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Introduction

HTPEM fuel cells can with great benefit be used in systems with fuel reformers, because they have a high tolerance towards carbon monoxide in the anode gas. Their performance is, however, affected by the presence of carbon monoxide. This effect is dependent on the fuel cell temperature, with the effect being smaller at high temperatures and larger at low temperatures. It is important to model this effect, when choosing optimal operating points for the fuel cell and fuel reformer, or constructing larger system models.

It can, however, be difficult to construct simple, fast evaluating models of the fuel cells performance, which works on a specific fuel cell, at a certain state of degradation. This work presents a method to do this, based on Adaptive Neuro-Fuzzy Inference Systems (ANFIS) trained on experimental data[1].

In this case the factors which are expected to influence the fuel cell voltage are the fuel cell temperature, the CO content of the anode gas and the fuel cell current density. Figure 1 shows a diagram of the ANFIS model structure employed in this work.

The model structure is split up into 5 layers. The first layer is the fuzzyfication layer, where the inputs are converted to fuzzy variables, which are numbers between 0 and 1. The conversion is done using a series of membership functions. Here the output of the membership functions can be interpreted as "to which degree are the inputs high or low." The membership functions used in this work are bell-shaped. These are used because they give smooth transition between functions. The equation for the first of the six membership functions in figure 1 is:

$$O_{1,i} = \frac{1}{1 + \left| \frac{T_{FC} - c_i}{a_i} \right|^{2b_i}}$$

Here $O_{1,i}$ is the degree of membership, the subscript i is the function number and a_i, b_i and c_i are adaptive premise parameters, which are optimized using gradient decent methods during the training of the system. More membership functions increases the ability to model non-linear systems, but also increases complexity and calculation time.

The next layer contains the calculation of the firing levels of the fuzzy rules, each represented by a circle called a node or a neuron. For the top rule firing level means: To which degree is T_{FC} AND x_{CO} AND I_{FC} high.

The next layer is the normalization layer. Here the sum of the firing levels of all the rules is normalized to be 1.

The second to last layer contains the output calculation, where the contribution of each rule to the output of the model is calculated. This is done using this equation.

$$O_{3,i} = \bar{w}_i \cdot (o_i \cdot T_{FC} + p_i \cdot x_{CO} + q_i \cdot I_{FC} + r_i)$$

Where $\bar{w}_i$ is the normalized firing level of the rule and o_i, p_i, q_i and r_i are adaptive consequent parameters optimized using least squares regression during the training of the system.

