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Prediction of Lead Corrosion Behavior Using Feed-Forward Artificial Neural Network

S. Jalili*, A. Jaberi, M.G. Mahjani and M. Jafarian
Department of Chemistry, K. N. Toosi University of Technology, P.O. Box 16315-1618, Tehran, Iran

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The Feed-Forward Artificial Neural Networks (FFANNs) were used to predict the corrosion behavior of lead. A 3-9-2 network was adopted to train the networks and predict the lead corrosion behavior. The descriptors (input) were obtained using experimental methods. Solution concentration, pH and passive time were selected as the ANN input to predict the corrosion current and potential. To this end 80 samples were selected. The criterion of TSE was 0.004. It was found that the FFANNs could be used to predict the corrosion of lead.

Keywords: Artificial neural networks, Back-propagation, Corrosion, Lead

INTRODUCTION

Corrosion protection is among the most important economic and safety concerns of the industrial world. To control corrosion effectively, the accurate prediction of corrosion behavior is a fundamental requirement [1]. At first glance, this may seem easy, but complex nature of corrosion mechanism does not allow to predict its behaviour, as expected. In recent years, soft computing techniques including artificial neural network (ANN), fuzzy logic (FL), evolutionary computation (EC), machine learning (ML) and probabilistic reasoning (PR) have been used to study different phenomena in complex systems. ANN can be used to predict the corrosion behavior of metals. ANN is a network of many simple processor or neurons, each having a small amount of local memory [2]. The interaction of the neurons in the network is roughly based on the principles of neural science. There are some training rules in ANNs, which are used to train the network based on some problems with or without known answers. In the training algorithm, the weights are being adjusted on the basis of presented patterns of the model system. The ANNs are particularly suitable for problems where pattern recognition is important and precise computational answers are not required. When ANNs input and output contain evolved parameters, their computational precision and extrapolation ability significantly will increase and can even outperform more traditional modelling techniques. ANN architecture is composed of a large number of highly interconnected processing elements that are analogous to neurons and are tied together with weighted connections that are analogous to synapses. Each artificial neuron receives information usually from several sources, as well as the sum of input, and uses a transfer function to produce an output. The multiple layer feed-forward artificial neural network (MLFFANN) with back-propagation training algorithm is the most popular ANN in chemistry [2,3]. The process of training a network consists of adjusting the weights to minimize disagreement between the output of the network and the desired values for a set of training patterns with known and correct output. Some researchers attempted to apply the artificial neural network to predict the corrosion behaviours [1,4-21]. The aim of the present work is to predict the

*Corresponding author. E-mail: sjalili@kntu.ac.ir

corrosion behavior of lead in acidic solutions using feed-forward artificial neural network and multiple linear regressions (MLR).

METHOD

In this work, a feed-forward artificial neural network model with the back-propagation algorithm was developed to predict the corrosion current and potential of lead. Polarization technique and Tafel curves were used to obtain the necessary data for training the networks.

Experimental Data

Electrochemical measurements were carried out using EG&G model 273 potentiostat/galvanostat. The working electrode was made of lead disc with 0.5 cm^2 exposing geometric surface. The potentials were measured against an Ag/AgCl saturated reference electrode with a Pt electrode forming the counter electrode. All measurements were carried out at 298 K. Potential sweep rate was 5 mV s^{-1}. Na_2SO_4 used in this work was a Merck product. Since in corrosion behavior prediction Na_2SO_4 concentration, pH and passive time are independent variables, they can be selected as an ANN input. Corrosion potential (E_{corr}) and corrosion current (I_{corr}) were obtained from Tafel curves (Figure 1a-b) and selected as an output of ANN (Table 1).

