Scientia Iranica, Vol. 6, Nos. 3 & 4, pp 165–176
© Sharif University of Technology, October 1999

SCIENTIA IRANICA

A Non-Parametric Approach for Estimation of Peak Horizontal Acceleration in Japan

S.M.R. Emami*, T. Harada[1] and Y. Iwao[2]

In this paper, an artificial neural network model is developed to predict peak horizontal acceleration in Japan. A complete data set with a large number of records of Japanese subduction zone data is considered for the analysis. The local site condition is included in the proposed model, where two types of ground were selected during analysis. Prediction curves related to the soil and rock sites are notably resolved. For comparison, some recent attenuation studies in Japan are investigated. It is found that the attenuation of peak horizontal acceleration provided by this study is compatible with other recent attenuation studies in Japan and has relatively superior performance in some instances.

INTRODUCTION

The empirical predictive relations of earthquake ground motion parameters have quite an important role in seismic hazard analysis. Such relations are generally expressed as mathematical functions relating a strong motion parameter to the parameters characterizing earthquake source, propagation path distance and local site conditions.

Peak horizontal acceleration is one of the earthquake ground motion parameters that is of considerable interest to earthquake engineers and seismologists. It is one of the major factors of earthquake resistant design in important engineering structures and huge industrial facilities especially in areas with high seismic activity.

During the past few decades, several attempts have been made to estimate peak acceleration with various pertinent properties of the strong motion records, e.g., [1-7].

In Japan, Kanai et al. [8] were the first who studied acceleration attenuation relation, using data observed in the Hitachi mine and the source region of Matsushiro earthquake swarm. Subsequent regression analyses have been conducted by numerous researchers as the amount of observed data has increased, such as studies on the Japanese subduction zone data during the last two decades [9-15].

Regression analysis, with various functional forms and procedures, has been widely utilized by Japanese researchers to estimate attenuation relations in Japan. In general, regression analysis is a technique for fitting curves (linear or nonlinear surfaces) to the data points. Simpson [16] points out that the nodal function used in many error correction learning algorithms of neural networks is a family of curves, and that the adjustment of the weights that minimize the overall mean-squared error is equivalent to the curve fitting. The capability of artificial neural networks to predict ground motion parameters has been proved in previous studies [17]. Here, an attempt is made towards prediction of peak horizontal acceleration in Japan. This paper deals with a relatively completed data set of Japanese subduction zone, while applying local site conditions as a part of the prediction model. The effect of ground conditions on the prediction of peak horizontal acceleration, rather than the other two main parameters (related to the size of the earthquake and the path effect) has been studied. The significance of this parameter is effectively evaluated through analysis of data from various ground conditions.

Furthermore, the effect of focal depth on the attenuation of ground motion, investigated by Annaka and Nozawa [11] and Molas and Yamazaki [14] is discussed. It is proved that the focal depth has a positive influence on the attenuation of ground motion. By increasing the focal depth, the magnitude of ground

* *Corresponding Author, K.M. Computer Company Inc., Fukuoka 815, Japan.*

1. *Department of Civil Eng., Miyazaki University, Miyazaki 889, Japan.*
2. *Department of Civil Eng., Saga University, Saga 840, Japan.*

Table 1. Summary of recent strong motion attenuation relations in Japan (1985-1995).

Reference	Applicability	Parameter*	Attenuation Relation	Number**
[9]	r = rock h = hard soil s = soft soil	$M = M_J$ $\triangle = R_e$	$\log PGA_r = 3.995 + 0.216M - 0.218\log(\triangle + 30)$ $\log PGA_h = 2.366 + 0.308M - 1.218\log(\triangle + 30)$ $\log PGA_s = 2.606 + 0.265M - 1.218\log(\triangle + 30)$	$N_r = 197^{*}$ $N_e = 90$ $N_s = 67$
[11]	$300 \leq V_s \leq 600$	$M = M_J$ $H = D_f$ $R = R_h$	$\log PGA = 0.627M + 0.00671H - 2.212\log D$ $+ 1.711 + 0.211P$ $D = R + 0.35\exp(0.65M)$	$N_r = 319$ $N_e = 45$
[12]	$0.1 < R < 300$ $4.5 \leq M \leq 7.8$	$M = M_s$ $R = R_c$	$\log PGA = 0.41M - \log(R + 0.032 \times 10^{0.41M})$ $- 0.0034R + 1.30$	$N_r = 686$ $N_e = 43$
[13]	$10 < R < 1000$ $4.0 < M < 8.0$	$M = M_J$ $\triangle = R_e$ $X = R_h$	$\log PGA = 0.552M - 1.965 \times \log(\triangle + 30) + 2.103$ $\log PGA = 0.559M - 2.0571 \times \log X + 2.187$ $\log PGA = 0.490M - \log X + 0.634$	$N_r = 726$ $N_e = 92$ $N_s = 55$
[15]	$1 \leq R \leq 700$ $4 \leq M \leq 7.8$	$M = M_J$ $R = R_h$ $H = D_f$ $C_i = S_c$	$\log PGA = 0.184 + 0.482M - \log R - 0.00149R$ $+ 0.00315H + C_i + 0.278P$ $\log PGA = 0.206 + 0.477M - \log(R + C(M))$ $- 0.00144R + 0.00311H + C_i + 0.278P$ $C(M) = d_1\exp(d_2 M) = 0.82$	$N_r = 2206$ $N_e = 388$ $N_s = 76 + 42$

* M_J : JMA magnitude; R_e: Epicentral distance; R_h: Hypocentral distance; R_C: Closest distance to the fault rapture; D_f: Focal depth; S_c: Site coefficient; V_s: Shear wave velocity.
** N_r, N_e and N_s are number of records, earthquakes and stations, respectively.

motion increases, but the behavior of a deep focus earthquake is not certainly known because of a high Q zone. However, since our interest is placed on empirical prediction of ground motion acceleration from shallow to middle events, focal depth is not used as a part of analysis. Some recent attenuation relations for peak horizontal acceleration in Japan are given in Table 1.

RECENT ATTENUATION STUDIES IN JAPAN

Herein a brief review of several recent attenuation studies in Japan will be described:

a) Kawashima et al. [9] studied attenuation of peak ground motion with various functional forms based on multiple regression analysis. A total of 197 sets of two horizontal components of strong motion accelerations were used in their analysis. For investigation of local site effects, the data was classified based on three types of soil condition: rock, hard and soft soil.

