Decision Tree-Based Approach for Online Management of Fuel Cells Supplying Residential Loads

Ahmed M. Azmy, Mohd. R. Mohamed and István Erlich, Member, IEEE

Abstract— **The paper demonstrates the online optimal management of PEM fuel cells for onsite energy production to supply residential loads. Classical optimization techniques are based on offline calculations and can not provide the necessary computational speed for online performance. In this paper a Decision Tree (DT) algorithm is employed to obtain the optimal, or quasi-optimal, settings of the fuel cell online and in a general framework. The main idea is to employ a classification technique, trained on a sufficient subset of data, to produce an estimate of the optimal setting without repeating the optimization process. The required training database is extracted by performing the optimization offline at different load demands as well as different natural gas and electricity tariffs using a Genetic Algorithm (GA). The approach provides the flexibility of adjusting the settings of the fuel cell online according to the observed variations in the tariffs and load demands. Results at different operating conditions are presented to confirm the high accuracy of the proposed generalization technique. In addition, the accuracy of the DTs to approximate the optimal performance of the fuel cell is compared to that of the Artificial Neural Networks (ANNs) used for the same purpose. The results show that the DTs can somewhat outperform the ANNs with certain pruning levels.**

Index Term— Artificial neural networks, Decision trees, Fuel cells, Genetic algorithm, Performance optimization

I. Introduction

THERE is a considerable interest in utilizing Distributed Generating (DG) units for both stand-alone and grid-connected operations [1]. This trend is motivated by the valuable benefits that DG units can provide for both the consumers and the electric-distribution systems [2]. Improving availability and reliability of utility system, voltage support and improved power quality, reducing the emissions and the power-losses and the possibility of cogenerations are some of these benefits. Furthermore, the transmitted power is reduced when the power is generated onsite and hence, the transmission and distribution expenditures are postponed or avoided. Therefore, the reduction of energy price produced in DG units in general and in fuel cells in particular is becoming increasingly important in order to bring them to competition with conventional centralized energy sources [3, 4].

Supplying residential loads would be a favourable application for fuel cells if the energy price in such units is reduced to a feasible level. The reduction of the operating costs in fuel cells by the optimal management of their electrical and thermal power can significantly contribute in achieving the required economical operation. However, the high computational requirements and the long execution time characterizing the conventional optimization make the online implementation of this management unpractical for residential applications. Therefore, it is required to find new procedures that perform based on optimization concepts and are suitable, at the same time, for online operation.

In a previous work [5], the Genetic Algorithm (GA) technique is used to optimize the electrical and thermal power generation in a fuel cell supplying a residential load at different operating conditions. Despite the success of the process to achieve a significant reduction in the operating cost, it is suggested to extend the approach in a general frame using a suitable tool. Therefore, the GA-based optimization is used only to provide a suitable database for training and testing an Artificial Neural Network (ANN), which is proposed for the onsite application. Accordingly, the problems related to the conventional optimization are avoided due to the use of the ANN alone in the online mode.

The decision tree (DT) classifier is an intelligent approach for multistage decision making, which is widely used in many applications [6, 7]. It is one of the simplest representations of complicated functions that can be successfully used to classify new unobserved data and thus, has a talented generalization feature. The main advantage of DTs is their capability to break up a complex decision into a set of simpler decisions, predominantly providing correct solutions similar to the desired targets [6]. Other benefits of DT techniques for classification problems include their robustness, nonparametric nature, and their high computational efficiency [7]. The employment of DTs as an alternative to the ANN is therefore proposed in this paper to extend the optimization approach in a generalized frame. Emphasis is directed to the online use of the DTs to define the optimal, or quasi-optimal, settings of the fuel cell depending on various load demands and operating tariffs.

A knowledge base is extracted from the GA-based optimization and used in constructing the DT. All decision variables and load demands are considered as input predictors to enable the online updating of these variables without carrying out a new time-consuming optimization procedure. The DT is then pruned to avoid overfitting the training data and to improve the generalization performance. The DT-based settings are compared with the optimal target to demonstrate the outstanding capability of the proposed approach to provide a fast and simple optimal management for the unit. In addition, the performance of the DT is compared with that of the ANN, where the DT exhibits better results, to some extend, than the ANN when specific pruning levels are used.

