers, the crucially ill and foreign speakers. Some of these weaknesses include a limited frequency area in which hearing ability can be determined, lengthy test times, the possibility of sedation and the level of expertise and expense required (Ferraro & Durrant, 1994; Musiek et al., 1994; Robinette, 1994; Weber, 1994). It is therefore with much hope that many researchers turned their investigations to otoacoustic emissions.

Kemp (1978) identified different classes of otoacoustic emissions, depending on the stimuli used to evoke them. Spontaneous otoacoustic emissions (SOAEs) are only prevalent in half of normal hearing persons and can therefore not be implemented as a screening test or diagnostically (Lonsbury-Martin, 1994; Norton & Stover, 1994). Stimulus frequency otoacoustic emissions (SFEs) are not currently clinically used due to difficulties in separating in-going stimuli and out-going emitted responses (Lonsbury-Martin & Martin, 1990). Transient evoked otoacoustic emissions (TEOAEs) have been proven as a clinical acceptable hearing screening procedure, but the fact that they are only recordable in normal ears limited their diagnostic hearing testing applications (Kemp & Ryan, 1993; Lonsbury-Martin et al., 1992; Stevens et al., 1990). Distortion product otoacoustic emissions (DPOAEs) on the other hand, revealed many possibilities as a potential test of auditory functioning. First, it has been proven useful in both clinical and research settings, for it is the only emission type that can easily be recorded in many laboratory animals, allowing for experimental control of certain factors (Mills, 1997). Second, it can be measured in ears with a hearing loss of up to 65dB HL, therefore revealing information regarding outer hair cell functioning of hearing-impaired populations as well (Moulin et al., 1994). Third, it is the most frequency-specific emission type, due to the frequency specificity of the stimuli that can be chosen to stimulate any specific region on the basilar membrane (Durrant, 1992; Lonsbury-Martin & Martin, 1990). Fourth, DPOAEs correlate well with pure tone thresholds and the configuration of the hearing loss (Durrant, 1992; Kimberly & Nelson, 1989; Stover et al., 1996a). Fifth, DPOAEs are only slightly influenced by aspects such as age and gender (Cacace et al., 1996; Karzon et al., 1994).

Many studies described the relationship between DPOAEs and pure tone thresholds (Avan & Bonfils, 1993; Bonfils et a; 1991; Gaskill & Brown, 1990; Gorga et al., 1993; Kimberley et al., 1994; Probst & Hauser, 1990; Stover et al., 1996a). Statistical methods used to date, such as multivariate (discriminant) analysis in the case of the study of Kimberley et al., (1994), but also in all the other studies previously named, indicated a correlation between DPOAE measurements and behavioral pure tones. These studies however, could not predict the actual pure tone thresholds given only the distortion product responses (Lee et al., 1993). The complexity of the data, the numerous variables involved and the possibility of a nonlinear correlation have been some of the reasons why conventional statistical methods could not predict pure tone thresholds given only DPOAEs, but only distinguish between normal hearing and hearing-impaired ears.

For this study, a mathematical model, called artificial neural networks, was used to investigate the relationship between DPOAE measurements and pure tone thresholds. This technique has excellent correlation finding capabilities, even in the case of a possible non-linear correlation. The neural network was used to predict pure tone thresholds given only the distortion product responses.

Artificial neural networks were initially developed to gain a better understanding of how the human brain works (Nelson & Illingworth, 1991). It is an algorithm for a cognitive task, such as learning or pattern recognition (Muller & Reinhardt, 1990). Various disciplines became interested in the use of ANNs to address complex problems in the last two decades, ranging from cognitive psychology, physiology, medicine, computer science, electrical engineering, economy and even philosophy. ANNs have been successfully applied to the field of Speech Pathology for speech recognition purposes (Metz, et al., 1992). It was with great expectations that neural networks were applied to the field of Audiology in this study.

