PERGAMON

Corrosion Science 41 (1999) 2001–2030

CORROSION SCIENCE

Phenomenological modelling of atmospheric corrosion using an artificial neural network

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Received 3 September 1998; accepted 20 January 1999

Abstract

World-wide data for the atmospheric corrosion of steel and zinc were used to train and test neural networks. The cross validity technique was employed as the criterion to stop training. The statistical performance of the neural network was expressed as an average of five training and testing results. Multiple correlation coefficients showed that the neural network could account for about 70% of the variance in the corrosion data for steel and zinc. The testing results showed that predictions of corrosion data not included in the original training were close to practical data. Sensitivity analysis also demonstrated the effects of sulphur dioxide, chloride and exposure time on atmospheric corrosion in specific environments. © 1999 Elsevier Science Ltd. All rights reserved.

Keywords: Atmospheric corrosion; Neural networks; Steel; Zinc; TOW; Sulphur dioxide; Chloride; Temperature; Exposure time

1. Introduction

The atmospheric degradation of materials is of great importance for the durability of structures and causes large economic costs. Unfortunately, it is difficult to model atmospheric corrosion because of the complex interactions between affecting factors. Some workers [1–8] have expressed corrosion damage

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PII: S0010-938X(99)00024-4

and kinetic equations using multiple linear regression techniques. For example, Haynie and Upham [2,3] modelled the effects of sulphur dioxide by this technique. Their results showed that, for steel, there was a relation: $Y = 9.013[e^{0.00161\ SO_2}[(4.768t)^{0.7512-0.00582\ OX}]$, where Y is corrosion depth of carbon steel, SO_2 is sulphur dioxide concentration, t is exposure time and OX is total oxidants; for zinc, $Y = 0.00104(RH-49.4)SO_2-0.00664(RH-76.5)$, where Y is corrosion depth of zinc, SO_2 is concentration of sulphur dioxide and RH is relative humidity. It is still questionable, however, whether these relationships are universally valid in other environments that include additional important factors (such as chloride) or other interactions. Feliu *et al* [1] compiled world-wide data and used the general equation, $C = At^n$, to describe the corrosion process (A is the first year corrosion data, t is exposure years). The linear regression technique was used to estimate A and n in terms of affecting factors. Products of variables (such as time of wetness and sulphur dioxide concentration) were introduced to simulate their interaction and to improve the regression results. Their work obtained the correlation coefficients for n of 0.44 and 0.62 for steel and zinc respectively. However, the approach is still relatively arbitrary and generally too simple to model an essentially non-linear problem.

In contrast, the artificial neural network (ANN) method is excellent for modelling non-linear and complex systems and can interpolate from past experience. It can be seen as a 'super-regression' technique and tends to be fault-tolerant. Given these features, artificial neural network may model atmospheric corrosion processes well.

Some previous applications of ANN in corrosion research [9–11] have been reported. Rosen and Silverman [10] applied the ANN technique for the prediction of different corrosion forms from polarization scans. The trained neural network predicted when crevice, pitting and general corrosion were important. It could give appropriate prediction using scans not included in the original training. Trassatti [11] studied the crevice corrosion of stainless steel and related alloys in a near neutral chloride containing environment by neural network technique. Smets *et al* [9] applied this technique for describing the risk of stress corrosion cracking (SCC) as function of temperature, chloride concentration and oxygen content. The network not only predicted whether SCC occurred or not, it even demarcated a real transition region where the SCC risk gradually increased. Thus, they considered that the neural network outperformed the traditional regression technique. So the aim of this paper is to apply this technique to the phenomenon of atmospheric corrosion.

2. Neural networks

References [12–14] discuss the principle and application of artificial neural network, A neural network is normally composed of 'processing elements' (PEs), which are arranged in connected layers. The PEs combine a number of weighted inputs, modify the sum by a transfer function and then send the result as output either to another set of PEs or out of the network, Fig. 1.

The multilayer perceptron [15] is used in this work. The transfer function is sigmoidal:

$$X_i^s = \frac{1}{(1 + e^{-s_i})}, \tag{1}$$

where

$$S_i = \sum_j w_{ji} x_j^{s-1}.$$

X_i^s is the output of node i in layer s, X_j^{s-1} is the output of node j from layer $s-1$, s_i is the weighted (weights w_{ji}) sum of the inputs to node i.

During training of the neural network, the weights are adjusted to decrease the total error, which is defined by:

$$E = \frac{1}{2} \sum_i \sum_j (y_{ij} - d_{ij})^2, \tag{2}$$

where y_{ij} is the output of the network and d_{ij} the desired response (or target signal).

However, a lower error does not always means a better network. If a network has too many internal degree of freedom compared to the numbers of training points, the network 'memorizes' the training data and does not generalize well. The best test for a network's performance is to apply a data set that it has not yet

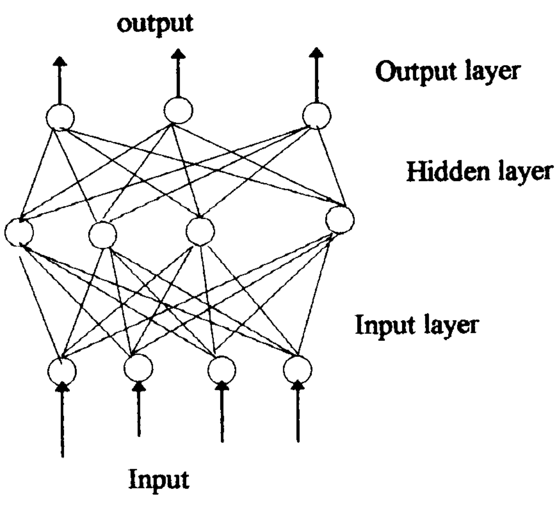

Fig. 1. A simplified three layer neural network.

been used in the training. The test is known as cross validity. As a rule-of-thumb, 10% of the data from the original database are set aside and used as test set for the validation. When the error in the validation set begins to increase, the training is stopped.

The trained neural network also can analyse the effects of variables. When the weights of the network are fixed and one of the inputs dithers (changes a little), then the effect of this input can be observed at the output. This provides a method for the sensitivity analysis of input variables.

The design of the ANN topology is normally left to experimentation and tests should be conducted before the final topology is determined. The normal procedure is to start with a single hidden layer and few PEs and then choose the network which gives acceptable performance and training time. To evaluate the test result, the multiple correlation coefficient [16] (R) and the relative error (e) are used in this study:

$$R = \frac{\sum(\hat{y}_k - \bar{y})(y_k - \bar{y})}{\sqrt{\sum(\hat{y}_k - \bar{y})^2 \sum(y_k - \bar{y})^2}} \tag{3}$$

and

$$e = \frac{1}{N}\sum_k \frac{|y_k - \hat{y}_k|}{y_k}, \tag{4}$$

where $\bar{y}$ is the average of the observed corrosion data y, for example, measured as corrosion depth, $\hat{y}_k$ is the predicted value of the kth y; y_k is the actual value of the kth y and N is the number of y.

3. Database

The data used to train and test the ANN reported here came from the literature of long term exposure tests of steel and zinc. The data are compiled from 42 references which are classified in Table 1 according to the countries from which the data came. In this database, 37 references are the same as those of Feliu *et al* [1].

Variables used include temperature, time of wetness (TOW), exposure time, sulphur dioxide concentration and chloride concentration. Temperature, sulphur dioxide and chloride concentration are annual averages. Some temperature data are available from climatological tables and some time of wetness data are indirectly estimated from rainfall data [17–19]. Many data were discarded because of the absence of full variables. Table 2 lists the range of the corrosion and variables data used in this work.

