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Optimization of Lead-Acid Characteristics for Better Performance using Genetic Algorithm (GA) and a Computational Fluid Dynamics (CFD) Model

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Abstract

Optimization of battery characteristics is really crucial due to the mass production. The optimization procedure requires a mathematical model representing the behavior of the system. The battery can be modeled by discretizing the governing equation of battery dynamics using computational fluid dynamics (CFD) techniques to a good accuracy in a reasonable time. However, the system of governing equations of the battery dynamic is highly nonlinear and the involved parameters are fully coupled; this nonlinearity makes it impractical to use the classical optimization methods and evolutionary algorithms are needed to optimize the battery configuration. In this paper, the characteristics of a battery cell have been optimized by using a real value Genetic Algorithm (GA) along with the CFD model to obtain a better performance.

1 Introduction

Lead–acid batteries are going to be considered as the main power source for electric vehicles (EV) in near future. The batteries used in EV should have special characteristics such as: a) Low weight b) High energy and power. The weight of the batteries affects the dynamical behavior of the EV. If the weight of the batteries is too high, the suspension system of the EV should be redesigned so that it would be able to bear this excess weight. This modification not only makes the EV heavier, but also affects all other EV's design and characteristics.

Another characteristics of the EV batteries are high specific energy and power. These are necessary because the EV needs enough energy to travel an acceptable range and enough power for hill climbing and reasonable acceleration.

For these reasons, the characteristics of the batteries should be optimized to achieve a good performance. However, optimization is a very difficult, complex and time consuming procedure and requires battery modeling. Traditionally, characteristics study of the batteries are based on experimental tests. Although it is a very valuable procedure, but generally, is time consuming and costly and also the repeatability of the tests is very hard to achieve. Mathematical models based on the first principles, however, are able to predict the dynamical behavior of the battery systems and can be considered as an alternative to experiments. Not only is this type of modeling very accurate and reliable, but also fast enough for optimization purposes.

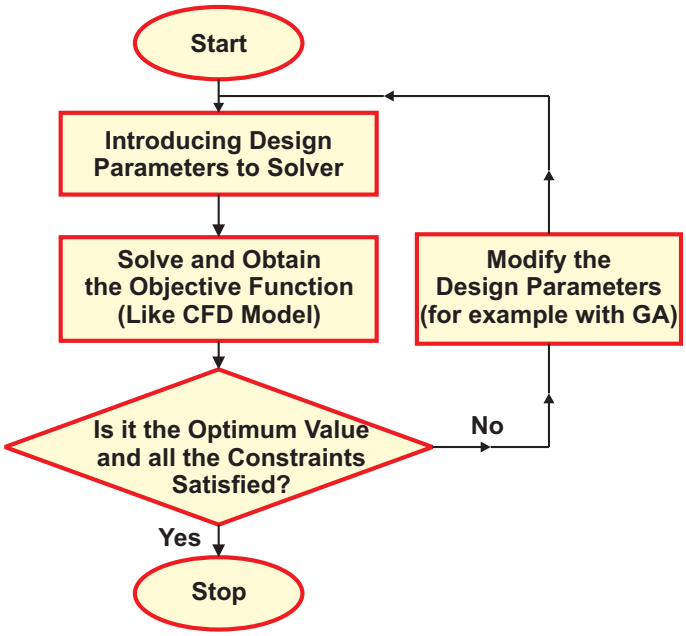

Figure 1: A typical model of optimization procedure.

Extensive efforts have been made to develop mathematical models for battery dynamics. Nguyen et al. [1] presented a mathematical model of discharge performance of the flooded lead–acid cell. Nguyen and White [2] presented a mathematical model for oxygen–recombination lead–acid cell. Bernardi and carpenter [3] developed this model to account for gas phase composition and prediction of the voltage maximum during charge. The most complete model was proposed by Wang and Gu [4, 5] and Gu et al. [6]. This model is multi dimensional, fully coupled and includes the acid stratification and convection. Esfahanian and Torabi [7] included the effect of acid concentration dependency of open circuit voltage to Gu model [8] and solved the whole system by Keller–Box method which requires no special routine for off–diagonal terms [9] (i.e. MBAND routine [10]).

