Abstract

Objective: Development of Mathematical model and implementation of PID control scheme for 500Watt Polymer Electrolyte Membrane (PEMFC) Fuel Cell system. Methods: Model is developed in the MATLAB/Simulink platform by using Box Jenkins, Output Error method, Polynomial State space method and Subspace method. Findings: Subspace method of identification provides good results with acceptable Final Prediction Error (FPE) and this model is considered for implementing PID control scheme. Tuning of PID parameters is carried out by Cuckoo Search (CS) algorithm which yields most challenging results.

Applications/Improvements: Residential power generation, Recreation vehicles, Light weight vehicles, Portable computers, Transportation.

Keywords: Cuckoo Search Algorithm, Heuristic Algorithms, Polymer Electrolyte Membrane Fuel Cell

1. Introduction

A fuel cell is a device which changes the chemical energy into electrical energy by using the hydrogen and oxygen. There are numerous types of fuel cells such Polymer Electrolyte Membrane Fuel Cell (PEMFC), Direct Methanol Fuel Cells, Alkaline Fuel Cell, Phosphoric Acid Fuel Cells, Molten Carbonate Fuel Cells, Solid Oxide Fuel Cells, and Reversible Fuel Cell. PEMFC have several advantages over the other types of fuel cells\(^1,2\). PEMFC is a device which uses hydrogen as a fuel which is treated at anode where electrons are disconnected from protons on the surface of a platinum-based catalyst. Polymer Electrolyte Membrane Fuel cell (PEMFC) frameworks have gotten significant consideration in the past 15 years and they are relied upon to assume a critical part in future force era offices. The potential for PEMFC to produce zero emissions creates a great prospect for clean energy in the transport industry. Lifetime and reliability appear to be important considerations to effectively achieve the commercialization of such systems. PEMFC’s use hydrogen and air to deliver power and water, have high power thickness, use strong electrolyte, have long stack life, and in addition low corrosion because of erosion. The working parameters are essentially the regulation of flow of air and hydrogen, weight, warmth and administration of water. The physics of the PEMFC can be regarded as the opposite of electrolysis. In electrolysis an electric current is delivered through water to yield hydrogen and oxygen. In the fuel cell, hydrogen and oxygen gases are distributed side of a polymer electrolyte membrane which generates an electric current, heat and water. Figure 1 shows the schematic diagram of PEMFC. It consists of a cathode and anode which constitutes the flow of hydrogen and oxygen flows through the membrane. Hydrogen enters into the membrane where it loses electrons and combines with oxygen to form water.

Water molecule contains the depleted Oxidant and product gases. The following electro-chemical reactions are taking place during the functioning of PEMFC\(^3-7\).

Anode Reaction: \( \text{H}_2 \rightarrow 2\text{H}^+ + 2\text{e}^- \) \hfill (1)

Cathode Reaction: \( \frac{1}{2}\text{O}_2 + 2\text{H}^+ + 2\text{e}^- \rightarrow \text{H}_2\text{O} \) \hfill (2)
Concentration loss relates to the reduction of the reactant’s attentiveness in the gas channels. The fuel and oxidant are used at the exterior of the electrodes. The entering gas must then take the place of the used reactant. The concentration of the fuel and oxidant is concentrated at the various points in the fuel cell gas channels and is less than the concentration at the inlet value of the stack. This loss develops significant at higher currents when the fuel and oxidant are used at higher rates and the attention in the gas channel is at a minimum. Mathematically, all these losses are combined and can be represented as:

\[ V_{DC} = V_{open} - V_{ohmic} - V_{act} - V_{con} \]

\[ V_{open} = N_0 \left( V_0 + \frac{RT}{2F} \ln \left( \frac{P_{H_2}}{P_{H_2}O_2} \right) \right) \]

\[ V_{ohmic} = I_{DC} \cdot R_{FC} \]

\[ V_{act} = N_0 \frac{RT}{2\alpha F} \ln \left[ \frac{I_{DC}}{I_0} \right] \]

\[ V_{con} = -C \cdot \ln \left[ 1 - \frac{I_{DC}}{I_{lim}} \right] \]

Where,
- \( R \) = Resistance of PEMFC
- \( T \) = Temperature of PEMFC
- \( V_{DC - stack} \) = Voltage from fuel cell stack
- \( V_{open} \) = Open circuit voltage
- \( V_{ohmic} \) = Ohmic voltage
- \( V_{act} \) = Activation voltage
- \( V_{con} \) = Concentration voltage
- \( N_0 \) = Number of stacks.

The values are more specific for a given PEMFC. The dynamic model is developed under MATLAB/Simulink platform using the above equations.