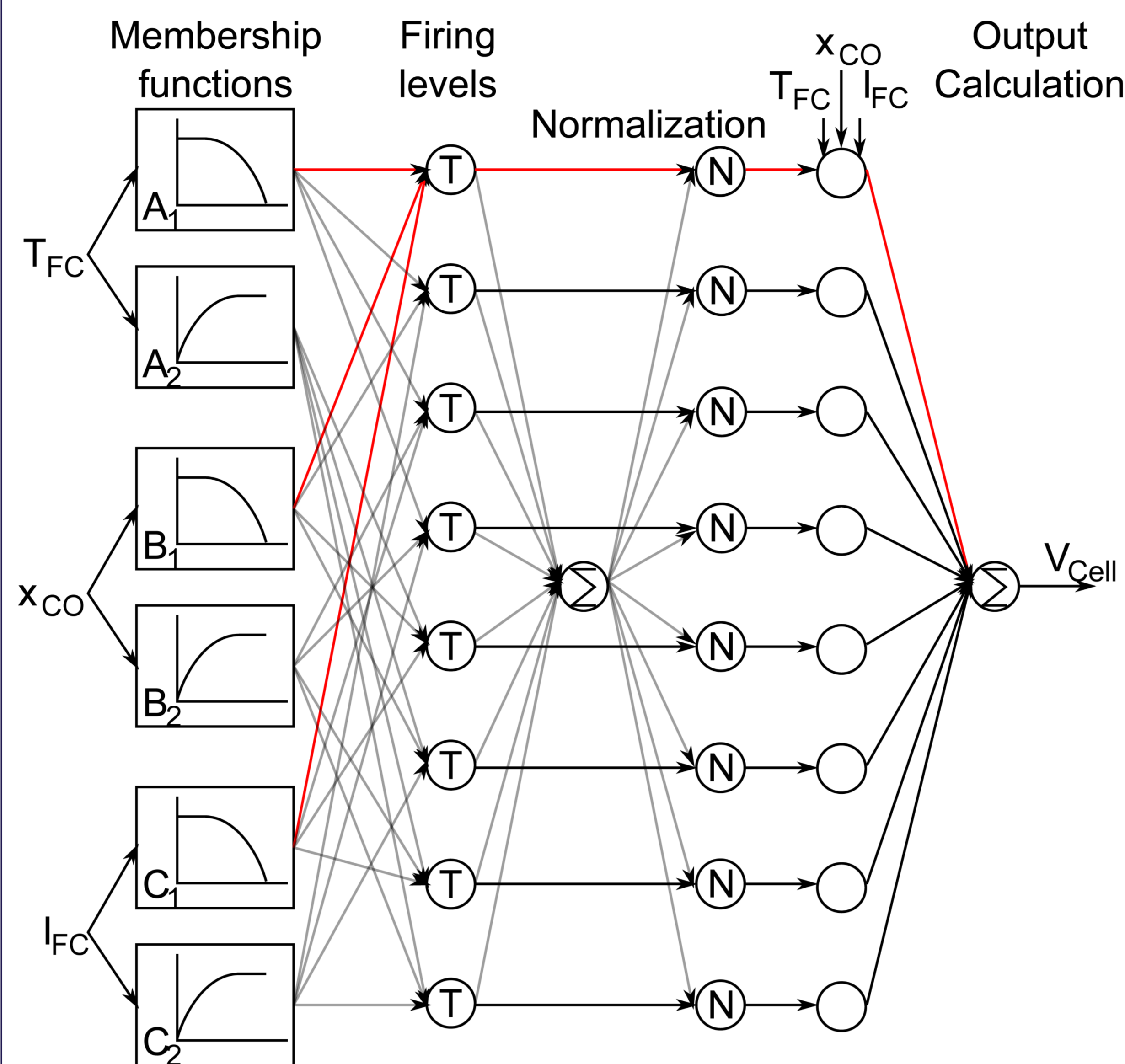The last layer contains the summation of the contributions.

