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Comparative study of PEM fuel cell parameter extraction using Genetic Algorithm

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Abstract In this paper, a new formulation based on the derivative of maximum power with respect to current is proposed for fuel cell parameter extraction. Compared to conventional extraction methods, the proposed method has various features such as faster convergence, higher efficiency and accuracy. In this work, the problem of parameter extraction is formulated as an optimization task and it is solved using simple GA. Explanations about the new formulation and its implementation using GA are elaborated. To validate the candidature of the proposed formulation, performance analysis is done with two sets of initial value ranges and the results are compared with the existing curve fitting method in terms of accuracy, convergence characteristics and objective function value. The results show that the proposed formulation employing GA is capable of extracting fuel cell parameters accurately with lesser computational steps and time.

1. Introduction

Increased power demand, continuous depletion of fossil fuels and emission of greenhouse gases urge researchers and practitioners to focus on new technologies that can efficiently harness the existing renewable energy resources. Fuel cell systems are prominent energy sources gaining momentum in recent past due to its high efficiency, reliability, durability and ease of application in diverse fields.

Fuel cell is an electrochemical device that converts hydrogen fuel into electric power. Fuel cell system comprises of two electrodes namely anode and cathode. Hydrogen is allowed to pass through the positive electrode and oxygen through the negative electrode, with an electrolyte between them facilitating the exchange of electric charges. The flow of electrons through the external circuit produces electric power [1].

Due to its robustness and higher efficiency, fuel cells have been extensively utilized in commercial, industrial and residential applications (such as primary and backup power generation) [2]. Fuel cells can be categorized based on the type of electrolyte used and the start-up time required. For instance, the start-up time for Proton Exchange Membrane (PEM) fuel

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cell is 1 s whereas for Solid Oxide (SO) fuel cell it is 10 min. Under normal operating conditions, a simple fuel cell typically produces output voltage in the range of 0.5–0.9 V. Since this low voltage becomes insufficient for real-time applications, a stack of fuel cells are arranged in series so that the required voltage can be attained [3].The most commonly used fuel cell is the PEM fuel cell. It is popular due to its distinctive features such as no waste is generated, high efficiency, low operating temperature and pressure [4].

It is appreciable to build an effective fuel cell model before proceeding into the installation part of the system so that the design and testing can be made much easier [5]. Modelling of fuel cell characteristics has drawn considerable attention of researchers over the last decade as it helps in the better understanding of the phenomena occurring within the cell. It is a major concern for researchers and practitioners to model fuel cell characteristics accurately since its behaviour largely depends upon the predicted characteristics as well as its model parameter values. The values of all the model parameters required for fuel cell modelling are not provided in the manufacturer's datasheet. Therefore, it facilitates the need to accurately compute the values of the unknown parameters by employing any suitable optimization technique.

From the past literature, it can be inferred that the previous attempts followed curve fitting method for fuel cell modelling [6–9,15,16]. In this procedure, model parameters are computed by considering the sum of square of errors between computed and measured values on predefined points on the fuel cell characteristics. The main shortcomings of this method are as follows: it consumes more time, is strenuous, error is large and is complex. Hence, in order to overcome these drawbacks a new formulation is proposed to accurately determine the model parameters. The proposed formulation is based on the fact that derivative of power with respect to current at Maximum Power Point (MPP) is zero. This formulation henceforth is named as Maximum Power Point (MPP) method and it applies simple Genetic Algorithm for solving the fuel cell parameter identification problem.

In the proposed formulation, only 3 points on the *I-V* characteristics namely V_{oc}, V_{mpp} and I_{sc} are utilized to estimate the model parameters unlike the curve fitting method which considers many points on the *I-V* characteristics to estimate the model parameters. This formulation is accurate, fast converging and simple since it requires the computation of only 3 points.

For validation and detailed analysis of the novel formulation, extensive evaluation and comparison are done between the conventional curve fitting method and the proposed MPP method. In order to estimate the goodness of proposed MPP method and for fair comparison, constraints such as fitness function value (best, worst, mean and standard deviation), convergence characteristics, matching of the computed and expected *I-V* characteristics and statistical tools like standard deviation, absolute error and histograms are taken into account.

