

Chapter 3: Parameters that Influence Pure Tone Threshold Prediction Accuracy with Distortion Product Otoacoustic Emissions and Artificial Neural Networks

3.1 Introduction

The preceding chapter formulated the need for an objective audiologic procedure to aid in the assessment of difficult-to-test populations. Limitations in current objective procedures inspired the ongoing effort to attempt to predict pure tone thresholds (PTTs) accurately across a wide frequency range. Despite the complex relation between DPOAEs and PTTs, many researchers turned to distortion product otoacoustic emissions as the possible new objective method due to promising predictions of normal hearing, especially in the high frequencies.

Efforts to predict impaired hearing thresholds, and hearing ability at low frequencies have been problematic for several reasons such as difficulties to determine a non-linear correlation between two data sets of which the one is complex and described in neural network terms as “fuzzy” or incomplete. Other relevant issues that contribute to the struggle are the interfering low frequency noise levels caused by subject breathing and electric equipment interference and the fact that pure tone thresholds involve a much broader evaluation of the whole auditory system and not just the evaluation of outer hair cell functioning as in the case of OAEs. Furthermore, the PTT prediction process is made more complex by the large number of critical factors or variables involved in the generation of the stimuli necessary to elicit a DPOAE. These factors are interrelated and influence the amplitude and occurrence of the distortion product. The choice of parameters used to elicit the DPOAE influences the DPOAE

data set, therefore also the correlation to be determined between DPOAEs and PTTs and the accuracy of the prediction. An optimal set of parameters has to be identified to attempt to find the best combination of variables to accurately predict PTTs with DPOAEs. Lastly, the efficiency and accuracy of the data processing technique used also influences the PTT prediction process. Conventional statistical methods used in multivariate correlation studies have been found to be limited in their ability to solve complex nonlinear problems where hundreds of factors are at play (Nakajima et al. 1998; Kimberley et al. 1994a). Artificial neural networks (ANNs) have been found to have a superior ability in dealing with correlation determination in noisy nonlinear data sets (Nelson & Illingworth, 1991) and prediction of outcomes where numerous factors influence the data set (Rahimian et al. 1993). There are however many different kinds of networks available with different topologies and training methods and the choice and design of an appropriate network is one aspect that greatly influences the accuracy of prediction of PTTs with DPOAEs.

The aim of this chapter is to discuss all the factors that influence prediction accuracy of PTTs with DPOAEs and ANNs. First, all the parameters of the distortion product that play a role in PTT prediction will be discussed and the second half will concern itself with all the factors of neural network choice and design that influence prediction accuracy.

3.2 Stimulus Parameters of DPOAEs

In the generation of DPOAEs, two pure tones are used as stimuli with a frequency ratio that results in a partial overlap of the vibration fields in the cochlea. The ratio of

the two stimulus frequencies f_1 and f_2 , as well as their loudness levels, L_1 and L_2 , determine where in the cochlea the maximum stimulation occurs (Kemp, 1997).

3.2.1 The f_2/f_1 Frequency Ratio

A study by Harris, et al. (1989) investigated which f_2/f_1 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 1 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 equal level primaries of 75 dB SPL. The results showed that a frequency ratio between 1.20 and 1.25 optimizes the amplitude of the distortion product. A frequency ratio between 1.20 and 1.25 is also most applicable to the standard frequencies used in pure tone audiometry.

Other studies that described the optimum frequency ratio included $f_1/f_2 = 1.225$ (Gaskill & Brown, 1990), $f_1/f_2 = 1.23$ (Avan & Bonfils, 1993) and $f_1/f_2 = 1.3$ (Stover, et al. 1996a).

It would therefore seem that a frequency ratio of $f_1/f_2 = 1.2$ 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 L_1 and L_2 . 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).

3.2.2 The Loudness Levels of the Primaries

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 Gaskill and Brown (1990) $L1 > L2$ by 15dB. Gorga, et al. (1993) found that 65/55 dB SPL primaries (L1/L2) resulted in maximal separation between normal and impaired ears. Some other studies reported best DPOAE amplitudes for $L1=L2$, but used very high stimulus levels, such as 75 dB SPL that might have triggered passive emissions from the cochlea (Rasmussen, et al. 1993). To elicit active DPOAE responses with the largest amplitude possible, most researchers recommend L1/L2 ratios in the range of 10-15dB” (Mills, 1997; Stover et al. 1996a; Gaskill & Brown, 1990).

3.2.3 High Versus Low Levels of Stimulation

It seems that there are different mechanisms involved in high and low level stimulated DPOAEs (Harris & Probst, 1997). DPOAEs evoked with low level primaries (< 62 dB SPL) are dominated by active cochlear mechanical processes and are strongly correlated with auditory thresholds. DPOAEs evoked with high level primaries on the

other hand, are dominated by passive cochlear mechanics and do not provide frequency specific information on the local cochlear state (Avan & Bonfils, 1993; Kummer et al. 1998; Mills, 1997).

Bonfils et al. (1991) investigated the level effect of the primaries on the distortion product. 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. They found that 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.

Apart from all the parameters that should be specified, there are also two different ways to construct DPOAE testing.

3.2.4 DP Gram Versus I/O Function

In the measurement of DPOAEs, either the frequencies are changed and the loudness level kept constant (this is sometimes referred to as a “distortion product audiogram” or DP Gram) or the frequencies are being kept constant while the loudness level is changed (an input/output function (I/O 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.

3.2.4.1 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). The DP Gram is analyzed by comparing DPOAE amplitudes with average amplitudes obtained from normal hearing persons. A DP Gram does not obtain “threshold” information, as does the conventional pure tone audiogram. Figure 3.1 represents a DP Gram of a normal hearing person.

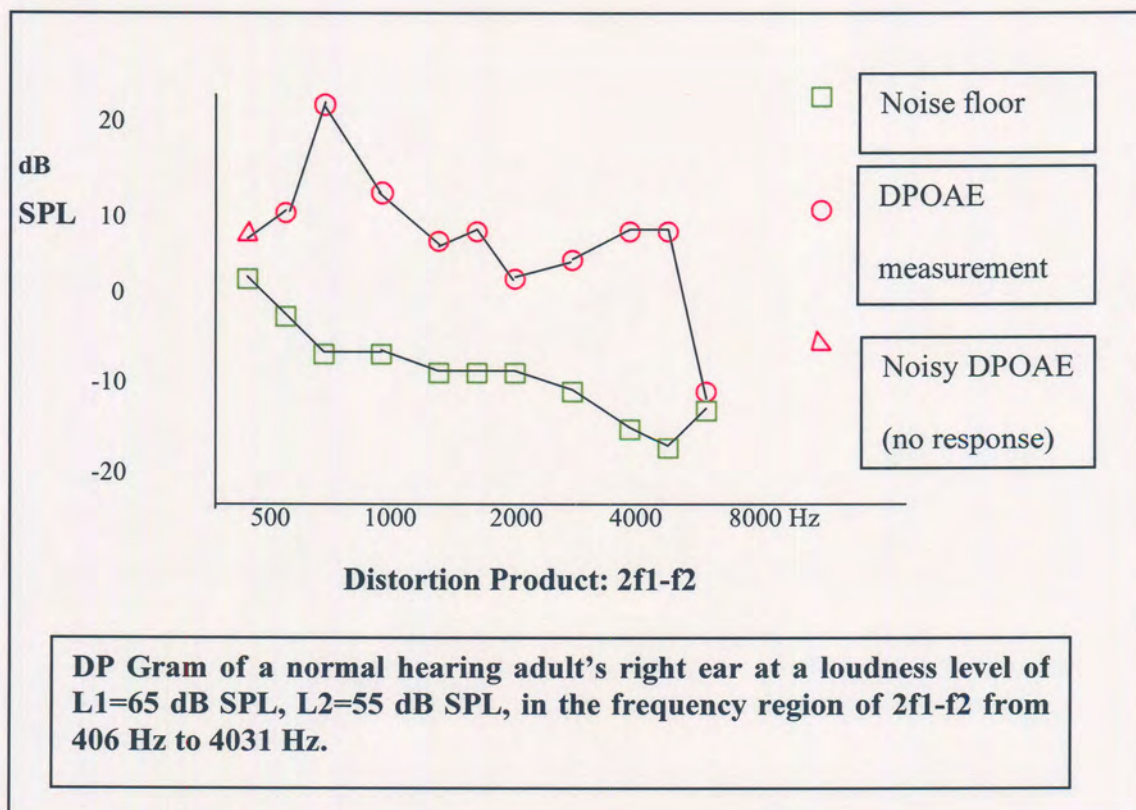


Figure 3.1: Example of a DP Gram.

3.2.4.2 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 changed (Norton & Stover, 1994).

An example of an I/O Function can be seen in Figure 3.2.

