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Application of adaptive neuro-fuzzy inference system techniques and artificial neural networks to predict solid oxide fuel cell performance in residential microgeneration installation

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Abstract

This study applies adaptive neuro-fuzzy inference system (ANFIS) techniques and artificial neural network (ANN) to predict solid oxide fuel cell (SOFC) performance while supplying both heat and power to a residence. A microgeneration 5 kW_{el} SOFC system was installed at the Canadian Centre for Housing Technology (CCHT), integrated with existing mechanical systems and connected in parallel to the grid. SOFC performance data were collected during the winter heating season and used for training of both ANN and ANFIS models. The ANN model was built on back propagation algorithm as for ANFIS model a combination of least squares method and back propagation gradient decent method were developed and applied. Both models were trained with experimental data and used to predict selective SOFC performance parameters such as fuel cell stack current, stack voltage, etc.

The study revealed that both ANN and ANFIS models' predictions agreed well with variety of experimental data sets representing steady-state, start-up and shut-down operations of the SOFC system. The initial data set was subjected to detailed sensitivity analysis and statistically insignificant parameters were excluded from the training set. As a result, significant reduction of computational time was achieved without affecting models' accuracy. The study showed that adaptive models can be applied with confidence during the design process and for performance optimization of existing and newly developed solid oxide fuel cell systems. It demonstrated that by using ANN and ANFIS techniques SOFC microgeneration system's performance could be modelled with minimum time demand and with a high degree of accuracy.

Keywords: Adaptive neuro-fuzzy inference system (ANFIS); Artificial neural network (ANN); Solid oxide fuel cell (SOFC); Microgeneration; Modeling; Simulation

1. Introduction

Microgeneration is defined as a notion of simultaneous generation of both heat and power in an individual dwelling. It is also known as micro combined heat and power generation (mCHP). Installed at the point of use mCHP plants will generate electricity and heat with high efficiency and low greenhouse emissions and are a viable alternative to central power generation stations. Currently, there are several microgeneration technologies under development such as fuel cells, stirling engines, IC engines, etc. However, SOFCs are starting to emerge as one of the most promising high efficiency/clean-fuel energy technology as most of the developed SOFC systems are suitable for both off-grid and grid connected applications. In either case, heat produced during the power generation process can be recovered and utilized to satisfy space and water heating load of the house during winter and to provide thermal cooling in the summer.

A combined heat and power 5 kW_{el} SOFC was installed and tested at the Canadian Centre for Housing Technology (CCHT) during 2005 winter season. The project objectives were to demonstrate the first SOFC mCHP residential installation in Canada and to examine the SOFC/building integration issues such as HVAC interface, control strategies, grid connection, system ability to follow the load, optimal SOFC size, etc. In addition to the testing, computer models were developed to optimize the SOFC and balance of plant (BOP) operations and to investigate and to predict the SOFC performance under a variety of external conditions.

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Nomenclature

e	experimental value
I	stack current (A)
MRE	mean relative error (%)
N	number of data points
p	predicted value
P	stack power (W)
RMSE	root mean square error
V	stack voltage (V)

Subscript

i	index for data points

It is well known that SOFC performance is directly related to the multi-physic processes taking place within the fuel cell stack. Electrochemical reactions, chemical reactions, mass and charge transport as well as heat transfer occur all at the same time and are tightly coupled [1–3]. In this complex environment mathematical models are a very useful tool and they have been applied to investigate and to improve the fuel cell stack performance for many years. However, most of the SOFC models found in the literature are physically based mathematical, numerical or computational fluid dynamic models [1–13]. Most of these models are fairly complex and it is time consuming to develop and build as in most cases the required input information is either incomplete or insufficient. It is due to these reasons that data driven adaptive models, such as neural network and fuzzy logic models, were considered in this study.

Artificial neural networks (ANN) have a history of some six decades but have found solid applications only in the past 20 years [14]. ANN is a type of artificial intelligence that mimics the behaviour of human brain and is famous for its robustness (adaptability) due to the use of a generalization technique instead of memorization. In recent years ANN has been successfully applied for modeling of different fuel cell systems [15,16]. However, in these two studies, ANN models were developed and trained with established baseline design points [15] or with data generated by a validated numerical model [16] but not with real life experimental data.

