A fair selection strategy for residential Demand Response participants

Christoforos Menos-Aikateriniadis National Technical University of Athens Intracom Telecom, Telco & Enterprise Software Dpt. Athens, Greece christoforosmenos@mail.ntua.gr Igyso Zafeiratou Intracom Telecom, Telco & Enterprise Software Dpt. Athens, Greece igyzaf@intracom-telecom.com Nikolaos Charitos Intracom Telecom, Telco & Enterprise Software Dpt. Athens, Greece charitosn@intracom-telecom.com

Pavlos S. Georgilakis Division of Electric Power National Technical University of Athens Athens, Greece pgeorg@power.ece.ntua.gr Isidoros Kokos Intracom Telecom, Telco & Enterprise Software Dpt. Athens, Greece isik@intracom-telecom.com

Abstract-Demand Response (DR) in the residential sector is a key facilitator of the energy transition, enabling consumers to assume a more active role in the efficient operation of the grid, whereas aggregators assume an important role in its realization. However, the wider adoption of residential demand-side flexibility faces several barriers, where low end-users engagement further increases the uncertainty around the estimation of residential DR market potential. Stimulated by the emerging need to increase end-users willingness to participate in DR programs, an innovative strategy for residential aggregators is being proposed, introducing fairness in the participants' selection methodology. The proposed framework takes into consideration reliability indicators, such as efficiency in flexibility delivery and events participation, as well as the level of inclusion (fairness) at a participant level. Case studies using a real residential data set indicate that when fairness-in-participation is considered, the same flexibility target can be obtained accompanied by the inclusion of all potential resources, when compared to an exclusively performance-based participants' selection methodology where only a few end-users are being constantly selected.

Index Terms—Residential Demand Response, Flexibility, Events, Fairness, Participants Selection, Customer Ranking

I. INTRODUCTION

A. Context

The integration of demand-side flexibility, and especially demand response, in energy markets is widely accepted as a crucial factor in the transition to a more reliable, costefficient and sustainable energy system [1]. Currently, demand response is the most established method in industry for reserves provision through demand-side control, which is usually remunerated via transmission system operator ancillary services provision or capacity mechanisms. On the other hand, flexibility provision from aggregated portfolios of distributed energy resources (e.g., electrical vehicles, renewable energy sources, residential loads), which can unleash a huge potential, is at an emerging deployment stage [1], [2].

Small-scale flexibility utilizing smart domestic appliances and residential distributed energy resources is yet to be unlocked, being at the forefront of research activity in recent years [3]. Except for balancing reserves, residential demandresponse can be of key importance for congestion management at a local level, contributing to a better matching between demand and supply. Among others, this can lead to investments deferral for system operators related to grid reinforcement and expansion [1]. The main barriers that halt the wider deployment of residential demand-side flexibility are mainly related to the lack of proper information and communication technology infrastructure, including smart metering systems, and volumetric scalability due to the low engagement rate of residential users in DR pilots [4]. The introduction of dynamic tariffs that incentivize end-users to participate in DR schemes can increase the engagement of participants by 30% - 50%, as shown in [5].

In this work, a data-driven selection strategy for residential DR participants is proposed, aiming at increasing the engagement of participants while ensuring that the targeted flexibility will be secured by the responsible party, i.e. the aggregator who coordinates and manages the energy generation and consumption of distributed energy resources or flexible loads. For that reason, fairness is introduced as a key factor in the design of the proposed DR selection framework. The latter defines the contribution of all the candidates in the DR programs to address the overall flexibility objectives, followed by rewarding to increase prosumers' incentivization [6]. Considering fairness of participation in DR frameworks will motivate a higher percentage of end-users to be active and engaged towards a wider integration of DR programs [7] in novel energy markets.

This project has received funding from the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie and iFLEX grant agreements, No 955422 and No 957670 respectively.

B. Related Work

In the literature, relevant work on the implementation of DR programs has been effectuated looking into different aspects of the problem. For instance, in [8] the authors propose an optimization framework concerning incentivization of prosumers (e.g., rewards or lotteries) to achieve effective flexibility management and aggregate the desired flexibility at specific time windows according to the DR aggregator's needs. They further study the optimal incentives to satisfy both cost minimization for the aggregator and optimal incentives, comfort and cost for the end-users. Research work in [9] presents a methodology that deals with uncertainties in consumers' response. Through this methodology, the aggregator identifies the most reliable consumers to be considered during flexibility events according to different parameters, such as peak hours, external temperature. Then, [10] describes the consumption behavioral patterns of several households. More specifically, through a survey, this work investigates the habits of the consumers using different flexible assets (e.g., heating/electric appliances, electric vehicles) and having different kinds of incentives (financial or environmental) when participating in flexibility services events.