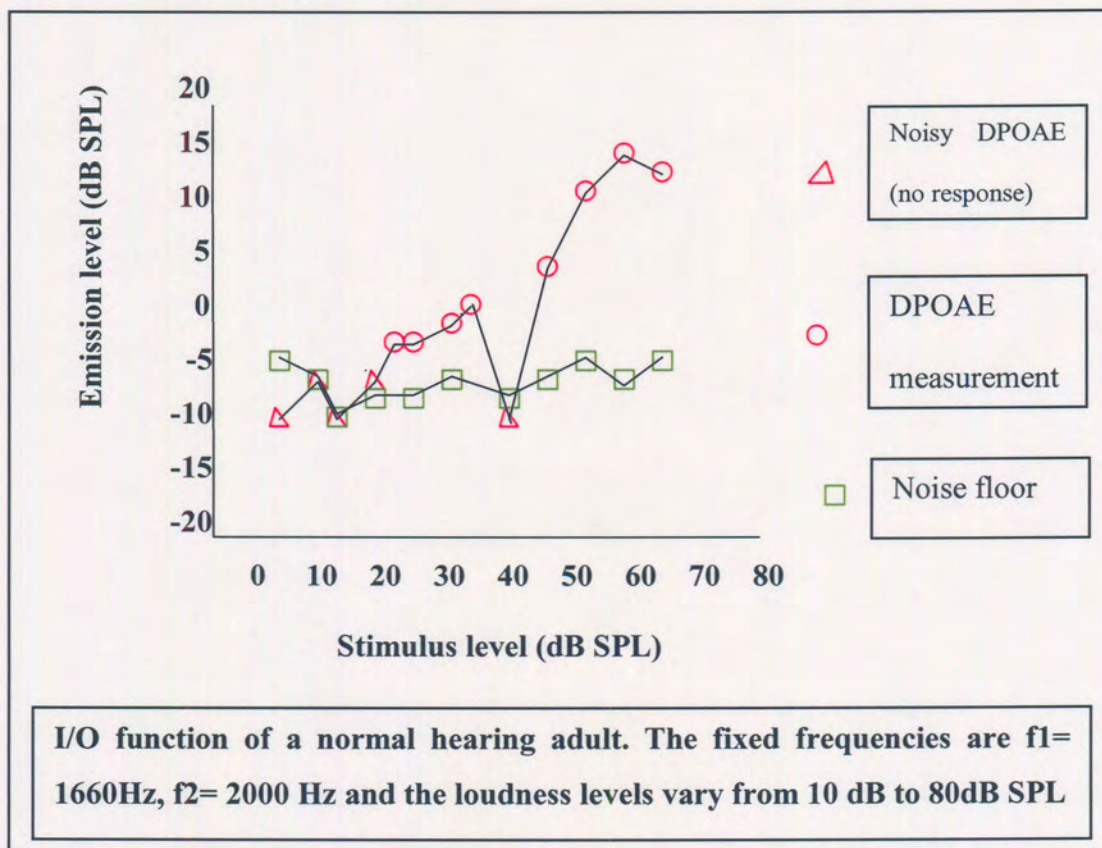


Figure 3.2: Example of an I/O function. (From Norton & Stover, 1994:457).

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 (Norton & Stover, 1994; Martin et al. 1990b).

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

There is not yet clear consensus on the best testing procedure to identify normal and impaired ears. Most researchers use a combination of the two procedures or perform both procedures separately (Martin, et al. 1990a, Spektor et al. 1991 and Smurzynski, Leonard, Kim, Lafreniere, Marjorie and Jung, 1990; Moulin et al. 1994; Kimberley & Nelson, 1989). It seems plausible to gain as much DPOAE threshold and amplitude information as possible by combining the two procedures.

The effect of age and gender on the prevalence of DPOAEs will be discussed next.

3.3 Subject variables: The Effect of Age and Gender on DPOAEs

Subject age and gender influence many aspects of auditory function (Hall III, Baer, Chase & Schwaber, 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) and are always investigated in new diagnostic audiology fields.

3.3.1 The Effect of Age on the Distortion Product

There is some debate about the effect of age on DPOAEs. 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 that DPOAEs are present from birth (Popelka, et al. 1998) and is as easily measurable in an infant as in an adult (Lasky 1998b). Some researchers believe that age affects the amplitude of DPOAEs negatively (Lonsbury-Martin et al. 1990) and others argue that age related differences could be attributed to sensitivity changes related with aging, rather than aging itself (He & Schmiedt, 1996). There are also researchers that found that DPOAE amplitudes for adults and neonates are similar, but some differences in the fine structure of the distortion product can be measured (Lasky, 1998a+b). Some of these studies will be discussed briefly.

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.

Another study by Karzon, et al. (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 and that the negative correlation between DPOAE levels and age is due to changes in hearing threshold associated with aging rather than age itself.

Lasky (1998b) found that I/O functions of newborns and adults were similar; it was only in the fine spectrum where differences could be observed such as a more linear I/O function in adults with saturation at higher primary levels. The amplitudes of DPOAE measurements in adults and neonates were within 1.5 dB of each other for all age groups (Lasky, 1998a). Abdala (1999) found that DPOAEs could even be measured in premature neonates although the fine structure characteristics at 1500 Hz and 6000 Hz were different than measured in adults and suspect that there may be an

immaturity in cochlear frequency resolution prior to term birth. No differences were observed at 3000 Hz.

When it comes to the prediction of PTTs with DPOAEs however, some researchers found that age enhanced predictive accuracy considerably (Lonsbury-Martin et al. 1991; Kimberley et al. 1994a; Kimberley et al. 1994b; De Waal, 1998). For all these studies, more accurate PTT predictions were made when subject age was included. It seems that subject age is a very important factor to be included in any prediction scheme based on DPOAE levels. Even though amplitudes of adults and children seem similar, there is much information in the differences measured in the fine structure across different age groups that enhances predictive accuracy of PTTs.

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

3.3.2 The Effect of Gender on the Distortion Product

Gender differences have been reported in other emission types. Cacace, et al. (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 (Moulin et al. 1994; Probst & Hauser 1990; Kulawiec & Orlando, 1995). 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 cannot 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 cannot 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.

3.4 Which Aspect of the DPOAE can best be Correlated with Pure Tone Thresholds

In the first two decades after DPOAEs were discovered, it was not clear whether it is the f_1 , f_2 , the GM frequency or the $2f_1-f_2$ frequency that is actually being stimulated on the basilar membrane. Most authors agreed that DPOAEs appear to be generated in the region stimulated between the primary frequencies, rather than the frequency at the distortion product (Martin et al. 1990b; Kimberley et al. 1994b; Smurzynski et al. 1990; Moulin et al. 1994; Harris et al. 1989). Some studies supported the notion that the generation of the distortion product correlates best with the cochlear place near the geometric mean (GM) of the primaries (Martin et al. 1990b; Lonsbury-Martin & Martin, 1990; Bonfils et al. 1991). These authors concluded that the acoustic distortion product at $2f_1-f_2$ should be correlated with PTTs near the GM of the primaries.

According to research conducted by Kimberley et al. (1994b) and Harris et al. (1989), the features that best correlate with PTTs are those associated with f_2 values close to the pure tone threshold frequency. The distortion product, according to these authors, is generated very close to the f_2 cochlear place and therefore they correlated PTTs with the f_2 frequency of the distortion product.

Recent research on the exact location of the basilar membrane that is simulated with the $2f_1$ - f_2 distortion product described a two source model for DPOAE generation (Knight & Kemp, 1999a; Mauermann, et al. 1999a+b; Talmadge, Long, Tubis & Dhar 1998; Shera & Guinan, 1998). According to this theory, there is not just one, but there are two areas on the basilar membrane that contribute to the energy measured in DPOAE testing. The first source of energy comes from the overlap region of the two primary frequencies. Although the waves of the two primaries are spread out over the whole basilar membrane, it is the area about 1mm around the f_2 region on the basilar membrane that contributes to most of the energy measured in a DPOAE. This area is known as the “ f_2 site” (Mauermann, et al. 1999a). DPOAE levels are however not just determined by the health of the cochlea at the f_2 place (Talmadge et al. 1998). There is a second source on the basilar membrane that contributes to the energy being measured and it comes from the distortion product wave component that travels apically from the overlap region and is reflected at the $2f_1$ - f_2 site, also known as the “re-emission site.” The spectral fine structure observed in the ear canal is a reflection of energy coming from both these sources.

The fact that more than one area of the basilar membrane contribute to a DPOAE response influences the method in which a correlation is determined between DPOAEs and PTTs. If the two source model of DPOAE generation is the case, it could be argued that one cannot merely correlate the f_2 value or merely the $2f_1$ - f_2 value with a PTT frequency, but that the data processing technique has to be able to use both frequencies in the correlation determination process. Artificial neural networks are capable of using any number of frequencies in the correlation

determination with one PTT frequency and can determine the significance of each frequency separately. This aspect makes it a very desired data processing technique to use for PTT prediction with DPOAEs.

The following section discusses the artificial neural network as a data processing technique and how it operates in more detail.

3.5 Aspects of the Artificial Neural Network that influences Prediction Accuracy of PTTs

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, partly because every data set and how the information can be presented to the network is highly unique. Another factor of importance influencing the learning process is the quality of the material that is used to train on, how noisy it is and how significant the correlation is between the data sets.

One has to have a clear understanding of what a neural network is, how it operates, learns and predicts to understand how the design of the network influences the outcome. The following discussion will serve as background to understand the whole process.

3.5.1 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 learning or optimization, recognition of a pattern or retrieval of large amounts of data (Muller & Reinhardt, 1990). Hiramatsu (1995:58) defined neural networks quite effectively: “A neural network is generally a multiple-input, multiple-output non-linear mapping circuit, which can learn an unknown non-linear input-output relation from a set of examples.”

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.

3.5.2 “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.

3.5.2.1 Biological Neural Networks

The human brain is composed of cells called neurons and 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 3.3) 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.

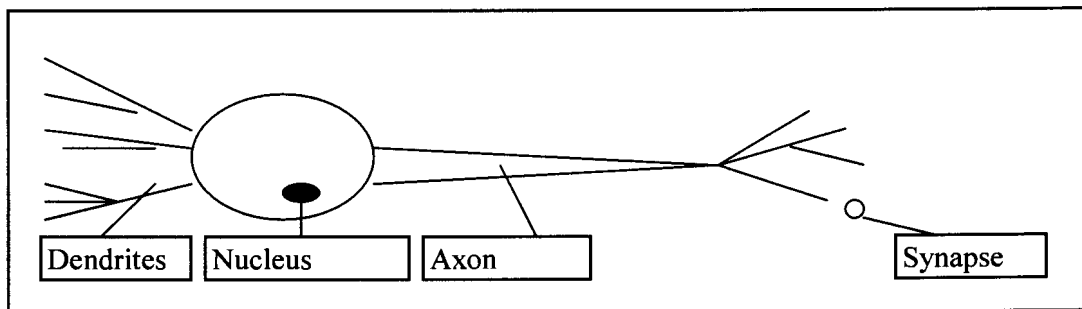


Figure 3.3: A biological neuron (From Medsker, et al. 1993:5)

“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.

3.5.2.2 Artificial Neural Networks (ANNs)

The building blocks of an artificial neural network are also referred to as neurons, or sometimes as a node, a perceptron or processing element. These artificial neurons (Figure 3.4) 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).