Table 1. ANN Input and Output

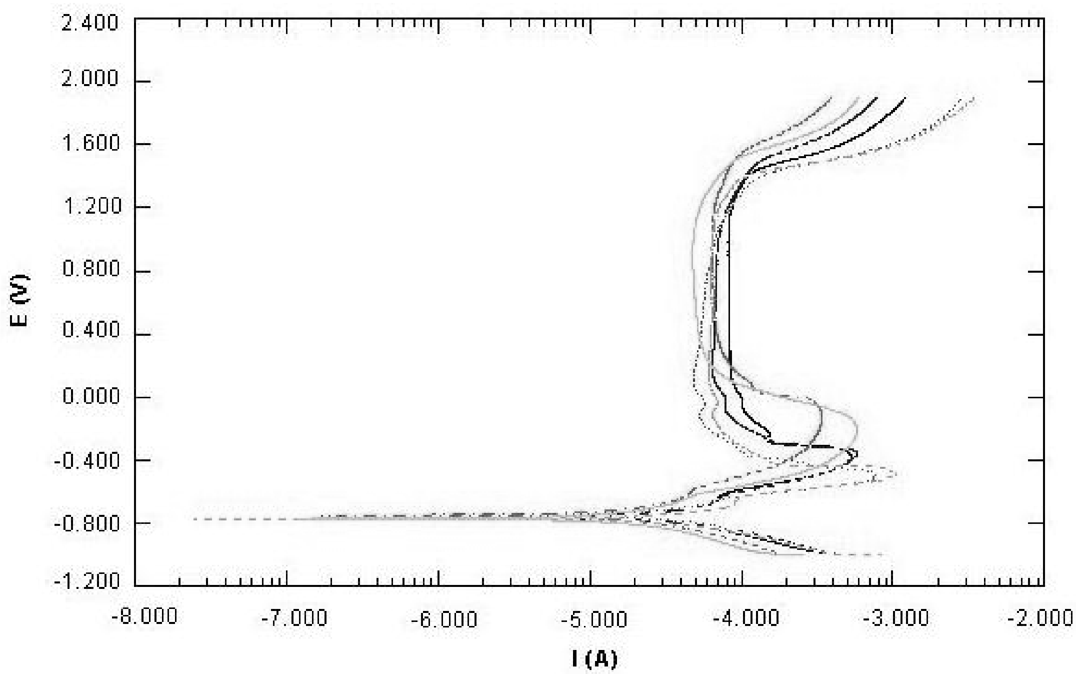
Input	Output
Na_2SO_4 concentration	Corrosion current
pH	
passive time	Corrosion potential

ANN Modeling

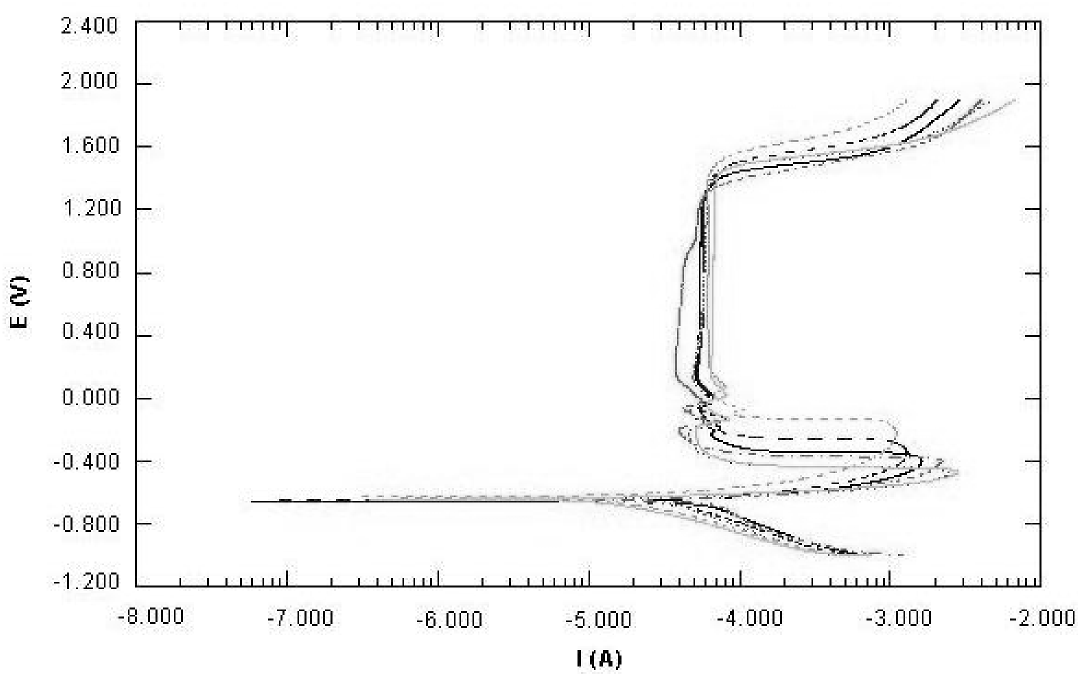
FFANN was applied to predict the corrosion current and potential of lead in Na_2SO_4. To this end, a three-layer feed-forward artificial neural network was designed to predict the corrosion current and potential of lead as a function of Na_2SO_4 concentration (0.1-1 M), pH (acidic and neutral) and passive time (0-10 s). 80 patterns were used to modeling the above-mentioned corrosion behavior. Stuttgart Neural Network Simulator (SNNS) 4.2 was used to obtain the ANN results [22]. All the calculations were performed on a Pentium IV (2 GHz) IBM-compatible machine. During the simulation, the total squared error was used as the criterion of the learning efficiency of the network in the training process. Several trainings with different numbers of hidden units, iterations, learning rate, momentum and transfer function were performed to find the best architecture of the ANN. To optimize the network structure, network pruning method was used. For this purpose the training was started with a network and slowly decreased the hidden units until hidden units degradation ended to a significant error.