To the best of our knowledge, limited literature exists considering fairness in the selection process. In work [6], the authors aim at achieving optimal power consumption for the consumers whilst a fair rewarding process compensates their participation in the DR programs. However, fairness in selection of the consumers is not being investigated. Furthermore, work [7] develops a fair DR scheme to encourage wider participation of end-users taking into account the type of user, the type of asset, and the income of the user without considering historical end-user participation rate and engagement in DR events. Then, in [11] the authors introduce an optimal approach for a DR management system including fairness for the enrolled end-users via their rejected/ignored responses to the DR events invitations.

C. Structure and Contribution

In this work, we go further introducing an innovative DR selection strategy to increase fairness in participation during DR events, while considering historical performance of participants in DR events. This is achieved not only by taking into account the end-users' actions and preferences (e.g., acceptance in participation, DR capacity), but also by promoting the participation of previously non-selected end-users in future DR events. The main goal is to give to all the eligible end-users the opportunity to participate in the DR program and, thus, increase their motivation and activity. The main contributions of this research work are the following:

- Introduction of a fair "Selection Score" as part of an inclusive, multi-criteria selection algorithm which aims at sorting potential DR event participants. A user-specific "Selection Score" is recalculated on an ongoing basis to shape the selected participants list, prior to an event.
- Development of a data-driven framework, considering engagement in past DR events as well as efficiency in

terms of flexibility provided. This framework aims at classifying end-users based on their suitability to provide flexibility in a DR event.

• Enabling adaptability through the introduction of algorithmic settings (e.g., weight factors), which can be modified by the user according to their objectives to prioritize the impact of some criteria over others.

This work is structured as follows. In Section II, the problem formulation and the proposed fair DR selection framework are described. In Section III, the experimental setup and algorithm evaluation results, in the form of case study outputs, are presented, and in Section IV the main conclusions and future steps of this work are explained.

NOMENCLATURE

DR	Demand Response
KPI	Key Performance Indicator
AcC	actual consumption (kWh) during a DR event
ReqF	requested flexibility (kWh) during a DR event
P90t	90^{th} percentile of consumption at time window t of a DR event
P-based	Performance-based use case

II. METHODOLOGY

In this section, the proposed methodology will be firstly demonstrated based on the notion of multi-criteria classification/sorting methods [12]. Then, the selection algorithm, which concludes with the top candidate participants who deliver the requested flexibility, will be presented. Each end-user is characterized by a Selection Score, which defines their suitability to be considered to participate in a DR event. The goal is to select the best set of end-users for a DR event in order to satisfy both the targeted flexibility and to achieve, via the fairness notion, the overall inclusion of the end-users in the DR program.

More specifically, a finite set H of h households, $h \in H$, is considered. Each household is composed by a number of end-users with varying preferences (e.g., DR program, consumption time slots) and a set L of l assets, $l \in L$. In this work, each household corresponds to a single end-user and is characterized by a single power consumption profile per asset, without taking into account the energy behavior of its inhabitants separately.

The problem is formulated considering a finite number of alternatives: $A = \{a_1, a_2, a_3, \ldots, a_{n-1}, a_n\}, n \in N$, with each alternative, a_n , being a possible course of action, solution, or option that will be compared and ranked [12]. Then, each alternative, in our case the end-users, is characterized by a group of selection criteria: $C = \{c_1, c_2, c_3, \ldots, c_{m-1}, c_m\}, m \in M$, where M is the set of m criteria. Therefore, based on the aforementioned methodology, each alternative corresponds to a household and is being divided into several classes, through sorting, according to the defined criteria. Each class is characterized by a set R of reference criteria, $R = \{r_{k1}, r_{k2}, r_{k3}, \ldots, r_{km-1}, r_{km}\}$, with $k \in K$ the corresponding class (1).