The remaining part of this paper is subdivided into 5 sections. Section 2 expounds the PEM fuel cell model. Section 3 explains the formulation of the objective function. Section 4 details the optimization technique used (i.e.) Genetic Algorithm (GA). Section 5 deals with results and discussions.

2. PEM fuel cell model

Fuel cell is an electrochemical device that converts the stored energy of fuel directly into electricity with the help of an oxidant [10]. It consists of a cathode and an anode with a proton-conducting membrane which serves as the electrolyte. The electrochemical equations occurring in electrodes of a PEM fuel cell can be described as follows [11].

Anode side:

$$H_2 \rightarrow 2H^+ + 2e^- \tag{1}$$

Cathode side:

$$2H^+ + \frac{1}{2}O_2 + 2e^- \rightarrow H_2O \tag{2}$$

Overall electrochemical reaction:

$$H_2 + \frac{1}{2}O_2 \rightarrow H_2O \tag{3}$$

The electrochemical model of fuel cell is proposed by Amphlett et al. [12]. The output voltage equation governing a single fuel cell is

$$V_{FC} = E_{Nernst} - V_{act} - V_{ohmic} - V_{con} \tag{4}$$

E_{Nernst} can be calculated using the following formula

$$E_{Nernst} = 1.229 - 0.85 \times 10^{-3}(T - 298.15) + 4.3085 \times 10^{-5} \times T[\ln(P_{H_2} + 0.5\ln(P_{O_2})] \tag{5}$$

where P_{H_2} and P_{O_2} are partial pressures (atm) of hydrogen and oxygen, respectively. T is the fuel cell absolute temperature (K).

The activation over potential can be expressed in a parametric form as follows,

$$V_{act} = \varepsilon_1 + \varepsilon_2 T + \varepsilon_3 T\ln(C_{O_2}) + \varepsilon_4 T\ln(i) \tag{6}$$

where the terms ε_i are semi-empirical coefficients, i is the cell current (A), C_{O_2} is the concentration of oxygen in the catalytic interface of the cathode (mol cm^{-3}).

$$C_{O_2} = \frac{P_{O_2}}{5.08 \times 10^{-6} e^{\left(\frac{-498}{T}\right)}}$$

The ohmic voltage drop is given by the expression [13]

$$V_{ohmic} = i(R_m + R_c) \tag{7}$$

And,

$$R_m = \frac{\rho_m l}{A}$$

$$\rho_m = \frac{181.6\left[1 + 0.03\left(\frac{i}{A}\right) + 0.062\left(\frac{T}{303}\right)^2\left(\frac{i}{A}\right)^{2.5}\right]}{\left[\lambda - 0.634 - 3\left(\frac{i}{A}\right)\right]\exp\left[4.18\left(\frac{T-303}{T}\right)\right]}$$

where R_m and R_c are the equivalent inner membrane resistance and outer contact resistance respectively. l is the thickness of the PEM (cm), which serves as the electrolyte of the cell, A is the active cell area (cm^2), ρ_m is the membrane specific resistivity and λ is an adjustable parameter.

The concentration voltage drop is given by,

$$V_{con} = -b\ln\left(1 - \frac{I}{I_{max}}\right) \tag{8}$$

where b is the parametric coefficient (V) that depends on the type of cell and its state of operation. I is the actual cell current (A), I_{max} is the maximum possible value of I.

