Fault Sensitive Modeling and Diagnosis of PEM Fuel Cell for Automotive Applications

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***Abstract*- In this paper the PEMFC fault diagnosis is based on neural network modeling approach combined to numerical simulation in which a new developed sensitive model of PEMFC has been especially used. In literature the voltage changing is evaluated according to a variation of the total electrical resistance by assuming the same physical parameters (temperature, pressure…) in whole area of the FC cells. The main contribution of this work is to consider a 2D variation of temperature, pressure and humidity within cathode-membrane-anode zone of the PEMFC by using a multi-loops/nods circuit model. Then a NN model has been developed to classify faults and to recognize them on line during the FC operating.**

***Index Terms*—model base, fault diagnosis, non-intrusive, neural network**

I. INTERODUCTION

There many ways proposed in the literature to categorize the different diagnosis schemes can be classified into two groups: Model-free and Model-based methods. The model-free methods for fault detection and isolation do not use a model of the plant; they simply range from physical redundancy and special sensors through limit-checking and spectrum analysis and logical reasoning. However, in model-based methods, the fault diagnosis is based on comparing the available measurements of the monitored system with its corresponding predictions obtained through a specific fault sensitive model. In general, this kind of methods use system (process) models in order to generate residuals [1, 2]. In this article such called residuals concern the measured changes in the output voltage and current of the fuel cell, according to the 2D variations of temperature, humidity and gas pressure. In general, the decrease of fuel cell output voltage can be associated to several variations of fuel cell parameters and it is very difficult to identify accurately the cause actually responsible of the voltage decreasing. The aim of the paper is to characterize different faults by simulating variations on equivalent voltages, resistances and capacitors of one cell according to its temperature, pressure and humidity, introduced at different geometrical zones of the FC cell. The so obtained results allow characterizing different faults in the FC such as overheating, freezing and floating. This non-intrusive method is applied only by measuring voltage and current at the FC output for which the changes are compared according to the pre-established characterization to detect the fault.

In this paper we firstly expose the principle of the proposed sensitive modeling of the fuel cell after a general review of the principals of the faulty models existing in literature. Thus, because of its great time consuming, the proposed model will be used to train a NN model more convenient for the FC diagnosis. Finally, the used diagnosis algorithm (strategy) is briefly given with some simulation results highlighting its validity and the main conclusions of this work.

II. PEMFC HEALTY AND FAULTY OPERATING CONDITIONS

The performance of fuel cell systems can be severely influenced by operating conditions such as temperature, fuel and oxidant flow rates, pressure, and fuel humidity. Performance can drop significantly if the cell is not properly operated [4]. In the polarization curve, three parts can be observed: kinetic, Ohmic, and mass transfer. In the kinetic part, the cell voltage drop is due to the charge-transfer kinetics, i.e., the O_2 reduction and H_2 oxidation rate at the electrode surface. In the Ohmic part, the cell voltage drop is mainly due to the internal resistance of the fuel cell, including electrolyte membrane resistance, catalyst layer resistance, and contact resistance. In the mass transfer part, the voltage drop is due to the transfer speed of H_2 and O_2 to the electrode surface [4]. The polarization curve of the stack according to experimental test is plotted in Fig. 1.

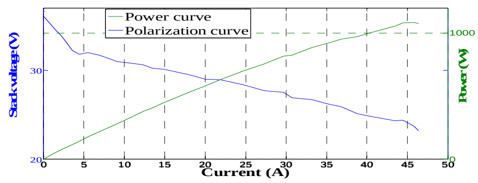


Fig. 1. polarization and power curves

A. Temperature Effect

Temperature is one of the most important operating parameters that need to be properly controlled. Temperature can also affect proton transport inside the membrane, resulting in membrane conductivity change. For example, at the same water content level, increasing temperature can reduce membrane resistance, thereby improving fuel cell performance. As shown in Fig. 2 variation voltages according to different temperature between 24 °C and 54 °C.

