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Impact of hydrogen production on optimal economic operation of a grid-parallel PEM fuel cell power plant

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Abstract

This paper presents an economic model of a PEM fuel cell power plant (FCPP). The model includes the operational cost, thermal recovery, power trade with the local grid, and hydrogen production. The model is used to determine the optimal operational strategy, which yields the minimum operating cost. The optimal operational strategy is achieved through estimation of the following: hourly generated power, thermal power recovered from the FCPP, power trade with the local grid, and hydrogen production. An evolutionary programming-based technique is used to solve for the optimal operational strategy. The model is tested using different seasonal load demands. The results illustrate the impact of producing hydrogen on the operational strategies of the FCPP when subjected to seasonal load variation. Results are encouraging and indicate viability of the proposed model.

Keywords: Fuel cell; Hydrogen; PEM fuel cell; Economical fuel cell model; Evolutionary programming

1. Introduction

In recent years distributed sources have received considerable attention because of the improvements in power quality, reliability, portability, and environmental emissions. Among the various types of distributed generators, fuel cell power plants (FCPPs) have been the focus of interest since such plants are capable of producing electricity, heat, and hydrogen. Due to low working temperature (80–100 °C), fast start up, extremely low emission, and very low noise PEM FCPPs are the best candidates for residential and isolated load applications. With cost effective operational strategies, the use of FCPPs is expected to become widespread in the near future, in spite of their current high capital cost.

Fuel cell economics and economical aspects have been presented in the literature [1–5]. In [1,2] an economic model has been introduced to estimate the optimal output power from the FCPP while satisfying system operational constraints. This simple model considers only the possibility of selling and buying energy from the local grid, and the utilization of thermal power output from the FCPP.

In this paper the model in [1,2] has been extended to include hydrogen production of the FCPP. The hydrogen production is considered at times when the electrical load is lower than the maximum capacity of the FCPP. Introduction of hydrogen generation in the model brings to completion all the operational aspects of the FCPP that have an impact on the reduction of the overall system cost and increase in the FCPP efficiency.

The economic model is represented as a cost optimization problem subject to system and operational constraints. To estimate the daily optimal operational strategy for the FCPP a hybrid technique based on evolutionary programming (EP) and Hill-Climbing (HC) method [1,6] is used. The evolutionary programming is employed to search for the near optimal solution while the HC method is used to ensure feasibility during the solution process.

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

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2. Fuel cell system economic model development

In this model many different strategies are developed to handle excess electrical and thermal energy and hydrogen production.

2.1. Fuel cell economic model

In [1,2], the authors introduced a mathematical model for the FCPP operational cost. In this paper, the model has been extended to include the economic aspects of hydrogen generation. The model considers electrical power generation, thermal power recovery, and hydrogen production. The model given below, represents the operational cost in US$ day^{-1}, and can be summarized as follows:

$$\min\left[C_{n1}T\sum_j\left(\frac{P_j+P_a+P_{Hj}}{\eta_j}\right)+C_{el,p}T\sum_j\max(L_{el,j}-P_j,0)-C_{el,s}T\sum_j\max(P_j-L_{el,j},0)\right.$$
$$\left.+C_{n2}T\sum_j\max(L_{th,j}-P_{th,j},0)+\alpha+\beta(1-e^{-t_{off}/\tau})+\mathrm{OM}-C_{Hs}T\sum_j P_{Hj}F\right] \quad (1)$$

Subject to:

