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NEURAL NETWORK ANALYSIS OF SEISMIC INTENSITY FROM INSTRUMENTAL RECORDS

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SUMMARY

Seismic intensity provides useful information on the distribution of earthquake effects. The concept of felt intensity has been used for a long time and is considered a method to classify the severity of the ground motion at a given location on the basis of effects observed either during the earthquake or afterwards. The Modified Mercalli Intensity (MMI) scale is the most common felt intensity scale in use and is used to indicate seismic hazard and level of damage.

With the more widespread use of strong motion recorders, it has become possible to obtain engineering parameters such as peak ground acceleration, velocity and displacement, spectral values and other measures of instrumental intensity. Many studies have compared these parameters, obtained from strong motion records, to the seismic felt intensity measured by damage, but found the correlation is usually poor and the relationships are highly nonlinear.

Artificial neural network (ANN) based methodology is not new, but has not been extensively applied to engineering seismology problems. This technique essentially uses large quantities of data to train a model which can then be used to explore the relationship. The ANN models allow complex and nonlinear behaviour to be tracked. In this paper, strong motion records from New Zealand have been analyzed using ANN methods to seek out the parameters, derived from strong motion records, which are important for an understanding of seismic felt intensity as measured by observed effects and damage.

INTRODUCTION

Seismic intensity is a qualitative or quantitative measure of the severity of ground motion at a specific site during an earthquake event. Over the years, various subjective scales of what is often called *felt intensity* have been devised. These scales assess the felt effects by observers present during the shaking, or the evidence, usually damage, which can be observed after the event. Such intensity scales are classifications of the strength of shaking and are essentially qualitative. This felt seismic intensity is one of the least-satisfactorily explained components of seismic hazard because, unlike a quantity such as peak acceleration, it cannot be directly measured, but must be estimated based on the observation of damage

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from the effects of shaking. It does, however, have the very great advantage of being defined in terms of, and therefore directly linked to, damage.

More qualitative, physically based, information has become available with the advent of strong motion recording instruments. The use of the recorded time history of the shaking should potentially provide a more objective measure of seismic intensity and numerous researchers have attempted to estimate the seismic felt intensity from strong motion records. Some of the simple methods which are reported try to fit a linear relationship between the variables, but the process of assessing seismic felt intensity from damage is highly non-linear in nature. Many researchers have emphasized the need for accurate estimates of intensity in risk or loss modelling studies. This requirement could be addressed through better models which address the inherent non-linearity in the process. Further, there is a requirement for methods which consider only a few variables, since estimates are often needed where limited data only is available.

Recently, there has been a growing interest in the modelling of non-linear relationships, and a variety of test procedures for detecting the non-linearities have been developed. If the aim of analysis is prediction, however, it is not sufficient to uncover the non-linearities. One needs to describe them through an adequate non-linear model. Unfortunately, for many applications, theory does not guide the model-building by suggesting the relevant input variables or the correct functional form. This particular difficulty makes it attractive to consider a flexible class of statistical models. The emergence of neural network technology provides many promising results owing to their inherently high parallelism. This provides an impetus to examine the neural network approach for better mapping of felt intensity from instrumental strong motion records.

Artificial neural networks (ANNs) are essentially semi-parametric regression estimators and are well suited for this purpose, as they can approximate virtually any measurable function up to an arbitrary degree of accuracy (Hornik et al. 1989). A significant advantage of the ANN approach in system modelling is that one does not need to have a well-defined process for algorithmically converting an input to an output. Rather, all that is needed for most networks is a collection of representative examples of the desired mapping. The ANN then adapts itself to reproduce the desired output when presented with training sample input.

This study investigates the relationship between parameters derived from the strong motion records obtained in New Zealand and the felt intensity information. The major objective was to evaluate the potential of ANNs for estimating seismic felt intensity from parameters derived from strong motion records. The motivation for this is to determine if there is some function of the parameter derived from the strong motion records which could be used as an analogue of seismic felt intensity. In previous studies of United States and Japanese data there has been strong interest in the peak acceleration. The focus here is also on this parameter derived from New Zealand strong motion records.