For the PEM fuel cell, the relationship between $P_{H_2}, P_{O_2}, P_{H_2O}$, and C_{O_2} can be expressed as [14]:

$$\log(P_{H_2O}) = 2.95\times10^{-2}(T-273.15) - 9.1810^{-5}(T-273.15)^2 + 1.44\times10^{-7}(T-273.15)^3 - 2.18 \quad (9)$$

$$P_{N_2} = \frac{0.79}{0.21}P_{O_2} \quad (10)$$

$$P_{O_2} = P_c - \mathrm{RH}_c P_{H_2O} - P_{N_2}\exp\left(\frac{0.291(i/A)}{T^{0.832}}\right) \quad (11)$$

$$P_{H_2} = 0.5\mathrm{RH}_a P_{H_2O}\left[\left(\exp\left(\frac{1.635(i/A)}{T^{1.334}}\right)\times\frac{\mathrm{RH}_a P_{H_2O}}{P_a}\right)^{-1} - 1\right] \quad (12)$$

where P_{H_2O} is the saturation pressure of water vapour (atm) P_{N_2} is the partial pressure of N_2 at the cathode gas flow channel (atm). P_a, P_c are the anode and cathode inlet pressures (atm), RH_a and RH_c are the relative humidity's of the vapour in anode and cathode respectively.

3. Problem formulation

From the equations mentioned above, it is evident that many parameters are involved for describing the fuel cell operation and most of them are unknown. Since they are not given in the manufacturer's datasheet, the calculation of these parameters should be carried out by applying some optimization procedure. The specific set of parameters required for fuel cell modelling are $\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, b, R_c$ and λ. For effective problem solving capability, it is important to define a clear objective function. At the same time, proper definition of objective function is crucial for extracting accurate parameter values as it ensures that the obtained model results perfectly synchronizes with the actual fuel cell characteristics. Hence, in this work objective function is formulated by applying the fact that the derivative of power with respect to current is equal to zero at Maximum Power Point (MPP). i.e. $\frac{dP}{dI} = 0$. The fuel cell DC power output is given by:

$$P = VI \quad (13)$$

Taking differentiation of above equation we get,

$$\frac{dP}{dI} = V + I\frac{dV}{dI} \quad (14)$$

Applying MPP condition to the above equation, RHS of equation is set to zero

$$\frac{dV}{dI} + \frac{V}{I} = 0 \quad (15)$$

Thus, the objective function for fuel cell parameter extraction can be expressed as

$$J = \left|\frac{dV}{dI}\right|_{(V_{mpp}, I_{mpp})} + \frac{V_{mpp}}{I_{mpp}} \quad (16)$$

In the above equation the value of $\left|\frac{dV}{dI}\right|_{(V_{mpp}, I_{mpp})}$ can be obtained from the basic voltage equation.

$$\left|\frac{dV}{dI}\right|_{(V_{mpp}, I_{mpp})} = -\left[\left(\varepsilon_4\frac{T}{I_{mpp}}\right) + \left(\frac{b}{I_{max} - I_{mpp}}\right) + \left(R_c + \left(\frac{l\times181.6}{A\exp\left(\frac{4.18(T-303)}{T}\right)}\right)\right)\times\Gamma\right] \quad (17)$$

where

$$\Gamma = \frac{((\lambda - 0.634) + J_p(0.6\lambda - 0.038) + J_p^{2.5}\Delta T^2(0.217\lambda - 0.1375 - 0.465J_p) - 0.9J_p^2)}{(\lambda - 0.634 - 3J_p)^2}$$

$$J_p = \frac{I_{mpp}}{A} \quad (18)$$

$$\Delta T = \frac{T}{303} \quad (19)$$

4. Optimization technique

4.1. Genetic Algorithm

Genetic Algorithm is an evolutionary computational technique which follows Darwin's principle of "survival of the fittest". The application of this concept for optimization was put forward by Holland in 1975 which was later modified by different authors. The essence of GA constitutes the encoding of optimization function arrays comprising of bits to emulate chromosomes and different operations are performed on chromosomes by various genetic operators [6,17].

The important processes employed in Genetic Algorithm are reproduction, selection, crossover and mutation. A set of probable solutions entitled as population is made to undergo GA operations and their values are frequently modified in order to converge to the best solution. In every step, the parents are chosen from the current population to produce offspring which is nothing but a new set of chromosomes. The flow chart emulating the process involved in GA is shown in Fig. 1.

