MANAGEMENT OF PEM FUEL CELLS FOR RESIDENTIAL APPLICATIONS USING GENETIC ALGORITHMS

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Abstract- A genetic algorithm "GA" approach is formulated to manage the daily electricity and heat generation in Proton Exchange Membrane "PEM" fuel cells for residential applications. Minimizing operating costs can contribute to reduce the high-energy price of fuel cells, which is the main barrier of utilizing this promising source yet. The study aims to evaluate the effectiveness of this management at a wide range of operating conditions. A detailed economic model for the PEM fuel cell is developed including the electrical and thermal energy production. A multi-population real-coded GA is used to define the optimal daily settings of the fuel cell satisfying the main operational and technical constraints. The optimization process is carried out at different load conditions and a variety of parameters in a large operating space. The influence of the natural gas and electricity tariffs on the settings is highlighted by introducing some results from the optimization process.

I. INTRODUCTION

As they provide possibility for both electrical and thermal energy production, fuel cells are candidate to be utilized for residential utilizations. Salient features, low impact on the environment and technical developments make fuel cells an attractive choice for this kind of applications [1]. Many attempts are directed to develop fuel cells for commercial, transportation, residential and space applications [2].

The high cost of the electricity produced in fuel cells represents the main barrier for the unit to be in competition with other energy sources. With cogeneration applications, the unit can be utilized more efficiently and hence the cost per unit energy is reduced. Although the capital cost forms the major part of the energy price, reduction of operating cost and thus of the price of energy produced in fuel cells may be considerable. A significant reduction can be achieved if the appropriate setting of the unit is chosen to get optimized operation.

The economic aspects of the fuel cell have been discussed in many literatures from different points of view [3]-[5]. More investigations, however, have to be directed to reduce both the capital and operating costs. In this paper, the economic issue of a Proton Exchange Membrane "PEM" fuel cell to supply a residential load is investigated. The PEM fuel cell has approved good features in many fields especially with low capacities, which is required for residential applications [6].

In this paper a cost function is introduced to describe the dependency of the PEM fuel cell daily cost on the operating parameters and both electrical and thermal load requirements. An economic model is developed to minimize the daily costs taking into account the various operational and technical constraints incorporated with the unit.

To solve such a highly constrained discontinuous nonlinear problem, a robust optimization algorithm is required. GA is a very powerful robust search algorithm, which can search through many points in the solution space. The high capabilities of GAs have been proven through their performance in many fields [7]-[12].

In this paper, a GA is proposed to solve the operation management problem depending on the developed economic model. The GA technique is chosen due to its adequately capability of handling the nonlinear discontinuous problems. GA is also advantageous due to its capability of handling the constraints by adding suitable penalty functions to the main objective function. This approach can simplify some cases when other techniques complicate the problem or completely fail to deal with it.

Various electrical and thermal load curves are used at the different seasons of the year and different electricity and fuel tariffs are considered to study their effects on the setting values.

Some results are introduced to clear the tendency of optimized settings depending on electrical and thermal demands and energy tariffs. Also, the cost reduction due to the proposed approach is introduced to evaluate the effectiveness of the process. Finally, the effect of each individual tariffs is tested by varying only one keeping the others constant.

It is planned to use these results to train an ANN to get the adequate optimized settings by adjusting the inputs, which include the pre-stage operating conditions and the forecasted loads.

II. PEM FUEL CELL ECONOMIC MODEL

a. Objective function

The management process aims to minimize the daily operating cost of the fuel cell under the following assumptions:

- The fuel cell will supply both electrical and thermal power to the load
- There is a possibility to sell back the excess of electricity at different tariffs. These tariffs are always lower than those of the purchased electricity
- A part of the generated power is utilized for auxiliary devices required with the unit.
- The prices of the natural gas for fuel cell are lower than or equal to those for residential thermal loads

The objective function is developed according to the mentioned assumption in the following form:

$$DOC = DFC + DCPE - DPSE + DCPG + O\&M + STC \quad (10)$$

where:

DOC : Daily total operating cost ($)

DFC : Daily fuel cost for the fuel cell ($)

DCPE : Daily cost of purchased electricity if the demand exceeds the produced electrical power ($)

