Incorporation of Survey-based Data into an Aggregation Algorithm for Residential Demand Response

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***Abstract*—Survey-based data of three home appliances are included in a residential demand response (DR) aggregation algorithm that performs resource re-allocation for peak demand reduction in a notional electric distribution system. In addition, new constraints are integrated into the resource allocation approach to alleviate the inconvenience of the participating customers due to rescheduling their home appliances. Our effort replaces some assumptions from prior work on the mathematical model of customer preferences with actual data from a survey to validate the prior work. The results confirm the feasibility of the DR aggregation approach in achieving profits for the aggregator while considering the comfort of the participating customers.**

***Index Terms*--Aggregator, appliance rescheduling, comfort level, peak load, pricing.**

I. Introduction

The 2007 Energy Independence and Security Act (EISA07) of the 110th United States Congress introduced the Smart Grid Initiative as the grid modernization drive in the U.S. Under this directive, the Smart Grid included the integration of demand side resources, demand response (DR), renewable resources, and smart appliances and customer devices [1]. The integration of diverse and prolific resources into the electricity distribution system—a hitherto ignored realm of relative modernization in the electricity grid—offers the potential for improved system flexibility, but with increased system complexity.

Motivated by the Smart Grid Initiative for enabling active participation by informed end-users of electricity, an aggregated Smart Grid resource allocation (SGRA) approach was proposed in [2]. However, in [2], the smart appliances involved in the proposed optimization framework were randomly created and their characteristics (e.g., start times and availability periods for rescheduling) were set somewhat arbitrarily. Because it is integral to the work presented in this paper, a section is dedicated to explaining the SGRA at an appropriate depth—the interested reader is referred to [2] for a more detailed description of the SGRA. Even though residential participation in DR programs could achieve 45% of peak load reduction for programs representing 17% of DR potential, only 10% of residential customers are willing to participate [4]. Reducing the impact of appliance scheduling on a customer's comfort is a key factor for the success of such programs. Monetary incentives may not be enough for ensuring customers' satisfaction, and the sustainability of these incentives is not clear in the long term [4]. The literature is rife with studies that address the appliance scheduling problem without considering the comfort level of participating customers [5]─[7]. In addition to the common objective of achieving financial savings for participating customers in DR programs, several studies integrated another objective for minimizing the discomfort caused by appliances scheduling [8]─[10].

In this paper, we extend the previous SGRA approach in [2] by adding rescheduling constraints for home appliances based on usage characteristics to increase customers' comfort levels while enabling financial savings. Data from an actual survey on preferences of residential customers in the US for operating home appliances is presented in [11]. The survey involves 1023 participants from various geographical areas in the U.S. and shows a preference-based prioritization mechanism for home appliances in summer and winter seasons. The purpose of the work in [11] is to inform designers of DR program such as the abovementioned SGRA approach. Our work here presents a simulation-based study to integrate the results of the survey from [11], particularly, the start times of three common home appliances into the SGRA from [2] and verify the effectiveness of the SGRA when randomized synthetic data is replaced with realistic data. Furthermore, new constraints for rescheduling these appliances, with the intent of enhancing customer comfort, are introduced. That is achieved by determining rescheduling periods for each appliance instead of rescheduling appliances to random times throughout the day as was the case in [2]. The key contribution of this manuscript is the incorporation of real-world information to extend the validation of the SGRA method.

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II. SGRA Approach

The SGRA approach [2] is a load shifting technique run by a third-party for-profit market entity, namely, the aggregator, as a DR program in the residential sector. The aggregator is involved in arbitrage between the system operator and the residential electricity customers. The aggregator uses a heuristic optimization framework to reschedule some participating smart appliances to other periods throughout the day with the objectives of maximizing the aggregator's profit and reducing the system peak demand. The rescheduling of the participating assets is determined one day in advance to enable seamless participation in day-ahead markets. To encourage consumers to participate, the aggregator offers a dynamic pricing called customer incentive pricing (CIP) that is designed to be competitive with the forecast utility pricing for retail electricity sales.

