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Fuzzy subtractive clustering technique applied to demand response in a smart grid scope

R. Pereira[a,b], A. Fagundes[b], R. Melício[a,c,*], V.M.F. Mendes[a,b], J. Figueiredo[a,c], J.C. Quadrado[b]

[a]Universidade de Évora, Department of Physics, 7004-516 Évora, Portugal
[b]Instituto Superior de Engenharia de Lisboa-ISEL, R. Conselheiro Emídio Navarro 1, 1959-007 Lisboa, Portugal
[c]IDMEC/LAETA, Instituto Superior Técnico, Universidade de Lisboa, 1049-001 Lisboa, Portugal

Abstract

This paper focuses on demand response in a smart grid scope using a fuzzy subtractive clustering technique for modeling demand response. Domestic consumption is classified into profiles in order to favorable cover the adequate modeling. The fuzzy subtractive clustering technique is applied to a case study of domestic consumption demand response with three scenarios and a comparison of the results is presented. The demand response developed model intends to support consumer´s decisions given a compromise between the consumption imperative needs and possible economical benefits due to reshape and reschedule.

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Keywords: Fuzzy subtractive clustering; demand response; smart grid

1. Introduction

Demand side management incorporate techniques such as energy efficiency, energy conservation and demand response (DR). DR is necessary to suitably shape the load consumption diagram [1] by consumer active role. Which is crucial for grid management in smart grids in order to contribute for a better balance between electric energy generation and usage, changing the load diagram profile? Requirements of time-scheduling or load shedding are improved when consumer performs an active role in demand side management strategy.

* Corresponding author. Tel.: +351-266-745-372; fax: +351-266-745-394.
E-mail address: ruimelicio@uevora.pt

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The DR technique aims to adequate the balance between load and generation, through a convenient shaping of energy usage in some specific time periods which are crucial in what regards the advantage to be with economical benefits. The energy usage shaping is achieved due to a modus operandi that efficiently considers the need to apply time-scheduling or load shedding. The modus operandi is intended not only at lowering expenditures, such as the ones resulting from the need to call expensive utilities, for instance, with peaking power plants in short-time or to avoid building new power plant in order to satisfy future forecasted energy consumption needs in the long-time; but also in case of incapability of avoiding the necessity of new power plants future deployment, then mainly discarding the ones with anthropogenic greenhouse gases emission [2].

In this paper consumer active role in grid management is supported by a DR model developed using a fuzzy subtractive clustering model. The proposed methodology provides a consumer with an intended efficient tool, which allows a technical support to consumer decisions on load management considering consumer consumption priorities and consumption needs along one day in an hourly basis, taking into account not only the associated costs, but also the eventual economical benefits. The effects of consumers' active role in grid management are directly related to the amount of consumers that assumes the referred active role through DR. A desirable massive consumer adherence to DR leads to a consumption pattern definition for the model implementation. This consumption pattern justifies the fuzzy subtractive clustering techniques applied. Although a different approach, supported by neural networks (NN), to define the controller model can be applied. Nevertheless, the NN model implementation of the required data sets characteristics in association with the controllable loads power consumption initial value definition lead to a complex controller design due to the need of a considerably detail for the data sets. As a result of this complexity a considerably more time dispend is introduced in the model implementation in comparison with the time dispend necessary for a fuzzy clustering model.

Fuzzy clustering techniques applied in DR can be found in diverse literature, for instances in [3,4]. In [3] a fuzzy C-means clustering method is used to generate and release interactive response modes for different consumers' types in a multi-agent context, with the purpose of supporting system operator to evaluate the overall system demand-side interactive response capability and promoting the terminal consumer participation. In [4] a fuzzy K-means clustering method is used to identify which costumers under a DR program have similar load consumption pattern with the load curve of system retailer, mainly during peak time periods. The purpose is to enable the system retailer to implement the most economic DR program in order to improve reliability by supply shortage mitigation during peak time periods.

The target of this paper is the domestic consumers. Domestic consumers can be classified accordingly to their consumption profiles by separation into groups. Each group has an equipment priority list of Controllable Loads (CL) to be eventually subjected to a change in the usage of energy, considering the decision based on load satisfaction, available generation capacity and the energy price. Besides that, consumer non-controllable loads are also considered. The paper focuses on DR actions and DR model behavior considering three scenarios: The first scenario is for comparison proposes and refers to a consumption diagram where no planning or restriction to CL connection exists, i.e., no DR model is on consideration; The second scenario refers to a moderate profile and intends to test the proposed DR model, considering changes on available power and energy price during one day period; The third scenario analysis refers to the integration of plug-in electric vehicle in the DR model analyzed on the second scenario. The resulting analysis indicates that if the consumer is concerned with the price, then by a convenient DR a change in energy usage along the day should be expected by rescheduling the CL in a way to be connected on hours where the price is lower. Hence, the issue is on the information to be send to consumers in order for the proper action to be exposed.