Having an accurate, reliable and fast battery solver, the battery characteristics can be optimized using optimization algorithms. The main idea of any optimization algorithm is to find an optimum set of design parameters for the system under consideration. Appropriate or inappropriate choice of decision parameters will cause the system to perform better or worse, as measured by some relevant objective or fitness function. In realistic systems, the interactions between the parameters are not generally amenable to analytical treatment due to the nonlinear nature of that system. Therefore, one has to resort to appropriate search techniques. Another difficulty arises for problems with multiple local optima, or even for problems where we do not know whether a single optimum is unique. The classical optimization algorithms such as the iterative incremental step and steepest descent methods can lead to the solution being trapped in a local optimum. Restarting the iteration from multiple starting points may provide some safeguard against entrapment in a local minimum. Even then, there are problems where any starting point could lead us to a local optimum before we reached the global optimum. For this type of problem,

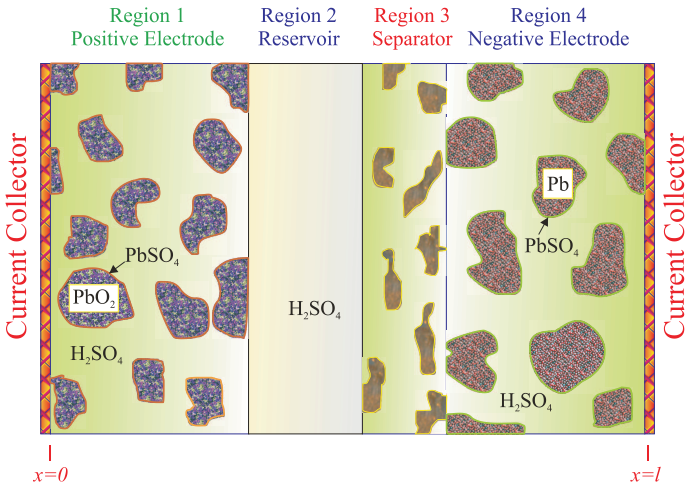

Figure 2: A lead–acid model.

genetic algorithms (GA) offer a preferable means of solution. GA offer the attraction that all parts of the feasible space are potentially available for exploration, so the global minimum should be attained if premature convergence can be avoided.

The basic principles of GA were proposed by Holland in 1975 [11]. Genetic Algorithms are inspired by the mechanism of natural selection where stronger individuals are likely the winners in a competing environment. They have been applied with success to domains such as: optimization, automatic programming, machine learning, economics, immune systems, ecology, population genetics, evolution and learning and social systems [12, 13]. The GA are defined as: *search algorithms based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. In every generation, a new set of artificial creatures (strings) is created using bits and pieces of the fittest of the old; an occasional new part is tried for good measure. While randomized, genetic algorithms are no simple random walk. They efficiently exploit historical information to speculate on new search points with expected improved performance* [14]. The main advantage of GA is that this method is capable to find an optimum even when the model is nonlinear and the design parameters are fully coupled. Such situation is seen in mathematical modeling of the battery dynamics.

As the system of governing equations of the battery dynamic is highly nonlinear and the involved parameters are fully coupled, it is impractical to use the classical optimization methods and evolutionary algorithms are needed to optimize the battery configuration. In this study, GA has been used in combination with the CFD model of the battery dynamics to optimize the characteristics of the battery to obtain a better performance.

Table 1: Governing equations of the battery dynamics.

Conservation of Charge in solid	$\frac{\partial}{\partial x}(\sigma^{\text{eff}}\frac{\partial \phi_s}{\partial x}) - Aj = 0$
Conservation of Charge in liquid	$\frac{\partial}{\partial x}(k^{\text{eff}}\frac{\partial \phi_l}{\partial x}) + \frac{\partial}{\partial x}(k_D^{\text{eff}}\frac{\partial \ln c}{\partial x}) + Aj = 0$
Species conservation	$\frac{\partial(\varepsilon c)}{\partial t} = \frac{\partial}{\partial x}(D^{\text{eff}}\frac{\partial c}{\partial x}) + a_2\frac{Aj}{2F}$

2 Optimization Procedure

The main goal of any optimization procedure is to reach one or more objectives, while some constraints are also satisfied. Therefore, the first step in any optimization is to determine the objective(s) and constraint(s) of the problem. Specifically, in battery systems, one may define the following cases:

1. The objective of the problem is to maximize the energy content of the battery. Obviously, the energy content of the battery increases by increasing the active material of the positive and negative electrode. On the other hand, this will, in turn, increase the weight of the battery. In this case, the weight (thickness of the electrodes) is the constraint of the problem.
2. Since the weight of the batteries is a crucial parameter in EV, one may consider the thicknesses of the electrodes (weight) as the objective of optimization. In this case the energy content should be the constraint of the problem. Because the weight of the battery will decrease by reducing the weight of active mass of electrodes. However, this reduction should not lead to a low energy content battery.