Table 1
References used to form database to train the neural networks

Country	References
Argentina	[7,29]
Australia	[8]
Brazil	[29,30]
Canada	[5,7,17,31]
Chile	[29]
China	[4]
Colombia	[29]
Costa Rica	[29]
Czechoslovakia	[7,32,33]
Cuba	[29,33]
Ecuador	[29]
France	[7]
Germany	[7]
Hungary	[33]
India	[34–36]
Japan	[7]
Mexico	[29]
New Zealand	[7,37,38]
Norway	[20,21,52]
Panama	[29,39,40]
Peru	[2]
Poland	[41]
Portugal	[29]
Russia	[7,24,33]
Spain	[6,7,25–29]
South Africa	[42]
Sweden	[7,20,52]
Taiwan	[23]
U.K.	[7,46]
Uruguay	[29]
U.S.A	[2,3,7,22,43–50]
Venezuela	[29]
Yugoslavia	[51]

4. Training and testing process

Before the neural network is trained, all the data in the database are scaled to fit within the interval 0–1, which is a fundamental operation prior to training known as data homogenisation. The input variables of temperature, sulphur dioxide and chloride concentration are linearly scaled; the input variables of exposure time and time of wetness are logarithmically scaled. The output variable of corrosion depth is logarithmically scaled. The fundamental characteristics of the ANN used in the present work are listed in Table 3.

The database was divided into three data sets: training set, validation set and test set, containing 81%, 9% and 10% data of database respectively. The

Table 2
Characteristics of the database used to train the neural networks

Materials	Variable	Smallest value	Largest value
Steel	Corrosion depth (μm)	5.0	1804.4
(number of data sets = 406)	Temperature (°C)	−3.03	27.9
	TOW (annual fraction)	0.01	0.95
	SO_2 (μg SO_2 m^{-3})	0	171
	Chloride (mg Cl^- m^{-2} d^{-1})	0	641
	Exposure time (years)	0.5	12
Zinc	Corrosion depth (μm)	0.2	90.8
(number of data sets = 315)	Temperature (°)	−3.03	27.9
	TOW (annula fraction)	0.001	0.95
	SO_2 (μg SO_2 m^{-3})	0	125
	Chloride (mg Cl^- m^{-2} d^{-1})	0	641
	Exposure time (years)	0.5	12

validation set was chosen at random but clustered sets were discarded, for example, the set only containing corrosion data for twelve years was discarded (because of paucity of the corrosion data for twelve years). To evaluate the ANN method, five different training sets, validation sets and test sets were used to get the ANN average performance. The training and validation processes were carried out using commercial software [51].

5. Results and discussion

5.1. Training and test

The trained network was evaluated by the multiple correlation coefficient Eq. (3) and relative error Eq. (4) and results are listed in Tables 4 and 5. Typical predictions for data that was not included in the original training or validation sets, are shown in Figs. 2 and 3.

From Tables 4 and 5, it can be seen that average correlation coefficients for

Table 3
Features of neural networks in our study

Description of ANN	Features
No. of neurons in input layer	5
No. of neurons in output layer	1
No. of neurons in hidden layer	8
Stop criterion	Cross validity
Transfer function	Sigmoid
Minimisation algorithm	Gradient

Table 4
ANN performance for steel

	Average error (e)	Correlation coefficient (R)
Testing set 1	51%	0.80
Testing set 2	32%	0.70
Testing set 3	42%	0.71
Testing set 4	43%	0.72
Testing set 5	37%	0.81
Average	39%	0.74

steel and zinc are 0.74 and 0.78 respectively. Statistically speaking, the ANN models can account for more than 70% of the variance of the atmospheric corrosion of steel and zinc. These results are better than those of Feliu *et al* [1]. Figs. 2 and 3 demonstrate the predicted data from ANN and the actual corrosion data. The larger errors at high corrosion data possibly derive from the paucity of very long-term corrosion data sets, which would degrade the correlation coefficient. Thus, it is not suitable to predict very long-term corrosion by our neural networks.

5.2. Sensitivity analysis

In industrial environments, TOW and sulphur dioxide have significant effects on atmospheric corrosion. Sensitivity analysis conducted on the trained neural network shows the effects of time of wetness and sulphur dioxide in Figs 4–7. In these figures, the neural network separates the effects of sulphur dioxide or TOW from those of other variables and simulates the effects of each individual factor. These figures show that, in the specified condition, the relation between TOW, sulphur dioxide concentration and atmospheric corrosion of steel is almost linear, but, interestingly, the sensitivity of corrosion of zinc to these variables is more complex. For example, the corrosion rates of zinc slow at high TOW; maybe this confirms that moisture inhibits corrosion of zinc [2] because of the formation of protective carbonate films. Also, the zinc corrosion rate increases significantly at high sulphur dioxide concentrations. This could reflect the known change of

Table 5
ANN performance for zinc

	Average error (e)	Correlation coefficient (R)
testing set 1	45%	0.91
testing set 2	58%	0.56
testing set 3	52%	0.78
testing set 4	60%	0.81
testing set 5	52%	0.86
average	53%	0.78

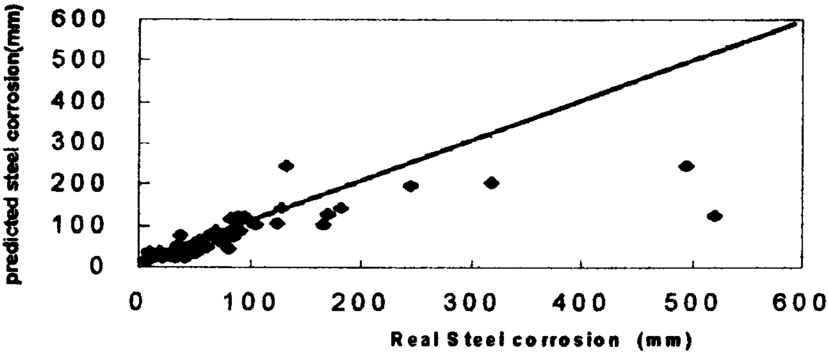

Fig. 2. Results of test set 4 for steel.

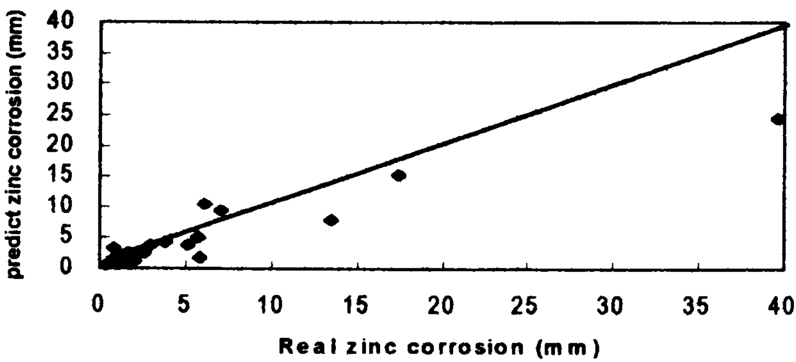

Fig. 3. Results of test set 1 for zinc.