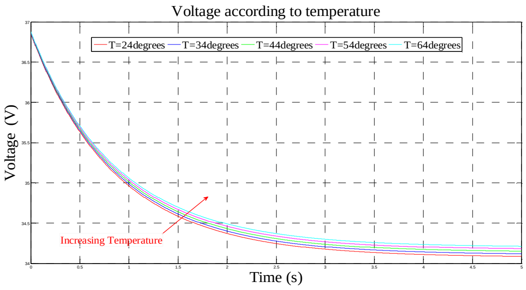


Fig. 2. Variations voltage according to temperature

B. Humidity Effect

Water management is an important issue in the performance of PEM fuel cells. At one extreme, a high water level can block oxygen transport. If water content is elevated due to its generation at the cathode, it can directly affect the Oxygen Reduction Reaction (ORR) kinetics and also contribute indirectly to the state of contact between the platinum (Pt) catalyst and the ionomer. If there is not enough water at the reaction interface, the ionomer will shrink, reducing both the surface contact of the catalyst with the ionomer and the proton conductivity of the ionomer. In this case, humidified gas streams are necessary for fuel cell feeding. At one extreme, a high water level can block oxygen transport. The humidification cut-off at the cathode causes a large difference in both the membrane resistance and the kinetic resistance. Dehydration of the anode also brings about a substantial increase in cathode impedance because a dry anode pulls water away from the cathode and across the membrane, which makes it hard to keep the cathode well Hydrated[4]. The sensitivity of the impedance to humidification of the reactant gases also depends on the membrane thickness. It has been reported that a thicker membrane is much more sensitive to humidification conditions. The Fig. 3 displays fluctuation of voltage according to alteration humidity in PEMFC.

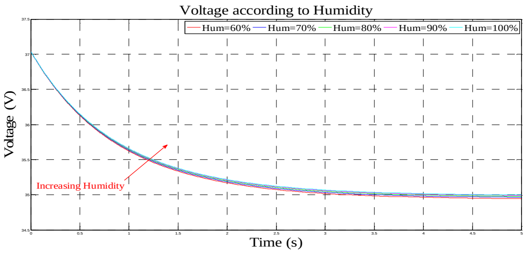


Fig 3. Variations voltage according to Humidity

C. Flow Rate Effect

It is generally recognized that the oxygen reaction in Oxygen Reduction Reaction kinetics is first order with respect to the oxygen concentration. In order to facilitate the Oxygen Reduction Reaction, a pressurized gas stream is often used to increase the reactant concentration, especially at high current densities, when mass-transport effects are more dominant than at low current densities [4]. The voltage variation due to different pressure of oxygen is shown in Fig. 4.

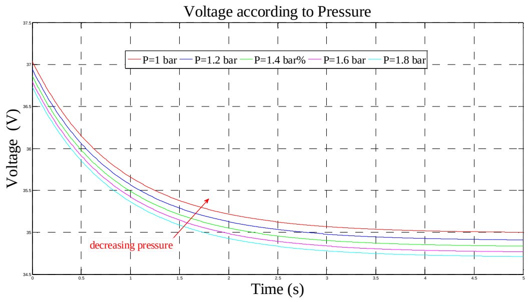


Fig. 4. Variations voltage according to pressure

III. PEMFC FAULT SENSITIVE MODELING

A. Model Presentation

For accurate diagnosis fault in PEMFC we suggest to decide each cell of the FC stack to divide in different elementary cells see Fig. 5a. In this presentation, the 2D variations of temperature, pressure and humidity can be taken into account by adopting a different equivalent circuit for each elementary cell. So, assuming an NxM elementary cells one can obtain NxM equivalent elementary circuit, see Fig. 5b. In each of the elementary circuit we assume a group of local physical parameters with the same way as proposed in literature for a complete cell [3]. The magnitude of the decrease in voltage, called the voltage variance, is associated with changes in fuel cell model parameters that include open-circuit voltage, types of losses in anode side (R_a) losses in cathode (R_c), double layer capacitance (C_{dl}) in anode and cathode and membrane losses(R_o)[3]. These parameters change with variation of temperature, humidity, pressure and aging effect. Generally all the losses, the cell voltage can be written as:

$$V_{fc,M\times N} = e_{M\times N} - V_{act,M\times N} - V_{ohmic,M\times N} - V_{con,M\times N} - V_c \tag{1}$$

$$V_{act,M\times N} = \frac{RT_{op}}{\alpha nF}\ln\left(\frac{i_{op}}{i_o}\right) \tag{2}$$

$$V_{ohmic,M\times N} = i_{op}(R_M + (R_C) \tag{3}$$

$$V_{con,M\times N} = -B\ln\left(1-\frac{J}{J_{max}}\right) \tag{4}$$

And also all resistance and double layer effect in anode and cathode (C_{dl}) can be written as:

$$R_{act,M\times N}=\frac{RT_{op}}{\alpha nFi_{op}}\ln(\frac{i_{op}}{i_o}) \tag{5}$$

$$R_{con,M\times N}=\frac{RT_{op}}{\alpha nFi_{op}}\ln(1-\frac{i_{op}}{i_{\lim}}) \tag{6}$$

