A Modified Particle Swarm Optimization based Method for Identification and Estimation of PEMFC's System Parameters

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Abstract— **In this paper a technique to identify Proton Exchange Membrane Fuel Cell (PEMFC)'s parameters using an optimization approach is proposed. The PEMFC is characterized by technological and empirical parameters and their identification is a hard and time wasting task if is intended to have precise simulation results in a wide range of operating conditions. The Modified Particle Swarm Optimization (MPSO) method is a powerful tool to identify the correct parameter value and used for fast and precise MPSO parameter's identification which is achieved by minimizing the difference between experimental and simulated result**.

Keywords- *Fuel Cell; Parameter identification; MPSO;PEMFC.*

I. INTRODUCTION

There are many approaches which have been proposed in literature to modeling statistical and dynamical behavior of fuel cells (FC). These methods differ from each other depending on the final goal of the model. Some of them put a strong emphasis in the chemical and mechanical phenomenon inside the FC, analyzing the performance of cathode sides, electrodes, water and heat management and membranes [1-3]. It is expected that such models can support the development FC with higher efficiencies or longer lifetimes by carrying out simulations and testing optimal operating conditions or materials performance. This class of models, usually referred as mechanistic models, has some drawbacks. They are very complex which difficult their implementation and typically require a large number of parameters that specifically characterizes the technology and physics of the materials involved. The lack of simple extraction procedure to identify those parameters makes this class of models not suited for an application designer interested in predicting by simulation the electric output performance of the FC.

A second class of models includes those based on empirical or semi-empirical equations, describing the main physical and electrochemical phenomena involved in the FC operation [4-7]. The model used in this paper is based on this approach. The model's fundamentals are described in Section 2. Although this class of model is best suited to perform an integrated analysis of a FC based energy system, the issue of parameter identification is still a key factor in order to get precise simulation results over a wide range of operating conditions. In fact, some parameters are of technological nature and other are of empirical nature, and all must be defined for each single FC, which is a challenge for an application designer. The issue of model parameters identification has been neglected by model developers or by researchers using FC models. In the lack of an identification procedure, researchers typically use parameter values published in literature that is only useful to get medium quality simulation results. Recent research studies [9, 10] have demonstrated that an optimization based approach to carry out the parameter identification process is a promising solution. This paper presents and discusses such approach using the Modified Particle Swarm Optimization (MPSO) method that belongs to the class of nature inspired algorithms to solve real optimization problems. MPSO is relatively recent algorithm that has demonstrated good results in several engineering applications [11-14]. The reminder of this paper is organized as follows: in section 2 the PEMFC model characterization is introduced briefly. The proposed algorithm is described in Section 3. Section 4 presents and discusses obtained results, and finally section 5 express conclusion of this paper.

II. PEMFC MODEL CHARACTERIZATION

The proposed PEMFC in [8] can be represented by the electrical equivalent circuit which shown in *"Fig. 1"*.

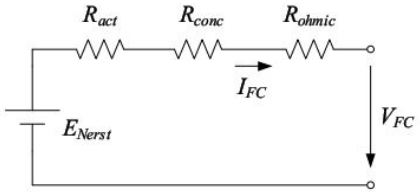


Fig. 1. Electrical equivalent circuit of the PEM fuel cell.

From the *"Fig. 1"*it is clear that the FC output voltage equals the open circuit voltage (without load) which is subtracted a sum of voltage drops, related to several FC phenomena, for a certain operation current, resulting in:

$$V_{FC} = E_{Nernst} - V_{act} - V_{con} - V_{ohmic} \tag{1}$$

E_{Nernst} is the thermodynamic potential of the cell and it represents its reversible voltage. V_{act} is the voltage drop due to the activation over potential of the anode and cathode. V_{ohmic} is the ohmic voltage drop, a measure of the ohmic voltage drop resulting from the resistance of the conduction of protons through the solid electrolyte and the electrons through its path. V_{con} represents the voltage drop resulting of the concentration or transport of mass of oxygen and hydrogen(concentration over potential).each term of (1) is defined by:

$$E_{Nernst} = 1.229 - 0.85\times10^{-3}\times(7 - 298.15) + 4.31\times10^{-5}\times7\times\left[Ln\left(P_{H_2}\times P_{O_2}^{0.5}\right)\right] \tag{2}$$

$$V_{act} = -\left[\xi_1 + \xi_2 TLn(C_{O_2}) + \xi_4 TLn(I_{FC})\right] \tag{3}$$

$$V_{con} = -B\times Ln\left(1 - \frac{J + J_n}{J_{\max}}\right) \tag{4}$$

$$J = \frac{I_{FC}}{A} \tag{5}$$

$$V_{ohmic} = I_{FC}(R_M) \tag{6}$$

The previous set of equations depend on some operation conditions, such as, the temperature *(T)*, the FC current **(** I_{FC} **),**the partial pressures of hydrogen(P_{H_2})and oxygen**(** P_{O_2} **),**and the concentration of oxygen in the catalytic interface of the cathode(C_{O_2})that is related with P_{O_2} by:

$$C_{O_2} = \frac{P_{O_2}}{5.08\times10^6\times\exp\left(-\frac{498}{T}\right)} \tag{7}$$