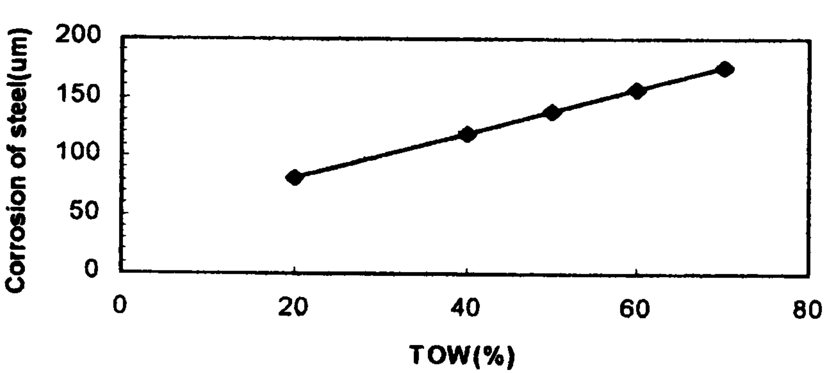

Fig. 4. Effect of TOW on steel (T = 20°C, $SO_2 = 120\ \mu g/m^3$, $Cl^- = 1.5$ mg/day/m^2, Exposure = two years).

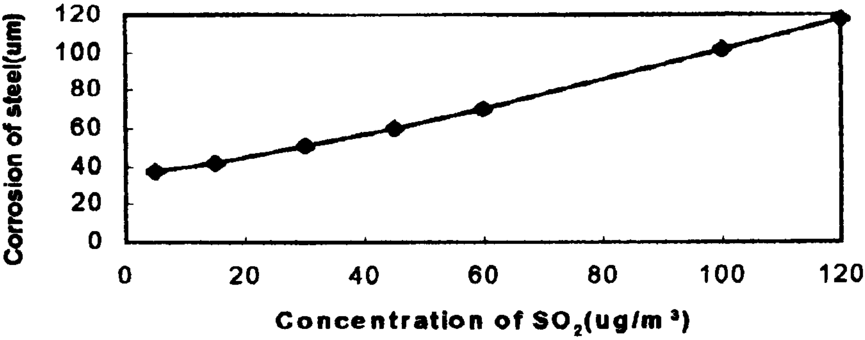

Fig. 5. Effect of SO_2 on steel (T = 20°C, TOW = 40%, Cl^- = 1.5 mg/day/m^2, Exposure = two years).

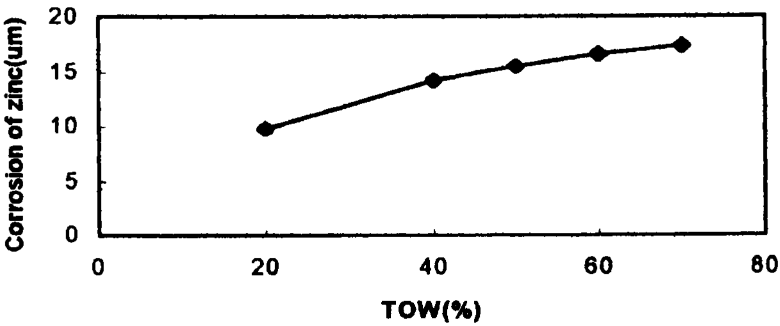

Fig. 6. Effect of TOW on zinc (T = 20°C, SO_2 = 120 μg/m^3, Cl^- = 1.5 mg/day/m^2, Exposure = two years).

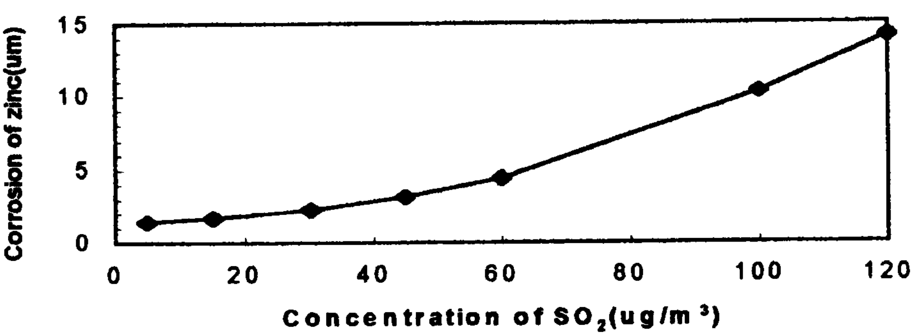

Fig. 7. Effect of SO_2 on zinc (T = 20°C, TOW = 40%, Cl^- = 1.5 mg/day/m^2, Exposure = two years).

corrosion product, for example, from sparingly soluble basic sulphates to soluble sulphates. In the kinetic equation, $C=At^n$, the value of n expresses the trend of long term corrosion. When the corrosion is controlled by diffusion through the corrosion product, the value of n is 0.5. In Figs 8 and 9, the values of n is 0.63 and 0.55 for steel and zinc respectively. This suggests that the corrosion products act as a form of diffusion barrier. Thus, sensitivity analysis can demonstrate the effect of variables and suggest possible mechanisms or future research direction.

5.3. Errors and variations

There are still considerable unexplained variances in the neural network prediction. Such unexplained variances are mainly attributable to two reasons: ignorance of other important affecting variables and inherent scatter in the data.

There are many possible affecting variables that have not been used in our analysis. For example, it is questionable whether the atmospheric corrosion at a given location depends on the annual averages of the environmental variables. Effects of microclimate may play a more important role in atmospheric corrosion. Although SO_2 and chloride are the most important aggressive pollutants, other pollutants, including dust, nitrogen oxides, ozone and hydrogen peroxide sometimes have a great effect on atmospheric corrosion [53–55].

The inherent scatter in the corrosion data also comes from a number of sources [17]. Different ways of measurement or estimation of data will cause errors. Some TOW in our database were estimated from climatological references, some were measured by monitor directly and some estimated from the RH. Chloride or sulphur dioxide was measured by a variety of methods and expressed in different units.

Nevertheless, the neural network has a strong capability of fault-tolerance and it is expected that the modelling capability of the neural network will increase with the consideration of more affecting factors and the availability of more accurate data.

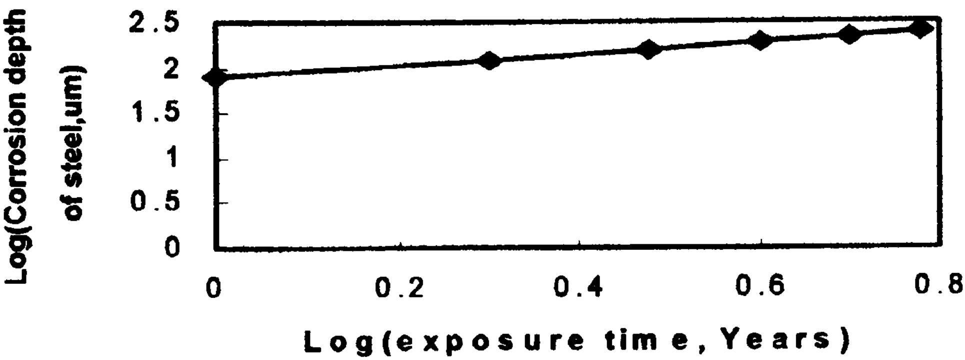

Fig. 8. Effect of exposure time on steel (T = 20°C, SO_2 = 120 μg/m^3, TOW = 40%, Cl^- = 1.5 mg/day (T = 20°C/m^2).

