INTELLIGENT OPERATION MANAGEMENT OF FUEL CELLS AND MICRO-TURBINES USING GENETIC ALGORITHMS AND NEURAL NETWORKS

Azmy A. M. and Erlich I.
Institute of Electrical Power System Engineering and Automation, University of Duisburg-Essen, D-47057, Duisburg, Germany

Abstract This paper demonstrates a new-two-stage intelligent technique to manage the operation of Distributed Generating “DG” units for residential utilization. In the first stage of the optimization process, a Genetic Algorithm “GA” is used to define the optimal settings of DG units depending on detailed economic models. For online applications and to avoid the repetitive time-consuming optimization process, the procedure is generalized in the second stage using an Artificial Neural Network “ANN”. The objective is to develop an intelligent management tool, which can be used in the online mode and depends only on the parameters obtained from the structure of the ANN. Variations of load demands and operating tariffs can easily be simulated online as they represent the main inputs of the ANN. The first stage of the management process is applied alternatively to a single fuel cell unit, three fuel cell units operating in parallel and a micro-turbine unit. However, the ANN generalization process is applied only with the single fuel cell unit as it shows the most economic operation regarding the operating costs. The results obtained in this research encourage the use of this technique in order to achieve a simple, fast and effective online management of DG units for residential applications.

Keywords Fuel cells, genetic algorithm, micro-turbines, neural networks, operation management, residential applications

INTRODUCTION

With the increasing demand on electrical energy, DG technology can offer important support to the conventional centralized power sources [1]. Therefore, DG is predicted to play a significant role in the electric power system in coming years [2, 3]. The DG, in general, can be understood as the integrated or stand-alone utilization of any generation near consumer’s load terminals [4]. DG technology can provide significant benefits for both consumers and electric distribution utility [5, 6]. This includes improving availability and reliability of power supply system, voltage support, improved power quality and postponing or avoiding transmission and distribution investments. Power loss reduction, possibility of cogeneration and emission reduction represent also additional advantages of utilizing DG units within distribution network [7].

Fuel cells and micro-turbines are candidates as DG units to be utilized either integrated into distribution systems or in the stand-alone mode [7-9]. Also, a hybrid configuration comprising the two units, which provides relatively high efficiency, is possible after solving some related technical difficulties [9]. One of the important applications of DG units, where fuel cells and micro-turbines are particularly suitable, is the utilization of small-modular commercial or residential units for onsite service. In this case, the capacity of the DG unit can be chosen to cover most of the load demand most of the time, where the surplus/shortage is exported to or imported from the main grid system. Therefore, the operation of the DG unit has to be properly managed, considering both electrical and thermal power, to reduce the operating cost to the minimum level. This reduction in the operating cost can significantly contribute to decrease the total energy price and hence, improving the economic feasibility of these units.

In this paper, the operation of Proton Exchange Membrane "PEM" fuel cells and micro-turbines with a residential load are managed using a new two-stage intelligent approach. This requires the development of suitable economic models to describe the daily operating cost of the selected units. Moreover, a robust optimization tool, which can deal with the nature of the problem, has to be applied. In the first stage, GAs are applied to define the optimal daily performance of the DG units under different operating conditions. This process is applied for three alternative scenarios: utilizing a single fuel cell, using three fuel cell units in parallel and utilizing a micro-turbine unit. In spite of the significant reduction in operating costs, the results from this stage show a strong impact of the fuel and electricity tariffs on the optimal settings of the units. In addition, the optimal settings depend on the load demand, which necessitates carrying out new optimizations after each change in the operating tariffs and load demands.

To avoid repeating the optimization process and to enable online updating of the operating parameters, a second stage is applied to the management process based on ANN generalization capability. In this stage, the ANN is trained and tested using database extracted from the first stage. This is carried out only with one fuel cell unit connected to the residential load as it shows the most economic operation among the three investigated cases regarding the operating cost. The ANN, which is trained and tested offline, succeeded to recognize and re-simulate the optimal behaviour of the fuel cell. The well-trained ANN can then be used onsite in the online mode. To simulate the variations in the operating conditions, fuel costs and load demands, as inputs to the ANN, are modified online. The results obtained in this research encourage the implementation of this approach with different

DG units to achieve both fast adaptation and optimal operation with the commercial and residential applications.

ECONOMIC MODELS OF THE SELECTED DG UNITS

Figure 1 shows the structure of the domestic system including both the electrical and the thermal energy paths. The electrical and thermal demands of the load are supplied mainly by the DG unit(s). However, the shortage in electricity and the surplus electrical power can be covered from or sold back to the main grid system at different tariffs. Two energy meters can separately measure the purchased and the sold electricity from/to the grid system depending on their tariffs of. The thermal energy produced in the DG source(s) is utilized for water and space heating of the residential building. The load is provided also by natural gas to compensate any possible deficiencies in the produced thermal energy. Most suppliers offer several natural-gas tariffs depending on the field of application (e.g. residential, industrial, electricity generation...etc). The consumptions of natural gas are measured independently for DG units and residential load to calculate the cost of each part depending on its tariff.