Ahmed M. Azmy is with the institute of Electrical Power System Engineering and Automation, University of Duisburg-Essen, Germany
(e-mail: azmy@uni-duisburg.de)
Mohd. R. Mohamed is with the Faculty of Electrical and Electronics Engineering, University College of Engineering & Technology, Malaysia
(e-mail: rusllim@kuktem.edu.my)
István Erlich is with the institute of Electrical Power System Engineering and Automation, University of Duisburg-Essen, Germany
(e-mail: erlich@uni-duisburg.de)

II. Problem Formulation

The structure of the residential system supplied by a fuel cell is shown in Fig. 1 including both the electrical and the thermal energy paths. The fuel cell is used as the main source for both the electrical and thermal load demands. However, the main electrical grid system is used to achieve the balance between the generated and the consumed electrical power. Two energy meters are separately used to measure the purchased and the sold electricity since two independent tariffs are assumed for them.

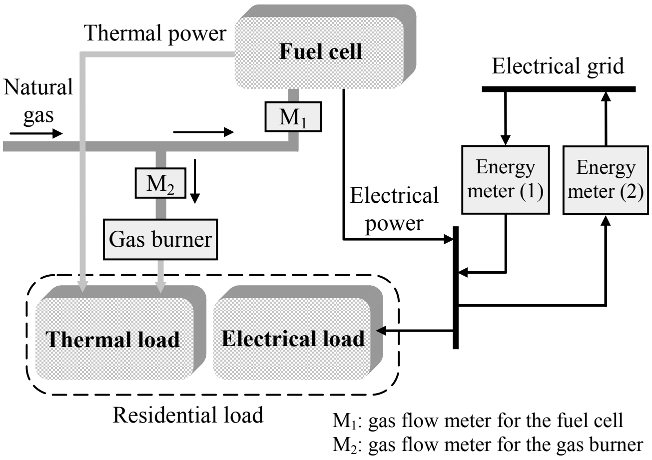

Fig. 1. Structure of the residential system supplied by a fuel cell

Since the exhaust air from the fuel cell still contains considerably large energy, the output thermal energy is utilized for water and space heating in the residential building. The thermal load can be supplied also by a natural gas burner to compensate any possible shortage in the produced thermal energy. The possibility of providing the natural gas for the fuel cell and the residential load at different tariffs is taken into account. Therefore, the natural gas consumptions in the fuel cell and gas burner are measured individually to calculate the cost of each part depending on its tariff.

A. *Economic model of the residential system*

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

$$\mathrm{DOC=DFC+DCPF+DCPE-DISE+O\&M+STC} \qquad (1)$$

The daily fuel cost "DFC $" to supply the fuel cell, 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:

$$\mathrm{DFC} = C_{\text{n-FC}} T \sum_J \frac{P_J + P_a}{\eta_J} \qquad (2)$$

$$\mathrm{DCPF} = C_{\text{n-RL}} T \sum_J \max\left(L_{th,J} - P_{th,J}, 0\right) \qquad (3)$$

$$\mathrm{DCPE} = C_{\text{el-p}} T \sum_J \max\left(L_{el,J} - P_J, 0\right) \qquad (4)$$

$$\mathrm{DISE} = C_{\text{el-s}} T \sum_J \max\left(P_J - L_{el,J}, 0\right) \qquad (5)$$

Where:

$C_{\text{n-FC}}$, $C_{\text{n-RL}}$: fuel price to supply the fuel cell and the residential load respectively ($/kWh)
$C_{\text{el-p}}$, $C_{\text{el-s}}$: tariffs of purchased and sold electricity respectively ($/kWh)
T : time duration between two successive settings of the fuel cell (h)
P_J : net electrical power produced at interval J (kW)
P_a : power required for auxiliary devices (kW)
η_J : fuel cell efficiency at interval J
$L_{th,J}$: thermal load demand at interval J (kW)
$P_{th,J}$: thermal power produced at interval J (kW
$L_{el,J}$: electrical load demand at interval J (kW)

The operating and maintenance cost "O&M" is assumed to be in proportional with the produced energy, while the start-up cost "STC $"depends on the temperature of the unit and consequently on the time terminated where the unit was in the off mode before starting it up once again:

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

where:

α : hot start up cost
$\alpha + \beta$: cold start up cost
t_{off} : the time terminated while the unit is off (h)
τ : the fuel cell cooling time constant (h)

In the presented model, the four operating tariffs, i.e. $C_{\text{n-FC}}$, $C_{\text{n-RL}}$, $C_{\text{el-p}}$ and $C_{\text{el-s}}$, represent the four decision variables that affect the optimal settings of the fuel cell.

The minimization of the objective function (1) is restricted by some 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 the previous paper [5].

B. *GA-based optimization process*

To simulate and solve the optimization problem associated with the economic model of the residential system, a special tool is required. The selected optimization algorithm has to be capable of dealing with such discontinuous and nonlinear models which comprise many constraints. The GA is a suitable technique for these cases taking into account its powerful probabilistic capability of searching in a population of points in parallel [8-10]. The optimization process is carried out using 10 different load curves selected at different season and also with various operating tariffs. This results in more than 940 optimization cases. The idea is to provide sufficient knowledge base for the generalization stage using the DT.