By collecting information on the schedulable smart appliances characteristics in a distribution system, the aggregator in [2] implements a heuristic optimization to determine a new schedule for a set of the schedulable smart appliances and the CIP. The aggregator's strategy for maximizing profits in the electricity spot market is as follows: (i) to promote customer participation, the aggregator offers a CIP that must be lower than the utility pricing during rescheduled times to justify the rescheduling discomfort for consumers; (ii) the aggregator aims to reschedule appliances—committed by customers that choose the CIP—away from peak times; (iii) the aggregator offers demand reduction and sells it to the system operator during peak times when spot market electricity prices are expected to be the highest; (iv) the aggregator reschedules the committed appliances to other periods of lower spot market prices (this means the aggregator must buy energy to supply its participating customers); and (v) the customers pay the aggregator the CIP rather than the utility prices. If the CIP is priced appropriately, this position should realize savings for customers and revenues for the aggregator.

In [2], the authors used a genetic algorithm in the SGRA framework to generate the CIP and the day-ahead appliance schedule. Using 5,555 residential customers, 56,642 schedulable appliances over a 24-hour period, and real-world pricing data, the SGRA approach was demonstrated via simulations to yield profits for the aggregator while performing peak reduction. However, the work in [2] did not use real data for appliance usage (i.e., appliances types and start times); rather, statistical and probabilistic models were used. The interested reader is pointed to [2] for the details of the SGRA.

III. User Preferences Prioritization for Home Energy Management System

Reference [11] presents data from a survey of 1023 responses for a multi-criteria decision-making approach to identify user preferences in the residential sector. The objective of the study in [11] is to determine the set of home appliances most likely to be offered by residential customers for DR programs that aim to reduce the system peak load during winter and summer seasons.

Ref. [11] prioritizes customers' preferences for several home appliances to be used in designing energy management programs. The prioritization method considers a set of criteria including functionality, cost, and carbon emissions. The survey participants were mostly from the contiguous U.S.; note that the authors of [11] describe the limitations of the data including a caveat against treating the data as nationally representative. The results of the survey in [11] are intended to inform the design of energy management systems for enabling DR programs. We endeavor towards that goal.

IV. Problem Statement

Here, the prioritization of customers' preferences for home appliances from [11] is used to inform the characteristics of reschedulable appliances that participate in the SGRA approach performed by the aggregators in [2]. The incorporation of actual data will show that the SGRA approach can achieve profits and peak demand reduction, not just with theoretical assumptions from [2], but also with a large set of real data. Hence, data from the survey in [11] corresponding to three home appliances—the dishwasher, the washing machine, and the clothes dryer—are considered here. These appliances from the survey are chosen for consideration because of their flexibility in operation hours and their uninterruptible nature of operation [12]. Table I shows the characteristics of these appliances derived from the survey data in [11].

Table I. Schedulable appliances charecteristics [11]

Appliance	Penetration level (%)	Rated power (kW)	Duration (hour)
Dishwasher	67	0.3	1
Washing machine	85	0.665	1
Clothes dryer	80	5.5	1

The penetration percentages of the appliances represent how many of the survey participants own these appliances. Based on the penetration percentages of the appliances shown in Table I, 12,888 reschedulable appliances are distributed among the 5,555 customers of the original case; this contrasts with the randomly created 56,642 reschedulable appliances used in [2]. The 12,888 reschedulable appliances used in this study represent only 6.4% of the total load for the 5,555 customers in the system. In [11], the 1023 participants polled indicated the (typical) start times for the abovementioned three appliances; Figs. 1-3 show this for dishwashers, washing machines, and clothes dryers, respectively. This data is incorporated in the SGRA approach. Here, the schedulable appliances that were randomly created and used in the SGRA approach in [2] are omitted and replaced with the 12,888 appliances described.