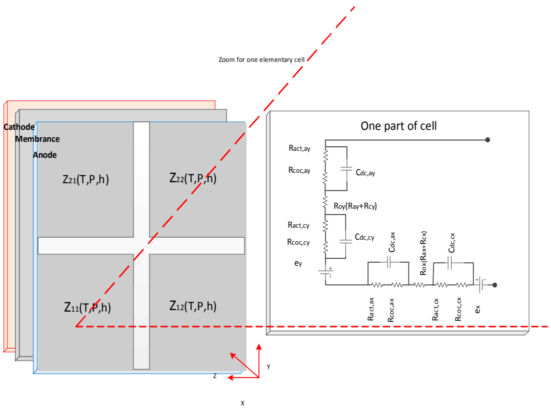
$$R_{o,M\times N}=R_{anode,M\times N}+R_{cathode,M\times N}+R_{mem,M\times N} \tag{7}$$

$$R_{mem,M\times N}=\frac{L_{mem}}{A(a\times humidity-b)\exp(c\times(\frac{1}{303}-\frac{1}{T}))} \tag{8}$$

$$a=5139\times10^{-6}, b=326\times10^{-5}, c=1268 \tag{9}$$

$$R_{anode,M\times N}=R_{cathode,M\times N}=\frac{\rho(L_a+L_{pb})}{A} \tag{10}$$

$$V_c=(1-C\frac{d_{vc}}{d_t})(R_{act}+R_{con}) \tag{11}$$



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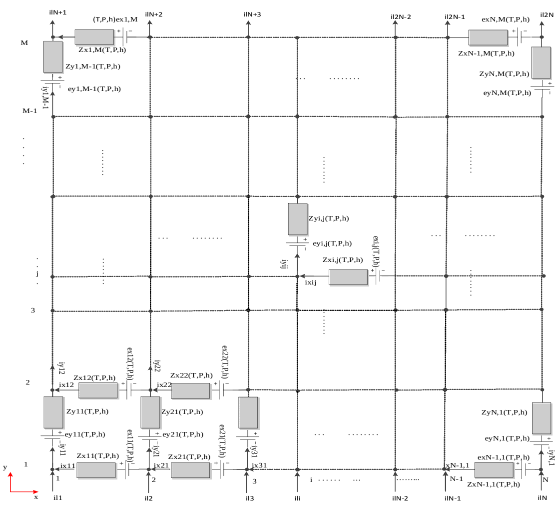


(b)

Fig. 5. 2D representation of one cell of PEMFC stack

The Fig. 6 shows the case of N= 3 and M=3. As we have seen above in the relation V=ZBUS.I, the node or bus voltage Vxyij,i=1,…N,J=1,..M is the open circuit voltages.

By using THEVENIN equivalent representation for T-network it can be easily proofed that:

$$Z_{(T,P,H)}\times I=V;\ for; M=3, N=3 \tag{12}$$

$$Z_{x11(T,P,H)}=Z_{y11(T,P,H)}=(R^a_{act,11}+R^a_{con,11})\parallel R^a_{cd,11}+R_{o,11}+(R^c_{act,11}+R^c_{con,11})\parallel R^c_{cd,11} \tag{13}$$

$$V_{x11}=V_{y11}=e_{11}-V_{act,11}-V_{ohmic,11}-V_{con,11}-V_c \tag{14}$$

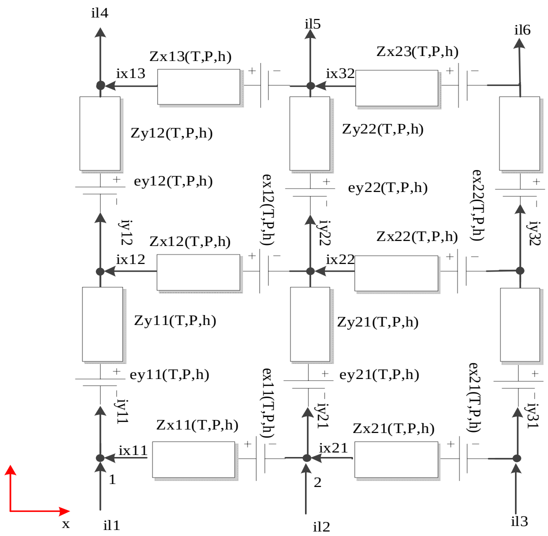


Fig. 6. Scheme of Impedance and voltage of one cell for M=3,N=3

B. *Model calibration in Healty Mode*

To obtain out voltage in PEMFC that we suggested (divided in 4 zones) we need to calibrate all the parameters of the 4 zones according to real operation conditions of fuel cell. For this purpose an iterative program has been developed and used to compute whole the parameters such as R_a, R_c, R_o, E_0 …etc. so that the obtained model gives the same polarization curve of the modeled FC in healthy mode. The Fig 7 shows the influence parameters in different regions of polarization curve. Specifically, R_o effect in linear region while, R_{con} and R_{act} effect in vertical axis (VA, HCR).

