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Neural Network to Evaluate Rotating Cylinder Electrode Performance for Metal Powder Deposition

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The parameters that influence the performance of rotating cylinder electrodes(RCE), a well defined high mass transfer device, are studied using neural network. The electrochemical reaction chosen is the cathodic deposition of copper in powder form from acidic solution. The input parameters to the neural network are cathode current density , copper concentration and temperature in the ranges of 389 to 833 A m^2 , 1 to 3 dm^{-3} & 35 to 45 ^{0} C ,respectively . The outputs of the network are current efficiency and space time yield (kg of product per hour, per unit volume of cell). The response curves generated shows the influence of the parameters . The prediction from the net work for unknown inputs is compared with the experimental value .

Key words : Rotating cylinder electrode, neural networks, copper powder

Introduction

Rotating cylindrical electrode (RCE) [1] is fairly well known in the context of metal removal from lean solution. Compared to rotating disc electrode (RDE), long known to electrochemists , the RCE enjoys the benefit of lower critical Reynold's number viz. 200. The critical Reynold's number at which turbulence sets in is achieved at low rotation speeds with consequent good solution agitation. In addition, the cylindrical geometry of RCE guarantees uniform potential distribution over the cylindrical surface .

Mass transfer characteristics improve when powdery deposition takes place. This is attributed to the rough surface which induces micro turbulence. The increase of electrode area is an additional benefit. It is reported [2-3] from experimental evidence that the exponent of the Reynold's number in the mass transfer correlation varies from 0.7 for a smooth surface to 0.9 for a surface with saturated roughness. This gives an added advantage with RCE wherever powder deposit is desired. Continuous harvesting of the metal powder by the use of scraper blade and filtering of the solution in a closed circuit is also practised [4]

General principles governing powder metal deposition were detailed in the classic review by Ibl[5]and its relationship to electrocrystallization is discussed in detail, in Calusarus book(6). Conditions favouring powder formation are: decrease of metal ion concentration, rate of agitation or temperature and increase of current density, viscosity of solution or concentration of indifferent electrolyte .

In this paper, we investigated the effect of current density, metal ion concentration and temperature, keeping the peripheral speed of RCE rotation speed the same, on copper powder formation. A set of 27 experiments (3 factors varied at 3 levels) were performed . Current efficiency and space time yield were found from the weight of metal obtained. The data were analysed using neural net works.

Neural networks

Neural networks[7-8] provide a methodology by which the dependency among a set of variables can be established through a learning process. This is similar to the learning process in human beings whose sensorial inputs are suitably processed by neurons of the brain and leads to actions as the output. Artificial neural networks (ANN) tries to imitate Gods biological neural net works of brain.

The architecture of ANN is as follows. ANN has a set of layers: one input, one output and one or more hidden layers. Each layer has a set of neurons. A neuron in each hidden layer takes as input a weighted sum of the outputs from the neurons in the previous layer, processes the weighted sum using a suitable activation function and delivers its output to each of the neutrons in the subsequent layer. The input layer is used to feed in the values of experimentally controlled parameters and the values of the output which are the system performance parameters are collected from the output layer. Experimentally measured input-output pairs are used to train the ANN initially. During training, the various weights in the net work are optimized for the known training set. Once trained, the trained network can be used for predictions. The trained ANN can as

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well be employed to study how the performance parameters depend on one or more of the controlled parameters. The resulting response curves are useful predictive tools.

Experimental

The electrolytic cell used is a jacketed glass vessel in which the RCE, made of titanium tube fitted over a p.v.c rod, is placed at the centre and a pure sheet of copper positioned near to the inner wall of the vessel and concentric to the RCE serves as anode. The RCE is rotated by means of a geared motor. Water at the required temperature is circulated through the jacket in the glass cell so as to get the desired solution temperature. The powder formed on the cathode is periodically brushed down and the period of brushing is at equal portion of the total Ah per trial, irrespective of the current density chosen. The powder obtained is washed well with demineralised water and treated with 1,2,3 benzotriazole to minimize oxidation. Current efficiency and space time yield are obtained from the weight of copper deposited.