SEISMIC INTENSITY MEASURES

The use of subjective scales of felt intensity is historically important because no instrumentation is necessary, and useful measurements of an earthquake can be made by an unequipped observer. They were introduced as an attempt to empirically quantify the intensity or severity of ground shaking in a given location by the observed effects. The most significant scales are the ten degree Rossi-Forel (Rossi, 1883); the Mercalli-Cancani-Sieberg, also known as MCS (Sieberg, 1923); the twelve degree Modified Mercalli, 1931 and 1956 versions (Wood & Neumann, 1931; Richter, 1958); and the eight degree Japan Meteorological Agency, JMA (Kawasumi, 1951) amongst others. The more recent scales have generally been the result of evolution of the older ones. A review of the early history of seismic intensity scales is given by Davison (1900, 1921, 1933).

The most widely used seismic felt intensity scale in the English speaking world is the Modified Mercalli intensity scale (commonly denoted as MM or MMI), which has twelve degrees or grades. A detailed description of a revision of this scale applicable to New Zealand conditions is given by Dowrick (1996).

The fact that the felt intensity scales are based on a classification rather than a physical parameter leads to some special conditions of their use. Every degree in a scale is a description of the effects of ground motion on the natural or the built environment. These effects are usually adverse and therefore they are associated with damage. Due to the physical nature of ground shaking, damage and thus intensity, ranges through a continuum of possible values from nothing to the maximum. Nevertheless, by using descriptions of typical observed effects at each level, discrete classes of felt intensity are assigned and are represented by an integer quantity.

Traditionally, Roman numerals have been used to represent felt intensity values to emphasise this point. Now the use of Roman numerals is largely a matter of taste, and most seismologists find Arabic numerals easier to write (e.g. 8 rather than "VIII") and process by computer.

Unfortunately this trend overlooks the fact that while the felt intensity scale grades are a set of ordered categories or classifications, they are certainly not numerical values. It is becoming a problem in that it is increasingly common to see them used as such. The concept of a "difference measure" between two categories just does not exist. While we can say that MM V is a higher intensity than MM IV, we cannot say by how much. Also the steps between levels may differ. For example, it cannot be ascertained that the change in intensity from MM IV to MM V is the same as from MM VII to MM VIII. These aspects lead to non-linearities in relating felt intensity to other qualitative measures.

A considerable amount of skill is required of the observer to assign felt intensity values at a location. With wide variation of earthquake effects over short distances due to local conditions, the complexity of ground motion, the variation in response of structures and uncertainty of the condition of the buildings before the earthquake, discriminating one scale grade from the adjacent ones can be difficult, particularly when only limited information is available. Changes to the building code and construction practices over the years have generally improved the earthquake resistance of the building stock and may have shifted the Modified Mercalli intensity scale.

A common way to present seismic felt intensity is by means of maps for specific earthquake events. As well as plotting intensity points, it is usually useful to draw contour lines of equal felt intensity, called isoseismals. This is a line bounding the area within which the intensity is predominately equal to, or greater than, a given value. The process of drawing the isoseismal requires some smoothing and extrapolation and so is to some degree, subjective.

REVIEW OF INSTRUMENTAL SEISMIC INTENSITY

Several parameters have been proposed by different researchers to represent earthquake shaking in an engineering sense, for design purposes, or to measure the potential for damage. These parameters are obtained with information extracted from a time series record, e.g. an accelerogram. Time series records are characterized by amplitude, duration and frequency. Many other parameters can be deduced from records. The frequency content of the record is often visualized by using the response of simplified models of structural behavior like single-degree-of-freedom systems, SDOF, as a filter. Fourier techniques are also employed to picture the frequency contents of seismic signals. Characterization of ground motion has the advantage that parameters are easier to predict than whole time series records. However, the wide number of available parameters reflects the complexity of this task. Amongst the best known parameters are the peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD), and response spectra for acceleration, velocity and displacement.