The equivalent membrane resistance to proton condition R_M in (5) is given by:

$$R_M = \frac{\rho_M\times l}{A} \tag{8}$$

where the membrane specific resistivity ρ_M is expressed by:

$$\rho_M = \frac{1816\left[1+0.03\left(\frac{I_{FC}}{A}\right)+0.062\left(\frac{T}{303}\right)^2\left(\frac{I_{FC}}{A}\right)^{2.5}\right]}{\left[\psi-0.634-3\left(\frac{I_{FC}}{A}\right)\times\exp\left[4.18\left(\frac{T-303}{T}\right)\right]\right]} \quad (9)$$

From equations (2)-(8) it can be observed that the FC model depends on a set of parameters listed in Table I. Once these parameters are identified,is also determined from:

$$\xi_2 = 0.00286 + 0.0002Ln(A) + (4.3\times10^{-5})Ln(C_{H2}) \quad (10)$$

With C_{O_2} related P_{O_2} by equation (6). The inputs are the PEMFC model parameters and a set of operation condition(T , I_{FC} , C , P_{O_2})and the output is the corresponding FC voltage(V_{FC}).

TABLE I
Fuel cell model parameters

Parameter	*Description*	*Unit*
A	Membrane area	cm^2
B	Constant depending on the cell type and its operation state	V
P_{H_2}	Hydrogen partial pressure	atm
P_{O_2}	Oxygen partial pressure	atm
l	Membrane thickness	m
ξ_0	Parametric coefficient	-
ξ_1	Parametric coefficient	-
ξ_2	Parametric coefficient	-
ξ_4	Parametric coefficient	-
T	Stack temperature	K

III. THE PROPOSED ALGORITHM

A. Particle Swarm Optimization

The PSO algorithm belongs to the class of direct search methods used to find an optimal solution to an objective function in a search space. Direct search methods are usually derivative-free, meaning that they depend only on the evaluation of the objective function. The PSO algorithm is simple, in the sense that even the basic form of the algorithm can produce good results, it can be easily implemented and does not require an extensive background in mathematical optimization theory. The PSO is a stochastic algorithm based on social psychological principles that was first described in 1995 by James Kennedy and Russell C. Eberhart [15]. PSO is inspired by this kind of social optimization. A problem is given, and some way to evaluate a proposed solution to it exists in the form of a fitness function. Then a population of individuals defined as random guesses at the problem solution is initialized. These individuals (particles) are candidate solution is set in motion. The particle iteratively evaluate the fitness of the candidate solution is set in motion. The particles iteratively evaluate the fitness of the candidate solution and remember the location where they had their best success, with the population usually converging, by the end of trial, on a problem solution better than that of non-swarm approach using the same methods. The swarm is typically modeled by particles in multidimensional space that have a position and a velocity. These particles fly through hyperspace and have two essential reasoning capabilities: their memory of their own best position and knowledge of the global best. In a minimization optimization problem, problems are formulated so that "best" simply means the position with the smallest objective value. Members of a swarm communicate good positions to each other and adjust their own position and velocity based on these good positions. So a particle has the following information to make a suitable change in its position and velocity:

a) A global best that is known to all and immediately update when a new best position is found by any particle in the swarm.

b) the local best, which is the best solution that the particle has seen.
The particle position and velocity update equations in the PSO simplest form are given by:

$$v_j(t+1) = w(t)v_j(t) + C_1 r_{1j}(t)\times \left(pbest_j(t) - x_j(x) + C_2 r_{2j}\left(gbest(t) - x_j\right)\right) \quad (11)$$