Beside the ANN technique, there is a rapid growth in the number and variety of applications of fuzzy logic. Among various combinations of methodologies in “soft” computing [17], the one that has highest visibility at this juncture is that of fuzzy logic and neurocomputing, leading to so-called neuro-fuzzy systems. Within fuzzy logic, such systems play a particularly important role in the induction of rules from observations. One effective method developed by Dr. Jang ([18–20]) for this purpose is called ANFIS (Adaptive Neuro-Fuzzy Inference System) and the ANFIS technique has been already applied in modeling and control of PEMFC systems [21].

The ANN and ANFIS models have the unique advantage that no clear relationship between the input and output variables needs to exist before the model is applied since the relationship is identified through a self-learning process. By utilising data samples from experiments, both ANN and ANFIS models can be applied to solve problems with no (or with too complex) algorithmic solutions, or in cases where the input information is incomplete or uncertain. The ability to learn by examples makes ANN and ANFIS models more flexible and powerful than the other traditional modelling methods.

This paper describes ANN and ANFIS models developed for the SOFC unit installed as a mCHP system at CCHT and their applicability for predicting SOFC power generation performance (stack current and voltage).

2. SOFC installation and data monitoring

2.1. SOFC installation at CCHT

Canadian Centre for Housing Technology’s (CCHT) research facility consists of two identical 2-storey research houses—the Experimental Research House and the Control Research House. Both houses are built to the highest R-2000 Canadian standard and feature identical simulated occupancies. The houses are wired with more than 500 sensors and are extensively monitored for energy performance and thermal comfort [22]. The Experimental House is used for testing where innovative energy saving components and systems are installed. The resulting changes in the energy performance of the Experimental House are assessed relative to the Control House.

A SOFC system with capacity of 5 kW_{el} and 5 kW_{th} was tested at CCHT during 2005 winter heating season. The fuel cell was installed in the Experimental Research House and connected to the house domestic hot water and forced air space heating system. Modifications were made to the house electrical wiring in order to accept the system and to provide means of importing/exporting power to the electricity grid [22]. The fuel cell stack was a tubular design with an operating temperature of 1000 °C. The fuel cell generated 3.5 kW_{el} ac output with 85% fuel utilization efficiency and internal reforming of the natural gas. A SOFC simplified flow diagram is shown in Fig. 1. The auxiliary burner inside the SOFC unit was fired at the start-up and used to maintain the thermal conditions of the fuel cell stack during steady-state operation. The thermal energy carried out by the exhaust stream was utilized through the Balance of plant heat utilization module. The BOP provided thermal storage for the excess heat from the cell and an additional backup or top-up burner installed in the thermal storage was used as a supplementary heat source in instances when the fuel cell was not able to satisfy the house entire thermal requirements. The generated dc power by the fuel cell was converted to ac and supplied to the house with excess power exported to the grid.

2.2. Data monitoring and collection

Data acquisition and control systems were developed and installed to collect data internal for the cell and from the external electrical and thermal utilization loops. More than 50 sensors were scanned every 10 s averaged and data recorded every minute. Six data were used to form one representative 1 min