The penalty-function technique is employed to handle the constraints in the economic model [10]. This technique depends on converting the constrained problem to an unconstrained one after adding suitable extra cost functions to the main objective function. The additional cost functions assign nonlinear costs for solutions that violate any of the constraints depending on their locations relative to the feasibility boundary [10]. To ensure fast rejection of the solutions that violate the constraints, a higher cost value is assigned to any infeasible solution than the feasible members. Thus, the priority will be to the solutions that satisfy all constraints.

A multi-population structure is used for the GA since it improves the quality of the obtained results. According to this structure, the individuals migrate periodically between subpopulation to exchange information between them. The real coding is used in the optimization processes since it provides better performance and faster conversion compared to other coding methods [10]. With other coding, it is required to alternate to the real coding in the phase of calculating the total operating cost, which results in additional processing time.

At the beginning of the evolution process, a number of individuals is randomly created to represent the possible output electrical power from the fuel cell over one day. The values within all individuals are limited between 0 and 4, which is equivalent to a maximum electrical power of 4kW. It is assumed that the setting of the fuel cell is updated every 15 minutes and hence 96 setting values have to be calculated for one day. To evaluate the performance of the individuals, the corresponding daily operating costs are calculated for each one and the penalty cost terms are added to the members which violate the constraints.

The individuals are then ranked and a suitable fitness value is assigned to each of them. The roulette wheel technique is used to select some individuals to perform the recombination process. It is expected that strings with higher fitness values will be selected by the roulette wheel technique. The two recombination processes, i.e. crossover and mutation, are then performed to produce the new generation. The 'Elitism' strategy is utilized, where 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. Thus, it is expected that the average fitness of the new generation is improved.

C. Results of the optimization process

The optimal settings of the fuel cell depend on the electrical and thermal load demands in addition to the four operating tariffs. Figs. 2 and 3 highlight the effect of varying both the load demand and operating tariffs on the optimal settings of the fuel cell. In Fig. 2, only the tariff of sold electricity is changed, while the other three tariffs are maintained constant. Fig. 3, on the other hand, illustrates the effect of varying the natural-gas tariff for supplying the fuel cell but under other load demands.

The strong variation of the optimal settings with the change of the tariffs and load demands is obvious. This obligates carrying out a new optimization process after any change in the operating condition, which prevents the online implementation of the technique and requires advanced knowledge and experience from the operator. Therefore, the GA-based optimization process is intended only to provide the required database for the next generalization stage.