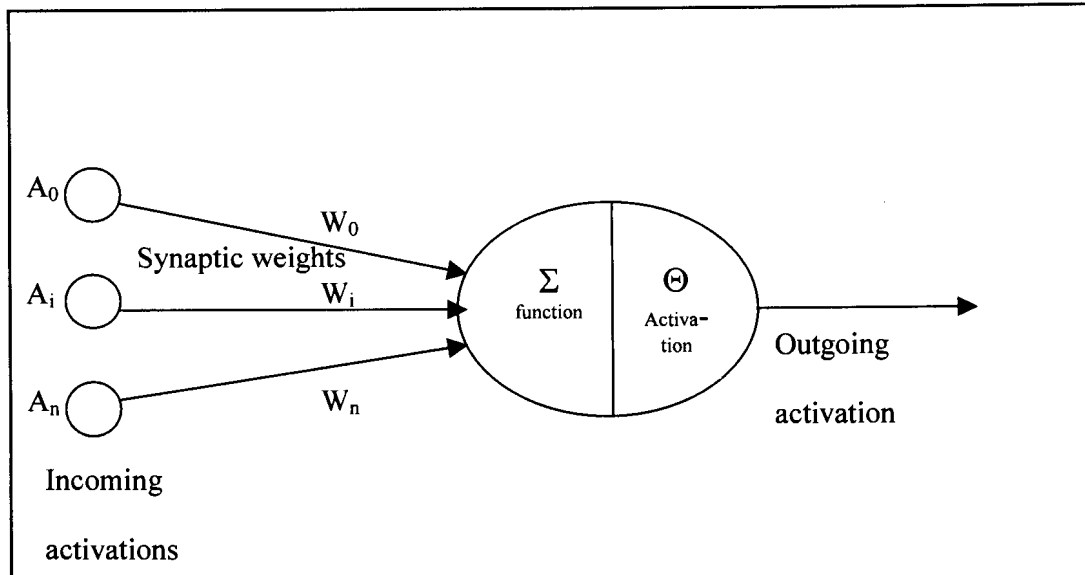


Figure 3.4: An artificial neuron (From Blum, 1992: 37).

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).

Several of these artificial neurons or nodes (indicated with circles in Figure 3.5) can be combined to make a **layer** of nodes. Figure 3.5 illustrates the middle or hidden layer been formed, connected to inputs, presented as input one (I_1) to any number of inputs (I_n) and also connected to outputs.

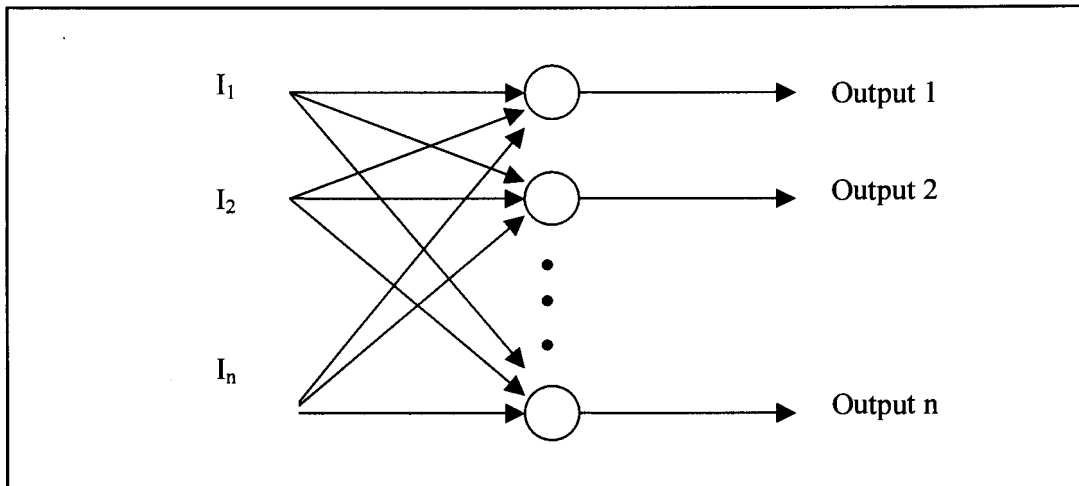


Figure 3.5: Inputs to several nodes to form a layer (From Nelson & Illingworth, 1991: 49).

In this representation, the middle layer is highly interconnected with the inputs (all inputs are connected to all middle level neurons) but only forwardly connected with the outputs. Middle layer neurons can also be highly interconnected to output neurons: the way in which neurons are connected to other layers is specified in the neural network design. The dots in the middle layer suggests that any number of neurons in this layer is possible and is determined by trial-and-error during network training so suit the complexity of the data. To form an artificial neural network, several layers are connected to each other. This is illustrated in Figure 3.6.

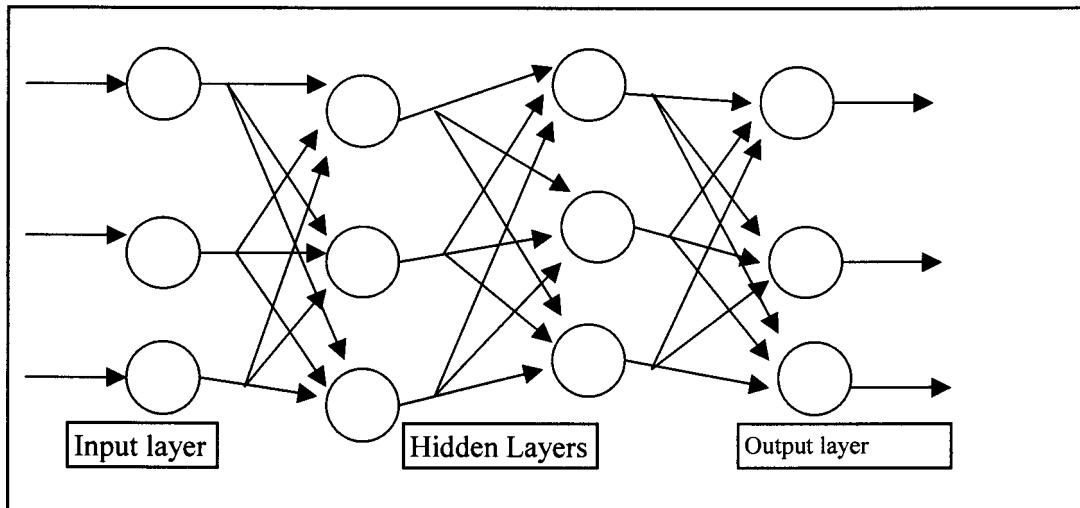


Figure 3.6: Connection of several layers to form a network (From Nelson & Illingworth, 1991:50).

From figure 3.6 it is clear that several different layers can be distinguished. 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**. In this four-layered network, all input and middle or hidden layers are highly interconnected with each other.

The “anatomy” of artificial neural networks has just been reviewed. The terminology used in the “physiology” or working 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, et al. (1993) 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." (Medsker et al. 1993:10)

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 the same 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; Nelson & Illingworth, 1991; Medsker, et al. 1993).

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 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.

3.5.3 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).

3.5.3.1 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.

3.5.3.2 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).

3.5.3.3 Multi Layer Networks

Several types of multi layer networks exist. The most common multi layer network is the feedforward network with a backpropagation learning algorithm. According to Rao & Rao (1995), over 80% of all neural network projects in development use backpropagation. "Back propagation is the most popular, effective, and easy-to-learn model for complex, multi layered networks." (Nelson & Illingworth, 1991:121). Most backpropagation networks consist of three layers, an input layer, an output layer and a hidden or middle layer (Figure 3.7). The connections between the layers are forward and are from each neuron in one layer to every neuron in the next layer.

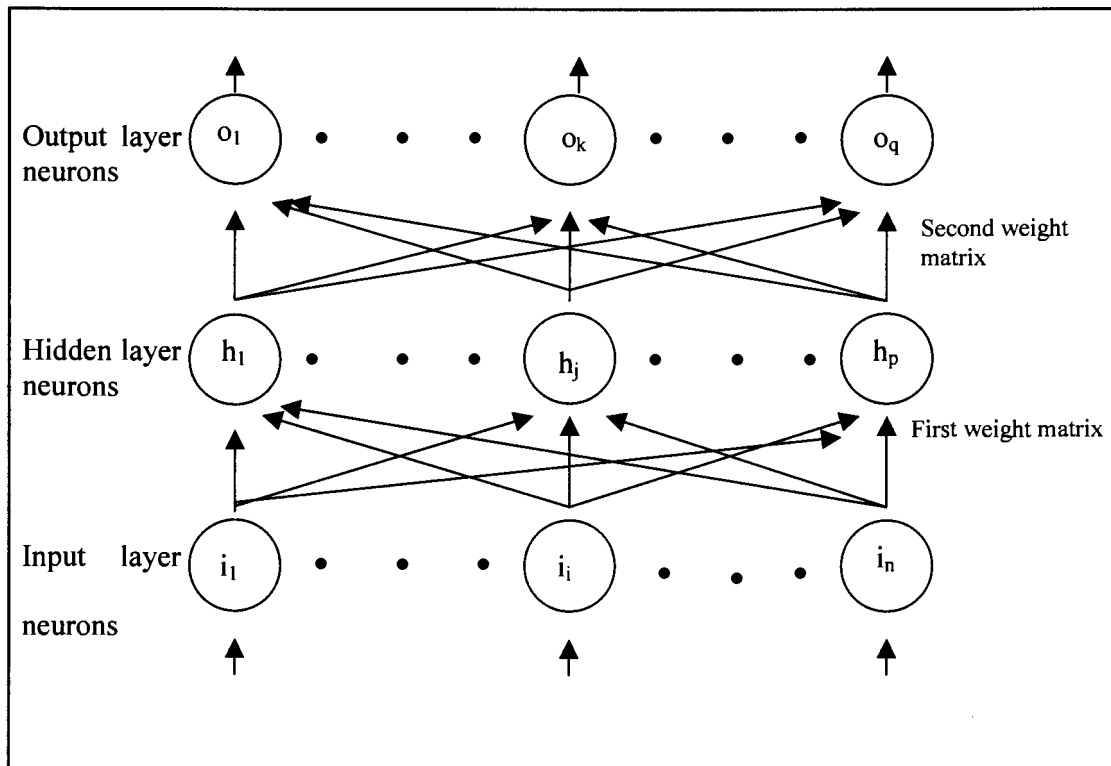


Figure 3.7: Diagram of a feedforward backpropagation neural network (From Blum, 1992: 56).

