Dynamic Modeling of SOFC Fuel Cell Black Box by Smart Methods

S.seyedarman shirmardi
Department of Electrical Engineering
Shahrdari ahwaz University of Technology
s.seyedarmanshirmardi @gmail,com

Mohammadali Tavosi
shoushtar Branch, Islamic Azad University, Shoushtar, Iran
Mtavosi325@ yahoo.com

Abstract

Smart modeling of fuel cell with solid oxide electrolyte (SOFC) was done by proposed algorithm in this study. The results were then compared with an accurate mathematical model. The results of simulations indicate that SVM model provides a better response than ANN model. Meanwhile, this model can properly replace the common mathematical models for dynamic and static studies.

Keywords: smart modeling, SVM, ANN, solid oxide fuel cell, mathematical model.

Introduction

Dynamic model of tubular solid oxide fuel cell is created based on the electrochemical and thermodynamic features of solid oxide fuel cell. Output voltage of cell (or heap) depends on the fuel compound, fuel and oxide flows, anode and cathode temperature pressure, thermal and electrical features of cell elements, cell temperature and electric current. Figure1 indicates dynamic model of tube solid oxide fuel cell which is simulated in research software.

 Issue 5, Vol. 1 January 2016
ISSN 2319 – 7277

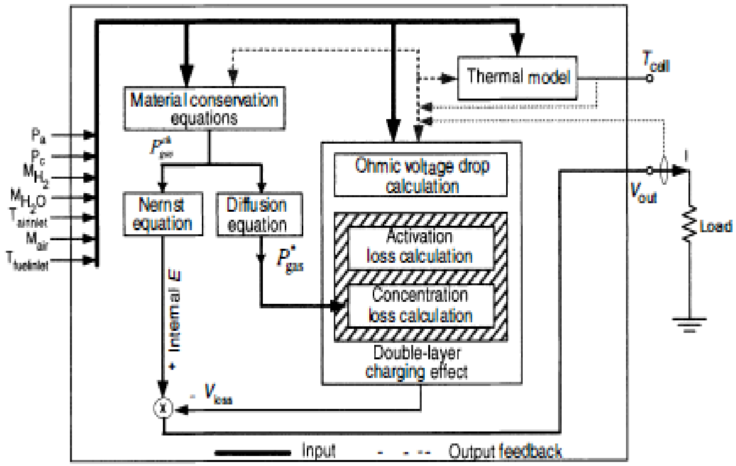


Figure 1. **Dynamic** model of solid oxide fuel cells [1]

Input quantities of model include anode and cathode pressure (MH_2),fuel flow Ratio and (hydrogen) (MH_2), steam flow ratio (MH_2), elements flow ratio (MH_2), primary fuel cell temperature (MH_2). Cell temperature (MH_2) is determined in each electric current and given time and both temperature and electric current are sent back into different pieces which participate in calculation of output voltage of fuel cell. The output of model is temperature and voltage.

1. The proposed method for dynamically modeling SOFC fuel cell by artificial neural network and support vector machine

Dynamic modeling of the mentioned fuel cells is done by explaining a proper algorithm in this section. This algorithm consists of four steps which are explained as follows.

2.1 First step: providing proper data for training and test (database creation)

Providing proper data which cover all the working areas of the mentioned fuel cells, is a crucial requirement for the training of smart systems. In addition, dynamic data for training must be provided for dynamic modeling. Dynamic data is produced by applying proper PRBS signal to entry. These data can be used for training every smart system. Support vector machine and artificial neural network are selected for dynamic modeling of black box.

PRBS signal is one of the well-known identification methods which is used to make proper data for dynamic modeling of systems. It is indicated in reference (49, 50) that this signal has extensive frequency spectrum and its autocorrelation function is very close to White Noise. This signal is applied to the selected entries for dynamic modeling and the produced data are used for training smart system.

2.2 Second step: selecting proper inputs based on decision tree

On the basis of decision tree characteristics final major parameters are selected for training. This reduces input data for training the system. Yet, the most important parameters which exert the most effect on output are selected for training.

2.3. Third step: training smart system by selecting the best parameters

The number of latent layers and neurons (in artificial neural networks method) or required parameters (in support vector machine method) is determined in this stage so that the voltage prediction error reduces to its minimum. Three indices of maximum error (ME), mean square error (MSE) and squared correlation coefficient (SCC) are used for assessment. They are introduced in the fourth stage.