Other parameters which have been proposed include a spectrum intensity by Housner (1952), an engineering intensity scale by Blume (1970), a measure of earthquake intensity by Arias (1970) and the JMA instrumental seismic intensity scale (JMA, 1996; Davenport 2001).

While the parameters mentioned above are directly determined from the strong motion record, other relevant parameters could be those associated with the recording site such as geotechnical data or those associated with the event source such as the distance, orientation, magnitude, depth and mechanism.

There is no doubt that the parameter most used for characterizing strong motion is peak ground horizontal acceleration. This value is read directly from the accelerogram as its maximum absolute ordinate. The largest value of the two horizontal components of a three component recording is generally selected, although sometimes the average of the two values is used. This parameter is associated with the process of sudden rupture of the fault.

STRONG MOTION RECORDS IN NEW ZEALAND

The New Zealand strong motion network has been operated by GNS over the period from the mid 1960s to the present. The early instruments were "scratch plate" devices which gave a trace of the motion from which only the peak acceleration values could be determined. Later instruments were film based with timing marks so the trace on the film could be digitized to an acceleration time history. More recent devices are electronic digital instruments which give better quality records directly in a digital format.

The raw records, as collected from a variety of different instruments, need to be subsequently processed to a standard digital format including the addition of a header containing summary information. Some of the film records collected from the early devices were of poor quality and so were not fully digitized but peak values were determined. Also, any records which are very small are only fully processed if required for a specific purpose. The most significant records collected over the period April 1966 to February 1998 have been placed onto a digital Compact Disk (CD-ROM) by Cousins (1998). There are 609 strong motion records in this collection. Since then, with more and better instruments available, more records have been collected and processed, with over 5000 digitized records available at present.

Some of the strong motion recorders are located for special studies such as on upper levels of buildings, on dams or at sites where topography is important. A record from such a site is not representative of the general ground motion in the area. In this study, only records from free field, building basement and building ground floor sites are used. Details of the strong motion instrument sites were presented by Cousins et al (1996).

Many of the earthquake events for which there are strong motion records were small or in remote areas and little felt intensity information is available to allow an isoseismal map to be constructed. Where sufficient felt intensity data is available for New Zealand earthquakes, isoseismal maps were presented by Downes (1995). There are 32 earthquake events for which an isoseismal map is available and there are suitable digitized strong motion records. The maps show the isoseismal contours which are the boundaries between one MMI class and the next. The MMI value for the site of a strong motion recording was determined by linear interpolation to one tenth the interval between the isoseismal lines on the map. There are 237 records available with an MMI value and an acceleration time history.

CORRELATION OF STRONG MOTION PARAMETERS AND FELT INTENSITY

Numerous researchers have attempted to estimate the seismic felt intensity from strong motion records. Cancani's early felt intensity scale amounted to little more than a table of intensity values and an equivalent PGA value. Such tables are often encountered in the literature.

The correlations obtained by Trifunac and Brady (1975), Murphy and O'Brien (1977), and McCann et al. (1980) are the most important historically but there are many other authors who have contributed to this subject. A recent study of Californian data by Wald et al. (1999) uses MM felt intensity and one of Northridge data by Boatwright et al. (2001) uses a different measure of intensity based on tagging data. MMI data from three Californian earthquakes was presented by Shabestari & Yamazaki (2001). In general these studies demonstrated that felt intensity and peak ground acceleration correlate very poorly and with a large scatter. There are a number of reasons for this and a significant one may be that as the peak value represents a single spike in the accelerogram record, this may not be representative of the ground motion as a whole. Indeed, where very high peak values have been recorded they have not been accompanied by either remarkably high felt intensity values or damage.