There are two phases in the learning process of a feedforward backpropagation neural network. 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 backpropagation, 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 is clearly summarized by Nelson and Illingworth as follows: (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.” Backpropagation networks require supervised learning where the network is trained with a set of data (training set) similar to the test set.

Now that the functioning of a neural network is understood, attention can be given to the factors in ANN design that influence prediction accuracy of PTTs with DPOAEs and ANNs.

3.5.4 ANN Factors Influencing Prediction Accuracy of PTTs with DPOAEs

Even when a standard preprogrammed artificial neural network is used, certain parameters has to be specified and can be experimented with to produce a more desired outcome. These parameters include the topology, error tolerance levels and the format of the input data.

3.5.4.1 The Topology

The topology of a network is determined by the number of layers in the network and the number of nodes in each layer.

3.5.4.1.1 Number of Layers in the Network

When there is good similarity between input and output data, only two layers are needed, but when the structure of the input pattern is quite different from the output, hidden layers are needed to create an internal representation from the input signals (Nelson & Illingworth, 1991). The ability of the network to process information increases in proportion to the number of layers in the network. In the design of a neural network, hidden layers can be added one by one until suitable outputs can be achieved. According to Hornik, Stinchcombe and White (1989) however, when a multilayered feedforward network is used, only one hidden layer is enough for any complex problem, provided that there are enough neurons in the hidden layer. According to these authors, failures in feedforward networks with one layer can be attributed to inadequate learning or the presence of a stochastic or random relation rather than a deterministic relation between two data sets. It would therefore seem that a feedforward backpropagation network with three layers, one input layer, one output layer and one hidden layer is sufficient for this application.

3.5.4.1.2 Number of Nodes in each Layer

The number of nodes in the input layer is determined by the amount of data that is fed into the network. For example, if all the present and absent DPOAE responses of 11 frequencies at eight loudness levels serve as input information, then there should be at least 88 input nodes to represent this data numerically. If gender is added as a variable then one more node has to be added to represent gender as either a one or a zero. Every additional input variable needs extra input nodes, and the number of nodes needed is determined by the way in which the data is presented to the network. The

input layer therefore only serves as a buffer in which information can be “fanned” through to the next layer (Blum, 1992).

The number of nodes in the output layer is determined by the objective of the neural network and the format in which it is presented. For example, if the objective is to predict a pure tone threshold at a certain frequency and the format is to predict it into one of eight categories of 10dB each, then there will be eight nodes in the output layer. The output layer merely makes the network information available to the outside world (Nelson & Illingworth, 1991).

The determination of the number of nodes in the hidden layer is less straightforward. This number influences network capacity, generalization ability, learning speed and the output response. Fujita (1998) argues that on the one hand it is best to have as many hidden layer neurons as possible for capacity and universality in application to function approximation. On the other hand, from the standpoint of generalization, the number should not be too large for heuristic learning systems in which the best network configuration is unknown beforehand. Too many hidden layer neurons can also reduce the speed of the network considerably. It is difficult to determine the middle level neuron quantity before the learning is done, and it is best to adjust node numbers during learning.

According to Blum (1992), the best size is determined by familiarity with the application. Nelson and Illingworth (1991) describe it as a trial and error effort to determine which size yields optimum results.

3.5.4.2 The Error Tolerance

A feedforward neural network propagates information from the input level to the middle level to the output level, but errors are backpropagated during training. The purpose of the backpropagation of errors is to change the weights between layers to handle the prediction better the next time it encounters the same information. Errors in the output indicates that there are errors in the two sets of weights connected to the hidden layer and are used as a basis for adjustment of the weights between the input and hidden layer and output and hidden layer. The weights connected to the hidden layer have to be adjusted repeatedly until prediction error falls within a specified level. Error tolerance therefore refers to how accurately a network predicts the answer, but also how effectively it trains or learns (Blum 1992; Rao & Rao 1995).

When prediction error is set as close to zero as possible, only answers that are completely correct are accepted. Although it might seem logical to set error tolerance levels as close to zero as possible, it is not always practical, for two reasons. A network with error tolerance of as close to zero as possible trains much longer before accurate enough predictions can be made. Sometimes the training phase becomes so long for each experiment (from hours to days to weeks) that it becomes unpractical to run hundreds of experiments, which is the case when 120 ears have to be predicted at four frequencies. The second disadvantage of very small error tolerance levels is the network's ability to generalize decreases. When a DPOAE data set slightly out of the ordinary has to be predicted, a network with very low error tolerance levels is often incapable of a general prediction and can not reach a training set that falls within the specified error tolerance level.

Error tolerance levels, just as in the case of the number of middle level neurons, have to be experimented with to find the optimal error tolerance level. Due to the fact that each data set, experiment objective and way in which data is presented to the ANN is so unique, there are not yet standards for acceptable error tolerance levels and it has to be determined for each situation by using a trial and error effort (Yuan & Fine, 1998).

3.5.4.3 The Format of the Input Data

“It has been suggested that most of the “black magic” in neural networks comes in defining and preparing the training input set” (Nelson & Illingworth, 1991:154).

Neural networks only deal with numeric input data. All factors that serve as input data has to be numerically transcribed, for example, the gender variable can be predicted with a one or a zero. Sometimes the network requires that the input information be scaled or normalized. For example if DPOAE amplitude serves as input data and could be any number from 0 – 40 dB, it can be scaled by depicting it as a fraction of 40 dB, a DPOAE level of 30 dB would therefore have a value of 0.75. Only one extra input node is needed in this case. Another option for depicting input values is the dummy variable technique where categories are created to depict a certain value and values are depicted with ones and zeros depending on the category in which it falls. In the case of the DPOAE level between 0 – 40 dB, four 10 dB categories can be created, category one depicts DPOAE levels from 0 – 10dB, category two from 11 - 20 dB, category three from 21 - 30 dB and category four from 31 - 40 dB. A DPOAE level of 30 dB would therefore be depicted as 0010, indicating that the DPOAE level falls in the third category. If this method is used, more input nodes are needed depending on the number of categories created to depict the value, in this case four

extra input nodes will be needed. With more input nodes, the neural network gets more complex and usually more middle level neurons are needed.

There are many ways in which input data can be presented to the network; the possibilities are as limited as the imagination of the person creating the neural network. Different input strategies often influence the prediction accuracy of the neural network and therefore there has to be experimented with different ways to present the information to the network. All the different ways in which input data was manipulated for this research project will be discussed in detail in Chapter 4, Research Methodology.

3.6 Interpretation and Conclusion

When it comes to the prediction of PTTs with DPOAEs and ANNs, there are many factors influencing the occurrence and levels of DPOAEs and therefore also the correlation that has to be determined between DPOAEs and PTTs and prediction accuracy of the ANN. From an in-depth literature study, the optimal set of stimulus parameters that influence DPOAE occurrence and levels were identified for the measurement of DPOAE. The identified stimulus parameters for DPOAE measurement are as follows:

3.6.1 Factors of the DPOAE Influencing DPOAE Occurrence and Levels:

- A primary $f2/f1$ frequency ratio of about 1.2 has been proven to elicit largest DPOAE amplitudes between 1 and 4 kHz (Gaskill & Brown, 1990; Avan & Bonfils, 1993; Stover, et al. 1996a).

- The loudness levels of the primaries should preferably be 10 – 15 dB apart (Gorga et al. 1993; Mills, 1997).
- The level of stimulation should not exceed 65 – 75dB to prevent the evaluation of passive properties of the cochlea and to gain more frequency specific information (Avan & Bonfils, 1993; Kummer et al. 1998; Mills, 1997).
- The way in which testing should be constructed is preferably a combination between I/O functions and DP Grams to gain as much information as possible of the DPOAE's threshold and amplitude (Kimberley & Nelson, 1989; Martin, et al. 1990a; Smurzynski et al. 1990).
- The subject variable age seems to have a positive influence for PTT prediction with DPOAEs and should be included in the correlation determination and prediction process (Lonsbury-Martin et al. 1991; Kimberley et al. 1994a; Kimberley et al. 1994b; De Waal, 1998).
- The frequency variable of the DPOAE to correlate with PTTs should preferably include not only the f2 frequency but the 2f1-f2 frequency as well (Mauermann et al. 1999a; Talmadge et al. 1998).

When it comes to the use of artificial neural networks as a data processing technique, several aspects regarding the choice, design and functioning of the network were identified. These aspects influence accuracy of predictions made by the network and are as follows:

3.6.2 Factors of the ANN that Influence Prediction Accuracy of PTTs with DPOAEs:

- From the description of the functioning of a neural network it became clear that a multi-layered ANN is needed for the prediction of PTTs with DPOAEs (Blum, 1992).
- The topology of the network influences prediction accuracy and experimentation is needed to determine the optimal number of neurons or nodes in each layer (Hornik et al. 1989; Nelson & Illingworth, 1991).
- Error tolerance during training and prediction is another factor that influences speed and efficiency of network operation and is also determined by trial-and-error experimentation (Rao & Rao, 1995; Yuan & Fine, 1998).
- There are many ways in which input data can be manipulated and the best way to present input information to the network requires careful consideration and experimentation (Nelson & Illingworth, 1991).

This chapter served as an identification and discussion of all DPOAE and ANN variables that influence PTT prediction accuracy. An optimal set of parameters were identified for the measurement of DPOAEs that will be applied in the testing procedure in the following chapter. However, the process to attempt to predict PTTs with DPOAEs and ANNs involve numerous possibilities in the experimentation to establish optimal neural network configuration and error tolerance levels. There are also different ways to present DPOAE measurements to the network that influence the accuracy of PTT predictions that lead to further necessary experimentation. These experiments to optimize PTT

prediction , as well as the research methodology for the entire research project will be discussed in the following chapter.

Chapter 4: Research Methodology

4.1 Introduction

One very interesting viewpoint on the essence of research methodology was given by Leedy (1993:9). “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.”