### 3. Identification of PEMFC

Identification refers to finding the mathematical model of the plant using available input/output data. It involves 4 major steps namely, conduct suitable experiment, examine the available input/output data, estimate proper model and validate the model. The dynamic model is excited by a step input of 350 and the response is recorded for 6000 seconds. The response reaches the steady state value of 320 Watt with large peak overshoot.

These input/output data is being used for identifying suitable model structure. Figure 2 shows the response of PEMFC for step change in input. The obtained model is validated.
3.1 Box Jenkins
Box Jenkins is a time series analysis based on the input and output data. It contains the four functions $B(z)$, $F(z)$, $C(z)$ and $D(z)$. The estimated model will be in the form as:

$$ Y(z) = \left[ \frac{B(z)}{F(z)} \right] u(t) + \left[ \frac{C(z)}{D(z)} \right] e(t) \quad (9) $$

Figure 3 shows the response of estimated and actual model. This model is validated and provides Final Prediction Error (FPE) of about 0.4913, Mean Square Error (MSE) value of about 0.4751 and 99.05% fit.

3.2 Output Error Method
Figure 4 shows the comparison of estimated and actual model wherein the FPE is about 1.577 and MSE is about 1.47.

Solid line represents actual output while dashed line represents estimated model. The fitness to the original data is about 98.43%.

3.3 Subspace Identification
Subspace method also known as n4sid, provides the model in the form of pole and zeros. The model is in transfer function form with 5 poles and 4 zeros. The validation data shows the FPE of about 0.001424 and MSE of about 0.001366. Figure 5 shows the estimation and actual input/output data.

This provides greater accuracy as compared to the above methods. The identified transfer function is in the following form.

$$ G(s) = \frac{591.6s^4 + 1472s^3 + 451.3s^2 + 0.9748s + 1.847 \times 10^{-5}}{s^5 + 21.72s^4 + 52.59s^3 + 16.12s^2 + 0.03318s + 4.35 \times 10^{-7}} \quad (10) $$

It gives the 99.95% of the fitness value to the original data.

3.3 Polynomial State Space
The Polynomial State space (PSS) method gives the output in state space form.

$$ Y(t) = Cx(t) + Du(t)e(t) \quad (11) $$

$$ \frac{dx}{dt} = Ax(t) + Bu(t) + Ke(t) \quad (12) $$

Where, $A$, $B$, $C$, $D$ are the system matrix, input matrix, output matrix and disturbance matrix respectively. Figure 6
shows the validation and estimated plot for Polynomial 
state space. This method yields FPE value of about 0.7644, 
MSE of about 0.7636 and 98.8% fit to the actual data. 

Table 1 shows the comparison of FPE, MSE and %fit 
for the different model structures used.

Subspace Identification method yields the accurate 
model with lesser FPE and MSE. The authors choose 
N4SID model for implementing closed loop control and 
to tune the PID controller parameters.

4. Heuristic Algorithm

4.1 Based Optimisation

Optimization refers to selecting a best optimal value from 
some set of available alternatives to meet the desired 
objective function. It is a step by step procedure which is 
executed iteratively by comparing the obtained solutions 
with new solutions during the iteration, till a satisfactory 
solution is attained. Almost all applications in engineering 
and industry, optimization is being done to minimize cost 
and energy consumption, or to maximize profit, output, 
performance, and efficiency\textsuperscript{14-21}. Depending on the prob-
lem the objective function may vary from one to many. 

Based on the number of objective functions involved, 
optimization can be classified as single objective optimi-
sation and Multi-Objective optimisation. Single objective 
optimization involves only one function to be optimized 
while multi objective optimization uses more than one 
objective function. Mathematically a nonlinear optimiza-
tion problem can be stated as;

\[
\text{Minimize } f_i(x), \quad i = 1, 2, 3, \ldots, M
\]

Subject to constraints,

\[
h_j(x) = 0, \quad j = 1, 2, 3, \ldots, J
\]

\[
g_k(x) \leq 0, \quad k = 1, 2, 3, \ldots, K
\]

Where, \( f_i \), \( h_j \) and \( g_k \) are general nonlinear 
f\(unctions. The decision variables or the design vector 
\( x = (x_1, x_2, x_3, \ldots, x_n) \) can be continuous, discrete or mixed in n-dimensional space. The function \( f_i \) is called objective 
or cost function.