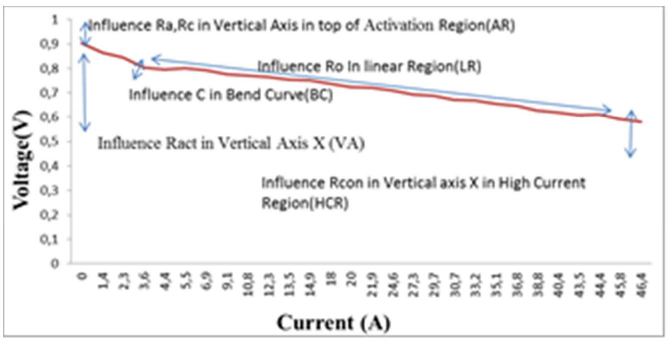
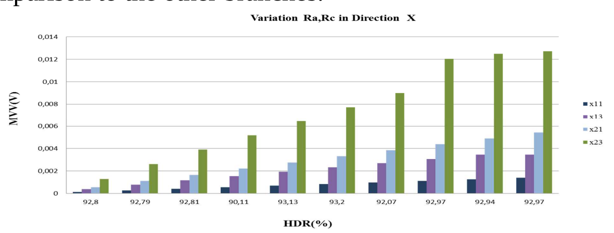


Fig. 7. Influence parameters in polarization curve fuel cell in healty mode

IV. NN MODEL FOR FUEL CELL FAULT DIAGNOSIS

A. *Explanation of the fault sensitive modeling approch*

In this section we consider two operating modes for PEMFC. First, healthy mode means the fuel cell operates during normal conditions while the degraded mode indicates that there is an abnormality in the FC operating conditions such as variations of temperature, humidity or pressure causing a fault and/or a performance loss in fuel cell. Due to the high time consuming of the proposed circuit model, it can't be used for on-line PEMFC diagnosis. For this reason we have proposed a neural networks model (NNs) obtained from the circuit ones in order to reduce the time consuming of the model but by maintaining an acceptable accuracy in terms of fault characterization. Parameters identification in the used NNs has been achieved starting from the simulation results of several faults introduced in different zones of the circuit model. For these simulations we assumed a given DC load current contain some typical harmonics identical to those one can find in a DC/DC boost converter generally associated to the PEMFC. The measurements of the mean value and the first three harmonics of the output voltage, in the steady states operation, allow computing the corresponding Harmonic Distortion Rate (HDR) and the mean values voltage variation according to the healthy value (MVV). These two parameters are used to characterize the different faults taking into account the 2D space coordinate of the FC cell. The Fig 8 where gives some examples of this characterization process where variations in resistances of different branches of the 4 zones of the circuit model are assumed. Only the X direction has been considered in these simulations. It can be clearly seen that the variations in the branch X_{23} induce most important effects in comparison to the other branches.



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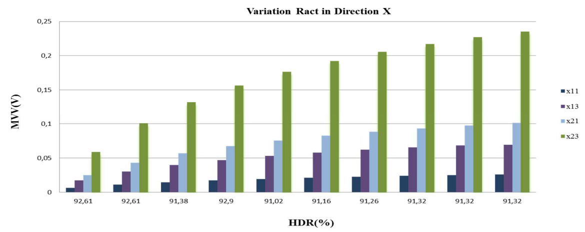

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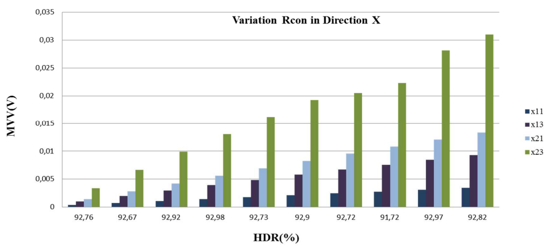
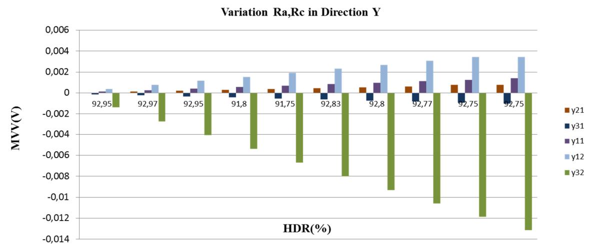


(c)

Fig. 8. MVV and HDR variations acoording to resistance changes in X direction.