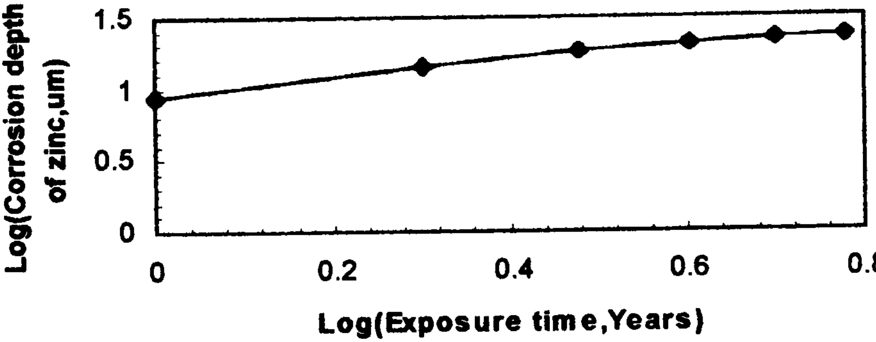

Fig. 9. Effect of exposure time on zinc (T = 20°C, SO_2 = 120 μg/m^3, TOW = 40%, Cl^- = 1.5 mg/day/m^2).

6. Conclusion

1. The application of an artificial neural network for modelling atmospheric corrosion is promising. In our work, the artificial neural network accounts for about 70% of the variance of the atmospheric corrosion of steel and zinc. This result is better than that of the previous linear regression studies.
2. Sensitivity analysis is a useful technique to demonstrate the effects of affecting variables and suggest corrosion mechanism.

Acknowledgements

The first author acknowledges financial support from the overseas research students award scheme, London, England.

Appendix A

Database of steel for ANN

Temperature (°C)	TOW (%)	SO_2 concentration (μg/m^3)	Cl^- concentration (mg/m^2/day)	Exposure year (years)	Corrosion of Fe (mm)
11.96	0.29	25*	4	1	34.2
11.82	0.29	25*	4	2	41.8
11.82	0.29	25*	4	4	59.2
11.82	0.29	25*	4	8	88.7

12.12	0.46	140*	14	1	95.1
12.12	0.46	140*	14	2	128.7
12.12	0.46	140*	14	4	200.3
12.12	0.46	140*	14	8	346.3
16.97	0.48	31*	1.4	1	50.8
16.97	0.48	31*	1.4	2	61.6
16.97	0.48	31*	1.4	4	69.7
16.97	0.48	31*	1.4	8	95.1
17.88	0.66	81*	0.8	1	92.9
17.88	0.66	81*	0.8	2	166.1
17.88	0.66	81*	0.8	4	200.3
17.88	0.66	81*	0.8	8	306.9
22.73	0.54	15*	0.9	1	60.4
22.73	0.54	15*	0.9	2	86.7
22.73	0.54	15*	0.9	4	128.7
22.73	0.54	15*	0.9	8	176.5
24.24	0.71	0*	5	1	31.1
24.24	0.71	0*	5	2	53.8
24.24	0.71	0*	5	4	156.6
24.24	0.71	0*	5	8	520.3
23.94	0.69	0*	13	1	50.8
23.94	0.69	0*	13	2	118.9
23.94	0.69	0*	13	4	547.1
23.94	0.69	0*	13	8	1804.4
1.21	0.18	5	0.3	1	6.0
5.15	0.39	5	0.7	1	17.0
6.37	0.33	32	2	1	35.9
7.28	0.37	5	89	1	66.8
7.28	0.37	5	38	1	33.7
6.97	0.42	16	12	1	34.8
4.85	0.36	20	3	1	38.4
4.85	0.47	10	15	1	35.9
4.55	0.36	15	2	1	29.7
4.85	0.37	3	2	1	17.9
3.94	0.36	15	1	1	30.7
6.06	0.31	85	6	1	81.0
6.06	0.31	30	5	1	34.8
5.76	0.33	5	10	1	15.0
3.94	0.4	4	5	1	17.0
4.25	0.35	8	1	1	17.9
6.37	0.35	7	29	1	49.0
6.06	0.35	6	641	1	86.7
7.28	0.46	22	22	1	41.1
6.67	0.46	3	31	1	23.8
6.97	0.46	3	17	1	34.8

6.67	0.46	8	58	1	28.0
7.28	0.46	4	10	1	24.9
7.28	0.46	4	17	1	28.0
7.28	0.46	22	22	1	34.2
1.21	0.18	5	0.3	2	8.0
5.15	0.39	5	0.7	2	26.0
6.37	0.33	32	2	2	55.9
7.28	0.37	5	89	2	81.0
7.28	0.37	5	38	2	44.0
6.97	0.42	16	12	2	53.8
4.85	0.36	20	3	2	62.9
4.85	0.47	10	15	2	77.5
4.55	0.36	15	2	2	52.8
4.85	0.37	3	2	2	34.2
3.94	0.36	15	1	2	53.8
6.06	0.31	85	6	2	135.9
6.06	0.31	30	5	2	57.0
5.76	0.33	5	10	2	19.9
3.94	0.4	4	5	2	28.0
4.25	0.35	8	1.19	2	28.0
6.37	0.35	7	29	2	60.4
6.06	0.35	6	641	2	132.3
7.28	0.46	22	22	2	52.8
6.67	0.46	3	31	2	32.1
6.97	0.46	3	17	2	39.7
6.67	0.46	8	58	2	35.9
7.28	0.46	4	10	2	33.7
7.28	0.46	4	17	2	38.4
7.28	0.46	22	22	2	46.4
1.21	0.18	5	0.3	4	16.8
5.15	0.39	5	0.7	4	41.8
6.37	0.33	32	2	4	86.7
7.28	0.37	5	89	4	99.8
7.28	0.37	5	38	4	66.8
6.97	0.42	16	12	4	90.8
4.85	0.36	20	3	4	99.8
4.85	0.47	10	15	4	122.1
4.55	0.36	15	2	4	86.7
4.85	0.37	3	2	4	49.9
3.94	0.36	15	1	4	88.7
6.06	0.31	85	6	4	228.9
6.06	0.31	30	4.6	4	88.7
5.76	0.33	5	10	4	26.0
3.94	0.4	4	5	4	48.1
4.25	0.35	8	1	4	44.8

6.37	0.35	7	29	4	99.8
6.06	0.35	6	641	4	156.6
7.28	0.46	22	22	4	84.7
6.67	0.46	3	31	4	50.8
6.97	0.46	3	17	4	65.5
6.67	0.46	8	58	4	55.9
7.28	0.46	4	10	4	55.9
7.28	0.46	4	17	4	54.8
7.28	0.46	22	22	4	74.2
1.21	0.18	5	0.3	8	30.2
5.15	0.39	5	0.7	8	55.9
6.37	0.33	32	2	8	107.4
7.28	0.37	5	89	8	176.5
7.28	0.37	5	38	8	104.8
6.97	0.42	16	12	8	125.3
4.85	0.36	20	3	8	115.9
4.85	0.47	10	15	8	200.3
4.55	0.36	15	2	8	88.7
4.85	0.37	3	2	8	62.9
3.94	0.36	15	1	8	107.4
6.06	0.31	85	6	8	346.3
6.06	0.31	30	4.6	8	107.4
5.76	0.33	5	10	8	37.1
3.94	0.4	4	5	8	69.7
4.25	0.35	8	1	8	64.1
6.37	0.35	7	29	8	135.9
6.06	0.35	6	641	8	206.9
7.28	0.46	22	22	8	132.3
6.67	0.46	3	31	8	82.8
6.97	0.46	3	17	8	128.7
6.67	0.46	8	58	8	88.7
7.28	0.46	4	10	8	88.7
7.28	0.46	22	22	8	125.3
6.06	0.38	79	6	1	69.7
6.06	0.38	79	6	2	110.1
6.06	0.38	79	6	3	147.8
6.06	0.38	79	6	4	182.1
6.06	0.38	25	7	1	35.9
6.06	0.38	25	7	2	55.9
6.06	0.38	25	7	3	71.1
6.06	0.38	25	7	4	88.7
3.94	0.26	8	0	1	18.2
3.94	0.26	8	0	2	29.3
3.94	0.26	8	0	3	39.0
3.94	0.26	8	0	4	47.3