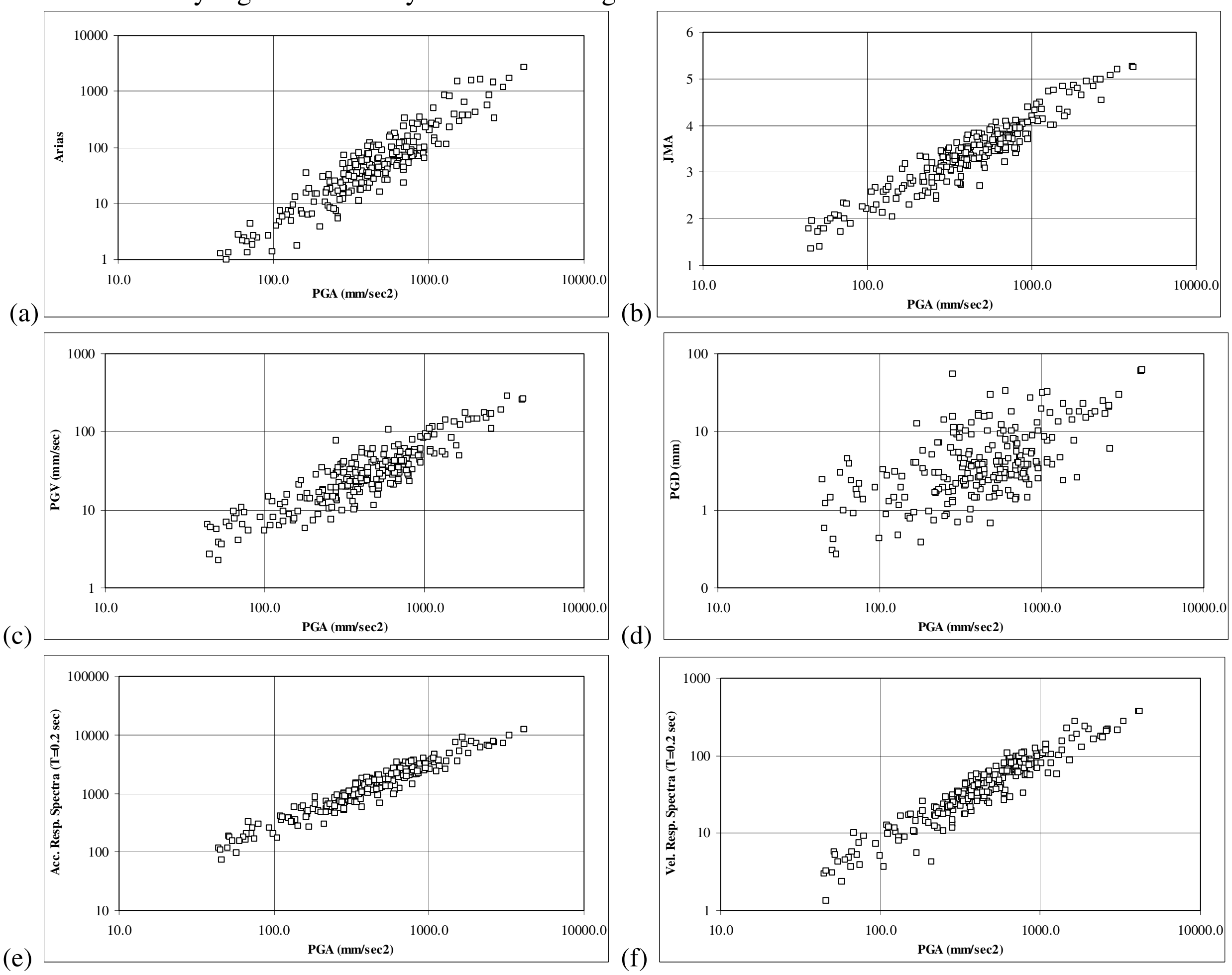


Figure 1: Comparison of several parameters from New Zealand strong motion records to PGA. (a) Arias intensity, (b) JMA intensity, (c) PGV, (d) PGD, (e) Acceleration response spectra for 0.2 second period, (f) Velocity response spectra for 0.2 second period.

All the New Zealand strong motion records were processed to obtain the parameters of interest. These include the PGA, PGV and PGD and spectral response for several periods, for each of the three components. The Arias intensity and the JMA intensity were also computed. Figure 1 shows a plot of several parameter values against the PGA value for a subset of the records.

As will be seen, the correlation of most of these measures is strong. This is consistent with a study of Japanese data by Karim and Yamazaki (2002). This result is not surprising since the different parameters are all derived from the same strong motion time history record.

