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Short communication

Evolutionary programming-based methodology for economical output power from PEM fuel cell for micro-grid application

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Abstract

This paper presents a methodology for finding the optimal output power from a PEM fuel cell power plant (FCPP). The FCPP is used to supply power to a small micro-grid community. The technique used is based on evolutionary programming (EP) to find a near-optimal solution of the problem. The method incorporates the Hill–Climbing technique (HCT) to maintain feasibility during the solution process. An economic model of the FCPP is used. The model considers the production cost of energy and the possibility of selling and buying electrical energy from the local grid. In addition, the model takes into account the thermal energy output from the FCPP and the thermal energy requirement for the micro-grid community. The results obtained are compared against a solution based on genetic algorithms. Results are encouraging and indicate viability of the proposed technique.

Keywords: Fuel cell; PEM fuel cell; Evolutionary programming; Micro-grid

1. Introduction

The progressive increase in electrical energy demand coupled with environmental constraints have made the fuel cell, as a renewable energy source, one of the most promising sources of electrical energy. Fuel cells are not only characterized by higher efficiency than conventional power plants, but they are also environmentally clean, have extremely low emission of oxides of nitrogen and sulfur and have very low noise. Due to low working temperature (80–100 °C) and fast start up, PEM fuel cells power plants (FCPP) are best suited for residential and vehicular applications.

Many models have been proposed to simulate fuel cells in the literature. The basis of a model can be fluid dynamics, electrochemical reaction, heat transfer and thermal [1–3]. Fuel cell economics and economical aspects have been presented in the literature [4–8]. An economic model [7,8] has been introduced to estimate the optimal output power from the FCPP while satisfying system operational constraints.

The model considers the possibility of selling and buying energy from the local grid, and the optimal usage of thermal power output from the fuel cell. The cost optimization problem using this model is solved using genetic algorithms (GA)-based technique. GA is a random search method. It has been widely used as an optimization tool and a machine learning technique. Premature convergence problems arise due to the nature of the GA's solution procedure, where all individuals of the current generation tend to converge to the closest optimum. The problem results from using the crossover operator. This paper introduces a hybrid technique based on evolutionary programming (EP) to search for the near optimal solution and Hill–Climbing method to ensure feasibility during the solution process. The technique remedies the premature convergence problems associated with the GA solution.

The paper is organized as follows: Section 2 introduces an economic model for a fuel cell system. Section 3 presents the solution methodology. Test results of this model are presented in Section 4. Section 5 presents the conclusions.

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2. Fuel cell system economic model

In refs. [7,8], the authors introduced a mathematical formulation for the FCPP operational cost. In this paper, the FCPP provides electrical energy as well as thermal energy to a small micro-grid community. The model is summarized as follows:

$$\begin{aligned}
\text{Min}\, & C_{n1} T \sum_j \frac{P_j - P_\text{a}}{\eta_j} \\
& + C_{\text{el,p}} T \sum_j \max(L_{\text{el},j} - P_j, 0) \\
& + C_{\text{el,s}} T \sum_j \max(P_j - L_{\text{el},j}, 0) \\
& + C_{n2} T \sum_j \max(L_{\text{th},j} - P_{\text{th},j}, 0) \\
& + \alpha + \beta(1 - \mathrm{e}^{-t_\text{off}/\tau}) + \text{OM}
\end{aligned} \quad (1)$$

subject to:

