A Novel Incentive-based Retail Demand Response Program for Collaborative Participation of Small Customers

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Abstract— **Integration of aggregated demand response into the wholesale electricity market is an emerging field of research. Contrary to conventional service providers, most of the demand side participants act voluntarily. However, due to wholesale market regulations, reliable and effective participation of huge numbers of customers is a vital task for aggregators. The existing retail programs aim to motivate customers to take part in events in return for static or individual performance-based incentives. These programs do not focus on engaging customers to act in a collaborative way and therefore have limited effectiveness. This study proposes a novel retail demand response program in which the incentives are dependent on the aggregated performance of participants. Considering the existing wholesale and retail market structures together with demand response aggregator responsibilities, an adaptable program is developed for more effective performance and indirect collaboration of customers. The contribution of the program is compared with a number of different DR programs adopting concepts from game theory.**

Index Terms—**Demand response, Demand side aggregators, Electricity markets, Game theory, Smart grids.**

I. Introduction

Power systems are facing significant changes, whereby integration of distributed generation from renewables is one of the major challenges due to source intermittency and system capacity constraints. These changes may lead to interesting daily load curves ranging from duck curves (steeper ramps, higher peaks and deeper valleys) in systems comprising PV generation to extreme ramps during stormy weather in systems comprising wind generation [1-2]. Since utility operators have limited number of options to cope with these difficulties threatening the grid stability (using of expensive peaking plants or temporary curtailment of renewables), they prefer more flexible resources. At this point, aggregated demand response is considered as a recent and promising option against aforementioned problems.

Demand response (DR) programs coordinating huge numbers of consumers can play an important role in electricity markets. Aggregators can bridge small customers with the wholesale markets (energy, capacity and ancillary services) through incentive-based programs [3]. Aggregated DR can be done either by distribution system operator (DSO) or by an independent entity that acts as the aggregator. Thereby, DR can be integrated into the market in different ways. It can provide a fast tool to DSO to change the local demand profile, it can help service providers not to get penalties in their long-term contracts or it can directly guide the wholesale market through demand reduction or increment bids. In all cases, there are three main actors; namely, the market operator, the DR aggregator and the customers. It is a major challenge for DR aggregators to obey the regulations of wholesale markets, while considering the comfort of customers. They are also responsible for achieving the response performance that was promised to the market for a given time period. In case of insufficient performance, the aggregator has to find another provider to fill the gap and pay in general a higher price for the related service. Otherwise, the market operator fills the gap with a new and more expensive agreement and asks the aggregator to pay the price difference. Note that renewable-based power plant operators have similar difficulties for bidding to the wholesale market due to uncertainty of the wind speed. Therefore, DR aggregators aim to ensure effective and reliable response from their customer portfolio by offering retail DR programs. The trend is preferring configurable DR programs which provide freedom to the customers in overriding control signals, instead of disconnectable ones providing direct load control.

There are some pioneer aggregated DR deployments in the field. Nest Company offers a program to its customers for peak reduction by automatically deploying DR actions on thermostatically controlled loads [4]. OhmConnect sends DR event requests to customers once or twice a week for managing their consumption through either manual or automated control, for which points can be earned that can be converted to money [5]. Both programs are configurable so that the participants are free to opt out from the program at any time.

The aforementioned DR programs provide either preannounced constant incentives or performance-based dynamic incentives to the costumers. These individual motivators are effective as long as no collaborative response of participants is needed. However, if a collaborative component enters a DR program, one of the most important aspects is specification, analysis and control of costumer behavior. At this point, game theory can be a useful tool, and

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has already been used. For example, [6] presented optimal demand response based on the interaction between multiple utility companies and residential users. In [7], the authors showed that if a strictly convex real time pricing (RTP) system depended on the total demand of energy was designed, the Nash equilibrium of all consumers was the optimal solution for each individual and the peak to average ratio (PAR) got minimized. This model was expanded with the possibility of energy storage in [8]. A cooperative demand response scheme for load management was proposed in [9], where a punishment mechanism demotivated non-cooperative (selfish) behavior. These studies were however not directly designed for the day ahead market, limiting their applicability. In this study, a collaborative incentive based program (that can be an alternative to constant or individual performance based programs) is proposed for improving aggregated response of customers. Within this market integrated program, a rewarding system is designed such that a customer's reward also depends on the behavior of other customers. Section 2 describes the novel program, Section 3 gives a case study to compare different options and the last section concludes the paper.