The Fig. 9 illustrates the parameters VV and HDR with variation of resistance in different branches in y direction. As shown in x branches variations, it can be clearly seen that the variations in the branches Y_{23} and Y_{21} induce most important effects in comparison to the other branches.

In this paper we considered one cell of a PEMFC by dividing in four parts, each part has x, y axis. According to the results of Fig. 8 and 9 we can conclude that the main axes sensitive to resistance changes are X_{21}, X_{23}, Y_{21} and Y_{23}.



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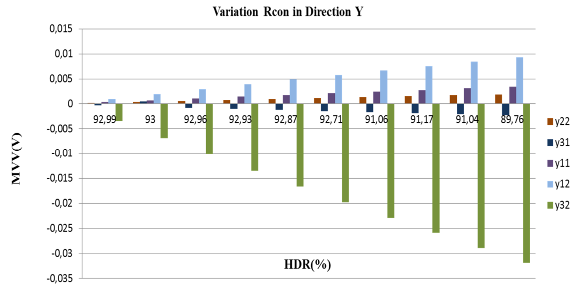

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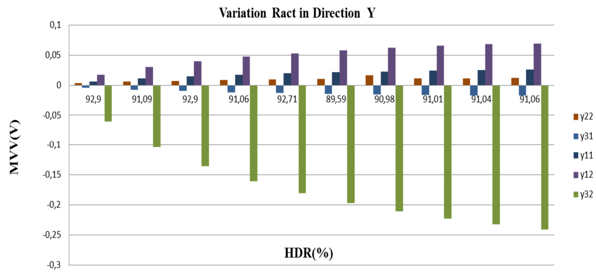

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Fig. 9. MVV and HDR variations acoording to resistance changes in Y driection

B. *Training and validation the NN Model*

A Neural Network (NN) consists of a number of processing units (neurons) that communicate by sending information to each other. The link between two neurons is done via weighted connections. The most common neural network is the multilayer perception (MLP) [5, 6]. For this type of NN, each unit performs a biased weighted sum of the inputs and sends it to a transfer function. The output is then an activation level reached by this function. The neurons are organized in a set of parallel layers and in feed-forward networks, all input signals flow in one direction, from input to output. Feed forward networks consist of a series of layers. The first layer has a connection from the network input. Each subsequent layer has a connection from the previous layer. The final layer produces the network's output. Feed forward networks can be used for any kind of input to output mapping. A feed forward network with one hidden layer and enough neurons in the hidden layers can fit any finite input-output mapping problem. Fig. 10 shows the main structure of feed forward of network with input, output and hidden layers.

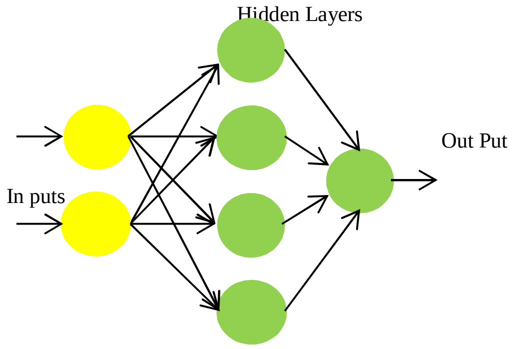
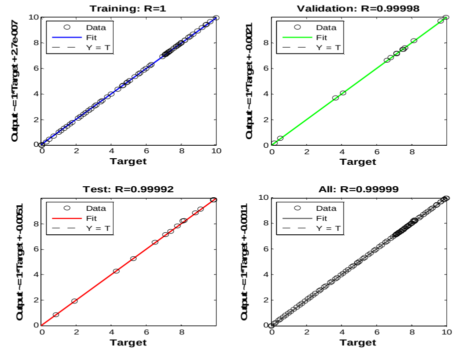


Fig. 10. Main structue of fewdforward network

According to the results presented on Fig. 11, one can say that the proposed neural network can detect the fault percentage with reasonable accuracy. The Fig 11a shows the regression plotted across all samples where it is seen that after above 10 neural network runs, average precision is reached to 99.9 percent. The following results are obtained as Fig. 11b first of all doesn't indicate any major problems with the training then the validation and test curves are very similar and final mean square error is small. The regression plot shows the actual network outputs plotted in terms of the associated target values. A third measure (see Fig. 11c) shows how the neural network has fit data in the error histogram (in other word how the error sizes are distributed). Typically most errors are near zero, with very few errors far from that [7].