The rationale for this study was to investigate DPOAEs as a possible new objective test of hearing. The research design of this study was a multivariable correlational study. The correlation between selected variables of DPOAEs and PTTs were studied with artificial neural networks. The correlation found by the neural network was then used to predict hearing ability at 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz with DPOAEs (the main aim of the study).

Data was obtained from 70 subjects (120 ears, in some cases only one ear fell in the subject selection criteria), 28 males and 42 females, ranging from 8 to 82 years old. Selection criteria included sensorineural hearing losses of varying degrees and normal middle ear functioning. The subject selection procedures included a short case history, otoscopic examination, tympanometry and a traditional audiogram.

Data collection procedures consisted of the specification of stimulus parameters and DPOAE testing procedure. The distortion product has numerous stimulus variables that should be specified to ensure optimal testing conditions. The choice of stimulus parameters in this study was based on an extensive literature study and the preliminary study. For this research project, eight DP Grams at 5dB intervals ranging from L1=70dB SPL to L1=35dB SPL were measured. A frequency ratio of 1.2 was selected for the two primaries and the loudness level ratio of the two primaries was L1>L2 by 10dB. The frequency range of F1= 500 to F1= 5031 was tested. The criterion for DPOAE threshold was that the distortion product had to be at least 3 dB above the noise floor and accepted by the GSI 60 DPOAE system during measurement.

Eight tests or DP Grams were performed in each ear. Every DP Gram consisted of eleven frequency pairs. Every frequency pair consisted of two pure tones, f1 and f2 presented to the ear simultaneously (see Table II for the eleven frequency pairs). The eleven frequency pairs were presented to the ear in a sweep, one at a time starting with the low frequencies, ending with the high frequencies.

A data file for each ear was created, consisting of 19 columns and 88 rows of numbers (an example of a data file for one DP Gram can be seen in Table III).

A back propagation network was chosen for this study for two reasons: **1)** A possible nonlinear correlation is suspected between DPOAE thresholds and traditional pure tone thresholds. Metz, et al. (1992) reported the back propagation neural network to be very successful in dealing with nonlinearities that potentially occur in complex data sets. According to Blum (1992), the back propagation neural network is capable of nonlinear mappings and able to generalize well. **2)** The purpose of this study is to predict pure tone thresholds with distortion product thresholds with the use of neural networks. According to Blum, (1992) and Tam and Kiang, (1993), the back propagation neural network is highly applicable in the areas of forecasting and prediction.

Several different trial runs were conducted to determine neural network topology and the way the input data should be presented to the neural network. The input data was presented to the neural network in a binary mode, and the data pattern of all absent and present DPOAE responses served as input stimuli. Hearing ability was divided into categories and the neural network had to predict hearing ability into one of the categories. Scenario four had seven 10dB categories and scenario five had five categories, spanning 10-15dB each. The network had 140 middle neurons, 88 input nodes and seven output neurons in scenario four, five output neurons in scenario five. The network's acceptable prediction error during training was set at 5%.

As a first level approach, average hearing ability (average of 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz) was predicted first, and hearing ability at the four frequencies thereafter. The variables age and gender were included in neural network runs where average hearing ability was predicted to determine the effect of these variables on the distortion product.

Data analysis consisted of analyzing the actual and predicted values of all 120 ears and to determine how many were predicted accurately, how many within one class and how many were predicted incorrectly.

Results indicated that normal hearing ability could be distinguished from hearing-impaired hearing quite accurately, as low as 500 Hz. Many researchers failed to predict normal hearing ability at 500 Hz due to the rising of the noise floor at the lower frequencies (Gorga et al., 1993; Moulin et al., 1994; Probst & Hauser, 1990; Stover et al. 1996a). In this study, normal hearing ability at 500 Hz was predicted accurately 92% of the time. Normal hearing at 1000 Hz was correctly identified 87% of the time, at 2000 Hz 84% of the time and at 4000 Hz 91% of the time. Another aspect that should be kept in mind, however, is the false negative rate of every test that evaluated auditory functioning. Even though the false negative values in this study are lower than reported elsewhere (Gorga et al., 1993; Moulin et al., 1994;

Probst & Hauser, 1990; Stover et al. 1996a), the high incidence false negative responses raises questions regarding the sensitivity of this procedure.