$$P^{\min} \le P_j \le P^{\max} \quad (2)$$

$$P_j - P_{j-1} \le \Delta P_\text{u} \quad (3)$$

$$P_{j-1} - P_j \le \Delta P_\text{D} \quad (4)$$

$$(T^{\text{on}}_{j-1} - \text{MUT})(U_{j-1} - U_j) \ge 0.0 \quad (5)$$

$$(T^{\text{off}}_{j-1} - \text{MDT})(U_j - U_{j-1}) \ge 0.0 \quad (6)$$

$$n_{\text{start–stop}} \ge N^{\max} \quad (7)$$

where C_{n1} is the price of natural gas for FCPP ($\$\,\text{kW}^{-1}\,\text{h}^{-1}$), T the length of time interval (h), P_j the electrical power produced at interval j (kW), P_a the power for auxiliary devices (kW), η_j the cell efficiency at interval j, $C_{\text{el,p}}$ the tariff for purchasing electricity ($\$\,\text{kW}^{-1}\,\text{h}^{-1}$), $C_{\text{el,s}}$ the tariff for selling electricity ($\$\,\text{kW}^{-1}\,\text{h}^{-1}$), $L_{\text{el},j}$ the electrical load demand at interval j (kW), C_{n2} the fuel price for residential loads ($\$\,\text{kW}^{-1}\,\text{h}^{-1}$), $L_{\text{th},j}$ the thermal load demand at interval j (kW), $P_{\text{th},j}$ the thermal load produced at interval j (kW), α and β the hot and cold start up cost, respectively, t_off the time the FCPP has been off (h), τ the fuel cell cooling time constant (h), $P^{\min}$ the minimum limit of generating power (kW), $P^{\max}$ the maximum limit of generating power (kW), ΔP_u the upper limit of the ramp rate, ΔP_D the lower limit of the ramp rate, T^{on} the FCPP on-time (number of intervals), T^{off} the FCPP off-time (number of intervals), MUT: minimum up-time (number of intervals), MDT the minimum down-time (number of intervals), U the FCPP on–off status, $U = 1$ for running, $U = 0$ for stopping, $N^{\max}$ the maximum number of start–stop events, $N_{\text{start–stop}}$ the number of start–stop events, and OM is the operation and maintenance cost.

First term of the objective function is the daily fuel cost for the fuel cell ($). Second term is the daily cost of electrical energy purchased if the demand exceeds the electrical energy produced ($). Third term is the daily income from the electrical energy sold if the electrical energy produced exceeds the demand ($). The fourth term is the daily cost of purchased gas for residential thermal loads if the thermal energy produced is not enough to meet the thermal energy demand ($). The fifth term is the start up cost ($). The last term is the operation and maintenance cost of the FCPP.

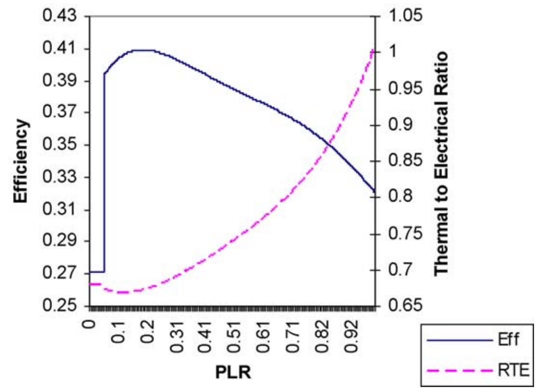

Fig. 1. Performance curves of FCPP.

The FCPP operates with approximately 40% efficiency. The efficiency is slightly higher at low load compared to full load operation. At all load conditions, the FCPP produces thermal energy approximately equal to the electrical energy [9]. In ref. [9], efficiency and thermal energy to electrical energy ratio curves have been developed (Fig. 1). These curves approximate the efficiency and the thermal output of the FCPP. The efficiency and the thermal energy to electrical energy ratio are functions of the part load ratio (equal to electrical generated power/maximum power). Mathematical expressions to approximate the curves have been developed in ref. [9] as follows:

$$\begin{aligned}
\eta &= 0.2716 \quad \text{for PLR} < 0.05 \\
\eta &= 0.9033\text{PLR}^5 - 2.9996\text{PLR}^4 + 3.6503\text{PLR}^3 \\
&\quad -2.0704\text{PLR}^2 + 0.4623\text{PLR} + 0.3747 \\
&\quad \text{for PLR} > 0.05
\end{aligned} \quad (8)$$

$$\begin{aligned}
r_\text{TE} &= 0.6801 \quad \text{for PLR} < 0.05 \\
r_\text{TE} &= 1.0785\text{PLR}^4 - 1.9739\text{PLR}^3 + 1.5005\text{PLR}^2 \\
&\quad -0.2817\text{PLR} + 0.6838 \\
&\quad \text{for PLR} > 0.05
\end{aligned} \quad (9)$$

where η is the FCPP efficiency, PLR the part load ratio, and r_TE is the thermal energy to electrical energy ratio.

3. The proposed evolutionary programming-based solution methodology

Evolutionary programming can be traced back to the early 1950s when Turing discovered a relationship between machine learning and evolution [10–12]. Later, Bremermann, Box, Friedberg, and others developed evolutionary computation as a tool for machine learning and optimization. Great attention was given to EP as a powerful tool when Fogal, Burgin, Atmar, and others used it to predict the events of finite state machines on the bases of old observations. During the 1980s evolutionary programming, with advances in computer technology, was used to solve difficult real-world optimization problems. In the power systems area, EP has been used to solve a number of power systems problems [12].