II. Collaborative Response-Based Retail DR Program

The regulations of the wholesale markets are designed for the market operator and the system operator to organize the whole market and are difficult to be modified. However, retail market has rather more flexibility of designing new programs and contracts. The DR aggregator is a sort of mediator with its own goals, but which has to satisfy the objectives of both the market and its customers. These customers are a large group which do not consider DR as their primary task. However, they require that their comfort is taken into consideration during DR events as an additional criterion.

If now an aggregator places a bid of x_B (kWh) at a price p_B (TL/kWh) on the wholesale market, and this DR bid gets accepted, he will receive an income of $|x_B| \times p_B$. If the aggregator is not able to realize this bid due to insufficient aggregated response, $|x_A|$, of its customers (i.e. $|x_B| > |x_A|$), the response gap $|x_B - x_A|$ should be bought back from the market, say for a price of p_P. However, as the supply price increased with the quantity provided in markets, it is in general costlier to buy from a new supplier. Therefore, it may be assumed that $p_P > p_B$. The net earning C_{net} of an accepted bid is now given by (1).

$$C_{net} = |x_B| \times p_B - |x_B - x_A| \times p_P \quad \text{if } |x_A| \leq |x_B|. \tag{1}$$

It can be inferred from equation (1) that, after a bid is placed, based on the estimation of the aggregated DR performance of a number of consumers, the aggregator should minimize the risk of insufficient response by providing incentives that engage customers. The main issue is that, neither constant incentives, nor individual performance-based incentives effectively reflect the needs of the aggregator. In practice, the aggregator most likely provides only a limited amount of incentives, based on the lowest expected participation to avoid possible losses, leading to a reduction in revenues.

In this paper, a novel incentive-based program is developed, considering the positive impact of an increase in the number of participating customers and of the response performance on the profits of both the aggregator and the participants. An aggregated-response based incentive is used to foster indirect cooperation between customers and improve effectiveness.

As formulated in (1), an increase in $|x_A|$ may reduce the gap between the bid and the actual response and consequentially increase C_{net} (for $|x_A| < |x_B|$). This increase in aggregator's profit can directly be incorporated in the user incentives. The highest incentive that the aggregator can give to customer *i*, is his fair share (FS_i), expressed as $\frac{|x_i|}{|x_A|} \times C_{net}$, which is given by

$$FS_i = |x_i| \times \left(\frac{|x_B|}{|x_A|} \times p_B - \frac{|x_B - x_A|}{|x_A|} \times p_P\right) \quad \text{if } |x_A| \leq |x_B|, \tag{2}$$

where x_i is the individual response of customer *i*. The unit reward *r* (TL/kWh) of a customer is defined as its fair share divided by the amount of its response and is equal for all customers:

$$r(x_A) = \frac{FS_i}{|x_i|} = \frac{|x_B|}{|x_A|} \times p_B + \frac{|x_A - x_B|}{|x_A|} \times p_P \quad \text{if } |x_A| \leq |x_B|. \tag{3}$$

The graph of (3) is shown in Fig. 1. Once a bid $|x_B|$ is made and prices p_B and p_P are known, the unit reward price *r* is only dependent on the aggregated shift x_A. The unit reward price for all customers increases with a higher aggregated shift, until $x_A = x_B$ and the maximum unit reward p_B is achieved.