The good predictions of normal hearing at the four frequencies can be attributed to two reasons. First, the different data analysis technique, or DPOAE variable that was used as input data, namely the use of all present and absent responses and not only the amplitude or threshold of one DPOAE measurement. Second, the different data processing technique, artificial neural networks, which excelled in the finding of a correlation between these two complex data sets.

The age variable had a positive effect on the prediction accuracy of average hearing ability. When the age variable was included as a neural network input, prediction of average hearing ability improved from 40% overall accuracy to 50% overall accuracy. Based on this improvement, it is suggested that future neural network runs should include this variable in the prediction of hearing ability at different frequencies. The gender variable did not have a remarkable effect on the prediction accuracy of the neural network. Prediction accuracy improved from 40% overall prediction accuracy to 44% overall prediction accuracy. The combination of the age variable and gender improved the prediction of normal hearing ability considerably.

The purpose of this study was to predict pure tone thresholds for 500 Hz, 1000 Hz, 2000 Hz and 4000 Hz. Hearing ability was divided into categories, and the neural network had to predict the most probable category of hearing ability. The frequencies were predicted in two scenarios, scenario four, with seven 10dB categories and scenario five, with five categories of different decibel intervals. Predictions of categories depicting hearing impairment were not satisfactory. Subjects were initially selected in such a manner that there were 40 ears with normal hearing, 40 ears with mild hearing loss and 40 ears with moderately severe hearing loss. The distribution of hearing loss at the four frequencies, however, resulted in an unequal amount of data in the different categories. Some categories were poorly represented and the neural network did not have enough data to train on, resulting in inaccurate predictions. A correlation between prediction accuracy and the number of ears in every category revealed that these two aspects are correlated strongly (correlation coefficient for scenario four was 0.94 and scenario five 0.92). All the categories and their predictions were plotted on a scattergram and the linear fit of the data plots suggests that the accuracy of the prediction increases as the number of ears in every category increases (linear fit of 1.703 for scenario four and 1.714 for scenario five). It can therefore be speculated that hearing ability can be predicted accurately (within 10dB) at various frequencies (500 Hz to 4000 Hz and possible even higher) over a range of 0 – 65dB HL with artificial neural networks. This can be achieved when every category is well represented and the network has enough data to train on, and also if the stimulus parameters for DPOAEs are chosen carefully.

Interesting cases were identified that had irregular neural network predictions. Some of these cases included subjects that were exposed to long periods of noise, always predicted as more hearing impaired, subjects with possible retrocochlear hearing losses that had normal emissions and subjects with minimal hearing losses that were predicted as normal. These irregularities once again stress the importance of the case history as part of the diagnostic battery.

The application of neural networks to the field of audiology was therefore very successful. The neural network extracted significant information from the input data and identified a correlation between pure tone thresholds and DPOAEs. The network then used this learned correlation to make predictions of pure tone thresholds effectively. If all categories of hearing ability had sufficient data for the neural network to train on, hearing ability would have been predicted accurately in all categories. Even with a shortage of data in some of the categories, the neural network was still able to distinguish normal from impaired hearing ability effectively and accurately.

The results in this study indicate strongly that DPOAEs are suitable as a diagnostic audiologic test of hearing. The research in this study should be viewed as a stepping stone for further research to develop the distortion product as a new objective diagnostic test of hearing.

7.2 Evaluation of Research Methodology

In the evaluation of research methodology, so many factors are at play that could influence the results in this study. Chapter 2 discussed the variables of the distortion product in detail and Chapter 3 the variables of artificial neural networks. Chapter 4 discussed reasons why certain variables and stimulus parameters were deemed as crucial for this type of study and chosen for this research project. The evaluation of research methodology will briefly look at the research design, the validity and reliability of this study and some limitations that were identified.

