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Demand Response Analysis in Smart Grids Using Fuzzy Clustering Model

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Abstract. This paper focuses on an analysis of demand response in a smart grid context, presenting the model considerations and architecture. Domestic consumption is divided into groups in order to cover the adequate modeling. A fuzzy subtractive clustering method is applied to demand response on several domestic consumption scenarios and results analyses are presented. The demand response developed model aims to support consumers decisions regarding their consumption needs and possible economical benefits.

Keywords: Demand response, smart grid, fuzzy subtractive clustering.

1 Introduction

The smart grid engages consumer active role. This is crucial for grid management in order to efficiently ensure electric energy generation and usage. For instance, time-scheduling or shedding of load requirements is more favorable when consumer has an active role. Demand Side Management (DSM) such as energy efficiency, energy conservation and Demand Response (DR) programs [1] are required in order to adequate the profile of energy load diagram to generation. DR aims at shaping energy usage in some specified time periods with opportunely economic advantage due to adequate balance between load and generation. The shaping is attained by a modus operandi efficiently taking into account the need to apply time-scheduling or shedding of the load. The modus operandi is intended not only at lowering expenditures, such as the ones resulting from the need to call utilities expensive peaking power plants in short-time or to avoid building new power plant in order to satisfy future forecasted augmented energy consumption needs; but also in case of impossibility to avoid new power plants building, then chiefly discarding the ones with anthropogenic greenhouse gases emission [2]. Already, a European Union program started in 2008 for decreasing the end-user consumption is on effect, aiming to achieve 1 % reduction in energy consumption in the following nine years [3]. Consumers have to be persuaded to adhere to a smart grid environment and be an active element in the smart grid management, implying the necessity to furnish adequate conveniences to take advantage of the capabilities given by smart grid. DR techniques allows the accomplishment of shifting or decreasing the energy usage in several economic

activity sectors, bringing benefits not only to consumers, but also to grid operators due to a reduction in system operation costs [4].

In this paper the consumer's active role in grid management is supported by a DR method developed using a fuzzy clustering model. The developed methodology provides the consumer an intended efficient tool which allows to support consumer decisions on load management regarding their consumption needs and consumption priorities along one day, taking into consideration the associated costs and possible economical benefits. The desirable massive consumer adherence to DR actions justifies a consumption pattern definition for the model implementation. This consumption pattern justifies the fuzzy clustering techniques applied.

This paper focuses on DR actions and modeling, giving details and results analysis. Domestic consumers are the target of the paper and are divided accordingly to their consumption profiles into three groups. Each group has an equipment priority list of Controllable Loads (CL) to be accomplished, considering for the decision on load satisfaction the available generation capacity and the energy price. Also, consumer non-controllable loads are considered.

The rest of the paper is organized as follows: Section 2 presents the contribution to innovation on DR involving research and customization of programming techniques. Section 3 presents aspects about DSM and DR. Section 4 presents DR model case study main assumptions. Section 5 presents the fuzzy subtractive clustering method to be applied to consumption scenarios. Section 6 presents results analysis based on the scenarios. Finally, concluding remarks are given in Section 7.

2 Relationship to Internet of Things

Internet of Things (IoT) is a name conceived to accommodate an extension of the web paradigm in order to consider the connection, monitoring and control of devices: things of everyday life [5].

The smart grid characteristics [6], the expectation to spread intelligence and control from some central core over peripheral nodes on electric energy usage entails the need to research, test and customize computing techniques for DR analysis, enabling opportune interfacing management of energy usage [5].

The DR analysis in this paper is on a line of technological contributions tied with the IoT aptitude to: (i) collect data on energy usage, (ii) provide this data to other participants on local utility grid, and (iii) get energy prices information [7].

3 Demand Side Management and Demand Response

The oil shocks of the 1970s brought a new research concerning policies and measures targeting energy demand. Since then development of DR and energy efficiency policies are on the way, aiming to influence quantities or patterns of energy [8]. A discussion and analyze DSM appeared in 1985 with alternatives related to load shape benefits derived from techniques concerning, for instance: valley filling of utility's loads, clipping of peaks, shifting of loads to off peak hours, strategic conservation to

reduce demand [9]. DSM became more ambitious with smart metering in domestic buildings and services and bidirectional communication provided in smart grids.