The accuracy of attenuation relations was determined through multiple correlation coefficient, which was considered as a basic parameter for selecting an adequate model. A model with the highest value of the correlation coefficient was finally selected, which is given in Table 1. Based on their relationship, the attenuation curves, regarding soft ground, have lower values for magnitudes: 5, 6, 7; the rock and hard soil have unsystematic trends in accordance with magnitudes 6.0 and 7.0. It can be concluded that the effect of ground condition on the attenuation of peak ground acceleration in their model seems to be unrealistic.

b) Anaka and Nozawa [11] proposed an attenuation model for estimation of seismic hazard in the Kanto district (Japan). The data collected by TEPCO's network was used to obtain the attenuation equation of peak horizontal acceleration. They noted that the provided equation is applicable to a site where Vs are between 300 and 600 m/s. The authors used records related to 45 earthquakes with focal depths less than 100 km. The obtained attenuation relation from multiple linear regression is given in Table 1.

The effect of focal depth on the attenuation equation was examined by investigating two major disastrous earthquakes: 1885 Ansei-Edo earthquake ($M_J = 6.9$) and 1894 Tokyo earthquake ($M_J = 7.0$), as is noted in their paper. This effect is introduced into the attenuation relation by considering a parameter related to the focal depth. The focal depth has a significant positive influence on the prediction of peak horizontal acceleration.

c) An attenuation relation of peak horizontal acceleration applicable to the near source in Japan is developed by Fukushima and Tanaka [12]. In their analysis, 1,372 horizontal components of peak ground acceleration from 28 earthquakes in Japan and 15 earthquakes in the United States and other countries were used.

The two-step stratified regression procedure was used for analysis of data. Their model accounts for geometrical spreading and anelastic attenuation, but has magnitude-independent shape at very short distances. Their attenuation model is also presented in Table 1.

d) An attenuation study of earthquake ground motion in Japan, including deep focus events, was conducted by Molas and Yamazaki [14]. Several recent large earthquakes are included in their data set. The data set consists of 2,166 horizontal components from 387 earthquake events. This data set is significantly unique in Japan for analysing the attenuation of ground motion so far. The effect of focal depth on the attenuation of ground motion has been investigated while examining two recent major earthquakes: January 15, 1993, Kushiro-Oki earthquake ($M_J = 7.8$, Focal depth = 103.2 km) and July 12, 1993, Hokkaido Nansei-Oki earthquake ($M_J = 7.8$, Focal depth = 34 km). The significant positive effect of focal depth on the attenuation of ground motion was investigated. By considering this fact, a parameter relating to focal depth was introduced into the attenuation relation. Later, the authors reconsidered their study with regard to data from the largest and most recent earthquake of January 17, 1995, of Kobe earthquake (Great Hanshin). The final attenuation relation for peak horizontal acceleration was formulated into two forms, as presented in Table 1.

For analysis of acceleration data, the iterative partial regression method was used based on the two-step regression procedure in their study. The local ground condition was considered through examining the station effect instead of the soil type classification. A coefficient regarding the station effect was included in the analytical model. The site coefficient is related to the site conditions, including geology, topography and other possible effective factors. The authors noted that if the proper site coefficient is obtained, then the determination of the seismic hazard will be more accurate. However, determining the adjusted site coefficient for a specific site under consideration is difficult. The various characteristics of previous studies in Japan were compared with the study presented here in Table 2.

THE ACCELERATION DATA

Data was recorded by Japan Meteorological Agency (JMA) recording networks around the Japanese territory. In the past, the recording instrument was SMAC-B2 accelerometers, which had sensitivity limitations at high frequencies. Since 1987, Japan Meteorological Agency (JMA) has started to install the new JMA-87-type accelerometer in the recording stations throughout Japan. The advantage of data supplied by the new accelerometers is that correction is redundant, and the errors involved in the correction procedure are avoidable. The records can be considered as free field because of small foundations in the base of the accelerometers and their detachment from the structure that houses them [14]. Since the geological conditions of the recording station were investigated, it is possible to study the effects of local site on the attenuation of earthquake ground motion.

Data from the period of August 1, 1988 to December 31, 1993, recorded at the 76 JMA station, was considered for the analysis. Recent damaging earthquakes, such as February 7, 1993 Noto Pensinsula-Oki earthquake ($M_J = 6.6$, Focal depth = 24.8 km) and July 12, 1993 Hokkaido Nasi-Oki earthquake ($M_J = 7.8$, Focal depth = 34 km) are included in the data set. The location of the JMA stations (triangles) and

Table 2. Comparison of recent attenuation studies in Japan.

Studies	Number of Records Two Component Pair	Number of Earthquake	Magnitude Range	Distance Range	Focal Depth	Recording Station	Definition of Peak Horizontal Acceleration	Analytical Method
[9]	197	90	$5.0 \leq M_J \leq 7.9$	$5.0 \leq$ Dis. ≤ 500	$h \leq 60$ km	67 free field	Maximum resultant of combination of two horizontal components	Single step regression (multiple linear regression)
[12]	486 (Japan) 200 (USA)	28 (Japan) 15 (USA)	$4.6 \leq M_s \leq 8.2$	$0.1 \leq$ Dis. ≤ 303	$h \leq 30$km (Japan) $h \leq 20$ km (USA)	not specified	Mean of two horizontal components	Two step stratified regression
[15]	2206	388	$4.0 \leq M_J \leq 7.8$	$0.2 \leq$ Dis. ≤ 1000	$0 < h \leq 200$ km	76 free field + 42 non JMA	Larger of two horizontal components	Two step regression (partial iterative regression)
This study	1652	313	$4.2 \leq M_J \leq 7.8$	$4.6 \leq$ Dis. ≤ 1000	$h \leq 65$ km	76 free field	Larger of two horizontal components	Artificial neural network (multilayer networks with B-P learning)

the epicenters of the earthquakes (circles) used in this study are shown in Figure 1.

The data set consists of 1,652 recordings of peak accelerations from 313 earthquake events, including data from the most recent earthquake of Kobe, January 17, 1995 ($M_J = 7.2$, focal depth = 20 km). Since there are few near field strong motion records available in Japan, the near field data provided by Kobe earthquake has created an opportunity to study attenuation characteristics at a near distance. However, due to lack of information regarding the soil conditions at the non-JMA recording stations, this data could not be included in the data set. Fukushima and Tanaka [12] used the near field data from USA to complete their database in the investigation of attenuation in the near field in Japan.

Earthquakes with focal depths greater than 65 km were not included in the data set in order to avoid the effect of high Q zone [12]. The distribution of the observed data, with respect to the magnitude, distance and depth are illustrated in Figure 2.

The analysis was performed on the peak horizontal acceleration. The peak horizontal acceleration is defined as the largest value of two horizontal components of a given record. Kawashima et al. [9] calculated the maximum ground motion on the horizontal plane while the mean value of two horizontal components was utilized by Fukushima and Tanaka [12].