DPSE : Daily incomings for sold electricity if the unit electrical output power exceeds the electrical demand ($)

DCPG : Daily cost of purchased gas for residential loads if the produced thermal power is not enough to meet the thermal demand ($)

O&M : Daily operating and maintenance cost ($)

STC : Daily start up cost ($)

The dependence of DFC on the generated electrical power and efficiency is given as:

$$DFC = C_{n1} T \sum_{J} \frac{P_J + P_a}{\eta_J} \quad (2)$$

where:

C_{n1} : Natural gas price for fuel cell ($/kWh)

T : Time duration (h)

P_J : Net electrical power produced at interval “J” (kW)

P_a : Power for auxiliary devices (kW)

η_J : Cell efficiency at interval “J”

The efficiency of the fuel cell depends on the active power [3] and hence, a typical efficiency curve is developed as a function of the electrical power and used in (2). The main grid system is assumed to balance for the difference between the load demand and the net output from the fuel cell. The price of electricity purchased from and sold back to the network are given by:

$$DCPE = C_{el,P} T \sum_{J} \max\left(L_{el,J} - P_J, 0\right) \quad (3)$$

$$DPSE = C_{el,S} T \sum_{J} \max\left(P_J - L_{el,J}, 0\right) \quad (4)$$

where:

$C_{el,p}$, $C_{el,s}$: Tariffs of purchased and sold electricity respectively ($/kWh)
$L_{el,J}$: Electrical demand at interval "J" (kW)

The thermal output power from the fuel cell depends on the electrical power. The relation is almost linear at the lower values, while the ratio of the thermal power is relatively higher at the upper operating limits [3]. A nonlinear equation is developed to give the thermal output power from the unit as a function of the produced electrical power. The daily cost of purchased natural gas for residential application when the thermal power from the fuel cell is not enough to meet the thermal load requirements is given as:

$$DCPG = C_{n2} T \sum_{J} \max\left(L_{th,j} - P_{th,j}, 0\right) \quad (5)$$

where:
C_{n2} : Fuel price for residential loads ($/kWh)
$L_{th,J}$: Thermal load demand at time interval "J" (kW)
$P_{th,J}$: Thermal power produced at interval "J" (kW)

The operating and maintenance cost is assumed to be constant per kWh and hence O&M is proportional to the produced energy. The start up cost depends on the temperature of the unit and hence on the time the unit has been off before start up:

$$STC = \alpha + \beta\left(1 - e^{\frac{-t_{off}}{\tau}}\right) \quad (6)$$

where:
α, β : Hot and cold start up cost respectively
t_{off} : The time the unit has been off (h)
τ : The fuel cell cooling time constant (h)

b. Constraints

The minimization of the objective function (1) is restricted by many constraints. The main operational and technical constraints associated with the PEM fuel cell are listed below:

Unit capacity constraints: $P_{min} \le P_J \le P_{max}$ (7)

Ramp rate constraints: $P_{J,t} - P_{J,t-1} \le \Delta P_U$ (8)

$P_{J,t-1} - P_{J,t} \le \Delta P_D$ (9)

In the above equations, P_{min} and P_{max} are the minimum and maximum limits of the generated power, ΔP_U and ΔP_D are the upper and bottom limits of the ramp rate, and $P_{J,t-1}$ is the power generated at interval (t-1). At the same time, the minimum up/down time limits (continuous running-stop time constraint) must not be violated:

$$\left(T_{t-1}^{on} - MUT\right) \cdot \left(U_{t-1} - U_t\right) \ge 0 \quad (10)$$

$$\left(T_{t-1}^{off} - MDT\right) \cdot \left(U_1 - U_{t-1}\right) \ge 0 \quad (11)$$

where T_{on}, T_{off} are the unit on and off times, MUT, MDT are the minimum up and down time limits and U is the unit on/off status: U=1 for running mode and 0 for stop mode. Finally, the daily number of start-stop times ($n_{start\text{-}stop}$) has not to exceed a certain maximum umber (N_{max}).

