Study of Optimizing The Current Density of Fuelcell Using Machine Learning Technique

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Abstract- *Proton exchange membrane (PEM) fuel cells have grown as a possible energy source over the last decade. PEM fuel cells are environmental friendly with a high efficiency power source and are not bound by Carnot efficiency. They are viewed as one of the promising candidates to be used for electric vehicles due to their qualities of zero pollution, high power density, quick start-up, and low operating temperature. In this project work, the impactful parameters associated with current density of fuel cell are taken into consideration for the optimization purpose. The analysis is carried out mainly for finding the suitable conditions to obtain maximum current density of fuel cell using Artificial Neural Network(ANN) & Genetic algorithm .The selected parameters are output voltage, temperature , relative humidity on anode side and cathode side are taken as the inputs for the ANN system. The analysis is done using Genetic Algorithm toolbox available in MATLAB R2017a software. The generated 900-training data was used to train the ANN, showed a good agreement with the original data with an error <1%. The ANN was then successfully used as a fitness function of the GA to predict the maximum voltage and efficiency. It was shown the maximum voltage decreases with the power density and experienced a rapid drop near the maximum power density. The proposed ANN-GA method can be implemented in practical PEMFC control to ensure maximum efficiency operation under varying load conditions.*

Keywords- Artificial Neural Network; optimization; Proton exchange membrane; MATLAB; fuel cells.

I. INTRODUCTION

Fuel cells are electrochemical devices which convert chemical energy directly into electrical energy. These energy device have the potential to be used in stationary and mobile applications and to replace combustion engines in vehicles. The production of electricity with very low levels of noise and vibration without the burning of fuel makes fuel cells environmentally friendly and a very suitable power system for terrestrial and space applications [1].

In recent years a large number of experimental studies have focused on the water management inside PEMFCs and have demonstrated that several liquid-phase flow patterns exist (i.e. slug, film and mist flow) [6]. In particular, for gas flow rates in the range of 0.1e100 m/s, slug, film and mist flows are possible for low, intermediate and high gas flow rates, respectively. It is difficult to directly visualize the liquid water transport through the porous GDL, but numerical simulation of the two-phase flow can aid the prediction of the two-phase transport in the flow channel. Thus, two-phase flow in gas channels has also been investigated through modeling and numerical simulation [7].

The study was performed in two parts. In the first part, a 3D-dimensional model was used to represent the entire fuel cell structure, allowing the determination of the global fuel cell performance and the consumption/generation rate of the compounds involved in the electrochemical reaction. This model takes into account the main influence of the lateral walls and non-uniformity in the over potential distribution, which cannot be computed by a simple two-dimensional model[9]. Moreover, the total amount of liquid water generated during the cell operation can be accurately calculated. From these results it is possible to determine the boundary conditions and these were applied in the second part, where the VOF model was employed to accurately track the air liquid water interface in tapered flow channels with different taper angles. Fuel cells come in many varieties; however, they all work in the same general manner. They are made up of three adjacent segments: the anode, the electrolyte, and the cathode. Two chemical reactions occur at the interfaces of the three different segments. The net result of the two reactions is that fuel is consumed, water or carbon dioxide is created, and an electric current is created, which can be used to power electrical devices, normally referred to as the load.

In this type of fuel cell, the membrane must be hydrated, requiring water to be evaporated at precisely the same rate that it is produced. If water is evaporated too quickly, the membrane dries, resistance across it increases, and eventually it will crack, creating a gas "short circuit"

where hydrogen and oxygen combine directly, generating heat that will damage the fuel cell. If the water is evaporated too slowly, the electrodes will flood, preventing the reactants from reaching the catalyst and stopping the reaction. Methods to manage water in cells are being developed like electro osmotic pumps focusing on flow control. Just as in a combustion engine, a steady ratio between the reactant and oxygen is necessary to keep the fuel cell operating efficiently.

The same temperature must be maintained throughout the cell in order to prevent destruction of the cell through thermal loading. This is particularly challenging as the, so a large quantity of heat is generated within the fuel cell. Durability, service life, and special requirements for some type of cells Stationary fuel cell applications typically require more than 40,000 hours of reliable operation at a temperature of −35 °C to 40

II. PARAMETER SELECTION

Although GA seems to be a robust algorithm which contains same operators and has the same algorithmic logic for different applications, in fact the algorithm itself is significantly different for distinct problems. The main reason is that GA has several parameters and any combination of these parameters has different impacts on the performance on GA. We classify these parameters into two classes, structural and numerical.