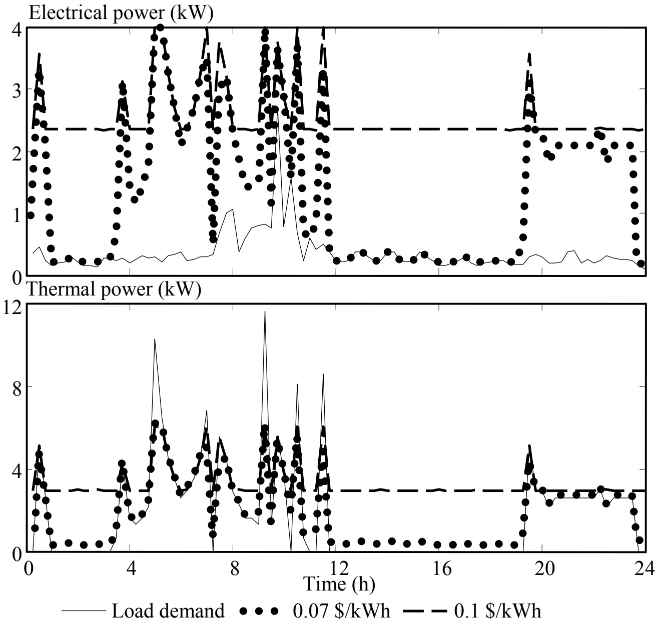

Fig. 2. Effect of varying the sold electricity tariff on the optimal settings

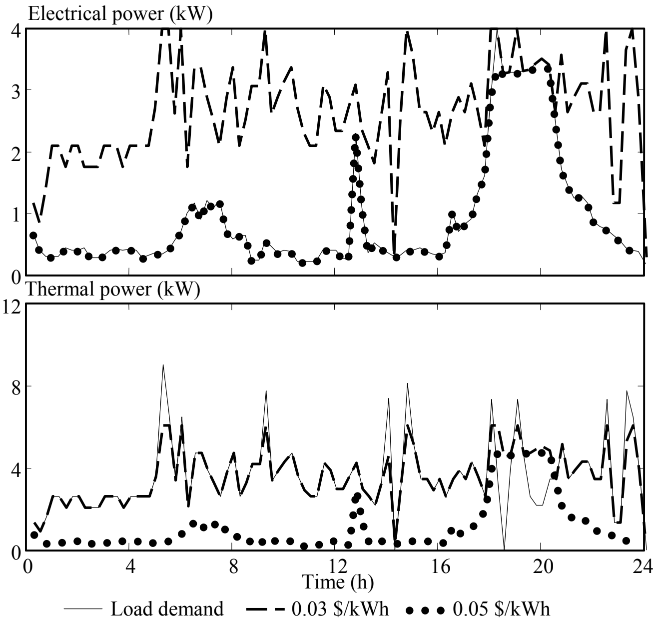

Fig. 3. Effect of varying the natural-gas tariff for supplying the fuel cell on the optimal operation

III. GENERALIZING THE OPTIMIZATION PROCESS USING DTs

Generalizing the optimization process refers to the possibility of identifying the optimal settings without carrying out new optimization by extending the obtained results to cover any expected operating condition. A sufficient knowledge base and a robust generalization tool are required to accomplish this process, which is carried out in a previous work using ANNs [5]. The focus in this paper is on the employment of DT classifiers to generalize the results obtained from the GA-based optimization.

The idea of the generalization is illustrated in Fig. 4. In addition to the four operating tariffs, the DT receives information about the current and the previous electrical and thermal load demands. Also, prognoses for a few hours ahead are required to account for the expected load status. The need for the prognoses only for a short time gives an advantage for this method since the accuracy in this case will be high. The optimization process using the GA requires the prognoses for the whole day since the GA will calculate the optimal setting through the entire day.

The task of the DT is to define the suitable quasi-optimal setting of the fuel cell for the next time interval. The process is updated at each time interval, e.g. every 15 minutes and the operating window is shifted one step ahead. At the same time with updating the prognoses for demand, it is possible to consider changes in fuel and electricity tariffs too. The use of previous and subsequent values of the load demand gives continuous information about the status of the load. On the other hand the required information about the previous setting values of the fuel cell itself to decide the following setting value is included indirectly through the learning process.

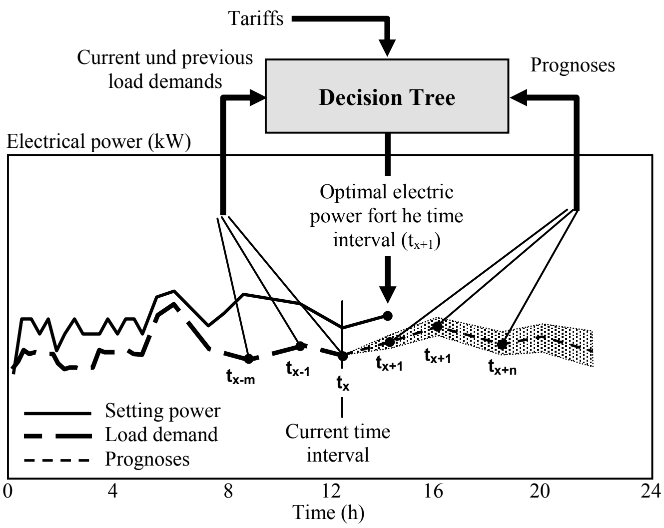

Fig. 4. Generalizing the optimization process using decision trees

A. Overview of DT

DTs are widely-used supervised learning techniques for approximating discrete functions [6]. The DT methodology represents a nonparametric approach that can provide classifications for complex problems and is used for deducing suitable decisions for new unobserved cases [11]. DTs depend in their work on dividing complex problems into simpler subproblems and solving each sub-problem separately [11]. They are constructed using a data base extracted from all possible states of the investigated problem and are proposed for deriving a model describing the behaviour of the original system. Conventionally, the knowledge base is divided into two sets: a learning set for deriving the structure of the DT and a test set for evaluating the generalization capability of the constructed DT with new unobserved data.

The configuration of DTs consists of nodes, branches and leaves. Every node in the DT stands for a specific decision rule. This rule is examined and a corresponding decision is taken. Excluding the root one, each node in the DT has only one incoming edge, while two branches start from all nodes to represent the two possible decisions. Every final leaf characterizes the corresponding output value, which satisfies all the given conditions [11]. The variables in the input vector to the DT are called predictors and the final decision value is called the target. Constructing the DT from training data is thus the process of finding a correlation between predictors and targets depending on a certain set of data. Any DT can be converted into a number of rules where the different paths are followed to reach a final leaf starting from the root. When new predictors are applied to the DT, the roles will be tested at each node to select the suitable branch until the final leaf is reached and thus the target value.