As the reward for a customer in this collaborative incentive based pricing scheme depends on the behavior of all other customers, a game theoretic analysis is done to investigate how different customers influence each other's behavior. For this, a game is analyzed with *n* players, which are the participating appliances of all the consumers. We assume, that all appliances have the freedom to participate individually, and have two possible strategies: shift (S) and not shift (NS). Not shifting results in a payoff of zero and shifting appliance *i* leads to a payoff of $x_i \times r(x_A) - c_i$, where $r(x_A)$ is the monetary unit reward (TL/kWh), depending on the aggregated shift $x_A = \sum_{i=1}^{n} x_i$ of the *n* players, and c_i is the comfort loss for customer *i* due to shifting. For this analysis, it is assumed for simplicity that $x_i = 1$ for all *i*. Then the payoff reduces to $r(x_A) - c_i$, and x_A is a natural number with $0 \leq x_A \leq n$.

To get insight in the resulting payoffs from different combinations of strategies, a 3 appliance scenario is used, of which the payoff matrix is shown in Table I. As an example, consider that appliance 1 and 3 have the strategy to shift, and appliance 2 not to shift, this yields an aggregated shift x_A of 2, so appliance 1 and 3 will have a payoff of $r(2)$ minus their corresponding comfort losses c_1 and c_3, and appliance 2 will have a payoff of 0 for not shifting.

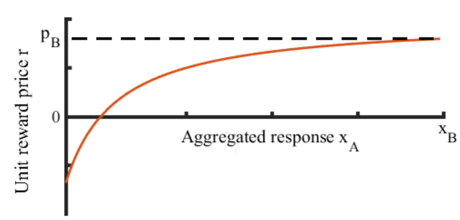

Fig. 1. Fair share unit reward price *r* against aggregated response x_A

TABLE I. PAYOFF MATRIX FOR DIFFERENT COMBINATIONS OF STRATEGIES

Strategy				**Payoff**		
1	**2**	**3**	x_A	**1**	**2**	**3**
NS	NS	NS	0	0	0	0
NS	S	NS	1	0	$r(1)-c_2$	0
NS	NS	S	1	0	0	$r(1)-c_3$
NS	S	S	2	0	$r(2)-c_2$	$r(2)-c_3$
S	NS	NS	1	$r(1)-c_1$	0	0
S	S	NS	2	$r(2)-c_1$	$r(2)-c_2$	0
S	NS	S	2	$r(2)-c_1$	0	$r(2)-c_3$
S	S	S	3	$r(3)-c_1$	$r(3)-c_2$	$r(3)-c_3$

Now it can be analyzed how different choices for the unit monetary reward $r(x_A)$ lead to different Nash equilibria. These equilibria can be found by checking which combinations of strategies result in a situation where no player has an incentive to change his/her strategy, if other players do not change their strategy either. In Table II the pure Nash equilibria are shown for all possible choices of $r(x_A)$, where it is assumed w.l.o.g. that $0 \le c_1 \le c_2 \le c_3$.

To get a feeling about these different equilibria, Case 13 in Table II is addressed in more detail. As $r(3) > c_3 \ge c_2 \ge c_1$, (S,S,S) is a Nash equilibrium because if all players decide to shift, changing to NS by one player results in a payoff of zero instead of a positive payoff. Furthermore, (S,NS,NS) is a Nash equilibrium, since as $c_1 \le r(1)$, appliance 1 will always shift, but because $c_3 \ge c_2 \ge r(2)$, appliances 2 and 3 will not change to strategy S, as this leads to a negative payoff (it only leads to a positive payoff if they simultaneously decide to shift).

Since the aggregator wants to engage as much appliances as possible, (S,S,S) is the most interesting Nash equilibria for him. Furthermore, it is desirable that this is the only one, because if more Nash equilibria exist (like in Case 13), the players have a risk to end up in the worse equilibrium. In Case 15, (S,S,S) is the only Nash equilibrium, and it is formed with the lowest rewards $r(x_A)$. Therefore, this is considered as our optimal case.