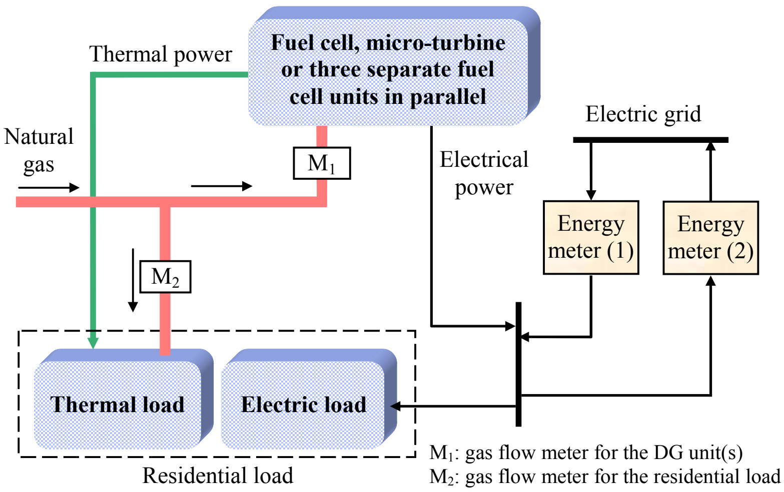

Figure 1. Structure of the residential system supplied by DG unit(s)

With the abovementioned structure, the daily operating cost "DOC ($)", which has to be minimized, can be developed in terms of payments (for natural gas and purchased electricity) and incomes (for sold electricity) in the following form:

$$DOC = DFC + DCPF + DCPE - DISE + O\ \&\ M + STC \tag{1}$$

The daily fuel cost "DFC \$" to supply DG units(s), daily cost of purchased fuel "DCPF \$" for residential load, daily cost of purchased electricity "DCPE \$", and daily income for sold electricity "DISE \$" are described by the following equations:

$$DFC = C_1 T \sum_J \frac{P_J + P_a}{\eta_J} \tag{2}$$

$$DCPF = C_2 T \sum_J \max\left(L_{th,J} - P_{th,J}, 0\right) \tag{3}$$

$$DCPE = C_3 T \sum_J \max\left(L_{el,J} - P_J, 0\right) \tag{4}$$

$$DISE = C_4 T \sum_J \max\left(P_J - L_{el,J}, 0\right) \tag{5}$$

Where:
C_1, C_2: Fuel price to supply DG and residential load respectively (\$/kWh)
C_3, C_4: Tariffs of purchased and sold electricity respectively (\$/kWh)
T: Time duration between two successive settings of the DG units (h)
P_J: Net electrical power produced at interval J (kW)
P_a: Power required for auxiliary devices (kW)
η_J: DG efficiency at interval J
$L_{th,J}$: Thermal demand at interval J (kW)
$P_{th,J}$: Thermal power produced at interval J (kW
$L_{el,J}$: Electrical demand at interval J (kW)

The operating and maintenance cost "O&M" is assumed as a constant value per kWh, while the start-up cost "STC \$"depends on the temperature of the unit and hence on the time terminated before start up and is given as:

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

where:
α: Hot start up cost and $\alpha + \beta$ represent the cold start up cost
t_{off}: The time duration, where the unit is off (h)
τ: The DG unit cooling time constant (h)

This objective function is applicable for a single fuel cell and a single micro-turbine by choosing adequate parameters. Considering the case of three fuel cells operating in parallel, the daily fuel cost is calculated depending on the fuel consumption of each unit individually, taking into account its efficiency depending on its operating point. On the other hand, the cost of purchased electricity, income for sold electricity and cost of purchased gas for residential applications are calculated depending on the accumulated electrical and thermal power from the three units together.

Typical efficiency curves for fuel cells and micro-turbine as well as typical relations between electrical and thermal powers produced in the units are used in the economic models. Nonlinear functions are developed to identify these relations depending on the supplied electrical power. Figure 2 shows the efficiency curves and the relation between the thermal and electrical powers in the fuel cell unit as used in the economic model.

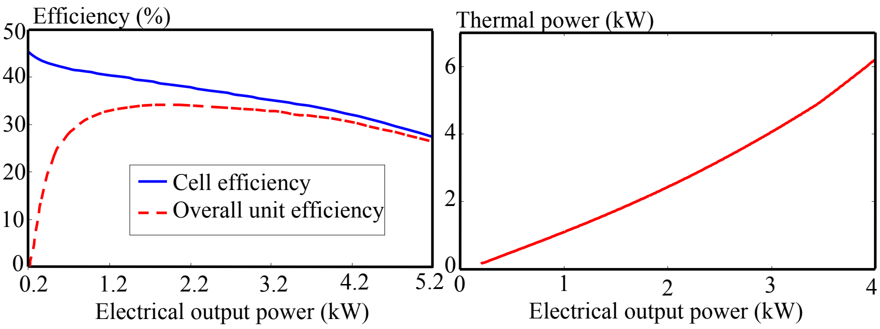

Figure 2. Efficiency curves and the thermal power in the fuel cell unit

In the given objective function, there are four tariffs affecting the setting points i.e. C_1, C_2, C_3 and C_4. These four tariffs represent the four decision variables, which affect the optimal settings of the energy source(s).