2.4. Fourth stage: the assessment of proposed model against test data

The prediction error of smart models are assessed by SCC, MSE and ME indices. These indices are defined as follows:

(1) $\mathrm{ME} = \mathrm{Max}\left|V_{act,i} - V_{pre,i}\right| \quad i = 1,2,\ldots,T$

The real amount of output voltage is in the i-point in the above formulas $\mathrm{ME} = \mathrm{Max}\left|V_{act,i} - V_{pre,i}\right| \quad i = 1,2,\ldots,T$. $\mathrm{ME} = \mathrm{Max}\left|V_{act,i} - V_{pre,i}\right| \quad i = 1,2,\ldots,T$ is the output model. T determines the number of points of data test.

(2) $\mathrm{MSE} = \frac{1}{T}\sum_{i=1}^{T}\left(V_{act,i} - V_{pre,i}\right)^2$

Issue 5, Vol. 1 January 2016
ISSN 2319 – 7277

(3) $SCC = 1 - \frac{SS_{err}}{S_{tot}}$

(4) $SS_{tot} = \sum_{i=1}^{T} \left(V_{act,i} - \overline{V}_{act}\right)^2$

(5) $SS_{err} = \sum_{i=1}^{T} \left(V_{act,i} - V_{pre,i}\right)^2$

(6) $\overline{V}_{act} = \frac{1}{T} \sum_{i=1}^{T} V_{act,i}$

Better capability of model in predicting output voltage closes ME and MSE to zero and SCC to 1.

Mathematical model is used for extracting data for smart modeling. The results of the trained smart models are compared with the above algorithm and the results of the accurate mathematical model of reference1 in subsequent sections of the article.

3. Smart modeling of fuel cell

Important input parameters which have the most influence on output voltage of SOFC fuel cell are determined in this section. The accurate mathematical model of reference1, introduced in the previous section, is used to indicate the effect of these parameters.

As the fuel cell with solid oxide electrolyte works in two operation states (CFU, CFF) [1], modeling is performed in two utilization states considering important inputs. Figure2 indicates the effect of CFU and CFF utilization states on the output voltage of fuel cell with solid oxide electrolyte.

Issue 5, Vol. 1 January 2016
ISSN 2319 – 7277

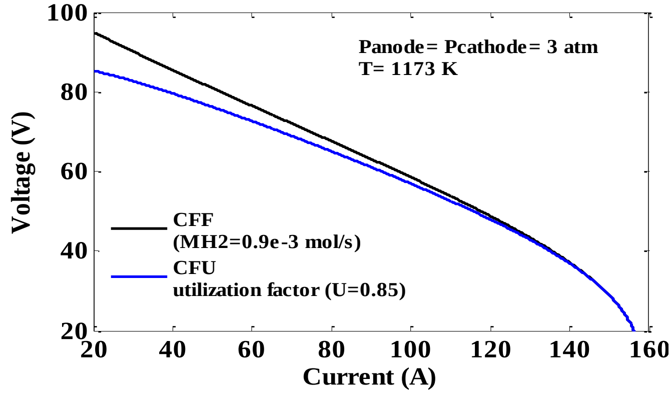


Figure2. the effect of CFF and CFU utilization state on output voltage of fuel cell with solid oxide electrolyte

Pressure and temperature flow are considered as input parameters in CFF utilization state. Figure 3 and figure4 indicate the effect of temperature and pressure of 5Kw fuel cell output voltage of solid oxide electrolyte.

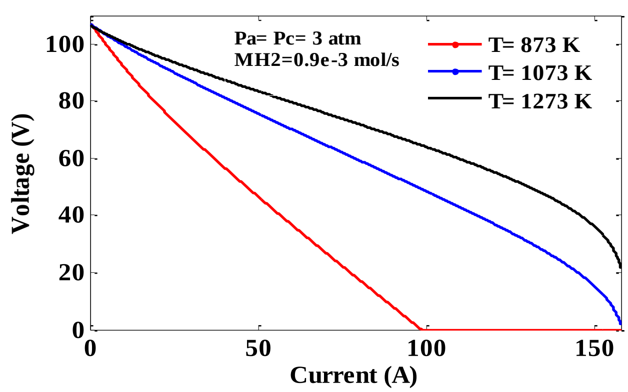


Figure3. the effect of temperature on output voltage of solid oxide electrolyte fuel cell (CFF)

