Load Flexibility for Price based Demand Response

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***Abstract*—We propose a framework to utilize load flexibility to be operated in a window of flexibility considering the price variations. The consumer inputs the window of flexibility, the period of operation and nominal power consumption trajectory governed by the load. We create a load shift matrix and minimize the cost of consumption of operating the device. For some devices such as electric vehicle, the nominal power consumption trajectory can be altered provided the total energy consumed in the window of flexibility is matched. The new power consumption trajectory can be found using profile steering. We also show that under the price taker assumption, the optimal control of aggregate of flexible loads is equivalent to optimally controlling each of the loads individually. Using real data from Pecan Street [1] and ERCOT wholesale market price [2] we conduct numerical experiment showing the efficacy of the proposed mechanism of performing price based demand response (DR).**

***Index Terms*—Demand response, load shift, profile steering**

I. Introduction

The push for increasing the share of electrical energy generation from renewable energy sources (RES) is a global phenomenon. However, connecting bulk RES will require a much bigger ancillary market for achieving load balancing. The conventional solution adopted is to install billions of dollars worth fast ramping generators to achieve this balance between supply and demand. A more cost-effective solution would be to induce responsiveness from consumer side to respond in exchange for incentives. Authors in [3] consider a case where each household wishes to optimally schedule its power consumption so as to maximize its individual net benefit subject to various consumption and power flow constraints. They show that appropriate time-varying electricity price design can align individual with social optimality. However, it has been observed that consumption patterns of users do not change significantly with real-time electricity price variations and hence consumers end-up paying more in their electricity bill [4]. Thus, consumers consume electricity without considering price variations, therefore, consumers have price inelastic demand. This is primarily because of two reasons. Firstly, the electricity price for consumers either does not vary or the variation is low. Secondly, consumers do not have smart devices which can use the flexibility in operation while considering the variation in electricity price in the flexible window of operation. For instance, a consumer puts the dishes in the dishwasher after lunch and wants the job of cleaning the dishes to be complete before the next meal in the evening. However, it will be hugely inconvenient for the consumer to monitor the prices and optimally turn on the dishwasher. In this work we propose a local control, where the consumer inputs the nominal power consumption trajectory of the appliance and its flexibility window. The local controller optimally completes the task, ensuring the cost of energy consumption is minimized. The flexibility window for the dishwasher example is between afternoon to evening, the power consumption depends on the load, i.e. the dishes, and the operational period is also governed by the load. There are many such daily energy usages where the user is not bothered by the exact time of operation if the task is completed before the next usage decided by the consumer. We believe the behavioral nuances are very complex to model and in this work we input these preferences directly from the consumer.

Prior work [5]–[7] present load flexibility to be used for performing demand response. Authors in [5] provide a framework to analyse consumer load profiles considering time of usage and temperature variations, essential for demand response. Authors in [6] identify the need for accurate local measurement for centralized control to perform demand response, such precise measurements are far from contemporary precision in measurements, therefore, we focus on distributed control of loads based on variation of electricity price. The ability to reduce peak load by just shifting the usage of water heaters in Norway is presented in [7]. The potential for demand response from 50% of Norwegian households is estimated at 1000 MWh/h, approximately 4.2% of peak demand.

Authors in [8] investigates the required communication and information system needed for differing the operation of flexible devices considering variation of electricity price. They verify through laboratory tests that price responsive consumers reduces the cost of consumption for the users and also provides an interface for the transmission system operator to utilize distributed energy resources and flexible loads as a regulating resources. According to [9] the challenge associated with usage of direct load control for controlling flexible loads for faster time scale regulation would be to maintain level of service desired by consumers. We propose a framework where the quality-of-service fed by consumers will ensure the use of flexibility for providing grid based services. Authors in [10] identify that flexible loads can be used as virtual batteries at the same time ensuring load quality of service bounds are met. The control of energy storage devices for grid based services is well established in prior works [11], [12].

Authors in [13] model deferrable electric loads parameterized my arrival time, departure time, the total energy required and maximum allowable power to operate the load. In our work, we also consider a load flexibility window input by the consumer directly. The power consumption trajectory can be shifted in time or for some loads a new power consumption trajectory can be obtained using profile steering.