The rest of the paper is organized as follows: Section 2 presents demand response as a demand side management strategy and the demand response model characterization and architecture. Section 3 presents the fuzzy subtractive clustering method applied to contingency scenario given by characterization of the DR behavior revealed by the relations between the input and output parameters required for the DR model. Section 4 presents a description and an analysis of the simulated results with and without DR model, considering three scenarios, respectively, indicated by: without DR model, used for comparison proposes; moderate profile under DR model, ideal profile and PEV integration, under DR model. Finally, concluding remarks are given in Section 5.

Nomenclature

m	dimensional space
n	number of data points
P_1^*	first cluster centre potential
P_i	potential cluster centre
P_k*	cluster centre potential value
r_a	cluster radius
x_1^*	first cluster centre location
x_i	data point
x_k*	cluster centre location
k	number of cluster centre
α	parameter related to cluster radius
β	parameter related to cluster radius and squash factor
η	squash factor

2. Demand response model

2.1. A demand side management strategy

The 70s oil shock effects triggered innovative research concerning policies and measures concerning to energy demand. Thenceforward energy efficiency policies and development of DR are on development, with the purpose to influence quantities or patterns of energy [5]. In the 80s, a Demand Side Management (DSM) debate and analyze brought alternatives associated to benefits on load shape resulting from techniques such as: clipping of peaks, shifting of loads to off peak hours, strategic conservation to reduce demand and valley filling of utility's loads, for example [6]. DSM techniques have become more challenging with smart grids due to smart metering in domestic buildings and services and bidirectional communication characteristics.

DR enables load adaptation to the generation essential due to the intermittent characteristic of renewable energy sources incorporated into the electric grid. DR programs are mostly restricted by grids requirements and consumers are driven to adjust the consumption in order to benefit from economical advantages. DR is a program which transfer information with the consumer and either encourages or enables the consumer to decrease or shift energy consumption during periods of inadequacy energy consumption to more adequate ones [7]. DR programs can be characterized by: Time-Based Programs (TBP) and Incentive Based Programs (IBP) [8].

2.2. Characterization and architecture

The proposed DR model is characterized as a TBP, assisting consumer's actions and decisions on load management, considered in this paper as CL management taking into consideration the available power capacity and energy price. The TBP model purpose is to give consumers flexibility and thus allowing exploiting possible economical benefits and enabling the load management, which are more adequate to consumer's life-styles or consumption profiles. Load management performed by consumers is possible throughout methods of load shedding and load time scheduling [9]. The economical benefits are mainly derived from shifting of loads to off peak hours and valley filling of utilities' loads.

The DR model regards that grid power dispatch present hourly information to consumers about available power and energy price. The DR model has the following considerations: available power is assumed as non-constant along the time horizon to capture the behavior of the available distributed generation in order to allow a convenient DR modeling; consumer can deselect priority on a CL with the purpose to allocate available power to the next priority CL; once the succession of CL power sum reaches the total available power, no further CL can be connected. The previous considerations are proposed to give to the consumer a chance to adapt the consumption diagram to what the consumer is predisposed to pay for energy price.

The consumer's operation modes and profiles are derived from the consumption behavior study. The proposed DR model considers the domestic consumer characterized by a middle class family without children. For the daily consumption definition it is considered that family is outside their residence during 10 hours in day time. In addition it is considered for each CL, if applicable, that its complete predefined program has to be accomplished, such as the case of laundry machine, for instance. Any predefined program can be canceled or interrupted. The family has adopted a CL priority list of to be followed, which was chosen according to its consumption needs and consumption profiles.

The referred consumption behavior study is intended to capture what is said as the definition of the consumption pattern. Three consumer profiles are defined to guarantee the coverage of DR model generalization and support consumers to deal with price adjustments over one day. These three consumer profiles are denominated as: economic, moderate and extravagant. Two operation modes respectively denominated as cleaning and comfort are considered and both operation modes are applied on each consumer profile.

As an example consider that a CL priority list is common to the three profiles, i.e., assume that the consumer list is due in response to requirements independently of the selected profile. In addition, consider the same common CL priority list for the three profiles assisting a DR comparison analysis for different operation scenarios. The consumer profile for instance can be organized in a CL priority list as shown in Table 1 [9].