Evolutionary programming is a search optimization method. It moves from one solution to another using a probabilistic search technique. Evolutionary programming starts with random individuals. Each individual represents a complete solution for the problem under study. The individuals are moved from one generation (or iteration) to the other after passing through two main steps, mutation and competition. During a mutation step a new individual is produced when a Gaussian random variable with uniform probability is added to the current individual. The competition step is a probabilistic selection scheme used to assign a weight to each individual according to a comparison between current individual and a randomly chosen one. It may happen that the new solution is infeasible. Therefore, using EP alone may require a long time to reach the optimal solution or it may get trapped in a local optimum. This limitation was overcome by the use of the Hill–Climbing technique (HCT) [13,14] to move new infeasible solutions into the feasible region. The following algorithm details the proposed approach to solve the problem:

1. Generate initial random solutions for the output power from the FCPP at each interval.

$$S_i = \{x\} \quad i = 1, \ldots, m \tag{10}$$

   where x is the set of output power from the FCPP at each interval and m is the number of individual in the current generation. The random solution is expected to satisfy the system constraints.
2. For each individual in the current generation, calculate the objective function value using (1).
3. Mutate each individual and assign it to S_{i+m} according to (11).

$$S_{i+m,j} = S_{ij} + N(0, \beta_i v(S_i) + z_j) \quad j = 1, \ldots, k \tag{11}$$

4. where S_{ij} is the jth output power of the ith individual, k the number of generating units to be maintained in the current individual, $N(\mu,\sigma^2)$ the Gaussian random variable with mean μ and variance σ^2, β_i the constant to scale $v(S_i)$, z_j the offset to guarantee a minimum amount of variance.
4. Check the feasibility of each new individual against the constraints. If there is no violation go to step 5. Otherwise go to step 6.
5. Calculate the objective function value for the feasible solution using (1) and go to step 7.
6. Use the Hill–Climbing algorithm to drive the infeasible individuals into feasibility. If no feasible solution can be found go to step 3.
7. Assign a fitness score $v(S_i)$ to each individual S_{i+m} (i = 1,. . .,2m). The score is assigned equal to the cost function.
8. Using (12), calculate a weight W_i for each individual S_i, i = 1,. . .,2m. These weights are to be calculated during a random competition between individuals based on the objective function value.

$$W_i = \sum_{j=1}^{N} W_{i,j} \tag{12}$$

   where N is the randomly generated competition number, $W_{i,j}$ the either 0 or 1 depending on the competition of the individual with another individual selected randomly from the population. The value of $W_{i,j}$ can be calculated as follows:

$$W_{i,j} = \begin{cases} 1, & \text{if } v(S_i) \leq v(S_p) \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

   where $p = [2mu_1 + 1]$, $p \neq$ i and $u_1 \sim U(0,1)$
9. Rank the solution S_i (i = 1,. . .,2m) in descending order according to their values of W_i (if more than one solution has the same W, use the actual score of $v(S_i)$ to rank them). Use the first m solutions along with their score values $v(S_i)$ as a new generation for the potential optimal solution.
10. Check for convergence. Criteria used for convergence include the maximum generation number and the average/maximum fitness ratio being less than a predetermined small value. If convergence is achieved, stop; otherwise go to step 3.

4. Tests and results

The proposed technique has been tested to find the optimal output power from an FCPP for the following cases:

4.1. Case 1

In this test case, a small FCPP of 4 kW capacity has been used. The purpose of this test is to validate the performance of the proposed technique by comparing the results against GA results [7]. The FCPP system and evolutionary program parameters are shown in Table 1.