Normally, the database is formulated to represent all the possible operating cases and, as a result, extremely large DT is often produced. However, it is more practical to create the smallest possible tree, which still accurately classifies the training data [12]. This is aimed not only to simplify the resulting set of rules but also to diminish the possibility of overfitting [12]. For this reason, the DT is commonly prunes by removing some branches from the structure and converting the corresponding nodes to leaves [12].

B. Creating the Knowledge Base

To create the required knowledgebase, a large number of patterns are extracted from the GA-based optimization process. Results corresponding to eight load curves are applied to create the DT, while results regarding the other two curves are kept for testing the trained DT. Different tariffs are used with each load curve resulting in about 60000 patterns in the training phase and about 15000 patterns in the test phase.

The predictors comprise 54 variables, while the target setting value is represented by a single variable representing the optimal setting for the next time interval. The predictors include two different natural gas tariffs for supplying the fuel cell and the thermal load and two different tariffs for purchased and sold electricity. In addition, information about the load demands in the past and at the present intervals as well as the expected values in the next time intervals is included. According to our experiences, the incorporation of load demand in the time range of ±3 hours back and ahead is sufficient to achieve acceptable results. Therefore, electrical and thermal load demands during the last three hours and prognoses in the next three hours are contained in the predictors.

C. Constructing the decision tree

Constructing the DT to fit the relation between the predictors and the targets is accomplished with the help of the MATLAB toolbox. Due to the large size of the database, the DT involves a total number of 2454 terminal nodes. The quality of the classification rules is evaluated by applying some sets of the same predictors to the tree and comparing the outputs with the optimal targets. Fig. 5 shows an example of these comparisons where the DT succeeded to provide high accuracy in defining the correct settings of the fuel cell through one day under certain circumstances.

Despite this high accuracy, the large size of the tree gives the opportunity for overfitting. Pruning the tree simplifies the rule base and improves the generalization performance.

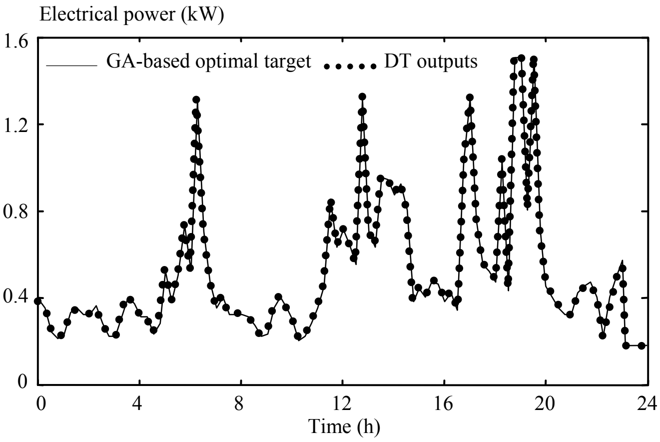

Fig. 5. A comparison between the GA-based optimal target and DT outputs

D. Pruning the decision tree

A DT constructed from a large training set usually fits the data until all leaves contain information for a single class [11]. Hence, many branches in the DT are specified only for this particular data and can not provide general underlying relationships. Such branching is not likely to take place under new situations, which results in poor performance with new unobserved cases. Removing these unreliable branches via the pruning process can achieve better classification over the expected operating space [11]. Thus, the pruning process, denoting the replacement of some nodes and the underlying branches by leaves, is required for reliable and robust operation of DTs under new cases. It is convenient to consider the full tree as a reference measure when evaluating the accuracy of the pruned tree.

The best pruned tree is selected based on evaluating the average daily cost regarding about 81 new cases, which are not used to create the DT. The average percentage increase in the daily operating cost is illustrated in Fig. 6 for different pruning levels considering the full tree as a reference measure. From this figure, the best pruning level can be defined as 1149 which represents about 47% reduction in the full tree size without significant change in the accuracy (about 0.0156% increase in the average daily cost).

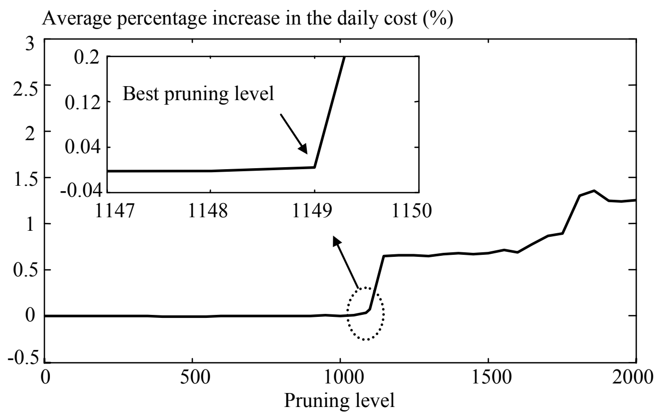

Fig. 6. Average percentage increase in the daily operating cost for the different pruning levels considering the full tree as a reference measure

The performance of the pruned tree is evaluated using the two new load curves that are not used in creating the DT under different operating tariffs. Figs. 7 through 10 show comparisons between the GA-based optimal settings as a target and the output from the DT for four selected cases out of 162 investigated cases. The first two cases belong to one load curve but under different operating tariffs, while the other two cases belong to the other load curve also under two different operating tariffs.