The economic profile is established to permit the CL use only when the energy price is low. The moderate profile is established to permit the CL use when energy price is low or medium and in extravagant profile any CL could be used independently of energy price. The requirement of pattern recognition in association with a control which assists consumers' decisions for DR model design is satisfied using fuzzy subtractive clustering method. The controller is accomplished in the Fuzzy Logic Toolbox, available in Matlab-Simulink software. The DR model scheme is shown in Fig. 1.

Table 1. Controllable load priority list for cleaning mode

Economic profile	Moderate profile	Extravagant profile
	1 Dishwasher	
	2 Washing machine	
	3 Dry Machine	
	4 Air Conditioner	
	5 Thermo ventilation	
Low price	Low or medium price	Low, medium or high price

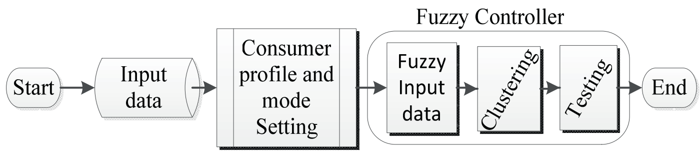

Fig. 1. Demand response model scheme.

The input data is taken from one residence with 6.9 kVA of installed power. The CL are air conditioner and home appliances and with the nominal reference power specified in [10]. The model input data considers CL available active power, consumption stages and energy price, i.e., the reactive power is not considered. Two consumption stages are considered respectively null or reference nominal power. For instance, considering the air conditioner, the consumption stages are off power or full power, which is 1.8 kW. Yet, for any other different consumption stages introduced as input data, this model remain valid. The model considers a power range between 1.8 kW and 6.9 kW, respectively given by the CL lower value and the installed electric power value [9].

3. Fuzzy subtractive clustering technique

Data clustering techniques can be considered a method for finding similarities in data sets and grouping similar information [11]. These groups consist on information points represented by cluster centers. It is expected that similarity among information points of a certain group represented by a cluster center is superior to the similarity of other information points represented by different cluster centers. In this paper the data sets are characterized by information points which copy the DR behavior. Considering the clustering techniques presented in [11], it is considered that for propose accomplishment of a fuzzy controller design which assure a standardized DR behavior, the subtractive clustering is one of the most adequate techniques to be applied. Mainly because it enables a controller design where the adjustment are performed into the predefined input data [11].

The necessary DR behavior is characterized by performing relations between the input and output parameters required for the DR model and are standardized in an Excel data sheet. For the DR behavior characterization in a fuzzy controller, data clustering technique is applied. Given an input, available in the Excel data sheet, data clustering seizes the pattern in it and gives the outputs. The outputs are cluster centers matching to the pattern, which can be applied in a fuzzy controller. Each cluster centre includes twelve elements. A total of 7 inputs are considered, referring to 5 CL consumption states required by the consumer, the energy price and the available power, and 5 outputs are given by the 5 CL states [9].

Data clustering techniques are required in order to adequately define the fuzzy controller, because otherwise it revealed that a large amount of fuzzy rules were necessary to conveniently define the fuzzy controller.

Fuzzy clustering consists on a planned distribution of the data space into fuzzy clusters [9]. Each fuzzy cluster is introduced in order to perform the convenient representation of one specific part of system behavior. After projecting the clusters on the input space, the antecedent parts of the fuzzy rules can be established [12].

The subtractive clustering technique is an expansion of the mountain clustering method based on data sets calculated using mountain function resulting in cluster centers. This technique operates on a collection of n data points in an m-dimensional space and stars by setting each data point x_i as a potential cluster centre with a defined potential as function of the Euclidian distances of all data points. This function specifying the potential at x_i, is given by:

$$P_i = \sum_{j=1}^{n} e^{-\alpha \, || \mathrm{x_i} - \mathrm{x_j} ||^2} \tag{1}$$

where α is a parameter given by:

$$\alpha = 4 / r_a^2 \tag{2}$$

In (2), r_a is the cluster radius, determining a hyper sphere of data points with relevant influence on the cluster centre potential in order to be accepted as neighbors. The r_a value has a strong effect on the numbers of the induced clusters. Three observations about this value are in order: a data point exterior to a neighborhood of radius r_a has minor influence on the potential of the neighborhood centre data point; a superior value for r_a usually results in a generation of a small number of clusters and consequently a model too generalized; while a low value can imply an excessive generation of clusters and consequently a model that has not sufficient generalization [13]. The r_a values are chosen in order to insert an adequate quantity of clusters which are associated to the resulting number of fuzzy rules. The r_a parameter can be fitted based on the desired model complexity and generalization capacity. In this paper the assessment of r_a values, by trial and error as result of multiple simulation analysis, led to a rule number which allows both a satisfactory control action and a satisfactory model time response. Accordingly, no main substantial advantage is for seen to be achieved in this case with improved mathematical methods or optimization methods applied on the r_a assessment. The estimated values for r_a and the corresponding numbers of fuzzy rules are shown in Table 2.