The problem inspiring this research project has already been extensively stated in Chapter 1 and 2. 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 despite the fact that there are many aspects contributing to pure tone thresholds that is not evaluated with otoacoustic emissions. Shortcomings in conventional statistical methods prevented accurate predictions of PTTs with DPOAEs due to the complex non-linear relationship between DPOAEs and PTTs and the noisy nature of DPOAE measurements. A new form of information processing called artificial neural networks (ANNs) was identified as a suitable data processing technique to attempt to solve this problem.

The study preceding this one (De Waal, 1998) attempted to predict pure tone thresholds with DPOAEs and artificial neural networks. First, PTTs were categorized as normal or impaired (normal defined as < 20 dB HL) with DPOAEs and ANNs and correct classification of normal hearing was 92 % at 500, 87% at 1000, 84% at 2000

and 91% at 4000 Hz. Predictions of impaired hearing was less satisfactory partly due to insufficient data for the ANN to train on and also possibly because of lack of experimentation with optimal topologies, error tolerance levels and optimal representation of input data for the neural network.

The aim of this chapter is to describe the research method that developed in the expansion and broadening of the basic work on DPOAEs and ANNs in order to enhance prediction accuracy of PTTs.

4.2 Aims of Research

The aims of this research project are as follows.

4.2.1 Main Aim

To improve prediction of pure tone thresholds (PTTs) at 500, 1000, 2000, and 4000 Hz with distortion product otoacoustic emission (DPOAE) responses in normal and hearing impaired ears with the use of artificial neural networks (ANNs).

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, 1000, 2000 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 experiment with different ANN error tolerance levels to enhance neural network performance and efficiency during training and prediction.

The third sub aim is to determine if different manipulations of input data into the neural network improves prediction accuracy of PTTs with DPOAEs such as different ways to present the age variable, and DPOAE amplitude to the neural network.

The fourth sub aim is to experiment with the inclusion and omission of noisy low frequency DPOAE data to determine its effect on prediction accuracy.

The last sub aim is to investigate the effect of DPOAE threshold on prediction accuracy with DPOAEs when DPOAE threshold is defined as 1, 2 or 3 dB above the noise floor.

4.3 Research Design

For this research project, the chosen research design was a multivariable correlational study (Leedy, 1993). The correlation between DPOAE measurements and pure tone thresholds (PTTs) was studied by the use of artificial neural networks (ANNs). This correlation was then applied to make predictions of hearing ability in subjects of various ages, demonstrating different levels of sensorineural hearing loss or normal hearing to investigate to what extent DPOAEs can be used as a diagnostic or screening procedure in the objective evaluation of pure tone sensitivity. If DPOAEs can accurately predict pure tone thresholds objectively in a population with varying degrees of sensorineural hearing loss and at different ages, it would be a significant contribution to aid in the evaluation of difficult-to-test populations.

For the purpose of this study, 70 subjects (42 females, 28 males, 8-82 years old) were recruited from a school for the hard of hearing and a private audiology practice. Subjects were evaluated in terms of their pure tone thresholds (PTTs) and DPOAE measurements. The results from these two tests were used to train a neural network to find a correlation between the two data sets, and to use that correlation to make a prediction of PTTs given only the DPOAEs.

The measured variables for this study consisted of:

- PTT measurements at 500, 1000, 2000 and 4000 Hz
- DPOAE responses at eleven $2f_1-f_2$ frequencies ranging from $2f_1-f_2 = 406$ Hz to $2f_1-f_2 = 4031$ Hz

(Both tests were measured in each subject within two hours.)

Controlled variables for this study included:

- The frequencies of the two primaries, f_1 and f_2 , ranging from $f_1 = 500$ Hz to $f_1 = 5031$ Hz, with a primary frequency ratio of 1.2.
- The loudness levels of the primaries ranging from $L_1 = 70$ dB to $L_1 = 35$ dB with a loudness difference of $L_1 > L_2$ by 10dB.

Manipulated variables for this study to investigate the effect on PTT prediction accuracy included:

- Subject age presented to the ANN as a 5-year category or a 10-year category (see 4.8.1.3).
- DPOAE threshold defined as 1, 2 or 3 dB above the noise floor (see 4.8.1.5).

- Presentation of the amplitude of the DPOAE to the ANN input as one of four possible methods (AMP 100, AMP 40, ALT AMP or No AMP-see 4.8.1.4).
- The inclusion or omission of noisy low frequency DPOAE results for ANN training (see 4.8.1.1).
- Three different middle level neuron counts for ANN training and prediction (see 4.8.3.4).
- Three different error tolerance levels for ANN prediction and training (see 4.8.3.5).

Neural network results do not consist of predictions of frequencies in a decibel form, but of predictions of PTTs into one of eight possible 10 dB categories. Interpretation of data consists of the analysis of prediction accuracy of the neural network's ability to predict hearing at a specific frequency accurately into a specific 10 dB category.

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 Normal and Impaired 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 was 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, 1000, 2000 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) modified Goodman's (1965) recommendations 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 subject selection, the second approach to classification of hearing impairment (as recommended by Clark, 1981) 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 PTT thresholds of the group with normal hearing ranged from 0 dB to 15 dB. The group with slight and mild hearing loss had PTT thresholds that ranged from 16 to 35dB and the moderately-severe hearing-impaired group had PTA's in the range of 36 - 65dB. It should be noted that according to Clark's (1981) 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 have 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) to determine the PTA, namely 0.5kHz, 1kHz, 2kHz and 3kHz, for this study 4kHz 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 Normal 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; Koivunen, et al. 2000). The requirement for normal middle ear functioning is also the reason why only sensorineural hearing impaired subjects are included in the impaired hearing group described in 4.4.1.1.

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

4.4.1.3 Good or Normal 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-Martin et 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 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 insignificant differences in DPOAE amplitudes and thresholds and therefore gender was not one of the selection criteria for this study.

Even though subjects were not selected regarding age or gender, a subject's age and gender were used as input information for the neural network. The reason for this is that previous studies that attempted to predict PTTs with DPOAEs found that age enhances prediction accuracy and recommended to use age as a variable in PTT prediction studies (Lonsbury-Martin et al. 1991; Kimberley et al. 1994a; Kimberley et al. 1994b). The previous study by De Waal (1998) also indicated that the combination of age and gender as prediction variables had a greater positive effect on prediction accuracy than the inclusion of age alone.

4.4.2 Subject Selection Procedures

The procedure in which subjects were selected started with a brief interview, following 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 firstly 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. Secondly, 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, et al. (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). Cases with exposure to noise, ototoxic medication or subjects with tinnitus and vertigo were included in the research project, this information merely serves as background to formulate reasons for possible abnormalities in DPOAE responses.

Appendix A reviews the aspects that were addressed in the short interview. This interview lasted approximately 10 minutes.

4.4.2.2 Otoscopic Examination

Otoscopic examination of both ears was performed to determine the amount of wax in the ear canal, for excessive wax might 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). Otoscopic examination's duration was about 3-5 minutes.

4.4.2.3 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 to 1.6 cc (Block & Wiley, 1994). Subjects demonstrating type A tympanograms within these specifications were accepted for the study.

Tympanometry was performed in both ears and the duration of the procedure was about 5 minutes.

4.4.2.4 Pure Tone Audiogram

Data obtained from the pure tone audiogram was not only used in the selection of subjects, but also forms part of the measured variables for this study and was used to train the artificial neural network. The determination of the pure tone audiogram will therefore be discussed in detail.

If the subject had normal middle ear functioning, the subject selection procedure continued. A pure tone audiogram was then obtained from the subject. The frequencies that were tested during pure tone air conduction were 125, 500, 1000, 2000, 4000, and 8000 Hz. Even though only 500, 1000, 2000 and 4000 Hz were used to train the neural network, pure tone results at 125 Hz and 8000 Hz could sometimes indicate a slight hearing loss even though hearing at the four middle frequencies was normal. Hearing thresholds at 125 Hz and 8000 Hz were never used in the determination of the category in which a subject fell for subject selection (see 4.4.1.1) but were used merely as background information to formulate reasons for possible abnormal DPOAEs.

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 to ensure that the hearing loss was of a sensorineural nature. 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, 1000, 2000, 3000 and 4000 Hz below 15 dB) were included in the first group. Audiograms indicating hearing loss were analyzed in terms of the degree of the hearing loss. Mild hearing losses, indicating a hearing loss between 16 - 35 dB in the frequency region 500 - 4000 Hz were categorized in the second group, namely mild hearing losses. Audiograms indicating hearing losses of 36 - 65 dB in the frequency region of 500 - 4000 Hz were categorized in the third group, namely moderately severe hearing losses. 40 audiograms were included in each category.

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 4.7 “Data collection procedures”.

4.5 Description of subjects

Figure 4.1 depicts the gender distribution for subjects included in this study. Figure 4.2 depicts the age distribution of subjects into 10-year categories.

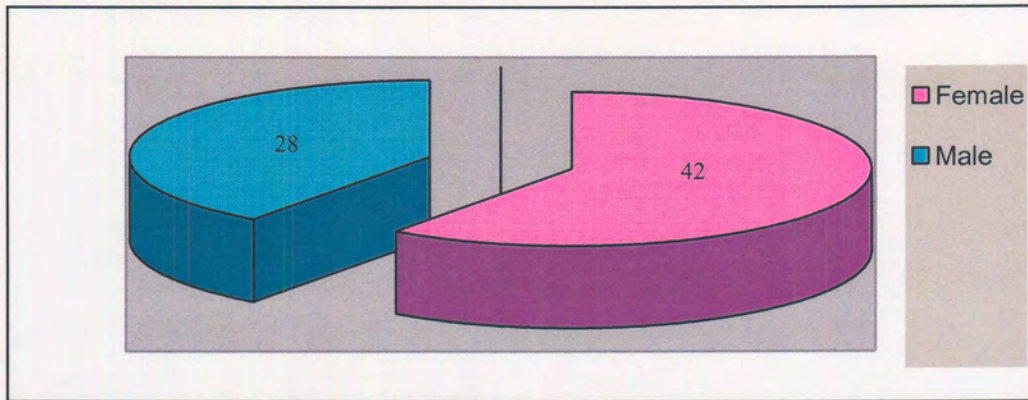


Figure 4.1: Representation of male and female subjects.