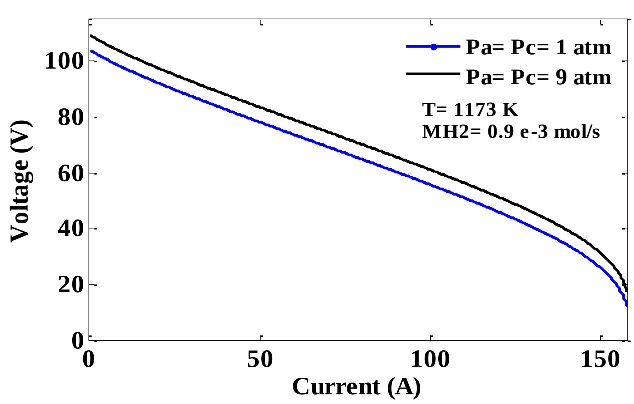


Figure4. the effect of pressure on output voltage of solid oxide electrolyte fuel cell (CFF)

Issue 5, Vol. 1 January 2016
ISSN 2319 – 7277

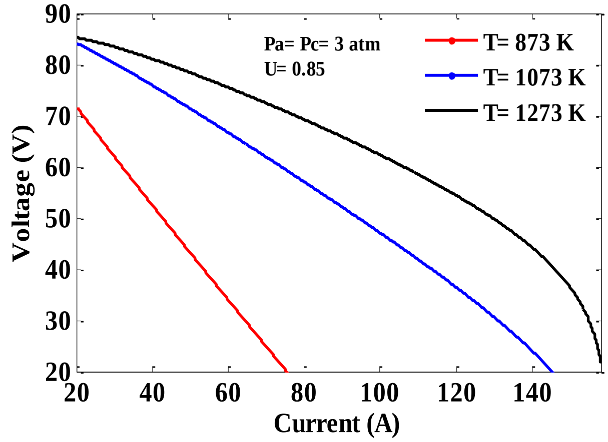
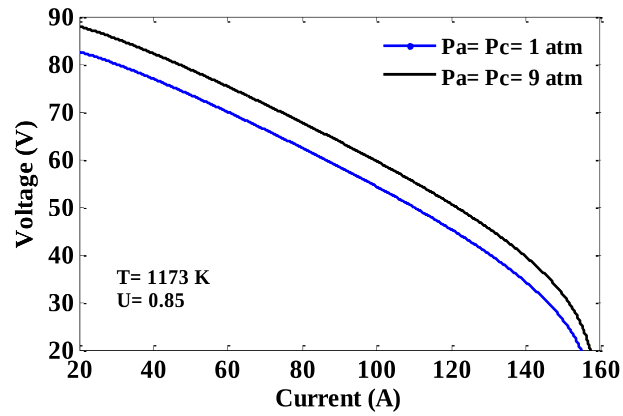


Figure5. the effect of temperature on output voltage of solid oxide electrolyte fuel cell (CFU)

In CFU utilization state, current, temperature, pressure and fuel utilization ratio are selected for input. Figure 5, 6 and 7 indicate the effect of temperature, pressure and fuel utilization



ratio on the mentioned fuel cell output voltage.

Figure6. the effect of pressure on output voltage of solid oxide electrolyte fuel cell (CFU)

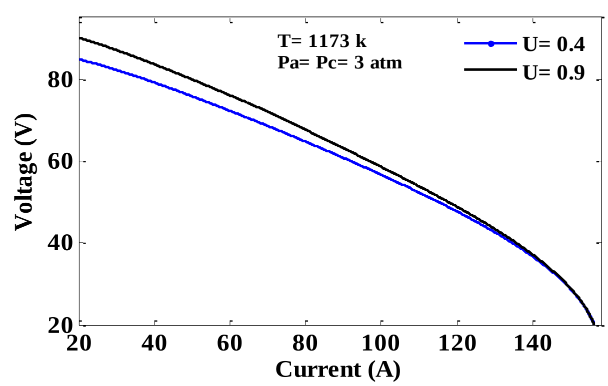


Figure7. the effect of fuel utilization ratio on output voltage of solid oxide electrolyte fuel cell (CFU)

Issue 5, Vol. 1 January 2016
ISSN 2319 – 7277

According to the above figures, considering both utilization states are important for dynamic modeling of fuel cell with solid oxide electrolyte. Meanwhile, important parameters of each utilization state must be considered in modeling.

The effect of important parameters on proton exchanging fuel cell output voltage is indicated in the later sections.

4. Smart modeling of fuel cells by support vector machines

At first the modeling of fuel cell with solid oxide electrolyte by support vector machine is introduced.