The minimization of the objective function (1) is restricted by many operational and technical constraints. This includes the unit capacity constraints, unit ramp rate constraints, minimum up/down time limits (continuous running/stop time constraint) and the maximum number of starts and stops per day. The mathematical description of these constraints is given in detail in a previous paper [10].

GA-BASED OPTIMIZATION PROCESS

Since the presented economic models of the DG units with domestic loads are discontinuous and nonlinear in nature, the GA will be a convenient choice as it represents a powerful probabilistic search algorithm taking into account its capability of searching in a population of points in parallel [11-13]. The multi-population structure is chosen, where individuals migrate periodically between subpopulations to transfer information between them. To handle the constraints in the economic models, the penalty-function method is used, whereby the constrained problem is converted to an unconstrained one by augmenting the main cost function with additional cost terms. The additional terms assign nonlinear costs for solutions that violate any of the constraints depending on their locations relative to the feasibility boundary.

The evolution process begins with initiating the population by formulating a number of individuals, which represent the possible output electrical power from the DG unit(s) over one day. The maximum values of these individuals are limited to 4 in the case of single fuel cell or micro-turbine and 1.3 in the case of three fuel cells operating in parallel. This is equivalent to a maximum electrical power of 4kW and 1.3kW respectively. For one day, 96 setting values have to be calculated as the setting of the unit is assumed to be updated every 15 minutes. The individuals are evaluated depending on the operating cost in addition to the penalty terms. Then, the individuals are ranked and suitable fitness values are assigned to them. Strings with higher fitness values are selected using the roulette wheel technique and then the recombination process is performed. Using the two well-known recombination processes, i.e. crossover and mutation, a new generation is produced. Some of the fittest members of each generation are saved and copied into the next one to ensure that best solutions are not lost when moving from one generation to the next.

Some modifications are introduced to the GA-optimization program to carry out the management of the three fuel cell units simultaneously. Now, each individual comprises 288 unknowns, with 96 unknowns belonging to each unit. Two times during the evolution process, the individuals are divided into three sub-individuals and the calculations are carried out considering each sub-individual separately. The first one is when the daily operating cost of each individual fuel cell is calculated. In this case, the computation has to be carried out for each unit according to its efficiency and the additional penalty costs, which depend on the operating points. The total cost is then calculated by adding the cost of the three units together, since the total power is required for further calculations rather than the power from individual units. The second time, where individuals are divided into three sub-individuals, is when the new offspring is create as the crossover and the mutation have to be applied to each unit separately.

Results of the optimization process

The GA-based optimization process is carried out to manage the performance of a PEM fuel cell at different electricity and fuel prices as well as at various daily load demands. More tan 540 cases are considered including ten typical load curves corresponding to different seasons and realistic tariffs. Figure 3 shows the optimal settings of the fuel cell for a certain load curve with three different tariffs of sold electricity (C_4). This involves the case where no electricity is sold back to the utility. The other 3 tariffs, i.e. C_1, C_2 and C_3, are held constant in the three cases. The strong variation of the optimal settings with the change of this tariff is obvious. The other three tariffs have also similar strong impact on the optimal performance of the fuel cell. This necessitates repeating the optimization if any of the operating tariffs is changed, which represents a real challenge and requires advanced knowledge and experience from the operator.

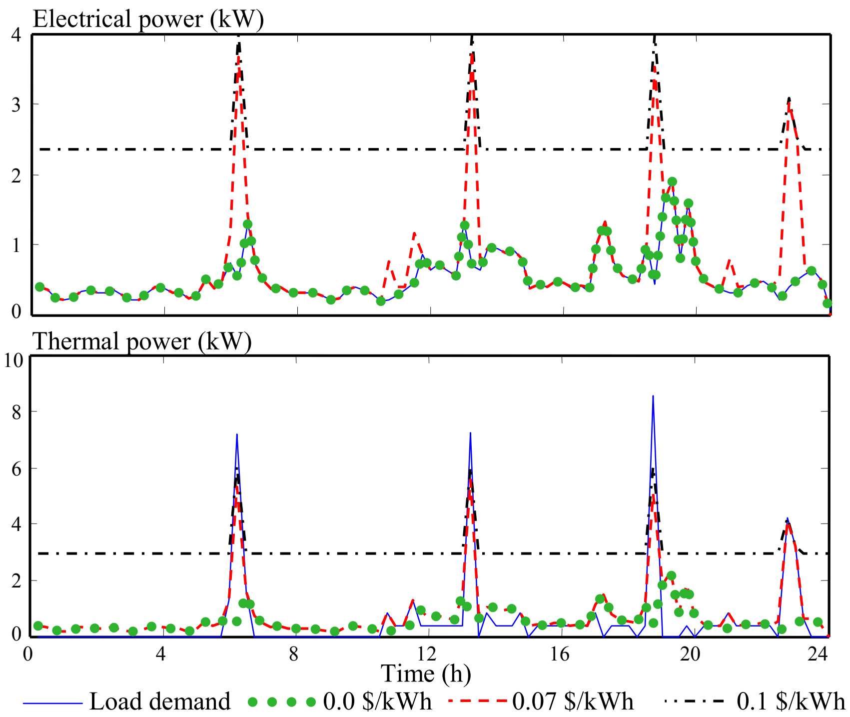

Figure 3. Effect of varying the sold electricity tariff on the optimal settings of the fuel cell

It is noticeable from the results that the fuel cell generates low power for prolonged periods within the day, which is also the case in most of the investigated cases. It supplies the rated or near rated power only for short time. Hence, it is necessary to answer the question whether the utilization of smaller identical units with equivalent total capacity can be more economic regarding the operating costs. In this case, one of the identical units is used as a base source and the other units are added as required.