The artificial forward neural network is used to classify the faults that occurred in PEMFC cell. The NN is trained by changing impedance and voltage in each elementary of cell and then normalized output in various categories with 0, 1 codes see in table 1. In this method all branches are trained with different inputs such as of variation resistance in cathode, anode and membrane also output normalized from measurements of the mean value and the first three harmonics of the output voltage, in the steady states operation in this system and code between 0,1. Then train with NN system to classification of fault will be happened in each branch due to different operation condition.

In table 1, neural network is used in order to detecting faults in direction X Y with different Impedance. In this case neural network has 5 binary outputs which can be 0 or 1. Moreover, desired output of neural network for each resistance due to variation condition is shown in table I.



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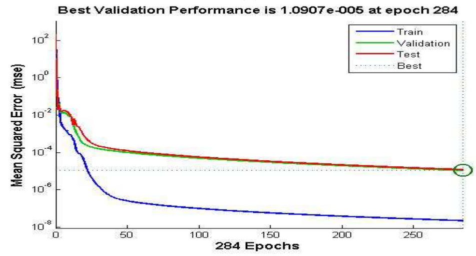

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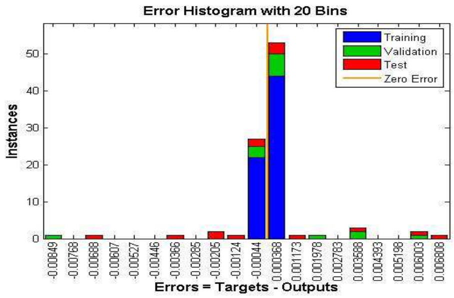

(c)

Fig. 11. Network training algorithms

Table 1 .Normalization output of neural network

R_{con}							R_{act}						
X_{11}	X_{13}	X_{21}	X_{23}	Y_{21}	Y_{23}	Y_{31}	X_{11}	X_{13}	X_{21}	X_{23}	Y_{21}	Y_{23}	Y_{31}
1	1	1	1	1	1	1	0	0	0	0	0	1	1
0	1	0	0	0	1	1	1	1	0	0	0	1	1
0	0	1	0	0	1	0	0	0	1	0	0	1	1
0	0	0	1	0	0	1	0	0	0	1	0	1	0
0	0	0	0	1	0	0	1	0	0	0	1	0	1
$R_{anode,cathode}$							R_{ohm}						
X_{11}	X_{13}	X_{21}	X_{23}	Y_{21}	Y_{23}	Y_{31}	X_{11}	X_{13}	X_{21}	X_{23}	Y_{21}	Y_{23}	Y_{31}
1	1	0	0	0	0	1	1	0	0	0	0	1	1
1	0	1	0	0	0	1	1	1	0	0	0	1	1
0	1	1	0	0	1	1	0	0	1	0	0	1	1
1	1	1	0	1	0	1	0	0	0	1	0	1	0
1	1	1	0	1	1	1	1	0	0	0	1	0	1

V. CONCLUSION

The main contribution of this work is to propose a circuit based model taking into account the 2D variation of temperature, pressure and humidity within one cell or one group of cells of the PEMFC stack. The goal is to characterize different faults by the means of variations of the different resistances and capacitors of this circuit according to the variations of temperature, pressure and humidity for diagnosing and localizing faults in the PEMFC. On the basis of this model, the neural network modeling is proposed to classify faults and to recognize them on line during the FC operating. Also a NN-based model will be trained for the case of a 9 nods circuit. Future efforts will be aimed at experimental study to validate the obtained results in this article according to different faulty operation conditions which will be performed on several PEMFC cells.

ACKNOWLEDGMENT

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Nomenclature			
A	anode (or cathode) area/cell useful area (cm^2)	F	Faraday constant ($96487 C mol^{-1}$)
I_{op}	operational cell current	R	universal constant of gases ($8314 J K mol^{-1}$)
T_{op}	operational temperature (K)	I_{lim}	Current limitation
I_{mem}	membrane thickness (cm)	n_c	number of moles of reagent in the cathode
I_o	Current activation	n_a	number of moles of reagent in the anode

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