RESULTS AND DISCUSSION

The training and testing sets contain 68 and 12 patterns, respectively. In this work, a 3:9:2 neural network was selected after different tests through pruning networks approach. Initial connection weights were randomly selected in the range -1 to 1. To improve the network performance, a bias was used. Sigmoid function was chosen as the transfer function. The learning rate and momentum were 0.5 and 0.4, respectively. To select the adequate transfer function, the learning rate and momentum of several trainings with different above mentioned parameters were performed. In each training, one parameter was variant and others were constant. To achieve a robust model, the order of patterns was randomly changed. The obtained results were the same. The criterion of total squared error was 0.004 after 72500 iterations. The root mean square error was 0.018. Further iterations led to the over-fitting of the network (Fig. 2). The optimized 3:9:2 structure contained 3 input units, 9 hidden units and 2 output units. All units are connected to the next higher level which means that are $3 \times 9 + 9 \times 2 = 45$ connections. Although the network was trained on 68 data points, its performance to predict the corrosion behavior of testing set was quite satisfactory. This proves that the network architecture was adequate and in the training process generalization and no memorization occurred. To predict the corrosion current and potential of lead, multi-linear regression (MLR) models were also obtained. The aforementioned corrosion models, namely, current and potential are respectively defined by Eqs. 1 and 2:



(a)



(b)

Fig. 1. The Tafel curves in 0.1-0.6 M Na_2SO_4 at pH 7 (a) and pH 5 (b).

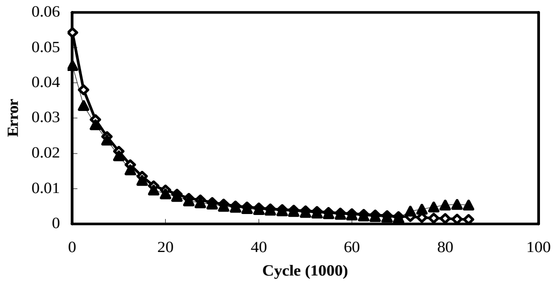


Fig. 2. A typical graph of the TSE against the number of Iterations: (◇) Training, (▲) Testing.

$$I_{corr} = -1.864 \times 10^{-2}\,[Na_2SO_4] - 3.867 \times 10^{-3}\,(pH) + 8.214 \times 10^{-4}\,(t) + 5.476 \times 10^{-2} \quad (1)$$

where the linear regression coefficients r and r^2 were 0.77 and 0.59, respectively.

$$E_{corr} = -2.539 \times 10^{-2}\,[Na_2SO_4] - 2.815 \times 10^{-2}\,(pH) + 1.862 \times 10^{-3}\,(t) - 0.568 \quad (2)$$

where r and r^2 were 0.90 and 0.81, respectively. The MLR coefficients standard error for Eqs. 1 and 2 are presented in Tables 2 and 3, respectively.