DR allows load adaptation to the generation; this adaptation is important due to the intermittent characteristic of renewable energy sources integrated into the electric grid. DR programs are mainly conditioned by grids requests and consumers have to adapt the consumption in order to take advantage of economical benefits. DR is defined as any program which communicates with the consumer and either enables or encourages the consumer to lower or shift energy consumption during periods of unfavorable energy prices to favorable periods [10]. DR programs can be divided into: Incentive-Based Programs (IBP) and Time-Based Programs (TBP) [11].

4 Demand Response Model Case Study

The proposed model is a TBP one, aiming to support consumer's decision and actions on load management also referred as CL management, taking into consideration the available power capacity and energy price. This TBP model intends to give consumers flexibility in order to take advantage of economical benefits allowing the load management that best fits consumer's profiles or life-styles. Consumers load management is possible throughout methods of load time-scheduling and load shedding. The economical benefits mainly come from valley filling of utilities' loads and shifting of loads to off peak hours.

The model assumes that grid power dispatch provides hourly information to consumers about available power and energy price. The assumptions considered in the model are the following: available power is considered non-constant along the time horizon to emulate available distributed generation behavior and consequently allowing a convenient DR modeling; consumer can deselect priority on a CL in order to allow available power to the next priority CL; once the in progress power sum of CL reaches the total available power, no further CL can be connected. These assumptions are intended to give to the consumer an opportunity to adapt the consumption diagram to what the consumer is willing to pay for energy price.

The consumers' profiles and operation modes were obtained from analysis of consumption behavior that allowed a consumption pattern definition. Three consumer profiles were set to ensure the coverage of DR generalization on the model and help consumers cope with price changes over one day period. These three consumer profiles were designated as follows: economic, moderate and extravagant. Two operation modes designated by cleaning and comfort are set for each consumer profile. An example of a priority list is shown in Table 1. In table 1 the CL priority list is the same for the three profiles because it guarantees that consumer decision is obeyed independently of the selected profile, regarding the energy price. For example, if economical profile is selected but for one time period the energy price is superior to the one allowed for the economical profile, consumer can change his profile to moderate, keeping the same CL priority list but with increased costs. Also, a common CL priority list to the three profiles allows a DR model comparison analysis for the scenarios considered in this study.

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

The economic profile is set to allow only the use a CL when the energy price is low. The moderate profile is set to allow the use a CL when energy price is low or medium and in extravagant profile any CL could be used independently of energy price. The necessity of pattern recognition associated with a control which supports consumers' decisions for DR model design is fulfilled using fuzzy clustering method. The controller is implemented in the Matlab-Simulink[®] software resorting to the Fuzzy Logic Toolbox.

The demand response model is shown in Fig. 1.

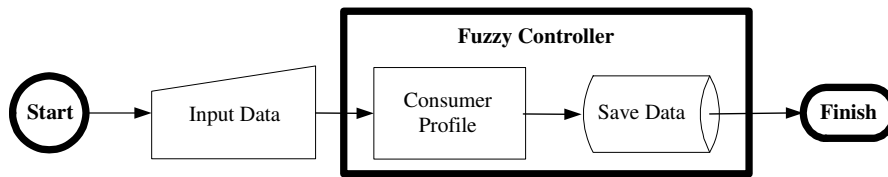


Fig. 1. Demand response model.

The input data was set considering one residence with 6.9 kVA of installed power and the CL are home appliances and air conditioner with nominal reference power given in [12]. The model input data are chosen considering CL consumption stages, available power and energy price. The reactive power is neglected.

The consumption stages assumed are the null power or the reference nominal power, i.e., for the air conditioner the consumption stages are off power or full power, which is 1.8 kW. Nevertheless, the model is valid for any other consumption stages introduced as input data. The model is applied considering a power range between 1.8 kW and 6.9 kW, respectively given by the CL lower value and the installed electric power value.

5 Fuzzy Clustering Model

The required DR behavior is standardized in an Excel sheet by creating relations between the input and output parameters desired for the DR model. In order to represent the DR behavior in a fuzzy controller, data clustering technique was used. Given an input, available in the Excel data sheet, data clustering apprehends the pattern in it and gives the outputs. The outputs are cluster centers corresponding to the

pattern, which can be utilized in a fuzzy controller. Each cluster center is composed by twelve elements. A total of 7 inputs are considered. These inputs are given by: 5 CL consumption states required by the consumer, the energy price and the available power. And 5 outputs given by the 5 CL states.

