Energy Consumption Management in Buildings in the Context of Voluntary and Mandatory Demand Response Programs in Smart Grids

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***Abstract*— Energy consumption is increasing around the world and has been made many consequences such as increasing greenhouse emissions, global warming, and climate changes. Demand response programs can be considered as techniques to manage and control electricity consumption based on user flexibility. There are several types of demand response programs that are categorized in price-based programs and incentive-based programs. This paper analyzes real demand response implementations according to a dataset provided by the Federal Energy Regulatory Commission. Real demand response programs are analyzed based on customer type, program type, potential and capability of the programs, and controllable loads. In the case study, an optimization approach is proposed to control the loads and achieve the power reduction goals of the demand response programs. The obtained results show how buildings can be participants in demand response programs, choosing the more advantageous program.**

Keywords*— Data Analysis, Demand Response, Direct Load Control, Energy Management, Optimization.

I. INTRODUCTION

Nowadays the electrical power systems are growing rapidly and the process of controlling them takes a high level of attention from generation to consumption, and this growth is expected to increase by 30% by 2035 [1].

A series of actions have been implemented by many countries to reduce pollution emissions. To mitigate those harmful effects there are some actions have been done such as use filtering technologies for the fossil fuel power plant and integrate renewables energy resources [2]. Other actions had been taken but for the customer side such as demand response programs (DR). Those programs defined as the programs that lead to change the electric usage of the final customers from their normal consumption patterns as a response to the variation of the electricity prices or to the incentive payments from the grid operators or when the stability of the power system is in a critical situation [3]. DR programs are the modification of electricity consumption profiles, which customer is paid by the grid operator due to the several economic or technical reasons [4]. This process got important attention from the regulators therefor "they made efforts in order to make DR a resource comparing to normal resources of generation. It is the order NO. 719 from Federal Energy Regulatory Commission (FERC) in the united states which said ''Accept bids from DR resources in their markets for certain ancillary services on a basis comparable to other resources'', also in the European Union there are regulators had set important changes in this section to be applied and the description of DR according to [3] is as follow "… DR is to be understood as voluntary changes by end-customers of their usual electricity use patterns – in response to market signals (such as time-variable electricity prices or incentive payments) or following the acceptance of customers' bids (on their own or through aggregation) to sell in organized energy electricity markets their will to change their demand for electricity at a given point in time. Accordingly, DR should be neither involuntary nor unremunerated." [5].

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DR supports the other energy generation resources and should be managed in a proper way to get the expected benefits from it, those benefits can be summarized as maximizing PV consumption, optimizing battery storage, exploiting the electric vehicle flexibility, manage reliability issues, manage emission such as work in [6] and should be considered as an energy source that can be used to ensure the system's stability and to optimize the power system operation in [7]. The market defined two types of demand: baseload that happens regularly and the peak demand that happens at certain times. And on the duration of the second type, the DR programs can provide resource adequacy, especially with the objective of load curve smoothing (peak shaving) in [8].

DR programs can be categorized into two main groups, Price-based and incentive-based methods. There are many types of DR programs such as Time-of-use (TOU), Real-time pricing (RTP), Critical-peak pricing (CPP) rates, Critical peak rebates (CPR); Demand Bidding/Buyback (DB) programs, Emergency Demand Response Program (EDRP), Capacity
Market program (CAP), Direct Load Control (DLC), and Interruptible/Curtailable Service (IC) [6].

Some studies refer that the consumption of building in all types is 40% of the world's energy consumption and in the United States of America (USA) is almost 35% is consumed by a commercial building regarding [4], [9]. Since the DR's purpose is to maintain the stability of the power systems and smooth the load curve, it would be easy to apply for the DR programs on a flexible and controllable load [9]. In this context, Air Conditioners (ACs) can serve this purpose due to their contribution to electricity consumption and because of their characteristics that make them suitable for DR programs, for instance, Direct Load Control (DLC) [9].

The main purpose of this paper is to present the important role of all customer types in DR programs. This paper presents an analysis of actual DR programs based on datasets provided by FERC [10] and [11]. This analysis surveys about the customer types, DR program type, available loads and characteristics of programs. An optimization algorithm proposes the possibility of residential buildings in participation in DLC programs to achieve the DR goals.