Fig. 1. Multicriteria methodology scheme showing the three proposed classes, based on end-users suitability to participate on a specific DR event

Three classes are considered: i) participants list (which includes the candidates selected for a DR event), ii) supplementary list (which concerns the candidates suitable for a DR event but not selected), iii) excluded list (which includes the candidates not suitable for a specific DR event according to their preferences in time, day, DR capacity or other). The criteria are defined as follows: i) c_1 : efficiency ratio, ii) c_2 : engagement ratio, iii) c_3 : fairness ratio.

More specifically, the aforementioned criteria represent specific KPIs, used in the selection algorithm leading to the best set of candidates to participate in a DR event. To demonstrate the different KPIs, the analysis is divided into three levels: i) the participant level, ii) the event level, iii) the program level (not being considered in this research work).

A. Participant Level

Participants are defined as the households (end-users) initially selected to be invited in a DR program. At participant level, pl, the efficiency ratio criterion, c_1^{pl} , and the engagement ratio criterion, c_2^{pl} , are introduced as follows:

1) Efficiency ratio: Each candidate participant is described by a DR capacity, which represents an amount of flexibility (energy) to be offered to the aggregator during a specific DR event. The efficiency ratio indicates the effectiveness of each participant to offer the expected amount of flexibility. Therefore, given that the aggregator could ask from their endusers to increase or decrease their power consumption, the following options exist to demonstrate the efficiency ratio Efper DR event e, household h and asset l:

• for power increase¹:

$$Ef_{e,h,l} = \frac{AcC_{e,h,l}}{ReqF_{e,h,l}},\tag{1}$$

• for power decrease²:

$$Ef_{e,h,l} = 1 - \frac{AcC_{e,h,l}}{ReqF_{e,h,l}}.$$
(2)

¹An amount of flexibility is requested by the aggregator according to which the end-user should increase its power consumption.

²An amount of flexibility is requested by the aggregator according to which the consumer should decrease its power consumption.

with $AcC_{e,h,l}$ representing actual consumption (kWh) and $ReqF_{e,h,l}$ the requested flexibility (kWh) by the aggregator. The average efficiency $\overline{Ef_h}$ represents the efficiency ratio, c_1^{pl} , for each participant across the total number E of DR events during which the household h participates. The efficiency ratio criterion on a participant level pl, c_1^{pl} , is formulated as:

$$c_1^{pl} = \overline{Ef_h} = \frac{\sum_{e=1}^{E} Ef_{e,h,l}}{E}.$$
(3)

2) Engagement ratio: When a flexibility request for a specific DR event is realized by the aggregator, the candidate participants (participants list k_1) are allowed to decide for their participation. Hence, three possible choices are considered: i) yes, ii) no, or iii) no answer. $PA_{e,h}$ variable corresponds to the amount of positive answers (yes) to the requested DR events reqE. Hence, the engagement ratio (ER) criterion per household h, c_2^{pl} , is equal to:

$$c_2^{pl} = ER_h = \frac{\sum_{e=1}^{reqE} PA_{e,h}}{reqE}.$$
(4)

3) Fairness ratio: The fairness ratio, c_3^{pl} , indicates the percentage of times a candidate end-user has not been selected to participate in a DR event and, according to the selection algorithm, is placed in the supplementary list k_2 . These end-users are not selected because the amount of requested flexibility is reached by the participants list k_1 . However, as long as they are in k_2 class, they are appropriate candidates for a DR event and should have the chance to participate at least once in a DR event in the future. The fairness ratio (*FR*) criterion per household h, c_3^{pl} , gives the opportunity to k_2 end-users to keep being considered as possible candidates for subsequent DR events and is defined below:

$$c_3^{pl} = FR_h = \frac{\sum_{e=1}^{reqE} NoS_{e,h}}{reqE}.$$
(5)

with NoS being the number of times the household's h enduser has not been selected to participate in a DR event e.