The optimization process is carried out again using the same load curves and tariffs as with one fuel cell unit to manage the performance of three fuel cell units simultaneously. Figures 4 and 5 show the optimum output electrical power from the three fuel cells as well as the total electrical and thermal power for two different cases. For comparison purposes, the optimum electrical and thermal powers from one fuel cell under the same conditions are also illustrated in the figures. Table 1 summarizes the used tariffs in the two optimization processes as well as the total operating costs when the load is supplied by one and three fuel cell units.

Table1. Operating tariffs and daily costs when optimizing the operation of a single fuel cell and three units operating in parallel

	C_1 (\$/kWh)	C_2 (\$/kWh)	C_3 (\$/kWh)	C_4 (\$/kWh)	Total operating cost (\$/day)	
					One unit	Three units
case (1)	0.03	0.07	0.16	0.1	1.6032	1.915
case (2)	0.03	0.09	0.16	0.0	3.6557	4.5912

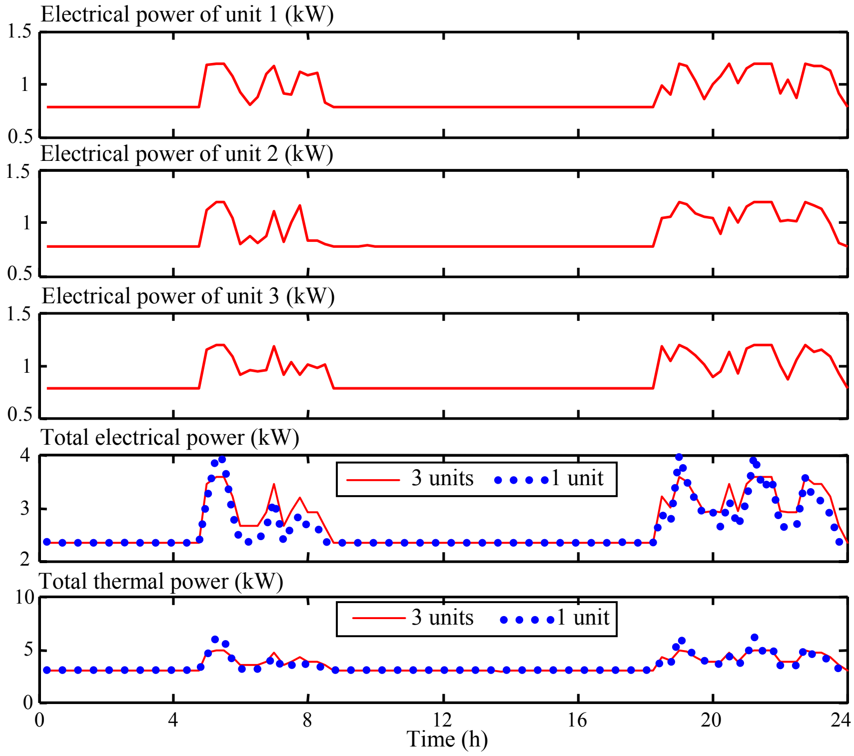

Figure 4. Optimal settings of one and three fuel cells to supply a residential load: case (1)

The total electrical and thermal output powers from the three units together are similar to that obtained from a single fuel cell. The contributions from the three units vary depending on load curves and operating tariffs. In some cases, one or two units are not used for the whole day. In other cases, one or two units operate only for a short period during the day as shown in figure 5. Generally, the total operating cost using three units is more expensive than utilizing only one unit. The operation of one or more units for a short time increases the operating cost as a result of the start-up cost. In addition, fuel cells exhibit lower efficiency at higher operating power as shown in figure 2. Since the three units are operating at relatively higher percent power, the resultant efficiency of each unit is lower than that of a single fuel cell.