For each utilization style of fuel cell with solid oxide electrolyte, a SVM is instructed and the results are compared with the accurate mathematical model of reference1.

Reference1 simulated the fuel cell with solid oxide electrolyte which has 96 cells. Voltage ranges from 55 to 110A and temperature ranges from 600 to 1000 centigrade in this fuel cell. In addition, in the CFU utilization state, fuel utilization ratio varies from 0.4 to 0.9.

According to the introduced algorithm in 2-4, dynamic modeling with SVM is performed in this section.

4-1. dynamic modeling of SOFC in CFF utilization state

4-1-1. first stage

Dynamic data for SVM and ANN training are prepared by PRBS (Pseudo Random Binary Sequence) signal. Figure8 indicates the applied PRBS signal to the current. The training data are provided in such a way that all the working area be considered. Meanwhile, several dynamics in different situations and 19883 points of the permanent performance of fuel cell are provided so that the performance of the proposed model in dynamic and permanent state is measured.

 Issue 5, Vol. 1 January 2016
ISSN 2319 – 7277

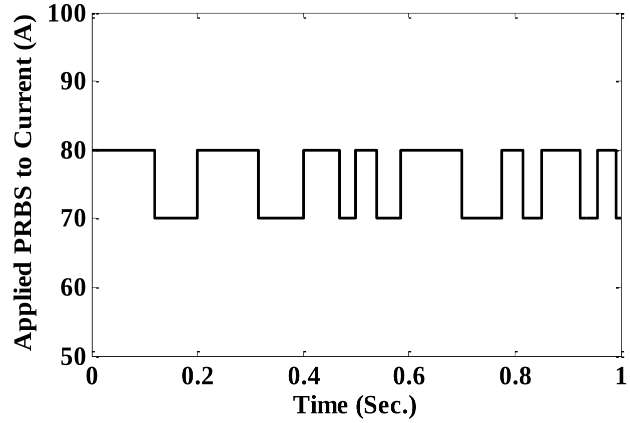


Figure8. the applied PRBS signal to current

4-1-2. second stage:

As part of decision tree is indicated in figure9, the three first ranks of voltage, one first rank of current, temperature and pressure are required to predict output voltage.

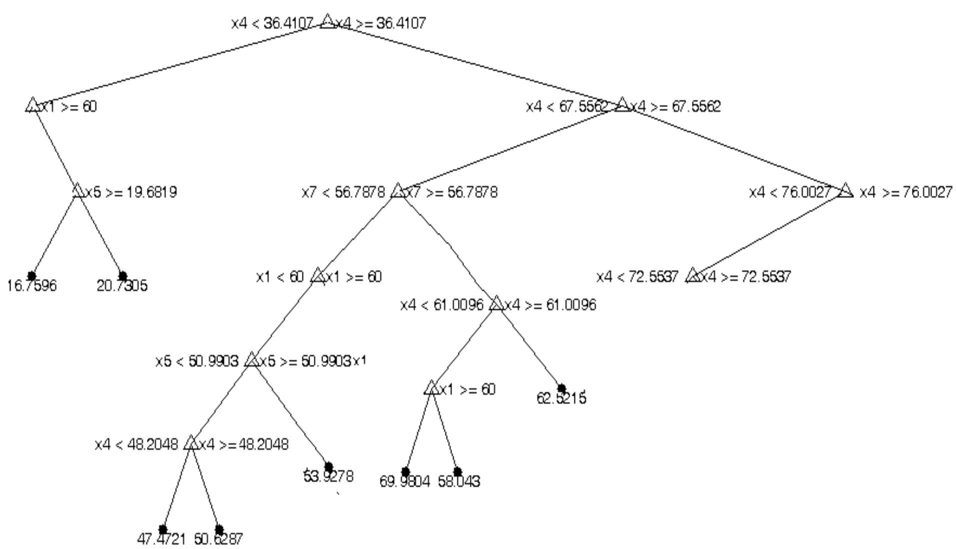


Figure 9. some part on decision tree

In fact, using decision tree reduces properly the input data for training. Therefore, the most important data are considered for training.

 Issue 5, Vol. 1 January 2016
ISSN 2319 – 7277

4-1-3. Third stage:

We found that by examining through try and error Inverse Distance Kernel Function with $\mu =$ 0.004 and $C = 100000$ are the best parameters for reducing the error of model prediction based on SVM.