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

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

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

$$(T_{j-1}^{on}-\mathrm{MUT})(U_{j-1}-U_j)\ge 0.0 \quad (5)$$

$$(T_{j-1}^{off}-\mathrm{MDT})(U_j-U_{j-1})\ge 0.0 \quad (6)$$

$$n_{start\text{-}stop}\le N^{max} \quad (7)$$

where

C_{n1}: price of natural gas for FCPP (US$ kW h^{-1});
T: length of time interval (h);
P_j: electrical power produced at interval j (kW) less the power for auxiliary devices;
P_a: power for auxiliary devices (kW);
η_j: fuel cell efficiency at interval j;
$C_{el,p}$: tariff for purchasing electricity (US$ kW h^{-1});
$C_{el,s}$: tariff for selling electricity (US$ kW h^{-1});
$L_{el,j}$: electrical load demand at interval j (kW);
C_{n2}: fuel price for residential loads (US$ kW h^{-1});
$L_{th,j}$: thermal load demand at interval j (kW);
$P_{th,j}$: thermal load produced at interval j (kW);
α, β: hot and cold start up cost, respectively;
t_{off}: time the FCPP has been off (h);
τ: fuel cell cooling time constant (h);
P^{min}: minimum limit of generating power (kW);
P^{max}: maximum limit of generating power (kW);
ΔP_u: upper limit of the ramp rate;
ΔP_D: lower limit of the ramp rate;
T^{on}: FCPP on-time (number of intervals);
T^{off}: FCPP off-time (number of intervals);
MUT: minimum up-time (number of intervals);
MDT: minimum down-time (number of intervals);
U: FCPP on-off status, $U = 1$ for running, $U = 0$ for stopping;
N^{max}: maximum number of start-stop events;
$N_{start\text{-}stop}$: number of start-stop events;
OM: operation and maintenance cost;
C_{Hs}: hydrogen selling price (US$ kg^{-1});
P_{Hj}: the equivalent electric power for hydrogen production (kW);
F: a conversion factor (kg of hydrogen/kW of electric power), where $F = 1.05\times10^{-8}/v_{cell}$ and v_{cell} is cell operating voltage, $v_{cell} = 0.6$ volt;
P_{Tj}: total power produced at interval j, where $P_{T_j}=P_j+P_a+P_{H_j}$

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

2.2. Excess electrical energy strategy

In the model, excess electrical energy can be sold to the local grid according to system economics. Under certain conditions, it might be beneficial to the system, in terms of the overall cost, to buy energy from the local grid to satisfy the load requirements while using the unused capacity to produce hydrogen and thermal energy.

2.3. Hydrogen production strategy

The hydrogen production strategy is based on the difference between the maximum capacity of the FCPP and the generated electric power at each interval.

To include the hydrogen in the FCPP model, an equivalent electric power for the generated hydrogen at each interval is considered P_{Hj}. The equivalent electric power is considered at the fuel cell stack output as shown in Fig. 1. Fig. 1 (upper figure) reflects the electric power output and hydrogen output locations in the FCPP stages. Fig. 1 (lower figure)

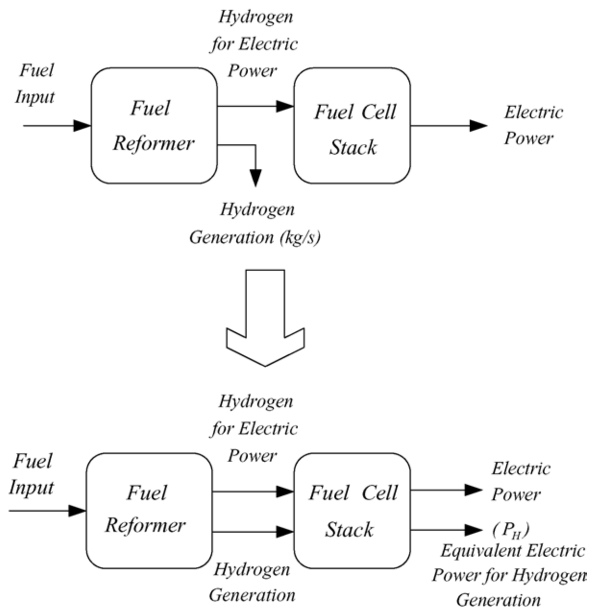

Fig. 1. Hydrogen insertion in the FCPP model.

shows the location of P_{Hj} in the FCPP. Considering P_{Hj} at the stack terminals makes it possible to quantify the production of hydrogen (kg s^{-1}) in terms of electrical energy. The hydrogen production in kg s^{-1} can be calculated using P_{Hj} as follows [7]:

$$(\mathrm{H_2})\,\text{amount} = 1.05 \times 10^{-8}\frac{P_{\mathrm{H}j}}{v_{\mathrm{cell}}} \tag{8}$$

