Parametric Study of the Hydrogen Fuel Cell Electrochemical Model

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1 Introduction

Polymer Electrolyte Membrane fuel cell (PEMFC) models are typically constructed from three separate modules; electrochemical module, energy balance and mass balance. The electrochemical behaviour (current-voltage characteristics) of polymer electrolyte fuel cell can be simulated with simple empirical or semi-empirical equations. However, the electrochemical behaviour is case-specific, so the parameters of the model need to be identified. In this work, two models modified from [1] and [2] are fitted for data of four different fuel cell stacks taken from literature. Model 1 consists of Nernst equation for the cell internal potential and three overvoltage loss terms including seven tuneable model parameters. Model 2 is considerably simpler, since it has only three tuneable parameters, one weighting factor for each loss term.

Genetic Algorithms have successful applications in parameter estimation and optimization in different areas e.g. biotechnical processes [3], catalytic cracking [4] and PID controller design [5]. Reference [6] reports on the use of real-coded genetic algorithms in the parameter identification of the wastewater treatment process modelled as Chemostat. This paper uses the similar algorithm. The objective function for the optimization is the squared sum of the error (SSE) between the simulated values and measured values.

2 Objectives of the research

The objective of the research is to optimize the parameters of the electrochemical model in order to produce as reliable simulation results as possible. In addition, the performance and flexibility of both models would be tested. Since genetic algorithms are a stochastic optimization method, it is necessary to examine the variation of the optimal solution when repeating the optimization. Results from this could be verified with a sensitivity analysis made for the electrochemical model.

3 Results

The search space used for Model 1 is based on values used in similar models in literature [1, 2, 7–10]. For Model 2, the range of weighting factors was from 0 to 3. Preset parameters for genetic algorithm are presented in reference [11] as well as the properties and operation conditions of the four fuel cells. For the three fuel cell stacks, there were only one dataset (i.e. polarization curve) available [8]. For the fourth fuel cell stack, four polarization curves in different operation conditions were available [9].

3.1 The effect of the number of datasets used in optimization

The parameter identification algorithm finds parameters, which produce tolerable results in

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each case. According to Fig 1 and Table 1, Model 1 shows better performance. From Fig 2 it is evident, that optimization with only one dataset does not give any generalizable results (Case 1). If two datasets are used in optimization, the model predicts the fuel cell electrochemical behaviour much better (Case 2 in Fig 2). The results are more visible when observing the SSE values in Table 1. The gained SSE value for 250W fuel cell is better than in a similar work in [9].

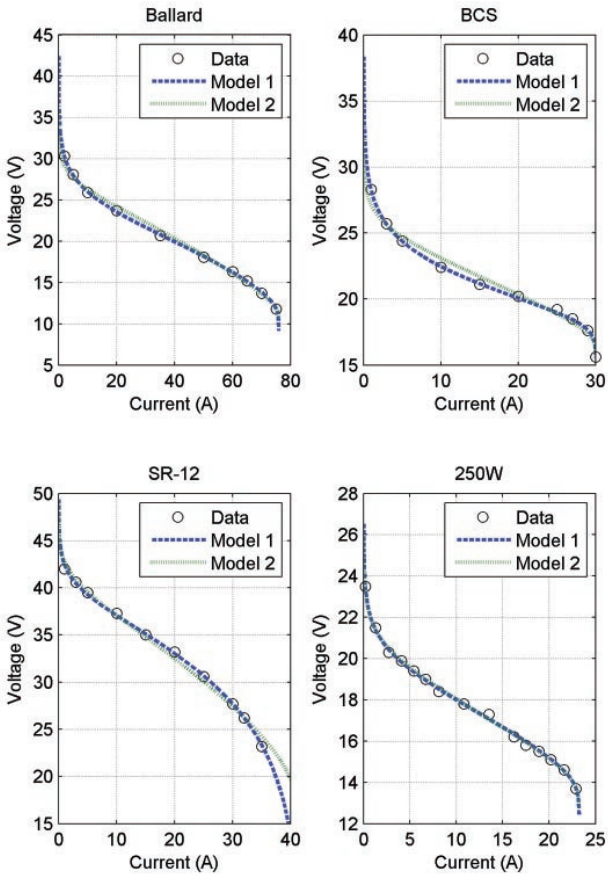

Figure 1 Simulated polarization curves for different fuel cells with both models.

Table 1 SSE values for different fuel cells with both models when using one dataset and SSE values for 250W fuel cell with Model 1 when utilizing four datasets.