$$n_{start\text{-}stop} \le N_{max} \quad (12)$$

III. MULTI-POPULATION REAL-CODED GA

The GA is a powerful search algorithm, which is based on the survival of the fittest theory. It differs from other traditional optimization methods in that: It searches a population of points in parallel, it uses probabilistic rules rather than deterministic ones, and it can process an encoding set of the parameter. To increase the efficiency of the evaluation process and to avoid the repetitive change between binary and real coding, a real-coded GA is applied [7]. In the multi-population structure, the individuals migrate periodically between subpopulations.

a. Problem representation

As a member of the chromosome structure, each individual represents the output electrical power from the fuel cell through one day. It is assumed that the setting of the fuel cell is updated each 15 minutes and hence, 96 unknown variables are associated with each individual. To initiate the population, the individuals are randomly formulated in the range between 0 and 4 kW to satisfy the first constraint (7). The main implementation steps of the GA following the initialization are given by the flowchart shown in Fig. 1.

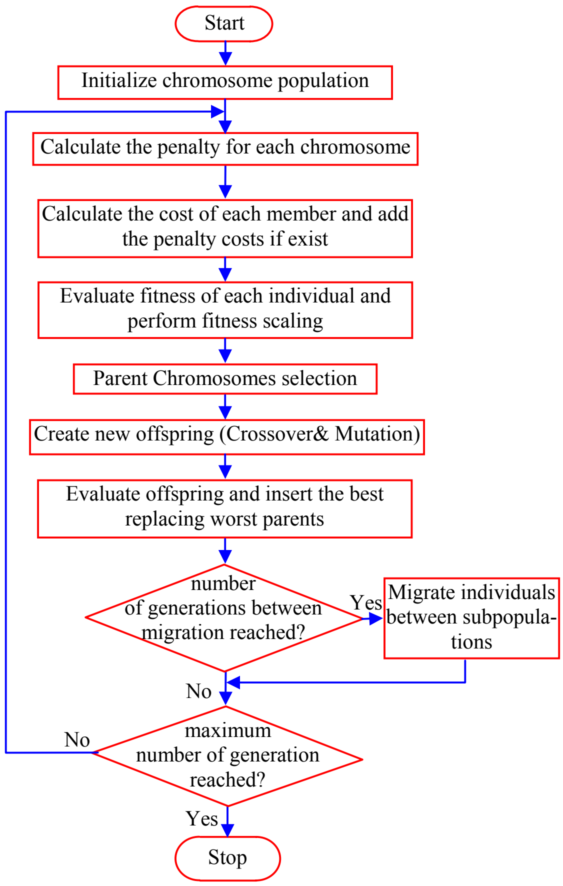

Fig. 1. Flowchart of the GA evolution process

To implement GA with a highly constrained problem, it is possible to generate only feasible solutions by avoiding individuals, which lead to unmet-constrained situations. As the infeasible solutions mostly cover the search space at the initial generation, the complete avoidance of the infeasible solutions gives a high possibility of missing the area of global minimum [8]. Another approach is to move the infeasible individuals to the nearest feasible area. This would be too complex and a very time consuming process. The penalty function approach is another alternative that converts the constrained problem to an unconstrained one by augmenting additional cost terms with the main objective function.

The adequate choice of the penalty functions and their parameters is an essential requirement to achieve rapid rejection of the infeasible solutions. The additional terms assign more costs for the individuals, which violate any of the constraints given in (8) through (12). These nonlinear costs depend on the location of each infeasible solution from the feasibility boundaries. To insure fast rejection of the infeasible solutions, a higher cost value has to be assigned to any infeasible solution than the feasible members. In this study, exponential penalty factors are used for ramp rate violation, while quadratic ones are applied when violating the minimum up/down time limits and maximum number of daily start-stop times constraints.

To evaluate the performance of each individual, the total cost is firstly calculated according to (1) and the corresponding penalty term is added if exists. The evaluation of each member is accomplished by ranking the individuals and assigning fitness value to each one according to its position within the population. Fitness values between maximum and minimum limits are calculated with fixed incremental steps and given to the ranked individuals. The fitness scaling represents a basic step for selection of parents to create a new offspring. Strings with higher fitness are selected using the roulette wheel technique and used in the recombination process.