7.2.1 The Research Design

The research design chosen for this study was a multivariable correlational study. Certain chosen variables of the distortion product were used as input information in an artificial neural network. The network was trained with DPOAE variables and selected variables of pure tone thresholds. During training, the network determined a correlation between these two data sets. After completion of training, the network used the found correlation to predict pure tone thresholds of an unfamiliar subject with DPOAE results alone. The multivariable correlational study method in this research project was therefore applied successfully.

7.2.2 Validity and Reliability

Ventry and Schiavetti (1980) identified several factors that can influence the validity and reliability of the data obtained. The validity of the data can be divided into internal validity and external validity.

Internal validity deals with factors such as history, where the amount of time elapsed between the first and last test could include certain factors such as medication or treatment which could affect the readings of the second test differently than the first test. To avoid this factor from influencing test data, the pure tone audiogram, tympanogram and distortion product measurement were performed in one session, lasting about an hour.

Internal validity also deals with instrumentation. The accuracy of the data obtained for the pure tone audiogram is a result of how well the audiometer was calibrated, how recently the audiometer has been calibrated, and the cooperation of the subject (Leedy, 1993). The audiometers used in this research project (calibrated annually) were calibrated less than a year before this project, in April 1997. Pure tone thresholds were double checked with speech reception thresholds when poor cooperation of the subject was suspected, the instructions for pure tone audiometry was repeated and a threshold was determined as 3 responses out of 6 stimuli presented.

The GSI 60 DPOAE system was calibrated for a particular quiet room in January 1998. Regarding the fit of the probe, closure was obtained or DPOAE testing even though closure is not considered necessary but helpful by some authors (Bright, 1994). The closure fit of the probe reduced any external noise.

Lastly, the accuracy of the prediction was determined by how accurately the neural network was trained. The training accuracy of the neural network was measured after every training set, and the neural network was trained until the accuracy of the prediction in the training set was at least 95%.

Another factor that influences internal validity according to Ventry & Schiavetti, (1980) is the differential selection of subjects. The subjects selected for this study were divided into three groups, normal hearing, slight to mild hearing losses and moderately severe sensorineural hearing losses. The subjects were selected carefully to ensure that no other factors than a sensorineural hearing loss is present that could influence the test data such as middle ear pathology in this case. Tympanograms were interpreted carefully to ensure normal middle ear pressure. Subjects that had normal hearing but no tympanogram due to a perforation in the tympanic membrane were not included in the study. The selection of subjects was strictly according to the subject selection criteria in Chapter 4.

Reliability deals with the accuracy of the data obtained (Leedy, 1993) or precision of measurement (Ventry & Schiavetti, 1980). Reliability can be assessed by examining the stability and consistency of the test or measure. Gaskill & Brown (1990) conducted a study to investigate stability and reproducibility of DPOAE audiograms over time and with different ear probes. These authors found DPOAE measurements to be extremely stable over time and that different probe fits do not significantly influence DPOAE measurements. DPOAE measurements therefore seem to be reliable. The fact that DPOAEs are so reliable makes it an ideal procedure to monitor cochlear function in Meniere's disease, the administering of ototoxic medication or during surgery of structures close to the cochlea (Cane, Donoghue & Lutman, 1992; Subramaniam, Henderson & Spongr, 1994; Teleschi, Roth, Stagner, Lonsbury-Martin, 1995; Teleschi, Widick, Lonsbury-Martin & McCoy, 1995).

Neural networks are also very reliable. Neural networks are completely deterministic, in other words, two neural network runs with exactly the same inputs yield exactly the same results (Blum, 1992).