Table 2. r_a values and number of fuzzy rules for cleaning mode

	Consumption profiles		
	Economic	Moderate	Extravagant
Cluster radius	1.5	1.4	1.5
Number of fuzzy rules	7	14	9

The subtractive clustering technique after calculate all the data point potentials, using the expression (1), identifies the first cluster center as the data point with the highest potential. Afterward, the potential of the data point is re-evaluated using the assignment given by:

$$P_i \Leftarrow P_i - P_1^* e^{-\beta \| x_i - x_1^* \|^2} \tag{3}$$

In (3) P_1^* and x_1^* are the first cluster centre potential value and centre location, respectively, and β is a parameter given by:

$$\beta = 4/(\eta\, r_a)^2 \tag{4}$$

In (4) η is the squash factor that sets the neighbourhood of data points that will have significant measurable reduction in the potential value. In general, a value of $\eta = 1.5$ is an appropriate choice.

After the first cluster centre has been determined and all the potential of the data points have been re-evaluated using the procedure given by assignment (3), the data point with the highest potential is chosen as the second cluster centre. Usually, after k^{th} cluster centre has been obtained, the potential of each data point is re-evaluated using the assignment given by:

$$P_i \Leftarrow P_i - P_k^* e^{-\beta \| x_i - x_k^* \|^2} \tag{5}$$

In (5) P_k^* and x_k^* are the k^{th} cluster centre potential value and centre location, respectively. A more wide explanation of details about the subtractive clustering technique used in this paper can be found in [13].

Based on the chosen cluster centres fuzzy rules are determined. The consideration presented in the model described in Section 2 and the data sets to be applied to the subtractive clustering technique are implemented in Excel. Each profile and corresponding operation modes have an appropriate data set. A file with Matlab extension .m is created, where the function *genfis2* accomplish the subtractive clustering technique on the data sets. After that the Matlab function fuzzy is applied, which allows adjusting the created clusters into if-then rules, determining the fuzzy control saved in a file with Matlab extension .fis.

4. Scenarios analysis

There scenarios are considered as a case study to illustrate how the fuzzy subtractive clustering technique applied to DR determines a reshape and a reschedule of the load consumption of a consumer.

4.1 Without DR model

The first scenario is a control scenario in accordance with: If the consumers is at home and wake the power consumption is only limit by the 6.9 kVA. Otherwise, the consumption is base power consumptions, i.e., minimum power value of non-controllable load consumptions. The power consumption is shown in Fig. 2.

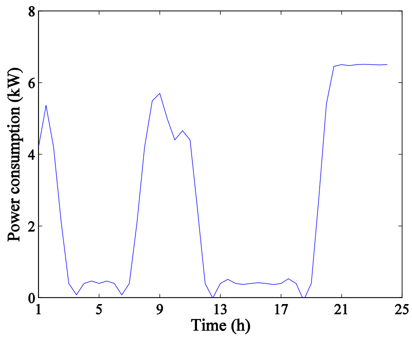

Fig. 2. Power consumption of consumer without DR model.

This scenario is intended for comparison purpose between the consumption diagram where no planning or no restriction to CL connection exists and a consumption diagram resulting from the DR modeling.

4.2 *Moderate profile under DR model*

The second scenario is the moderate profile with a cleaning operation mode subjected to the DR modeling. Accordingly, the consumer is concerned with the price, because the price changes along the day. The base power consumption, available power, price, and power consumption for the moderate profile are shown in Fig. 3.

a b

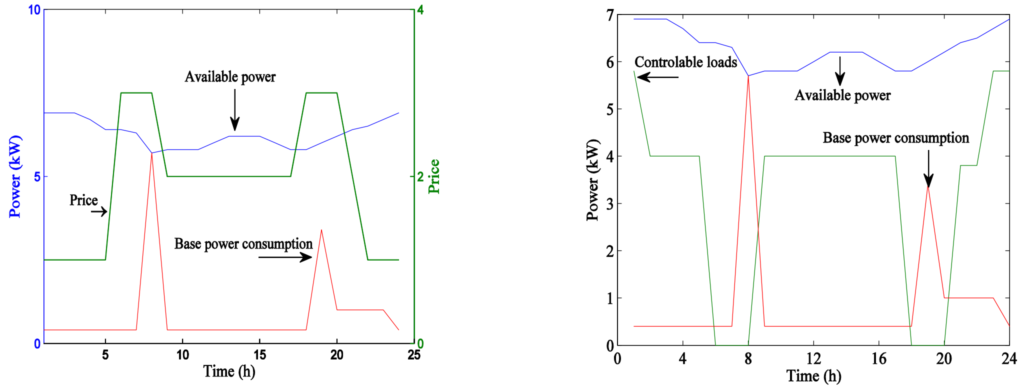

Fig. 3. (a) Base power consumption, available power and price; (b) Power consumption for moderate profile.