The optimal setting values vary within the day according to the electrical and the thermal load demands, which are not given in the figures to better clarify the comparison. The coincidence between the DT-based settings and the optimal ones confirms the robustness of the proposed approach. In all cases, the DT classifier shows a high capability of identifying settings for the fuel cell very close to the optimal ones.

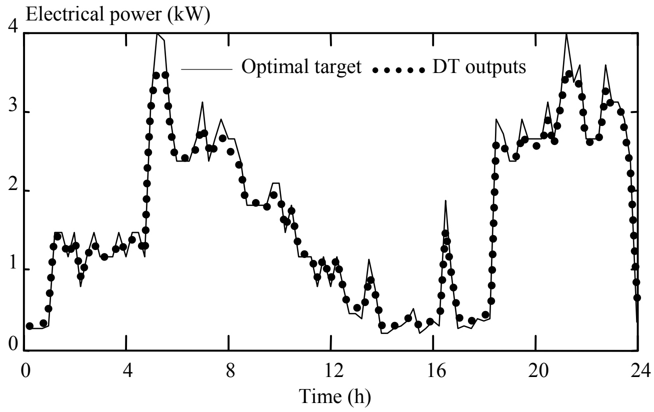

Fig. 7. A comparison between the optimal target and the PDT output: case 1

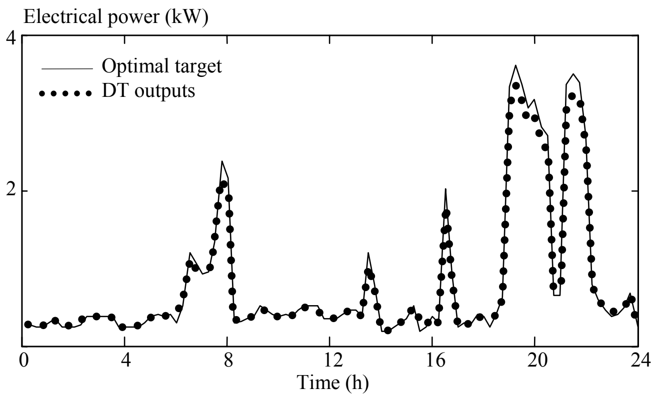

Fig. 8. A comparison between the optimal target and the PDT output: case 2

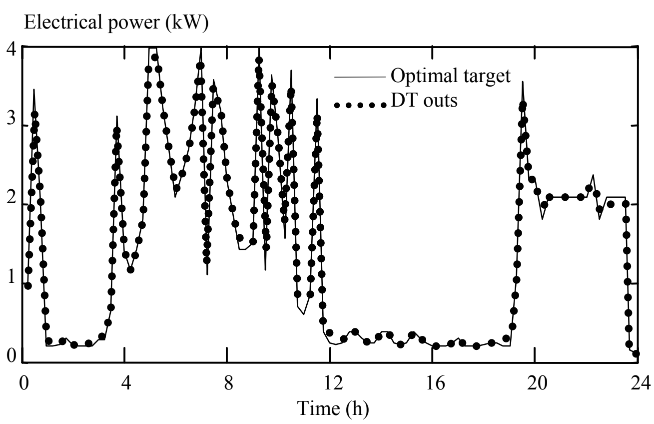

Fig. 9. A comparison between the optimal target and the PDT output: case 3

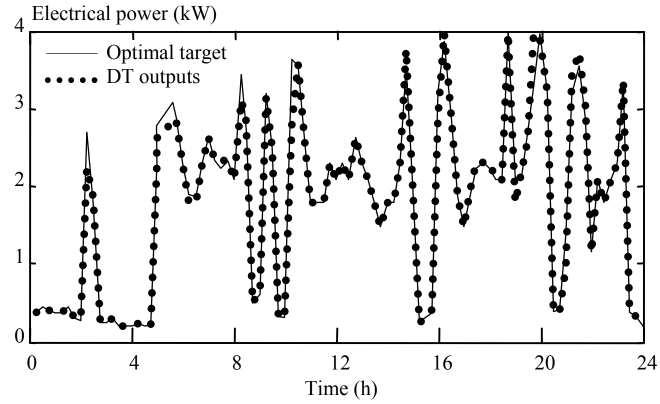

Fig.10. A comparison between the optimal target and the PDT output: case 4

IV. Decision Trees Versus ANN

Both the ANN and the DT can provide the required general frame to implement the proposed approach in the online mode. Their high accuracy and generalization capability have been proven through the results introduced in this paper and the previous one [5]. Compared with the ANN, DTs learning time is much smaller and, hence, they are more suitable for frequently-requisite training [13, 14]. At the time where the DTs are sequential in nature, the ANNs depend on parallel processing in the training [11]. ANN continually tests the whole training data for updating its weights [8, 9]. Conversely, the DT learning is accomplished by dividing the training data into smaller subsets and testing the subsets separately [11].

So far, there is no definitive evidence to prefer one of the two approaches on the other. However, ANNs are generally more likely to give better results for highly nonlinear problems since DTs approximate the nonlinear behaviour with a set of linear relations. On the other hand, the nature of the DTs makes them much more practical for data interpretation than ANN [11].

A comparison between the performance of the ANN and the DT to handle the current problem is carried out based on the average daily cost of the 162 new cases. These cases are related to the two new load curves at different operating tariffs. The results of this comparison are illustrated in Fig. 11.

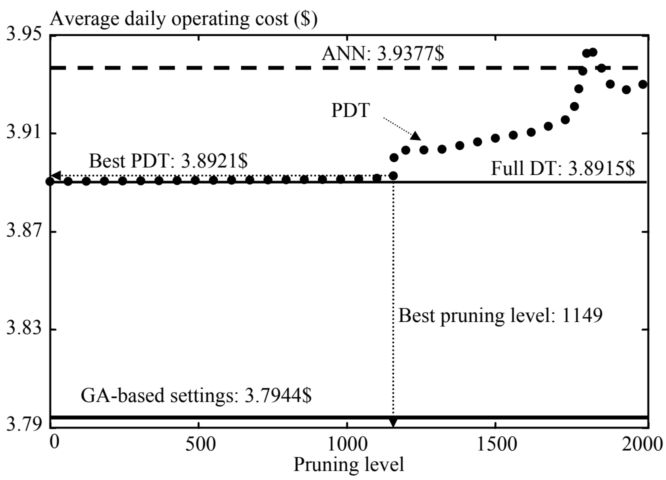

Fig. 11. Average daily operating cost with the GA-based settings, ANN-based settings and DT-based settings at different pruning levels