Structural parameters are the main factors affecting the GA performance, and the most difficult set of parameters to be dealt with in a GA application. As understood from its categorical name, they are concerned with the structure of GA. The change in any parameter value requires significant alterations in the coding pattern of GA's, i.e. you have to rewrite the whole algorithm from scratch. The coding scheme, operator types and stopping criterion are the main parameters. There have been extensive studies on selecting the levels of each structural parameter; hence GA can obtain sufficient insight from the well-established literature. For instance, it is known that the sequence representation of coding schemes is better for scheduling problems. Moreover, the applicability of the structural parameters constructs a constraint in front of decision-maker, and forces to eliminate some parameter values. For instance, the simple one point crossover cannot be applied to the problems having sequence representation Numerical parameters contribute to the second class of the taxonomy we proposed. The initial population type, population size, maximum generation number, crossover and mutation probabilities are the main factors considered in this category. These parameters are easy to handle when the coding structure is considered. Although alterations in these parameter levels do not require extensive coding, different combination of them leads to drastic changes in GA performance[12]. Similar to structural parameters, there are several studies conducted on the analysis of numerical parameters; but the very problem-specific nature of GA hinders making general conclusions about the suitable levels of them. Moreover, these studies analyze these parameters one at a time, ignoring the interaction between the parameter types. The literature on this class of parameters is more ambiguous than the previous class. In this study, all of the numerical parameters of GA are examined with a priori known level of structural parameter setting. General insights about the best combination of these parameters are presented on particular problem domains. More detailed explanation about numerical parameters is provided in the following sections. Testing Scheme A test problem is taken from the literature for GA based simulation-optimization application, and significance of different values of the parameters on GA performance is analyzed on this test problem by factorial designs and ANOVA (Analysis of Variance)[23]. Two types of performance measure are considered throughout the analysis.

Table1: Parameters used for optimization

Sl.no	Parameters	Value	Unit
1	Operating temperature	298/323	K
2	Operating pressure	1.5/2	Bar
3	Relative humidity at anode	100	%
4	Relative humidity at cathode	100	%
5	Open circuit voltage	0.7	V

III. SOLID WORKS SOFTWARE

Solid works is a 3D mechanical CAD program that runs on Microsoft Windows which was developed by Solid Works Corporation. Solid works provides a full range of integrated modeling, simulation, visualization; communication and validation tools that product designers need to develop better products faster and at lower cost.

Solid works enable the design engineer to:

- Precisely turn creative concepts into 3D designs
- Create the most ergonomic designs possible

- Produce design in iterations in less time
- Reduce prototyping time and cost

Solid works mechanical design automation software is a feature-based, parametric solid modeling design tool which advantage of the easy to learn windows TM graphical user interface. We can create fully associate 3-D solid models with or without while utilizing automatic or user defined relations to capture design intent. Parameters refer to constraints whose values determine the shape or geometry of the model or assembly[5]. Parameters can be either numeric parameters, such as line lengths or circle diameters, or geometric parameters, such as tangent, parallel, concentric, horizontal or vertical, etc. Numeric parameters can be associated with each other through the use of relations, which allow them to capture design intent.

A two phase assumption in ECM comprising of brine as the primary phase along with formation of hydrogen bubbles as the secondary phase and the subsequent analysis may provide a real insight into the complex ECM process. In this project work, the two phase flow of electrolyte is analyzed by using Computational Fluid Dynamics. Computational Fluid Dynamics is considered to be the most powerful tool for analyzing the flow of fluid. The analyzing is concluded by comparing the results through the contours. The software used for the analysis is ANSYS. Various process parameters like temperature, velocity profile are evaluated from the simulated environment.

The temporal evolution of water saturation is reported. We note that even increasing the hydrophobicity is observed that the formation of the first small slugs occurs faster for the smaller contact angles. It worth to underline that to the formation of these slugs correspond the first water removal inside the channel. However, the amount of water removed is greater for greater angles. This occurs because the decrease in the angle of approach facilitates the droplets coalascence and therefore the formation of structures with a minimum size to be carried off. Nevertheless, the total amount of water present in the channel is quite similar for allthe investigated angles.

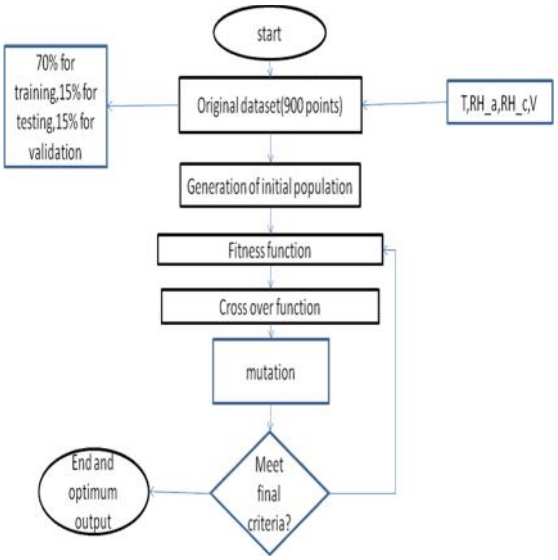

Fig1: Procedure of ANN-GA system

MESHING

For CFD analysis by Fluent software, the model was first prepared and meshed in the Gambit and a mesh file was generated which is then reopened in fluent for the analysis where the element type and the boundary conditions were applied.