Hall III et al. (1993), identified more factors influencing measurement and analysis, and therefore the validity and reliability of the study. First, it is important to determine the status of the middle ear and external ear canal, for DPOAEs depend on both an inward and outward propagation of stimulus energy. These two factors were carefully assessed during subject selection procedures. Second, the measurement parameters for DPOAEs should be carefully chosen to ensure optimal measurement conditions. In this study, measurement parameters were chosen after an extensive literature study and also based on finds during the pilot study. The third aspect that influences measurement and analysis according to Hall III et al. (1993), is the signal-to-noise ratio and the criteria for when a DPOAE is present. Based on recommendations in literature, the presence of a DPOAE (DPOAE threshold) was taken as 3dB above the noise floor for this study (Lonsbury-Martin, 1994; Lonsbury-Martin et al., 1990). The last factor identified by Hall III et al. (1993) that could influence data analysis was subject variables such as age and gender. Both these variables were included in network runs to determine their effect on the distortion product.

The last aspect that could have an effect on the validity of this research project is human error during data preparation, analysis, and processing. Human error was eliminated or reduced where possible by electronic preparation, processing and analysis of data. DPOAE results were read into Microsoft Excel directly from the GSI-60 DPOAE system database to eliminate human error during the creation of subject files in data preparation. The computer extracted data that was used for the training of the neural network. Data analysis, where the correct answers were compared to the predicted answers, was also conducted on the personal computer to eliminate human error. Even the Figures, depicting prediction accuracy and correlation between number of ears and prediction accuracy were done on the computer with data directly from Microsoft Excel.

According to Leedy (1993) validity looks at the end results of the measurement. "Are we really measuring what we think we are measuring?" (Leedy, 1993:41). This research project attempted to find a correlation between DPOAEs and PTTs and to use that correlation to predict PTTs with DPOAEs and neural networks. It can be stated with reasonable certainty that this research project did in fact do what it was intended to do. Reliability, according to Leedy (1993) deals with the accuracy of the measurement. All measurements in this study were measured as accurately as technology currently allows on calibrated equipment.

7.2.3 Limitations of the Study

A few limitations were identified in this study. These are all aspects that should be kept in mind in the interpretation of results.

First, as stated previously, some of the categories depicting hearing impairment, were not represented adequately by the amount of data that the neural network had to train on. Even though subjects were initially selected to include an equal number of ears in three different categories of hearing ability, the pattern distribution of many sensorineural hearing losses is such that hearing loss is more prevalent in the higher frequencies than in the lower frequencies (Yantis, 1994). This resulted in an unequal number of ears in the categories that the neural network had to predict. Some of the categories were represented so poorly, that the neural network did not have enough data to train on. The network could not form adequate midway representations of the hearing ability of a subject in a category where only a few examples were present. To address this problem, more subjects should be included in neural network studies to ensure more data in every category.

The second limitation, is the fact that this study did not investigate every possible neural network type and configuration available to determine their effectiveness as predictors of hearing ability. There are so many combinations of neural network configurations available, and even though numerous combinations were tried and tested for this application, it can not be stated with certainty that this network type and configuration is the optimal choice. It is quite possible that better results can be obtained with other neural network types, or different topologies.

The third limitation is that it has not yet been determined what the acceptable percentage error should be that was chosen during the training of the neural network. Even though prediction and generalization abilities of the neural network were optimal in this study with a percentage error of 5%, this percentage is not necessarily acceptable for the clinical application of DPOAEs as a diagnostic procedure. It is possible that 5% error during training is not accurate enough for a diagnostic procedure. This aspect requires further investigation.

The fourth limitation is the fact that this study did not use the amplitude of the DPOAE in conjunction with its presence (in this study, the pattern of present and absent responses were used, depicted as a one or a zero). In some of the initial neural network runs, it was attempted to include amplitude and threshold data, but due to inability of the neural network to converge with all these extra inputs, the inputs were simplified by presenting it to the neural network in a binary fashion. By not using amplitude information, it is possible that a whole dimension of the data was lost, that could have enabled the network to make much more accurate predictions.