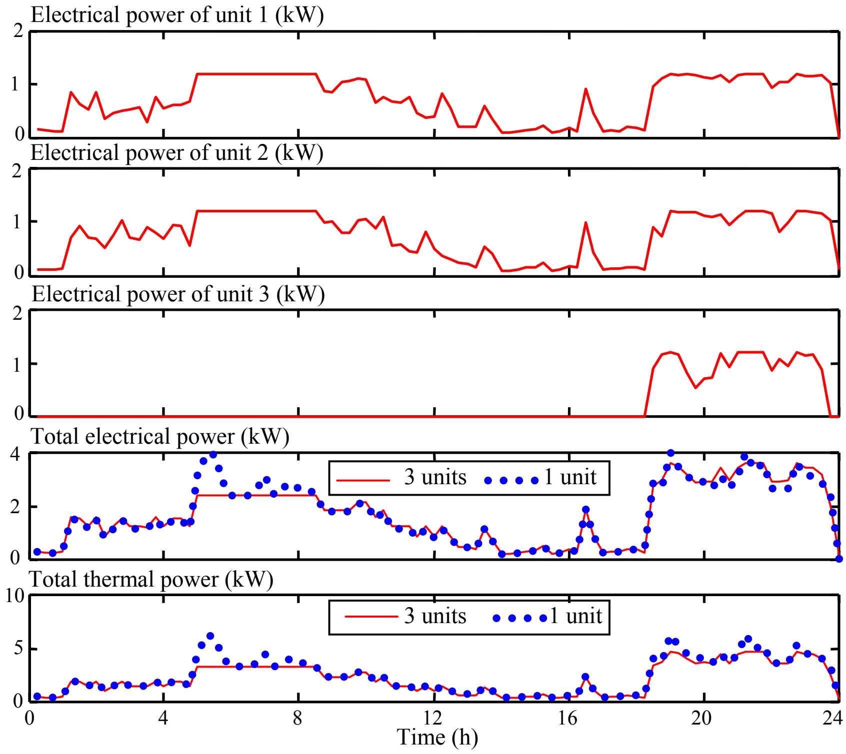

Figure 5. Optimal settings of one and three fuel cells to supply a residential load: case (2)

As an alternative DG source, the management process is carried out for a micro-turbine to optimize its performance with the same strategy. In spite of the similarity of the economic models of the fuel cell and the micro-turbine, the dissimilarity between the parameters of the two units as well as the type of efficiency and thermal power curves result in significant changes in the optimal operation of the two units. Figure 6 shows the efficiency curve and the relation between thermal and electrical powers in the micro-turbine as used in the economic model. Compared to the curves of the fuel cell shown in figure 2, a considerable difference can be observed regarding both the nature and magnitudes of the efficiency and the thermal power.

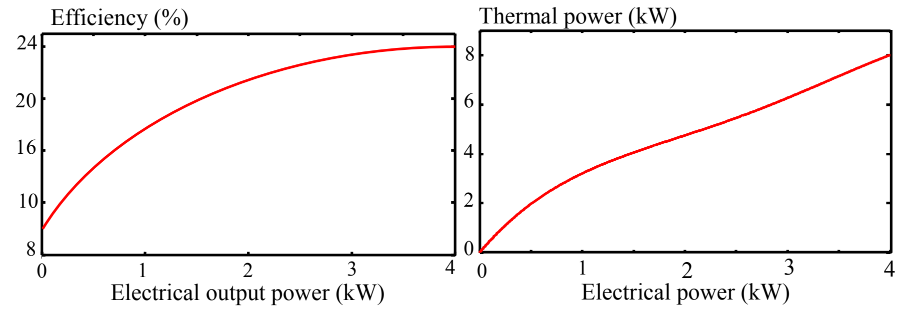

*Figure 6.*The efficiency curve and the thermal power of the micro-turbine unit

To evaluate the performance of the micro-turbine compared to that of the fuel cell, two cases from the optimization process are given, where the operating tariffs and the total operating cost are given in Table 2. Figures 7 and 8 illustrate the electrical and the thermal output power from the micro-turbine for the two cases. The load demand and the optimal output power from a single fuel cell unit are also illustrated in the same figures.

Table2. Operating tariffs and daily costs using a fuel cell unit and a micro-turbine unit

	C_{n1} (\$/kWh)	C_{n2} (\$/kWh)	$C_{el\text{-}p}$ (\$/kWh)	$C_{el\text{-}s}$ (\$/kWh)	Total operating cost (\$/day)	
					Fuel cell	Micro-turbine
case (1)	0.03	0.07	0.14	0.1	1.2412	2.8997
case (2)	0.04	0.05	0.12	0.07	3.6942	4.3213

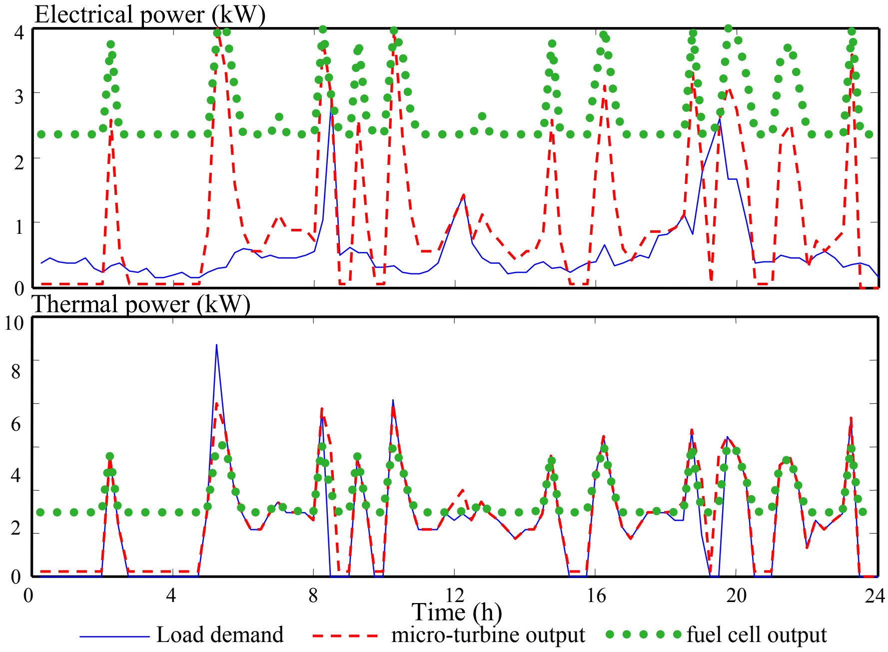

Figure 7. Optimal settings of a micro-turbine unit and a fuel cell unit: case (1)

