
Application of Artificial Intelligence (AI) methods to engineering seismology

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ABSTRACT

In the study of seismicity it is found there is still much uncertainty in the relationships of parameters describing the process. Consequently it requires statistical methods and empirical relationships based on observations. Traditionally linear correlation is preferred for modelling processes, but it is clear that non-linear effects are very important. This is generally catered for by applying transformations to observations, typically logarithmic or exponential. However, it is found that as there are differing relationships for weak and strong seismic actions, this approach is not completely satisfactory.

The use of AI has now become very topical and its main feature is the ability for pattern recognition. A major characteristic of using AI is that it requires a very large amount of input data in order to satisfactorily train models. AI can also provide for varying non-linear relationships depending on the input observations. The author has previously utilised this approach (Davenport 2004 and Davenport 2009). It was concluded that while the technique was promising, it required more data than was available at that time. With the expansion of the GeoNet seismic recording network in New Zealand, and the occurrence of several large earthquakes, there is now much more data available and AI is more viable.

This paper presents the application of AI to some seismicity situations. It concludes that while it is a useful technique, caution is needed in verifying the training data that is used.

1 INTRODUCTION

As an engineer, the interest of the author is the study of seismic effects on the built environment, particularly buildings. At low level, the effects may just be minor movement and rattling of components. Stronger shaking can lead to damage to items and the structure of the building. It is desired to be able to assess this response rapidly during and immediately after an earthquake.

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. The most significant scales are the ten-degree Rossi-Forel; the Mercalli-Cancani-Sieberg,

also known as MCS; the twelve-degree Modified Mercalli, 1931 and 1956 versions; and the eight degree Japan Meteorological Agency, JMA amongst others. These scales assess the felt effects by human 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. A review of the early history of seismic intensity scales is given by Davison (1900, 1921, 1933). Davenport and Dowrick (2002) present a review of some characteristics of these scales and references to their development. Dowrick (1996) gives a detailed description of a revision of the MMI scale applicable to New Zealand conditions. A further revision is given by Dowrick et al (2008).

This felt seismic intensity is one of the less 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 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 quantitative 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.

Characterization of ground motion has the advantage that parameters are easier to predict than whole time series records. 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). Some of the simple methods which are reported attempt to fit a linear relationship between the felt intensity and one or more of the parameters derived from the strong motion time history recording.

However, the process of assessing seismic felt intensity from plastic deformation and rupture damage is highly non-linear in nature and, as 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 this inherent non-linearity in the process.

For this we consider a flexible class of statistical models to investigate the relationship of parameters derived from non-linear analysis of strong motion records to the seismic felt intensity, which essentially becomes a 'pattern matching' problem. We call ourselves Homo Sapiens, because our mental capacities are so important to us. For a long period we have tried to understand how we think, that is, how a small amount of matter in our head, which is our brain, can perceive, understand, predict, and manipulate a world far larger and more complicated than itself. The fields of artificial intelligence (AI) goes further still as it attempts not just to understand but to also build intelligent models.

In the last few years, we have seen an astonishing change in the perception and recognition of AI as a science and technology. Many large industrial firms have committed large amounts of money to the establishment of AI laboratories. Newspapers, magazines, and broadcast features on AI are common.

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 is to evaluate the potential of AI methods 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 parameters derived from the strong motion records which could be used as an analogue of seismic felt intensity.

This paper describes the development of AI methods and specifically the use of Neural Networks (NN) that are now in more common use. The requirements for a large volume of data is emphasised and the preparation

of New Zealand strong motion data is described. Following that, the requirements for application of Neural Networks to seismic strong motion records is described. There is still work to do on this project and the conclusions summarises what has been achieved and what remains.

2 BACKGROUND OF AI METHODS

There are a number of approaches to provide artificial intelligence to a computer system. They differ in the fundamental way they encode knowledge and develop solutions to problems. Some are outlined below.

2.1 Expert systems

One approach of AI is expert systems used in science, medicine and education. These rule-based systems, which vary widely in structure and behaviour, all focus on one important methodology, called the transfer of expertise. Early in AI's history, researchers agreed that high performance on difficult problems would require large amounts of real-world knowledge; the knowledge that a human expert in a particular domain has extracted from their experience with the problems they solve. The idea of expert-systems research was to find ways of transferring the necessary kinds and quantities of knowledge from human experts to AI systems. They rely on developing multiple rules from input by human experts.