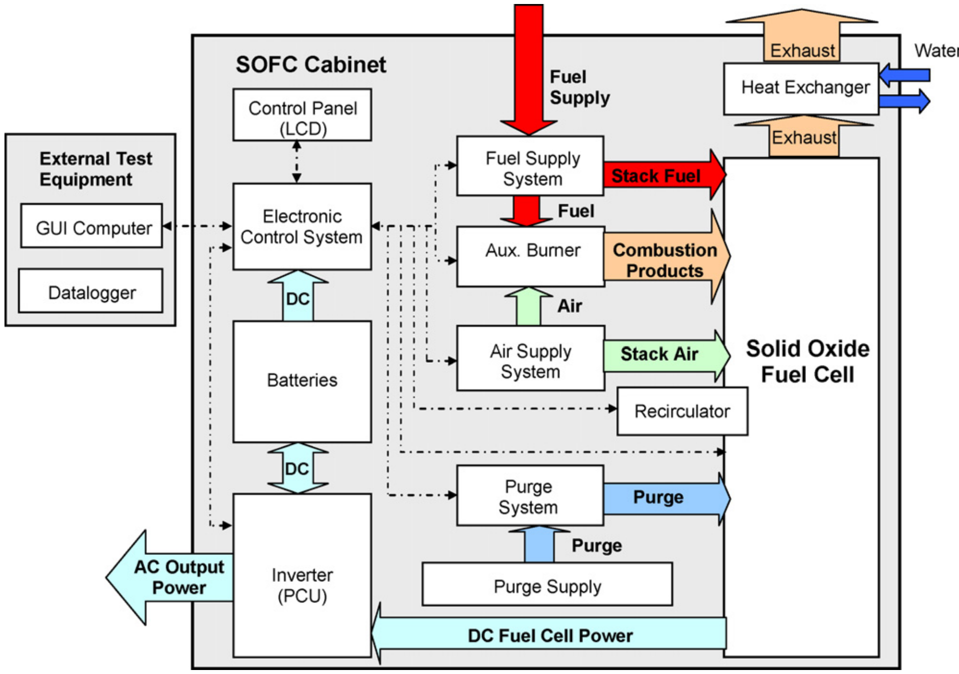

Fig. 1. Schematic flow diagram of solid oxide fuel cell unit tested at CCHT.

data to avoid any deviations due to random fluctuations that occur some times when only one instantaneous measurement is taken every minute.

A control strategy (independent of the one employed by the fuel cell alone) was implemented to manage the interaction between the thermal energy storage and space and water heating systems in the house [22]. Among the set of available data the following parameters were considered important in the context of this study:

- FC stack fuel (natural gas) consumption
- FC stack current
- FC stack voltage
- FC stack temperature
- FC stack air flow and inlet temperature
- FC stack exhaust temperature
- Burner fuel (natural gas) consumption
- Burner combustion temperature
- Burner air flow
- Burner air inlet temperature

The above parameters were chosen based on preliminary expert technical analysis of the FC system operation and data availability. However, there were some other parameters influencing the fuel cell power output but they were either not accessible for measurements during the FC testing or their importance was at a subsystems' level only.

Two experiments were conducted at CCHT during the 2005 heating season—26 days and 46 days respectively. The data sets covered all three modes of SOFC operation—start-up, steady-state and shut-down. The collected data provided extensive information for the fuel cell performance and was used for training and testing of ANN and ANFIS models.

3. Artificial neural network (ANN) model

Artificial neural network is a type of artificial intelligence technique that mimics the behaviour of human brain. It can approximate a nonlinear relationship between the input and output variables of nonlinear, complex systems without requiring explicit mathematical representations. The ANN architecture usually consists of three parts: an input layer, hidden layers and an output layer. Neurons in one layer are connected to all the neurons of previous and subsequent layers. Each connection between two neurons is associated with an adaptable synaptic weight. Using a suitable learning method, the network is trained to perform a particular function by adjusting the weights and biases. The training process continues until the error between the network output and the desired target falls below a predetermined tolerance or the maximum number of iterations (epochs) is reached.

Fig. 2 shows the architecture of the developed neural network model. The ANN network has an input layer with 8 inputs, 1 hidden layer with 10 neurons and an output layer with 2 outputs: SOFC stack current and voltage. The system is fully cross-connected. A number of ANN networks consisting of 3 and 4 layers with 5, 10, 15, 20 neurons in the hidden layers have been simulated. The final ANN structure (3 layers and 10 neurons in the hidden layer) was chosen as the one that gave comparable results (±2%) with the others and used less computational time.

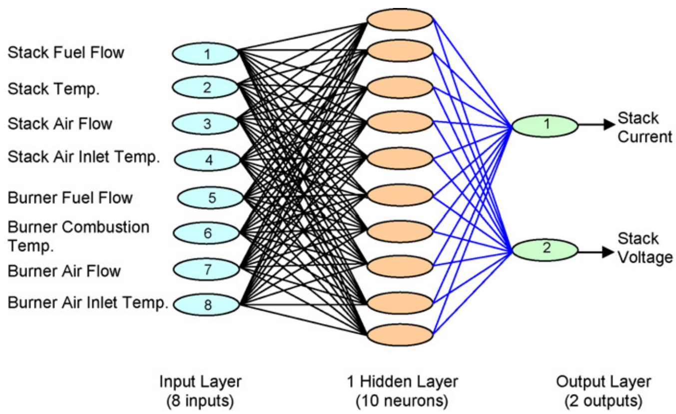

Fig. 2. Neural network architecture used in ANN8 (8 inputs) SOFC Model.