After determining the objective(s) and constraint(s) of the problem, the optimization loop will start to find the optimum values for design parameters. A typical optimization loop is shown in Figure 1. The optimization algorithm adjusts the design parameters until the objective(s) of the problem is reached while all the constraints are also satisfied.

3 Optimization Motivation

A lead–acid battery cell model was solved by Gu et al. [8], and Esfahanian & Torabi [7, 15]. This model (Figure 2) consists of four regions, namely positive electrode, reservoir, separator and negative electrode. The governing system of equations consists of

1. Conservation of mass.
2. Conservation of momentum.

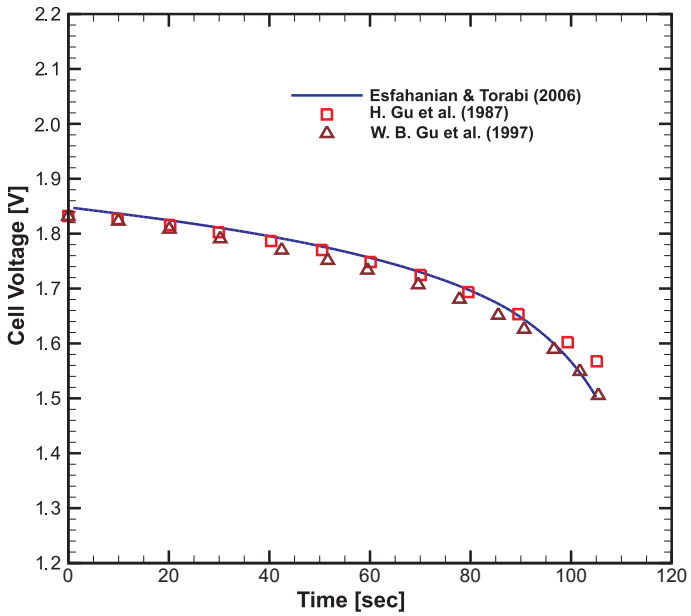

Figure 3: Variation of cell voltage vs time of the base model.

3. Conservation of species.
4. Conservation of charge.

This system with one–dimensional assumption is summerized in Table 1. The governing system of equation is highly nonlinear and fully coupled which is lead to a stiff system of equations. A CFD code was developed to numerically solve this system of equations by the Keller–Box method [7]. The dimensions and parameters used in simulation can be found in [7, 8]. One of the advantages of CFD modeling is that this model provides spatial distribution of distributed parameters of battery with respect to time. This advantage gives deep information about inside phenomena which helps one to have a very good insight understanding of battery behavior.

As an example, consider the results of the above mentioned battery cell. The cell voltage, acid concentration and active material distribution of this model is shown in Figures 3, 4 and 5, respectively. As it can be seen, at the time it reaches the cut–off voltage (i.e. 105 sec), the acid is totally consumed in positive electrode, while there still exists a lot of acid in negative electrode. In the same time, both electrodes still have a lot of active material. These conditions indicates that this model is not well designed and it can be optimized to gain more energy and less weight.

4 Optimization

To optimize the base model, two different strategies are chosen:

1. The objective is to maximize the energy content of the cell, while the total length of the four regions is at most the same as the base model.

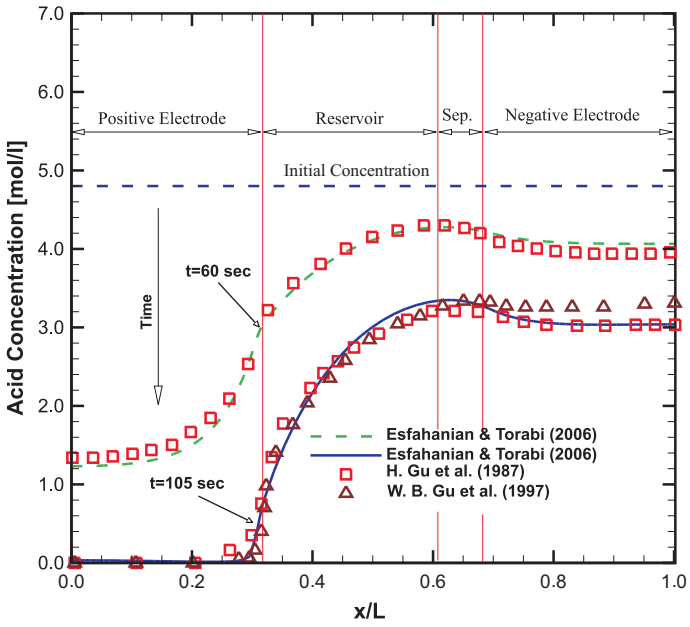

Figure 4: Acid concentration distribution of the base model.