$$x_j(t+1) = v_j(t+1) + x_j(t) \quad (12)$$

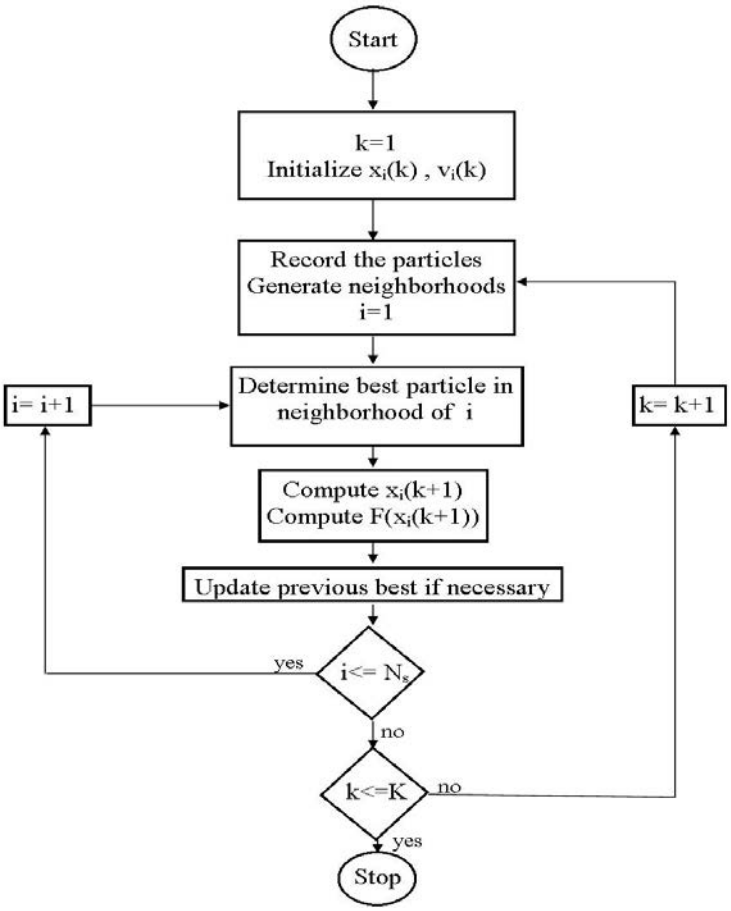


Fig. 2. The MPSO algorithm follow chart.

where each particle's position x_j (corresponding to a set of fuel cell parameter values) represents a possible solution point in the problem space,r_{1j} and r_{2j} are random numbers between zero and one. The different random numbers are used in each dimension of all particles.$C_1$and C_2 are learning factors, usually aboutC_1=C_2=2 and w is an inertia weight, which plays an important role in balancing the global search and local search. a large inertia weight facilitates a global search while a small inertia weight facilitates a global search. It can be positive constant or a positive decreasing linear function of inertia index $t=1,2,\ldots, t_{max}$ in which t_{max} is the maximum iteration times. In this investigation, the inertia weight is the following decreasing linear function:

$$w(t) = w_{\max} - (w_{\max} - w_{\min})\frac{t}{t_{\max}} \quad (13)$$

where w_{max} and w_{min} are the initial weight and the final weigh, respectively. using the above equation, the diversification characteristic is gradually decreased and certain velocity, which gradually moves the current searching point close to the $pbest_j$ and gbest can be calculated. By using a linearly decreasing inertia weight, the performance of PSO, whose inertia weight is a positive constant. Eq.(12) represents the position update, according to its previous position and its velocity.

For the solving parameter identification problem of PEMFC model, the fitness function equals to the objective function F as Eq.(14).

The PSO algorithm follow chart used in this work is shown in Fig. 4. PSO equations (11)-(13) require definition of some controls parameters. typically values were taken from literature [12, 16, 17]: $C_1=C_2=2$, $w_{min}=0.4$, $w_{max}=0.9$. The algorithm was tuned resulting in swarm size of 43 and 50 iteration.

B. Modified Particle Swarm Optimization (MPSO)

MPSO is proposed by Eberhart and Shi in 1997 and 1998. In this algorithm, the birds have a memory about the previously best and worst positions so particles have 2 experiences, bad experience helps each particle to remember its previously worst position. To calculate the new velocity, the bad experience of each particle is considered. [18]

The new velocity update equation is given as following:

$$V_{i+1} = \omega \times V_i + C_{1g} \times r_1 \times \left(P_{best_i} - S_i\right) + C_{1b} \times r_2 \times \left(S_i - P_{Worst_i}\right) + C_2 \times r_3 \times \left(g_{best_i} - S_i\right) \quad (14)$$

Where, C_{1g} is acceleration coefficient, which accelerate the particle towards its best position, C_{1b} is Acceleration coefficient, which accelerate the particle away from its worst position, P_{Worst_i} is acceleration coefficient, which accelerate the particle away from its worst position of the particle i, and *r1, r2, r3* are uniformly distributed random numbers in the range (0 to 1).