5.76	0.4	6	13	1	16.6
5.76	0.4	6	13	2	19.9
5.76	0.4	6	13	3	23.5
5.76	0.4	6	13	4	27.6
6.37	0.38	8	5	1	21.0
6.37	0.38	8	5	2	33.7
6.37	0.38	8	5	3	41.1
6.37	0.38	8	5	4	53.8
6.97	0.36	2	15	1	35.9
6.97	0.36	2	15	2	44.8
6.97	0.36	2	15	4	64.1
6.97	0.36	2	15	6	77.5
7.58	0.43	35	27	1	30.7
7.58	0.43	35	27	2	45.6
7.58	0.43	35	27	4	66.8
7.58	0.43	35	27	5	77.5
7.58	0.43	35	27	6	82.8
7.58	0.43	35	27	8	97.4
6.06	0.43	35	46	1	44.8
6.06	0.43	35	46	2	64.1
6.06	0.43	35	46	4	99.8
6.06	0.43	35	46	6	125.3
6.06	0.43	35	46	8	147.8
6.06	0.43	21	46	1	36.5
6.06	0.43	21	46	2	54.8
6.06	0.43	21	46	4	81.0
6.06	0.43	21	46	6	99.8
6.06	0.43	21	46	8	113.0
7.58	0.43	20	22	1	32.1
7.58	0.43	20	22	2	52.8
7.58	0.43	20	22	4	79.2
7.58	0.43	20	22	5	90.8
7.58	0.43	20	22	6	99.8
7.58	0.43	20	22	8	113.0
6.67	0.37	8	57	1	21.3
6.67	0.37	8	57	2	54.8
6.67	0.37	8	57	4	81.0
6.67	0.37	8	57	6	99.8
6.67	0.37	8	57	8	113.0
7.58	0.37	4	14	1	20.5
7.58	0.37	4	14	2	33.1
7.58	0.37	4	14	4	51.8
7.58	0.37	4	16	1	21.3
7.58	0.37	4	16	2	31.1
7.58	0.37	4	16	3	44.0

7.58	0.37	4	16	4	50.8
6.67	0.37	3	30	1	21.6
6.67	0.37	3	30	2	33.1
6.67	0.37	3	30	4	50.8
6.67	0.37	3	30	6	64.1
6.67	0.37	3	30	8	75.8
19.09	0.5	0	129	1	40.4
17.88	0.49	0	116	1	32.6
17.58	0.45	0	148	1	37.7
17.27	0.47	0	194	1	35.3
17.88	0.5	0	245	1	43.2
26.67	0.82*	0*	520	1	376.7
24.24	0.49*	56*	22	1	42.5
24.24	0.49*	56*	22	2	64.1
24.24	0.49*	56*	22	4	88.7
24.24	0.49*	56*	22	8	139.7
24.24	0.49*	83*	18	1	50.8
24.24	0.49*	83*	18	2	86.7
24.24	0.49*	83*	18	4	143.7
24.24	0.49*	83*	18	8	245.4
5.15	0.37	116	0.62	0.5	21.0
5.15	0.37	116	0.62	1	30.2
5.15	0.37	116	0.62	2	44.8
5.15	0.37	116	0.62	5	55.9
5.15	0.37	116	0.62	8	61.6
3.64	0.6	17	0.16	0.5	9.2
3.64	0.6	17	0.16	1	17.7
3.64	0.6	17	0.16	2	36.5
3.64	0.6	17	0.16	5	72.7
3.64	0.6	17	0.16	8	95.1
14.55	0.52	25	3	0.5	15.2
14.55	0.52	25	3	1	26.8
14.55	0.52	25	3	2	42.5
14.55	0.52	25	3	5	55.9
14.55	0.52	25	3	8	82.8
17.88	0.15	0	0	1	16.0
18.18	0.16	0	0	1	13.7
14.85	0.24	0	0	1	11.1
14.85	0.32	0	0	1	11.9
17.27	0.27	0	0	1	11.3
18.18	0.29	0	0	1	11.1
13.03	0.52	0	0	1	36.5
13.64	0.49	0	0	1	32.6
12.12	0.56	0	0	1	37.1
12.43	0.57	0	0	1	38.4

13.34	0.42	0	0	1	23.2
13.03	0.49	0	0	1	21.3
10.91	0.59	0	0	1	26.4
11.21	0.58	0	0	1	25.2
15.15	0.33	0	0	1	10.4
15.76	0.4	0	0	1	11.9
14.55	0.32	0	0	1	8.7
14.85	0.31	0	0	1	10.8
10.00	0.29	0	0	1	7.8
10.31	0.28	0	0	1	10.7
12.73	0.4	0	0	1	9.7
13.64	0.31	0	0	1	9.5
13.34	0.16	26*	31	1	29.7
13.34	0.16	171*	31	1	64.1
13.34	0.16	6*	2	1	25.6
13.34	0.16	65*	31	1	33.7
13.34	0.45	26*	31	1	27.6
13.34	0.16	65*	182	1	54.8
13.34	0.16	6*	26	1	29.7
13.34	0.16	26*	182	1	48.1
13.34	0.16	26*	2	1	22.2
13.34	0.16	26*	31	2	49.0
13.34	0.16	171*	31	2	84.7
13.34	0.16	6*	2	2	41.8
13.34	0.16	65*	31	2	52.8
13.34	0.45	26*	31	2	42.5
13.34	0.16	65*	182	2	79.2
13.34	0.16	6*	26	2	44.0
13.34	0.16	26*	182	2	81.0
13.34	0.16	26*	2	2	31.1
13.34	0.16	26*	31	3	58.1
13.34	0.16	171*	31	3	88.7
13.34	0.16	6*	2	3	38.4
13.34	0.16	65*	31	3	55.9
13.34	0.45	26*	31	3	36.5
13.34	0.16	65*	182	3	88.7
13.34	0.16	6*	26	3	53.8
13.34	0.16	26*	182	3	95.1
13.34	0.16	26*	2	3	35.9
16.06	0.37	68*	27	1	59.2
13.34	0.24	64*	0	1	41.8
13.34	0.45	11*	0	1	8.0
16.97*	0.59	28*	152	1	49.9
12.43*	0.39	110*	55	1	69.7
13.34*	0.24	55*	0	1	34.8