MATLAB® (The MathWorks Inc.) Neural Networks Toolbox was used to build ANN models. The hyperbolic tangent sigmoid transfer function ("tansig") was used in the hidden layer and linear transfer function ("purelin") was applied in the output layer. The two-layer sigmoid/linear network usually can represent any functional relationship between inputs and outputs if the sigmoid layer has enough neurons [14]. The nonlinear transfer function in the hidden layer allows the network to learn nonlinear and linear relationships between input and output vectors and the linear output layer lets the network produce values outside the range -1 to $+1$. The weights and biases were initialized using "init" function which calculates the weight and bias values using the Nguyen–Widrow initialization method. Lavenberg–Marquart backpropagation training algorithms ("trainlm") was used as a training function to update weight and bias values, as it is the fastest training algorithm for networks of moderate size although it can require additional memory. Memory problems did not occur during the simulations for all developed ANN models.

The available data from the CCHT experiments were divided into two sets: training and testing data sets. The first data set was used for training the network. The second set, which was not included in the training process, was used to verify the generalization capability of the network model. The selection of training and testing data is discussed in more detail in Section 6.

4. Adaptive neuro-fuzzy inference system (ANFIS) model

The basic idea behind the neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modelling procedure to learn about the data set, and to compute membership function parameters that will best suit the associated fuzzy inference system (FIS) for given input/output set. The ANFIS learning method works similarly to the neural networks one [18–20].

Fuzzy Logic Toolbox of MATLAB was used to build an ANFIS model and to predict the SOFC stack current and voltage. The model generates an initial FIS for ANFIS training by first implementing subtractive clustering on the given input/output data. The function "genfis2" was employed to accomplish this procedure by extracting a set of rules that models the data behaviour. The "radii" parameter required by the "genfis2"function is a vector that specifies a cluster center's range of influence in each of the data dimensions, assuming the data falls within a unit hyperbox [23]. Its value was 0.5, both for the stack current and voltage models. The parameters associated with the initial membership functions are then tuned (adjusted) through the learning ANFIS process by applying a combination of the least squares method and the back propagation gradient decent method.

It should be noted that there are some constraints of the "anfis" function. Unlike ANN, the "anfis" function only supports single output, which means an ANFIS model has to be developed and trained for the current and voltage respectively. The "genfis2"function applies all training data to identify coefficients of output equations. These constraints of the "anfis" and "genfis2" functions may increase the model computation time compared to the ANN models.

The same data set was used for ANN training and for ANFIS learning process. A separate data set, not included in the training set, was employed for verifying the ANFIS model generalization capabilities.

5. Criteria for models' performance evaluation

Models' performance can be evaluated through different criteria. In this study root mean square error and mean relative error were chosen for evaluation purposes.

The root mean square error, RMSE, is calculated by:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(e_i - p_i)^2}$$

where e is actual value from experiments, p is predicted value by models and N is the number of data points.

The mean relative error, MRE, is given by the following:

$$\mathrm{MRE}\ (\%) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{p_i - e_i}{e_i} \times 100\right|$$

6. Input/output variables and training/testing data sets

A number of different experiments were conducted at CCHT to examine the SOFC system performance. However, for the purpose of this study two data sets were extracted from the data base representing two different tests performed with the mCHP system. The first data set contains 21,000 data points and was used for training purposes while the second one contains 53,000 data points and was used for testing and verification of the developed ANN and ANFIS models.

6.1. Model input and output variables

The SOFC system preliminary analysis defined a cluster of input parameters that have an impact on the fuel cell system power output (voltage and current) level:

1. Stack fuel (natural gas) flow
2. Stack temperature
3. Stack air flow
4. Stack air inlet temperature
5. Burner fuel (natural gas) flow
6. Burner combustion temperature
7. Burner air flow
8. Burner air inlet temperature

Two rounds of simulations were performed with ANN and ANFIS models. In the first round all eight variables were used as inputs to the models. Then backward stepwise multiple linear regression ("stepwise") was applied to identify statistically significant variables. It started with all terms in the model and removes the least significant terms until the results were still satisfied with all the remaining terms. An important assumption behind the method is that some input variables in a multiple regression do not have important explanatory effect on the response. It is a convenient simplification to keep only the statistically significant terms in the model [24]. Before the stepwise multiple regression was applied the initial number of 8 input parameters was increased to 16 as the new parameters entered into the regression were presented as nonlinear functions of initial set of 8 parameters such as X_1^2, $X_1 \times X_2$, etc. This transformed the stepwise regression to one that corresponds to the nonlinear structure of ANN and ANFIS models. Based on the regression findings and follow up analysis of the impact of the linear and nonlinear input parameters on the outputs, the number of input parameters was reduced to four in the second round of simulations. Table 1 shows the multiple regression coefficients for predicting stack current and voltage.