In addition to employing the usage data of each appliance, rescheduling constraints are added to lessen the inconvenience for customers participating with the aggregator. Each appliance type has a unique constraint depending on its task, e.g., a dishwasher may be delayed from its intended start time without affecting the expected task of dishwashers, which is washing used dishes after meals. Therefore, rescheduling a dishwasher to a random time in the day, as in the original case, may cause significant inconvenience for its owner.

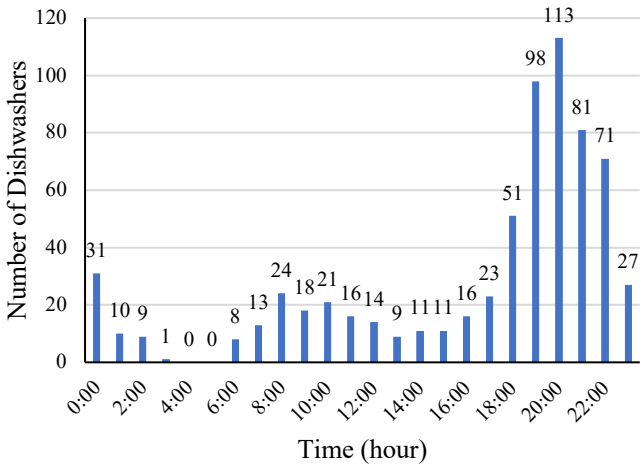

Fig. 1. Intended start times of dishwashers at each hour through the day from the survey [11]

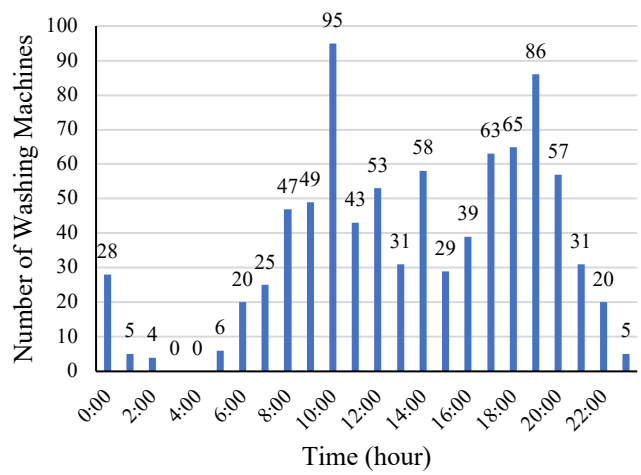

Fig. 2. Intended start times of washing machines at each hour through the day from the survey [11]

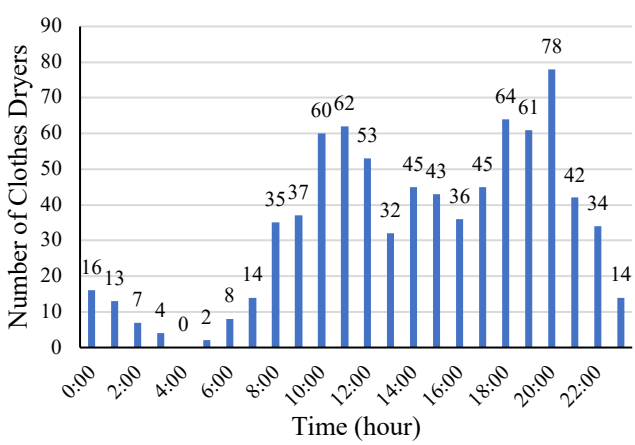

Fig. 3. Intended start times of dryers at each hour through the day from the survey [11]