	Ballard	**BCS**	**SR-12**	**250W**
Model 1	0,0918	0,1040	0,4475	0,1679
Model 2	2,4432	2,6729	3,0958	0,2931
Case 1				16,3265
Case 2				8,4854

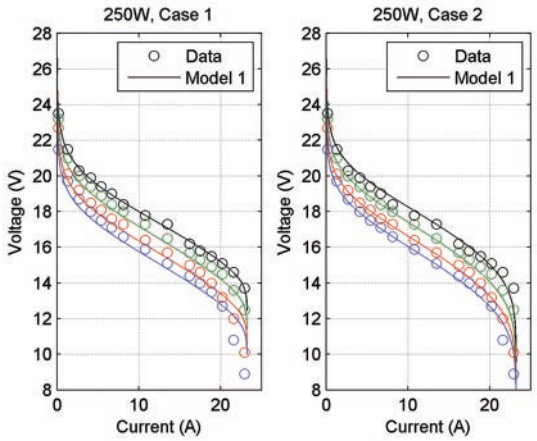

Figure 2 Simulated polarization curves for 250W fuel cell with Model 1. In Case 1, one dataset is used for optimization and three datasets for validation. In Case 2, two datasets are used for optimization and two datasets for validation.

3.2 Statistical validity of the optimization

Optimization was repeated 500 times and histograms of optimal parameters in each case were drawn. The distributions for Model 2 are almost normal and concentrated around the optimal value (Fig 3). This describes more or less a better confidence on the parameter values compared with Model 1, which produces quite uniform distribution for several parameters. Using more than one dataset for optimization of Model 1 does not improve the situation. In general, it seems that the parameter ξ_1 is dominating the optimization and the behaviour of the Model 1.

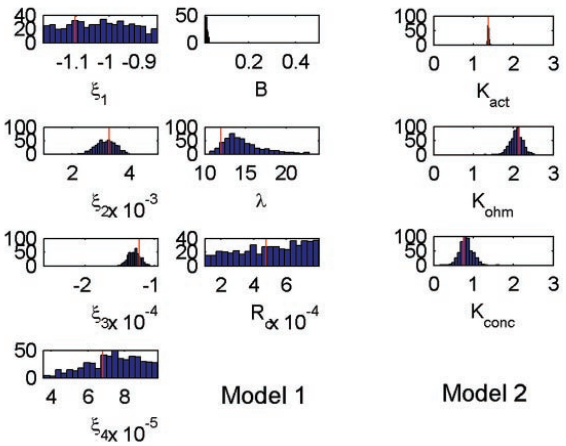

Figure 3 Parameter histograms for 250W fuel cell for both models. The optimal value for each parameter is shown as vertical line.

3.3 Sensitivity analysis for Model 1

Normalized sensitivity analysis was used since it gives values, which are comparable between different cases. The results verified that ξ_1 is an important parameter, although ξ_2 had a lit-

tle bit higher sensitivity. Also, ξ_4 showed quite high sensitivity when comparing to the other remaining parameters. The results are in good conformance with [10].

4 Relevance of the research

The results show that Genetic Algorithms are an efficient way to identify electrochemical parameters of the fuel cell model when simulating different fuel cells. Optimization should contain several datasets in order to simulate different operation conditions. Statistical information and sensitivity analysis indicate that the model is mostly affected by the parameter ξ_1. Identified parameters for the electrochemical model give a more reliable starting point for the whole fuel cell stack model.

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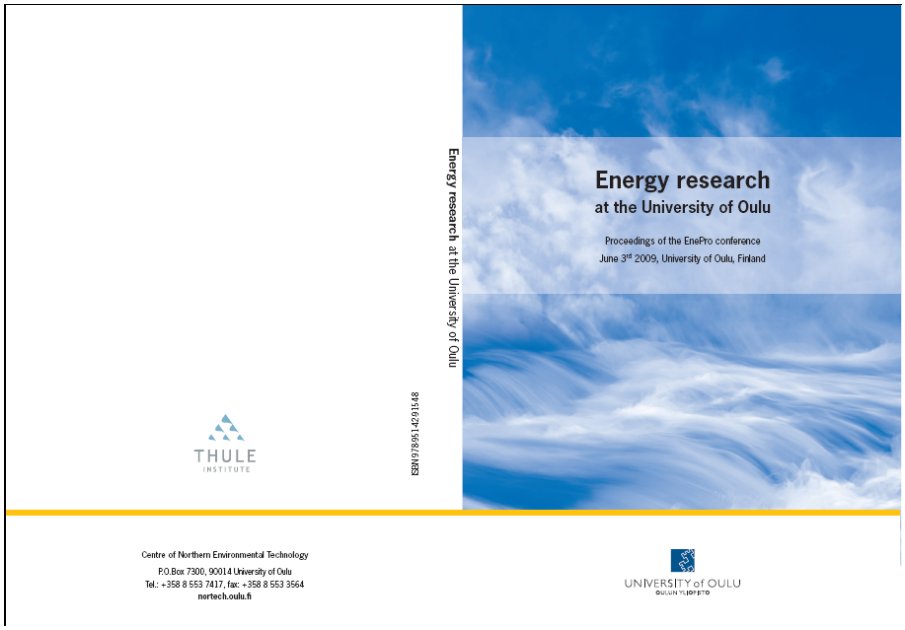

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