TABLE II. PURE NASH EQUILIBRIA FOR DIFFERENT CASES

Case	$r(1)$	$r(2)$	$r(3)$	**Nash eq.**
1	$(-\infty, c_1]$	$(-\infty, c_1]$	$(-\infty, c_1]$	(NS,NS,NS)
2	$(-\infty, c_1]$	$(-\infty, c_1]$	$(c_1, c_2]$	(NS,NS,NS)
3	$(-\infty, c_1]$	$(-\infty, c_1]$	$(c_2, c_3]$	(NS,NS,NS)
4	$(-\infty, c_1]$	$(-\infty, c_1]$	(c_3, ∞)	(S,S,S), 3x(NS)
5	$(-\infty, c_1]$	$(c_1, c_2]$	$(c_1, c_2]$	(NS,NS,NS)
6	$(-\infty, c_1]$	$(c_1, c_2]$	$(c_2, c_3]$	(NS,NS,NS)
7	$(-\infty, c_1]$	$(c_1, c_2]$	(c_3, ∞)	(S,S,S), 3x(NS)
8	$(-\infty, c_1]$	$(c_2, c_3]$	$(c_2, c_3]$	(S,S,NS), 3x(NS)
9	$(-\infty, c_1]$	$(c_2, c_3]$	(c_3, ∞)	(S,S,S), 3x(NS)
10	$(-\infty, c_1]$	(c_3, ∞)	(c_3, ∞)	(S,S,S), 3x(NS)
11	$(c_1, c_2]$	$(c_1, c_2]$	$(c_1, c_2]$	(S,NS,NS)
12	$(c_1, c_2]$	$(c_1, c_2]$	$(c_2, c_3]$	(S,NS,NS)
13	$(c_1, c_2]$	$(c_1, c_2]$	(c_3, ∞)	(S,S,S), (S,NS,NS)
14	$(c_1, c_2]$	$(c_2, c_3]$	$(c_2, c_3]$	(S,S,NS)
15	$(c_1, c_2]$	$(c_2, c_3]$	(c_3, ∞)	(S,S,S)
16	$(c_1, c_2]$	(c_3, ∞)	(c_3, ∞)	(S,S,S)
17	$(c_2, c_3]$	$(c_2, c_3]$	$(c_2, c_3]$	(S,S,NS)
18	$(c_2, c_3]$	$(c_2, c_3]$	(c_3, ∞)	(S,S,S)
19	$(c_2, c_3]$	(c_3, ∞)	(c_3, ∞)	(S,S,S)
20	(c_3, ∞)	(c_3, ∞)	(c_3, ∞)	(S,S,S)

In a general scenario with n appliances, the results are somewhat similar. Like in Case 15, the monetary rewards should be chosen such that $r(i) > c_i$ for all i, i.e. the lowest monetary unit reward for only one appliance shifted should be higher than the appliance with the lowest comfort loss, the unit reward for two shifted appliances should be higher than the second lowest comfort cost, etc. This way, the only Nash equilibrium in the n appliance game is when all appliances shift.

From this game theoretic analysis two conclusions can be drawn for the design of the collaborative incentive based DR-program. Firstly, as for some appliances it is assumed that their comfort loss c_i is 0 (see case study), it follows that the lowest unit reward price r_{min} should be greater than zero, i.e. $r_{min} > 0$. Secondly, it is expected that the comfort losses c_i which are not 0, are approximately uniformly distributed. Therefore, the unit rewards $r(x_A)$ should be strictly increasing, to satisfy $r(i) > c_i$ for all i (assuming $c_1 \le \ldots \le c_n$).

Looking back at Fig. 1, it can be inferred that the fair share pricing scheme (3) does not fulfill both requirements. It is strictly increasing, but as the unit reward price r is negative for small values of the aggregated shift x_A, all the appliances will choose the strategy not shift as they fear losing both money and comfort. To resolve this, a DR-aggregator can introduce a guaranteed unit reward price $C_g > 0$, such that the first requirement is met. However, by offering this guarantee, the aggregator takes a risk of losing money in case of low aggregated response. The aggregator may finance this risk by taking a share AS of the total profits C_{net}, resulting in a customer share of $CS = 1 - AS$.