The distance in which the data is obtained ranges from less than 4 to 1000 km. Various definitions of distance were used by researchers in the study of attenuation relations, such as epicentral distance, hypocentral distance, closest distance to the fault rapture and so forth. For the near field data, the reliable distance definition becomes more important, especially for earthquakes with a large fault extent. The nearest distance to the earthquake source (hypocentral distance) was considered here, except for Kobe earthquake in which the shortest distance to the fault rapture was used.

ANALYTICAL PROCEDURE

In Japan, typically, one- and two-step procedures of regression analysis have been used for prediction of ground motion parameters so far. As mentioned in the previous section, Kawashima et al. [9] examined various functional forms based on the multiple regression analysis to predict ground motion parameters. A two-step stratified regression analysis was considered by Fukushima and Tanaka [12] to predict peak ground acceleration. The authors point out that the distance coefficient depends on the value of the magnitude coefficient if the event's magnitude and measured distance are simultaneously used in the regression analysis. They proved this fact through a numerical experiment and actual data. To avoid this interaction between the coefficients of magnitude and distance, the two-step stratified regression method using a dummy variable was found to be originally effective by Joyner and Boore [4]. (For a detailed explanation of one- and two-step regression analysis, see [18].)

The capability of artificial neural networks to predict ground motion parameters was first proved by Emami et al. [19]. This method provides an analytical procedure in which neither functional forms nor independency of inside variables are needed. This shows that the dependency between two measured

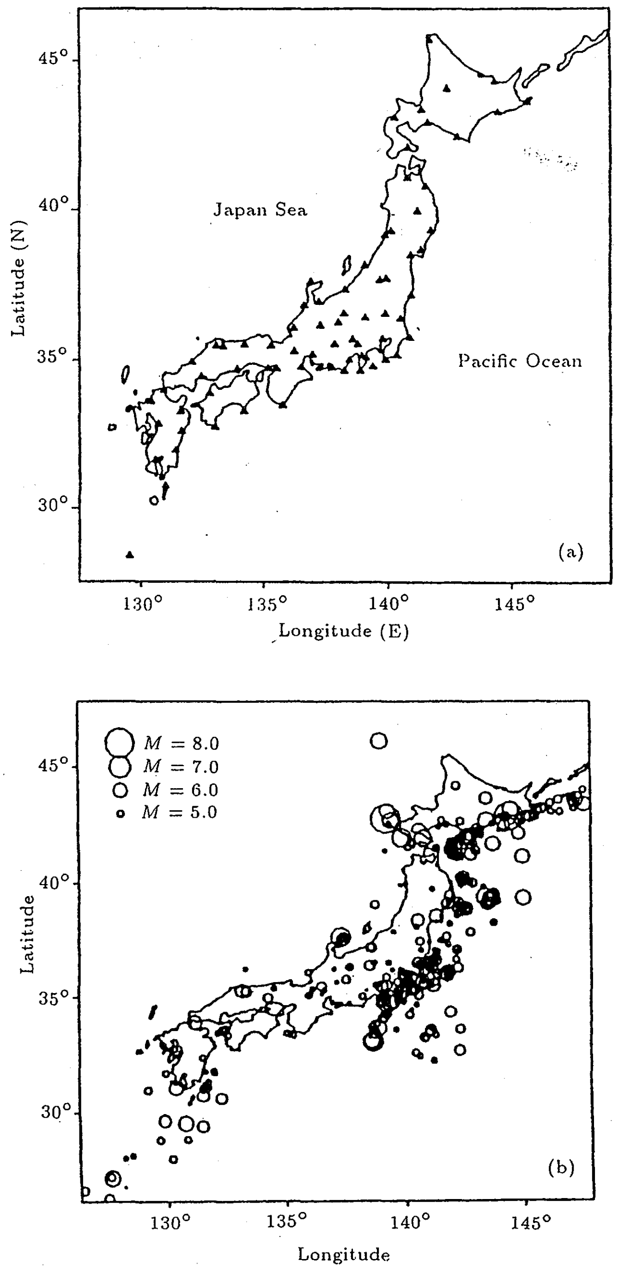

Figure 1. Location of JMA recording stations (a) and epicenters of earthquakes (b) used in this study (after [15]).

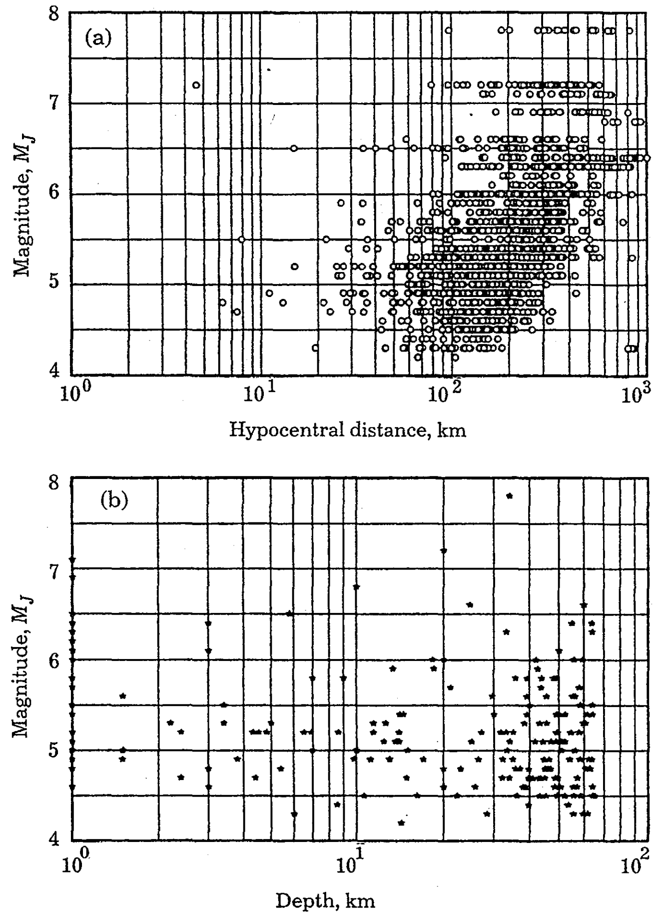

Figure 2. Distribution of observed data with respect to magnitude-distance (a) and magnitude-depth (b).

predictive parameters, magnitude and distance, has no negative effect on the accuracy of the prediction. In general, artificial neural network is inspired by the neurological system of the human body, which consists of a large number of simple processing units. These processing units/nodes have interconnections in the various artificially designed structures, with varying degrees of analytical strength as indicated by their connection weights. Neural network models are specified by the net topology, node characteristics and training or learning rules.

An artificial neural network model based on multilayer network was considered for the analysis of acceleration data in Japan. The detailed specification of the designed network model is provided in Table 3. Multilayer network has significant competence for prediction and classification aims in engineering fields. The proposed network model has a hidden layer consisting of 45 units. The output layer is

Table 3. The characteristics of our neural network predictive model.