Table 1
Linear regression coefficients for predicting stack current and voltage

	Coefficients	
	Stack current, *I*	Stack voltage, *V*
Stack fuel flow	24.4469	−0.0920
Stack temperature	0.5680	−0.0018
Stack air flow	0.0184	0.0026
Stack air inlet temperature	0.1477	−0.0509
Burner fuel flow	0.4009	0.1241
Burner combustion temperature	−0.0063	0.0011
Bruner air flow	0.0128	−0.0202
Burner air inlet temperature	0.0008	−0.0020

1. Stack fuel (natural gas) flow
2. Stack temperature
3. Stack air inlet temperature
4. Burner fuel (natural gas) flow

Fig. 3 illustrates the measured values of the above four input parameters from both experiments. The data points in Experiment 1 and 2 are continuous in terms of time with 1-min resolution and the vertical line in the graph separates the data obtained from each experiment.

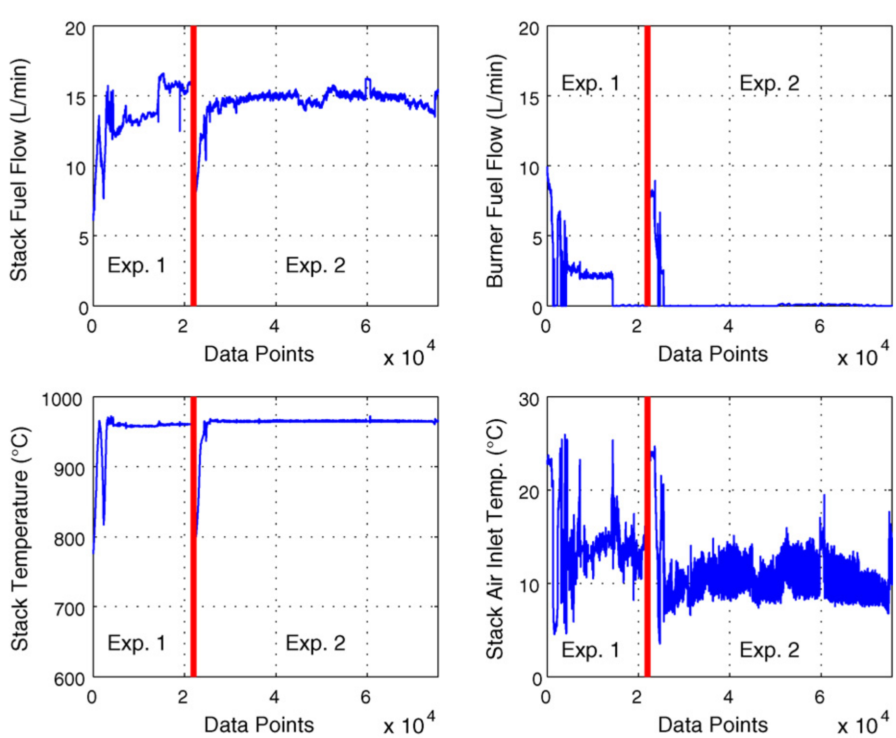

Fig. 3. Measured stack fuel flow, burner fuel flow, stack temperature and stack air inlet temperature during Experiments 1 and 2.

Table 2
Training and testing data in various ANN and ANFIS models

ANN and ANFIS models	Training data	Testing data
M1: start-up period	Experiment 1	Experiment 2
M2: steady operation period	Experiment 1	Experiment 2
M3: entire experiment period (start-up and steady operation periods)	Experiment 1	Experiment 2

6.2. Training and testing data sets

Two tests were conducted at CCHT to generate data needed for modeling purposes. All three modes of SOFC operations—start-up, steady-state and shut-down were covered. In this study the time periods before the system reached its capacity are called start-up periods and the time periods when the output power is at its controlled or design capacity are called seady-state periods.

