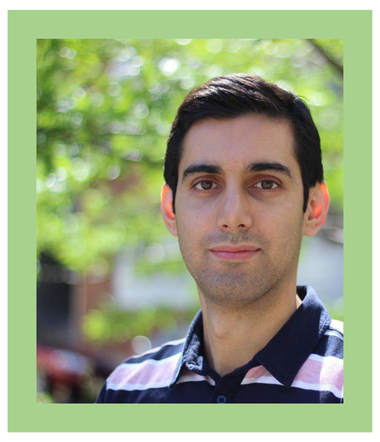

Modeling of active chlorine production from a synthetic saline effluent by electrolysis using Artificial Neural Networks

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Motivation

- Complexity and nonlinearity within electrochemical processes are not always described well with the conventional modeling approaches.
- Artificial neural networks (ANNs) represent promising alternative tools for classical process modeling.

Objective

- Implementation of artificial neural networks (ANNs) for the prediction and simulation of active chlorine production from a synthetic saline effluent by electrolysis.

Experimental setup

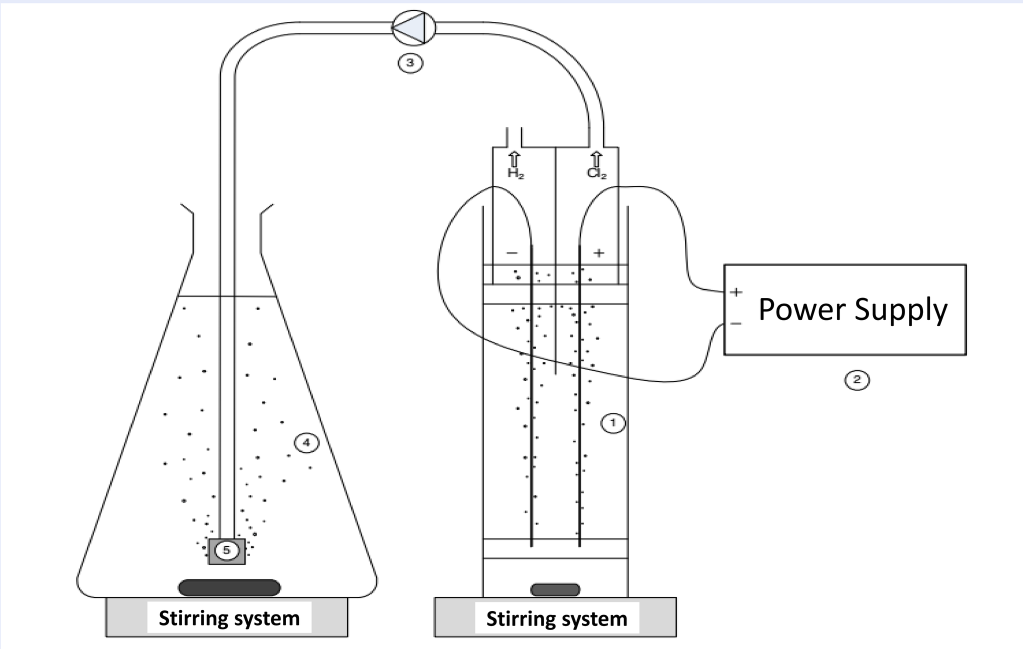

Figure 1. *Schematic diagram of the experimental unit for chlorine gas production: (1) electrolytic cell; (2) power supply; (3) peristaltic pump; (4) glass tank; (5) air diffuser*

30 assays were carried out in a batch system (Figure 1). Four important operational parameters used as ANN inputs:

- **Electrolysis time**
- **Current intensity**
- **Hydrochloric acid conc.**
- **Chloride ion concentration**

Table 1. *Experimental operating conditions range*

Parameter	Min. value	Max. value
Electrolysis time (min)	**15**	**35**
Current intensity (A)	**0.8**	**1.6**
$[H_3O^+]$ (M)	**0.05**	**0.11**
[NaCl] (M)	**0.3**	**0.8**