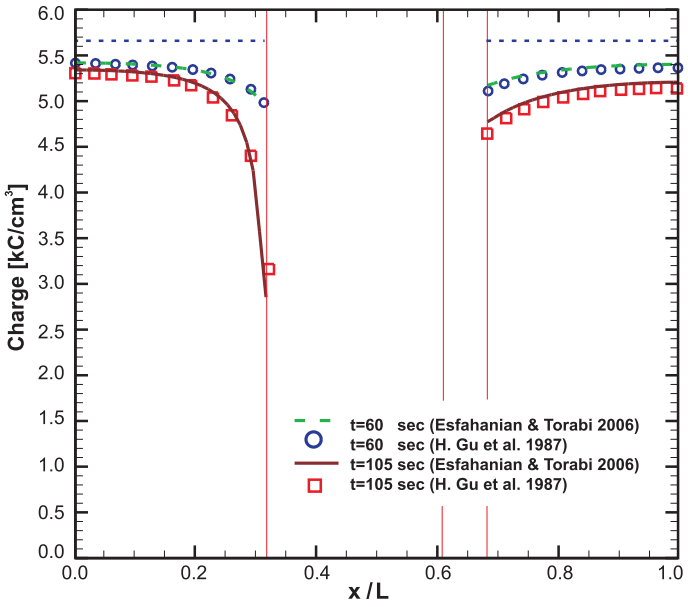

Figure 5: Active material distribution of the base model.

Table 2: Design parameter values of the base cell.

Region	Length (cm)
Positive Electrode	0.06
Electrolyte	0.055
Separator	0.014
Negative Electrode	0.06

Table 3: Comparison of the design parameters (first case).

Region	Base Cell (cm)	Optimized Cell (cm)
Positive Electrode	0.06	0.085
Electrolyte	0.055	0.058
Separator	0.014	0.0175
Negative Electrode	0.06	0.029

2. The objective is to minimize the weight of the cell while the energy content is desired to be at least the same as the base cell.

In both cases, it was assumed that all the design parameters such as porosity, maximum active area, transfer current density etc., are the same as the base cell and we are looking for the optimum set of the thicknesses of different regions of the cell.

It also worth noting that there are always some manufacturing constraints. For example, one may consider that the thickness of the electrodes can not be technologically less than a specific value. These constraints can also be easily implemented into the optimization algorithm.

5 Results

Table 2 shows the thicknesses of different regions of the base cell. The discharge of this cell at constant current (I=-340 mA) takes place in 105 sec. The variation of the voltage of the cell is shown in Figure 3. The energy of this cell is 61.82 J.

The two above mentioned strategies were implemented and the results are as follows.

1. In the first strategy, the objective is to maximize the energy content. This optimization were made by combination of GA and CFD code. The results of the optimization is shown in Table 3. As it can be seen, the total length of the positive and negative electrodes is reduced about 5%, while the energy content of the battery is increased to 71.15 J. It means that with a proper design, it is possible to have a lighter cell with more energy content. In this case, the energy content is increased