C. Objective function definition

The objective function is a scalar equation that measures how good each trail set parameters is. This comparison is done using simulated data and experimental data.

TABLE II
PEMFC Model Parameter's Limit

Parameters	Minimum Value	Maximum Value	Unit
P_{H_2}	0.5	2	atm
P_{O_2}	0.5	2	atm
λ	10	20	-
ξ_1	-1	1	-
ξ_3	7×10^{-8}	9×10^{-8}	-
ξ_4	-2.5×10^{-4}	-1×10^{-4}	-

Objective function is defined as:

$$F_{obj} = \frac{\left(V^{\exp} - V^{sim}\right)^2}{swarm \quad size} \quad (15)$$

Finally, a method to initialize MPSO particles must be defined. A typically approach is to randomly select values from a uniform distribution within a previous defied range of admissible values. Table II lists the proposed range for each fuel cell model parameter.

IV. Discussion of Results

Validation of the proposed approach involves comparing simulation and experimental results. Experimental results are taken from [2]. Simulation results are performed in MATLAB. In this study it is used a 35-coupled PEMFC, composed by NFION 115 membrane with a surface area of 232 cm^2. This type of membrane is known to have a 115 μm thickness. With this information the PEMFC model parameters *A* and *l* are already identified and

are out of the optimization process. The operating PEMFC data used in the optimization consist of polarization curve at deferent temperatures. *"Fig. 3"* illustrates the experimental polarization curve using the optimum set of parameters which brought in (Table III). *"Fig. 4"* illustrates the optimization process convergence.

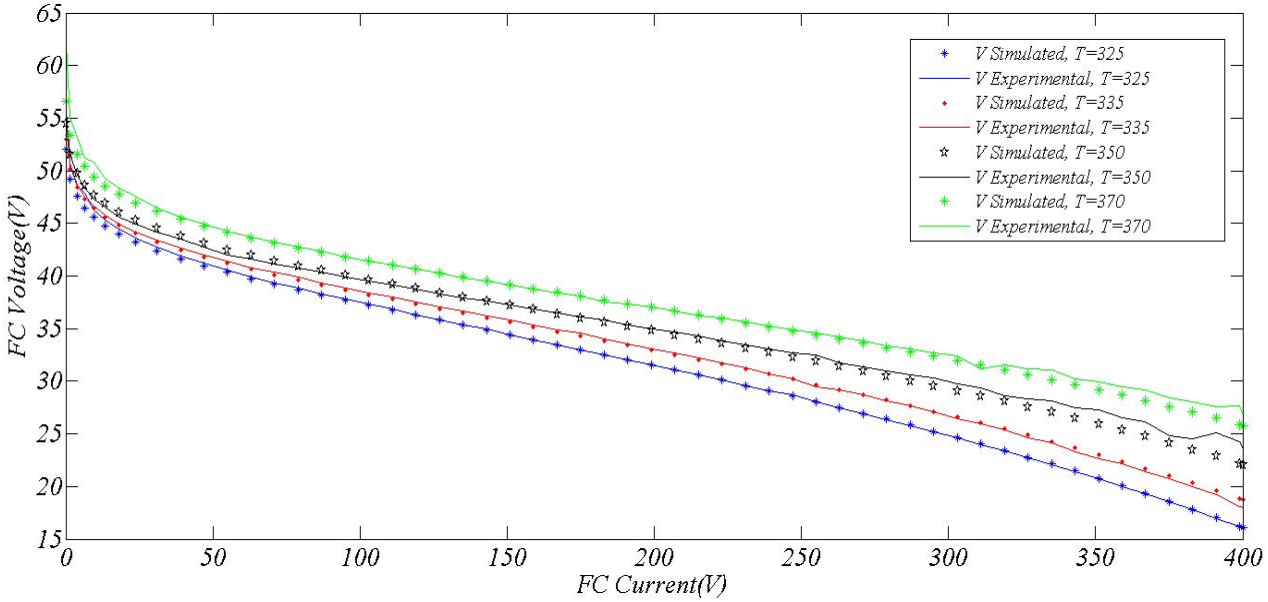
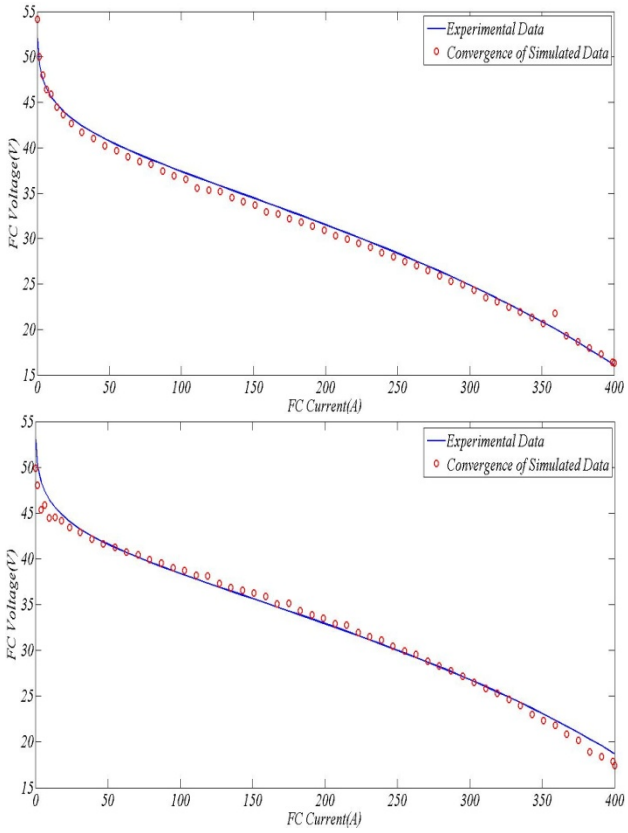