The comparison is shown for the GA-based optimal settings, the ANN-based settings, the full DT-based settings and the Pruned DT-based settings (PDT). The comparison indicates that the DT can be better than the ANN if the pruning level is lower than 1790. Once again, the best pruning level is 1149, which confirms the previous results shown in Fig.6. With this pruning level, the DT somewhat outperforms the ANN in this application.

Table 1 gives the average daily cost in $/day and the average difference of the quasi-optimal settings with respect to the GA-based optimal values. From these results, it is obvious that following the settings from the ANN or the DT will not cause a significant increase in the average daily cost compared to the GA optimal ones. It is also clear that the DT is slightly better than the ANN but the latter still gives good results close to the optimal values.

Table 1. Average cost and the average difference of the quasi-optimal settings with respect to the GA-based optimal values

	Average cost ($/day)	Average difference with respect to the optimal case	
		Average difference in $/day	Average percentage difference
GA-based settings	3.7944	0	0%
ANN-based settings	3.9377	0.1433	3.7766%
DT-based settings	3.8915	0.0971	2.5590%
PDT-based settings	3.8921	0.0977	2.5748%

V. Conclusion

In this paper, an intelligent approach is introduced to enable the online management of fuel cell when used to supply residential loads. It has been demonstrated that a DT trained with a suitable database is able to define the optimal settings of the fuel cell under different operating conditions avoiding the repetitive optimization process. The DT is trained using a knowledgebase extracted from a GA-based optimization for different load curves and under various operating conditions. The full DT is pruned to increase its generalization capability, where the best pruning level is selected by evaluating the overall performance under a variety of operating conditions. The performance is compared with that of an ANN as an alternative to the DT. Both methodologies succeeded to provide high accuracy even with new unobserved cases.

The results show that the DT can be better than the ANN for this application if a suitable pruning level is selected. However, the ANN will give better results if the DT is pruned beyond a certain level. In all cases, the reduction achieved in the daily operating cost and the conformity of the outputs with the optimal settings defined by the GA-based optimization approve the validity of the proposed approach. This approach can also be employed with other types of small modular distributed generating units.