In this paper two strategies for generating hydrogen are adopted:

2.3.1. *Strategy 1*

The amount of the generated hydrogen is equal to the difference between the maximum capacity and the generated power level of the FCPP as given in Eq. (9).

$$P_{\mathrm{H}j} = P_{\max} - P_j - P_{\mathrm{a}} \tag{9}$$

This strategy ensures rated capacity operation of the reformer of the FCPP all the time. Rated capacity output allows the reformer to be more stable and work at high efficiency.

2.3.2. *Strategy 2*

In this strategy hydrogen production can vary between zero and the difference between the maximum capacity and the generated electric power. This strategy allows the model to produce hydrogen when it is more profitable to the overall cost of FCPP operation.

2.4. *Recovered thermal energy strategy*

The FCPP operates with approximately 36% efficiency. The efficiency is slightly higher at low load compared to full load operation. At full load, the FCPP produces thermal energy approximately equal to the electrical energy [8]. In [8], efficiency and thermal energy to electrical energy ratio curves have been developed (Fig. 2). 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 [8] as follows:

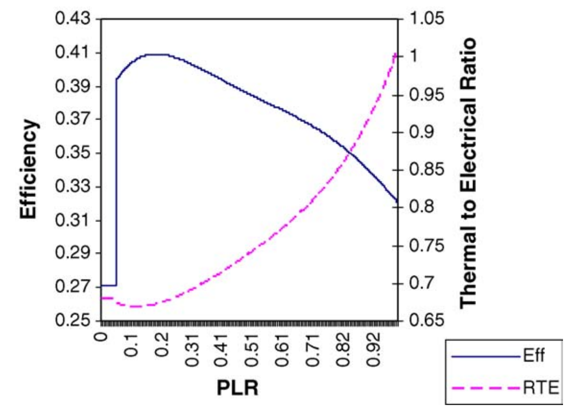

Fig. 2. Performance curves of the FCPP.

For $\mathrm{PLR}_j < 0.05$

$$\eta_j = 0.2716, \qquad r_{\mathrm{TE},j} = 0.6801 \tag{10}$$

For $\mathrm{PLR}_j \geq 0.05$

$$\eta_j = 0.9033\mathrm{PLR}_j^5 - 2.9996\mathrm{PLR}_j^4 + 3.6503\mathrm{PLR}_j^3 - 2.0704\mathrm{PLR}_j^2 + 0.4623\mathrm{PLR}_j + 0.3747 \tag{11}$$

$$r_{\mathrm{TE},j} = 1.0785\mathrm{PLR}_j^4 - 1.9739\mathrm{PLR}_j^3 + 1.5005\mathrm{PLR}_j^2 - 0.2817\mathrm{PLR}_j + 0.6838 \tag{12}$$

where η_j is the FCPP efficiency, PLR the part load ratio, r_{TE} the thermal energy to electrical energy ratio.

The thermal power recovered from the fuel cell according to electric and hydrogen power outputs can be calculated as follows:

$$P_{\mathrm{th},j} = r_{\mathrm{TE}}(P_{\mathrm{H}j} + P_j + P_{\mathrm{a}}) \tag{13}$$

The efficiency of the FCPP given in Fig. 2 is based on the electrical output power versus the input gas power. Neglecting the thermal power in efficiency calculation results in efficiency range of 30–40% approximately. On the other hand, including the utilized thermal power recovered from the FCPP and hydrogen production enhances the overall efficiency considerably. The overall efficiency can be calculated as follows:

$$\eta_{\mathrm{overall}_j} = \frac{P_j + P_{\mathrm{a}} + P_{\mathrm{H}j} + \min(L_{\mathrm{th},j}, P_{\mathrm{th},j})}{[(P_j + P_{\mathrm{a}} + P_{\mathrm{H}j})/\eta_j]} \tag{14}$$

3. Evolutionary programming (EP)-based solution methodology

Evolutionary programming can be traced back to the early 1950s when Turing discovered a relationship between machine learning and evolution [9–11]. 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 basis 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 [11].