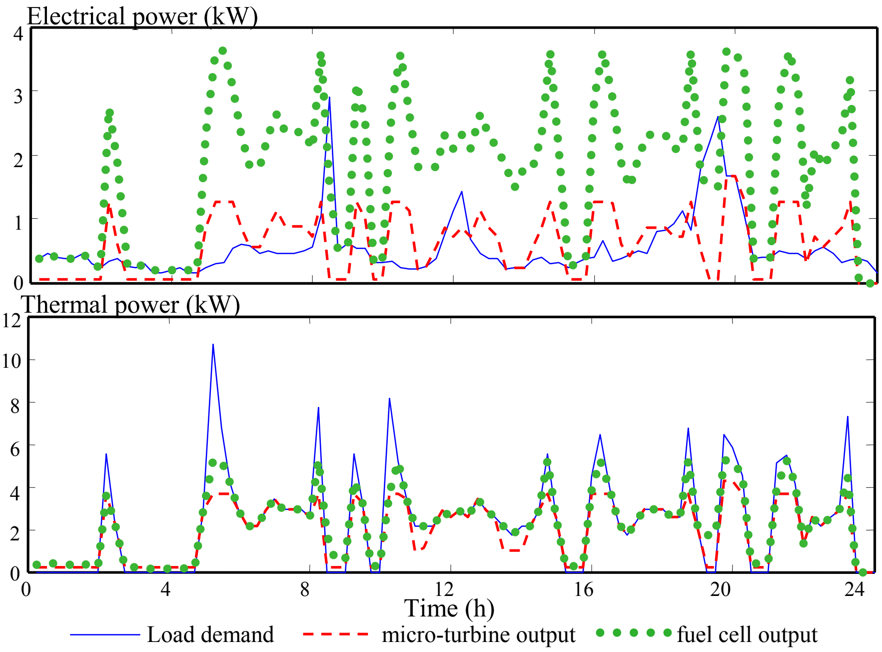

Figure 8. Optimal settings of a micro-turbine unit and a fuel cell unit: case (2)

In most investigated cases, the settings of the micro-turbine are mainly affected by the thermal demand. In figure 7, the fuel cell produces a high value of electrical power due to the high tariff of sold-electricity and the low tariff of purchased fuel, while the outputs from the micro-turbine are close to the thermal load demand. This is due to the high thermal power generated in the micro-turbine compared to the electrical power as seen in figure 6. Covering the electrical load demand results in excess thermal energy, which would be wasted. The higher electrical efficiency of the fuel cell causes lower operating cost in most investigated cases. This is due to the high price of electrical energy compared to that of the thermal energy. For loads with high thermal and low electrical demands, micro-turbine units may be favourable in terms of operating costs.

To evaluate the potential reduction in the total daily cost when this approach is applied, the results of optimizing the fuel cell, as the most economic choice among the three cases, are compared with three conventional settings. The first one is to operate the unit at its rated power. The second and third cases are to track the electrical and thermal load demand respectively. Table 3 gives the average cost as well as the average difference of the three conventional settings with respect to the GA-based optimal case for one load curve under 81 different operating conditions.

Table3. Cost savings by optimization the operation of the fuel cell

	Average cost ($/day)	Average difference with respect to the optimal case	
		Average difference ($/day)	Average percentage difference
Optimal settings (from GA)	3.722	0.0	0.0
Settings=rating	8.582	4.860	130.575 %
Settings=electrical demand	4.855	1.133	30.441 %
Settings=thermal demand	4.637	0.915	24.584 %

MANAGEMENT GENERALIZATION USING ANN

The results from the first stage of the optimization process showed the possibility of reducing the operating cost considerably by optimizing the power generated in the DG units. However, the need for new optimization after each change in the load demand or the operating tariffs restricts the online application of this approach. In the second stage of the management process, an ANN is used to generalize the results obtained in the first stage. The ANN has high capability of generalizing such nonlinear complicated problems [13-15]. This is carried out only for the single fuel cell as it is the most economic choice as explained earlier. After training and testing the ANN, it can be used onsite for the online application.

The ANN comprises three hidden layers, with 40, 30, and 20 neurons. The tan-sigmoid transfer function is chosen for all neurons in the hidden layers, while the log-sigmoid transfer function is used for the output neuron. 54 inputs including the four operating tariffs and present electrical and thermal demands are used. In addition, historical and forecast powers for three hours are introduced at the input layer. As it is assumed that the setting point will be updated 4 times each hour, 12 previous values and 12 prognoses of both the electrical and thermal load demands are introduced at the input layer. The single output represents the desired optimal electrical-power of the fuel cell in the next time step.