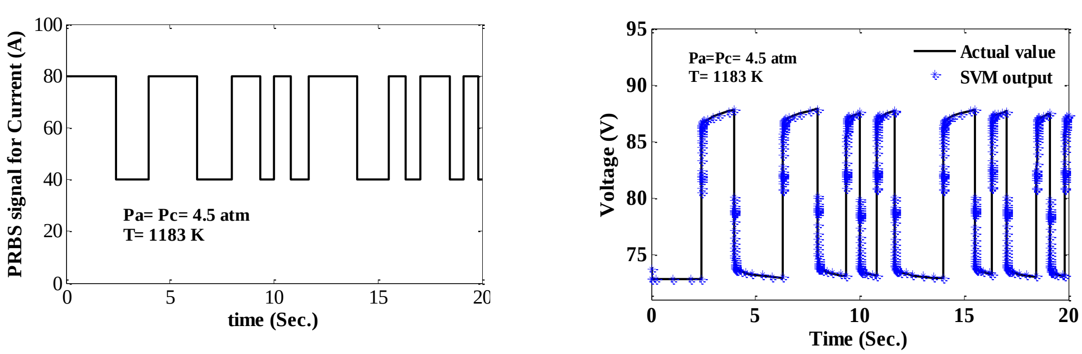
4-1-4. fourth stage

The proposed indices in the algorithm of chapter2 , time of training and other information in table1 are calculated for the proposed model against test data of static and dynamic state.

Table1. proposed indices for model based on SVM (CFF utilization state)

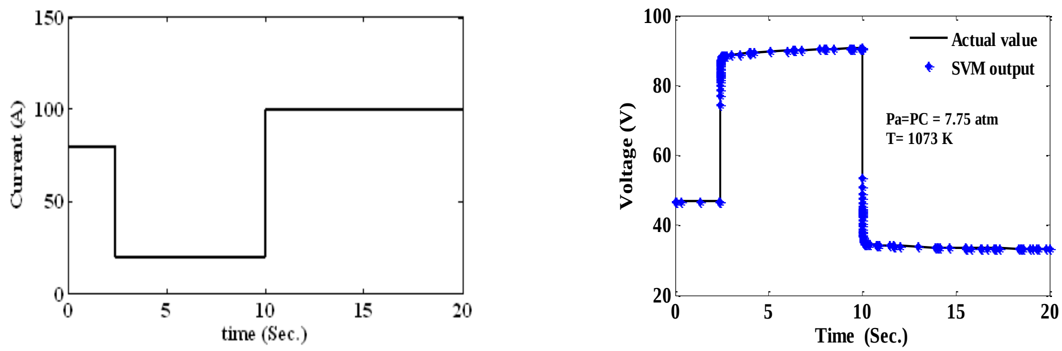
	ME (Volt)	MSE	SCC	Time of training (Sec.)	Number of support vectors
SVM	1.76	0.288	0.9988	278	3567

Figure10a and figure 10c indicate two applied dynamics to fuel cell current . Figure10b and figure10d compare the order of mathematical model output and SVM for the applied dynamics.



(a) (b)

Issue 5, Vol. 1 January 2016
ISSN 2319 – 7277



(c) **(d)**

Figure10. a) the first applied dynamic to current, b) comparison of SVM output voltage and mathematical model, c) the second applied dynamic to current, d) comparison of SVM output voltage and mathematical model.

As it is evident from the figures, the proposed model models properly the system dynamic.

4-2. dynamic modeling of SOFC in CFU utilization state

Similarly, the proper dynamic data were prepared with PRBS signal in the acceptable range of fuel cell utilization ratio for training. In addition, 15600 points of the performance of permanent state of fuel cell were prepared for the assessment of the proposed model in permanent state in this utilization state.

According to the decision tree output of previous utilization state, 3 voltage ranks, one rank of current, temperature, pressure and fuel utilization ratio are the most important inputs of the model. The fuel cell voltage in this utilization state is also the output of model.

Similarly, investigating through try and error, we found out that Inverse Distance kernel Function with $\mu = 0.004$ and $C = 100000$ are the best parameters for reducing model prediction error based on SVM.

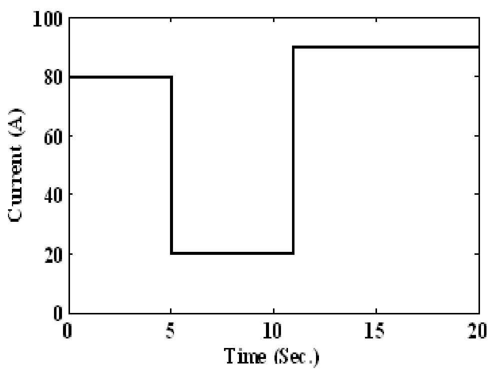
The proposed indices, time of training and other information in table2 for the proposed model in this utilization state are calculated against test data of static and dynamic state.