After the introduction, section II presents materials and methods which show the steps taken to perform data analysis about DR program pilots. After that section III illustrates a case study to optimize the power consumption of the buildings based on DR programs and the obtained results are included. Finally, section IV describes the main conclusions.

II. MATERIALS AND METHODS

The main characteristics of the data analysis technique are presented in this section. The excel spreadsheet has been chosen for implementing analysis methods using the Data Analysis toolbox. Datasets can be mentioned as the main component of the present analysis. A dataset should contain raw statistical data and information which are related to the research subject. Data quality can be guaranteed by data cleaning to detect, correct or eliminate the inappropriate data in order to increase productivity. Correlation analysis is an applied method in the present paper. Correlation is a statistical technique that can determine the strength of the relation between the pair of variables. This technique is useful in the present study to survey possible connections between variables related to DR program implementations. The present DR programs dataset includes detailed information about 2314 implemented DR programs. Different peak loads and different capacities to reduce are in each program. Fig. 1 illustrates the process of data analysis.

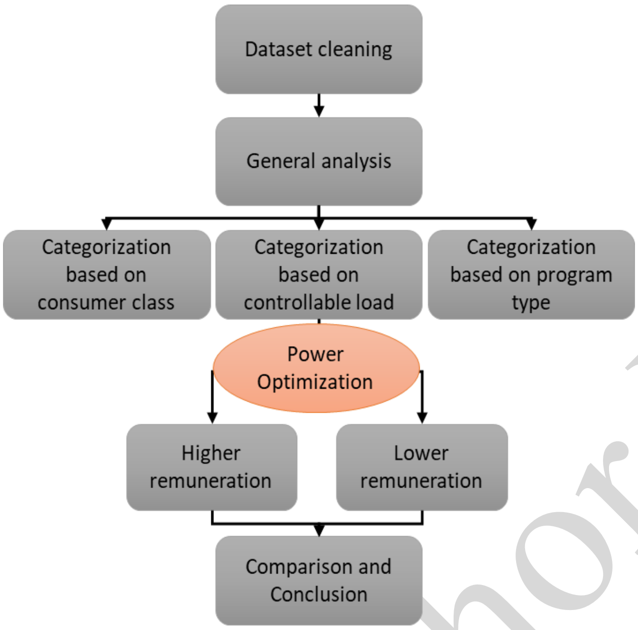

Fig. 1. Process of present data analysis.

As seen in Fig. 1, after data cleaning, the dataset is analyzed regarding all types of customers and programs. It should be noted that the clean dataset includes 2093 programs. In order to have a detailed information analysis, the dataset should be classified based on the customer's class. After that, the program types are considered as the leader of each category. According to the different program's contracts and descriptions, each program may control various flexible devices. The most feasible case for authors to implement the case study will be considered for power optimization. The results of this algorithm would show three programs with different remuneration levels and power reduction in order to compare and gain the most efficient DR program.

A. General Analysis

This subsection analysis all existing DR programs to investigate the information and compare the customers based on their class. The percentage of participation in each DR program type should be determined. It also surveys about voluntary or mandatory programs in each sector and each type. Fig. 2 presents the participation share of customers based on the class.

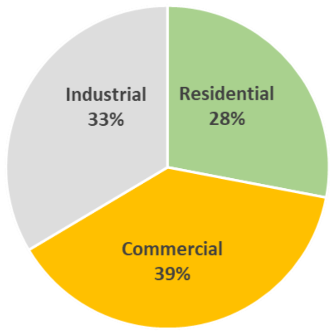

Fig. 2. Percentage of participants in each customer class.

As Fig. 2 show, the commercial sector has the highest participation in DR programs in the present data set. According to [4], commercial buildings are considered ideal for DR programs. It should be mentioned that Heating ventilating and air conditioning (HVAC) and lighting are the systems most commonly adjusted for DR in commercial buildings. Each DR program type has a specific property and focuses on a different target. Fig. 3 shows the percentage of participants in each program.

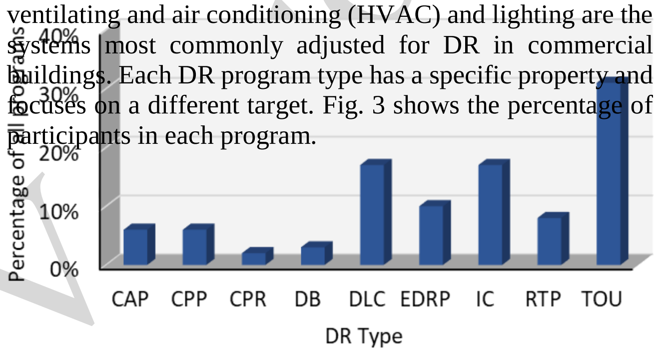

Fig. 3. Percentage of participants in each DR program type.