Data clustering techniques are necessary due to the fact that otherwise the required number of rules is a large number in order to acceptably define the fuzzy controller. Fuzzy clustering consists on a strategic division of the data space into fuzzy clusters. Each fuzzy cluster is introduced in order to stand for the convenient representation of one specific part of system behavior. After projecting the clusters onto the input space, the antecedent parts of the fuzzy rules can be found [13].

The subtractive clustering technique is an extension of the mountain clustering method based on data sets evaluated using mountain function resulting in cluster centers. Accordingly to this technique, given a collection of n data points in an m -dimensional space, the technique starts by setting each data point x_i as a potential cluster center with a defined potential in function of the Euclidian distances of all data points. This function, specifying the potential at x_i , is given by

$$P_i = \sum_{j=1}^n e^{-\alpha \|x_i - x_j\|^2}. \quad (1)$$

α is a parameter given by,

$$\alpha = 4/r_a^2. \quad (2)$$

r_a is the cluster radius, setting a hypersphere of data points with significant influence on the cluster center potential in order to be acknowledged as neighbors.

The r_a value has a strong effect on the numbers of the generated cluster. Three observation about this value are in order: a data point outside a neighborhood of radius r_a has little influence on the potential of the neighborhood center data point; a higher value for r_a generally results in a generation of few clusters and therefore a model too generalized; while a low value can lead to an excessive generation of clusters and therefore a model that has not enough generalization [14]. The r_a values were chosen in order to introduce an adequate amount of clusters which are related to the resulting number of fuzzy rules. The r_a parameter can be adjusted based on the required model complexity and generalization ability. In this paper the r_a values determined resulted in a rules number which allowed an adequate control action with an adequate model time response. Hence, it was considered that no major advantages arrived with improved mathematical methods or optimization methods applied on the r_a determination. The values for r_a are shown in Table 2.

The subtractive clustering technique after computing all the data point potentials, using the expression (1), identifies the first cluster center as the data point with the highest potential.

Table 2. Fuzzy rules number and r_a value

Profile	Operation mode	Rules number	r_a
Moderate	Cleaning	14	1.4
	Comfort	10	1.5

Then, the potential of the data point is revised using the assignment given by

$$P_i \Leftarrow P_i - P_1^* e^{-\beta \|x_i - x_1^*\|^2}. \quad (3)$$

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

$$\beta = 4/(\eta r_a)^2. \quad (4)$$

In (4) η is the squash factor defining the neighborhood of data points that will have significant measurable reduction in the potential value. Normally, a value of $\eta = 1.5$ is a good choice. After the first cluster center has been obtained and all the potential of the data points have been revised using the procedure given by assignment (3), the data point with the highest potential is selected as second cluster center. In general, after k^{th} cluster center has been obtained, the potential of each data point is revised using the assignment given by

$$P_i \Leftarrow P_i - P_k^* e^{-\beta \|x_i - x_k^*\|^2}. \quad (5)$$

In (5) P_k^* and x_k^* are respectively the k^{th} cluster center potential value and center location. A description of further details about the subtractive clustering technique employed in this paper can be seen in [14]. Fuzzy rules are defined based on valid cluster centers. The assumptions considered in the model presented in section 4 and the data sets to be submitted to the subtractive clustering technique were implemented in Excel[®]. Each profile and respective operation modes have a proper data set. A file with Matlab[®] extension .m was created, where the function *genfis2* perform the subtractive clustering technique on the data sets. Then the Matlab[®] function *fuzzy* is applied, which allows articulating the created clusters into if-then rules, establishing the fuzzy control saved in a file with Matlab[®] extension .fis.

Other approach, such as neural networks (NN) can be applied to the model controller. However, for the model implementation in NN the required data sets characteristics in association with the controllable loads power consumption initial value definition, revealed a controller design complexity which have leded to considerably more time dispended in this model implementation then with the fuzzy clustering model developed.

6 Results Analysis

Two scenario analyses are performed with and without the DR model, considering a residence with a limited power of 6.9 kVA and with a base power consumption shown

in Fig. 3. The base power consumption represents the consumption of all loads excluding the CL.