* **Network Topology**
  Multilayered, partially connected neural networks. Three-layer feedforward networks consisting of four, one and forty five units in the input, hidden and output layers respectively.

* **Activation Function**
  Sigmoid function is used as a squashing function in both hidden and output layer's units.

* **Learning Algorithm**
  Classic backpropagation learning rule.

* **Inputs and Output**
  Earthquake magnitude, distance and local site conditions is considered as input parameters and peak horizontal acceleration as the output.

constructed using a sigmoidal or linear unit, while the hidden layer is built using only sigmoidal units. Through the analysis of acceleration data, it has been shown that the sigmoidal unit in the output layer produces more accurate estimation than the linear unit. To train this feedforward network, the classic backpropagation learning algorithm [20] was utilized. It is an efficient algorithm that is usually used in multilayer artificial neural networks. The backpropagation algorithm trains the network model within several hundred iterations, depending on the number of hidden units installed. The Appendix is presented for a better understanding of the proposed model.

As indicated in Figure 3, the network model has three layers containing 45 sigmoidal nodes in the hidden layer and a sigmoid output unit. Inputs to the network are the earthquake magnitude, distance and local ground condition as described earlier. Peak horizontal acceleration is expressed as the logarithm of acceleration (cm/s^2), normalized and considered as a target. The input data in the network was also normalized based on maximum values of each input parameter in order to homogenize the weight values.

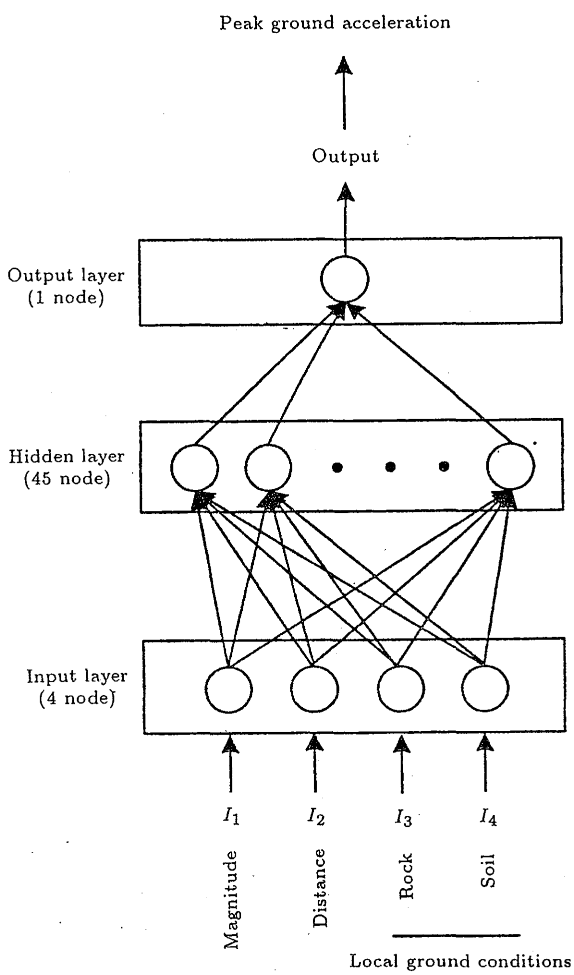

Figure 3. The structure of our neural network model.

The network has been examined through many training procedures in order to find out the suitable structure and eventually reach a better adjustment for the root-mean-square error cost function.

Simpson [16] noted that creating the best possible set of features and properly representing those features is the first step toward success in any neural network application. In this regard, the input parameters to the network model were reconsidered from the previous studies. The ground condition is also successfully included as a predictive parameter and is considered as the dummy variable. This variable is introduced into the network as the third and fourth input parameters. Various types of ground conditions were examined during the peak horizontal acceleration analysis. In the end, two ground types were selected, namely rock and soil. Soft soil could not be properly included into the analytical model due to insufficient data. Only 83 records from four recording stations were available which was approximately 5 percent of the complete data set.

RESULTS AND DISCUSSION

Local Ground Conditions

As mentioned earlier, in the recent study of attenuation relations in Japan conducted by Kawashima et al. [9] and Molas and Yamazaki [14], the effects of local ground conditions were examined. In the final attenuation model introduced by Kawashima et al. [9], the effect of ground condition is not correctly defined by their predictive curves related to $M_J = 5$, 6 and 7 as seen in Figure 4. In all cases, soft soil has a lower value of acceleration than rocky terrain. Molas and Yamazaki [14] introduced a term into their predictive model based on the local site effect for each recording station. This effect was also verified by examining the residuals with respect to the recording station. Although other effective factors of site rather than soil type are included in this term, but from a practical point of view, the determination of the term for a specified site under consideration is not easy based on their model.

The ground condition in this analysis is considered as an effective factor in the prediction of peak horizontal acceleration. The acceleration data was recorded by several stations located on various ground conditions and investigated by Japan Meteorological Agency based on their classification system. In that system, four types of terrain were introduced: rock; hard soil, medium soil and soft soil. In the predictive model of neural networks, the effect of ground conditions on the prediction of peak horizontal acceleration was examined by introducing a dummy variable into the model as the third and fourth input parameters. This