4.2. Application of GA towards parameter estimation

The fuel cell parameter identification problem aims at finding an optimal set of parameters that exactly reproduces the actual fuel cell characteristics. The optimization technique applied for the above problem must have the capacity to explore the

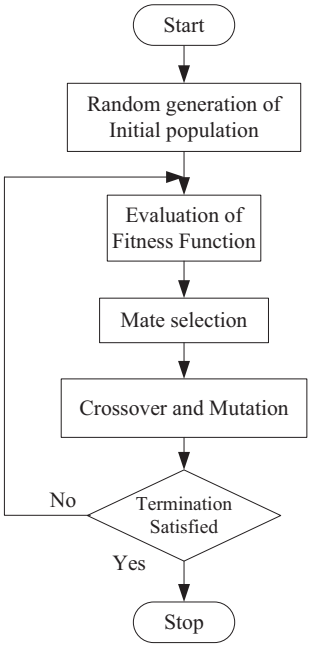

Figure 1 Flow chart of GA.

solution space and arrive at optimal solution set in shorter time. The various steps involved when GA is applied to the present problem are described as follows:

Step 1: Parameter setting
Fix the GA parameters namely population size, cross over rate, mutation rate and termination criteria.
Step 2: Create an initial population
In this step, chromosomes i.e., individuals of the population are created. In this work, binary coded GA is used with chromosome length of 70. Generate an initial population with each chromosome (i.e., parameter values) representing a potential solution to the problem.
Step 3: Evaluation of objective function
Fitness i.e., goodness of a solution, of each individual generated in previous step is evaluated. In the present work, the fitness value assigned to each chromosome is same as the objective function value; since it is a minimization function. After objective function evaluation i.e., Eq. (16), each chromosome is assigned a sector proportional to its fitness value in a virtual roulette wheel. Roulette wheel selection procedure is adopted to select the parents for the next generation.
Step 4: Cross over and mutation operation
The parents selected performing the above steps are allowed to undergo cross over, i.e., bits of chromosomes are exchanged, multipoint cross over is followed in this work for better efficiency. The offspring's generated via cross over are mutated. Bits of chromosomes are toggled based on the value of mutation probability.
Step 5: Creation of new population
In this step, old population is replaced with the newly generated population.
Step 6: Termination criteria
Check whether a termination criterion is met. If it is satisfied, stop and print the result; else go to step 3.

4.3. GA parameter selection

For obtaining the exact model parameters applying GA, proper selection of predefined GA parameters is crucial. If the selection of the values is not accurate, the result obtained will be erroneous which results in the mismatch between the computed fuel cell characteristics and the actual characteristics. Further, in order to rule out the possibility of getting inaccurate results completely the values of population size, crossover probability, mutation rate and maximum generations are judiciously adjusted in such a way that better results are obtained. Each of the values is modified via continuous tuning within a certain range and the best value is evolved. Thus, the best set of GA parameters arrived which are mentioned herein. The value of population size is 100, mutation rate is 0.3 and cross over rate is 0.8 and the number of iterations to be performed is 250. Selection of parents is performed with the aid of Roulette wheel selection method and multi point crossover is employed.

4.4. Importance of range selection

The proper selection of GA parameters alone does not guarantee faithful results as its convergence and the obtainment of faithful results also depends on the chosen initial population. Further, the range of fuel cell model parameters namely $\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, b, R_c$ and λ also plays a significant role in the proper modelling of fuel cell system. Unfortunately, there is a lack of proper knowledge about the model parameter values as well as their range. This flaw can be concealed up to a certain extent by allowing large number of iterations with entirely different random initial values so that the desired results are obtained. However, increased number of iterations can yield poor results. Hence, to refine the search process in a proper manner as well as to guarantee sufficient class of accuracy between the computed and actual characteristics, the model parameters are subjected to a definite range and the results obtained are analysed. Further, the range should be constrained by considering the physical meaning of the parameter as well so that it becomes realizable. There are two possibilities in the range selection process 1. Wide range and 2. Narrow range. If the chosen range is wide, the search space is large and the applied optimization technique takes longer time to converge to the best possible solution. Moreover, there is a great possibility that the method may converge to any of the local best solution which resembles the best one and further deteriorates the efficiency of search process. To avoid the drawbacks of wide range selection, a narrow range can be chosen. The issue of settling to local best value and higher convergence time can be expelled with this performance, but care should be taken such that the best value should also be contained in the prescribed range. Thus, it is evident that proper selection of parameter ranges assures the expected class of accuracy.