ANN output (Table 1):

- **Active chlorine production**

Modeling results

- High variance problem
- No need for more complex model

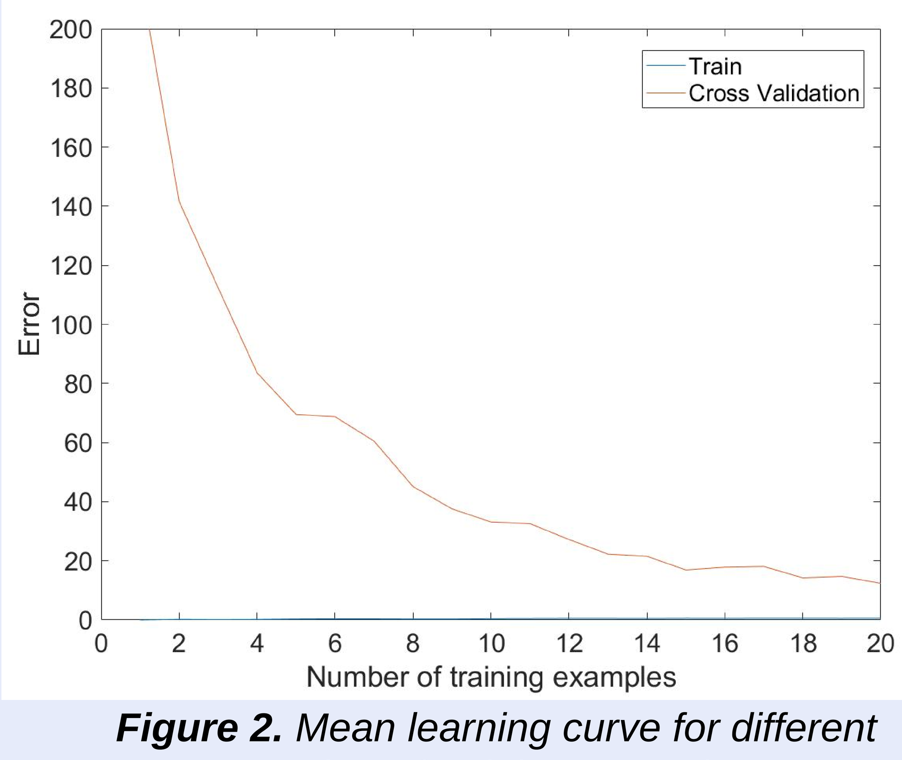

Figure 2. *Mean learning curve for different number of training examples*

Table 2. *Feed-forward backpropagation neural networks*

Configuration	R^2 training	R^2 validation	R^2 test
# Samples	**20**	**5**	**5**
5 hidden neurons	**0.9475**	**0.9186**	**0.8951**
6 hidden neurons	**0.9556**	**0.9096**	**0.8929**
7 hidden neurons	**0.9605**	**0.8996**	**0.8882**

Impact and selection of Regularization Factor

Regularization:

- ✓ Makes slight modifications to the learning algorithm such that the model generalizes better.
- ✓ Improves the model's performance on unseen data.

A graph of Error vs regularization factor (lambda) helps to optimally select the best lambda (Figure 3).