In order to keep meeting the second requirement (a strictly increasing unit reward function $r(x_A)$), the guaranteed price should not be constant, but increasing with x_A. It is chosen as a linear function such that at $x_A = 0$ it takes the value $r = C_g$ and at $x_A = x_B$ it takes the value $r = CS \times p_B$, which is the new maximum possible unit reward. Now for small values of x_A this linear guaranteed unit reward is offered, up to the point where the reduced fair price becomes higher than that of (3). This price is denoted with q. Mathematically this leads to the following unit reward function for which the graph is shown in Fig. 2.

$$r(x_A) = \begin{cases} C_g + \frac{CS \times p_B - C_g}{x_B} \times x_A & 0 < |x_A| < q \\ CS \times \left(\frac{|x_B|}{|x_A|} \times p_B + \frac{|x_A - x_B|}{|x_A|} \times p_P \right) & q \le |x_A| \le |x_B|. \end{cases} \quad (4)$$

Note that the individual responses and so the aggregated response depend on the unit reward price, since the more money that is offered, the more that the appliances shift. This

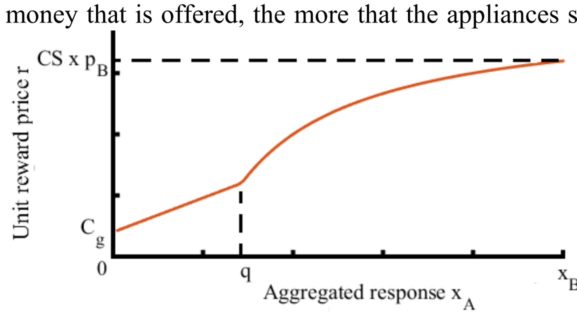

Fig. 2. Unit reward price r against aggregated response x_A for reduced fair share pricing with linear guaranteed reward

means that the unit reward price r and the aggregated response x_A are positively correlated, so that an increase in one of them is expected to increase the other. In a game theoretic setting, this results in a snowball effect.

In this paper a mechanism is designed that deals with the behavior of these intertwined variables, which is schematically depicted in Fig. 3. First, the guaranteed unit reward C_g is offered to all customers. The amount of shifted load is calculated according to this price. This aggregated load leads to a unit reward price, which is expected to be higher than the guaranteed reward. This may lead to a possible higher aggregated shift, etcetera. This process will continue as long as there is a change in the aggregated shift and this shift does not surpass the bidden value x_B, i.e. $x_A < x_B$.

III. Case Study

The performance of the proposed program is evaluated by comparing its performance with an individual performance-based incentive program, an existing Time of Use (ToU) and a prospective Real Time Pricing (RTP). For the case study it is assumed that an appliance has several DR-options and it makes an automated decision about which option to choose. This decision is made by outweighing the monetary reward against the comfort loss that is caused by choosing a particular DR-option.

The monetary reward MR of a DR-option is calculated by multiplying the amount of shifted energy with the unit reward price $r(x_A)$. More formally, if I is the set of all appliances and D_i the set of possible DR-options for appliance i, the monetary rewards are given by:

$$MR_{d,i} = r(x_A) \times x_{d,i} \qquad \forall d \in D_i, \forall i \in I, \tag{5}$$

where $x_{d,i}$ is a measure for the amount of shifted energy. This value is found by calculating the difference between the load profile LP of an appliance with and without the demand response option over the time interval between the signal start time SST and the signal end time SET:

$$x_{d,i} = \sum_{t=SST}^{SET} LP_{d,i,t} - LP_{0,i,t} \qquad \forall d \in D_i, \forall i \in I. \tag{6}$$

We use $d = 0$ for the option where no DR is used.