B. Event Level

At an event level, el, the reliability of the DR event is estimated considering the total number of participants, during this particular DR event. The reliability is based on the aforementioned efficiency ratio criterion, c_1^{el} , and the engagement ratio criterion, c_2^{el} , which are analyzed below:

1) Efficiency ratio: For power increase and power decrease, $Ef_{e,h,l}$ has already been described at participant level in (1) and (2). However, average efficiency differs since it indicates the efficiency ratio criterion for each DR event taking into account the set of the active participants from k_1 :

$$c_1^{el} = \overline{Ef_e} = \frac{\sum_{h=1}^{H} Ef_{e,h,l}}{H}.$$
 (6)

2) Engagement ratio: The engagement ratio, ER_e , at event level is equal to:

$$c_2^{el} = ER_e = \frac{\sum_{h=1}^{H} PA_{e,h}}{H}.$$
 (7)

3) Fairness ratio: The fairness ratio at event level describes the percentage of suitable candidates not selected to participate in a DR event and is presented below:

$$c_3^{el} = FR_e = \frac{\sum_{h=1}^H NoS}{H}.$$
(8)

Taking into account the set of alternatives A and the set of criteria C, as they were described by the KPIs at participant and event level, both are employed to proceed to the classification of the participants through a utility function that represents the "Selection Score". This score can be attributed to each class k independently, and is defined as follows:

$$f_k(c) = \sum_{m=1}^{M} w_m c_m = w_1 c_1 + w_2 c_2 + w_3 c_3 =$$

= $w_1 \overline{Ef} + w_2 ER + w_3 FR,$ (9)

where w_m are the weighting factors and c_m are replaced by the equations given above at participant ((3), (4), (5)) and event level ((6), (7), (8)).

C. Selection algorithm

As aforementioned, the selection algorithm is built upon the described methodology in order to conclude to the best set of participants for a specific DR event. Once the basic specifications of a DR event are determined, such as start time of a DR event, duration of a DR event, and requested flexibility, the end-users' selection process is initiated. This process starts after an amount of flexibility is requested by the aggregator, thus a DR event needs to be created. Afterwards, the algorithm initiates to select the best set of participants (k_1) for the DR event. The different steps are enumerated as follows (Fig. 2):

- 1) The initial list of the registered consumers in the relevant DR program is filtered based on their time preference to use specific assets and their initially declared DR capacity. The lists of filtered (participants list k_1 and supplementary list k_2) and excluded participants (k_3) are derived from this step.
- 2) Subsequently, the filtered list of participants is sorted based on the selection strategy determined by the aggregator and the selection score of each participant. The score of each participant is calculated after a DR event based on the weights set in the strategy as presented in section II-A. Then, during a new DR event, the participants are allocated to the lists depending on their availability and scores. For the 1st iteration a random selection of the eligible consumers was performed.
- 3) Finally, the selection of the final set of participants (k_1) is performed considering the sorted participant list and the DR event specifications, more specifically the total requested flexibility through this DR event. The outcome of this process comprises the participant list (k_1) , in which the participants who will be invited to this DR event are included, and the supplementary list (k_2) , in which potential participants that can be invited in case of negative responses are stored.



Fig. 2. Flowchart of the proposed DR framework.

Here, it is important to highlight that end-users filtering is conducted on an initial stage by the corresponding DR aggregator, based on its client base as well as the technical/market requirements that define the provided flexibility services. The concept of "Fairness" in this work applies on the filtered list, as shown in 2, as part of the participants' selection strategy.

In the following section, the evaluation of the proposed DR framework is presented through simulations based on a real residential dataset.

III. EVALUATION

A. Experimental Setup

In this work, a DR program with a set of 20 DR events is formulated. The lack of publicly available datasets, specifically dedicated to participants' actual consumption and behavior during DR events, is a typical challenge related to the evaluation of research works in the area of demand-side management. Therefore, historical household consumption from the Pecan Street Dataset [13] has been used to replicate potential DR participants behavior in DR events and, eventually, showcase the applicability of the recommended framework.

In the designed experimental setup, two case studies have been selected to showcase the applicability of the proposed fair DR participants selection framework, namely a "Fair" and a "Performance-based" (P-based) case study, applied over the same replicated DR Events presented in section III. The utility function (9) is used at participant level (replacing the criteria by (3), (4), (5)) to calculate the selection score of each end-user. The weighting factors in (9), w_1 , w_2 , w_3 , of the corresponding criteria, $c = \{c_1^{pl}, c_2^{pl}, c_3^{pl}\}$, are considered as: i) for k_1 , $w_{k_1} = \{0.7, 0.3, 0\}$, for k_2 , $w_{k_2} = \{0.1, 0.1, 0.8\}$, and ii) for k_1 , $w_{k_1} = \{0.7, 0.3, 0\}$, for k_2 , $w_{k_2} = \{0.7, 0.3, 0\}$ for the Fair and P-based use cases respectively. In the Pbased use case the weight factor w_3 is set to zero, meaning that non-invited users will not be prioritized over others in future DR events, in contrast to the Fair use case. As aforementioned, in the participants list k_1 high importance is given in participation and efficiency of residential users, while fairness weight w_3 remains zero, since these users have been offered the opportunity to participate in a DR event. On the contrary, in the supplementary list k_2 the highest priority is to increase diversity in the DR event participants list by prioritizing non-selected candidates in future DR events. Furthermore, since we focus on the candidates selection after the filtering process of the selection algorithm, it is assumed that all the end-users are appropriate candidates for the DR events. Therefore, the excluded list in k_3 will remain empty and will not be considered.