A variable price structure will incentivize users to differ the power consumption in presence of smart appliances and smart metering technology. Authors in [14] identify that consumer profit under such a scenario will be moderate. Due to modified consumer behavior, new peak loads will appear based on the amount of aggregate flexible loads. Authors in [15] identify that load flexibility will play a key role in a power network with high volatility. Flexible loads will provide fast ramping and ensure stable operation of entire power network. Our work focuses on price based demand response using load flexibility. The key contributions of this paper are:

• *Defining load flexibility*: We define flexibility defined by three parameters: the shiftable device consumption vector, the nominal starting time of the device and the end time of flexibility window in which the task needs to be completed.

• *Price based DR*: We propose a mechanism to differ operation of flexible device in a user specified flexibility window by shifting the load in time or by profile steering.

• *Optimal control algorithm*: We present an algorithm to optimally shift the device operation based on the price variations in the flexibility window. We show that controlling each device independently is equivalent to controlling all of them simultaneously.

• *Numerical evaluation using real data*: Using real data from Pecan Street [1] and price data from ERCOT in Texas [2] we show that the proposed price based DR algorithm minimizes the cost of consumption for the user.

The rest of the paper is organized as follows. In Section II we describe the system and assumptions. In Section III we discuss the mechanism of price based demand response in terms of shifting in time and profile steering. Section IV presents the numerical results. Section V concludes our work.

II. System Description

Consumers of electricity use many different appliances, some of them are completely inelastic and cannot be altered in time. For example television when commanded to be turned on, should turn on, a delay might discomfort the user. However, prior work in load flexibility have demonstrated how the aggregate flexibility in operation of pool pumps [16], thermostatic controlled load [17], electric vehicles [13] can be used for grid stabilization [18]. We consider a residential customer in this work with some of the loads as flexible. These devices are operated optimally to minimize the cost of consumption for the user.

Pecan Street Dataport has a vast database which includes ERCOT market operations, minute-interval appliance-level customer electricity use from nearly 1,000 houses and apartments in Pecan Street's multi-state residential electricity use research [1]. As a representative example we use Home ID 5357. We intend to provide a way of analyzing one such home. Similar analysis can be conducted for other homes, of course the analysis will be personalized with a user. For home id 5357 for the month of January 2017 the share of power consumption by type is given in the Table I. The end user partially generates its own consumption needs using rooftop solar PV system.

TABLE I
Home ID 5357 load disaggregation for January 2017

Column Name: Description [19]	Share in %
use home electricity use	100
grid power from grid	67.63
gen solar PV generation	31.07
bathroom1 includes local loads	24.98
poolpump1 Pool pump circuit	16.36
air1 Air compressor	12.76
waterheater1 Electric water heater	10.50
car1 Electric vehicle charger	4.23
refrigerator1 Refrigerator circuit	1.81
bedroom1 includes local loads	1.61
oven1 Oven circuit	1.16
dishwasher1 Dishwasher circuit	0.74
kitchen1 includes local loads	0.55
microwave1 Microwave circuit	0.49
dryg1 Natural gas-powered clothes dryer	0.39
oven2 Second oven circuit	0.22
livingroom1 includes local loads	0.17
range1 stand-alone cooktop	0.0089
disposal1 kitchen sink	0.0048

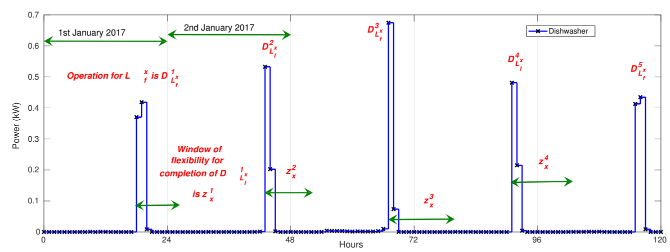

Fig. 1. Dishwasher power consumption for House ID 5357 for 1st to 5th January 2017 [1]

Fig. 1 shows the power consumption by dishwasher. It is evident from Fig. 1 that user initiates the use of dishwasher around 7pm. However, the power consumption trajectory of the dishwasher is visibly unique for different days, this is primarily because of two reasons. Firstly, the load each day is different, creating a unique duty cycle. Secondly, the hourly data used in this paper averages the power consumption withing the sampling time. When the end-user participates in DR then this power consumption trajectory of a flexible device is shifted in time or a new power consumption trajectory is steered such that it is within the time defined in the flexible window period and total energy consumed under the nominal case is equivalent to the optimal case. The Quality-of-Service (QoS) for day i for appliance x is given as the operational duty cycle D^i_x. It can be observed that end-user uses dishwasher only once in a day, this implies the task of washing these dishes can be completed anytime before the next time end user wants to use the dishes for the next meal or whenever the user wants the dishes clean (whichever is lower will be selected as the flexible window for the device). This period of flexibility is called as window of flexibility. For day i and the operational duty cycle D_x^i, the window of flexibility is given as z_x^i as shown in Fig. 1.