Not all of the recorded strong motion records were of sufficient strength or at locations that they were felt by people. Where such felt information is available for locations near where a strong motion record was obtained, the MMI value has been associated with that record. This is only sensible for free field recording sites and not for records obtained from sites on upper levels of multi storey buildings or crests of dams and the like. Figure 2 shows a plot of the MMI values against the PGA value for this subset of the records.

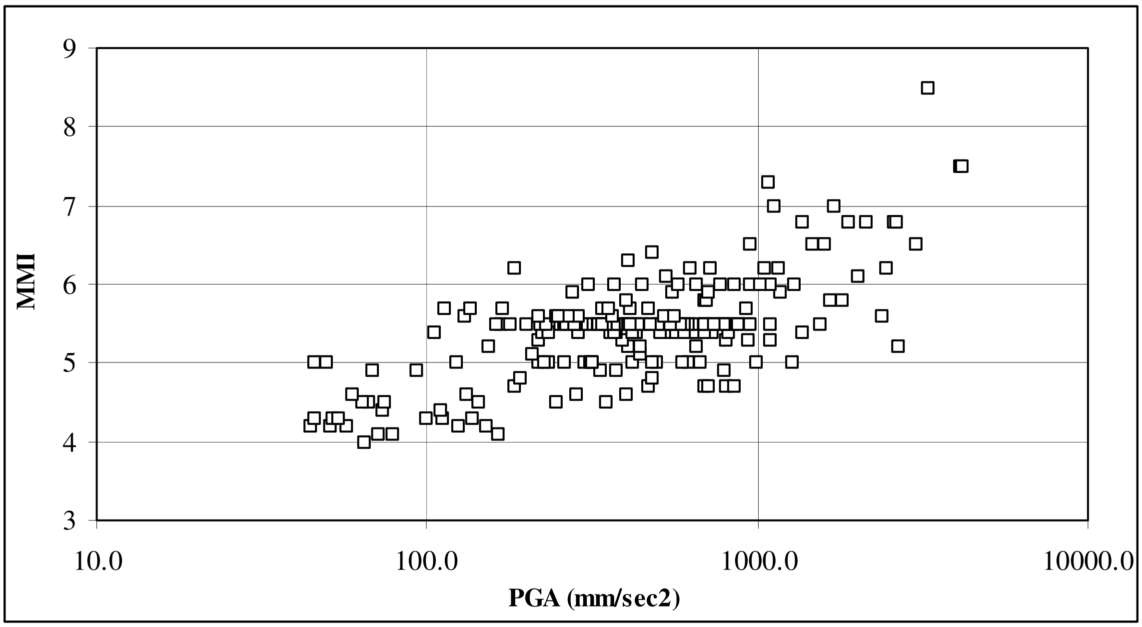


Figure 2: Comparison of site MMI to the PGA from New Zealand strong motion records.

In contrast to parameters derived from the strong motion records, MMI is an independent quantity determined from other information, specifically felt effects and damage reports. The correlation between these two approaches to describing intensity is inherently weak, because of the high variability and non-linearities of both subjective and instrumental parameters.