B. Data Analysis

Given the lack of real data reflecting residential users' participation in DR pilots, the Pecan Street dataset has been used to evaluate the proposed fair DR framework under realistic case studies that have been replicated with the use of historical domestic load consumption data. 73 different households from the areas of California, New York and Austin in the USA have been obtained through the Pecan Street Dataport [13], providing aggregated and sub-metered household electricity consumption measurements with a 15minute granularity. More specifically, the loads of water heater, electric vehicle and air conditioning have been selected and aggregated to a total "flexible load" per user that can participate in a DR event. The conducted data analysis aims at identifying appropriate days for DR, meaning days with a considerable aggregate consumption at any 15-minute timestep. The data analysis pipeline, followed in this work, is described below:

- Data Cleaning: Isolated sub-metered readings referring to the selected flexible loads.
- Data Quality Check: Excluded days with negligible daily power consumption (<10kW) per flexible load.
- Time Window Selection: The top 20 15-minute time windows with the highest historical aggregate flexible consumption have been selected.
- Flexibility potential calculation: Flexibility potential per user at each time window is defined as the $P90_t$, meaning the 90^{th} percentile of consumption at that time t.

The 20 selected DR events dated in the period between 03/07/2018 to 02/09/2018, where 26 out of the 73 different households are eligible and thus considered that participated in the simulated DR events. In the absence of actual DR event-related measurements, the underlying assumption that the engagement ratio, c_2^{pl} , is within the range of 0.3 - 0.5 has been made, in line with a large scale DR pilot in Belgium [5]. More specifically, for each one of the 20 DR events a randomly selected value within the aforementioned range has been used to replicate the scenario for a number of users to decline the participation invite they received after passing the initial screening stage. Furthermore, the flexibility target for the DR aggregator has been assumed as the 30% of the aggregated flexibility potential of all consumers at each time window of the DR event. Additionally, a 5% flexibility target

Participants Range of participant invitations in DR events



Fig. 3. Comparison between Fair and Performance-based use cases by the range of participant invitations in DR events.

surpass threshold has been introduced to ensure security of achieving the target.

C. Results

The experimental results of each use case can be seen in Table I. In the Fair use case all users are invited to participate in a DR event within the first 5 events while in the P-based use case only 10 participants are being invited constantly to DR events, with 8 of them been invited in the first 5 DR. From Fig. 3, where participants number is being presented for both use cases over the range of DR events, it is noticeable that under the proposed Fair DR framework around half of the participants are invited to 3-8 events, providing both more robust historical data for the evaluation of their flexibility potential as well as the opportunity to engage more the participants' portfolio on DR events. As a results, after 20 DR events, the participants are fairly ranked based on their historical performance on invited DR events, where responsive and efficient users are prioritized over inefficient and/or unresponsive participants.

In addition, the number of total invitations in the Fair use case is higher than in the case of a P-based selection strategy, while the activated flexibility in both cases is around 135 kWh, over the 20 DR events, as shown in 3, and converges to the flexibility target (Fig. 4). This reflects the highest inclusiveness a Fair DR framework introduces.

IV. CONCLUSIONS

In this work, an innovative DR selection strategy has been proposed to increase fairness in participation in DR events while considering historical performance and engagement of participants. Experimental use cases show that the proposed algorithm invites all 26 potential participants to more than 4 out of 20 DR events, while an exclusively performancebased approach would include only 10 out of 26 participants in the invitations process, without compromising convergence to flexibility target. Therefore, fairness consideration enhances energy democratization, since participants are being invited



Fig. 4. Deviations of the actual flexibility from the flexibility target for the 20 DR events in Fair and Performance-based use cases.