The fifth limitation is the high incidence of false negative responses recorded in this study. This high incidence of false negatives influence the sensitivity, and therefore the clinical acceptability of DPOAEs as a potential screening or diagnostic procedure. Further research is necessary to investigate possible neural network runs with different topology, different inputs and better measurement of DPOAEs to attempt to lower this high rate of false negatives.

The last limitation identified in this study is the duration of DPOAE measurement to obtain adequate information for one ear. The way in which this research project was constructed, 8 DP Grams were conducted in each ear. The pattern of all present and absent DPOAE responses from all eight DP Grams was used as input information. The duration of one DP Gram was about 2 minutes. It therefore took about 15 minutes per ear to obtain the necessary information. Even though it is still only half the time that is required to obtain a single threshold for one ear in ABR testing (Weber, 1994), it could be argued that 15 minutes is not such a rapid test of auditory functioning as was hoped for.

7.3 Recommendations for Future Research

The first recommendation for a study attempting to predict PTTs with DPOAEs and ANNs is to increase the number of subjects. According to Figure 6.3 and Figure 6.4, prediction accuracy of the neural network will be most accurate if there is at least 65 ears in every category.

The second recommendation is to include the age variable as one of the inputs of the neural network when hearing ability at specific frequencies is predicted. The age variable influenced the overall prediction accuracy of the neural network considerably.

The third recommendation is to attempt to find a network configuration that would allow the researcher to include amplitude information of the distortion product. By including this dimension of the distortion product as well, the network might be able to make much more accurate predictions of hearing ability.

The last recommendation is that the application of neural networks to this particular field of audiology should be further investigated. Neural networks offer so many possibilities. It is possible that different types of networks or different types of configurations would yield more accurate predictions.

7.4 General Implications of the Study and Concluding Remarks

Audiologists are currently relying heavily on objective audiological tests to assess hearing ability in difficult-to-test populations. There are however, still many limitations in current objective procedures despite the enormous progress in the last few decades. Some of these limitations include the limited frequency area of objective hearing assessment, the expenses, time and expertise required, and the possibility of sedation. It is with much hope that many researchers turned to the investigation of distortion product otoacoustic emissions as a possible new rapid, objective, accurate and cost effective test of auditory functioning. The distortion product has been proven as an acceptable screening procedure. Otoacoustic emissions however, have never been used as a diagnostic test of hearing where specific thresholds for frequencies were determined due to shortcomings in conventional statistical methods (Kimberley et al., 1994; Lee et al., 1993).

The investigation of DPOAEs indicated strongly that DPOAEs are suitable as a diagnostic audiologic test of hearing. It is suggested that pure tone thresholds can be accurately predicted within 10dB as low as 500 Hz and for hearing levels of up to 65dB HL with ANNs. The successful application of ANNs in the field of Audiology opened the door to the development of an objective, rapid, accurate and economical test of hearing to aid in the assessment of difficult-to-test populations. It is strongly believed that this breakthrough will play a leading role in the efficiency with which the pediatric population will be assessed in the next decade.

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APPENDICES:

Appendix A: The interview

PERSONAL INFORMATION			
Name:	**Subject file #**		
Date of birth: ____/____/____ **YY MM DD**	**Gender**	**M**	**F**

INFORMATION REGARDING HEARING STATUS
Complaints of a hearing loss? If Yes, what is the degree of the hearing loss? When was the onset of the hearing loss? What was the cause of the hearing loss? Is there a history of hearing loss in the family? If yes, what was the cause: genetic /trauma /unknown?
Complaints of current middle ear problems? If Yes, what is the current status of the middle ear problem, for example, does the subject experience any hearing loss, pain or fluid discharge. What was the frequency of past middle ear infections. Any allergies?

Complaints of tinnitus? If yes, what is the perceived pitch and loudness level of the tinnitus? **Complaints of vertigo?** If yes, how severe and how frequent?
Has the subject been exposed to high noise levels? If yes, amount of noise exposure: Type of noise exposed to for example gun shots, machinery, loud music.
What types of medication does the subject currently use?