Table 2. The MLR Coefficients and Standard Errors for Eq. 1

Coefficients	Standard error
5.476E-02 (constant)	0.003
-1.864E-02	0.004
-3.867E-03	0.001
8.214E-04	0.000

Table 3. The MLR Coefficients and Standard Errors for Eq. 2

Coefficients	Standard error
-0.568 (constant)	0.011
-2.539E-02	0.012
-2.815E-02	0.002
1.862E-03	0.001

The results of the training and testing the FFANN in comparison with MLR method are presented in Tables 4-6.

Table 4. The MLR and FFANN Calculated and Experimental Values of Corrosion Current and Potential for the Patterns Included in the Training Set

No.	Corrosion potential (V *vs*. Ag/AgCl)			Corrosion current (mA)		
	MLR	ANN	Exp.	MLR	ANN	Exp.
1	-0.7677	-0.7611	-0.7639	0.0258	0.0474	0.0482
2	-0.7701	-0.7570	-0.7593	0.0239	0.0328	0.0326
3	-0.7727	-0.7630	-0.7543	0.0221	0.0206	0.0214
4	-0.7777	-0.7794	-0.7850	0.0183	0.0191	0.0187
5	-0.7803	-0.7605	-0.7630	0.0164	0.0131	0.0114
6	-0.7828	-0.7740	-0.7757	0.0146	0.0226	0.0246
7	-0.7853	-0.8037	-0.8021	0.0127	0.0201	0.0213
8	-0.7879	-0.8158	-0.8353	0.0108	0.0192	0.0182
9	-0.7904	-0.8304	-0.8301	0.0089	0.0196	0.0201
10	-0.7490	-0.7107	-0.6748	0.0340	0.0168	0.0161
11	-0.7540	-0.7235	-0.7421	0.0303	0.0151	0.0157
12	-0.7616	-0.7474	-0.7877	0.0265	0.0114	0.0138
13	-0.7591	-0.7667	-0.7359	0.0247	0.0118	0.0121
14	-0.7642	-0.7809	-0.7814	0.0228	0.0125	0.0134
15	-0.7667	-0.7966	-0.7890	0.0209	0.0098	0.0079