According to Fig. 3, TOU is the most popular program type for customers. Second place and third place can be considered for DLC and IC respectively. The general analysis of programs regarding be mandatory or voluntary shows that only 15% of all programs are mandatory. Fig. 4 shows the percentage of mandatory programs in each DR program type.

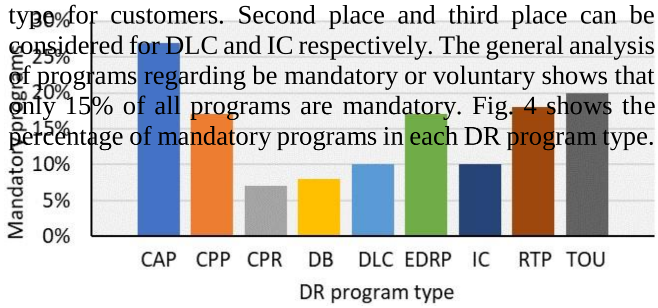

Fig. 4. Percentage of mandatory programs in each DR type.

As it can be seen in Fig. 4, 26% of CAP programs are mandatory which is the highest number compared to the other programs type. It can be interpreted that the DR programs mostly are implemented as voluntary.

B. Categorization based on Customer Class, Controllable Load, and Program Type

In this subsection, firstly, the programs are classified into three classes as residential, commercial, and industrial. The desire program type for each class of customers may be varied. In fact, the trigger criteria of each customer may be different from reliability or economic purposes. The customers may act as load response or price response based on the definition of proposed DR types. Fig. 5 shows the percentage of implemented DR programs in residential, commercial, and industrial classes.

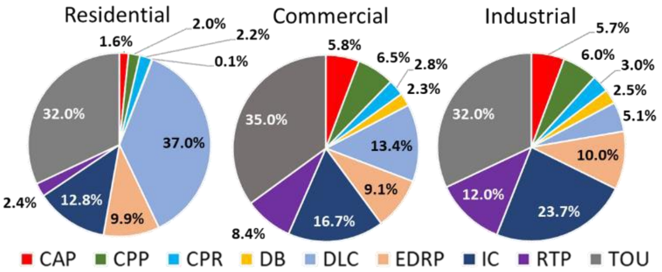

Fig. 5. Categorization of all programs based on customer's classes and DR program type.

Residential customers are mostly motivated to participate in the DLC program. Household appliances can be considered as flexible and deferrable loads to be directly controlled. Comparison of DLC share in three classes shows that commercial and industrial sectors are not as flexible as residential customers in direct control. TOU is another method of DR program which is shown with an almost equal share in three types of customers. EDRP percentage in three classes are in the same range. It shows that customer class is not correlated to this type of DR programs, since, most of the customers have the option, but not the obligation, to sell their forgone energy to the grid during an emergency event.

There are a different number of customers that are enrolled in each type of program. According to the dataset, the maximum number of enrolled customers is related to a residential load control of ACs, space heating, water heaters, and pool pumps. This program has been positioned in the DLC method of DR programs and 761569 customers are its participants. Regarding the main target of the DR program, each program performs a power reduction in peak periods. The available load, Potential of Peak Reduction (PPR), Actual Peak Reduction (APR), Potential Energy (PE), and Actual Energy (AE) are specified to each distinct program. For instance, Table I presents the characteristics of the mentioned program with the highest number of customers.

TABLE I. CHARACTERISTICS OF A PROGRAM WITH THE HIGHEST NUMBER OF PARTICIPANTS

Residential DLC Program					
Cust	Load (MW)	PPR (MW)	APR (MW)	PE (MWh)	AE (MWh)
761569	2274	868	542	13838	203

There are more than 2000 programs with various characteristics, in order to specify the connection between the number of participants, power, and energy aspects, the correlation technique has been applied to three class of customers separately. Table II, Table III, and Table IV present the correlation outcome for residential, commercial, and industrial respectively. In residential class, the number of customers is correlated to the ability of the program to reduce the peak demand. However, in commercial and industrial classes the number of customers is not so correlated to any other factors. It can be justified as residential DR is a different kind of business, since, thousands of customers should be involved, and each user should reduce its power individually to reach to one big commercial and industrial facilities. Additionally, a lot of money should be spent to install smart meters and smart appliances in each house. It does not mean that investing in residential customers is wasting time since it can have benefits with plenty number of customers. Residential customers also can appear more successful in long term contracts compared to commercial and industrial.