12.43*	0.58	125*	125	1	95.1
12.43*	0.49	17*	31	1	30.2
16.97*	0.47	42*	29	1	39.7
16.06*	0.37	68*	27	2	84.7
13.34*	0.24	64*	0	2	60.4
13.34*	0.45	11*	0	2	12.0
16.97*	0.59	28*	152	2	88.7
12.43*	0.39	110*	55	2	118.9
13.34*	0.24	55*	0	2	60.4
12.43*	0.58	125*	125	2	152.1
12.43*	0.49	17*	31	2	44.8
16.97*	0.47	42*	29	2	61.6
16.06*	0.37	68*	27	3	107.4
13.34*	0.24	64*	0	3	74.2
13.34*	0.45	11*	0	3	19.9
16.97*	0.59	28*	152	3	99.8
12.43*	0.39	110*	55	3	152.1
13.34*	0.24	55*	0	3	64.1
12.43*	0.58	125*	125	3	228.9
12.43*	0.49	17*	31	3	49.9
16.97*	0.47	42*	29	3	79.2
16.06*	0.37	68*	27	4	128.7
13.34*	0.24	64*	0	4	84.7
13.34*	0.45	11*	0	4	21.9
12.43*	0.39	110	55	4	200.3
13.34*	0.24	55*	0	4	79.2
12.43*	0.49	17*	31	4	54.8
16.97*	0.47	42*	29	4	95.1
16.06*	0.37	68*	27	5	171.2
13.34*	0.45	11*	0	5	28.0
16.97*	0.59	28*	152	5	206.9
12.43*	0.39	110*	55	5	254.4
13.34*	0.24	55*	0	5	90.8
12.43*	0.58	125*	125	5	376.7
12.43*	0.49	17*	31	5	79.2
16.97*	0.47	42*	29	5	104.8
16.06*	0.37	68*	27	6	182.1
12.43*	0.39	110*	55	6	319.3
12.43*	0.58	125*	125	6	393.4
12.43*	0.49	17*	31	6	84.7
16.06*	0.37	68*	27	8	221.2
12.43*	0.39	110*	55	8	411.1
12.43*	0.58	125*	125	8	495.3
12.43*	0.49	17*	31	8	95.1
16.97*	0.47	42*	29	8	161.3

16.06*	0.37	68*	27	10	254.4
12.43*	0.39	110*	55	10	495.3
12.43*	0.58	125*	125	10	547.1
12.43*	0.49	17*	31	10	118.9
16.97*	0.47	42*	29	10	171.2
16.06*	0.37	68*	27	12	306.9
12.43*	0.39	110*	55	12	607.2
12.43*	0.49	17*	31	12	139.7
5.76*	0.15	16	59	1	23.2
6.37*	0.41	19	4	1	33.1
9.40*	0.69	24	171	1	99.8
14.24*	0.65	8	67	1	43.2
14.24*	0.25	15	4	1	39.7
6.06*	0.3	14	2	1	25.2
6.37*	0.38	44	8	1	61.6
8.18*	0.51	9	7	1	19.7
16.97*	0.32	49	21	1	26.8
17.88*	0.49	10	182	1	37.7
26.67*	0.87	52	607	1	376.7
0.31*	0.37	5	20	1	30.7
13.34*	0.37	26	1	1	30.7
4.55*	0.45	28	18	1	26.0
13.94	0.7	0*	49	1	49.9
16.97	0.5	0*	10	1	14.9
23.03	0.65	0*	0	1	7.9
20.00	0.1	0*	0	1	7.9
-3.03	0.28	0*	40	1	39.7
16.97	0.6	5*	0	1	30.2
22.12	0.59	20*	5	1	9.9
23.03	0.6	23*	8	1	49.9
24.85	0.6	5*	237	1	171.2
23.03	0.6	50*	8	1	161.3
22.12	0.6	3*	182	1	221.2
20.00	0.65	30*	0	1	19.9
22.12	0.6	3*	15	1	99.8
26.06	0.7	0*	0	1	19.9
20.91	0.45	0*	0	1	19.9
26.97	0.95	10*	55	1	39.7
13.03	0.8	0*	0	1	19.9
26.06	0.55	0*	0	1	30.2
26.97	0.58	5*	50	1	79.2
24.85	0.81	4*	140	1	376.7
23.03	0.82	8*	25	1	90.8
19.09	0.71	3*	20	1	19.9
26.06	0.49	18*	18	1	39.7

26.06	0.49	9*	125	1	346.3
23.94	0.59	3*	18	1	30.2
14.85	0.31	23*	20	1	39.7
13.94	0.78	22*	20	1	39.7
12.12	0.7	85*	25	1	182.1
2.12	0.25	4*	25	1	30.2
26.06	0.58	5*	0	1	19.9
10.91	0.29	18*	0	1	19.9
13.03	0.41	5*	8	1	9.9
16.06	0.19	18*	8	1	19.9
17.88	0.31	5*	0	1	24.9
16.06	0.2	5*	0	1	9.9
16.97	0.32	40*	25	1	24.9
13.03	0.41	4*	20	1	19.9
7.88	0.1	10*	5	1	5.0
16.06	0.25	15*	0	1	9.9
23.03	0.2	9*	0	1	13.0
17.88	0.19	20*	0	1	39.7
27.88	0.6	10*	35	1	30.2
26.97	0.6	23*	8	1	34.8
26.97	0.65	50*	12	1	110.1
26.97	0.6	20*	15	1	19.9
26.97	0.59	10*	10	1	24.9
23.94	0.3	0*	0	1	19.9
13.64	0.85	22*	45	1	39.7
19.09	0.8	30*	20	1	30.2
16.06	0.01	0*	0	1	19.9
12.12	0.35	0*	0	1	5.0
26.06	0.5	0*	0	1	19.9
16.97	0.35	70*	100	1	90.8
17.88	0.5	30*	200	1	376.7
16.97	0.4	10*	8	1	30.2
16.97	0.6	2*	8	1	10.0
16.97	0.5	2*	8	1	10.0
16.97	0.69	2*	9	1	49.9
2.12	0.4	19*	5	1	19.9
26.97	0.45	0*	0	1	69.7
26.97	0.52	8*	55	1	39.7
26.06	0.55	3*	38	1	30.2
26.97	0.45	10*	20	1	30.2
24.85	0.55	2*	25	1	59.2
26.06	0.6	2*	23	1	39.7
11.96	0.427	27*	36	3	84.1

* Estimated or converted value.

Appendix B

One of the sets of weights of ANN for steel

1. Weights between nodes of input layer and nodes of hidden layer

-0.57777	1.140111	-3.54036	-1.24392	-1.89332
-1.11068	3.394332	-6.71652	-4.88921	-1.77891
0.040114	-0.02346	-1.1538	0.101141	-0.09404
1.211222	-2.23737	6.29048	4.483582	1.812292
0.368515	-2.63031	4.351193	0.095261	2.020031
0.14778	1.18903	-2.00757	-0.09262	-0.93955
0.996577	-3.51733	5.180875	2.768956	2.011905
-1.11434	2.51425	-5.90903	-3.75693	-1.84378

2. Weights between nodes of output layer and nodes of hidden layer

−0.26685	-0.56979	-0.05243	0.48512	0.314396	-0.1361	0.420847	-0.4527

Appendix C

Database of zinc for ANN

Temperature (°C)	TOW (%)	SO_2 concentration ($\mu g/m^3$)	Cl^- concentration ($mg/m^2/day$)	Exposure time (years)	Corrosion of Zn (mm)
1.21	0.18	5	0.3	1	0.8
5.15	0.39	5	0.7	1	0.7
6.37	0.33	32	2	1	0.9
7.28	0.37	5	89	1	1.9
7.28	0.37	5	38	1	1.1
6.97	0.42	16	12	1	1.3
4.85	0.36	20	3	1	1.1
4.85	0.47	10	15	1	1.2
4.55	0.36	15	2	1	1.8
4.85	0.37	3	2	1	0.7
3.94	0.36	15	1	1	1.1
6.06	0.31	85	6	1	3.7