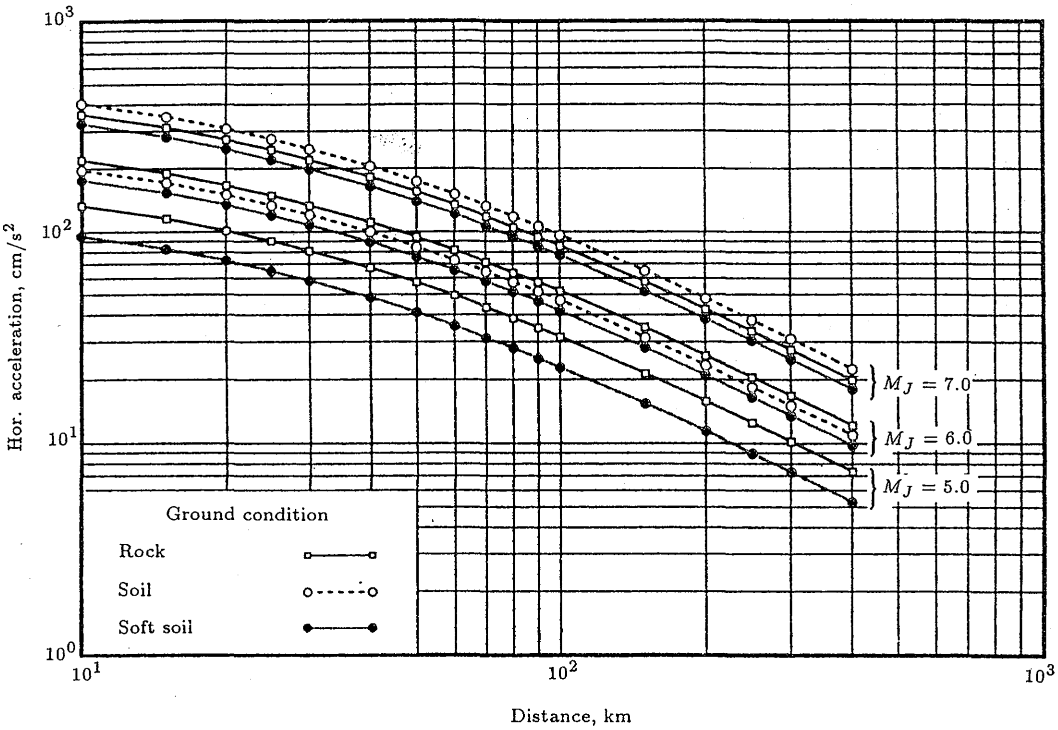

Figure 4. Alternative curves of peak horizontal acceleration, proposed by Kawashima et al. [9].

technique is commonly used by several investigators to verify the performance of the ground condition on the ground motion parameters at the specific site [21,22]. The technique is based on a soil-type classification by using a dummy variable for each ground type. Due to lack of sufficient recording data for soft soil, the two major types of ground, rock and soil, are effectively investigated in this analysis. The attenuation curves belonging to the soil and rock types of ground for magnitudes 6.0 and 7.0 are illustrated in Figure 5. The

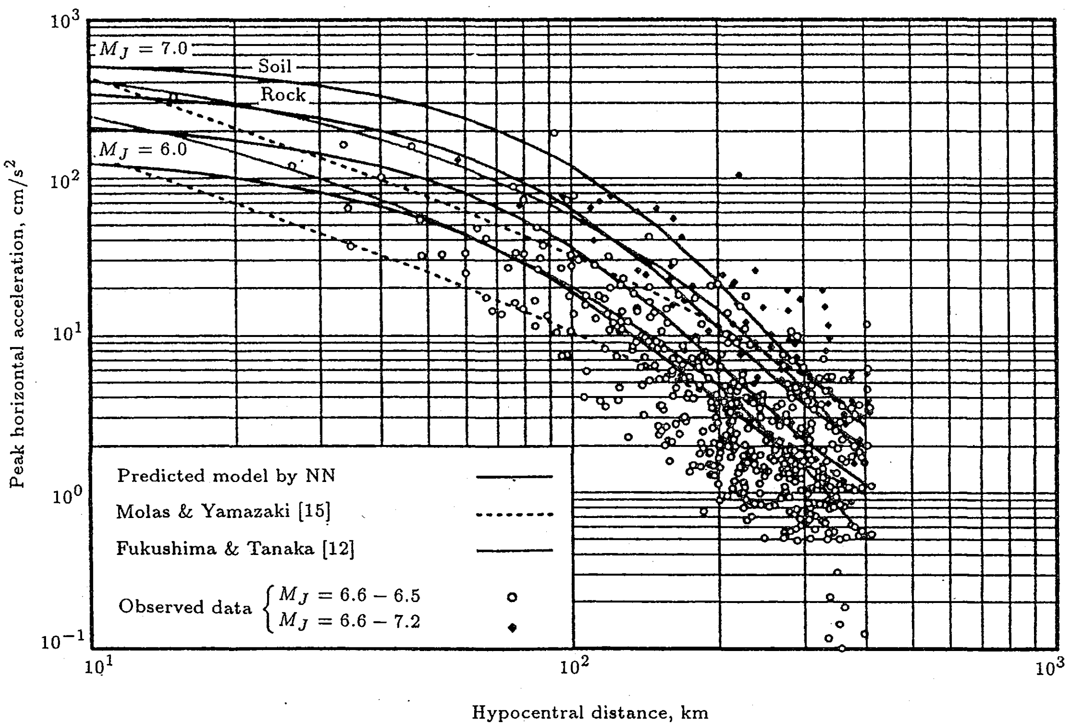

Figure 5. Observed peak horizontal acceleration and model-based predictions for magnitudes 6 and 7 compared with attenuation curves of Fukushima and Tanaka [12] and Molas and Yamazaki [15].

soil type has values of acceleration about 50 percent higher than those of the rocky type.

Analysis of Residuals

The overall adequacy of the model is best assessed from an analysis of residuals [23]. A residual is simply defined as the difference between the observed and predicted values of acceleration on the basis of a logarithmic scale. The residuals were normalized to have a mean and a standard deviation of unity. Analysis of residuals is done to test the potential biases in the prediction. In the first step, in order to define biases in the prediction, plots regarding the residuals with respect to the data number, magnitude and distance are made. The plots are carefully inspected to define any systematic trends in the data. If the systematic trends are not accounted by statistical analysis, it should be evident from these plots. The mentioned plots are presented in Figure 6. No significant trend in the residuals appears in these plots. A correlation analysis is performed for residuals and all parameters are considered in the model to test the statistical significance of the probable trends in the residuals with respect to the parameters. This analysis confirmed that the residuals were uncorrelated with respect to these variables.

The adequate model requires a normal distribution of residuals. The normalized residuals resulting from the analysis are perfectly and normally distributed, as can be seen in Figure 7. The normal distribution of residuals is emphasised by Campbell [5,24], as a fundamental requirement of the model adequacy. A qualitative assessment of normality may be obtained by inspecting a histogram of the residuals, which as Campbell [24] noted should resemble the standard bell shape of the normal distribution.

The designed network model could effectively provide an accurate estimation of peak horizontal acceleration. Prediction curves of the proposed neural network model for magnitudes 6.0 and 7.0 are compared with attenuation relations of Fukushima and Tanaka [12] and Molas and Yamazaki [15] in Figure 5. The prediction obtained from this study is relatively high compared to the other studies. It may be due to the provided data of the Kobe earthquake, 1995. The forms of both attenuation curves of this study and the ones belonging to the study of Fukushima and Tanaka [12] are nearly similar.

Figures 8a and 8b are constructed in accordance with the proposed neural networks and might be adapted to estimate the peak horizontal acceleration in Japan for practical use. Due to the limited amount of data in the near field (only four records for a distance less than 10 km), the prediction is valid for distances ranging from 10 to 400 km. With regard to the magnitude range of the data, the analysis is limited to magnitudes in the range of 4.5 to 7.5 on the JMA scale.