Results

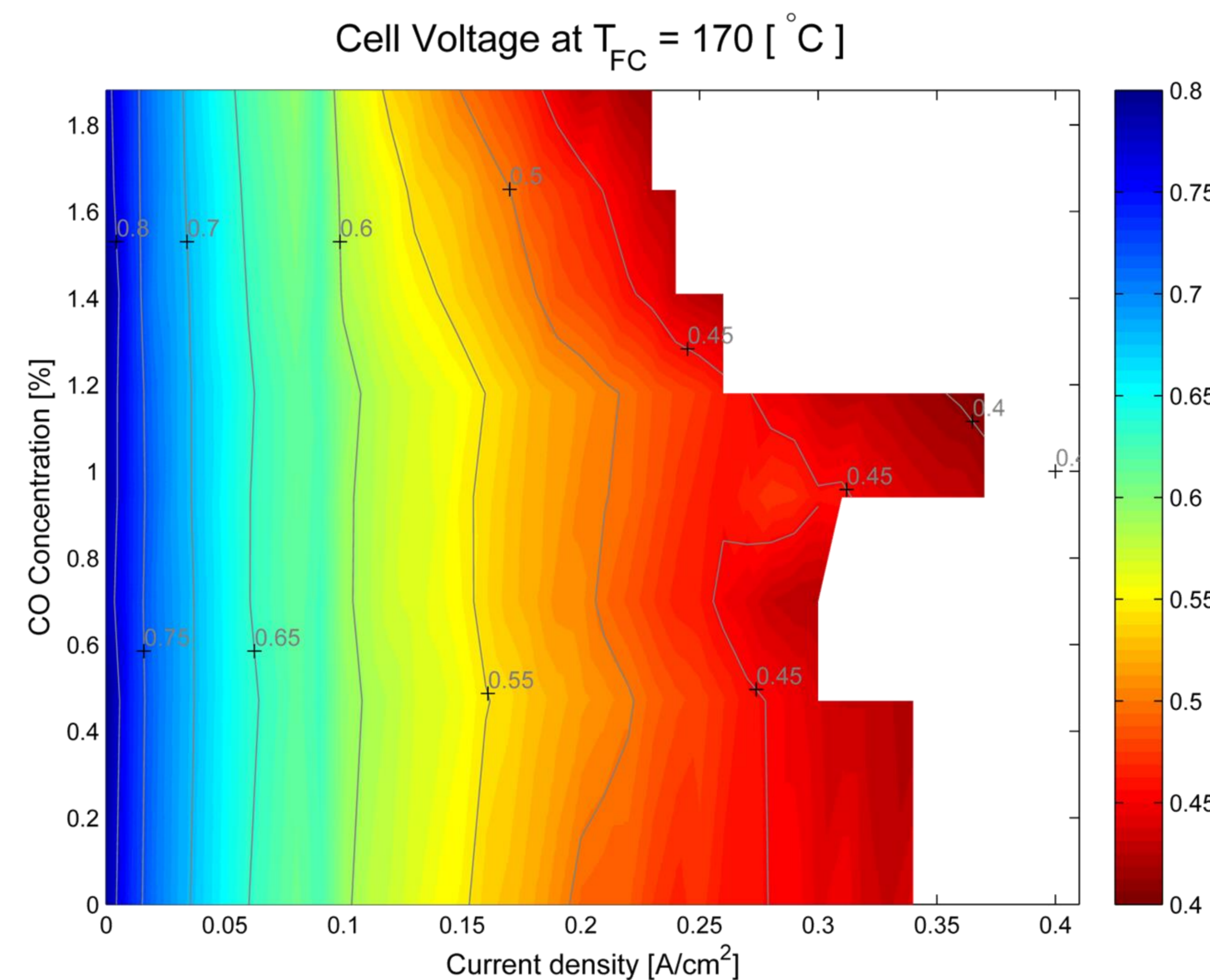**Figure 1:** Diagram of the ANFIS structure used in this work.