The comfort losses caused by shifting can differ per type of appliance. Following the approach in [10], the appliances are categorized in three different types:

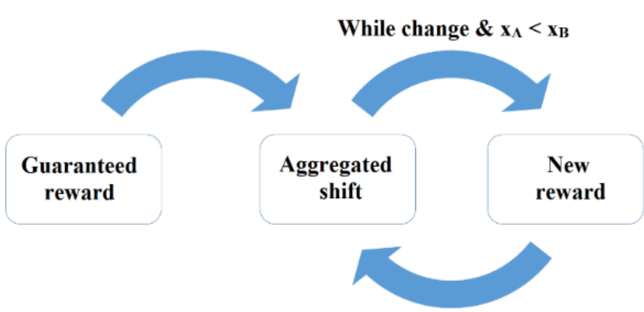

Fig. 3. Schematic representation of the snowball effect mechanism

- Shiftable appliances $I_S \subseteq I$: These are the appliances of which the load can be shifted over time, like washing machines, clothes dryers and dish washers. It is assumed that the comfort is affected as the appliance operation times are changed.
- Thermal appliances $I_T \subseteq I$: Appliances that manage the temperature in a space, like air conditioners. It is assumed that the comfort is affected if there is a significant difference between the actual and the set temperature values.
- Neutral appliances $I_N \subseteq I$: For these appliances it is assumed that the shifting of their loads (to a certain level) does not result in a comfort loss, like refrigerators and water heaters.

To compare the comfort loss for these different types, comfort penalty points CPP are introduced. They consist of a shifting penalty SP and a temperature penalty TP:

$$CPP_{d,i} = \begin{cases} SP_{d,i} & \forall d \in D_i,\ \forall i \in I_S, \\ TP_{d,i} & \forall d \in D_i,\ \forall i \in I_T, \\ 0 & \forall d \in D_i,\ \forall i \in I_N. \end{cases} \tag{7}$$

The shifting penalty consists of one point per minute that the appliance scheduled end time ASE is delayed:

$$SP_{d,i} = ASE_{d,i} - ASE_{0,i} \qquad \forall d \in D_i, \forall i \in I_S. \tag{8}$$

For thermal appliances half a point is given for both the average and the maximum difference between the actual temperature AT and the set point temperature SPT:

$$TP_{d,i} = \tfrac{1}{2} \times \max_t |SPT_i - AT_{d,i,t}| + \tfrac{1}{2} \times \overline{|SPT_i - AT_{d,i,t}|} \quad \forall d \in D_i, \forall i \in I_T \tag{9}$$

As comfort losses can be judged differently by different customers, all customers i give a penalty parameter PP to their appliances, as a value for how much money they want to receive for changing their load. Therefore, the comfort loss c is calculated as in (10).

$$c_{d,i} = CPP_{d,i} \times PP_i \qquad \forall d \in D_i, \forall i \in I. \tag{10}$$

Each appliance now has to decide which DR-option results in the highest benefit, leading to:

$$\max_{d \in D_i} \ MR_{d,i} - c_{d,i} \qquad \forall i \in I. \tag{11}$$

Using this decision mechanism, a simulation is done in MATLAB with 2000 households. A DR-signal is given for the timeframe 6.00 p.m. – 7.00 p.m. and the response of the consumers is measured. It is assumed that a household can have six possible smart appliances, with load profiles taken from [11]. From [11] both the probability that a household has a certain appliance P_{ex} and the probability that this appliance is functioning at the given DR-signal timeframe P_{on} are taken and multiplied for the total probability P_{tot}. In Table III, these probabilities, the DR-options and the penalty parameters PP (chosen uniform randomly from the given interval) are given for the six different appliances; a washing machine (WM), a dish washer (DW), a clothes dryer (CD), a refrigerator (Ref), a water heater (WH) and an air conditioner (AC). Note that

TABLE III. INPUT PARAMETERS FOR THE SIX SIMULATED APPLIANCES

Appl.	*Type*	*DR-opt.*	*PP*	P_{ex}	P_{on}	P_{tot}
WM	Shiftable	Delay	(0,2)	0.95	0.06	0.057
DW	Shiftable	Delay, Interrupt	(0,3)	0.42	0.08	0.034
CD	Shiftable	Delay	(0,8)	0.35	0.05	0.018
Ref	Neutral	Precool, Interrupt		0.2	0.7	0.14
WH	Neutral	Preheat		1.32	0.07	0.092
AC	Thermal	Precool	(0,10)	0.2	0.7	0.14

since there is on average more than one water heater in a moderate household, $P_{ex} > 1$. Furthermore, due to the lack of manual and automated DR deployment options for refrigerators, their P_{ex} is assumed to be quite low.