The new generation is produced by means of two main processes: crossover and mutation. Crossover is a genetic process by which information can be exchanged between the members of the population, possibly creating more highly fit members. For the real-valued encoding, the max-min arithmetical crossover operator [7] is used in the form:

$$G_1 = \alpha \cdot P_1 + (1-\alpha) \cdot P_2 \tag{13}$$

$$G_2 = (1-\alpha) \cdot P_1 + \alpha \cdot P_2 \tag{14}$$

where G_1, G_2 are the new strings, P_1, P_2 are the parents and α is a scaling factor.

Mutation is the second process in the recombination, which is used to escape from possible local minimum. The mutation in non-binary representations is achieved by disturbing the gene values with low probability.

Care has to be taken to ensure that the best solutions are not lost in moving from one generation to the next. According to this strategy, which is known as 'Elitism' some of the fittest members of each generation are saved and copied into the next generation. With this process it is expected that the average fitness of the new generation is improved. The periodic migration of individuals between subpopulations, which is used in this study, is found to achieve some improvements in the results.

b. GA parameters

Table 1 summarize the genetic algorithm parameters.

Table I Summary of the GA parameters

NUMBER OF SUBPOPULATIONS	10
Number of individuals per subpopulation	20
Total population size	200
Generation gap	0.8
Insertion rate	0.9
Probability of crossover	0.9
Probability of mutation	0.01
Maximum generations	1000
Migration rate between subpopulations	0.2
Number of generations between migration	20

IV. RESULTS OF OPTIMIZATION PROCESS

Fig 2 shows the output power from the unit when no electricity is sold back to the main grid. The output power covers the electrical demand and a part of the thermal demand. Another example is illustrated in Fig. 3 where the excess of electricity is sold back for 0.07$/kWh.

The optimized daily operating cost in the first case is 3.47$ while operating the unit with full capacity at the same conditions results in a cost of 7.13$. Similar reductions have been achieved with the other cases ranging from 0.3$ up to 5.5$ per day. For instance in the case shown in Fig. 3, the obtained costs are 2.44$ while the full-capacity costs 3.36$. If the unit is only operated to cover the electrical demand, the required costs will rise to 3.57$

If an average reduction of 2.0$/day is assumed, more than 700$/year will be saved. To evaluate the significant of this reduction, it is enough to know that the capital cost of such 3-4kW units is about 12000$. This is equivalent to an annualized cost of 1700$/year assuming 0.07 interest rate, 5 years life time for the stack, which represents about 33% of the total capital cost, and 20 years life time for the reformer and the power conditioner.

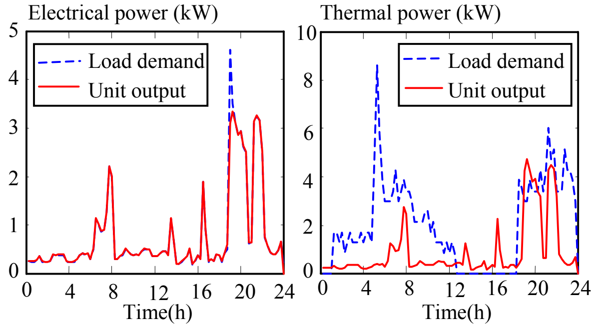

Fig 2. Electrical and thermal outputs without selling electricity

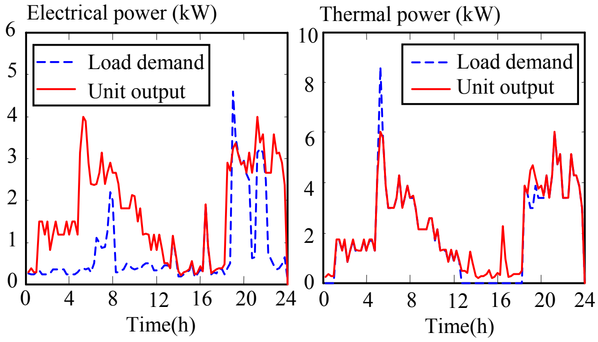

Fig. 3. Unit electrical and thermal output when selling electricity

Some comparisons are introduced in Figs. 4-7 to show the effect of the four individual tariffs. One tariff is changed each time while the others are held constant.