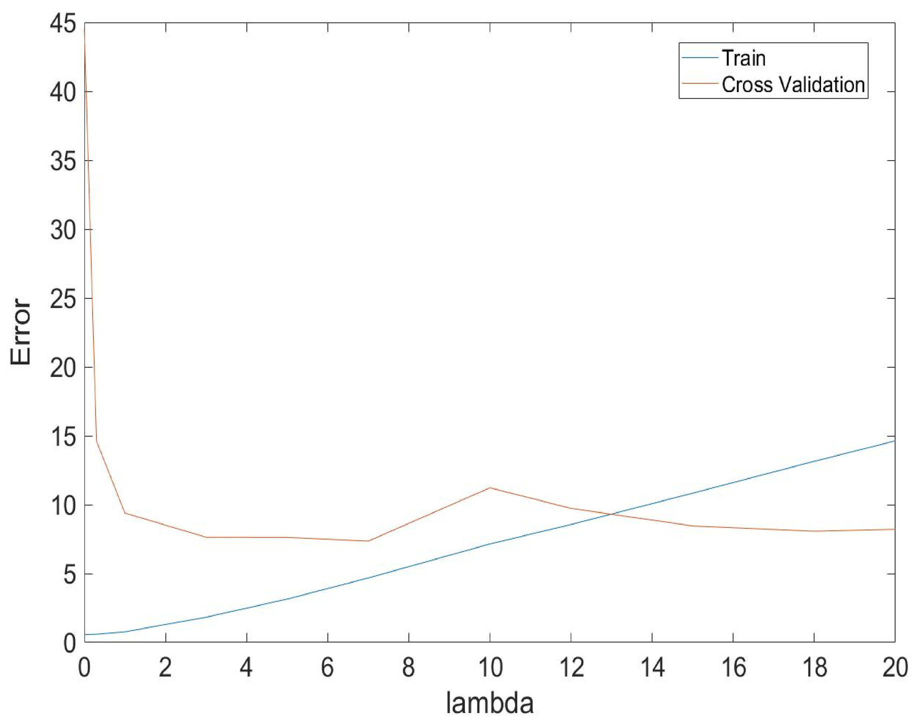

Figure 3. *Impact of regularization factor on the model performance*

Outcome: 3-layer feedforward back propagation network with 5 hidden neurons and lambda=7

Relative importance of input variables (*Garson's algorithm*)

- About 88% influence for **treatment time** and **current intensity** on active chlorine production.

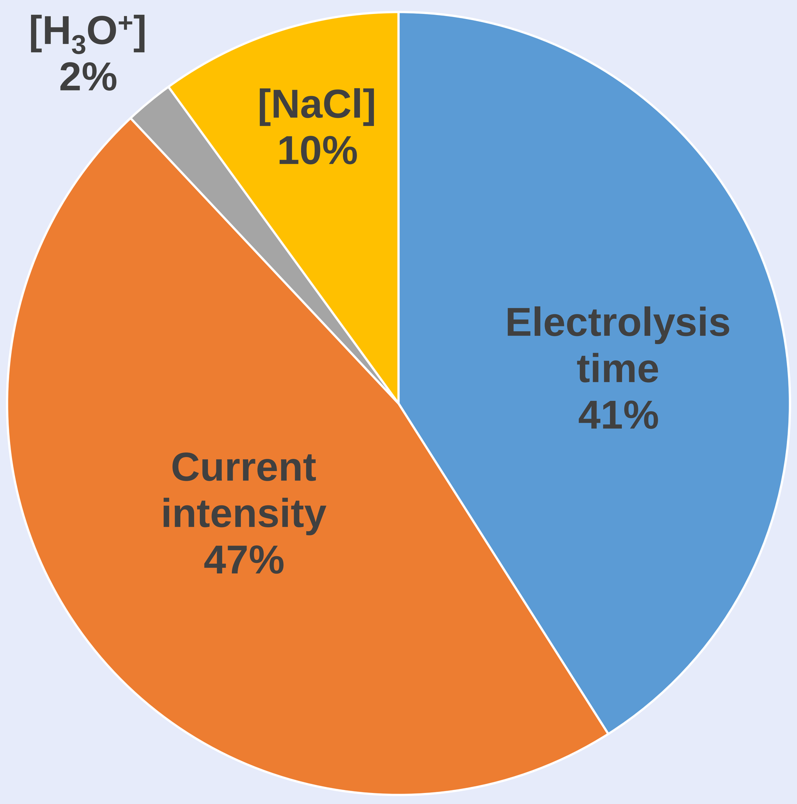

Figure 4. *Importance (%) of the input variables on the electrochemical active chlorine production*