Issue 5, Vol. 1 January 2016
ISSN 2319 – 7277

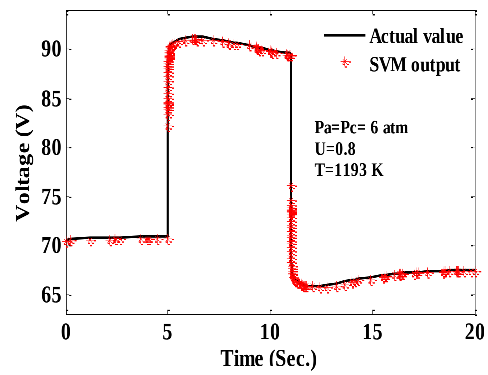
Table2. the proposed indices for model based on SVM (CFU utilization state)

	ME (Volt)	MSE	SCC	Time of training (Sec.)	Number of support vectors
SVM	1.85	0.311	0.997 8	312	3765

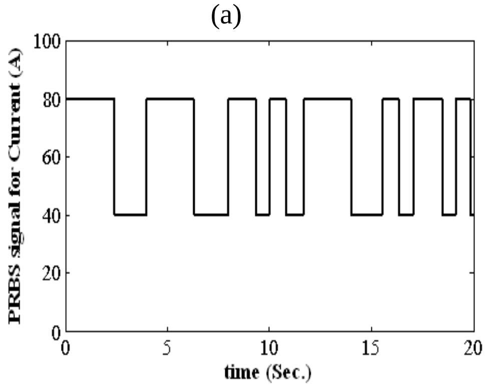
Figure11a and figure11c indicate the applied dynamic to fuel cell current. Figure 11b and figure11d show the compared output of mathematical model and SVM with respect to the applied dynamic.



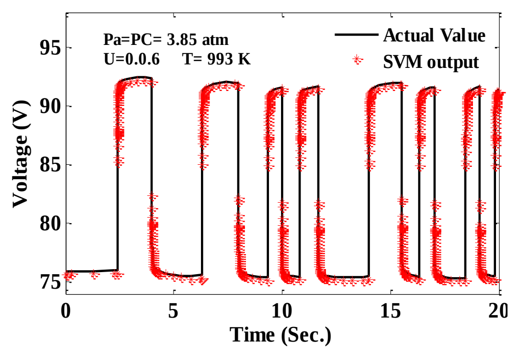
(a)



(b)



(c)



(d)

Figure11. a) the first applied dynamic to current, b) comparison of SVM output voltage and mathematical model, c) the second applied dynamic to current, d) comparison of SVM output voltage and mathematical model (CFU).

It can be concluded from the above figures that the proposed model possesses a good ability in dynamic studies and permanent state and can replace the current models.

5. Smart modeling of SOFC fuel cell by Artificial Neural Network

5-1. dynamic modeling of SOFC in CFF utilization state

5-1-1. first stage:

The prepared dynamic data in the previous section are used again for training and testing ANN method.

5-1-2. second stage

According to decision tree output, three voltage rank, one rank of current, pressure, temperature and fuel utilization ratio are the most important inputs of the model. The fuel cell voltage is considered as the output of the model.

5-1-3. third stage

Selecting the number of latent layers and neurons of the layers are the most important factor in Artificial Neural Network. We found out through try and error that 2latent layers with 9neurons in the first layer and 7neurons in the second layer are the best result.

5-1-4. fourth stage:

An ANN model was trained and the results were compared with the results of SVM model in table3 by training data.

Table3. Comparison of the model based on SVM and ANN (CFF utilization state)

	ME (Volt)	MSE	SCC	Number of support vectors	Time of training (Sec.)
SVM	1.76	0.288	0.9988	3576	278
ANN	2.63	0.452	0.9931	-	520

Figure 12a and figure12c indicate the applied dynamic to the fuel cell current. Figure12b and figure12d compare the mathematical model output and ANN for applied dynamics respectively.