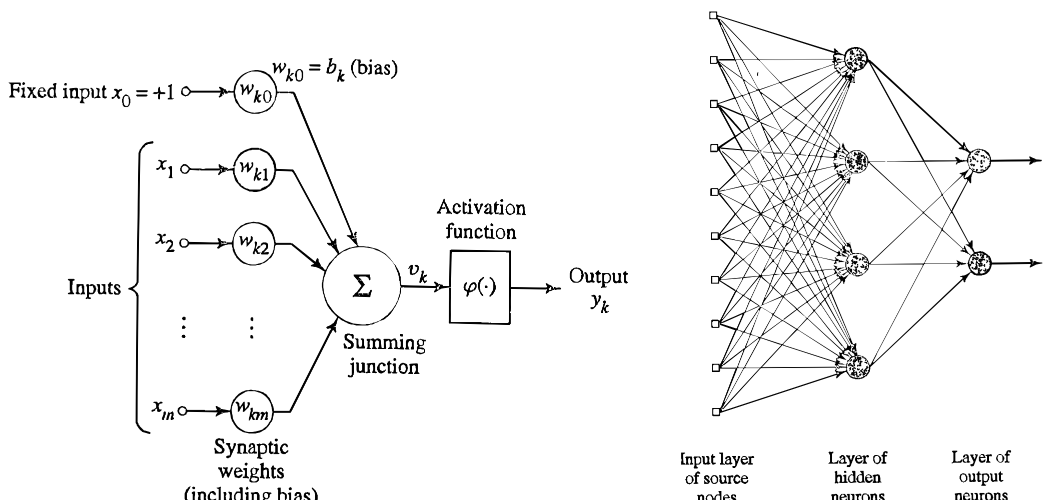
NEURAL NETWORK METHODS

Researchers have found the potential of artificial neural networks (ANNs) in the modelling of various physical systems. Neural networks attempt to reproduce some of the flexibility and power of the human brain by artificial means. A neural network is a parallel distributed processor which has a natural propensity for storing experiential knowledge (Haykin 1999).

The common features of some of these successful applications of ANNs in prediction and modelling are that the quantities being modelled are governed by multivariate interrelationships and the data available are “noisy” or incomplete. Neural networks are capable of handling system nonlinearity. Moreover, when neural network models are developed, there is no need to assume any functional relationship amongst the various variables unlike in regression analysis. ANNs automatically adapt, and construct the relationship, based on the data used for training.

ANN models have been widely applied in various fields of science and technology involving time series forecasting, pattern recognition and process control. For this reason, ANNs should be of interest to engineers and scientists as a tool to support their task related to the modelling and prediction of behavior of engineering and natural systems (Flood & Kartam 1994).

An ANN can be characterized as massively parallel interconnections of simple neurons which function as a collective system. The network topology consists of a set of nodes, or neurons, (Figure 3a) connected by links and usually organized in a number of layers (Figure 3b). Each node in a layer receives and processes weighted input from a previous layer and transmits its output to nodes in the following layer through the links. Each connecting link is characterized by a "weight", which is a numerical estimate of the connection strength. The weighted summation of inputs to a node is converted to an output according to a transfer function.



(a) (b)

Figure 3: Neural network components and architecture. (a) Basic non-linear model of a neuron, (b) Fully connected feed-forward network with one hidden layer.

In mathematical terms, a neuron may be described by the following equations.

$$v_k = \sum_{j=0}^{m} w_{jk} x_j \tag{1}$$

$$y_k = \varphi(v_k) \tag{2}$$

where x_j is the input value, w_{jk} is the weight of the connecting link, v_k is the intermediate output of the summation process, $\varphi(.)$ is the activation or transfer function and y_k is the output value.

The transfer function selected for the network introduces the non-linear behavior and a common choice is the sigmoid function, which is defined for any variable s as:

$$\varphi(s) = \frac{1}{1+\exp(-s)} \tag{3}$$

The S-shaped sigmoid curve is relatively flat at both ends, and has a rapid rise in the middle. It acts as a threshold between high and low values of input, whilst limiting the output value. The hyperbolic tangent function and the identity function are also used as transfer functions.

Most ANNs have three or more layers: an input layer, which is used to present data to the network; an output layer, which is used to produce an appropriate response to the given input; and one or more intermediate or hidden layers, which are used to act as a collection of feature detectors. However, many issues related to the network architecture are still not well understood. Determination of an appropriate network architecture is one of the most important, but also one of the most difficult, tasks in the modelling.

The connection weights of the network learn through a process called training in which large numbers of input-output pattern pairs are presented to the network. The training phase of ANNs is implemented by using a learning algorithm such as the popular and effective backpropagation network (BPN) algorithm and its variants. This is a supervised learning technique and the training phase of the algorithm consists of two passes. The forward pass computes the network output for a given set of connection weights and input data. The backward pass computes the error of the network with respect to the target output and this error is passed backward to the network and is used to modify the connection weights.