Comparison of the different cost components of the EP and the GA solutions (Table 2) shows that the proposed EP algorithm arrived at a better production cost. The other cost components are slightly lower in the EP solution except the residential natural gas cost. The overall cost of the EP solution is lower than the GA solution. The EP solution saves $0.47 per day amounting to a saving of $171.55 yearly. For a larger

Table 1
FCPP and evolutionary program parameters

Maximum limit of generating power, P^{max} (kW)	4.0
Minimum limit of generating power, P^{min} (kW)	0.0
Length of time interval, T (h)	0.25
Upper limit of the ramp rate, ΔP_u (kW)	2.5
Lower limit of the ramp rate, ΔP_D (kW)	3.0
Price of natural gas for FCPP, C_{n1} ($\$\,kW^{-1}h^{-1}$)	0.04
Tariff for purchasing electricity, $C_{el,p}$ ($\$\,kW^{-1}h^{-1}$)	0.13
Tariff for selling electricity, $C_{el,s}$ ($\$\,kW^{-1}h^{-1}$)	0.07
Fuel price for residential loads, C_{n2} ($\$\,kW^{-1}h^{-1}$)	0.05
Hot start up cost, α ($)	0.05
Cold start up cost, β ($)	0.15
The fuel cell cooling time constant, τ (h)	0.75
Minimum up-time, MUT (number of intervals)	2
Minimum down-time, MDT (number of intervals)	2
Maximum number of start-stop time, N^{max}	5
Maximum number of evolutionary generation	20,000
Number of individuals	200

Table 2
Cost comparison between EP and GA

	GA ($)	EP ($)
Daily fuel cost	4.82	4.28
Daily profit from electricity sold	1.54	1.52
Daily cost of purchased electricity	0.14	0.13
Daily cost of residential natural gas	0.06	0.10
Operation and maintenance cost	0.20	0.21
Start up cost	0.00	0.00
Total cost	3.67	3.20

unit as in Case 2, the cost saving is expected to be more in the case of EP solution. The electrical and thermal power output from the FCPP and the electrical and thermal loads are shown in Figs. 2 and 3. The power trade between the FCPP system and the local network is shown in Fig. 4.

4.2. Case 2

In this test case the model is tested using an actual residential load profile. The load profile for a micro-grid of ten identical houses is used. The micro-grid houses have all electrical appliances except the heat related appliances and the home space heater. Fuel cell user's group publications indicate that for small residential applications, where major heating appliances are natural gas operated, a 5 kW unit is adequate. According to the above assumption, a soft limit for the maximum power for each house is set equal to 5 kW. The load profile for a 24 h period with a 15 min sampling interval is used. Due to the lack of information of the thermal load for the micro-grid community, the thermal load of Case 1 is multiplied by a factor of 50/4 = 12.5. Table 1, parameters for the FCPP and the EP are used except for the following: maximum power is set to 50 kW, the upper and lower limit of the ramp rate are 25 and 30 kW, respectively, and the number of individuals is 150. The different cost components for using the proposed EP to find the optimal output power from the FCPP are shown in Table 3. The electrical and thermal power outputs from the FCPP are shown in Figs. 5 and 6. Fig. 7 shows the power trade with the local network. The daily cost for the FCPP working at full capacity is $97.78. Comparing the

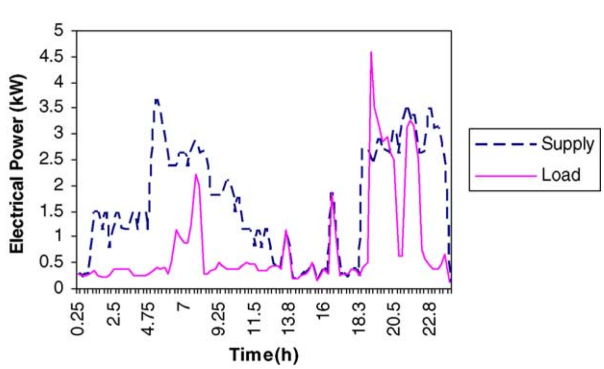

Fig. 2. Electrical power output from FCPP.

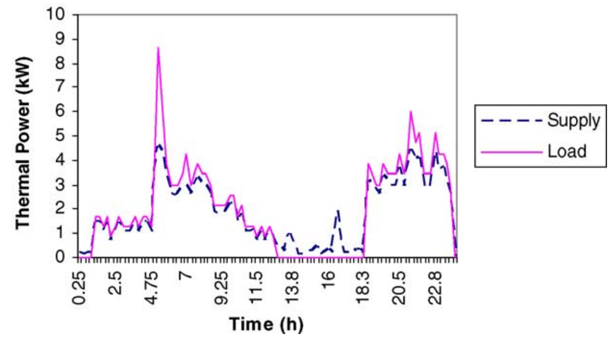

Fig. 3. Thermal power output from FCPP.