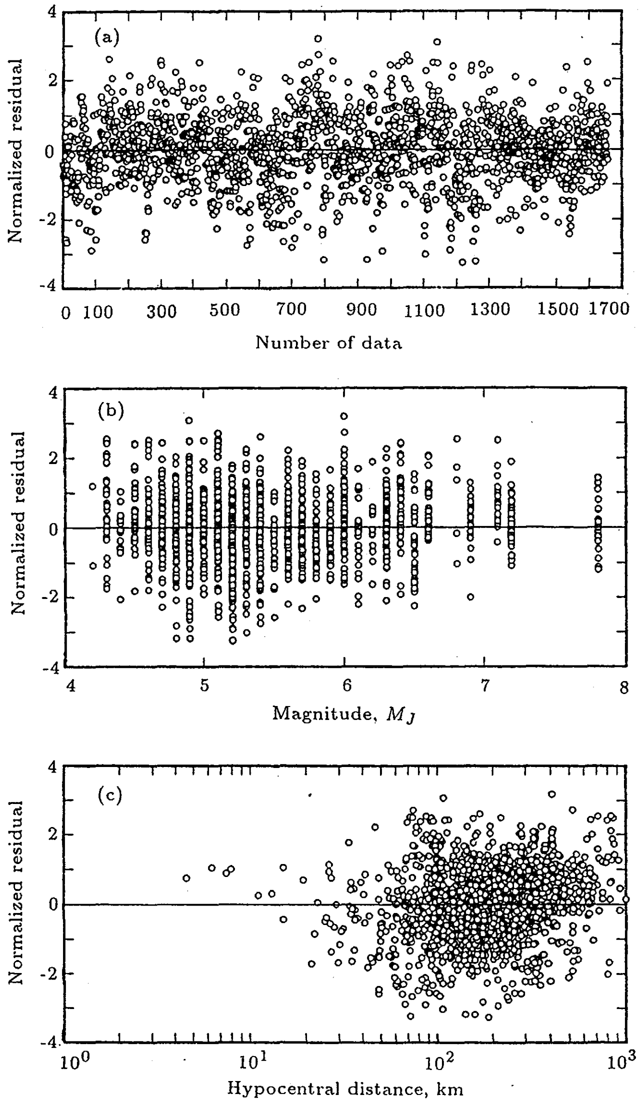

Figure 6. PLots of residuals with respect to time (a), magnitude (b) and distance (c) according to the presented model.

CONCLUSION

A large and complete set of data, well distributed over the distance and magnitude range was available for analysis and the near source data provided by the very recent Kobe earthquake in Japan (January 15, 1995) was included in this set.

Japanese subduction zone data were analysed by the artificial neural network model which is free from dependency of magnitude and distance. The results show that the attenuation of peak horizontal acceleration provided by this study is compatible with other recent attenuation studies in Japan and has relatively superior performance in some instances. These results

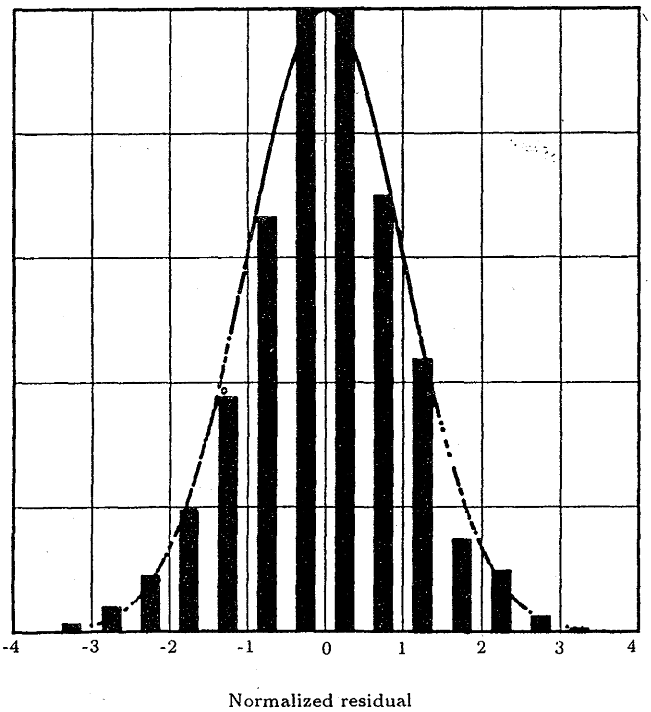

Figure 7. A normal probability plot of normalized residuals.

are suitable for use in Japanese territories and/or other regions with similar tectonic environments. It is recommended that the obtained results be used in distances ranging between 10 and 400 km and magnitudes ranging between 4.5 and 7.5, in the practical field. The residual analysis confirms that the developed predictive model is adequate for consideration in the estimation of peak horizontal ground acceleration in Japan.

It can be concluded that the obtained attenuation of peak horizontal acceleration is in agreement with that of Fukushima and Tanaka [12], from the attenuation characteristics point of view. Effectively, site condition is included in the prediction of peak horizontal acceleration by the artificial neural network model. Prediction curves related to the soil and rock sites are notably resolved. The resulting efforts make this study one of the few successful studies on the effects of ground conditions on the prediction of peak horizontal acceleration in Japan.

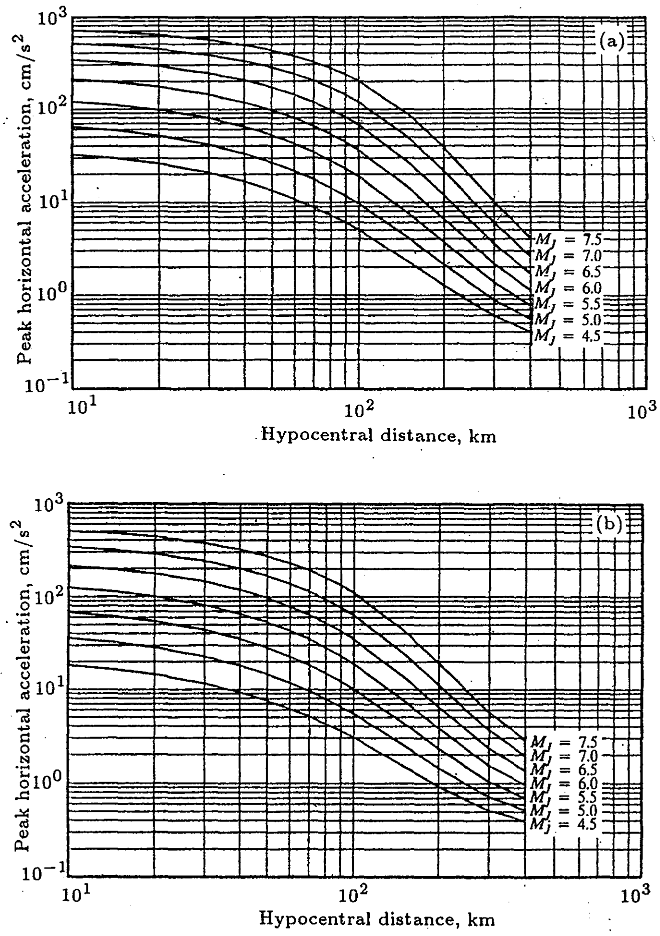

Figure 8. Predicted values of peak horizontal acceleration as a function of distance and magnitude, using the neural network model for soil (a) and rock (b) sites which can be used in the practical fields.