Using the values of Table III, the response of the customers $x_A(r)$ can be determined, by offering them various values for the unit reward price *r*. This result is shown in Fig. 4, whereby the x-axis is now the dependent axis.

The parameters that are used for the simulation for the unit reward price $r(x_A)$ of (4), are given in Table IV.

Based on $r(x_A)$ from (4) and $x_A(r)$ as given in Fig. 4, the result of the snowball effect sketched in Fig. 3 can be presented. First, the guaranteed reward C_g is offered and the aggregated response is calculated. Based on this new response, a higher unit reward is offered. This process repeats itself six times and stops after it reaches a response of 191,000, just below the bidden shift x_B. This mechanism is shown with the yellow circles in Fig. 5.

The contribution to the aggregated shift of the different appliances is shown in Fig. 6. As expected, the contribution of the refrigerator and the water heater is constant for all iterations, as their response does not result in a reduction of comfort and therefore the guaranteed reward is high enough to shift. As the air conditioner has both a high electricity demand and a high value for P_{tot}, it is the largest contributor.

TABLE IV. INPUT PARAMETERS FOR THE UNIT REWARD PRICE IN (4)

Variable	x_B	CS	p_B	p_P	C_g	q
Value	200,000	0.8	0.2	0.25	0.025	59,000

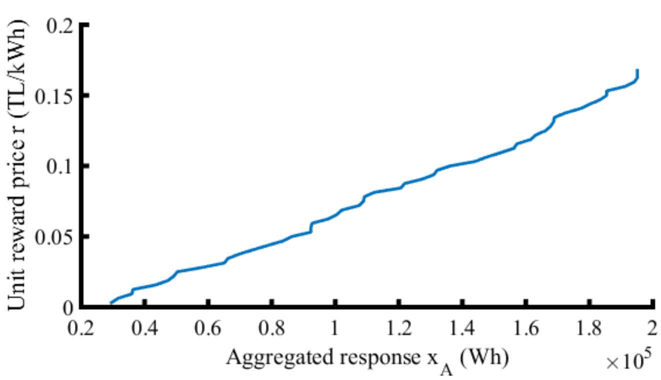

Fig. 4. Response x_A of customers on different unit reward prices r

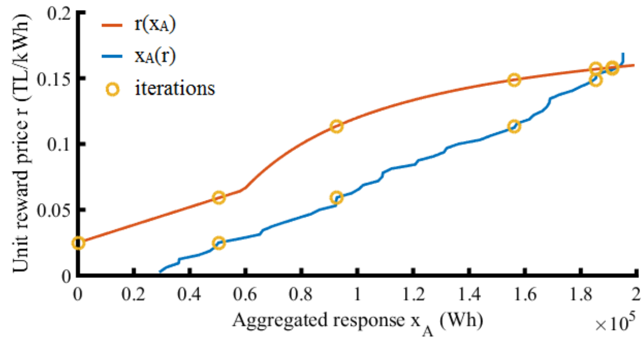

Fig. 5. Simulation of the snowball effect mechanism

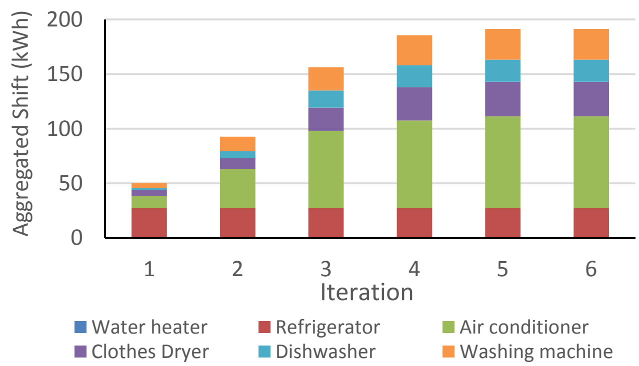

Fig. 6. Contribution of appliance types to the aggregated shift per iteration

One of the advantages of the collaborative incentive based DR-program over an individual performance incentive, is that it reduces the chance of an inappropriate response. Because the response of the customers $x_A(r)$ is not an explicit function and can be very unsmooth (see Fig. 4), offering a constant unit reward *r* or a constant static reward can lead to a high variety of responses of the customers. The collaborative incentive based DR-program, in combination with the snowball effect mechanism, makes sure that the risk of over-response ($x_A \gg x_B$) and under-response ($x_A \ll x_B$) of customers is minimal. Note that statistical analysis of data of previous responses $x_A(r)$ can improve the choice for the bidden value x_B.

Comparing the collaborative incentive based DR-program with price based programs is challenging as they are of a different nature. However, the response of the customers can be compared when applying the same balancing between monetary rewards and comfort losses. For this, a Time of Use (ToU) pricing offered in Turkey [12] and an artificial Real Time Pricing (RTP) based on Turkish market data [13] are used for comparison, they are shown in Table V and Fig. 7.