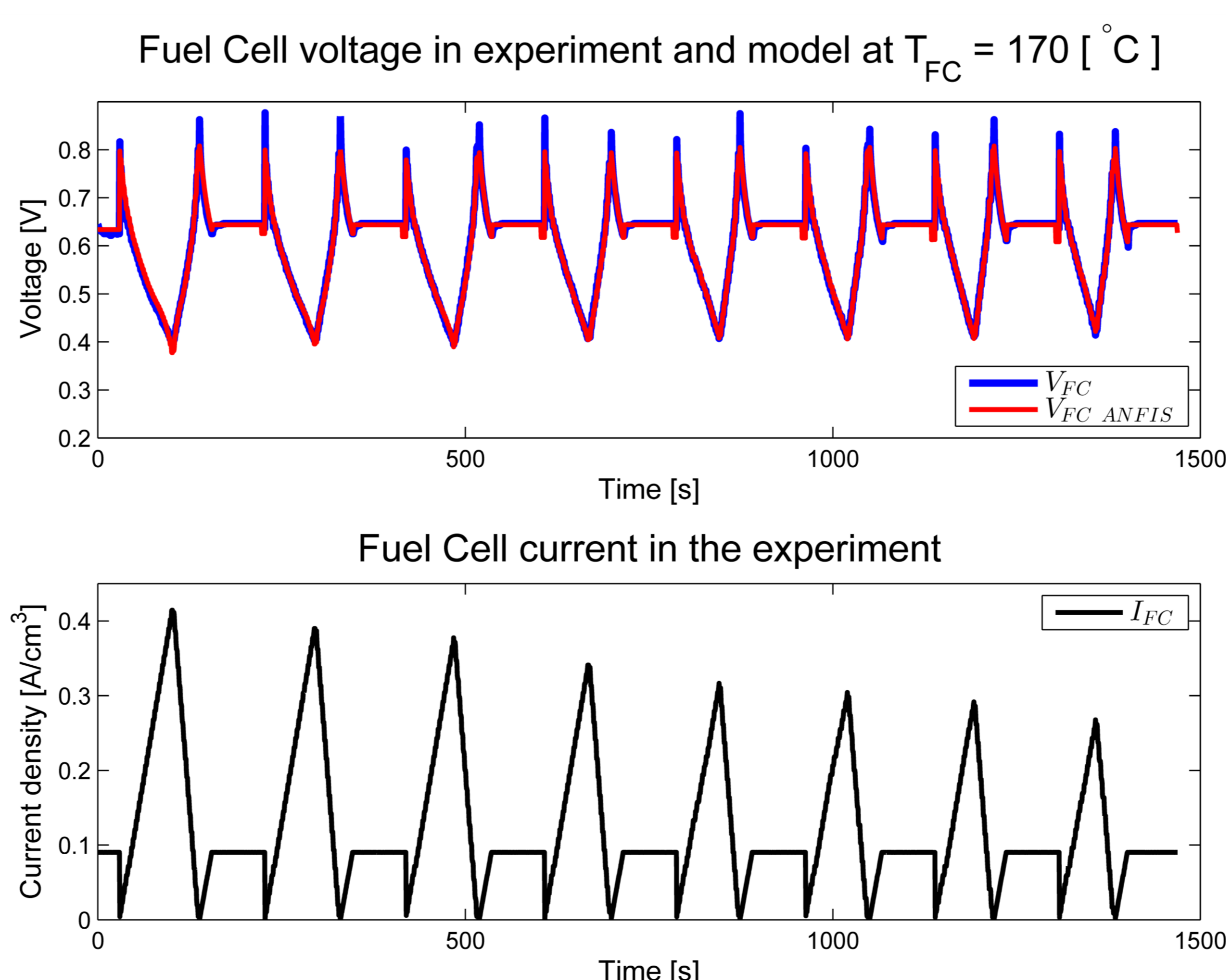**Figure 2:** Surface plot of the fuel cell voltage in the experiment.

Figure 3: Plot of the fuel cell voltage and current in experiment and model.