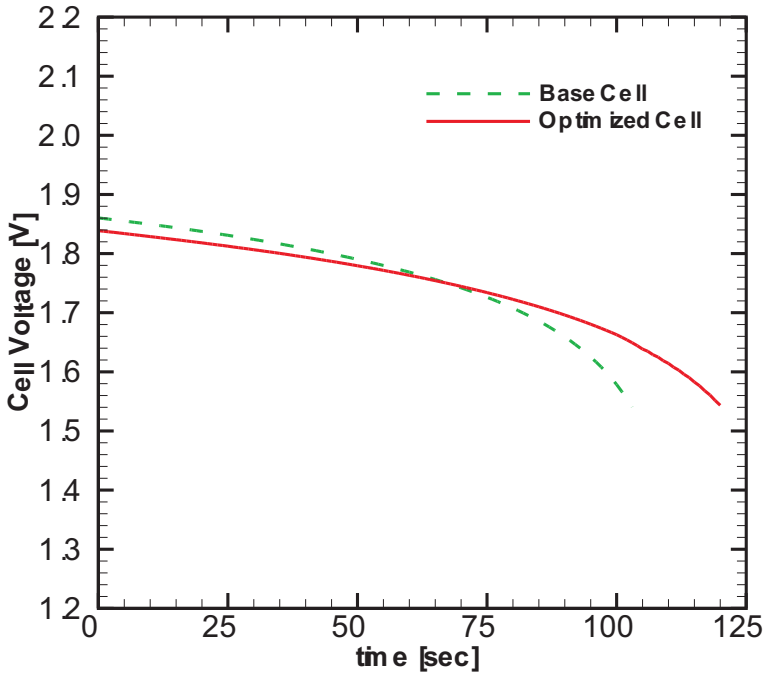

Figure 6: Variation of cell voltage vs time.

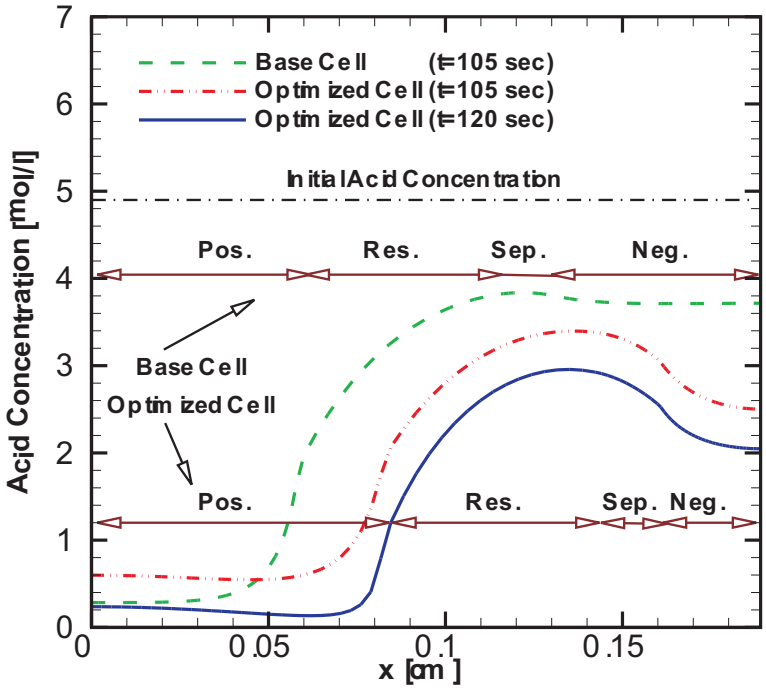

Figure 7: Acid concentration distribution of the optimized model.

Table 4: Comparison of the design parameters (second case).

Region	Base Cell (cm)	Optimized Cell (cm)
Positive Electrode	0.06	0.075
Electrolyte	0.055	0.035
Separator	0.014	0.0175
Negative Electrode	0.06	0.023

about 15 %. Figure 6 compares the variation of voltage of the cell in two cases. Figure 7 shows the acid concentration of the optimized and the base cell at the end of their discharge time. As the figure shows, the acid is more consumed in both electrodes of the optimized cell.

2. The second strategy was also solved by the same optimization procedure. The results of the optimization is shown in Table 4. As it can be seen, in this case, the sum of the thicknesses of the positive and negative electrodes is reduced about 0.22 mm or 18.5%. The energy content of the cell is about 61.7 J which is more or less the same as the base cell (only 0.2% energy reduction). The variation of the voltage is shown in Figure 8. Figure 9 shows the variation of the acid concentration at the end of discharge. As it can be seen, in this case also, the acid is more consumed in both electrodes than the base cell.

6 Discussion

In this paper, optimization of the battery cells has been discussed. After describing the main idea of optimization algorithms, it was mentioned that since the governing equations of battery dynamics are highly nonlinear and fully coupled, conventional optimization algorithms fail to find the optimum point. In this case, however, a real value genetic algorithm is capable to find an optimum for the solution. Hence, in this study, GA was chosen as the main optimization algorithm. Two different optimization strategies were discussed. In the first one, the objective was to maximize the energy content and in the latter to minimize the weight of the cell. In the first case, the energy content of the cell increased about 15% and the weight of the cell decreased about 5%. In a typical lead–acid battery with the weight of 20 kg, the reduced weight is about 1 kg.

In the latter case, the weight of the cell decreased about 18.5%. This means that the weight of the same typical battery will reduce 3.7 kg. This weight reduction shows the importance of the battery characteristics optimization.