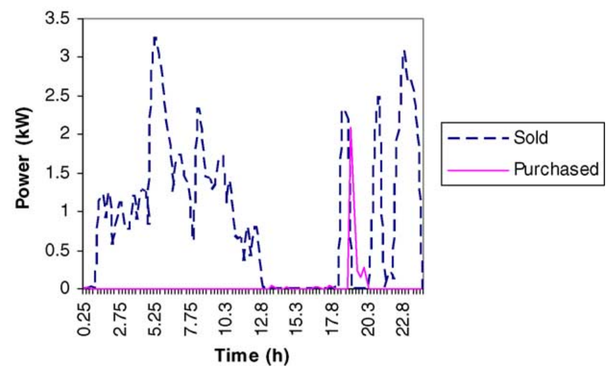

Fig. 4. Power trade with the local network.

Table 3
Cost components for 50 kW FCPP

Daily fuel cost ($)	54.92
Daily profit of sold electricity ($)	13.66
Daily cost of purchased electricity ($)	2.95
Daily cost of residential natural gas ($)	12.21
Operation and maintenance cost ($)	1.97
Start up cost ($)	0.00
Total cost ($)	58.39

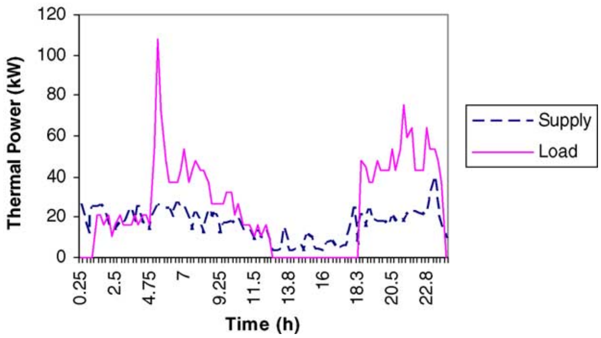

Fig. 5. Electrical power output form 50 kW FCPP.

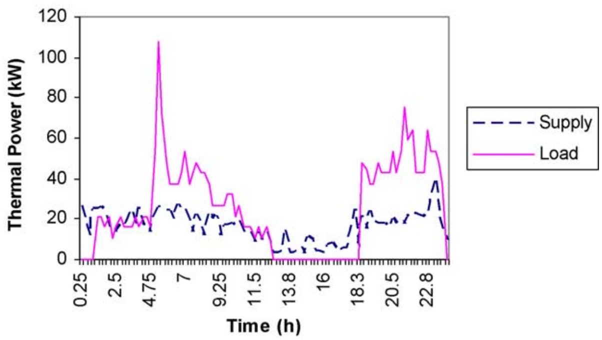

Fig. 6. Thermal power output from FCPP.

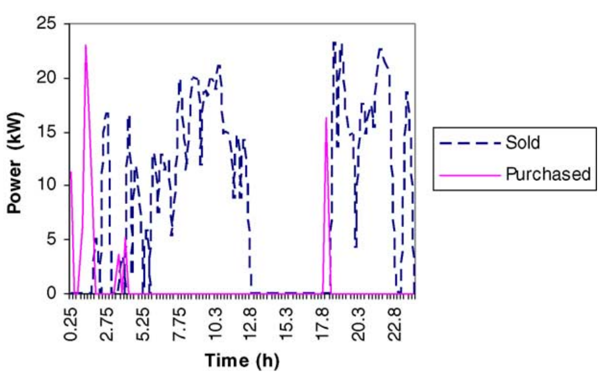

Fig. 7. Power trade with the local network.

full capacity cost with the cost obtained through scheduling the power output from the FCPP using EP shows that the proposed technique saved $14,377.35 annually.

5. Conclusions

This paper introduces a new method based on a hybrid technique involving evolutionary programming and Hill–Climbing techniques to optimize the power output from a fuel cell power plant. The proposed method uses evolutionary programming to find a near-optimal solution of the problem and the Hill–Climbing method to maintain feasibility during the solution process. The fuel cell power plant supplies both electrical and thermal power to a small micro-grid community. Comparison of the results obtained from the proposed technique and a genetic algorithm technique showed that the proposed technique was more effective. Test results on a 4 and 50 kW fuel cell power plant indicate the viability of the proposed approach and its potential to find the optimal power output from the fuel cell power plant subject to the associated constraints.

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