VI. 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] Bruno Delfino, "Modelling of the integration of distributed generation into the electrical system", Power Engineering Society Summer Meeting, 2002 IEEE, Chicago USA, Volume: 1, 21-25 July 2002, Pages:170 - 175
[3] M. W. Ellis, M. R. Von Spakovsky, D. J. Nelson, "Fuel cell systems: efficient, flexible energy conversion for the 21st century", Proceedings of the IEEE, Volume: 89 Issue: 12, Dec 2001, Page(s): 1808 –1818
[4] M. C. Williams, "Fuel cells and the world energy future", Power Engineering Society Summer Meeting, 2001. IEEE, Volume: 1, Page(s): 725
[5] Ahmed M. Azmy, and István Erlich, "Online Optimal Management of PEM Fuel Cells Using Neural Networks" Accepted for further publication in the Power Delivery, IEEE Transactions on
[6] K. Mei, S. M. Rovnyak, "Response-based decision trees to trigger one-shot stabilizing control" Power Systems, IEEE Transactions on, Volume: 19, Issue: 1, Feb. 2004, Pages:531 – 537
[7] E. S. Karapidakis, N. D. Hatziargyriou, "Online preventive dynamic security of isolated power systems using decision trees" Power Systems, IEEE Transactions on, Volume: 17, Issue: 2, May 2002, Pages:297-304
[8] 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
[9] S. Mishra, P. K. Dash, P. K. Hota, and M. Tripathy, "Genetically optimized neuro-fuzzy IPFC for damping modal oscillations of power system", Power Systems, IEEE Transactions on, Volume: 17, Issue: 4, Nov 2002, Page(s): 1140 –1147
[10] 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
[11] S. R. Safavian, D. Landgrebe, Systems, Man and Cybernetics, "A Survey of Decision Tree Classifier Methodology" IEEE Transactions on ,Volume: 21 , Issue: 3 , May-June 1991, Pages:660 - 674
[12] Almuallim, Hussein, "An efficient algorithm for optimal pruning of decision trees" Artificial Intelligence, Volume: 83, Issue: 2, June, 1996, pp. 347-362
[13] L. Atlas, et. al., "A performance comparison of trained multilayer perceptrons and trained classification trees," Proceedings of the IEEE, vol. 78, No. 10, 1614-1619 (1990).
[14] L.O. Hall, X. Liu, K.W. Bowyer, R. Banfield, "Why are neural networks sometimes much more accurate than decision trees: an analysis on a bioinformatics problem", Systems, Man and Cybernetics, 2003. IEEE International Conference on, Volume: 3, 5-8 Oct. 2003, Pages:2851-2856

VII. BIOGRAPHIES

Ahmed M. Azmy (1968) was born in El-Menoufya, Egypt. He received the B.Sc. and M.Sc. degrees in electrical engineering from the El-Menoufya University, Egypt in 1991 and 1996, respectively. Since 1992, he has been with the Power Engineering and Electrical Machines Department, Faculty of Engineering, University of Tanta, Egypt. He started his Ph.D. in the university Duisburg-Essen, Germany in 2001 supported by an Egyptian government scholarship. His Ph.D. thesis focuses on the Modelling and Intelligent management of Interconnected Decentralized Power Generating units

Mohd R. Mohamed (1977) was born in Kelantan, Malaysia. He received his Diploma in Electrical Power in 1998 from Mara University of Technology in Malaysia. He then continued his study in B.Eng. Electronics in University of Warwick, United Kingdom which was awarded the degree in 2001. Knowing that his interest more in electrical power, he then started his Master in Electrical Engineering (Power) at University College of Technology Tun Hussien Onn (KUiTTHO) in Malaysia and was attached at University of Duisburg-Essen, Germany in 2004 to do his Master project thesis which supported by his employeer, University College of Engineering & Technology Malaysia (KUKTEM). He is now working as an academic staff at KUKTEM and member of KUKTEM's Electrical Power Focus Group.

Istvan Erlich (1953) received his Dipl.-Ing. degree in electrical engineering from the University of Dresden/Germany in 1976. After his studies, he worked in Hungary in the field of electrical distribution networks. From 1979 to 1991, he joined the Department of Electrical Power Systems of the University of Dresden again, where he received his PhD degree in 1983. In the period of 1991 to 1998, he worked with the consulting company EAB in Berlin and the Fraunhofer Institute IITB Dresden respectively. During this time, he also had a teaching assignment at the University of Dresden. Since 1998, he is Professor and head of the Institute of Electrical Power Systems at the University of Duisburg/Germany. His major scientific interest is focused on power system stability and control, modelling and simulation of power system dynamics including intelligent system applications. He is a member of VDE and IEEE.