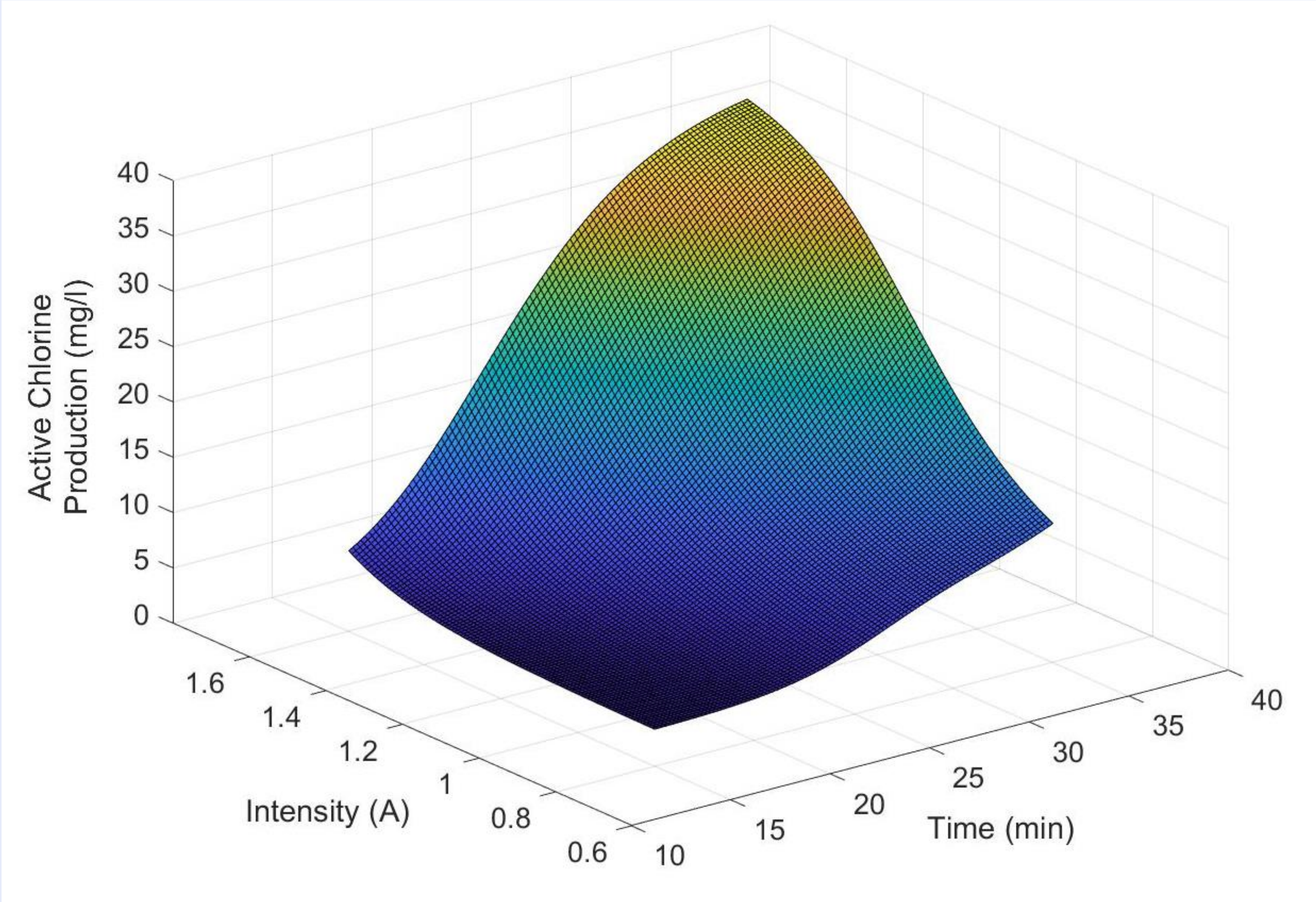

Figure 5. *Effect of the electrolysis time and current intensity on active chlorine production*

Conclusions

- Artificial neural network modeling can effectively predict and simulate the behavior of the electrolysis process.
- This approach can be used besides statistical and empirical modeling for optimization of electrochemical processes.

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