Table 4. Continued

16	-0.7692	-0.8113	-0.8237	0.0190	0.0143	0.0144
17	-0.7718	-0.8269	-0.8245	0.0179	0.0186	0.0188
18	-0.7113	-0.7336	-0.7405	0.0335	0.0449	0.0498
19	-0.7138	-0.7355	-0.7369	0.0317	0.0321	0.0330
20	-0.7163	-0.7363	-0.7345	0.0298	0.0262	0.0241
21	-0.7189	-0.7357	-0.7412	0.0279	0.0212	0.0225
22	-0.7239	-0.7328	-0.7341	0.0242	0.0148	0.0137
23	-0.7265	-0.7307	-0.7412	0.0223	0.0265	0.0284
24	-0.7316	-0.7381	-0.7310	0.0186	0.0191	0.0189
25	-0.7341	-0.7488	-0.7265	0.0167	0.0220	0.0219
26	-0.6927	-0.7052	-0.7095	0.0417	0.0493	0.0503
27	-0.6952	-0.7005	-0.7043	0.0399	0.0401	0.0426
28	-0.6977	-0.6980	-0.7014	0.0379	0.0321	0.0317
29	0.7002	-0.7104	-0.7125	0.0361	0.0343	0.0333
30	-0.7028	-0.7019	-0.7064	0.0343	0.0246	0.0244
31	-0.7053	-0.7071	-0.7180	0.0324	0.0281	0.0269
32	-0.7079	-0.7135	-0.7001	0.0305	0.0387	0.0395
33	-0.7104	-0.7145	-0.7082	0.0286	0.0405	0.0429
34	-0.7129	-0.7138	-0.7139	0.0268	0.0340	0.0354
35	-0.7155	-0.7064	-0.7053	0.0249	0.0309	0.0300
36	-0.6550	-0.6528	-0.6365	0.0412	0.0501	0.0518
37	-0.6575	-0.6462	-0.6365	0.0394	0.0383	0.0351
38	-0.6601	-0.6388	-0.6417	0.0375	0.0301	0.0303
39	-0.6651	-0.6325	-0.6288	0.0337	0.0209	0.0201
40	-0.6677	-0.6305	-0.6223	0.0319	0.0161	0.0145
41	-0.6702	-0.6411	-0.6415	0.0300	0.0328	0.0320
42	-0.6728	-0.6280	-0.6359	0.0281	0.0299	0.0309
43	-0.6753	-0.6275	-0.6149	0.0263	0.0210	0.0200
44	-0.6778	-0.6463	-0.6490	0.0244	0.0239	0.0241
45	-0.6364	-0.6018	-0.6144	0.0494	0.0541	0.0542
46	-0.6389	-0.6001	-0.6032	0.0475	0.0522	0.0564
47	-0.6414	-0.6028	-0.6135	0.0457	0.0416	0.0436
48	-0.6440	-0.6102	-0.6133	0.0439	0.0408	0.0399
49	-0.6465	-0.6177	-0.6111	0.0420	0.0418	0.0419
50	-0.6516	-0.6240	-0.6040	0.0382	0.0443	0.0491
51	-0.6541	-0.6038	-0.6098	0.0364	0.0393	0.0360
52	-0.6567	-0.6089	-0.6040	0.0345	0.0438	0.0464
53	-0.6592	-0.6101	-0.6034	0.0326	0.0412	0.0403
54	-0.5986	-0.6179	-0.6181	0.0489	0.0625	0.0607
55	-0.6012	-0.6201	-0.6243	0.0471	0.0519	0.0536
56	-0.6037	-0.6208	-0.6271	0.0452	0.0376	0.0386
57	-0.6030	-0.6225	-0.6233	0.0434	0.0291	0.0273

Table 4. Continued

58	-0.6113	-0.6281	-0.6248	0.0396	0.0198	0.0193
59	-0.6139	-0.6310	-0.6334	0.0377	0.0418	0.0467
60	-0.6190	-0.6287	-0.6287	0.0340	0.0245	0.0212
61	-0.6215	-0.6242	-0.6232	0.0321	0.0231	0.0265
62	-0.5800	-0.6368	-0.6239	0.0571	0.0632	0.0464
63	-0.5826	-0.6276	-0.6327	0.0553	0.0611	0.0621
64	-0.5851	-0.6230	-0.6264	0.0534	0.0486	0.0475
65	-0.5927	-0.6190	-0.6218	0.0478	0.0491	0.0481
66	-0.5953	-0.6187	-0.6192	0.0459	0.0525	0.0541
67	-0.5978	-0.6181	-0.6243	0.0440	0.0497	0.0491
68	-0.6029	-0.6141	-0.6128	0.0403	0.0429	0.0427

Table 5. The MLR and FFANN Calculated and Experimental Values of Corrosion Current and Potential for Testing Set

No.	Corrosion potential (V *vs*. Ag/AgCl)			Corrosion current (mA)		
	MLR	ANN	Exp.	MLR	ANN	Exp.
1	-0.7752	-0.7698	-0.7641	0.0201	0.0202	0.0206
2	-0.7515	-0.7411	-0.7498	0.0321	0.0118	0.0113
3	-0.7566	-0.7380	-0.7401	0.0284	0.0138	0.0143
4	-0.7214	-0.7237	-0.7298	0.0260	0.0197	0.0195
5	-0.7291	-0.7130	-0.7118	0.0204	0.0221	0.0243
6	-0.6626	-0.6350	-0.6440	0.0356	0.0235	0.0257
7	-0.6491	-0.6038	-0.6075	0.0401	0.0447	0.0457
8	-0.6088	-0.6207	-0.6239	0.0415	0.0241	0.0223
9	-0.6164	-0.6301	-0.6288	0.0358	0.0374	0.0372
10	-0.5876	-0.6228	-0.6264	0.0516	0.0460	0.0452
11	-0.5902	-0.6232	-0.6237	0.0497	0.0448	0.0431
12	-0.6003	-0.6216	-0.6287	0.0422	0.0471	0.0459