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 HC technique [12] 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.

   $$S_i = \{x\}, \quad i = 1, \ldots, m \tag{15}$$

   where x is a set of output power from the FCPP at each interval; m 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 (16).

   $$S_{i+m} = S_i + N(0, \beta_i v(S_i) + z_i) \tag{16}$$

   where S_i is 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 a constant to scale $v(S_i)$; z_j an 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 Eq. (17), 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.

   $$W_i = \sum_{j=1}^{N} W_{i,j} \tag{17}$$

   where N is a randomly generated competition number; $W_{i,j}$ 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:

   $$W_{i,j} = \begin{cases} 1 & \text{if} \quad v(S_i) \leq v(S_p) \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

   where

   $$p = [2mu_1 + 1], \qquad p \neq i \quad \text{and} \quad u_1 \sim U(0, 1)$$
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 model has been applied to a 250 kW grid-parallel FCPP that supplies a residential neighborhood. The IEEE-RTS load profile with a peak of 250 kW [13] is used to simulate the hourly electrical load profile of the system. In this test system, the weekly, daily and hourly peak load values are given in percent of annual, weekly and daily peak loads, respectively. The winter hot water usage and space heating load for Atlanta, Georgia [8] is considered to represent the thermal load profile. Due to the lack of thermal load information for the summer and spring/fall, thermal load data are estimated from the available winter data. The thermal load

Table 1
FCPP and evolutionary program parameters

Maximum limit of generating power, P^{max} (kW)	250
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 s^{-1})	20
Lower limit of the ramp rate, ΔP_D (kW s^{-1})	25
Price of natural gas for FCPP, C_{n1} (US$ kW h^{-1})	0.04
Tariff for purchasing electricity, $C_{el,p}$ (US$ kW h^{-1})	0.13
Tariff for selling electricity, $C_{el,s}$ (US$ kW h^{-1})	0.08
Fuel price for residential loads, C_{n2} (US$ kW h^{-1})	0.06
Hydrogen selling price, C_{Hs} (US$ kg^{-1})	1.80
Hot start up cost, α (US$)	0.05
Cold start up cost, β (US$)	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	20000
Number of individuals	150

is used along with the electrical load profile to simulate total hourly operation of the FCPP. In the following case studies, the optimum operational cost is evaluated and compared with a Base Case. The gas prices, hydrogen selling price, and FCPP/EP parameters for all test cases are given in Table 1.

4.1. Base Case

In this case the above thermal and electrical loads are used to estimate the optimum operational strategy for FCPP operation without hydrogen production. The obtained cost components for different seasons are given in Table 2.

4.2. Case 1

In Case 1, Strategy 1 is tested with different seasonal thermal and electrical loads. The results for the cost components for different seasons are given in Table 3. It is evident from comparison of Tables 2 and 3 that hydrogen production saves US$ 62.28, US$ 27.42 and US$ 15.15 daily in the winter, summer and spring/fall cases, respectively. The total saving for the winter, summer and spring/fall seasons are US$ 5698.62, US$ 2508.93 and US$ 2772.45, respectively. Thermal load impacts hydrogen production significantly as shown in the spring/fall case. Fig. 3 shows electrical power generation and load for the spring/fall case. In this case, there was no electrical power trade with the local network. Fig. 4 shows

Table 2
Cost component for Base Case

Cost components (US$)	Winter	Summer	Spring/fall
Daily fuel cost	613.91	602.90	539.72
Daily cost of purchased electricity	0.00	0.00	2.31
Daily profit from electricity sold	76.60	115.82	99.48
Daily cost of residential natural gas	149.79	29.16	45.55
Operation and maintenance cost	26.37	26.04	23.79
Total cost	713.47	542.27	511.88