The ANN is trained offline using more than 56000 patterns and is then tested using new load curves as well as new operating tariffs. Figures 9 and 10 compare between the GA-based optimal targets and the actual output from the ANN in two cases. The operating tariffs and the corresponding daily costs depending on both GA-based optimized settings and the ANN output are given in table 4

Table4. Comparison between daily costs using GA-based optimal settings and ANN outputs

	C_{n1} ($/kWh)	C_{n2} ($/kWh)	C_{el-p} ($/kWh)	C_{el-s} ($/kWh)	Total operating cost ($/day)	
					GA-based settings	ANN outputs
case (1)	0.03	0.05	0.12	0.0	3.4734	3.6371
case (2)	0.04	0.09	0.16	0.1	3.0473	3.1723

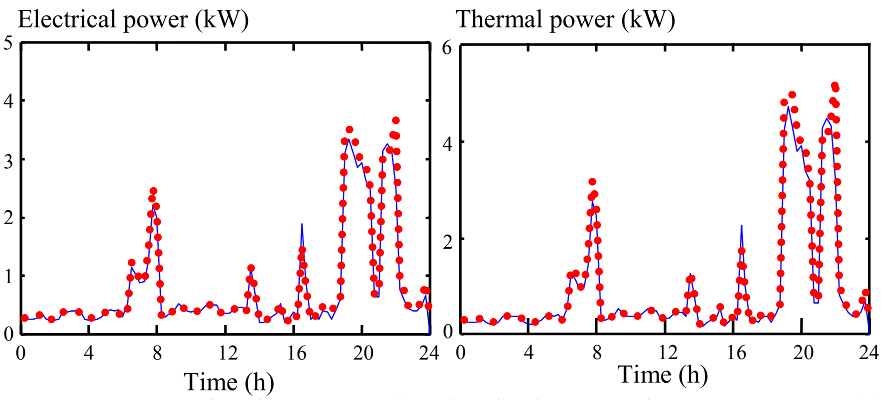

Figure 9. A comparison between GA-based optimal target and ANN output: case (1)

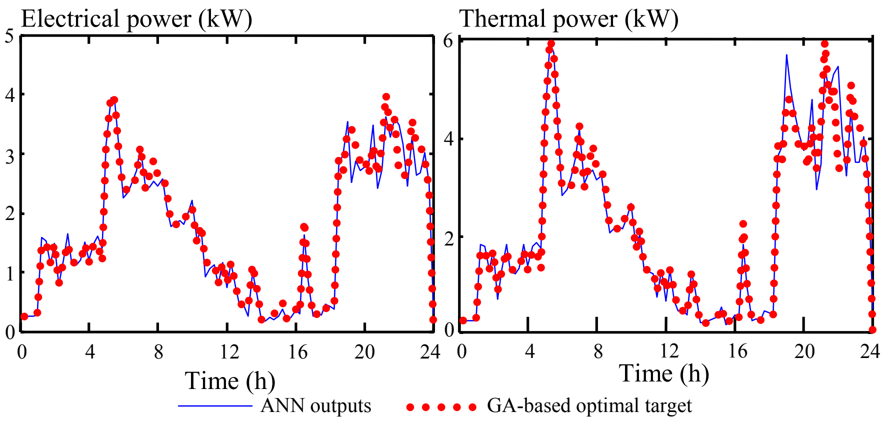

Figure 10. A comparison between GA-based optimal target and ANN output: case (2)

The comparisons give an indication about the agreement between the outputs from the ANN and the optimal settings. Hence, it is expected that defining the settings depending on ANN decision will not lead to a significant increase in the operating cost compared to the optimal case. To emphasize this fact, a comparison between the daily operating cost using GA-based optimization and ANN outputs is carried out for 78 different cases at various operating tariffs and the results are illustrated in figure 11.

The average daily cost using the GA-based optimal settings is about 3.689 $/day for the 78 investigated cases. Using the quasi-optimal settings, which are defined by the ANN, increases the daily operating cost to 3.869$/day. Compared to the reduction achieved using the proposed technique, this difference represents a minor increase in the daily operating cost. These results reflect the success of the ANN to capture the optimal behaviour of the unit.