TABLE II. PARAMETERS CORRELATION IN RESIDENTIAL PROGRAMS

	Cust	Load	PPR	APR	PE	AE
Cust	1	-	-	-	-	-
Load	0.982	1	-	-	-	-
PPR	0.954	0.983	1	-	-	-
APR	0.988	0.980	0.956	1	-	-
PE	0.306	0.270	0.290	0.305	1	-
AE	0.044	0.016	0.044	0.056	0.942	1

TABLE III. PARAMETERS CORRELATION IN COMMERCIAL PROGRAMS

	Cust	Load	PPR	APR	PE	AE
Cust	1	-	-	-	-	-
Load	0.279	1	-	-	-	-
PPR	0.361	0.677	1	-	-	-
APR	0.369	0.713	0.857	1	-	-
PE	0.009	0.030	0.151	0.124	1	-
AE	0.009	0.011	0.067	0.105	0.769	1

TABLE IV. PARAMETERS CORRELATION IN INDUSTRIAL PROGRAMS

	Cust	Load	PPR	APR	PE	AE
Cust	1	-	-	-	-	-
Load	0.199	1	-	-	-	-
PPR	0.144	0.547	1	-	-	-
APR	0.072	0.325	0.752	1	-	-
PE	-0.01	0.048	0.175	0.030	1	-
AE	-0.01	0.156	0.123	-0.01	0.010	1

Fig. 6 compares the total number of customers, PPR, and APR in three customer classes. The participants of industrial and commercial classes can have monthly payments based on their performance during an event. The remuneration method in each class is different. In order to compare the compensation rate in different classes, two programs have been selected:

- Residential DLC with 13692 customers and 30.60 MW PPR: "Direct load control program that uses a paging signal to cycle residential air conditioners at various intervals. Operates in June, July and August provide a $7 per month credit."
- Commercial DLC with 114 customers and 0.001 MW PPR: "Commercial customers who allow us to install a load control unit on their air conditioner receive a $20/month credit for 4 summer months."

According to [10] dataset, different loads are employed to achieve the goals of the program. Fig. 7 shows the percentage of participation of devices in DR programs. It can be seen that ACs, water heaters, and electric heaters are the most participant devices in DR programs. It should be noted that 54% of ACs, 81% of water heaters, and 79% of electric heaters are participating in DLC programs without considering customer class.

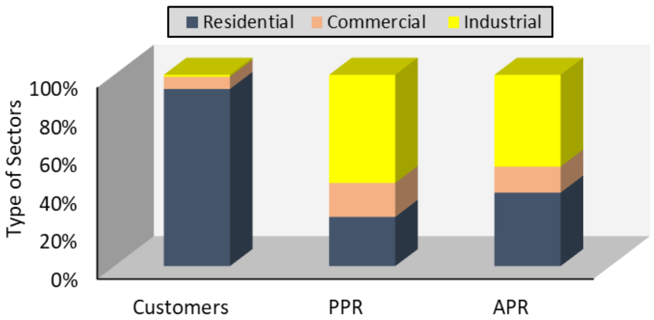

Fig. 6. Three customers classes regarding the number of participants and the capability of programs in each class.

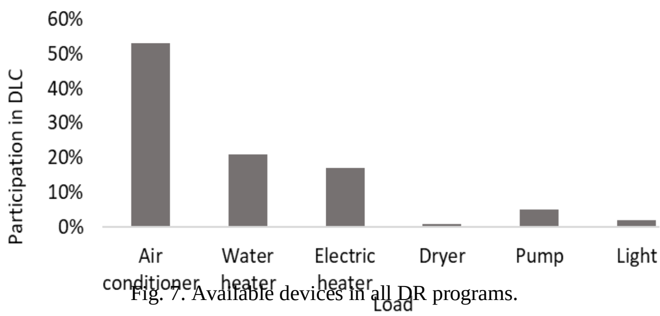

Fig. 7. Available devices in all DR programs.