Table 3
Cost component for Strategy 1

Cost components (US$)	Winter	Summer	Spring/fall
Daily fuel cost	748.60	748.60	748.60
Daily cost of purchased electricity	0.00	2.38	0.00
Daily profit from electricity sold	0.00	0.00	0.00
Daily cost of residential natural gas	71.87	1.24	10.39
Operation and maintenance cost	21.58	18.71	17.66
Daily hydrogen selling profit	190.86	256.07	279.92
Total cost	651.19	514.85	496.73

hydrogen production, and thermal power load and generation for the spring/fall case. Examining the thermal power load in Fig. 4b shows that the system experiences a low thermal load between 8:15 a.m. and 6:00 p.m. During this period the FCPP is seen to produce more thermal power than the thermal load demand. This is because the FCPP is forced to produce hydrogen equal to the difference between the rated capacity and the generated electric power. Producing thermal power more than the requirements of the thermal load makes the system lose money. Comparing the total cost for spring/fall from Tables 2 and 3 shows that the system only saves US$ 15.15 daily when producing hydrogen during low thermal demand periods.

4.3. Case 2

In this case hydrogen production is based on the system economics as in Strategy 2. Hydrogen production varies between zero and the difference between the rated capacity of the FCPP and the generated electric power.

Using the thermal and electrical load profiles for different seasons, the model gives the optimum cost as shown in Table 4. Figs. 5–10 show the following: electrical power trade with the grid; electrical power load and generation; hydrogen production; and thermal load and generation for different seasons. In the winter case, there was no electrical power trade with the local network. Comparing different cost components in Tables 3 and 4 shows that Strategies 1 and 2 yield the same daily cost for the winter season because of the high thermal demand. For summer and spring/fall cases Strategy 2 gives lower operating cost. In the summer season, Strategy

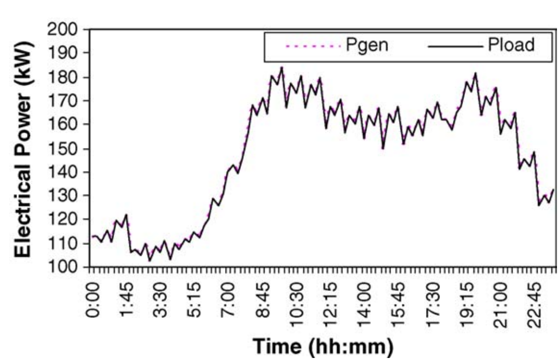

Fig. 3. Spring/fall electrical load and power generation.

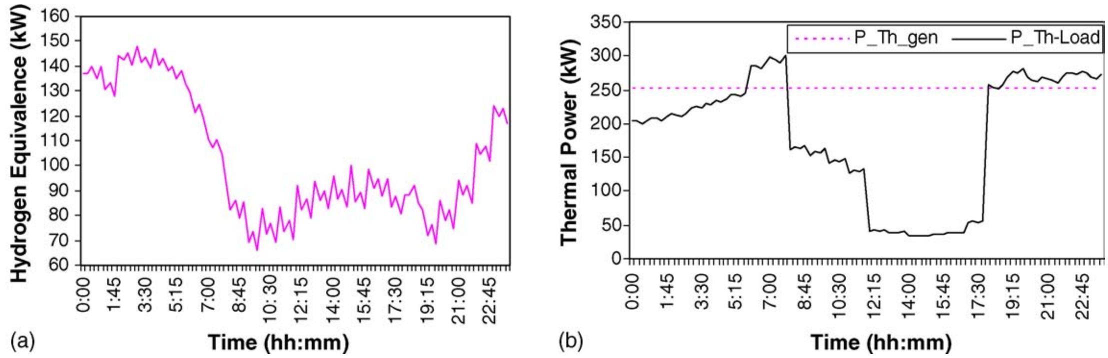

Fig. 4. (a) Spring/fall hydrogen production; (b) spring/fall thermal load and generation.

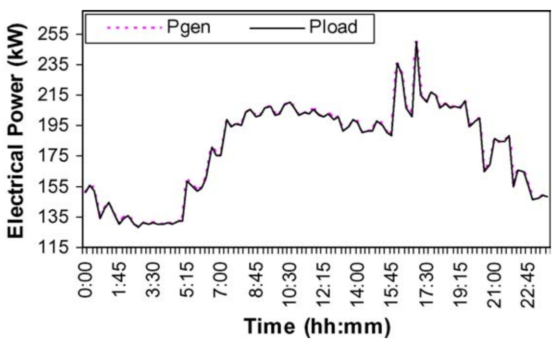

Fig. 5. Winter electrical load and power generation.