The following constraints are added to the SGRA optimization for rescheduling the 12,888 reschedulable appliances from the three appliance types mentioned above. First, the period for rescheduling dishwashers is *subjectively* set to five hours after the originally intended start time. That is, dishwashers are to be rescheduled to a time no later than five hours from the originally intended start time. This constraint is modeled mathematically as in (1), where t_{start}^{dish} is the originally intended start time of a dishwasher, and t_{resch}^{dish} is the rescheduled start time of that dishwasher so that

$$t_{start}^{dish} < t_{resch}^{dish} < t_{start}^{dish} + 5. \tag{1}$$

Second, washing machines and clothes dryers must be rescheduled chronologically to account for their interrelated functions. In addition, for the comfort of customers, the laundry appliances are rescheduled in a *subjectively* set period of six hours around the originally intended start times set by the owners. Equations (2) and (3) account for these two constraints that pertain to rescheduling a washing machine and a clothes dryer for an individual customer, where t_{start}^{w} is the originally intended start time of a washing machine, t_{resch}^{w} is the rescheduled start time of that washing machine, and t_{resch}^{d} is the rescheduled start time of a dryer of the same customer that owns the corresponding washing machine so that

$$t_{start}^{w} - 3 < t_{resch}^{w} < t_{start}^{w} + 3 \tag{2}$$

$$t_{resch}^{w} < t_{resch}^{d} \quad . \tag{3}$$

The spot market energy prices and the utility prices are inputs for the aggregator. The utility pricing and spot market pricing information used in the simulation are real data from a randomly selected day (Wednesday July 1, 2020), acquired from ComEd residential real-time pricing [13] and PJM [14], respectively. This data includes forecast and actual hourly prices for the utility and spot market. We choose PJM and ComEd to align with the base case in [2].

V. Results

The aggregator determines a reschedule for a set of 12,888 schedulable appliances by performing the SGRA approach. Fig. 4 shows the load profiles of the schedulable appliances before and after performing the SGRA approach for a 24-hour period. To maximize its profits, the aggregator reschedules appliances from peak hours when spot market prices are high to other times when spot market prices are lower according to the rescheduling constraints in (1)-(3). As the schedulable load is part of the total load, the new schedule affects the total load as well. Fig. 5 shows the total load including schedulable and base loads of the entire 5,555 customers before and after performing the SGRA approach. More than half of the schedulable load, i.e., 53%, is moved from peak times, i.e., 16:00—19:00, to other times; this accounts for 4.2% of the total peak load on the system. Note that this effort in peak reduction causes the base loads during off-peak to increase by 6.7%.