III. Case Study And Results

This section introduces an optimization algorithm that aims to optimize the power consumption of the AC and water heater based on DLC. The algorithm starts with importing the initial data of customers such as the actual power consumption of the loads, the required reduction of the program and the priority number of each customer. The proposed methodology is defined as a Linear Programming (LP) optimization problem. The Objective Function (OF) is shown in (1) in order to minimize the power consumption of loads.

$$Minimize\ OF = \sum_{t=1}^{T} \sum_{l=1}^{L} Priority_{(l,t)} \times P_{(l,t)} \quad (1)$$

Priority is a number between 0 and 1 that is dedicated by each user for loads to present the level of being a volunteer of each customer. It should be noted that the smaller priority numbers are dedicated to loads that are prior to the other devices. P is the decision variable of the algorithm that shows the amount of power that should be reduced from each load in each period. Also, T and L are the maximum numbers of periods and loads respectively. Eq. 2 is modeled to present the peak power reduction demand in each period.

$$\sum_{l=1}^{L} P_{(l,t)} = PRD_{(t)}\ ;\ \forall\ t \in \{1, \ldots, T\} \quad (2)$$

PRD is the abbreviation of Peak Reduction Demand in each period. The PRD should be responded by customers based on their priority numbers. Three DLC programs with different Remuneration (Rmn) in the residential sector have been selected as real cases to run in the optimization algorithm. Scenario A, scenario B, and scenario C propose the characteristics of each program. Table V shows the characteristics of selected programs. In scenario A, a program has been implemented in residential customer class and has been proposed as "Air Conditioner Direct Load Control". In this program, residential customers who allow the program to install a load control unit on their ACs, receive 8 dollars per month. 1392 customers participate in the summer months program. The algorithm controls the consumption of the ACs in peak hours to achieve the program goals and the obtained results of 1 month of implementation will be presented.

TABLE V. Characteristics of Programs in Scenario A, B, C

Residential DLC Program					
Scenario	Cust	Load (MW)	PPR (MW)	APR (MW)	Rmn
A	1392	2.5	0.8	0.8	8 $
B	13692	13	3	1.5	7 $
C	4899	19.4	3.9	2	4 $

In scenario B, a program also has been implemented in residential class and has been proposed as "AC Cool Credit". In this program, the DLC program uses a paging signal to cycle residential ACs of 13692 customers at various intervals. This program operates in June, July and August, and provide 7 dollars per month credit. The proposed optimization algorithm controls the ACs in peak hours to achieve the program goals in scenario B. In scenario C, a program has been implemented in the residential class named "Water Heater Control". This DLC program is designed to reduce peak load during times of extreme cold or heat. Members receive a $4 monthly credit. The consumption curves using in this case study are the real consumption profiles of a building located in Portugal. Fig. 8 shows the power consumption of 1392 ACs in scenario A before DR implementation and after DR implementation. It should be noted that the algorithm runs for 30 days and Fig. 8 presents the consumption and reduction of each AC in 1 day which is the average of 30 days.

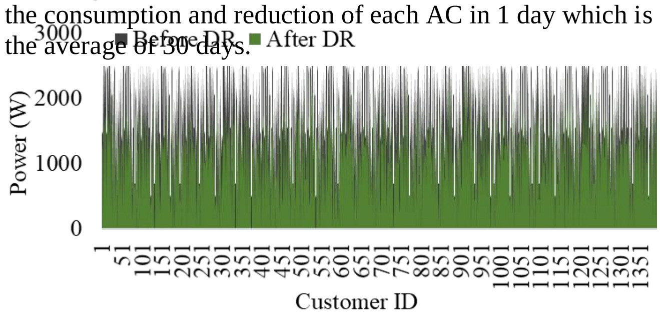

Fig. 8. ACs consumption, scenario A, before and after DR.

As it is shown in Fig. 8 the power consumption of 1392 ACs have been reduced to fulfill the DR program goal. Fig. 9 present the results of scenario A, regarding the power consumption of 1 AC in 1 day, before and after optimization. The peak hours start from 16h and end in 20h and the DLC program controls the AC power consumption in peak hours.