6.06	0.31	30	5	1	1.4
5.76	0.33	5	10	1	0.4
3.94	0.4	4	5	1	0.8
4.25	0.35	8	1	1	0.6
6.37	0.35	7	29	1	1.6
6.06	0.35	6	641	1	2.1
7.28	0.46	22	22	1	1.6
6.67	0.46	3	31	1	1.8
6.97	0.46	3	17	1	0.7
6.67	0.46	8	58	1	2.0
7.28	0.46	4	10	1	1.3
7.28	0.46	4	17	1	1.1
7.28	0.46	22	22	1	2.3
1.21	0.18	5	0.3	2	0.9
5.15	0.39	5	0.7	2	1.5
6.37	0.33	32	2	2	2.1
7.28	0.37	5	89	2	2.4
7.28	0.37	5	38	2	2.0
6.97	0.42	16	12	2	3.1
4.85	0.36	20	3	2	2.5
4.85	0.47	10	15	2	2.5
4.55	0.36	15	2	2	3.4
4.85	0.37	3	2	2	1.7
3.94	0.36	15	1	2	2.5
6.06	0.31	85	6	2	7.0
6.06	0.31	30	5	2	2.3
5.76	0.33	5	10	2	0.4
3.94	0.4	4	5	2	1.6
4.25	0.35	8	1	2	1.3
6.37	0.35	7	29	2	2.8
6.06	0.35	6	641	2	3.2
7.28	0.46	22	22	2	2.8
6.67	0.46	3	31	2	2.9
6.97	0.46	3	17	2	1.3
6.67	0.46	8	58	2	2.6
7.28	0.46	4	10	2	2.5
7.28	0.46	4	17	2	2.4
7.28	0.46	22	22	2	3.8
1.21	0.18	5	0.3	4	1.4
5.15	0.39	5	0.7	4	2.1
6.37	0.33	32	2	4	4.2
7.28	0.37	5	89	4	5.0
7.28	0.37	5	38	4	4.5
6.97	0.42	16	12	4	5.9
4.85	0.36	20	3	4	4.0

4.85	0.47	10	15	4	3.8
4.55	0.36	15	2	4	5.9
4.85	0.37	3	2	4	2.6
3.94	0.36	15	1	4	4.1
6.06	0.31	85	6	4	15.0
6.06	0.31	30	5	4	4.8
5.76	0.33	5	10	4	0.9
3.94	0.4	4	5	4	2.6
4.25	0.35	8	1	4	2.2
6.37	0.35	7	29	4	6.4
6.06	0.35	6	641	4	7.6
7.28	0.46	22	22	4	5.7
6.67	0.46	3	31	4	4.8
6.97	0.46	3	17	4	2.8
6.67	0.46	8	58	4	4.1
7.28	0.46	4	10	4	3.2
7.28	0.46	4	17	4	3.8
7.28	0.46	22	22	4	7.6
6.06	0.38	79	6	1	5.0
6.06	0.38	79	6	2	9.9
6.06	0.38	79	6	3	15.6
6.06	0.38	79	6	4	17.5
6.06	0.38	25	7	1	1.8
6.06	0.38	25	7	2	2.4
6.06	0.38	25	7	3	3.3
6.06	0.38	25	7	4	5.1
3.94	0.26	8	0	1	0.9
3.94	0.26	8	0	2	1.2
3.94	0.26	8	0	3	1.7
3.94	0.26	8	0	4	2.2
5.76	0.4	6	13	1	0.4
5.76	0.4	6	13	2	0.6
5.76	0.4	6	13	3	0.7
5.76	0.4	6	13	4	0.8
6.37	0.38	8	5	1	0.8
6.37	0.38	8	5	2	1.3
6.37	0.38	8	5	3	1.8
6.37	0.38	8	5	4	2.4
5.15	0.53	8	5	1	1.4
5.15	0.53	8	5	2	2.2
5.15	0.53	8	5	5	3.5
6.06	0.43	35	46	1	2.5
6.06	0.43	35	46	2	5.3
6.06	0.43	35	46	4	10.7
6.06	0.43	35	46	5	13.5

6.06	0.43	35	46	6	14.9
6.06	0.43	35	46	8	18.7
6.06	0.43	21	46	1	2.4
6.06	0.43	21	46	2	3.7
6.06	0.43	21	46	4	7.2
6.06	0.43	21	46	5	9.1
6.06	0.43	21	46	6	11.2
6.06	0.43	21	46	8	15.0
7.58	0.37	4	14	1	1.5
7.58	0.37	4	14	2	2.7
7.58	0.37	4	14	4	4.0
7.58	0.37	4	14	5	5.1
7.58	0.37	4	14	6	6.2
7.58	0.37	4	14	8	6.3
7.58	0.37	4	16	1	1.0
7.58	0.37	4	16	2	2.0
7.58	0.37	4	16	3	2.5
7.58	0.37	4	16	4	3.3
19.09	0.5	0	129	1	2.2
17.88	0.49	0	116	1	1.6
17.58	0.45	0	148	1	2.5
17.27	0.47	0	194	1	2.1
17.88	0.5	0	245	1	1.6
18.18	0.51	0	264	1	1.8
17.88	0.46	0	161	2	3.6
18.18	0.48	0	166	4	3.3
27.27	0.83	0	520	1	19.9
26.67	0.82	0	520	1	17.9
5.15	0.37	116	0.62	0.5	1.1
5.15	0.37	116	0.62	1	1.7
5.15	0.37	116	0.62	2	3.2
5.15	0.37	116	0.62	5	7.6
5.15	0.37	116	0.62	8	13.8
3.64	0.6	17	0.16	0.5	1.5
3.64	0.6	17	0.16	1	2.2
3.64	0.6	17	0.16	2	2.5
3.64	0.6	17	0.16	5	4.8
3.64	0.6	17	0.16	8	8.8
14.55	0.52	25	3	0.5	0.6
14.55	0.52	25	3	1	1.2
14.55	0.52	25	3	2	2.5
14.55	0.52	25	3	5	5.1
14.55	0.52	25	3	8	10.6
13.94	0.7	0*	49	1	1.9
16.97	0.5	0*	10	1	1.7

23.03	0.65	0*	0	1	1.9
20.00	0.1	0*	0	1	0.3
-3.03	0.28	0*	40	1	2.0
16.97	0.6	5*	0	1	1.0
22.12	0.59	20*	5	1	0.9
23.03	0.6	23*	8	1	1.2
24.85	0.6	5*	237	1	4.8
23.03	0.6	50*	8	1	1.2
22.12	0.6	3*	182	1	6.5
20.00	0.65	30*	0	1	1.2
22.12	0.6	3*	15	1	1.5
26.06	0.7	0*	0	1	1.2
20.91	0.45	0*	0	1	2.0
26.97	0.95	10*	55	1	6.1
13.03	0.8	0*	0	1	3.9
26.06	0.55	0*	0	1	3.9
26.97	0.58	5*	50	1	1.8
24.85	0.81	4*	140	1	2.9
23.03	0.82	8*	25	1	2.0
19.09	0.71	3*	20	1	0.9
26.06	0.49	18*	18	1	1.0
26.06	0.49	9*	125	1	5.8
23.94	0.59	3*	18	1	1.0
14.85	0.31	23*	20	1	2.0
12.12	0.7	48*	25	1	4.0
12.12	0.7	85*	25	1	7.9
2.12	0.25	4*	25	1	8.1
10.91	0.29	18*	0	1	0.8
13.03	0.41	5*	8	1	0.3
16.06	0.19	18*	8	1	1.0
17.88	0.31	5*	0	1	0.3
16.06	0.2	5*	0	1	0.2
16.97	0.32	40*	25	1	0.8
13.03	0.41	4*	20	1	0.3
7.88	0.1	10*	5	1	0.2
16.06	0.25	15*	0	1	0.8
23.03	0.2	9*	0	1	2.0
17.88	0.19	20*	0	1	2.2
27.88	0.6	10*	35	1	2.2
26.97	0.6	23*	8	1	1.8
23.94	0.3	0*	0	1	2.4
13.64	0.85	22*	45	1	2.6
19.09	0.8	30*	20	1	2.0
16.06	0.01	0*	0	1	0.3
12.12	0.35	0*	0	1	0.8