ACKNOWLEDGMENT

Special thanks to Professor F. Yamazaki of The University of Tokyo for his great kindness in providing us with a portion of his database. Sincere thanks to Mr. T. Otsuka, President of K.M. Computer Company Inc. (Fukuoka, Japan) for creating a conducive atmosphere to complete this study. The first author would also like to acknowledge the kind assistance of Dr. K. Meguro of The University of Tokyo, regarding data and for valuable discussion with Professor K. Watenabe of Saga University.

REFERENCES

1. Gutenberg, B. and Richter, C.F. "Earthquake magnitude, intensity, energy and acceleration", *BSSA*, **46**, pp 105-195 (1956).

2. Housner, G.W. "Engineering estimates of ground shaking and maximum earthquake magnitude", *Proc. 4th World Conf. Earthquake Eng.*, Santiago, pp 1-13 (1969).

3. Trifunac, M.D. "Preliminary analysis of the peaks of strong earthquake ground motion-dependence of peaks, on earthquake magnitude, epicentral distance, and recording site condition", *BSSA*, **66**, pp 189-219 (1976).

4. Joyner, W.B. and Boore, D.M. "Peak horizontal acceleration and velocity from strong motion records including records from the 1979 Imperial Valley, California earthquake", *BSSA*, **71**, pp 2011-2038 (1981).

5. Campbell, K.W. "Near source attenuation of peak horizontal acceleration", *BSSA*, **71**, pp 2039-2070 (1981).

6. Campbell, K.W. "The dependence of peak horizontal acceleration on magnitude earthquake in California and Eastern North America", *BSSA*, **79**, pp 1311-1346 (1989).

7. Anderson, J.G. and Yutian, L. "Nonparametric description of peak acceleration as a function of magnitude, distance and site in Guerrero, Mexico", *BSSA*, **84**(4), pp 1003-1017 (1994).

8. Kanai, K., Hirano, K., Yoshizawa, S. and Asada, T. "Observation of strong earthquake motion in Matsushiro area", (in Japanese) *Part 1, Bull. ERI, Univ. of Tokyo*, **44**, pp 1269-1296 (1966).

9. Kawashima, K., Aizawa, K. and Takahashi, K. "Attenuation of peak ground acceleration, velocity and displacement based on multiple regression analysis of Japanese strong motion records", *Earthquake Eng. Struc. Dyn.*, **14**, pp 199-215 (1986).

10. Tanaka, T., Fukushima, Y., Sakaue, M. and Yoshizawa, S. "Statistical investigation on peak acceleration data of the strong motion accelerograph records", (in Japanese) *Proc. 7th Japan Earthquake Eng. Symp.*, pp 439-444 (1986).

11. Annaka, T. and Nozawa, Y. "A probabilistic model for seismic hazard estimation in the Kanto district", *Proc. 9th World Conf. on Earthquake Eng.*, Tokyo, Japan, **2**, pp 107-112 (1988).

12. Fukushima, Y. and Tanaka, T. "A new attenuation relation for peak horizontal acceleration of strong earthquake ground motion in Japan", *BSSA*, **80**, pp 757-783 (1990).

13. Iai, S., Matsunga, Y., Morita, T., Sakurata, H. and Mukai, K. "Attenuation of peak ground acceleration in Japan", *Proc. of Int. Workshop on Strong Motion Data*, California, USA, **1**, pp 67-69 (1993).

14. Molas, G.L. and Yamazaki, F. "Attenuation of earthquake ground motion in Japan including deep focus events", *BSSA*, **85**(5), pp 1343-1358 (1995a).

15. Molas, G.L. and Yamazaki, F. "Attenuation of ground motion during the 1995 great Hanshin earthquake", *Bull. ERS*, **28**, pp 25-41 (1995b).

16. Simpson, P.K. "Foundations of neural networks", *Artificial Neural Networks*, E. Sanchez-Sinenco and C. Lau, Eds., IEEE Press, New York, pp 3-24 (1992).

17. Emami, S.M.R., Iwao, Y. and Harada, T. "A method for prediction of peak horizontal acceleration by artificial neural networks", *Proc. 11th World Conf. Earthquake Eng.*, Acapulco, Mexico, Paper No. 1238 (1996).

18. Joyner, W.B. and Boore, D.M. "Methods for regression analysis of strong motion data", *BSSA*, **83**(2), pp 469-487 (1993).

19. Emami, S.M.R., Harada, T. and Iwao, Y. "Prediction of peak horizontal acceleration using an artificial neural network model", *J. of Struc. Mechanics and Earthquake Eng., JSCE*, No 549/I-37, pp 19-26 and *J. Struc. Eng. Earthquake Eng., JSCE*, **13**(2), pp 123s-129s (1996).

20. Rumellhart, D.E., Hinton, G.E. and Williams, R.J. "Learning internal representations by backpropagation errors", *Nature*, **323**, pp 533-536 (1986).

21. McGuire, R.K. "Seismic ground motion parameter relations", *J. Geotech. Eng. Div., ASCE*, **104**, pp 481-490 (1978b).

22. Boore, D.M. and Joyner, W.B. "Prediction of ground motion in North America", *Proc. of Semi. on New Development in Earthquake Ground Motion Estimation and Implication for Eng. Design Practice, ATC 35-1, Applied Technology Council*, USA (1994).

23. Draper, N. and Smith, H., *Applied Regression Analysis*, Second Ed., Wiley, New York (1981).

24. Campbell, K.W. "An empirical assessment of near source strong motion for a 6.6 mb (7.5 Ms) earthquake in the eastern United States", *U.S. Nuclear Regulatory Commission Rept.*, NUREC/CR-3839 (1984a).

25. Lippmann, R.P. "An introduction to computing with neural nets", *IEEE ASSP Magazine*, pp 4-22 (April 1987).

26. Pham, D.T. "Neural networks in engineering", *Proc. 9th Int. Conf. on Artificial Intelligence in Engineering*, Malvern, USA, pp 3-36 (1994)

27. Rumelhart, D. and McClelland, J., *Parallel Distributed Processing: Exploitations in the Micro-Structure of Cognition*, Cambridge, MIT press, **1&2** (1986).