TABLE V. TOU PRICING FOR DIFFERENT TIMES OF THE DAY

Time Range	6:00-17:00	17:00-22:00	22:00-06:00
TL/MWh	312	482	190

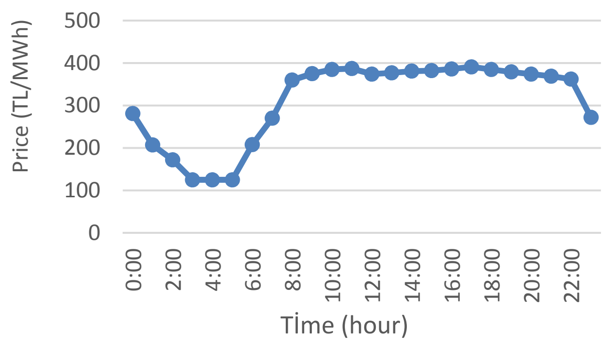

Fig. 7. Artificial RTP, based on day-ahead prices of Turkish energy market

For the collaborative incentive based DR-program, the same input as in Table IV is chosen, except that the bid price is $p_B = 0.217$ TL/kWh (which is the maximum day ahead market price of an average day) and the penalty price is $p_P = 0.22$ TL/kWh (which is the intraday price at the same time). As the biggest price difference for both the ToU and RTP is at 22:00, this time is used to analyze the response of the customers. The result of this comparison is shown in Table VI. As the ToU has a very big price drop in a short time, this program results in a bigger shift than the collaborative incentive based DR-program. However, this price drop happens only once a day and is not flexible, in contrast to RTP and CIBP. Furthermore, Turkish energy market prices are quite stable because of a low share of renewable energy sources in the Turkish energy mix. This is expected to change, and a higher volatility may result in higher prices (and therefore responses) for the collaborative incentive based DR-program.

V. Conclusions and Discussion

The study proposes a novel retail demand response program that provides incentives proportional to aggregated performance to foster cooperation between the customers. It is offered as an alternative to existing constant incentive and individual performance based programs. The outcome of the new program for both the aggregator and the participants are evaluated in the case of single DR events using game theoretical concepts. The results are compared with that of other DR programs.

The results showed that the novel program is effective at increasing the number of participators and at achieving an aggregation performance close to the bidden amount. It needed a small number of iterations (6 for the case study) and ensured the aggregator to not encounter any overpricing issues.

The proposed program can be a useful alternative to the current retail DR programs, since it motivates customers in an indirect way to collaborate and to achieve in this way a better performance. Reflection of aggregated performance on incentives can help mitigating the response gap and provide more effective response performance. In future work, real time deployment of DR and network topology considered DR applications are studied.

TABLE VI. Responses for the different kind of DR-programs

DR-program	CIBP	ToU	RTP
Aggregated shift (kWh)	191	301	96

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