This technology has advanced to the point where these systems can perform at the level of human experts and some are available commercially. Successful uses for expert systems are medical diagnostics and chemical synthesis.

When working for computer services of the NZ Ministry of Works and Development in the 1980s, the author developed a trial expert system for design of reinforced concrete buildings to the NZ design standards of the time.

2.2 Genetic algorithms

Another approach was a method of making a series of small mutations to a model to improve the performance for the task it is to do. The idea is to try random mutations, then using a selection process to preserve mutations that seemed useful. This is known as machine evolution or more commonly as genetic algorithms as it is similar to genetic changes as an organism evolves over many generations. This method is often applied to optimisation problems.

2.3 Neural networks

Neural networks (NNs) attempt to mimic some of the flexibility and power of the human brain by artificial means and researchers have found them useful in modelling of various physical systems. The fundamental approach is to present it with 'training data' that demonstrates the relationship of the input and output parameters. Neural networks were initially investigated in the 1940s even before general purpose computers were available. Further research and development of neural networks took place in the 1950s and 1960s with improvements to the training processes, using faster and larger computer systems and more available data.

The AI systems developed from the 1950s were directed at simple problems and showed promise. Most of the early systems contained little or no knowledge of their subject matter as they succeeded by means of simple syntactic manipulations. A typical situation in early machine language translation between Russian and English was based on grammar matching and word replacement using a dictionary. An example text of "the spirit is willing but the flesh is weak" becomes "the vodka is good but the meat is rotten" illustrates the fact that translation requires a general knowledge of the subject matter in order to resolve ambiguity and establish context.

Another difficulty was the small scale of problems that were tackled and that there were only a few steps needed for a solution. Extending to larger problems was not just a requirement of faster hardware and larger memories. In effect, AI systems did not scale well to deal with more realistic problems.

In the 1970s, neural networks fell out of favour when it was realized that there were limitations on what they could represent with contemporary equipment and available data. Research funding became limited. However there was a resurgence of the use of neural networks in the 1980s resulting from improved training methods, particularly the back-propagation process, and larger, faster computers were available. Larger volumes of data for training could be acquired as internet use became widespread. The end result has been the development of deep neural networks with many more layers and parameters than previously. This has led to the current use as generative AI and Large Language Models (LLM).

A NN 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 1a) connected by links and usually organized in a number of layers (Figure 1b). 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 or activation function.

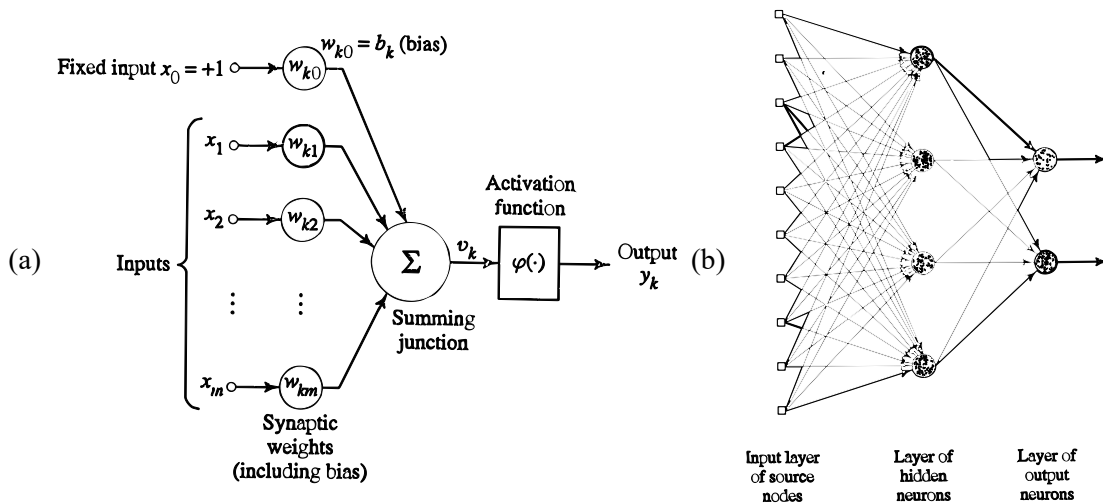


Figure 1: Neural network components and architecture. (a) Basic non-linear model of a neuron, (b) Fully connected feed-forward network with one hidden layer.