APPENDIX

Multilayer Neural Networks

Neural networks are an information processing system, inspired by the neuronal architecture of the brain. It is composed of a large number of simple processors, called nodes or units, and numerous connections between them.

Multilayer neural network is one of the neural network architectures with feedforward characteristics, consisting of several layers including an input layer and an arbitrary number of intermediate or hidden layers, each containing an arbitrary number of units and an output layer. A typical multilayer neural network with S layers of hidden units is shown in Figure A1. The number of hidden layers and hidden units depends on the problem under consideration, the number of inputs and the size of data set. Multilayer neural networks are widely used for pattern recognition, classification and function approximation and havd been proved to be useful in most engineering applications.

As mentioned, each layer in a neural network consists of a collection of processing units. The unit can be considered as an operator, receiving real numbers as input and transforming them into a single output value. The output from a unit is then transmitted by the link to connect to the next layer units. In a node,

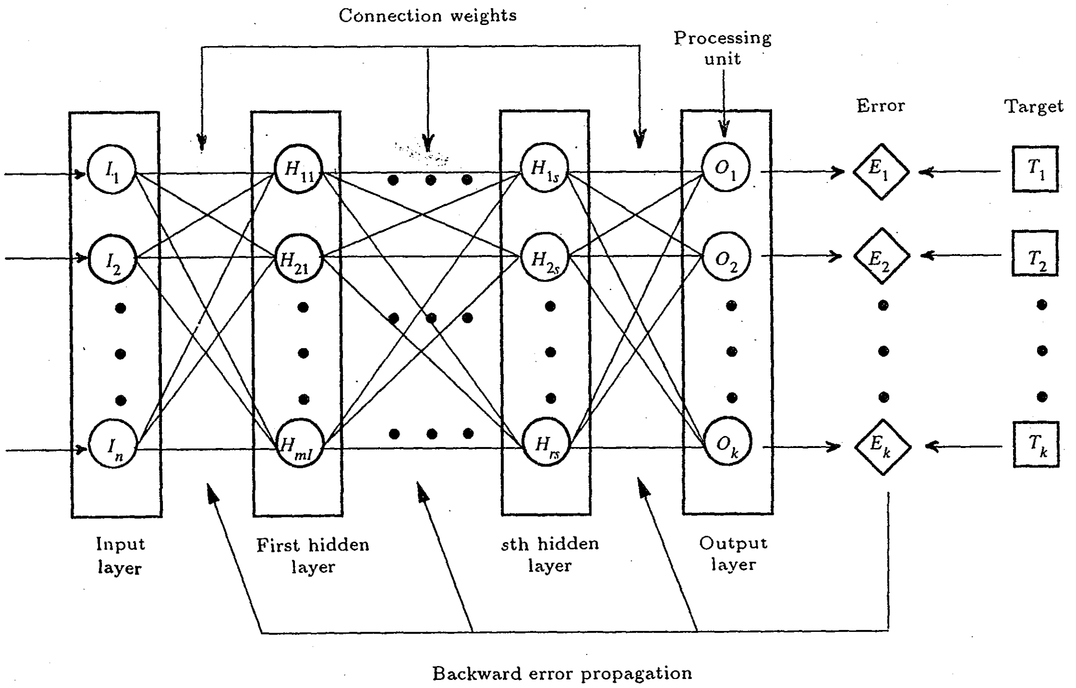

Figure A1. The structure of a typical multilayer neural network with backpropagation error correction.

the values are firstly multiplied and then transformed by the activation function to produce a single output value. A schematic view of an artificial neuron is shown in Figure A2. Several activation functions have been introduced for the multilayer neural networks such as linear, threshold, sigmoid, radial-basis and Gussian functions. Sigmoid is found to be a very effective function for this kind of network. In the network presented here, transformation is done through the squashing sigmoidal function as,

$$N_j = \sum_{i=1}^{n} W_{ji} I_i + \theta_j \ , \tag{A1}$$

$$I_j^{\text{next}} = f(N_j) = \frac{1}{1+\exp(-\alpha N_j)} \ , \tag{A2}$$

where N_j is the weighted sum of the units I of the input from a previous layer with n units; W_{ji}, the weight between units j and i; I_i, the input element from unit I; θ_j, the bias; I_j^{next}, the transformed output from unit j (unit output) which will be an input for the next layer; and α, a constant which defines the steepness of the transfer function. The above description is also related to Figure A2.

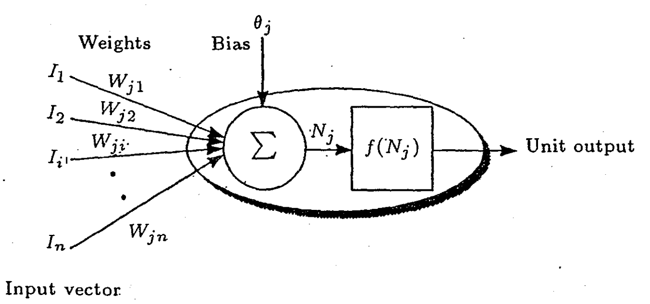

Figure A2. The generic representation of a neural network processor.

The output is transmitted by a link to connect to the other neurons. On each link a real number, the weight, is defined. The weight reflects the strength of the individual connections. Finally, the transformed values from the output layer are compared with the corresponding desired value for error calculation on the basis of the following equation:

$$E(W) = \frac{1}{2}\sum_{p=1}^{q}\sum_{l=1}^{k}(O_l^p - T_l^p). \tag{A3}$$

Let O_l be the output value for the pth pattern and let T_l be the desired or target component of the output pattern for this unit. q and k are the number of samples and units in the output layer, respectively.

The error E depends only on the weights W. Modifying the weight values by repeated application of learning rules permits the network to approximate the function, mapping the input patterns on the desired output patterns. These learning rules determine an initial set of weights and indicate how weights should be adapted during training to optimize error and improve performance. Backpropagation learning algorithm is usually used to train feedforward network. Here, it was utilized in a classic form. The backpropagation learning algorithm uses a least-squares error minimization criterion to minimize the error $E(W)$. This can be accomplished through adjusting the weights according to the negative gradient of the error with respect to the weights:

$$\triangle W = -\eta \frac{\partial E}{\partial W^{\text{old}}} , \tag{A4}$$

$$W^{\text{new}} = W^{\text{old}} + \triangle W . \tag{A5}$$

W is a typical weight which could belong to any layer and is adjusted from its old value W^{old} to the new value W^{new} during an iteration procedure based on the learning rules. The term η is the learning rate which is usually constant during a training. During the training process, here, the value of 0.1 was selected for η. Generally, it depends on the nature of the data set and is defined during a trial and error efforts. Detailed explanation of multilayer neural networks and backpropagation learning algorithm can be found in [25-27].