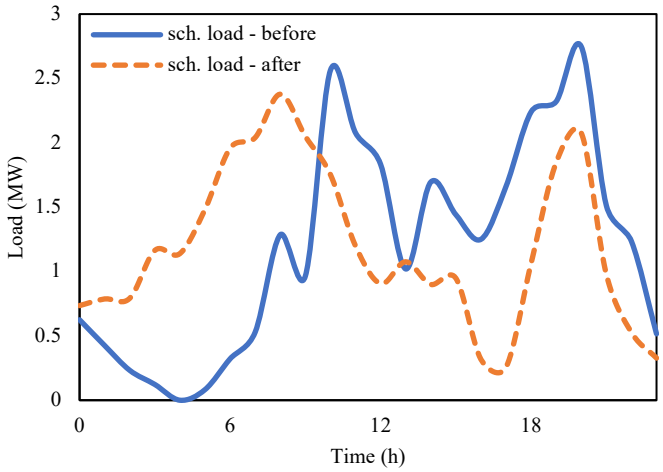

Fig. 4. Schedulable load profile before and after aggregation

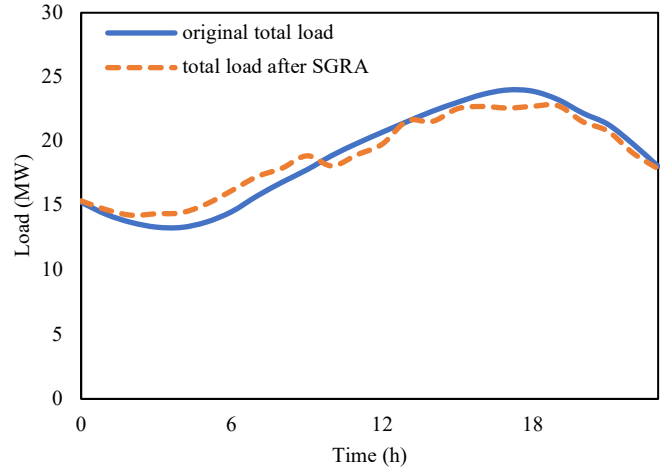

Fig. 5. Total load profile before and after aggregation

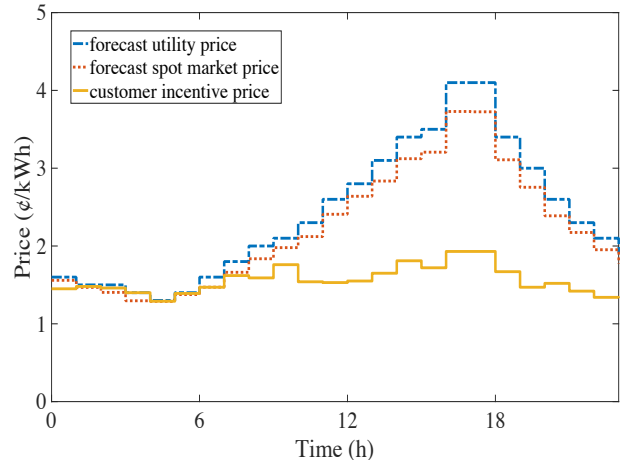

Fig. 6. Forecast utility price, forecast spot market price, and CIP

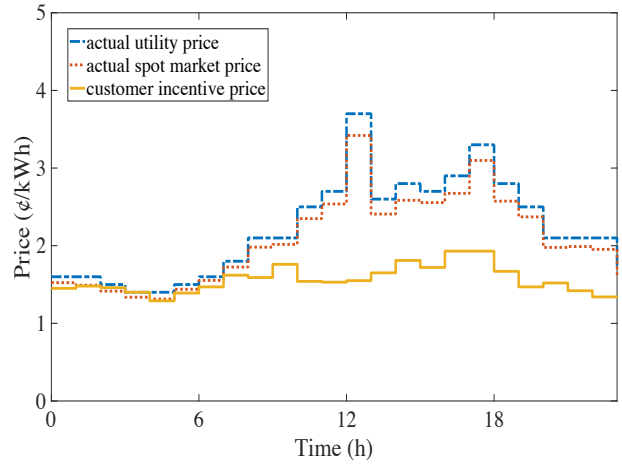

Fig. 7. Actual utility price, actual spot market price, and CIP

Fig. 6 shows the CIP offered by the aggregator compared with the forecast spot market price and forecast utility price. The forecast aggregator profit, which is the final objective value, achieved by the SGRA optimization is $484.37. When the actual utility and spot market pricing are used for evaluating the actual profit of the aggregator, the schedule determined by the SGRA optimization resulted in an actual profit of $450.52. This reduction in actual profit from forecast profit is because the actual spot market pricing at peak hours is lower than forecast as shown in Fig. 7, which leads to a decrease in the actual profit.

VI. Conclusion

Data on three home appliances from an actual survey are used to evaluate the optimization framework of the SGRA approach. Unlike the base case of the SGRA approach in [2], which uses random data for the schedulable smart appliances, the use of real data from the survey in [11] validates the feasibility of SGRA for practical applications. Using real data about the behaviors of customers on operating smart appliances also allows the SGRA program designer to account for the comfort of the participating customers. This takes into consideration the task of each appliance when rescheduling it. Dishwashers may be rescheduled as late as five hours after the usual start time because this kind of appliance is mostly correlated to customers' habits in consuming food and then doing dishes. Hence, delaying the use of dishwashers a few hours is more realistic than rescheduling it to a random hour through the day. In addition, setting random rescheduled start times for a dryer does not account for the appliance's sequential nature related to another appliance, i.e., the washing machine; not considering such practical constraints may cause significant discomfort for participating customers and introduce unreliable results in expected DR.