The ranges for model parameters employed in this work are presented in Table 1 where Range 1 is a narrow range whereas range 2 is a wider range. These ranges are helpful in identifying the best objective function for the proposed problem.

5. Results and discussion

To accentuate the supremacy of the new formulation, its performance is compared with that of the conventional curve fitting method. To make a fair comparison, same GA method is applied for both the approaches and the performance is evaluated. Further, the performance of the proposed MPP approach and conventional curve fitting approach is evaluated in terms of fitness function value (best, worst, mean and standard deviation), convergence characteristics, matching between computed and expected I-V characteristics, standard deviation, absolute error graph and histograms. The results obtained

Table 1 Different parameter ranges for performance evaluation.

	ε_1	ε_2	ε_3	ε_4	b	R_c	λ
Range 1, Min	−0.95	2e−3	6e−5	1.1e−4	0.02	1e−4	16
Range 1, Max	−0.944	4e−3	8.5e−5	1.88e−4	0.06	8e−4	24
Range 2, Min	−0.9	1.5e−3	5.5e−5	1.05e−4	0.01	0.5e−4	10
Range 2, Max	−0.87	4.5e−3	9e−5	1.93e−4	0.07	8.5e−4	24

Table 2 Best, worst, mean and the standard deviation values of both the approaches for 150 runs.

	Approach	Best	Worst	Mean	Standard deviation
Range 1-GA	Proposed method	0.003366	0.003749	0.003532	0.0000793
Range 1-GA	Point by point method	0.5147	1.44003	0.7511	0.209617
Range 2-GA	Proposed method	0.001259	0.00199	0.001544	0.00013793
Range 2-GA	Point by point method	0.35283	2.46632	1.122	0.384907

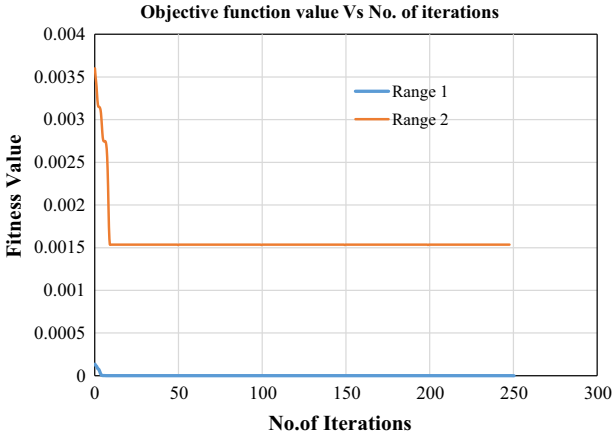

Figure 2 Variation of objective function for the proposed method for range 1 and range 2.

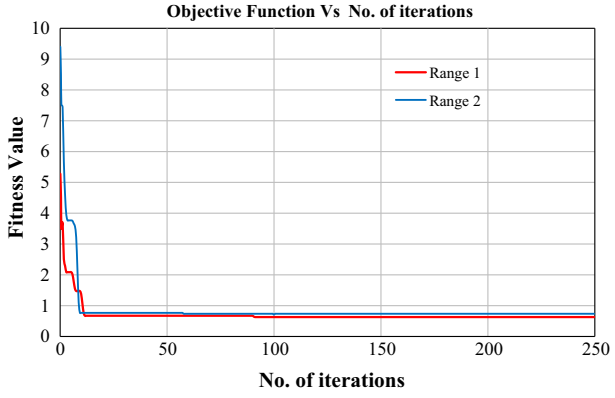

Figure 3 Variation of objective function by the conventional curve fitting method for range 1 and range 2.