Results and discussions

The results of the statistically designed experiments are presented in Table 1. It can be seen that the concentration of copper in solution increases with time in all cases. This is attributable to the cathodic efficiency being lower than the anodic efficiency. As the anode C.D. does not exceed 250 Am^{-2} it is safe to assume 100% current utilization for anodic dissolution of copper. The increase in the copper concentration must be in tune with the difference in the efficiencies. However a higher increase is observed. This is most probably due to chemical dissolution in addition to the anodic dissolution. This aspect requires further investigation.

The experimental data were analysed by neural networks. The architecture of the neural network used has 3 layers; one input layer, one hidden layer and one output layer. The input layer takes current density, concentration and temperature as the inputs and the output layer delivers either current efficiency or space-time yield as the output in separate neural networks. The hidden layer has 3 neurons. The networks were tested using several training algorithms and Quasi-Newton was found to be the most suitable. The neural network for current efficiency was optimized with a correlation coefficient of 0.982 and a standard deviation ratio (S.D) of 0.185. The neural network for the space time yield produced a correlation coefficient of 0.999 and an S.D ratio of 0.0357. Statistica neural network software version 4.0 C was used in this work. The training error was about 10% .

Table 1. Current efficiency and space time yield for deposition of copper powder onto RCE: Results of statistical experiments. Cathode area : 36 cm^2 ; Anode area: 170 cm^2; A.Hr:1.5 Volume of cell: 300 cm^3 : Volume of solution: 250 cm^3; Peripheral velocity: 0.16 m sec^{-1}

C.D Am^{-2}	Ci gm dm^{-3}	Cf Gmdm^{-3}	C.E %	STY Kg hr^{-1} dm^{-3}
Experiments at 45 deg C temperature				
389	1.25	2.99	91	5.1
555	1.25	3.62	87	6.9
833	1.25	4.61	71	8.33
389	2.08	3.9	100	5.55
555	2.08	4.3	94	7.4
833	2.08	5.4	76	8.9
389	2.86	3.94	98	5.5
555	2.86	4.64	96	7.6
833	2.86	6.0	87	10.33
Experiments at 40 deg C temperature				
389	1.25	3.56	96	5.34
555	1.25	4.11	66	5.20
833	1.25	4.64	54	6.40
389	2.08	3.81	88	4.88
555	2.08	4.83	76	6.00
833	2.08	4.96	57	6.80
389	2.86	4.13	72	4.00
555	2.86	4.50	82	6.40
833	2.86	5.53	68	8.10
Experiments at 35 deg C temperature				
389	1.25	3.50	73	4.10
555	1.25	4.61	69	5.40
833	1.25	5.4	63	7.50
389	2.08	3.75	79	4.38
555	2.08	4.73	73	5.79
833	2.08	5.88	62	7.33
389	2.86	4.73	93	5.16
555	2.86	4.96	86	6.80
833	2.86	5.75	62	7.33

Sensitivity analyses were also carried out for current efficiency and space time yield as a function of one or more of the input parameters. The response curves generated are used to predict current efficiency or space time yield for values of inputs not tested experimentally.

The neural network predicted 91.42% for C.E. and 6.86 Kg $hr^{-1}m^{-3}$ for S.T.Y for 528 Am^{-2} (c.d.), 2.57 gmdm^{-3} (C) and 43 ^0C(T). The corresponding experimental values of C.E, and S.T.Y are 97.34 and 7.34. The errors are within the training error limits.

Current efficiency(C.E) predictions

Figure 1 shows a response curve of C.E vs current density (c.d) at 45 C and for 2.08 g dm^{-3} concentration. As c.d. is varied from 389 to 833 A m^{-2}, C.E falls gradually from 95% to 75%. C.E vs concentration graphs in Figs. 2-4 are more interesting in that the C.E exhibits a distinct maximum for the low as well as the high values of the c.d and a monotonic increase for the intermediate c.d.

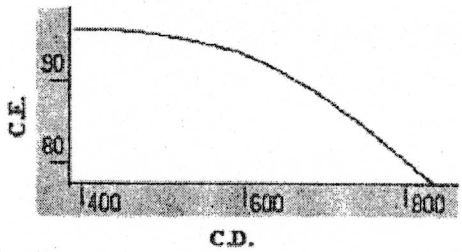

Fig. 1. C.E. vs c.d. for T=45 deg. and C=2.08 gl

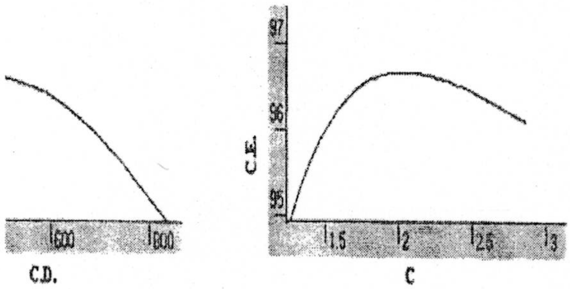

Fig. 2. C.E. vs c.d. for T=45 deg. and c.d.=389 Ampere per square metre.