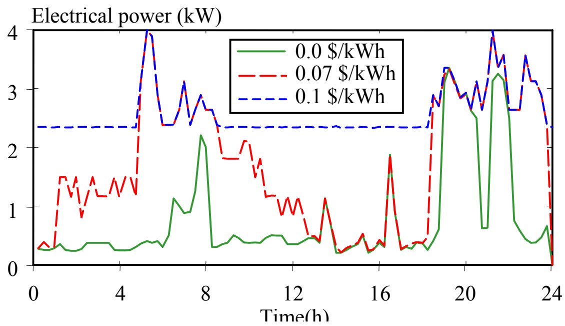

Fig. 4. Effect of the sold electricity tariff

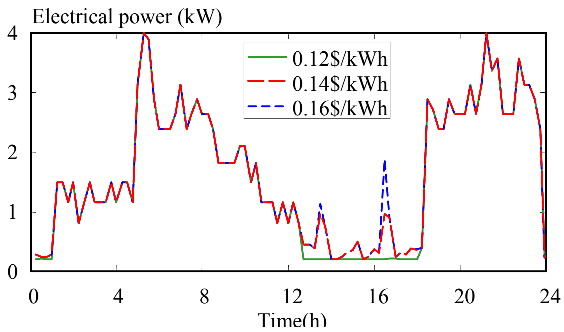

Fig. 5. Effect of the purchased electricity tariff

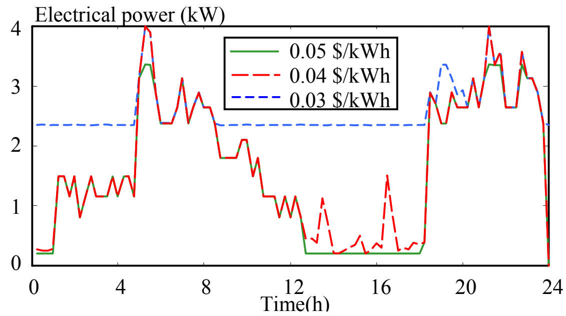

Fig. 6. Effect of the natural gas tariff for fuel cell

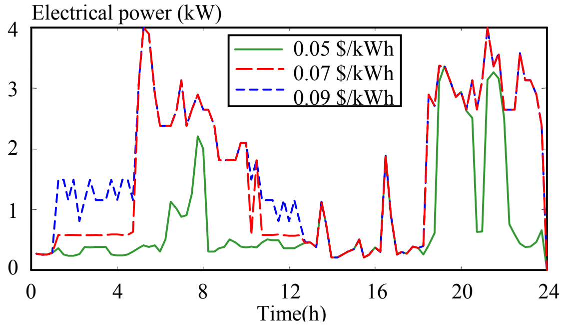

Fig. 7. Effect of the natural gas tariff for residential load

The settings are strongly affected by the sold electricity tariff, which is illustrated in Fig. 4. A remarkable impact is also obtained with the variation of the natural gas prices for the fuel cell as well as for the residential load as shown in Figs. 6 and 7 respectively. As the electrical power from the fuel cell covers the electrical demand in most cases, the purchased electricity price does not provide significant changes in the results.

The management process has to be generalized to avoid repeating the optimization after each variation in the operating conditions or load demand. It is planned to train an ANN with these results to give the optimized setting of the fuel cell. It will be enough in this case to adjust the inputs, which represent the pre-stage operating conditions and load forecasts, to simulate the new situation.

V. CONCLUSION

The operation management of PEM fuel cells for residential applications is presented in this research. A detailed economic model is developed considering both electrical and thermal relations. A real-coded GA is used to carry out the optimization process for different operating conditions and load curves. The results showed a significant reduction compared with the full capacity operation, which reflects the possibility of achieving a reasonable decrease in the energy price.

The sold electricity tariff is found to have a strong influence on the results and the natural gas price for both the fuel cell and residential loads showed also a remarkable effect. The variation of the purchased electricity tariff did not introduce a notable change in the results as the electrical demand is almost supplied by the fuel cell in most cases. A future work will be done to develop an ANN-based tool to get suitable optimized settings without the need to repeat the optimization.

VI. REFERENCES

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