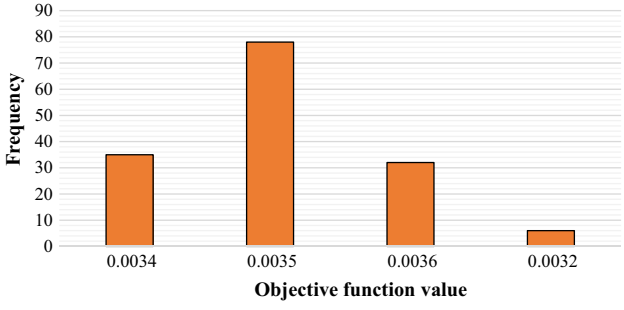

Figure 4 Histogram of the objective function value for Range 1 for proposed MPP method.

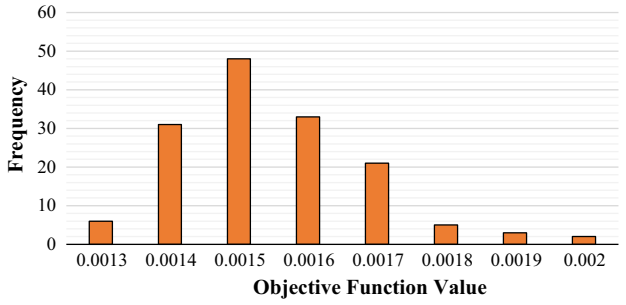

Figure 5 Histogram of the objective function value for Range 2 for proposed MPP method.

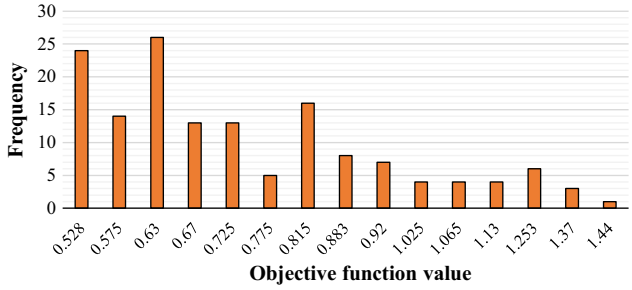

Figure 6 Histogram of the objective function value for Range 1 for conventional curve fitting method.

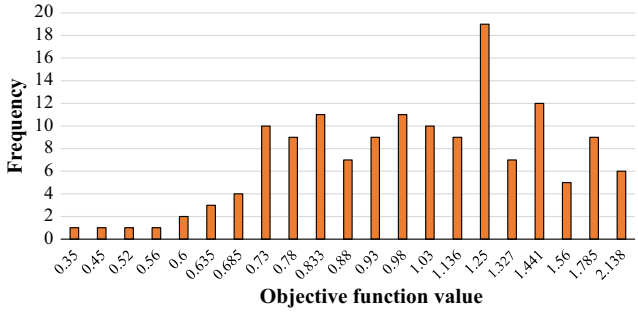

Figure 7 Histogram of the objective function value for Range 2 for conventional curve fitting method.

are explicitly discussed. Programs were developed in MATLAB for GA with both methods. Simulations are performed using Pentium 4 INTEL 4 GB RAM 2.4 GHz processor.

GA is made to run 150 times for both the approaches and comparison is made in terms of best, worst, mean and standard deviation of objective function value obtained for all the iterations is described in Table 2.

From Table 2, it is clearly evident that the proposed MPP method provides better results for all range of initial values.

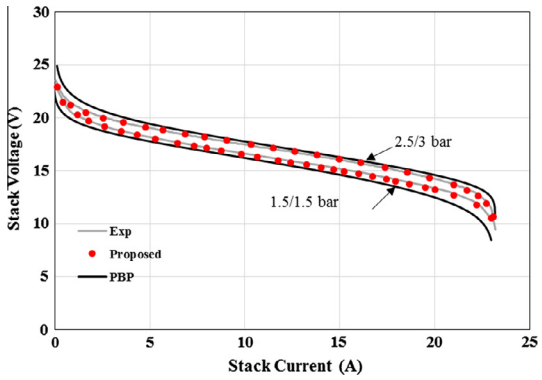

Figure 8 Comparison of the proposed MPP, point by point method and expected curves under 2.5/3 bar and 1.5/1.5 bar pressure.