Table 6. The FFANN Obtained Data in Comparison with MLR Method Results for Testing Set

No.	Corrosion potential (V *vs*. Ag/AgCl)			Corrosion current (mA)		
	Exp.	Δ_{ANN}	Δ_{MLR}	Exp.	Δ_{ANN}	Δ_{MLR}
1	-0.7641	0.0057	0.0111	0.0206	0.0004	0.0005
2	-0.7498	-0.0087	0.0017	0.0113	-0.0005	-0.0208
3	-0.7401	-0.0021	0.0165	0.0143	0.0005	-0.0141
4	-0.7298	-0.0061	-0.0084	0.0195	-0.0004	-0.0065
5	-0.7118	0.0012	0.0173	0.0243	0.0022	0.0039
6	-0.6440	-0.0090	0.0186	0.0257	0.0022	-0.0099
7	-0.6075	-0.0037	0.0416	0.0457	0.0010	0.0056

Table 6. Continued

8	-0.6239	-0.0032	-0.0151	0.0223	-0.0018	-0.0192
9	-0.6288	0.0013	-0.0124	0.0372	-0.0002	0.0014
10	-0.6264	-0.0036	-0.0388	0.0452	-0.0008	-0.0064
11	-0.6237	-0.0005	-0.0335	0.0431	-0.0017	-0.0066
12	-0.6287	-0.0071	-0.0284	0.0459	-0.0012	0.0037

The plots of the FFANN results to predict the corrosion current and potential *vs*. experimental values for training and testing set are shown in Figs. 3-6. The achieved points are distributed around the trend line. The mentioned concentrated distribution illustrated the low difference between the predicted and experimental values. The accurate prediction shows the efficiency of selected FFANN. The results in tables 4-6 revealed that the FFANN results are better than those of the MLR methods. The results clearly demonstrate the ability and adequacy of the chosen architecture in above mentioned corrosion behavior prediction.

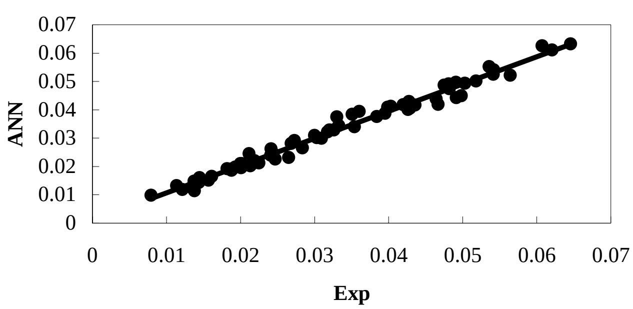


Fig. 3. Calculated I_{corr} *vs*. experimental values for training set.

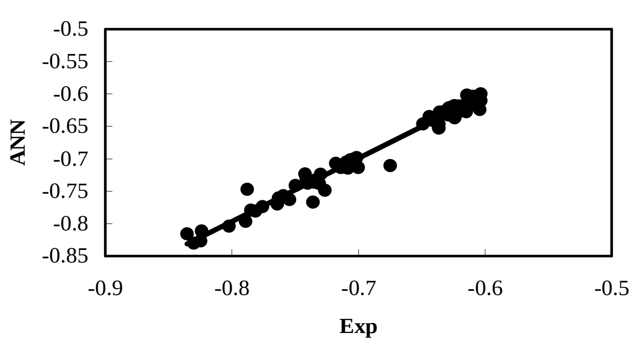


Fig. 4. Calculated E_{corr} *vs*. experimental values for training set.

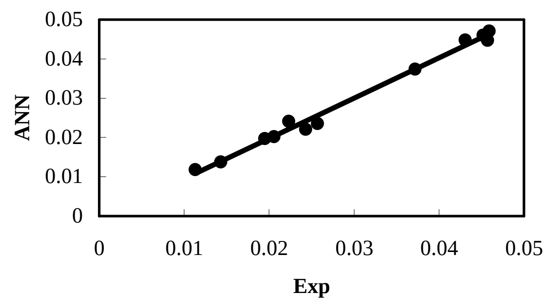


Fig. 5. Calculated I_{corr} *vs*. experimental values for testing set.