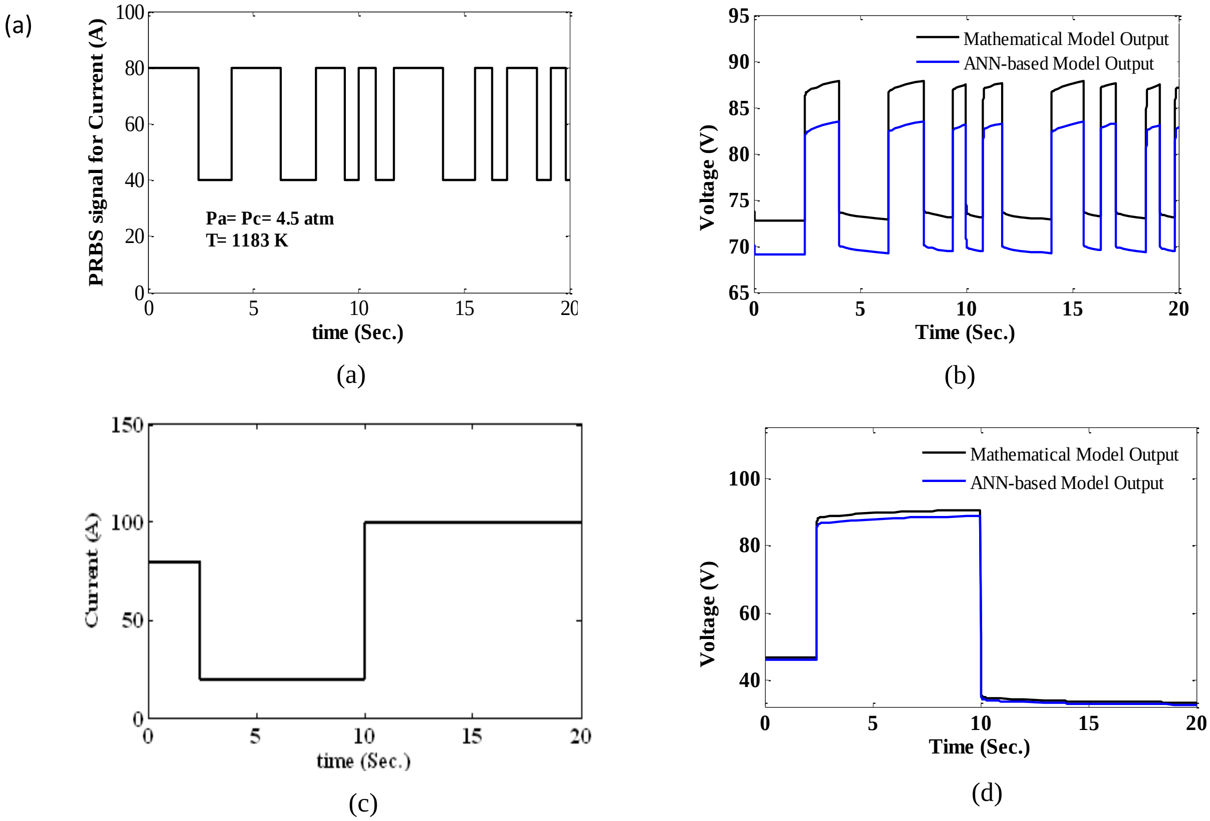


Figure12. a) the first applied dynamic to current, b) comparison of ANN output voltage and mathematical model, c) the second applied dynamic to current, d) comparison of ANN output voltage and mathematical model (CFU).

As it can be seen from the figures, the proposed model can adequately model the system dynamic.

5-2. SOFC dynamic modeling in CFU utilization state

Similarly, proper dynamic data were prepared with PRBS signal in the acceptable range of fuel utilization ratio for training.

Like the previous utilization, 3voltage ranks, one rank of current, pressure, temperature and fuel utilization ratio are considered as the most important inputs of the model.

Similarly by examining through try and error we observed that 2latent layers with 9neurons in the first layer and 7neurons in the second layer are the best result.

By using training data, an ANN model was trained and the results were compared with SVM model in table4.

Table4. Comparison of model based on ANN and SVM (CFU utilization state)

	ME (Volt)	MSE	SCC	Number of support vectors	Time of `training(Sec.)
SVM	1.85	0.311	0.9975	3765	312
ANN	3.54	0.583	0.9969	-	613

Conclusion

1. Dynamic models of SOFC fuel cell black box with smart methods of support vector machine and artificial neural networks can properly replace the common mathematical models. Smart models can provide accurate models without parameters and equations of fuel cells. Meanwhile, this model requires less memory for dynamic studies, real time, static, etc. as compared with mathematical models. At the same time, SVM-based model is more accurate than ANN-based model and has less error. Therefore, it is more recommended.