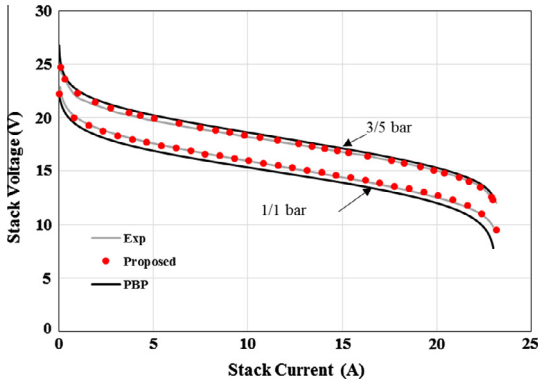

Figure 9 Comparison of the proposed MPP, point by point method and expected curves under 3/5 bar and 1/1 bar pressure.

Further, there is a remarkable improvement in the fitness function value obtained through the novel proposition compared to conventional curve fitting procedure which again proves the effectiveness of the proposed formulation. The results confirm that the proposed approach is robust and it can be employed for any chosen parameter range which exactly meets the required standards.

Figs. 2 and 3 show the variation of fitness function value against the number of iterations for best run of the proposed MPP and conventional curve fitting approach respectively. From the graphs, it is observed that there is a drastic reduction in the objective function value when the new approach is employed. Further, independent of the model parameter range, the novel formulation converges to a very low fitness value after settling which is in the order of 10^{-2}. However, the objective function value is very close to unity when conventional approach is applied. Moreover, the ultimate aim of the optimization technique is to achieve a very small objective function value which basically interprets that the error between extracted and actual characteristics is very low. This is achieved in the proposed MPP method. Further the time taken for GA optimization technique with the proposed MPP method and point by point method is found to be 3.54 s and 8.62 s respectively. The difference in time taken is due to the large computations involved in the point by point method.

Figs. 4 and 5 show the histograms for the frequency of fitness function value for two ranges with the proposed MPP method and Figs. 6 and 7 show for conventional curve fitting approach. From the histograms, it is evident that the frequency of getting best objective function values with less magnitude is higher for the proposed method compared to that of the conventional curve fitting method. However, due to larger exploration area in range 2, as well as higher computational data, the curve fitting method produces poor results in both the cases. Further, the curve fitting procedure may end in local optima in range 2 due to vast search space.

The extracted model parameters for both the approaches are subsequently substituted in the MATLAB/SIMULINK fuel cell model to plot the *I-V* characteristics of the fuel cell stack. For comparison, experimental data are taken from manufacturer's datasheet and compared with computed values for the same fuel cell stack. The comparison between actual and

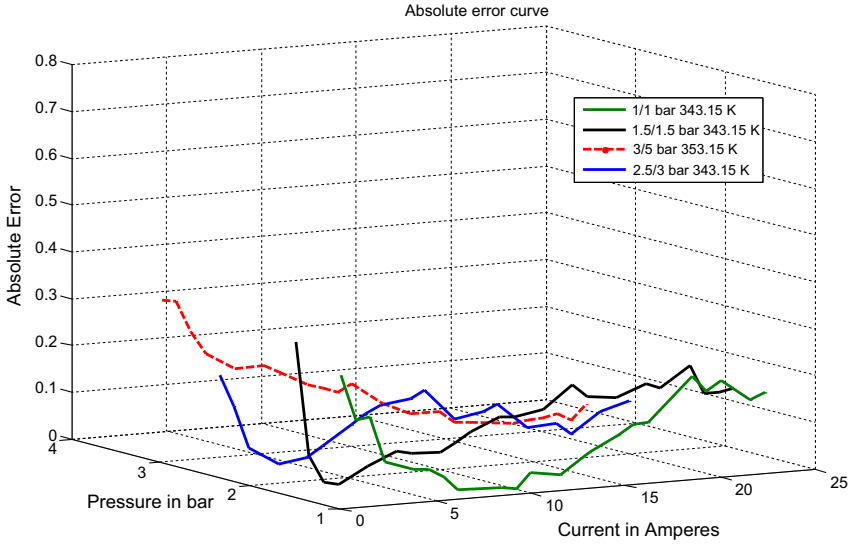

Figure 10 Absolute error curve-proposed MPP method.