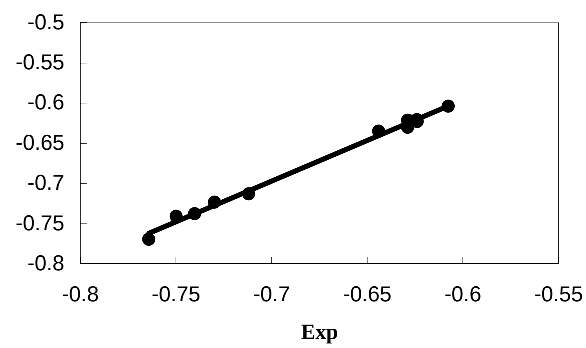


Fig. 6. Calculated E_{corr} *vs*. experimental values for testing set.

CONCLUSIONS

It was found that feed-forward artificial neural networks result in suitable methods to predict the lead corrosion behavior in Na_2SO_4 solutions. The obtained data illustrate the priority of FFANN over MLR method in lead corrosion behavior prediction. A comparison between the two methods revealed that the corrosion behavior of lead is not linear; thus, the use of a non-linear transfer function gives better results.

REFERENCES

[1] R.A. Cottis, L. Qing, G. Owen, S.J. Gartland, I.A. Helliwell, M. Turega, Mater. Design 20 (1999) 169.
[2] S. Jalili, M. Tafazzoli, M. Jalali-Heravi, J. Theor. Comp. Chem. 2 (2003) 335.
[3] J.A. Burns, G.M. Whitesides, Chem. Rev. 93 (1993) 2583.
[4] H.M.G. Smets, W.F.L. Bogaerts, Mater. Perform. 31 (1992) 64.
[5] D.C. Silverman, E.M. Rosen, Corros. Sci. 48 (1992) 734.
[6] M. Ben-Hain, D.D. Macdonald, Corros. Sci. 36 (1994) 385.
[7] S.P. Trasatti, F. Mazza, Brit. Corros. J. 31 (1996) 105.
[8] S. Nesic, M. Vrhovac, J. Corros. Sci. Eng. 1 (1998) 6.
[9] C. Jianping, R.A. Cottis, S.B. Lyon, Corros. Sci. 41 (1999) 2001.
[10] S. Pintos, N.V. Queipo, O.T. Rincón, A. Rincón, M. Morcillo, Corros. Sci. 42 (2000) 35.
[11] T.T. Pleune, O.K. Chopra, Nucl. Eng. Des. 197 (2000) 1.
[12] M.E. Haque, K.V. Sudhakar, Int. J. Fatigue 23 (2001) 1.
[13] S. Nesic, M. Nordsveen, N. Maxwell, M. Vrhovac, Corros. Sci. 43 (2001) 1373.
[14] M. Bucolo, L. Fortuna, M. Nelke, A. Rizzo, T. Sciacca, Control Eng. Pract. 10 (2002) 227.
[15] S. Malinove, W. Sha, Comp. Mater. Sci. 28 (2003) 179.
[16] N. Daneshvar, M.T. Zaafarani Moattar, M. Abedinzadegan Abdi, S. Aber, Sep. Purif. Technol. 37 (2004) 135.
[17] S. Malinov, W. Sha, Mater. Sci. Eng. A365 (2004) 202.
[18] T. Parthiban, R. Ravi, G.T. Parthiban, S. Srinivasan, K.R. Ramakrishnan, M. Raghavan, Corros. Sci. 47 (2005) 1625.
[19] L.A. Dobrzański, M. Drak, J. Trzaska, J. Mater Process. Tech. 164-165 (2005) 795.
[20] W. Cheng, S. Kanemoto, I. Komura, M. Shiwa, NDT&E Int. 39 (2006) 374.
[21] V. Díaz, C. López, Corros. Sci. 49 (2007) 949.
[22] Stuttgart Neural Network Simulator, Developed at University of Stuttgart, 2002.