Most NNs 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 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 NNs 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.

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 NN, 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.

A neural network is a parallel distributed processor which has a natural propensity for storing experiential knowledge (Haykin 1999). Artificial neural networks 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). All that is needed for most networks is a collection of representative examples of the desired mapping. NNs automatically adapt and construct the relationship based on the data used for training.

NN models have been widely applied to time series forecasting, pattern recognition and process control. The common features of successful applications of NNs in prediction and modelling are the quantities being modelled are governed by multivariate interrelationships and that the data available are “noisy” or incomplete. Neural networks are capable of handling system nonlinearity. When neural network models are developed, there is no need to assume any functional relationship amongst the various variables unlike in regression analysis. NNs should be of interest to engineers and scientists as a tool to support modelling and prediction of behaviour of engineering and natural systems (Flood & Kartam 1994).

However it is noted that the quality of the training data is a crucial aspect on the final quality of the model and resulting output. In using data 'scraped' from the internet, the development of general LLM has resulted in 'hallucinations' in the results. Thus when applied to seismicity problems, checking on the data integrity is essential to ensure reliable results.

3 DETAILS OF STRONG MOTION RECORDS IN NEW ZEALAND

The author had investigated the application of neural networks to NZ seismic data in earlier presentations (Davenport 2004; Davenport 2009). However as stated at that time there was very limited NZ strong motion data available, particularly at higher intensities, so the modeling was not ideal.

The data available at that time was from about 800 events and recorded at about 250 sites resulting in about 3000 strong motion records. However, not all records were usable as some events could not be matched to actual earthquakes in the NZ seismic catalogue (GNS Science 1970). They may have been spurious records of cultural origin. In addition, not all recording sites were representative of ground motion as some were at higher levels in multi-storey buildings. The characteristics of the data used in the earlier studies are shown in Table 1.

The comment was made of the prior analysis that it should be repeated when more data becomes available. With a more extensive set of recording sites, and several very large, damaging, earthquakes, that time has now arrived and data was extracted from GeoNet (GNS Science, GeoNet Strong Motion Data Products). Only processing level V1A records were obtained, and a summary is given in Table 1 where it is noted that about 84000 records are now available compared to the previous 3000 records. The date range is 1966 to January 2022. The format of the stored records was changed at this time so different processing would be required. This extended period will be done at a later stage.

It is also noted that there are far more records that have been excluded. Prior to 2000, there were a limited number of records and each one was considered 'precious' and treated individually. With the more extensive network and number of events, more automation was needed to handle the volume. Detailed examination of the data indicated several problems. 313 V1A records have a zero file length so no data was actually present. 6222 records are assigned to two or more events. The reality of this is that two events that are nearby in time and position have contributed to a common record and thus it cannot be attributed to a specific single event but is a composite record of multiple events. These are special records and would warrant a special study on their own. With data acquired from the V1A repository, some records had a type of 'V1A_', 'V2A_' or 'V3A_' and thus did not comply with the naming convention. While the 'V1A_' files may have been valid, they would have required close inspection to confirm this. A total of 2728 records were in this category. In addition, records from events that were not in the earthquake catalogue (GNS Science 1970), or were at excluded sites not at ground level, were also considered as not being usable. A total of 19233 records were excluded.

	1968 to 1998	1966 to 2009	1966 to 2022
Number of events	842	3599	7020
usable events	780	3210	6217
Magnitude range	2.7 to 7.9	2.4 to 7.9	2.4 to 8.13
Number of sites	253	532	697
usable sites	218	484	649
Number of records	3048	18444	93160
usable records	3048	18414	83927
Events with MMI available	32	na	na
Records with MMI available	232	na	na

Table 1. Details of seismic and strong motion data available from GeoNet.

The resulting usable records were processed to determine the characteristics of the motion. This included the usual peak ground acceleration (PGA), strong motion duration, arias intensity (Arias 1970), JMA intensity (Japan Meteorological Agency 1996; Davenport 2001) and other spectral parameters.