Three distinct models were developed for SOFC prediction by applying ANN and ANFIS techniques. The first one was intended to model the SOFC start-up periods and the second one was intended for periods when the SOFC was in steady-state operation. A third integrated model was developed to predict both start-up and steady-state SOFC operations. Data used for models' training and testing are listed in Table 2.

7. Results and discussions

Total of 12 ANN and ANFIS models, with 8 and four 4 input variables, were developed and tested. Models' performance was evaluated by root mean square (RMSE) and mean relative error (MRE) for the entire data set (including training and testing data). Fig. 4 summarised the evaluation results both for ANN and ANFIS models. A comparison between the predicted and measured data for ANFIS4-M3 models (4 inputs, covering entire experimental period) are shown in Figs. 5 and 6. The first subplot in these two figures shows the predicted and measured current/voltage; the second one shows the difference between the predicted and measured values and the third one shows the relative error (%) of the model. Figs. 7 and 8 illustrate the predicted versus experimental SOFC current and voltage respectively.

Results in Fig. 4 show that for all ANN and ANFIS models the RMSE values, for stack current and stack voltage, were small relative to their target values (experimental values). The mean relative errors (MRE) were less than 2% for all models. As shown in Figs. 5 and 6, the relative errors of the two output parameters were all within ± 10% and within ± 5% for majority of data points.

The results indicate that both ANN and ANFIS models can give good predictions of the stack current and voltage. However, the ANFIS model performs better than ANN model in predicting the FC current. In some instances the ANN performed better than ANFIS in predicting the FC voltage which is mainly due to less deviation of the voltage data which diminished the advantage of fuzzy logic part of the ANFIS model.

It also illustrates that models with reduced number of inputs had the same degree of accuracy as initial detailed model. The results obtained from the third model (M3) confirmed that there is no need of separate models for various operating stages as one model can simulate all operational modes of SOFC with high degree of accuracy.

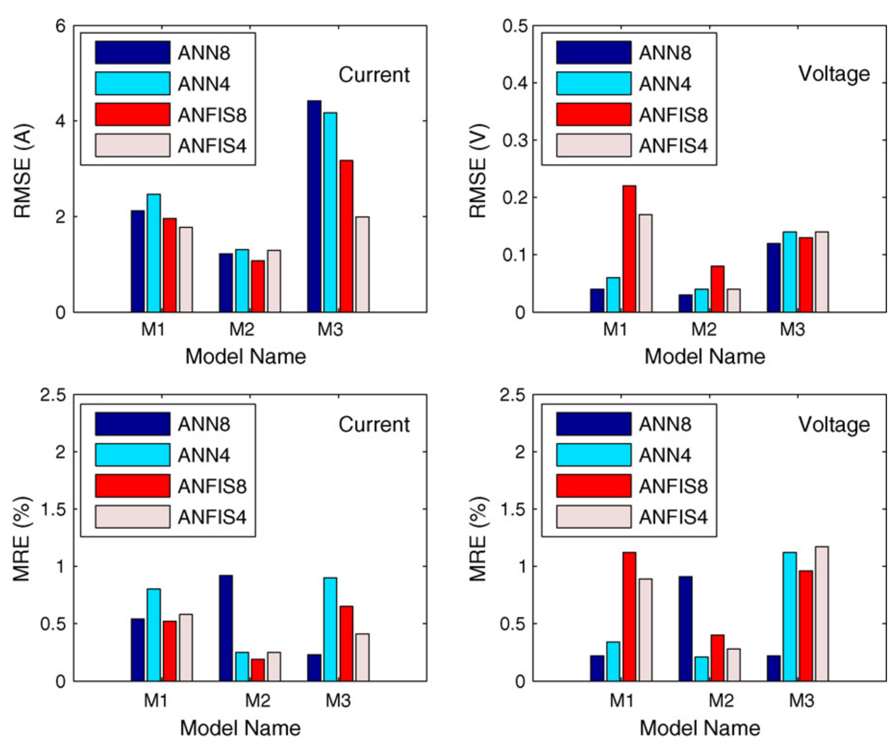

Fig. 4. Evaluation of model performance: root mean square (RMSE) and mean relative error (MRE) of ANN and ANFIS models with 8 and 4 inputs. M1, M2 and M3 refer to model names described in Table 2.