26.06	0.5	0*	0	1	1.7
16.97	0.35	70*	100	1	2.5
17.88	0.5	30*	200	1	4.2
16.97	0.4	10*	8	1	0.8
16.97	0.6	2*	8	1	0.3
16.97	0.5	2*	8	1	1.8
16.97	0.69	2*	9	1	1.7
2.12	0.4	19*	5	1	3.0
26.97	0.45	0*	0	1	13.7
26.97	0.52	8*	55	1	0.8
26.06	0.55	3*	38	1	0.3
26.97	0.45	10*	20	1	2.2
24.85	0.55	2*	25	1	2.2
26.06	0.6	2*	23	1	4.3
17.88	0.15	0	0	1	0.6
18.18	0.16	0	0	1	0.6
14.85	0.24	0	0	1	0.5
14.85	0.32	0	0	1	0.5
17.27	0.27	0	0	1	0.5
18.18	0.29	0	0	1	0.6
13.03	0.52	0	0	1	2.1
13.64	0.49	0	0	1	1.1
12.12	0.56	0	0	1	2.0
12.43	0.57	0	0	1	1.5
13.34	0.42	0	0	1	1.3
13.03	0.49	0	0	1	0.8
10.91	0.59	0	0	1	1.5
11.21	0.58	0	0	1	0.8
15.15	0.33	0	0	1	1.9
15.76	0.4	0	0	1	1.1
14.55	0.32	0	0	1	1.3
14.85	0.31	0	0	1	1.4
10.00	0.29	0	0	1	1.5
10.31	0.28	0	0	1	1.2
12.73	0.4	0	0	1	1.3
13.64	0.31	0	0	1	0.7
16.06*	0.37	68*	27	1	2.5
13.34*	0.24	64*	0	1	1.5
13.34*	0.45	11*	0	1	0.9
16.97*	0.59	28*	152	1	9.0
12.43*	0.39	110*	55	1	5.2
13.34*	0.24	55*	0	1	1.3
12.43*	0.58	125*	125	1	6.1
12.43*	0.49	17*	31	1	0.9
16.97*	0.47	42*	29	1	1.8

16.06*	0.37	68*	27	2	5.9
13.34*	0.24	64*	0	2	2.5
13.34*	0.45	11*	0	2	1.2
16.97*	0.59	28*	152	2	12.0
12.43*	0.39	110*	55	2	8.0
13.34*	0.24	55*	0	2	2.2
12.43*	0.58	125*	125	2	14.9
12.43*	0.49	17*	31	2	1.5
16.97*	0.47	42*	29	2	3.0
16.06*	0.37	68*	27	3	7.0
13.34*	0.24	64*	0	3	3.6
13.34*	0.45	11*	0	3	1.5
12.43*	0.39	110*	55	3	15.0
13.34*	0.24	55*	0	3	2.5
12.43*	0.58	125*	125	3	17.9
12.43*	0.49	17*	31	3	2.0
16.97**	0.47	42*	29	3	4.0
16.06*	0.37	68*	27	4	9.9
13.34*	0.24	64*	0	4	4.1
13.34*	0.45	11*	0	4	1.9
12.43*	0.39	110*	55	4	17.9
13.34*	0.24	55*	0	4	4.2
12.43*	0.58	125*	125	4	21.9
12.43*	0.49	17*	31	4	2.5
16.06*	0.37	68*	27	5	14.9
13.34*	0.24	64*	0	5	5.0
16.97*	0.59	28*	152	5	24.9
12.43*	0.39	110*	55	5	19.9
13.34*	0.24	55*	0	5	4.9
12.43*	0.58	125*	125	5	22.9
12.43*	0.49	17*	31	5	3.0
16.97*	0.47	42*	29	5	5.5
16.06*	0.37	68*	27	6	18.9
13.34*	0.24	64*	0	6	6.1
16.97*	0.59	28*	152	6	37.7
12.43*	0.39	110*	55	6	24.9
13.34*	0.24	55*	0	6	6.0
12.43*	0.58	125*	125	6	24.9
12.43*	0.49	17*	31	6	3.9
16.97*	0.47	42*	29	6	6.0
16.06*	0.37	68*	27	8	24.9
13.34*	0.24	64*	0	8	7.0
13.34*	0.45	11*	0	8	2.3
12.43*	0.39	110*	55	8	34.8
13.34*	0.24	55*	0	8	7.0

12.43*	0.58	125*	125	8	32.1
12.43*	0.49	17*	31	8	4.5
16.97*	0.47	42*	29	8	7.0
16.06*	0.37	68*	27	10	30.2
13.34*	0.24	64*	0	10	9.0
13.34**	0.45	11*	0	10	2.7
16.97**	0.59	28*	152	10	60.4
12.43*	0.39	110*	55	10	39.7
13.34*	0.24	55*	0	10	10.0
12.43*	0.58	125*	125	10	49.9
16.97*	0.47	42*	29	10	8.5
16.06*	0.37	68*	27	12	39.7
13.34*	0.24	64*	0	12	12.0
13.34*	0.45	11*	0	12	4.0
12.43*	0.39	110*	55	12	59.2
13.34*	0.24	55*	0	12	13.0
12.43*	0.58	125*	125	12	90.8
12.43*	0.49	17	31	12	10.0
5.76*	0.15	16	59	1	1.4
6.37*	0.41	19	4	1	1.3
9.40*	0.69	24	171	1	5.1
14.24*	0.65	8	67	1	1.4
14.24*	0.25	15	4	1	1.5
6.06*	0.3	14	2	1	1.4
6.37*	0.38	44	8	1	3.8
8.18*	0.51	9	7	1	2.3
16.97*	0.32	49	21	1	1.0
17.88*	0.49	10	182	1	2.0
26.67*	0.87	52	607	1	17.5
0.31*	0.37	5	20	1	1.1
13.34*	0.37	26	1	1	1.6
4.55*	0.45	28	18	1	2.3
11.65*	0.42	26	40	3	5.6

* Estimated or converted value.

Appendix D

One of the sets of weights of ANN for zinc

1. Weights between nodes of input layer and nodes of hidden layer.

0.68738	-6.51382	3.265869	4.627529	4.475553
2.17687	3.678443	-2.60406	0.049256	-3.17152

-0.34349	3.842795	-1.43363	-2.31219	-1.50128
0.645004	-4.98806	3.118155	2.035764	3.000088
-1.39647	-2.257	1.904514	1.343381	2.594028
-0.48983	1.791726	-1.59715	0.027514	-0.78773
-2.16151	-2.06532	1.369414	1.871065	1.726695
1.055368	3.820316	-2.79531	-2.64286	-0.82639

2. Weights between nodes of output layer and nodes of hidden layer.

0.547742	-0.6102	-0.36932	1.106768	0.757516	-0.31774	0.546618	0.156878

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