Table 4
Cost component for Strategy 2

Cost components (US$)	Winter	Summer	Spring/fall
Daily fuel cost	748.60	652.08	596.07
Daily cost of purchased electricity	0.00	32.99	40.92
Daily profit from electricity sold	0.00	12.32	4.08
Daily cost of residential natural gas	71.87	1.33	10.46
Operation and maintenance cost	21.58	18.30	16.34
Daily hydrogen selling profit	190.86	206.79	202.27
Total cost	651.19	485.59	457.44

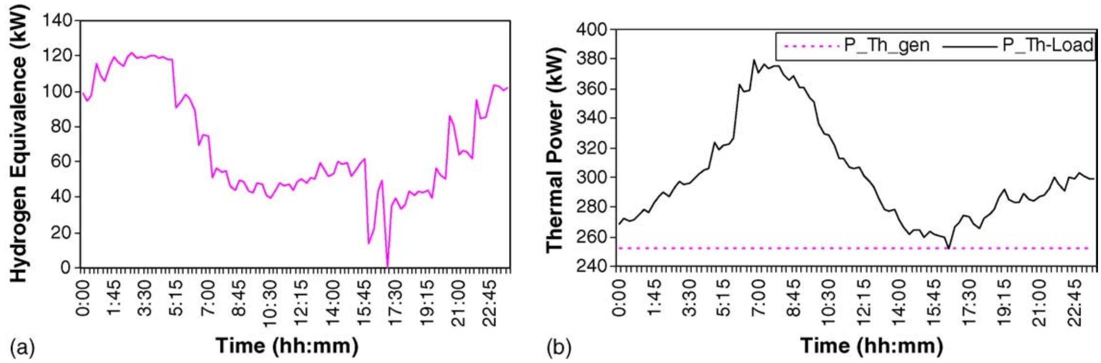

Fig. 6. (a) Winter hydrogen production; (b) winter thermal load and generation.

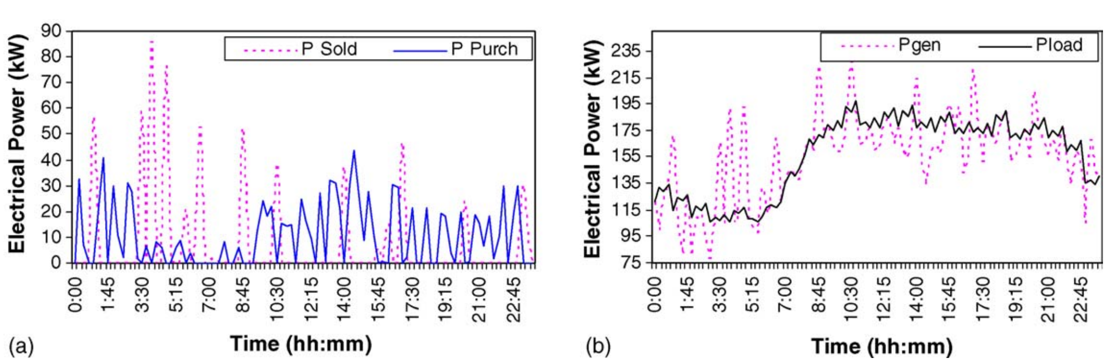

Fig. 7. (a) Summer electrical power trade with the grid; (b) summer electrical load and power generation.