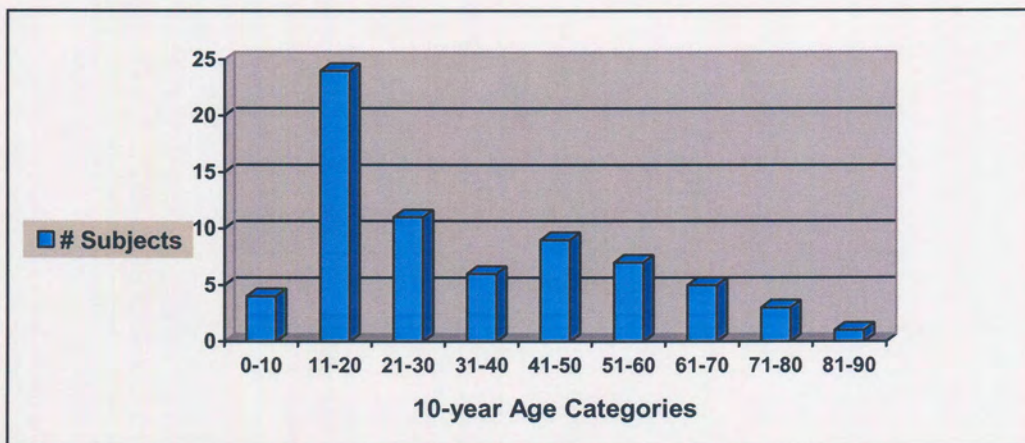


Figure 4.2: Age representation of subjects in 10-year categories.

Table 4.1 indicates the distribution pattern for different types of hearing loss that the 120 ears in the data set exhibited.

Table 4.1: Distribution pattern for different types of hearing loss in the 120 ear data set.

	# Ears Group 1: PTAs 0-15 dB HL	# Ears Group 2: PTAs 16-35 dB HL	# Ears Group 3: PTAs 36- 65dB HL
Flat audiogram: Not more than 20dB variation between 0.5 – 4 kHz.	40	11	16
Gradual slope: PTTs increases gradually as frequency increases	0	9	24
Ski-slope: Flat configuration up to 2 kHz with >20dB PTT drop in high frequencies	0	10	1
Low frequency loss: 0.5 - 1 kHz more impaired than 2 – 4 kHz	2	0	0
Notch: Notch shaped loss around 1 -3 kHz	4	3	0

4.6 Apparatus

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

4.6.1 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.

4.6.2 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.
- 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.

4.6.3 Data Preparation Apparatus

- For the preparation of data files, a 600 MHz Pentium computer was used. The software included Excel for Windows 2000.
- For the training of the neural network, the backpropagation neural network from the software by Rao and Rao, 1995 (software supplied in addition to their book) was used. The neural network was trained on three 600 MHz Pentiums.

4.6.4 Data Analysis Apparatus

- Analysis of data was performed in Excel for Windows 2000.

4.6.5 Preliminary Study

The reason for the preliminary study was twofold: Firstly, to confirm subject selection criteria and secondly, which stimulus parameters to use in the measurements of DPOAEs.

4.6.5.1 Confirmation 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 cases in the preliminary study will be discussed briefly in Table 4.2.

Table 4.2: Confirmation of subject selection criteria in the preliminary study.

Purpose	Result	Outcome
Confirmation of normal middle ear functioning (Type A tympanogram, and compliance of >0.3cc) as subject selection criteria in cases where PTT results fell within selection criteria but with small variations in tympanometric results.	Case one had perfect PTTs (0dB) 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.	Only cases with air tight seals of the probe in the external meatus to allow measurement of a tympanogram were included in the study.
	Case two had a mild sensorineural hearing loss but displayed compliance measurements of less than 0.3cc during tympanometry. DPOAE responses were virtually indistinguishable from the noise floor due to high levels of low and mid frequency noise.	Only cases demonstrating at least 0.3cc in tympanometry were allowed in the study.



Table 4.2 Continues		
Purpose	Result	Outcome
Confirmation of levels for primary tone pairs not to exceed 70 dB SPL.	Some tests 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 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 traveling waves can cause these “passive” emissions that do not correspond well to hearing sensitivity and has poor 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.
Confirmation of subject selection criterion that hearing loss should not exceed 65dB HL.	Another aspect that became apparent after a few tests were conducted was the absence of DPOAEs in persons with hearing losses greater than 65dHL. 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 cannot 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.

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

4.6.5.2 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 (chosen at 1.2), the loudness levels of L1 and L2 ($L2 > L1$ by 10dB) and whether to measure DP Grams or I/O functions (eight DP Grams at eight loudness levels were used to gain the same information that both procedures would yield) were selected on recommendation of other previous studies. The choice for these stimulus parameters is described in 4.7.1.2.1 “Specification of stimulus parameters for DPOAE measurement.”

There are however a few stimulus parameters that require 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. These options will be reviewed in more detail than the section of the preliminary study concerned with confirmation of subject variables in a table format because a thorough understanding of test acceptance conditions is required to clarify later definitions of DPOAE threshold as 1, 2 or 3 dB above the noise floor.

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 is 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 60 minutes to 105 minutes 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 also should frequency values from one tone pair to the next 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 4.3, 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 4.3: Time required testing one subject

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

4.7 Data Collection Procedures

The following procedure was conducted during research.

4.7.1 Data Collection Procedures Conducted during Research

Two sets of data are needed to train a neural network to predict PTTs with DPOAEs: each subject's pure tone thresholds and each subject's DPOAEs.

4.7.1.1 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. Pure Tone Audiogram.

4.7.1.2 Data Obtained from DPOAE Measurements

The second set of data that was collected was each subject's DPOAE responses. There are many stimulus parameters that should be specified to be able to repeat this research project and need to be fully described.

4.7.1.2.1 Specification of Stimulus Parameters for DPOAE Measurements

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 f_1 and f_2 ($f_1 > f_2$), the frequency ratio of f_2/f_1 (how many octaves apart the two frequencies are), the loudness level of f_1 (which is L_1) and the loudness level of f_2 (which is L_2). Furthermore, the difference in loudness level between L_1 and L_2 should also be specified.

4.7.1.2.1.1 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 were 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 3 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 1 or in extreme cases 2 in-between frequencies were evaluated. The selection of 3 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 3 data points per octave is specified amount to 11 frequency pairs. The eleven frequency pairs are presented in Table 4.4.

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

Table 4.4: The eleven 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

4.7.1.2.1.2 The Selection of the Frequency Ratio of the Primary Frequencies (f_2/f_1)

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 $f_2/f_1 = 1.2$ was therefore selected for this study.

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

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 $L_1 = 70$ dB; $L_2 = 60$ 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 $L_1 = 35$ dB; $L_2 = 25$ dB. Eight loudness levels were therefore evaluated resulting in eight DP “audiograms” for each ear.

4.7.1.2.1.4 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 10 dB (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.

4.7.1.2.1.5 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 amplitude less than the noise floor cannot be detected (Kimberley & Nelson, 1990; 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 $2f_1-f_2$ 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, there will be experimented with detection thresholds for DPOAEs as 1 dB, 2 dB or 3dB above the noise floor to investigate if more accurate PTT predictions can be made with lower detection thresholds.

4.7.1.2.2 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, f_1 and f_2 presented to the ear simultaneously. (See Table 4.4 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.

The first DP Gram was conducted on the loudness levels $F_1 = 70\text{dB SPL}$, $F_2 = 60\text{dB SPL}$. The second DP Gram was conducted 5 dB lower at $F_1 = 65\text{ dB SPL}$, $F_2 = 55\text{ dB SPL}$. 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 $F_1 = 35\text{ dB SPL}$, $F_2 = 25\text{ dB SPL}$.

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.

4.8 Data Preparation Procedures

In the data preparation process, there were three interrelated processes that happened in parallel and influenced each other in such a way that it is challenging to describe the process with a logical serial or start-to-finish approach. One of the processes was to determine how input information was to be presented to the neural network and which variables or combinations of variables to experiment with. Another process was to determine optimal neural network error tolerance levels and topology, specifically the number of hidden layer neurons. The last process was the creation of data files that serve as input into the neural network that represent all the chosen variables and combinations thereof.

These three processes were highly interrelated: The combination of variables to use and how to present them determined how the data file looked that served as input information into the ANN. The input, or specifically the number of nodes in the input layer necessary to represent all variables, determined the complexity of the network and therefore the number of hidden layer neurons needed as well as suitable error tolerance levels. Failures in network operation and prediction in its turn influenced how new experiments were constructed to present input data in new ways, to include new variables or new combinations thereof, or to experiment with different numbers of middle level neurons and error tolerance levels, all in an attempt to make more accurate predictions.

The three interrelated processes namely the choice of how input data is presented to the network, the creation of the data file and the determination of network topology and error tolerance and will be discussed one at a time.

4.8.1 Experiments to Determine ANN Prediction Accuracy by Manipulating the Input and Output Data

The data that served as possible input information into the ANN was the presence or absence of DPOAE responses, defined by 1dB, 2dB and 3dB thresholds, the DPOAE amplitude of all present responses, subject gender and subject age.

4.8.1.1 DPOAE Data at High and Low Frequencies

For some experiments, DPOAE occurrence at all eleven frequencies and all eight loudness levels (or DP Grams) were used. For some experiments only DPOAE occurrence at the eight high frequencies for all eight DP Grams were used ($f_1 = 500$, 625 and 781 Hz were omitted). DPOAEs measured at the low frequencies are often noisy or absent and these experiments attempted more accurate predictions by omitting the noisy data to prevent pollution of data.

When DPOAE occurrence at all eleven frequencies were used for all eight DP Grams, at least 88 input nodes were needed in the input layer to present this map of all present and absent responses to the ANN. When only the eight high frequencies (starting at $f_1 = 1000$ Hz to $f_1 = 5031$ Hz) for all eight DP Grams were used, only 64 input nodes were needed to present DPOAE responses to the ANN.