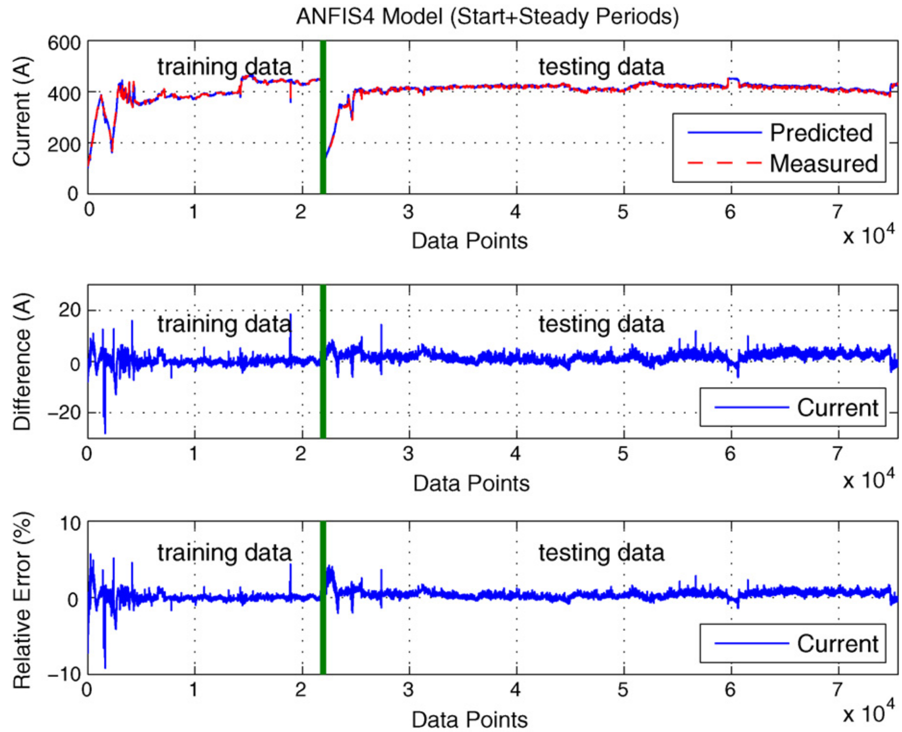

Fig. 5. Comparison of predicted and measured SOFC current—ANFIS4 (M3) model.

The trained ANN and ANFIS models applied to the second data set showed that models' predictions were in line with the test data even without retraining the models. However, further verification of the generalization capability of these models should be performed when more experimental data from a fuel cell system with a modulating power output become available for the same or different SOFC units.

Evaluation results showed that, with same number of inputs and data points, the required computer computational time for ANN model was approximately 20% of the required by ANFIS model. It is mainly due to the "genfis2" function which is inevitably slow since it applies all training data to identify the coefficients of the output equations, but also due to the "anfis" function which only supports single output.

The evaluation results also showed that, by excluding the four least statistically significant variables, the computation time could be reduced by more than 30% compared to the same type of model with all eight input variables, e.g. ANN4 (M3) versus ANN8 (M3).

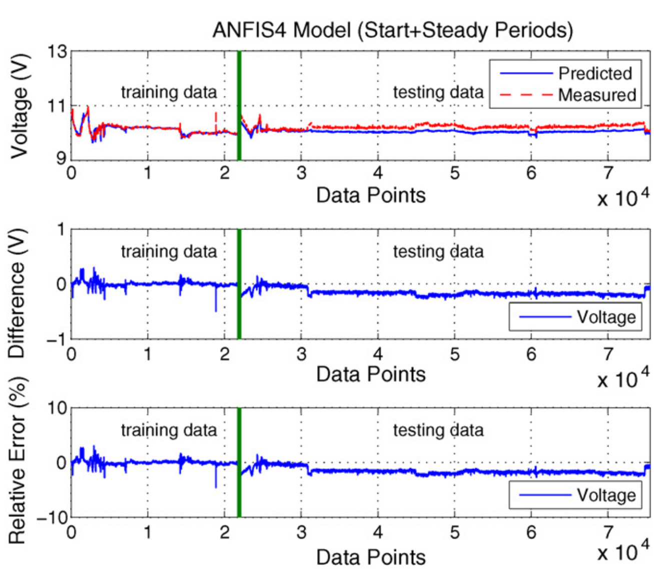

Fig. 6. Comparison of predicted and measured SOFC voltage—ANFIS4 (M3) model.