The goal of the training process is to present a sufficient number of unique input-output pattern pairs, which when coupled with a suitable method for weight correction, produces a final set of weights which minimizes the error. The value of the mean square error (MSE) is used as the index to check the ability of a particular architecture. The MSE is defined as

$$MSE = \frac{1}{P}\sum_{i=1}^{P}(y_i^d - y_i^o)^2 \qquad (4)$$

in which y^d is the desired response, y^o is the output response from the ANN, and P is the number of patterns presented.

If the network “learns”, the error will approach a minimum value. In addition to the error criteria, it is usual to set a maximum number of cycles to provide a condition for terminating. After the training phase, the ANN, using the final values of the weights, can be tested with the independent input data not used in the training phase. No weight modification is involved in this testing phase.

NEURAL NETWORK MODELS FOR SEISMIC INTENSITY

Data from events and sites for which both MMI data and New Zealand strong motion records are available was used to build an ANN model. Each of the 237 strong motion records that matched this criteria were processed to obtain the seven parameters listed as follows;

- Peak ground acceleration (PGA)
- Peak ground velocity (PGV)
- Peak ground displacement (PGD)
- Response spectral acceleration for 5% damping and 0.2 second period
- Response spectral velocity for 5% damping and 0.2 second period
- Arias intensity
- JMA intensity

These seven parameters were used as input layer variables to a multi-layered feed-forward neural network. The single output layer variable was the MMI value. The network contained one hidden layer resulting in a total of three layers. The sigmoid function was used for the transfer function of the hidden neurons and the identity function for the output neuron. The backpropagation training method was used and this requires some training parameters for “initial weights”, “learning rate” and “momentum” (Haykin 1999). The model building process can be very sensitive to these parameters.

The range of values of the input parameters, other than the JMA intensity, was quite wide (Figure 1) and to reduce this range they were transformed or scaled before use in the ANN. The derivation of the JMA intensity involves a $\log_{10}$ function (Davenport 2001) and this same function would seem appropriate to transform the other six input parameters. One example of this is seen in Figure 2 which uses a log scale for PGA to show a less non-linear relationship than a linear scale would. It should be noted that this transform does not dictate a functional form to the relationship of MMI to the input parameters, but allows faster convergence of the model building process and may requires less neurons to represent the relationship.

For supervised training of the ANN, a subset of two thirds of the total set of records was used. The individual records assigned to this training set were selected at random from the complete set of records. The other third of the data were used for testing the ANN after it had been trained.

The number of neurons in the hidden layer of the network is finalized with a trial-and-error procedure. If there are too few, the network may not have sufficient degrees of freedom to learn the process correctly. On the other hand, if the network is too large, it may not converge during training or it may overfit the data. The trial-and-error procedure started out with a model with one neuron in the hidden layer and training was carried out on this. The process was then repeated with more neurons (two, three, four, etc.).

In each case training was done for 100,000 sweeps, or epochs, of the training data. The value of MSE for the ANN model was computed and monitored as training is carried out. Figure 4 shows how the MSE for three models reduces as training proceeds.

The MSE values for the three models shown reduces quite quickly and after only 5 passes, is near the final value with only small changes after that. This reflects that this problem, with the $\log_{10}$ scaling of inputs, is not highly non-linear. The ANN with 15 hidden neurons provides a lower MSE and hence is a better model than a network with 10 hidden neurons. The performance was found to deteriorate as the number of hidden neurons was increased further as shown by the MSE for 20 hidden neurons. While this gets closer with additional training, with a greater number of neurons, there is a risk of over-fitting the training data. A model with a smaller number of hidden neurons is more desirable.

From this the most appropriate number of hidden neurons can be determined as 15 in this case. The testing data was used to check that the model has generalized the form of the data and not merely memorized the specific training data.

CONCLUSIONS

The major conclusions at this stage of this study are:

- Measures of seismic intensity based on felt effects can be difficult to determine as it requires considerable skill on the part of the observer and may be subjective.
- Felt intensity scales are based on real damage.