2. The important point in dynamic modeling by smart techniques is providing proper dynamic data for training so that it can properly train dynamic features of system with smart training. It is indicated in this thesis that proper data can be generated and an accurate dynamic model extracted by PRBS signal.

3. SVM and ANN techniques can be adequately employed for non-linear and multi-variant modeling of system (like fuel cell modeling). SVM has less prediction error as compared with ANN technique because of discussed features.

4. We can select proper features for training smart networks by decision tree. In other words,

decision tree can best reduce input data for training.

References

[1]M. Kazemi nejhad. Fuel Cells. Iranian Institute of electric engineers. (http://www.aeesiau.com)

[2]A.-M. Borbley, and J .F. Kreider (editors), Distributed Generation: The power paradigm for the new millennium, CRC Press, Boca Raton, FL, (2001).

[3]D. Cheddie, and N. Munroe, Review and comparison of approaches to proton exchange membrane fuel cell modeling, J. Power Sources 147 (2005) pp. 72–84.

[4] Fuel Cell Handbook, 7th edn, EG&G Services, Inc., Science applications international corporation, DOE, office of fossil energy, National Energy Technology Laboratory, (2004).

[5]G. Hu, J. Fan, S. Chen, Y. Liu, and K. Cen, Three-dimensional numerical analysis of proton exchange membrane fuel cells (PEMFCs) with conventional and interdigitated flow fields, J. Power Sources 136 (2004) pp. 1–9.

[6]G .M. Masters, Renewable and efficient electric power systems, IEEEWiley, Hoboken, NJ, (2004).

[7]H.B. Putgen, P.R. Macgregor, and F.C. Lambert, Distributed generation: semantic hype of the dawn of a New Era? , Power & Energy Magazine, 1 (2003).

[8]H.J. Allison, A new approach to high-pressure, high-temperature hydrogen-oxygen fuel cell and electrolysis-cell design, PhD Thesis, Oklahoma State University, Stillwater, OK, (1967).

[9]H.L. Willis, and w.G. Scott, Distributed power generation: planning and evaluation, Marcel Decker, New York, (2000).

[10] H. Schichlein, A.C. Müller, M. VoigtsM. Voigts, A. Krügel, and E. Ivers-Tiffée, Deconvolution of electrochemical impedance spectra for the identification of electrode reaction mechanisms in solid oxide fuel cells, J. Applied Electrochemistry 32 (2002) pp.

875-882.

[11] J.J Baschuk, and X. Li, Modelling of polymer electrolyte fuel cells with variable degrees of water flooding, J. Power Sources 86 (2000) pp. 181-196.

[12] J. Li, G.Y. Cao, X.J. Zhu, and H.Y. Tu, Two-dimensional dynamic simulation of a direct internal reforming solid oxide fuel cell, J. Power Sources 171 (2007) pp. 585–600.

[13] J. Yang, X. Li, J. H. Jiang, L. Jian, L. Zhao, J. G. Jiang, X. G. Wu, and L. H. Xu, Parameter optimization for tubular solid oxide fuel cell stack based on the dynamic model and an improved genetic algorithm, Int. J. Hydrogen Energy 36 (2011) pp. 6160-6174.

[14] M.H. Nehrir, and C. Wang, Modeling and control of fuel cells distributed generation applications, New Jersey: John Wiley & Sons, (2009).

[15] N. Akhtar, S. P.Decent, D. Loghin, and K. Kendall, A three-dimensional numerical model of a single-chamber solid oxide fuel cell, Int. J. Hydrogen Energy 34 (2009) pp.8645–8663.

[16] R. T. Jagaduri, and G.Radman, Modeling and control of distributed generation systems including PEM fuel cell and gas turbine, Electr. Power Syst. Res. 77 (2007) pp. 83–92.

[17] R. Bovea, P. Lunghi, and N.M. Sammes, SOFC mathematic model for systems simulations—Part 2: definition of an analytical model, Int. J. Hydrogen Energy 30 (2005) pp.189 – 200.

[18] S.H. Ge, and B.-L. Yi, A mathematical model for PEMFC in different flow modes, J. Power Sources 124 (2003) pp. 1-11.

[19] www.Wikipedia.com.

[20] Y. Zhu, and K. Tomsovic, Development of models for analyzing the load-following performance of microturbines and fuel cells, Electr. Power Syst. Res. 62 (2002) pp. 1–11.