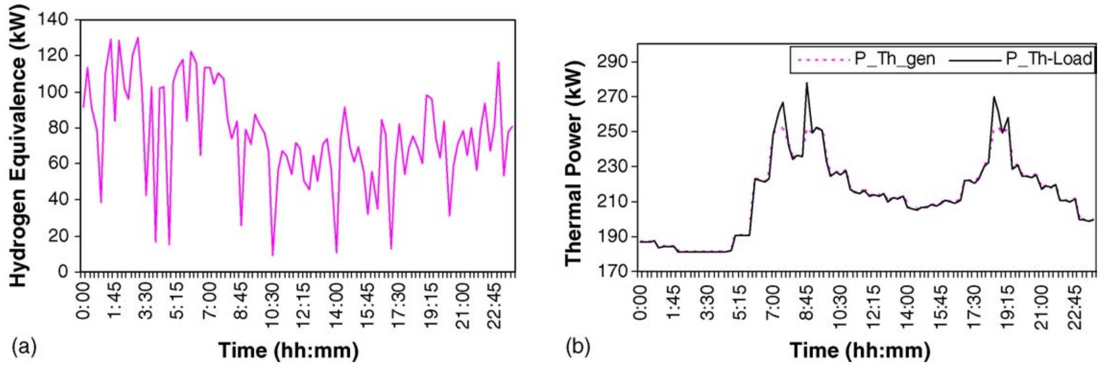

Fig. 8. (a) Summer hydrogen production; (b) summer thermal load and generation.

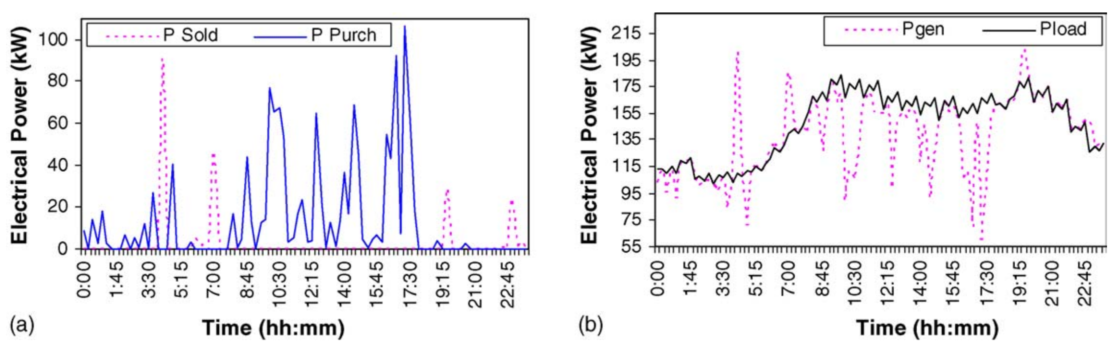

Fig. 9. (a) Spring/fall electrical power trade with the grid; (b) spring/fall electrical load and power generation.

2 saves US$ 29.26 daily compared to Strategy 1, and US$ 56.68 compared to the Base Case (no hydrogen production); which totals to US$ 2677.29 and US$ 5186.22 for the summer season. Lower cost in Strategy 2 is because of the fact that Strategy 2 produces enough hydrogen that is profitable to the system while satisfying the thermal power requirements. This can be seen from Fig. 8b where the thermal load and generation are almost identical except for the peak values.

In spring/fall season, Strategy 2 saves US$ 39.29 daily compared to Strategy 1 and US$ 54.44 daily compared to the Base Case, which sum to US$ 7190.07 and US$ 9962.52 per spring/fall season, respectively. In spring/fall season, Strategy 2 buys power from the grid during the low thermal power demand period (8:15 a.m.–6:00 p.m.). In this period the FCPP produces low electrical power and hydrogen so as to produce enough thermal power to satisfy the thermal load requirements. This can be seen in Figs. 9a,b, and 10a,b.