- Instrumental parameters are more objective but have sparse coverage and are not directly associated with real damage.
- There is a high correlation between parameters derived solely from the strong motion records.
- Correlation between felt intensity (MMI) and various individual strong motion parameters (e.g. PGA) show there is some relationship but there is a large scatter of the values. There is a low precision in using one to estimate the other.
- Artificial neural network methods are a viable modelling tool to determine the relationship of felt intensity to the many parameters determined from strong motion records.

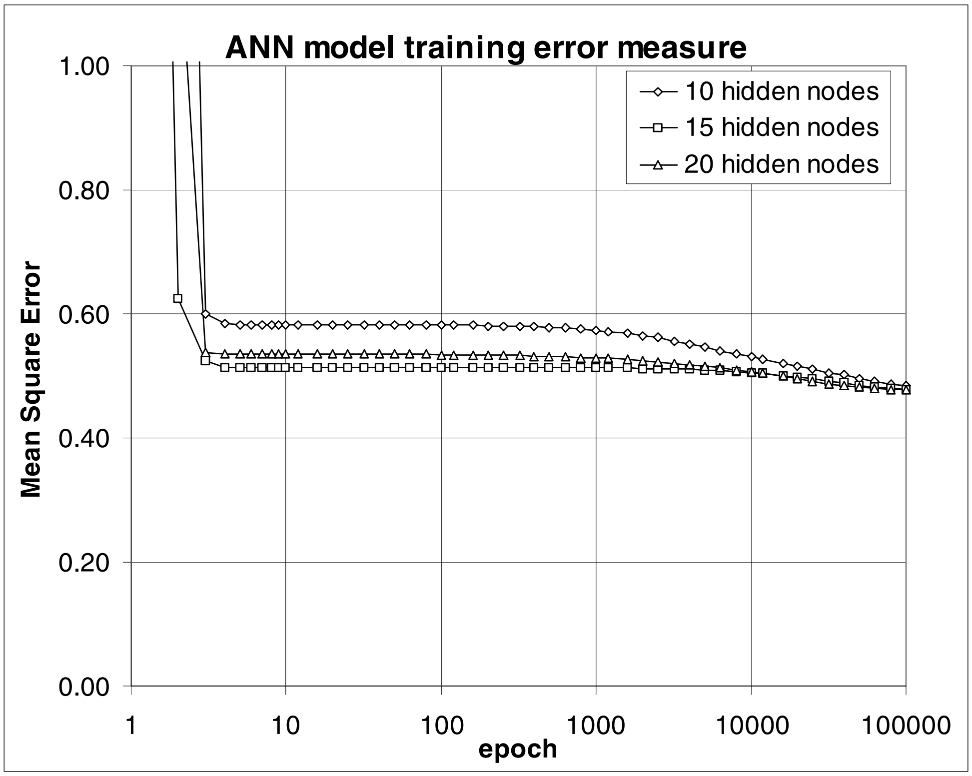


Figure 4: Neural network mean square error (MSE) progress for models with 10, 15 and 20 hidden nodes, during training up to epoch 100,000. Note the use of a log scale for epoch.

It is clear that instrumental seismic intensity measures can not completely replace the subjective felt intensity measures which are currently in use. There are many more people out there on the ground who can observe the effects of an earthquake, than the sparse network of instruments used to record the strong motion waveform during the event.

While the results presented here are for records which were collected in the past, one of the major benefits is to carry out the processing in real time or at least immediately after the shaking has finished. With modern digital recorders, this could be done at the site of the strong motion recorder, allowing a single number to be sent to a central control site. This avoids overloading communication channels and possible contention for service which can happen when many recording sites are trying to report back with large quantities of data contained in the full length strong motion records. In the period immediately following strong shaking, a clear overview of the extent of shaking is needed rather than the fine detail contained in the full records. With such a setup, many sites can report the quick result of seismic intensity and at a later time, when the immediate urgency is over, the full strong motion record can be sent.

The reported results are based on data for moderate values of MMI. More strong motion records and MMI values at higher intensities are required to refine the results. This project is ongoing and further results derived for other input parameters and a more extensive set of records will be presented at a later date.

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