A comparison with Fig. 2 shows the influence of price on consumer consumption, accommodating reschedules on CL in order to adequate the consumption profile.

4.3 *Ideal profile and PEV integration, under DR model*

The third scenario is an addition of PEV in a scenario resulting from a combination of the three available profiles, considering the same cleaning operation mode. This combination of economical, moderate and extravagant profiles is made in order to allow consumers to take advantage of the DR model, assuring that the same consumption profile where no planning or restrictions to CL connection exists, can be implemented in the DR model. PEV is assumed as non CL because it is considered that the batteries are on charge between 10 p.m and 04 a.m where the price assumes lower values. The base power consumption, available power, price, and power consumption for the ideal profile are shown in Fig. 4.

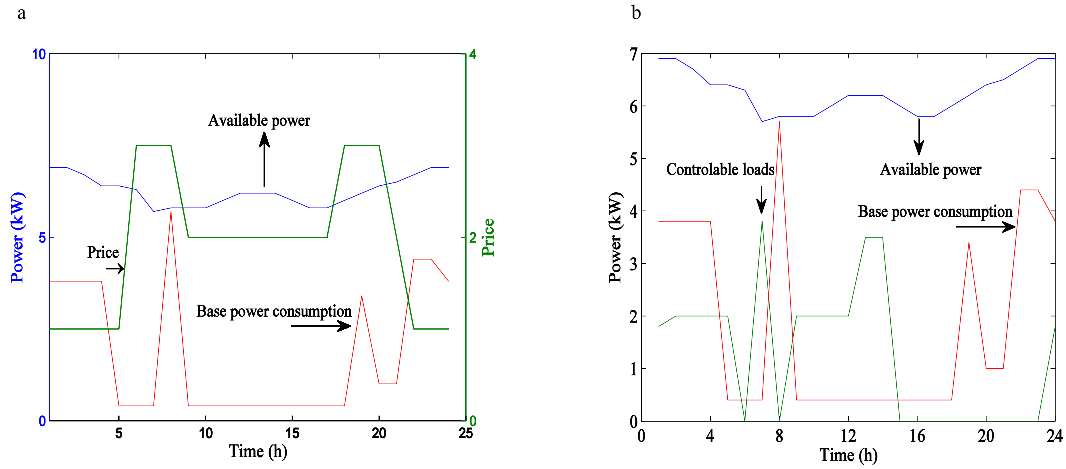

Fig. 4. (a) Base power consumption, available power and price considering PEV; (b) Power consumption considering PEV.

A comparison between Fig. 3b and Fig. 4a shows that the power consumption increases when the batteries are on charge. Even considering a more exigent consumption profile the power consumption value remains inferior to the available power value.

The Fig. 4b shows that the priority list defined for CL in the ideal profile is modified because consumer is limited on the CL power consumption value.

5. Conclusion

Consumers are able to evidence flexibility to reshape and reschedule consumption when data on energy price or available power are given in order to be taken into account in due time in a smart grid scope. But in order to take the most appropited decision is necessary to have a support DR modeling available for consumers as the modeling proposed in this paper.

The proposed DR modeling is a fuzzy subtractive clustering technique and is a simple one able to ensure that the power consumption is not greater than the available power. The DR modeling is able to allow the consumer to combine the available consumption profiles and operation modes which best fits the consumption needs, taking into consideration the data for the energy price and the available power.

A reshape and reschedule on consumption is presented, showing that the CL priority list is satisfied accordingly to the consumption profile and operation model selected by the consumer. The inclusion of PEV assuming that batteries are charged during the night time again shows that the power consumption is feasible, i.e., the DR modeling conveniently identifies an adjustment on the CL list.

The new consumption diagram is mainly accommodated by the behavior of the energy price, where load shedding and valey filling can be found from the results shown by the DR modeling. The proposed DR modelling can lead to a more efficient grid because the consumption diagram can be conveniently adapted as seen by the comparison between the scenarios of the case study.

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