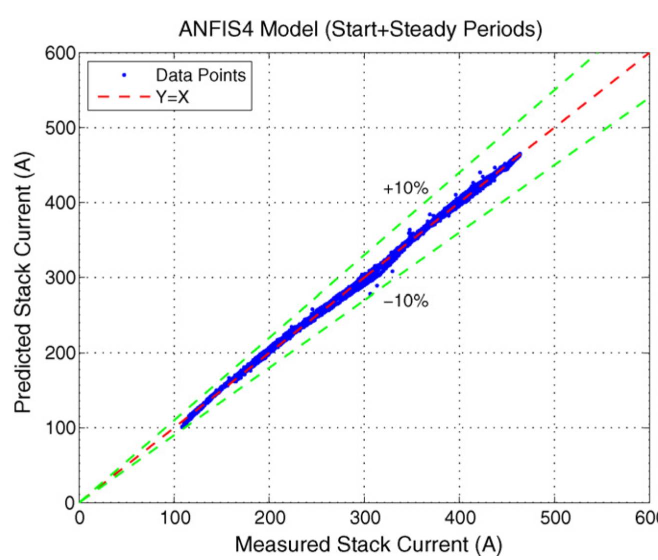

Fig. 7. Predicted versus measured SOFC current—ANFIS4 (M3) model.

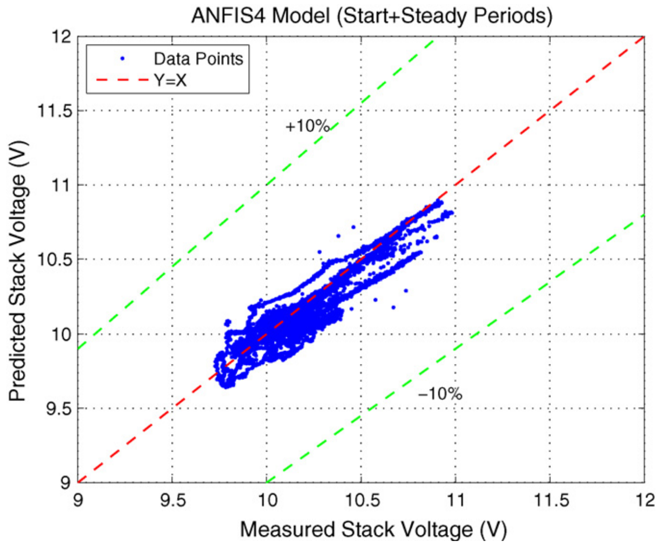

Fig. 8. Predicted versus measured SOFC voltage—ANFIS4 (M3) model.

8. Conclusions

Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) techniques were used to predict performance parameters stack current and voltage of a residential SOFC system installed at the Canadian Centre for Housing Technology.

Three models (M1, M2, M3) based on ANN and ANFIS techniques were developed for predicting the SOFC operation. By applying multiple regression method, four important input variables were identified with significant contribution for SOFC stack current and voltage generation. The evaluation results indicated that the integrated (M3) model was able to predict with a good accuracy the SOFC performance over a range of different operational conditions. All ANN and ANFIS models developed and evaluated in this study had a maximum relative error of $\pm$ 10% (with $\pm$ 5% for majority of data points) and mean relative error of less than 2% for all output parameters. Furthermore, the root mean square errors were small relative to their target values (experimental values).

The comparison of computational time revealed that running time for ANN model was five times shorter than for ANFIS model (with same number of inputs and data points). By reducing the number of input parameters the computation time was reduced by more than 30% without affecting models' accuracy.

Based on the results from this study it can be concluded that by using the ANN and ANFIS techniques, SOFC system can be modelled with relative high accuracy. The ANN and ANFIS ability to learn by examples makes the developed models a good addition to the existing modelling techniques. The ANN and ANFIS models can be applied either separately as stand-alone modules or as an addition to the existing conventional mathematical models. The fuel cells are still under development and there is a constant need for adjustment of the already developed models to answer the challenges from the FC industry. In comparison to the conventional models the ANN and ANFIS models are able to predict and optimize system performance faster and deliver better results in many instances. The developed models could be applied as part of fuzzy and/or fuzzy/NNT controllers to optimize the complex fuel cell operations in the field.

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