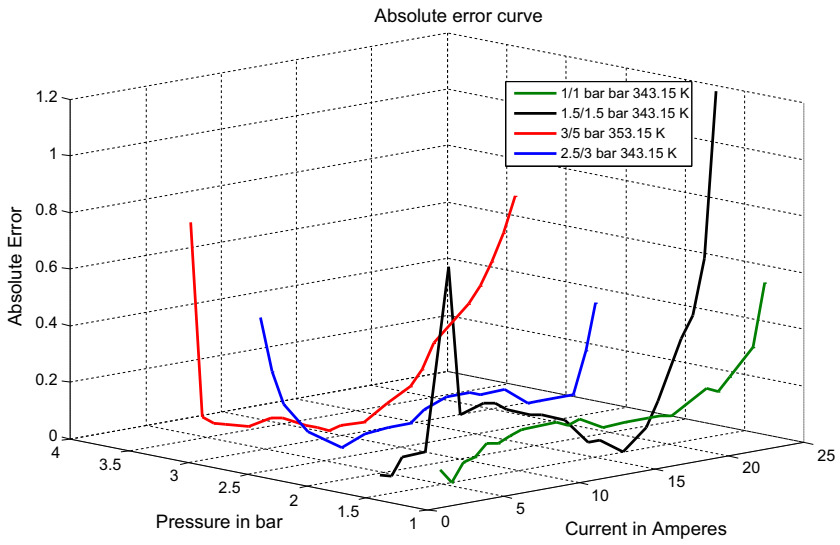

Figure 11 Absolute error curve-conventional curve fitting method.

extracted *I–V* characteristics for different conditions of pressure and temperature is done in detail.

A closer observation of the graphs Figs. 8 and 9 indicates that the computed and expected fuel cell characteristics are exactly matching when the proposed approach is employed even under different test conditions however there is a noticeable drift in the characteristics when point by point approach is executed. Hence, the proposed formulation always promises to provide appropriate matching between the computed and the actual characteristics irrespective of the test conditions.

For further justification of the proposed method, the absolute error is calculated by comparing the difference between computed and actual *I-V* curve values. The calculation of the absolute error from *I-V* curves is based on the following equation:

$$\text{Absolute error} = \left|V_{\text{experimental}} - V_{\text{computed}}\right|$$

The absolute error curves plotted for four different operating conditions (for 1/1 bar 343.15 K, 1.5/1.5 bar 343.15 K, 2.5/3 bar 343.15, and 3/5 bar 353.15 K) for both the approaches are presented in Figs. 10 and 11 respectively.

It is noteworthy to mention that the absolute error value is considerably reduced when the new method is implemented and it is undoubtedly noticeable in Figs. 10 and 11. The maximum error is less than 0.2 for the new proposition whereas it rises up to a value close to unity in the conventional curve fitting approach. Moreover, the deviation in error value is very less even under different test conditions. This again gives strong evidence that the proposed MPP approach is robust and reliable under all test conditions and it always promises to provide error value within a limited low range.

6. Conclusions

In this paper, a novel problem formulation based on derivative of power with respect to current at maximum power point is proposed. A simple Genetic Algorithm is used to solve the above formulation. The seven model parameters $\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, b, R_c$ and λ are extracted via GA procedure. For demonstration, results obtained with GA are benchmarked with the widely used curve fitting approach. The results demonstrate that the new MPP formulation applying GA performs better than curve fitting method in terms of accuracy, convergence characteristics, convergence speed and objective function value.

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