The other major parameter required for the analysis is the felt intensity, MMI, at the recording location. This would need to be determined by knowledgeable observers. In previous studies, this has been obtained from isoseismal maps (Downes 1995). Unfortunately not every seismic event has such a map prepared. GeoNet have been collecting 'felt reports' from the general public and these may be useful. The location of the observers is scattered and there may only be a few near any one recording site, although it may be possible to determine an average felt intensity over a region nearby. The observers are not specifically trained but are given a general description of what effects to consider. However there are some obvious outliers that would not be consistent with the physics of the situation. This measure is the weak link in this analysis, so alternatives need to be considered.

4 ANALYSIS OF STRONG MOTION RECORDS

Nonlinear processes are relevant for seismic intensity as the MMI scale has many references to damage, particularly at higher intensities, with cracking and collapse of buildings mentioned. Even at low intensities,

some effects, such as ‘glassware and crockery rattle’ at MMI IV, are clearly nonlinear behaviour. These are generally non-linear responses to the shaking motion.

To model the seismic intensity from the accelerogram record parameters such as acceleration forces, velocity, frequency content and duration of shaking are relevant. Initial concepts were to consider the response of a number of building-like structures with differing heights, and thus periods, and also differing strength capacities. Descriptions of seismic felt intensity are not limited to building structures alone and it was realized that the response of a simple one degree of freedom oscillator to the earthquake motion would suffice. This is traditionally done as a linear elastic process, but here nonlinear behaviour is important, and an elasto-plastic material is used.

The model components and parameters are illustrated in Figure 2. The inverted pendulum of height L , and mass M , has the stiffness K , chosen to give the desired initial elastic period. The yield force F_y , of the support is chosen to represent the desired strength. A computer program has been developed to carry out the nonlinear analysis for each time step. The input motion is applied at the base and the response of the top is the output motion. The output record from this analysis is summarised and the peak values of acceleration, velocity and displacement for each of the three components and for the resultant are produced. Other parameters such as the duration of strong shaking and a measure of the ductility are also determined.

This process is carried out for a variety of yield strengths and oscillator periods. The intent is to cover the responses representing the physical phenomena people observe on the ground. At low intensities the long period, linear response of hanging objects swinging (MMI 3) is modelled. At higher intensities the short period, nonlinear response of poor quality buildings (type 1) being damaged or collapsing (MMI 8) is also modelled.

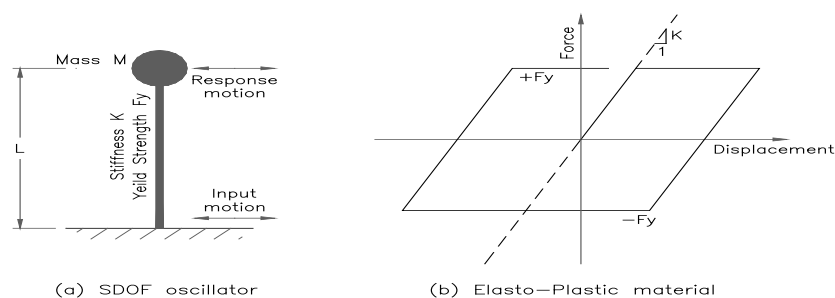


Figure 2: Single-degree-of-freedom oscillator (SDOF) with nonlinear response. (a) Basic layout, (b) Nonlinear elasto-plastic material force-displacement properties.

From these response parameters, an equivalent felt intensity can be assigned. When many input accelerogram records are processed, the result is a considerable volume of data and the task is to recognise patterns in this data. This will be a future task to use a neural network to determine this relationship.

5 CONCLUSIONS

This project involved the processing of New Zealand seismic strong motion records. Prior analysis had used limited data and it was apparent that a much larger volume of data would be required. This paper stressed the importance of verifying the validity of the training data and describes the initial screening of the now available much large number of strong motion records. This screening is to improve the quality of the data. by excluding records that were faulty or did not represent shaking at ground level.

A method of determining a felt intensity based on the strong motion records has been presented. The result is a large volume of data that can be used to train a neural network. This research investigation is a "work in progress" and further analysis and results will be produced.

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