The first scenario, shown in Fig. 2, refers to a consumption diagram where no planning or restriction to CL connection exists, i.e., no DR model is on consideration. This scenario considers that, when consumers are at home and awake the consumption is high and limited by the 6.9 kVA, otherwise the consumption values are low and limited by the base power consumption. This scenario is used as a comparison basis between the consumption diagram where no planning or restriction to CL connection exists and a consumption diagram resulting from the DR model.

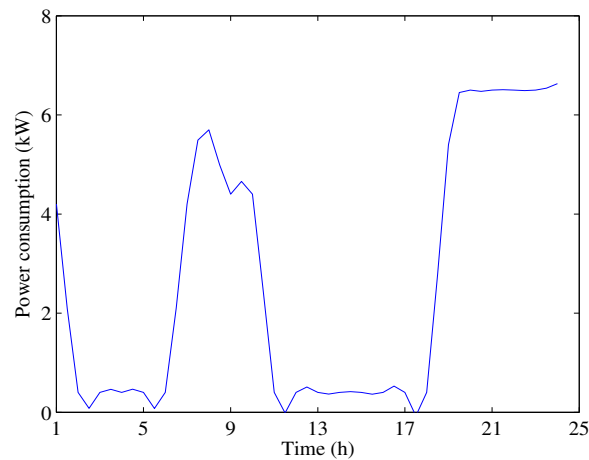


Fig. 2. Power consumption of consumer in first scenario.

The second scenario has data information, shown in Fig. 3, about power and energy prices available in one day period on an hourly basis and consumer selects operation mode accordingly with – when at home and awake, comfort mode is selected, otherwise cleaning mode is selected, considering two hypotheses: i) consumer sets an economic profile; ii) consumer sets a moderate profile.

The input data to simulate the DR model for moderate profile is shown in Fig. 3.

A comparison between Fig. 2 and both DR model responses shown in Fig. 4 and Fig. 5, shows the influence of price on consumer consumption. On Fig. 2 the consumer is not influenced by the price because it is always the same, so the consumer consumes where is more convenient. On the other hand, accordingly to Fig. 4 and Fig. 5, the consumer is concerned with the price because it changes along one day, so the consumer reschedules the CL in a way to be connected on hours where the price is lower. A comparison of responses in the second scenario from hypotheses i), Fig. 4 and ii), Fig. 5, shows for the moderate profile that CL has more favorable conditions to be connected in one day period, than for the economic profile. Hence, the consumer is subjected to a lesser restricted DR due to the higher acceptance of the energy price in moderate profile than in economic profile. The extravagant profile allows the consumer a DR only depending on available power. It can be observed in Fig. 4 and Fig. 5 that DR model guarantees that the sum of base power consumption

with CL consumption power is never superior to the available power. The individual CL power consumption for moderate profile in one day period is presented in Fig. 6.

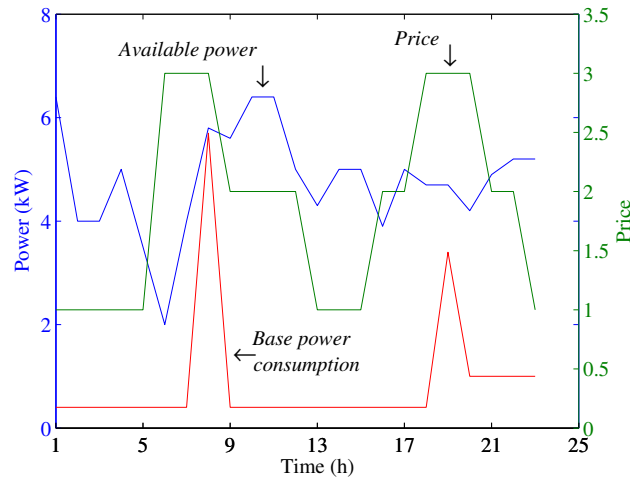


Fig. 3. Base power consumption, available power and price evolution.

Together, both Fig. 3, Fig. 4, Fig. 5 and Fig. 6 allow to confirm that the energy price is satisfactory associated with CL power consumption.