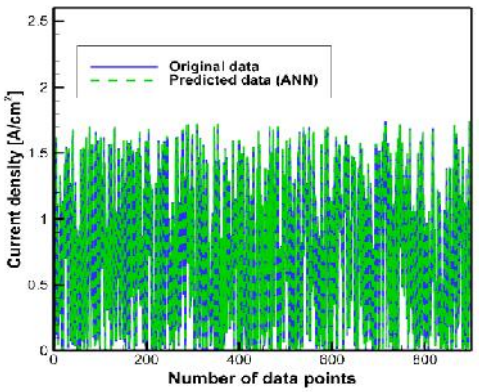

Fig2: Comparison Between Predicted And Original Data

CFD ANALYSIS

Finite Element Analysis (FEA) is a computer-based numerical technique for calculating the strength and behavior of engineering structures. It can be used to calculate deflection, stress, vibration, buckling behavior and many other phenomena. It also can be used to analyze either small or large-scale deflection under loading or applied displacement. It uses a numerical technique called the finite element method (FEM).

Computational fluid dynamics (CFD) is a branch of fluid mechanics that uses numerical analysis and data structures to solve and analyze problems that involve fluid flows. Computers are used to perform the calculations required to simulate the interaction of liquids and gases with surfaces defined by conditions. With high speed super computers,

Better solutions can be achieved. Ongoing research yields software that improves the accuracy and speed of Complex simulation scenarios such as transonic or turbulent flows. Initial experimental Validation of such software is performed using a wind tunnel with the final validation coming in full-scale testing, e.g. flight tests.

Like solving any problem analytically, you need to define (1) your solution domain, (2) the physical model, (3) boundary conditions and (4) the physical properties. You then solve the problem and present the results. In numerical methods, the main difference is an extra step called mesh generation. This is the step that divides the complex model into small elements that become solvable in an otherwise too complex situation. Below describes the processes in terminology slightly more attune to the software. The layout of ANSYS Fluent workbench used for CFD analysis.

Build Geometry Construct at three dimensional representation of the object to be modeled and test educing the work plane coordinates system within ANSYS.

Define Material Properties Now that the part exists, define a library of the necessary materials that compose the object (or project) being modeled. This includes thermal and mechanical properties.

Generate Mesh At this point ANSYS understands the makeup of the part. Now define how the Modeled system should be broken down into finite pieces. The geometry of meshing in ANSYS fluent.

Define Boundary Conditions Once the system is fully designed, the last task is to burden the system with constraints, such as physical loadings or boundary conditions.

Obtain Solution This is actually a step, because ANSYS needs to understand within what state (steady state, transient… etc.) the problem must be solved. This can be achieved by using the ANSYS Fluent software.

IV. RESULT AND DISCUSSION

Fluent software contains the broad, physical modeling capabilities needed to model flow, turbulence, heat transfer and reactions for industrial applications. These range from air flow over an aircraft wing to combustion in a furnace, from bubble column stool platforms, from blood flow to semiconductor manufacturing and from clean room design to wastewater treatment plants. Fluent spans an expansive range, including special models, with capabilities to model in-cylinder combustion, aero-acoustics, turbo machinery and multiphase systems. Fluent also offers highly scalable, high-performance computing (HPC) to help solve complex, large-model computational fluid dynamics (CFD) simulations quickly and cost-effectively.

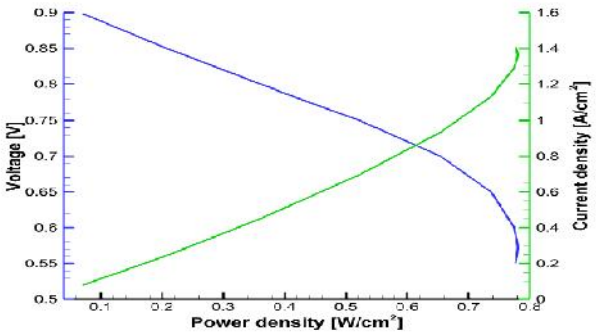

Fig3: P-V & P-I Curves

Volume fraction pattern of brine in the IEG for a standard 40m/s inlet electrolyte velocity is shown. It depicts that the brine volume fraction is continuously reduced from the outlet point of the groove towards the boundaries of the contact area. The reduction in volume fraction of brine has the potential to reduce MRR and may affect the heat transfer rates.

The same is consistent with the temperature contour as shown, which shows that, highest temperature occurs near the outlet of the groove and it goes on decreasing outwards. This may be attributed to the increase in hydrogen volume fraction. As hydrogen has very low convective heat transfer coefficient than brine solution, so transfer of heat is inhibited resulting in temperature rise.

V. CONCLUSION

In this project work the optimization of current density of PEM fuel cell was carried out using MATLAB R2017a. The analyses have been carried out for the selected factors like Temperature, Relative humidity and voltage. The significance of the PEM fuel cell and current density was described earlier in the previous chapter with the objective of

reducing the complexity of solving multi-physics models, Experimental cost and computational time of PEM fuel cells.

The 900-training data, was used to train the ANN, which showed a good agreement with the original data with an error <1%. The ANN was then successfully used as a fitness function of the GA to predict the maximum voltage and efficiency. This ANN-GA method can be implemented in practical PEMFC control to ensure maximum efficiency operation under varying load conditions.

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