Another important parameter in any optimization procedure is the optimization time. As it was mentioned, a fast solver is really important for optimization; otherwise, the optimization time would be too long to be managable, specially for industery. The developed CFD solver is capable to simulate a whole discharge in approximately 10 sec. The optimization procedure typically (for this problem) requires about 400 loops. It means

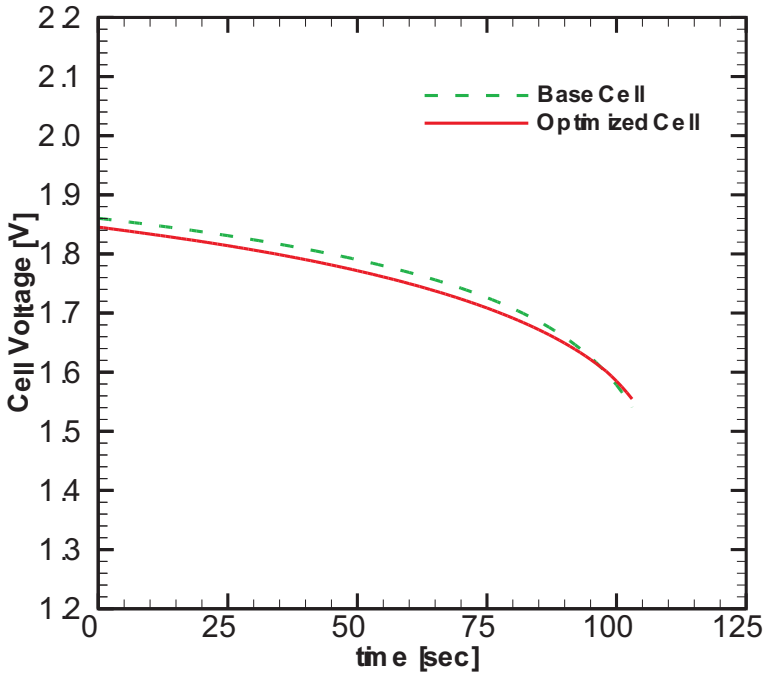

Figure 8: Variation of cell voltage vs time.

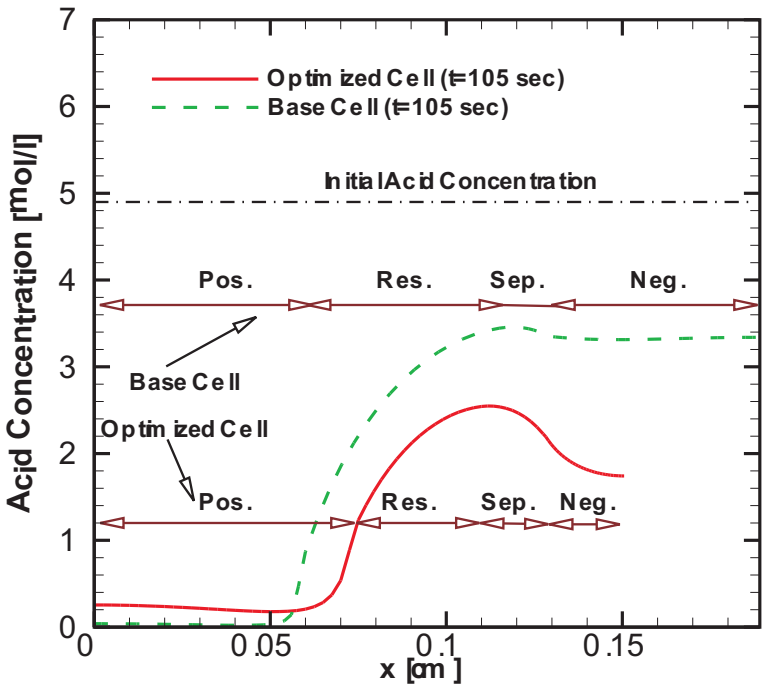

Figure 9: Acid concentration distribution of the optimized model.

that the total optimization time of this problem takes about 4000 sec ($\approx$ 67 min). This amount of time is quite managable and shows that a fast solver (like the developed CFD code) plays a critical role in optimization.

Finally, it should be noted that in this research only the thicknesses of the four cell regions have been taken as design parameters. Other parameters such as porosity, maximum active area, transfer current density etc., are also crucial design parameters which can be easily taken into account in this model. However, the results of this paper shows that an optimum cell can be made by minor modification of the cell characteristics

7 Acknowledgments

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