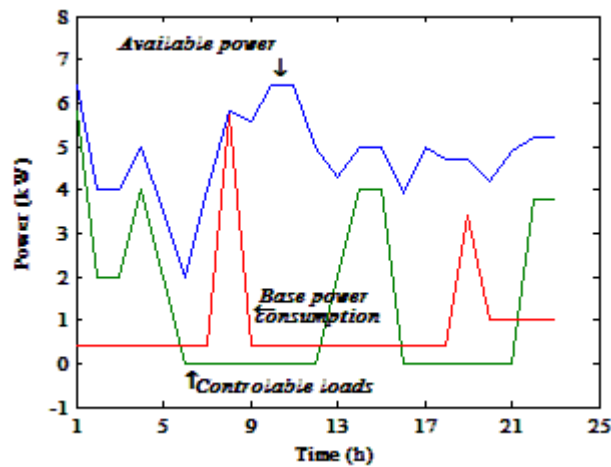


Fig. 4. Power evolution for economic profile.

Both Fig. 3 and Fig. 6 allow to conclude that in the time period between 6 a.m and 8 a.m there is no CL available because the energy price is higher than the energy price assigned to moderate profile. The analysis of Fig. 5 and Fig. 6 allows to conclude that only at 8 a.m there is no sufficient power available to connect any CL. However, regarding the energy price shown in Fig. 3 and taking into account the defined CL priority list shown in Table 1, no CL is connected in the period between 6 a.m and 8 a.m as shown in Fig. 6.

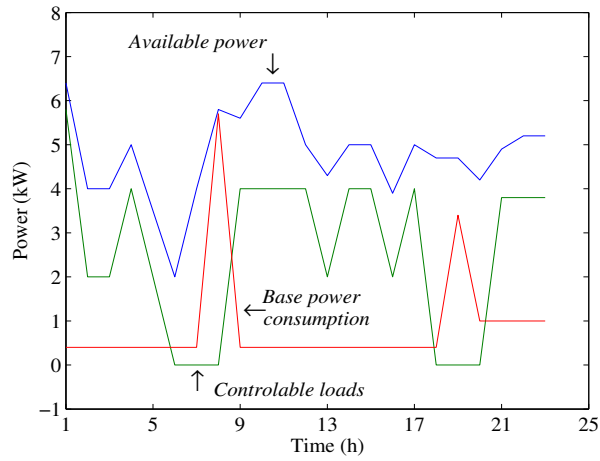


Fig. 5. Power evolution for moderate profile.

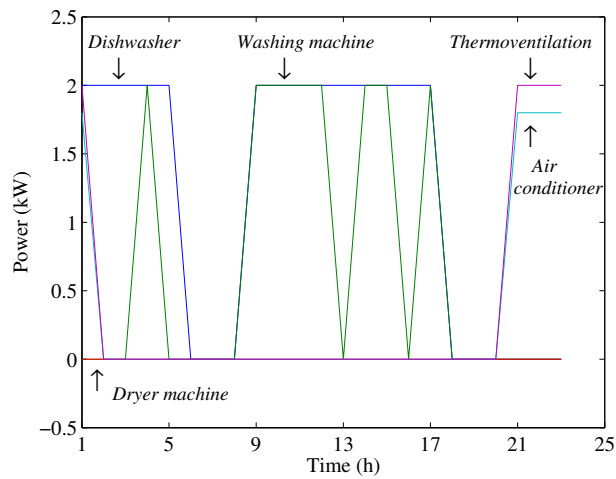


Fig. 6. Controllable loads evolution stage for moderate profile.

7 Conclusion

The proposed model ensures that power consumption is never superior to the available power and that no CL can be connected if energy price is superior to the correspondent energy price assigned to the selected consumption profile.

Consumer is subjected to a lesser restricted DR in moderate and extravagant profiles than in economic profile due to a higher acceptance of the energy price.

The consumption diagram can be shaped by the price changes along one day, which can lead to a more efficient grid because the consumption diagram can be conveniently adapted as it can be seen by comparison between the first and second scenarios, where a flatten diagram is desirable.

Consumer evidences a flexibility on consumption schedule when data on available power and on energy price are to be taken into account in due time. Hence, collecting and providing data on energy usage to participants on local grid, having energy prices information and model development, as the one proposed in this paper, are crucial for IoT to conveniently assist on a successful DR.

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