In summary, the daily cost for different seasons and strategies are shown in Table 5. Comparing costs for Strategies 1 and 2 reveals that Strategy 2 gives a lower cost over the entire year. Using Eq. (14), the overall efficiency for the Base Case, and Strategies 1 and 2 for the spring/fall season are given in Fig. 11. Also included in the figure is the basic efficiency curve (without considering hydrogen and the recovered ther-

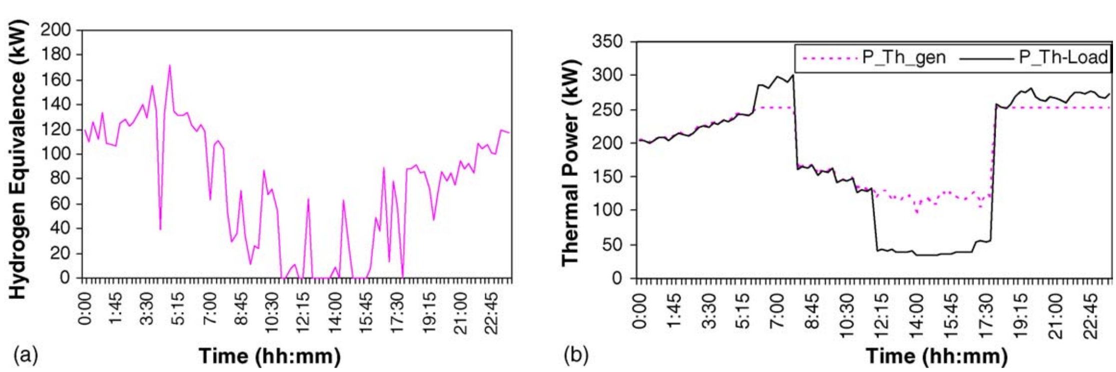

Fig. 10. (a) Spring/fall hydrogen production; (b) spring/fall thermal load and generation.

Table 5
Cost summary (US$)

	Base Case		Strategy 1		Strategy 2	
	Cost	Saving	Cost	Saving	Cost	Saving
Winter	713.47	0.0	651.19	62.28	651.19	62.28
Summer	542.27	0.0	514.85	27.42	485.59	56.68
Spring/fall	511.88	0.0	496.73	15.15	457.44	54.44

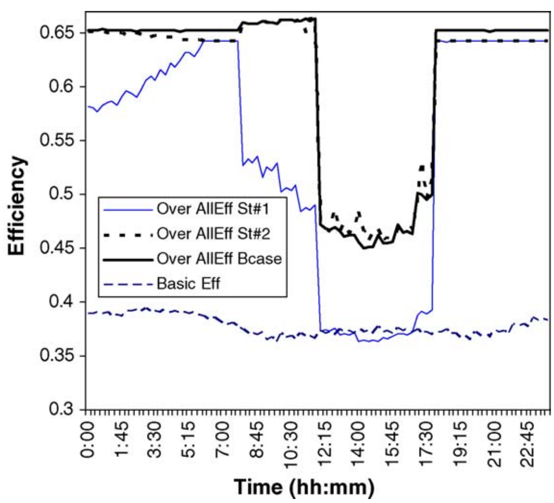

Fig. 11. FCPP efficiency plots for spring/fall season.

mal energy) for the same season. It is clear that considering the hydrogen and the recovered thermal energy enhances the overall efficiency as shown in Fig. 11. Comparison of the different efficiency values shows that Strategy 1 overall efficiency is lower than the basic efficiency value when the system experiences low thermal power demand. Strategy 1 efficiency is lower than that of the Base Case and Strategy 2 efficiency at all load conditions. Strategy 2 gives lower efficiency than the Base Case at high thermal load demand intervals. At low thermal demand periods Strategy 2 efficiency is higher than the Base Case. Although the efficiency of Strategy 2 is lower than that of Base Case, Strategy 2 yields a lower operating cost as described previously.

5. Conclusions

In this paper, the impact of hydrogen production on the optimal cost of operation of a PEM FCPP operating in a grid-parallel mode is presented. The economic model of the operational cost of the FCPP has been developed which includes power trade with the local grid, thermal recovery and hydrogen production. The paper offers practical concepts concerning operational cost modeling of the FCPP. The model incorporates two different strategies for hydrogen production. The two strategies were evaluated using IEEE test system load profiles for different seasons. From the results, it can be concluded that while Strategy 2 offers lower overall efficiency of the FCPP than the Base Case, Strategy 2 yields lower operating cost.

The figures presented in this paper are based on generic load profiles. Therefore, region-specific load profiles would yield results that necessarily differ from those presented in this paper.

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