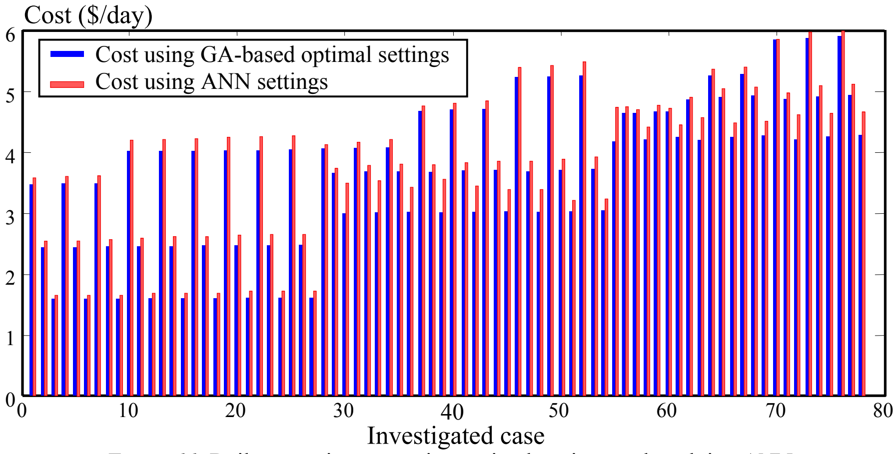

Figure 11. Daily operating cost using optimal settings and applying ANN

CONCLUSION

This paper deals with the optimal management of electrical and thermal power in DG units when used to supply residential loads. The investigation involves the management of a single fuel cell, three fuel cells operating in parallel and a single micro-turbine unit. Analysis of the obtained results revel a significant reduction achieved in the daily operating costs using the management process, which contributes in improving the economic feasibility of DG units. Supplying the residential load using a single fuel cell unit resulted in lower daily operating cost compared to the other two cases. The high electrical efficiency of the fuel cell results in lower operating cost compared to the use of a micro-turbine. Also, the nature of the fuel cell efficiency curve, which decreases with the increase of the supplied power, shifts the optimum allocation in favour of using a single unit rather than using smaller identical units operating in parallel.

The paper proposes also formulating the management process in a general frame using ANN to avoid the need for repetitive optimization after changes in operating conditions take place. The ANN is trained and tested using data-base extracted from the GA-based optimization for different load curves and operating tariffs. The inputs of the ANN, which represent the load demand and the operating tariffs, can be updated online to simulate the variations in the operating conditions. The effectiveness of the suggested approach is confirmed by the agreement between the optimized settings and the outputs from the ANN. The online adjustment of the fuel cell settings in a fast and simple manner demonstrates the viability of this approach for optimum deployment of different DG units for residential applications.

REFERENCES

1. Thomas E Hoff, Howard J. Wenger and Brian K. Farmer, “Distributed generation: an alternative to electric utility investments in system capacity”, Energy policy, vol. 24, No. 2, pp. 137-147, 1996
2. Philip. P. Barker and Robert. W de Mello, “Determining the impact of distributed generation on power systems: Part I. Radial distribution systems”, Power Engineering Society Summer Meeting 2000, IEEE, Volume: 3, 16-20 July 2000, Pages: 1645 – 1656
3. Philip. P. Barker and Bradley K. Johnson, ”Power system modeling requirements for rotating machine interfaced distributed resources”, Power Engineering Society Summer Meeting, 2002 IEEE, Volume: 1, 21-25 July 2002, Pages:161 - 166
4. Peter A. Daly and Jay Morrison, “Understanding the potential benefits of distributed generation on power delivery systems”, Rural Electric Power Conference, 2001, 29 April-1 May 2001, Pages: A2-1 - A2-13
5. Bruno. Delfino, “Modelling of the integration of distributed generation into the electrical system”, Power Engineering Society Summer Meeting, 2002 IEEE, Volume: 1, 21-25 July 2002, Pages:170 - 175
6 Thomas E. McDermott and Roger C. Dugan, “Distributed generation impact on reliability and power quality indices” Rural Electric Power Conference, 2002 IEEE, 5-7 May 2002, Pages:D3-D3-7
7. Ahmed M. Azmy, and István Erlich, “Dynamic Simulation of Fuel Cells and Micro-Turbines Integrated with a Multi-Machine Network”, The 2003 IEEE Bologna Power Tech conference, June 23-26, 2003, Bologna, Italy
8. F. Ordubadi, “PEM fuel cells and future opportunities“, Power Engineering Society Summer Meeting, 2001, IEEE, Volume: 1, 15-19 July, 2001, Page(s): 710-716, vol.1
9. Ahmed M. Azmy, Erlich I., “Dynamic Simulation of Hybrid Fuel Cell/Micro-Turbine Units Integrated into Large Power Systems”, the Ninth International Middle-East Power Systems Conference (MEPCON), Egypt, December, 16-18, 2003
10. Ahmed M. Azmy, Erlich I., “Management of PEM fuel cells for residential applications using a real coded genetic algorithm”, the Ninth International Middle-East Power Systems Conference (MEPCON), Egypt, December, 16-18, 2003
11. Ioannis G. Damousis, Anastasios G. Bakirtzis, and Petros S. Dokopoulos “Network-Constrained Economic Dispatch Using Real-Coded Genetic Algorithm”, IEEE Transactions on Power Systems, Vol. 18, No. 1, February 2003
12. S. H. Ling, H. K. Lam, F. H. F. Leung, and Y. S. Lee, “A genetic algorithm based fuzzy-tuned neural network”, Fuzzy Systems, 2003, FUZZ '03, the 12th IEEE International Conference on. Volume: 1, May 25-28, 2003 Page(s): 220 –225
13. T.T. Chow, Z. Lin, C.L. Song and G.Q. Zhang, “Applying neural network and genetic algorithm in Chiller system optimization“, Seventh International IBPSA Conference, Rio de Janeiro, Brazil, August 13-15, 2001
14. Liang-Hsuan Chen and Cheng-Hsiung Chiang, “An Intelligent Control System Based on Multiobjective Genetic Algorithms and Fuzzy-Neural Network”, Systems, Man and Cybernetics, 2002 IEEE International Conference on, Volume: 3, 6-9 Oct. 2002, Page(s): 6 pp. vol.3
15. Wiktor Charytoniuk, and Mo-Shing Chen, “Very short-term load forecasting using artificial neural network”, IEEE transactions on Power Systems, Vol. 15, No. 1, Feb. 2000