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REFERENCES

[1] M. Simoes, R. Roche, E. Kryiakides, S. Suryanarayanan, B. Blunier, K. McBee, P. Nguyen, P. Ribeiro, and A. Miraoui, "A comparison of Smart Grid technologies and progresses in Europe and the U.S.," *IEEE Transactions on Industry Applications*, vol. 48, no. 4, pp. 1154-1162, July-Aug. 2012.

[2] T. Hansen, R. Roche, S. Suryanarayanan, A. A. Maciejewski, and H. J. Siegel, "Heuristic optimization for an aggregator-based resource allocation in the Smart Grid," *IEEE Transactions on Smart Grid,* vol. 6, no. 4, pp. 1785–1794, July 2015.

[3] T. Hansen, "The Smart Grid resource allocation simulator to model aggregator-based demand response using residential smart appliances," *Github.com*, Feb. 2016. [Online] Available: https://tinyurl.com/y29falno [Accessed: Oct. 6, 2020].

[4] N. Ahmed, M. Levorato, and G. P. Li, "Residential Consumer-Centric Demand Side Management," in *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 4513-4524, Sept. 2018.

[5] K. C. Sou, J. Weimer, H. Sandberg, and K. H. Johansson, "Scheduling smart home appliances using mixed integer linear programming," in 50th IEEE Conference on Decision and Control and European Control Conference, Dec 2011, pp. 5144–5149.

[6] G. Xiong, C. Chen, S. Kishore, and A. Yener, "Smart (in-home) power scheduling for demand response on the Smart Grid," in *Innovative Smart Grid Technologies*, 2011, pp. 1–7.

[7] Z. Zhu, J. Tang, S. Lambotharan, W. H. Chin, and Z. Fan, "An integer linear programming based optimization for home demand-side management in Smart Grid," in 2012 IEEE PES Innovative Smart Grid Technologies (ISGT), Jan 2012, pp. 1–5.

[8] G. Huang, J. Yang, and C. Wei, "Cost-Effective and Comfort-Aware Electricity Scheduling for Home Energy Management System," 2016 IEEE International Conferences on Big Data and Cloud Computing (BDCloud), Social Computing and Networking (SocialCom), Sustainable Computing and Communications (SustainCom) (BDCloud-SocialCom-SustainCom), , 2016, pp. 453-460

[9] Z. Garroussi, R. Ellaia, and E. Talbi, "Appliance scheduling in a smart home using a multiobjective evolutionary algorithm," 2016 International Renewable and Sustainable Energy Conference (IRSEC), , 2016, pp. 1098-1103.

[10] R. Reghukumar, S. Sambhu, and V. Ravikumar Pandi, "Multi-Objective Optimization for Efficient Home Energy Management System using Differential Evolution Algorithm," 2018 3rd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), 2018, pp.

[11] R. Kadavil, S. Lurbé, S. Suryanarayanan, P. A. Aloise-Young, S. Isley, and D. Christensen, "An application of the Analytic Hierarchy Process for prioritizing user preferences in the design of a Home Energy Management System," *Sustainable Energy, Grids and Networks*, vol. 16, pp. 196–206, 2018.

[12] Z. Chen, L. Wu, and Y. Fu, "Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1822–1831, Dec. 2012.

[13] ComEd, *ComEd Residential Real-Time Pricing Program*, [Online]. Available: https://hourlypricing.comed.com/live-prices/. [Accessed Sept. 22, 2020].

[14] PJM, *Data Miner 2*. [Online]. Available: https://dataminer2.pjm.com/list. [Accessed Sept. 22, 2020].