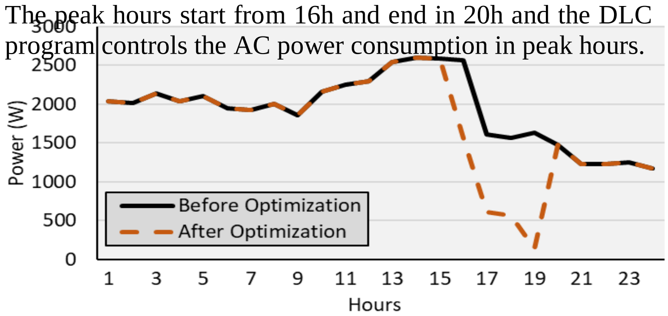

Fig. 9. 1 AC consumption, scenario A.

Fig. 10 presents the power consumption of the 13692 ACs in scenario B before DR implementation and after DR implementation. The obtained results of the optimization algorithm in scenario B is for 1 month, however, the total behavior of each AC in 1 day, which is the average of 30 days has been shown in Fig 10.

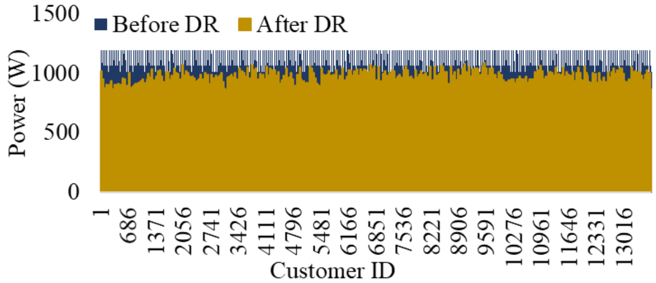

Fig.10. ACs consumption, scenario B before and after DR.

According to the comparison of Fig. 8 and Fig. 10, it can be seen that scenario B has more participant and higher load than scenario A, but the power reduction in ACs of scenario A are more than scenario B. 1 AC has been selected to propose the details of optimization algorithm results. The high number of participants in scenario B has been caused a lower power reduction in ACs. As it can be seen in Table VI, each customer in scenario A has been provided more power reduction during the program.

TABLE VI. CHARACTERISTICS OF PROGRAMS IN SCENARIO A AND B

Residential DLC Program				
Scenario	Rmn	PPR (MW)	APR (MW)	Overall APR of each load (MW)
A	8 $	0.8	0.8	0.07
B	7 $	3	1.5	0.01
C	4 $	3.9	2	0.05

Although the PPR and APR in scenario B are more than scenario A, scenario A is more capable and efficient. It can be interpreted that scenario A, can achieve the goals of scenario B with 20% of existing customers in scenario B, and more 1dollar remuneration. It can be seen that scenario C can reduce 2 MW in peak periods by 0.05 MW power reduction in 30 days, however, the remuneration is rather low compared to scenarios A and B. The comparison of remuneration in three scenarios shows the comfort cost of AC and water heater.The productivity ratio of each scenario is calculated by (3).

$$\text{Productivity ratio} = \frac{APR}{Cust \times Rmn} \tag{3}$$

According to (3), the productivity ratio of scenario A, B, and C is equal to 7.1%, 1.5%, and 10.1% respectively. Therefore, the productivity of scenario B is not desirable, and scenario A and C are more efficient in this context.

Table VII shows the Pros and Cons of each implemented DR program. It shows that scenario A is efficient from the perspective of aggregator, however, the comfort of the user can be affected by the high reduction. The program in scenario B is the fare for consumers, however, is a costly program for the aggregator.

In scenario C, the water heater is more flexible than AC in terms of power reduction and comfort of the user. The program cost is also reasonable, although, this kind of program is mostly interesting for the residential sector.

TABLE VII. PROS AND CONS IN THREE SCENARIOS

Scenario	Advantages	Disadvantages
A	High productivity	Low comfort
B	High comfort	High Cost
C	High flexibility, High productivity	Only for residential

IV. CONCLUSIONS

This paper provides an analysis of 2314 demand response programs in three categories of residential, commercial, and industrial customers. Different type of demand response programs has been actually implemented with the various number of participants. Three random programs have been selected for the case study to be employed by an optimization algorithm to achieve the program goals. The results of the case study show how the desired level of demand reduction in the program can be achieved in each specific load on the demand side. This proves the applicability of the proposed optimization algorithm in this paper. Such an algorithm can be implemented in the building energy management systems in order to implement demand response programs, such as direct load control and interruptible/curtailable programs.

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