Fig. 3. PEMFC polarization curve in deferent temperatures.



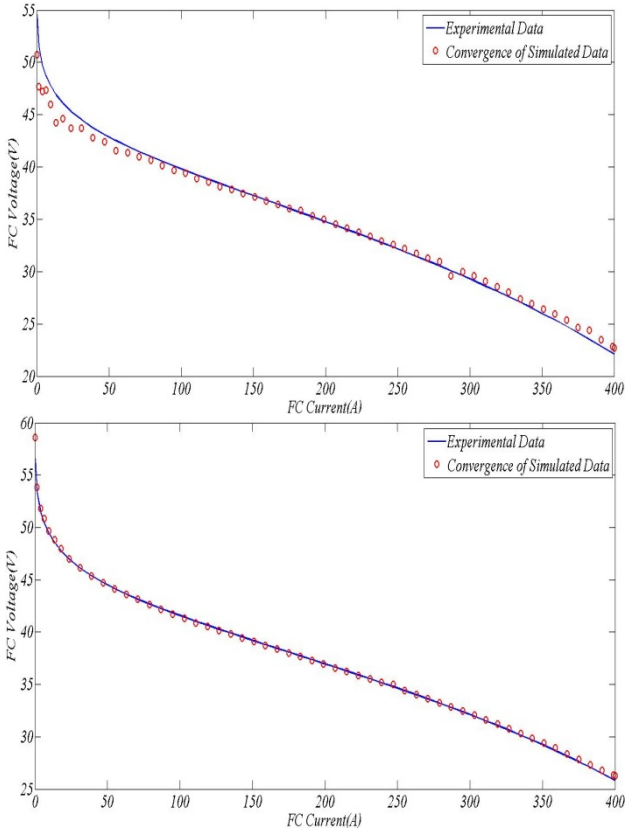


Fig.. 4. Experimental and Convergence of simulated polarization curve for (a)*T=325K*, (b) *T=335K*, (c) *T=350K*, (d) *T=370K*.

TABLE III
Identified Parameters

Temperature(K)	ξ_1	ξ_3	ξ_4	P_{H_2} (atm)	P_{O_2} (atm)	λ
325	-0.9655	8.41×10^{-8}	-0.00018	0.8073	1.1438	13.1342
335	-0.8544	8.01×10^{-8}	-0.00019	0.9901	1.1361	11.2775
350	-0.8149	7.56×10^{-8}	-0.00025	0.8946	0.9825	15.4431
370	-0.8570	7.72×10^{-8}	-0.00023	1.6392	1.2531	11.3245

V. Conclusion

This paper have presented a semi-empirical PEMFC model with parameters identified using an optimization approach. By using MPSO algorithm we extracted optimum parameters for this kind of fuel cell. Precise identification is a hard task if is intended to have precise simulation results in a wide range of operating conditions. The proposed method not only can identify PEMFC parameters in normal condition but also it can estimate its parameters value on different temperature. The proposed algorithm possesses greater anti-deceptive search ability, more reliable stability and higher search accuracy. The accuracy of the algorithm has been verified under different conditions.

The MPSO is an effective technique for identifying the parameters of PEM fuel cell models. Furthermore, although the processes are focused on the parameter identification of PEM fuel cell models, the proposed method can also be used to solve other complex parameter identification problems of fuel cell models.

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