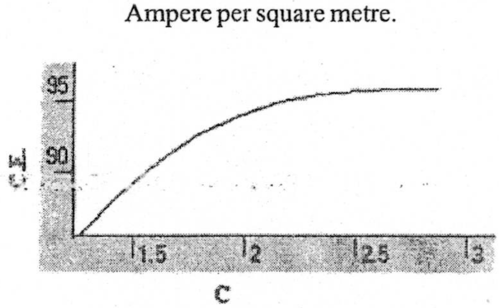

Fig. 3. C.E. vs c.d. for T=45 deg. and c.d.=555 Ampere per square metre.

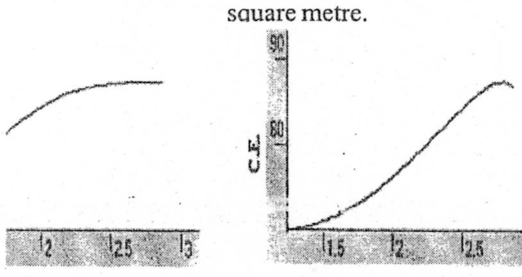

Fig. 4. C.E. vs c.d. for T=45 deg. and c.d.=833 Ampere per square metre.

The experimental data in Table 1 points to ups and downs in the variation of C.E against temperature. This is also seen to be reflected in the corresponding response curve of neural network which shows a maximum and a minimum. However these features could not be confirmed due to the insufficient numbers of temperature levels employed in the present investigation.

Space time yield (S.T.Y) predictions

Figures 5 and 6 show the space time yield as a function of concentration and current density respectively. Clearly S.T.Y increases with either. Both these response curves are monotonic without features. However it is noteworthy that the variation of S.T.Y with concentration is much less pronounced than with C.D in the ranges investigated here.

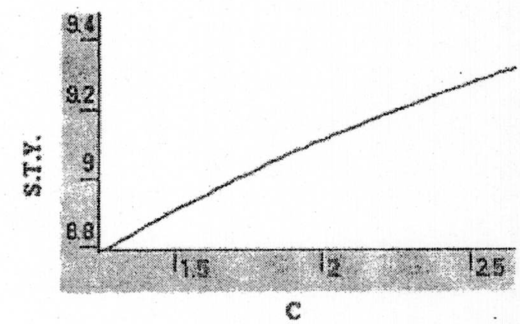

Fig. 5. S.T.Y. vs. c for T=45 deg. and c.d.=833 Ampere per square metre.

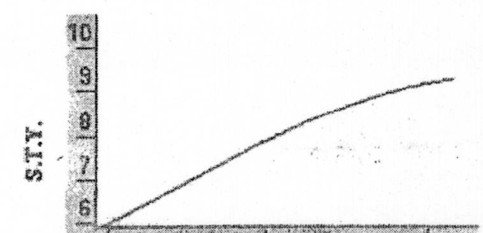

Fig. 6. S.T.Y. vs. c for T=45 deg. and C=2.86 gpl.

A comparison of Figs. 1 and 6 shows that S.T.Y increases and C.E decreases with c.d. As for the cost of production is concerned, a lower C.E demands a higher energy cost and a higher S.T.Y results in a lower cost of the electrolyser which determines the fixed cost. Hence the c.d requires to be optimized with respect to a suitably weighted combination of S.T.Y and C.E responses. Thus the neural network predictions are useful in optimizing electrolytic reactors.

Conclusion

Copper powder deposition on RCE was studied experimentally and the resulting data analysed by neural networks. The current density, copper ion concentration and temperature were the variable inputs and current efficiency and space- time yield were the outputs. The response curves generated from the neural network are found to be useful in predicting the performance of the cell. Besides point predictions, the utility of these response curves for global optimizations of the fixed and operational costs of the electrolysor was also discussed.

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