4.2 Cuckoo Search Algorithm

Cuckoo Search (CS) algorithm is one of the recently de-
veloped nature inspired Heuristic algorithms suggested\textsuperscript{22}. CS 
is based on the breeding behaviour of certain species of 
cuckoos. Cuckoos lay their eggs in other birds’ nests even 
it may remove others’ eggs to increase the hatching prob-
ability of their own eggs. If a host bird discovers the eggs 
that are not their own, they will either throw these alien 
eggs away or abandon its nest and build a new nest el-
sewhere. Cuckoo search algorithm is framed by integrating 
the following rules:

- Each cuckoo lays one egg at a time, and dumps it in a 
randomly chosen nest.
- The best nests with high quality of eggs will carry over 
to the next generation.

With fixed number of available host nests, the egg laid by 
a cuckoo is discovered by the host bird with a probability 
P_e \in [0,1]. In such a case the host bird can either through 
away the alien egg or abandon the nest and build a new 
nest (new random solutions). This can be approximated 
by a fraction of n nests being replaced by new nests (i.e. 
new random solutions at new locations).

CS algorithm has been widely used by researchers 
across the world. \textsuperscript{22}Validated and compared the perfor-
mance of CS with PSO and GA, discussed unique search 
features and concluded that CS algorithm in combination 
with exploring the search space via Lévy flight provide
superior results in almost all test cases.\textsuperscript{22–23} Applied CS algorithm for solving engineering design optimization problem and proved that the solutions obtained are far better than PSO. Further.

### 4.3 Cuckoo Search based PID Tuning Scheme

The flow chart for Cuckoo Search algorithm is shown in Figure 7 for minimization problem, the fitness of a solution is inversely proportional to the objective function and vice versa. Few simple representations are made during the implementation such as each egg in a nest represents a solution, and a cuckoo egg represents a new solution. The aim is to replace a not-so-good solution by better solutions in the nests. When this algorithm is to be used for set of solutions then, this algorithm uses a complicated approach where each nest has multiple eggs and there is no distinction between egg, nest and cuckoo\textsuperscript{24–25}.

The new solutions $x_i(t+1)$ for $i^{th}$ cuckoo is generated via Levy flight as:

$$ x_i(t+1) = x_i(t) + \alpha \odot \text{Levy}(O) \quad (15) $$

Where, $\alpha > 0$ is the step size and $\odot$ is the entry-wise multiplications. Random walk via Levy flight is more efficient in exploring search space as its step length is much longer in the long run. Random step lengths of Levy flight are distributed as

$$ \text{Levy} u = t^\gamma (\sim") , \quad (16) $$

This has an infinite variance with an infinite mean. Consecutive steps of a cuckoo essentially form a random walk process which obeys a power-law step-length distribution with a heavy tail.

Tuning the parameters of PID controller so as to reduce the Peak Overshoot is the prime concern of this work. Hence, the parameters of PID controller (Kp, Ki and Kd) are taken as decision variables and Peak Overshoot is assumed as objective function (Figure 8).

Let Np, D, Pa, $\alpha$ and n are the population size (number of nests) number of decision variable, discovering probability, step size parameter and maximum number of iterations respectively are initialised as 20, 2, 0.25 and 100 respectively. The generation of new Cuckoos and the discovery of the alien eggs steps are performed alternately until maximum iterations $n$.

At the end of the search the solutions are ranked and the best solution is determined. The algorithm is executed for few times to initialize the optimum CS parameters. It is observed that CS algorithm converges at 0.0991 in 38th iteration. The decision variable corresponding to this fitness value is the optimized controller parameters which are listed in Table 2. These controller settings are used for further analysis. The closed loop control response gives the power at step value zero. Without the use of controller the graph settled at around 340V. Figures 9 and 10 shows
the closed loop response for PEMFC at different operating points.

PEMFC along with PID controller yields best output, settling at 350 Watts exactly with faster rise time (around 3.5 seconds), settling time (around 7 seconds) and zero Peak overshoot.

5. Conclusion

In this work, Box Jenkins (BJ), Output Error Method (OE), Polynomial State Space method (PSS) and Subspace method (N4SID) modelling methods are employed to identify the model of PEMFC. Subspace identification method yield good results with lesser FPE and MSE. Open loop response shows peak overshoots at the start of the simulation which can be appropriately corrected by having properly tuned PID controller. PID parameters are adjusted by Cuckoo Search algorithm. The cost function is assumed as minimization Peak overshoot and the controller parameters are taken as decision variable. PEMFC along with the tuned PID controller provides challenging result with lesser rise, settling time and 0% Peak overshoot.

Table 2. PID controller parameters

| Sl. No | Controller Parameters | Parameter values |
|-------|-----------------------|------------------|
| 1     | Kp                    | 1.2              |
| 2     | Ki                    | 0.662            |
| 3     | Kd                    | 0.0843           |
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