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Experiment

To be able to train the ANFIS model it is necessary to have an identification experiment, which spans the likely operating range of the fuel cell. In this work, a 14 cell stack, which is a shortened version of a Serenergy S 165L-25, is used. The cell is in an advanced state of degradation, but this doesn't prevent a proof of concept. Figure 4 shows a picture of this fuel cell stack.
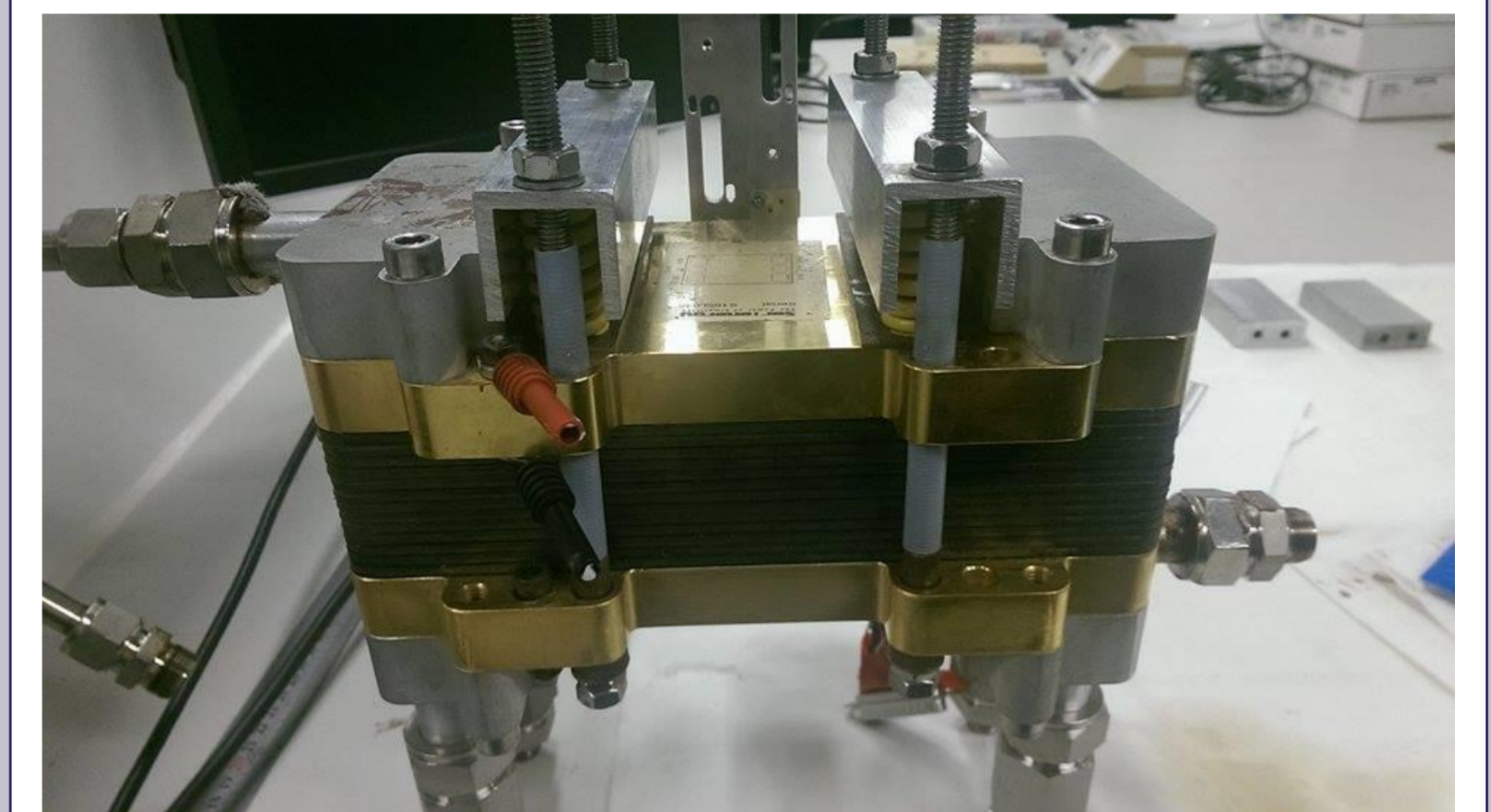

Figure 4: Picture of the fuel cell stack used in this work.

The fuel cell stack is mounted in a Greenlight G200 test station, which can supply an anode gas of the desired composition and temperature as well as the cooling oil, which controls the temperature of the fuel cell.

The maximum expected CO concentration, based on reformer experiments, is 1.9 % so the experiment is performed at 8 equally spaced concentrations from 0 to 1.9. The maximum rated current density is 0.6 $[A/cm^2]$ and the minimum allowable cell voltage is 0.4 $[V]$. The stop condition for the experiment will be that of these parameters, which is reached first. The experiment is performed for fuel cell temperatures of 160, 165 and 170 [°C].

Results and conclusion

A surface plot of the fuel cell voltage at a fuel cell temperature of 170 [°C], which is representative of the other temperatures, can be seen in Figure 2. This shows, that at higher current densities the CO concentration has a larger influence than at low concentrations.

The ANFIS models are trained in Matlab and the optimal number of membership functions is found to be 2, which gives a mean absolute error of 0.9%. Adding further complexity to the model is found to give no significant advantage.

Figure 3 shows the fuel cell voltage at a fuel cell temperature of 170 [°C] from the experiment and the model, as well as the current density. Again this plot is representative of the performance at 160 and 165 [°C].

It is concluded that a model of this type can be precise and useful for system optimization and modeling

Future work

To extend the usefulness of the model degradation in the form of the number of operating hours of the fuel cell could be added to the model.

References

[1] Roger Jang Jyh-Sing. ANFIS: adaptive-network-based fuzzy inference system. IEEE Transactions on Systems, Man, and Cybernetics 1993;23:665e85.