 TABLE I

 FAIR / P-BASED USE CASES - RESULTS AFTER 20 DR EVENTS

n	Invitations during		Total DR events		Fairness
	the first 5 DR events		Invited		ratio (%)
ID#	Fair UC	P-based UC	Fair UC	P-based UC	Fair UC
1731	2	0	6	0	70
8342	1	0	5	0	75
9278	3	0	6	8	70
3039	1	2	13	16	35
8156	1	5	6	19	70
8565	4	0	19	0	5
7536	4	0	19	0	5
2335	5	5	13	20	35
7901	2	0	9	0	55
2818	3	0	11	0	45
9922	2	0	13	0	35
4373	4	5	5	20	75
7800	4	0	19	0	5
4767	1	5	4	20	80
1642	2	5	6	13	70
5746	4	0	19	0	5
6139	1	0	10	0	50
661	2	0	6	0	70
9019	1	0	6	0	70
9160	2	0	10	0	50
7719	2	5	10	18	50
3538	1	0	6	9	70
3456	2	0	6	0	70
2361	1	0	7	0	65
7951	5	5	20	20	0
8386	2	0	6	0	70

more often to DR events and newcomers in the DR program will have the opportunity to opt in as well.

As a future work, the program level will be introduced and the selection score in (9) will include further crucial criteria to mitigate uncertainties and increase reliability during DR events. Furthermore, participants' rewarding and optimal energy behavior of the end-users will be investigated through different optimization strategies (e.g. cost minimization, flexibility maximization). The algorithm under development will be validated on a real pilot under the iFLEX H2020 project.

REFERENCES

- I. Saviuc, C. Zabala López, A. Puskás-Tompos, K. Rollert, and P. Bertoldi, "Explicit Demand Response for small end-users and independent aggregators – Status, context, enablers and barriers," JRC, Tech. Rep., 2022.
- [2] IRENA, "Demand-side flexibility for power sector transformation," IRENA, Abu Dhabi, U.A.E., Tech. Rep., 2019, [Online].
- [3] C. Menos-Aikateriniadis, I. Lamprinos, and P. S. Georgilakis, "Particle swarm optimization in residential demand-side management: A review on scheduling and control algorithms for demand response provision," *Energies*, vol. 15, no. 6, 2022.
- [4] C. B. Kobus, E. A. Klaassen, R. Mugge, and J. P. Schoormans, "A real-life assessment on the effect of smart appliances for shifting households' electricity demand," *Applied Energy*, vol. 147, no. C, pp. 335–343, 2015.
- [5] M. Afzalan and F. Jazizadeh, "Residential loads flexibility potential for demand response using energy consumption patterns and user segments," *Applied Energy*, vol. 254, p. 113 693, 2019.
- [6] Z. Baharlouei, M. Hashemi, H. Narimani, and H. Mohsenian-Rad, "Achieving optimality and fairness in autonomous demand response: Benchmarks and billing mechanisms," *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 968–975, 2013.
- [7] S. K. Vuppala, K. Padmanabh, S. K. Bose, and S. Paul, "Incorporating fairness within demand response programs in smart grid," in *ISGT 2011*, 2011, pp. 1–9.
- [8] T. G. Papaioannou and G. D. Stamoulis, "An optimization framework for effective flexibility management for prosumers," in 2022 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), IEEE, 2022, pp. 103–109.
- [9] C. Silva, P. Faria, Z. Vale, J. M. Terras, and S. Albuquerque, "Rating the participation in demand response events with a contextual approach to improve accuracy of aggregated schedule," *Energy Reports*, vol. 8, pp. 8282–8300, 2022.
- [10] A. Sridhar, S. Honkapuro, F. Ruiz, *et al.*, "Toward residential flexibility—consumer willingness to enroll household loads in demand response," *Applied Energy*, vol. 342, p. 121 204, 2023.
- [11] I. Kokos and I. Lamprinos, "Demand response strategy for optimal formulation of flexibility services," 2016.
- [12] C. Zopounidis and M. Doumpos, "Multicriteria classification and sorting methods: A literature review," *European Journal of Operational Research*, vol. 138, no. 2, pp. 229–246, 2002, MCDA Methodologies for Classification and Sorting, ISSN: 0377-2217.
- [13] Dataport Pecan Street Inc. https://www.pecanstreet. org/dataport/, [Online; accessed 20-May-2023], 2009.