4.8.1.2 Subject Gender

Subject gender was always included and always depicted with a one or a zero. Subject gender therefore always added just one input neuron to the input layer.

4.8.1.3 Subject Age

Subject age was always included in the training and prediction of the ANN but different ways were used to present it to the neural network. Subject age in this study varied from 8 – 82 years old. The dummy variable technique was used to depict a subject's age into either a 10-year category, or a 5-year category.

In the 10-year category method, there were ten possible 10-year categories and the subject's age was depicted with zeros and a single one corresponding to the appropriate category: A 12 year old subject was therefore depicted as 01000 00000. When this method was used to depict subject age, ten extra input nodes were needed for the input layer.

In the 5-year category method, there were 20 possible 5-year categories. A 12 year old subject would therefore be depicted as 01000 00000 00000 00000. This method required 20 extra input nodes for the input layer. This method specified subject age more accurately but also made the neural network more complex due to a larger number of input nodes.

4.8.1.4 DPOAE Amplitude

There were four different amplitude experiment types.

4.8.1.4.1 AMP 100

The first amplitude representation of the DPOAE response was depicted as a fraction of 100 (This experiment is referred to as AMP 100). Instead of depicting the presence or absence of a response with a one or a zero, the magnitude of the response was used. A present DPOAE response of 30 dB's input into the neural network would therefore be 0.3. The same 88 input nodes were used that depicted presence or absence of a response, only now with a value indicating the amplitude of the DPOAE. This method of amplitude representation caused the neural network to spend much more time to converge (to reach the required error tolerance level for every ear in the training set). It took about 2 hours per experiment for the network to converge, which is incredibly long if 120 ears have to be predicted at 4 frequencies. 960 hours (40 days) were needed just to reach the optimal error tolerance level before prediction can begin. Some of the experiments were run with this method of amplitude representation but other more effective ways were needed to present amplitude to the ANN.

4.8.1.4.2 AMP 40

The second amplitude representation of the DPOAE response was depicted as a fraction of the largest DPOAE amplitude measured in this population of subjects in other words a percentage (This experiment is referred to as AMP 40). (The largest DPOAE response ever measured in this population of subjects was 39dB.) This experiment also used the original 88 input nodes that depict DPOAE occurrence but instead of just a zero indicating absence or a one indicating a present response, the magnitude of the response as a fraction of 40 was used. A 30 dB DPOAE was

therefore depicted as 0.75. For AMP 40 convergence was much faster, only about 40 minutes per experiment.

4.8.1.4.3 ALT AMP

The third amplitude representation of the DPOAE response was depicted with the dummy variable technique by indicating into which one of four 10 dB categories the amplitude fell (This experiment is referred to as **ALT AMP**). A 30 dB DPOAE was depicted as 0010. For this experiment, every one of the 88 input nodes had to receive four categories to indicate the category in which the amplitude fell. This increased the number of nodes in the input layer needed to represent this information with four times. An experiment involving all 11 frequencies for all eight DP Grams therefore needed 352 input nodes, instead of the usual 88. This drastic increase in input neurons contributed to a much more complex neural network that required more middle level neurons. For this experiment, the middle layer neurons were always doubled to compensate for the large quantity of input data.

4.8.1.4.4 No AMP

The last amplitude experiment was when the amplitude of the DPOAE was omitted (This experiment is referred to as **No AMP**). The usual 88 input nodes were used and a DPOAE response was indicated as present with a one and absent with a zero. The presence of a DPOAE response is defined as a certain dB level above the noise floor. This brings us to the next experiment type, regarding the threshold of a DPOAE.

4.8.1.5 DPOAE Threshold

Harris and Probst (1991) and Krishnamurti (2000) defined DPOAE threshold as DPOAE response ≥ 5 dB above the noise floor, According to Lonsbury-Martin & Martin (1990) the DPOAE should be 3 dB above the noise floor to be regarded as present.

For this research project, it was decided to use different thresholds for DPOAE responses namely 1dB, 2dB and 3dB above the noise floor. This threshold reduction had more present DPOAE responses as a result. If the 1dB and 2dB thresholds yield more valid DPOAE responses, the network will be able to make more accurate predictions. If the extra responses gained are not valid but just part of the noise floor, prediction accuracy will not be increased but may be decreased.

4.8.1.6 Number of Ears or Data in Every Output Category to be Predicted

From the previous study (De Waal, 1998) it became apparent that the number of ears in every category to be depicted had a great influence on prediction accuracy of the neural network. The reason for this is that the network needs adequate representation in every category to learn the correlation between DPOAEs and PTTs to make an accurate prediction. In some instances in the previous study, certain categories had very little hearing-impaired data such as 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 influenced the accuracy of the prediction. To test the significance of the number of ears in every category, it was decided in the previous study to enlarge the categories depicting hearing impairment to 15 dB, in order to attempt to include more hearing-impaired data in every category. It was referred to as **scenario five**, and 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 4.5.

Table 4.5 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 significance of the number of ears in every category was also tested for this research project. The best experiments for each frequency were selected after the completion of ANN training and prediction and were run in this scenario five method, by enlarging the categories depicting hearing loss to 15 dB for the output of the neural network. The input data, number of middle level neurons, error tolerance, dB threshold above the noise floor and presentation of the age and amplitude variables to the network were kept exactly the same, only in this scenario, the output of the

network was changed to predicted hearing loss into three possible 15 dB categories in stead of the usual seven. It will also be referred to as scenario five method in the present study.

Lastly, one aspect that was experimented with was the amount of data or number of pure tone thresholds in the input data of every category.

4.8.1.7 Number of PTTs in every Input Category for ANN Training

Pure tone thresholds are routinely evaluated in 5 dB increments (Hall III & Mueller III, 1997), as was also the case in this study. The possibilities for pure tone threshold values are therefore always rounded up to an increment of 5 dB. In the previous study (De Waal, 1998), all the first categories of all experiments spanned 0 – 10 dB. This implied that pure tone threshold values of 0 dB, 5 dB and 10 dB were included in this category, a total of three possible measurements from the audiogram. All second categories in the previous study always spanned 11-20dB, but since thresholds are only evaluated in 5 dB increments, the possible values to be included in the second category only consisted of measurements obtained at 15dB and 20dB, therefore only two possible measurements from the audiogram. This lead to an uneven distribution of the number of measurements in every category that possibly lead to poorer predictions of categories with less input information for the ANN to train on.

For this study, it was decided to have an equal number of possible thresholds in every category to ensure optimal distribution of input data across all categories for the network to train on. Two possible threshold values from the audiogram were allowed into every category. Category one therefore consisted of data from ears that exhibited

threshold values at 0 dB and 5 dB, category two consisted of PTT values of 10 dB and 15 dB and so forth. The PTT data distribution for each category can be seen in Table 4.6.

Table 4.6: PTT data distribution for every input category

	PTT data permitted into each category (dB HL)	
Category 1	0 dB	5 dB
Category 2	10 dB	15 dB
Category 3	20 dB	25 dB
Category 4	30 dB	35 dB
Category 5	40 dB	45 dB
Category 6	50 dB	55 dB
Category 7	60 dB	65 dB
Category 8	70 dB	75 dB

For the previous study, the first two categories were evaluated to investigate prediction accuracy when it comes to the separation of normal hearing and hearing impaired ears. Normal hearing was defined as 0 – 20 dB, according to the definition of normal hearing by Jerger, (1980). For the present study, the first three categories were investigated to determine how accurately the network could separate normal from hearing impaired ears (normal = 0 – 25 dB HL) according to the definition of Goodman (1965), which is also the recommendation of the American Academy of

Otolaryngology and the American Council of Otolaryngology (AAO-ACO) in 1979 for normal hearing.

A few experiments were run with the same PTT distribution as the previous study (De Waal, 1998) of three values in the first category and two in every category thereafter for two reasons: The first reason was to be able to make valid comparisons between the previous and present study. To make accurate comparisons between category one of the previous study and category one of the present study, the PTT distribution for ANN training have to be the same. The second reason was to accommodate Jerger (1980)'s definition of normal hearing, which is 0 – 20 dB HL and spanning the first two categories of this procedure.

Another process in the data preparation involved transcribing raw data into data files suitable for ANN input.

4.8.2 Creation of a Data File for each Ear at each Frequency

The way in which the raw data was transcribed into files was constructed in such a way that each ear had its own file for every frequency. Each ear therefore had four files depicting information at 500, 1000, 2000 and 4000 Hz. A file is merely a row of numbers, depicting the test results in a certain order. Table 4.7 represents a raw data set for one DP Gram. 8 DP Grams for each ear were conducted. The complete raw data set 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 Table 4.7.

Table 4.7: Example of a raw data set 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 4.7:

- 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 program that wrote the raw data into files was named CSV 2 EXP (Comma separated values to experiments) and the C++ code for this program can be seen on the accompanied CD. The newly created data files looked different for every experiment, depending on which variables were chosen for that specific experiment and the way the input data was presented to the neural network. If, for example, all frequencies were used for an experiment and age was presented to the network in 5 year categories, that data file would look different from a data file where only the high frequencies were used or if age was presented to the network in 10 year categories.

Table 4.8 is an example of a fraction of a newly created data file for a “No AMP” experiment where all 11 frequencies were used as input data, threshold was defined as 3 dB above the noise floor, gender was included and age was depicted in 10 year categories to attempt to predict the PTT frequency 500 Hz.

After the data manipulation and creation of data files it became clear what the requirement for neural network topology is.

4.8.3 Experiments to Determine Neural Network Topology and Error Tolerance Levels

For this project a three-layer backpropagation neural network was chosen. One input layer presented all data to the network, one output layer gave the prediction of pure tone threshold at a given frequency and one hidden layer with a set of weights on each side of it connected the input and output layers. According to Hornik et al. (1989), one hidden layer is enough provided that there are enough middle level neurons for the complexity of the problem.

Many of the ideas on requirements for network topology and data manipulation techniques came from trial runs that were done in the previous study (De Waal, 1998). A short overview of the previous study's trial runs will be given to promote understanding of current topology and the history of methods tried and how it influenced the current way of thinking.

4.8.3.1 History of Trial Runs Done in the Previous Study (De Waal, 1998)

At first, a very simple approach was tried: The neural network had 11 input nodes, representing the L1 dB SPL value where the DPOAE threshold was measured. The neural network had to predict hearing ability at 500, 1000, 2000 and 4000 Hz in dB SPL and had 4 output neurons. The number of middle level neurons was 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. The reason was lots of missing data due to absent responses: 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”. 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.

As a second approach, the input data was manipulated to present absent and present responses in a different way. 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 this approach 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 were 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 its pressure value (watt/m^2), and then subtracted.)

It was during this approach that the 88 input nodes, all zeros and ones, depicting DPOAE presence or absence for all eight DP Grams and 11 frequencies were formulated. 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 and no information regarding the amplitudes of DPOAEs were available. For the present study, DPOAE amplitude was reintroduced as described in 4.8.1.4 “DPOAE amplitude.”

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.

The way in which the output data was presented was also changed from dB SPL output at a given frequency to the binary dummy variable technique where PTTs were predicted into one of seven 10dB categories.

The effects of in the inclusion of gender and age variables were determined. Age was presented in the dummy variable technique into one of nine 10-year categories, gender with a one or a zero. The network had 98 input nodes, 140 middle level neurons and seven output neurons for prediction into one of seven 10dB categories.

Prediction error during training was set at 5%. Age had a very positive effect on prediction accuracy. Gender had very little effect. The neural network run that included both variables at the same time had the best prediction accuracy. It was therefore decided to include both these variables in the present study for every neural network run.

A very important aspect to keep in mind is that for the previous study, the network was trained with the data of 119 ears to predict the one remaining ear. This process was repeated 120 times to predict every ear once. This means that a subject's one ear was included in the training set while the other ear was predicted. It is quite possible that a subject's PTTs for both ears might be related, for example in the case of noise exposure, the two ears might look very similar. For this research project, both ears of a subject were removed out of the training set. The network was trained with 118 ears and predicted the remaining two ears one at a time. The following section discusses network topology for the present study.

4.8.3.2 The Number of Nodes in the Input Layer

As described in the input data manipulation section, the number of input data sets determines the number of nodes that are needed in a neural network's input layer. The number of input neurons needed for each experiment was determined by the variables that served as input data as well as the way in which they were represented. Table 4.9 is a summary of how to determine how many input nodes were needed for each type of experiment. The base input of nodes is when low frequency DPOAEs were omitted. The other columns serve as an indication of how many input nodes have to be added for that situation or experiment.

Table 4.9: Determination of the number of input nodes

	Base input # of nodes	Low Hz Included	Age 5 year categories	Age 10year categories	Gender
No AMP	64	+24	+20	+10	+1
AMP 100	64	+24	+20	+10	+1
AMP 40	64	+24	+20	+10	+1
ALT AMP	256	+96	+20	+10	+1

Example: When a AMP 40 experiment is run where the low frequencies are included and age was depicted in 5 year categories, the total number of input nodes needed for that experiment is 64 (base number) + 24 (low frequencies included) + 20 (age) + 1 (gender) = 109 input nodes.

4.8.3.3 The Number 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.

A network predicted the pure tone threshold (PTT) for just one frequency at a time. The PTT was predicted into one of eight possible 10 dB categories. There were therefore eight output neurons, each with a value between zero and one, indicating the likelihood of the PTT to be in that specific category. The category with the highest value was chosen to predict a PTT for a certain frequency.

4.8.3.4 The Number of Neurons in the Hidden or Middle 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 subtract 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.

Experiments for AMP 100, AMP 40 and No AMP were run with 80, 100 and 120 middle neurons. Prediction accuracy was studied to determine if an increase in middle level neurons had more accurate PTT predictions as a result. In the case of the ALT AMP experiment where the amplitude of the DPOAE was presented with the dummy variable technique, the number of input nodes increased so much that 80, 100 or 120 middle level neurons were not enough. For the ALT AMP experiments, the number of middle level neurons was doubled to compensate for network complexity due to the large number of input nodes. ALT AMP was therefore run with 160, 200, and 240 middle level neurons.

4.8.3.5 Error Tolerance Levels

As was described in 3.5.4.2 “Error tolerance”, the error tolerance refers to how accurate the network learns and predicts. This value determines if the weights will be

changed to lengthen the training process or if the weights will be frozen to start with the prediction phase. The lower (closer to zero) the error tolerance level, the more accurate the learning and prediction but also the longer the training phase. Another aspect that is influenced by error tolerance levels is the networks' ability to generalize. For error tolerance set close to zero, the network might have difficulty predicting a PTT for a DPOAE set that is slightly out of the ordinary. Higher error tolerance levels might have slightly less accurate predictions but training is faster and generalization is better.

For this study, all experiments were run with error tolerance levels of 0.001 (within 0.1% accurate), 0.002 (0.2%) and 0.003 (within 0.3% accurate). The effect of the difference in prediction accuracy for the various error tolerance levels will be discussed in the chapter interpreting results.

Now that network topology, error tolerance and representation of input data in files are finalized, the network is ready to start the training and prediction processes.

4.8.3.6 The Training and Prediction Phase

The possibilities for experiment configuration were:

- Threshold of DPOAEs specified as 1, 2 or 3 dB above the noise floor.
- Age depicted as 10-year or 5-year increments.
- Amplitude depicted as ALT AMP, AMP 100, AMP 40 or No AMP.
- Middle level neurons as 80, 100 or 120 for AMP 100, AMP 40 and No AMP.
- Middle level neurons as 160, 200 or 240 for ALT AMP.

- Error tolerance levels as 0.1%, 0.2% or 0.3%.
- Low frequency DPOAE responses present or absent during training.

If all combinations of variables were run, the number of possible experiments would be 1728 possible combinations. All 1728 were run to determine the optimal set of DPOAE and ANN parameters for the prediction of PTTs. An additional 24 experiments were run: 12 in the “scenario five method” described in 4.8.1.6 “Number of ears or data in every output category to be predicted” to investigate the effect that the number of ears in each category has on prediction accuracy of PTTs. The other 12 were run with the same PTT input distribution as the previous study (De Waal, 1998) described in 4.8.1.7 “Number of PTTs in every input category for ANN training” to make comparisons between the two studies possible. That brings the total number of experiments to 1752. Each experiment took 80 minutes to run. 94 days were needed for neural network training and prediction. This process was done in parallel on three 600 MHz Pentiums. A third of the experiments were run on each computer to save time. It therefore took four and a half weeks for training and prediction of the four pure tone threshold frequencies.

The C++ program that fetched every data file and presented it to the neural network for training was called EXP 2 RES: (experiments to results) and the C++ code for this program can be viewed on the accompanied CD.

For the training of the neural network, both ears of a subject were left out to prevent contamination of data due to the inclusion of a related ear. The three-layered

backpropagation neural network by Rao and Rao (1995) was used (software was supplied in addition to their book).

4.9 Data Analysis Procedures

At the end of the four and a half weeks, the output data consisted of 1752 predictions of a pure tone threshold at a certain frequency depicted as different values in all of the eight possible 10-dB categories. The 10 dB categories were presented in Table 4.6. An example of the raw output file of the network's predictions is presented in Table 4.10.

In order to determine which category the PTT was predicted, the category with the highest value were chosen. The program that performed this task was called RES 2 ANA (results to analysis) and the C++ code for this program can be viewed on the accompanied CD.

The second function of RES 2 ANA was to determine how many predictions were accurate (within the same 10 dB category), how many were one 10 dB category out and how many predictions were wrong (more than one 10 dB category out). These calculations were made for each of the 10 dB categories as well as for the overall prediction ability of the network across all categories for that specific frequency. False positive and false negative predictions were calculated for each category. Another calculation made by RES 2 ANA was to determine how accurately normal hearing (0 – 25 dB) was predicted as normal, and also how accurately very good hearing (spanning 0 – 15 dB) was predicted as normal (within 0 – 25 dB). An example of how the data looked after this step can be seen in Table 4.11. The reason why category eight has no information is because maximum hearing loss at 500 Hz was 65 dB HL and falls in category seven. Category eight was created for 4000 Hz: Nine ears exhibited a PTT of larger than 65dB HL at 4000 Hz. There were therefore no data in category eight at 500, 1000 and 2000 Hz.

The last function of RES 2 ANA was to create a file that was compatible with Microsoft Excel 2000's spreadsheet to be able to use Excel to manipulate data and make visual representations of results.

Table 4.11: RES 2 ANA experiment result representation.

Experiment 62308								
AI = 10, LF, Mid = 200, Err = 0.002, Th = 1 dB, Hz = 500, ALT AMP**								
category	Correct prediction		One category out		Wrong prediction		False positive	False negative
C1	35/42	83.3%	4/42	9.5%	3/42	7.1%	2%	0%
C2	8/31	25.8%	17/31	54.8%	5/31	16.1%	8%	0%
C3	1/16	6.3%	10/16	62.5%	5/16	31.3%	0%	9%
C4	2/12	16.7%	2/12	16.7%	8/12	66.7%	0%	5%
C5	0/9	0%	1/9	11.1%	8/9	88.9%	0%	4%
C6	0/7	0%	0/7	0%	7/7	100%	0%	1%
C7	0/3	0%	0/3	0%	3/3	100%	0%	1%
C8	0/0	0%	0/0	0%	0/0	0%	0%	0%
Overall correct prediction for all categories					46/120	38%		
Overall one category out for all categories					34/120	28%		
Overall wrong predictions					40/120	33%		
0 – 10 dB predicted as normal (0 – 20 dB)					39/42	92%		
0 – 20 dB predicted as normal (0 - 20 dB)					60/73	82%		

****Key for Table 4.11:**

AI = Age increment represented as 10 or 5 year categories
 LF = Low frequencies present, No LF = Low frequencies absent
 Mid = number of middle level neurons
 Err = Error tolerance level
 Th = Threshold specified as 1, 2 or 3 dB above noise floor
 Hz = Frequency to be predicted
 ALT AMP = method of amplitude presentation

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 10 dB class and how many were predicted incorrectly. Data was further manipulated in Excel for Windows 2000 to create visual representations.

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 reveal 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.