A. Defining Load Flexibility

The objective of this work is define flexibility in electricity consumption by some devices and provide a framework to use these devices to perform price based demand response and/or dynamic regulation at fasted temporal scales using a centralized controller. In the present work we consider the former application. We would also present how much an end user can gain financially by participating in these roles.

In the present work we assume:

- We assume that end user presently starts the device manually when needed. However, with this additional feature the user could select a window in which the operation should be completed.
- Device once turned ON, then is assumed to have no flexibility to be turned OFF.
- Power consumption trajectory symbolize QoS being achieved for end-user application. This trajectory is shifted in the window of flexibility ensuring:

- power consumption trajectory is not altered
- the task of the appliance is completed in the window of flexibility defined by the user.

- Profile Steering: For loads such as electric vehicle, the nominal power consumption trajectory can be altered considering power constraint of in the flexibility window specified by user.

Total time T is divided into N samples with sampling time h. For example, t_i represents time instant $i \in \{1, 2, ..., N\}$ is equal to ih. The total electrical load consumed by an user at time step i is given as $L(i)$. The total load consists of non-flexible and flexible components. The usage of non-flexible loads, $L_{nf}(i)$ cannot be altered, for example lighting load, television etc. The flexible loads, $L_f(i)$ can be altered in time of operation depending on how much the user can delay. The total load is represented as $L(i) = L_f(i) + L_{nf}(i) \quad \forall i \in \{1, 2, ..., N\}$. The flexible loads can be further sub-divided into cumulative of individual flexible device and denoted as $L_f(i) = \sum_{j=1}^{m} L_f^j(i)$, where m is the number of flexible device the user has.

Each flexible load is characterized by three parameters:

- Shiftable consumption vector, $D_{L_f^x} = [D_1 \quad D_2 \quad ... \quad D_k]$
- Starting time, t_S^x
- End time of load flexibility window is denoted as z_x.

The flexibility of a device is defined as $V_x = (D_{L_f^x}, t_S^x, w_x)$. Let t_e be the end of time horizon, then the length of the window of flexibility is given as $w_x = \min(t_e - t_S^x, z_x - t_S^x)$.

Corollary II.0.1. *If the consumers are price takers of electricity having m flexible devices, then minimizing total cost of consumption by using flexible devices in predefined window of time will be equivalent to minimization of cost of consumption of individual devices.*

Proof. The objective function of consumer is to minimize the cost of consumption without reducing the total energy consumed in the nominal case. The objective function of the user is represented as

$$\min \sum_{i=1}^{N} L(i)p_i = \min \sum_{i=1}^{N} L_f(i)p_i + \min \sum_{i=1}^{N} L_{nf}(i)p_i, \quad (1)$$

where p_i represents the price of electricity at time instant i. Since the non-flexible loads cannot be modified implying $\sum_{i=1}^{N} L_{nf}(i)p_i$ is a constant. Therefore, the cost minimization will only be governed by flexible devices. Thus, the equivalent consumer objective function is

$$J_1 = \min \sum_{i=1}^{N} L_f(i)p_i = \min \sum_{i=1}^{N} \Big(\sum_{j=1}^{m} L_f^j(i) \Big) p_i. \quad (2)$$

Since the consumer is assumed to be the price taker of electricity where the end user does not influence the price by consuming more or less, therefore, J_1 is equivalent to individual minimization of cost of consumption of each device, represented as

$$J_2 = \min \sum_{i=1}^{N} L_f^1(i)p_i + \min \sum_{i=1}^{N} L_f^2(i)p_i + ... + \min \sum_{i=1}^{N} L_f^m(i)p_i \quad (3)$$

As p_i is a constant for time instant i, thus, $J_1 = J2$, implying individual minimization leads to overall minimization. □

III. Price Based Demand Response

In this section we present a mechanism to perform price based demand response. We propose two different ways to perform price based DR, firstly, shifting the operation in time and secondly, performing an optimization to find the optimal power trajectory. Load such as electrical vehicle can charge in multiple power trajectories, however, for a washing machine the power consumption trajectory is easy to be shifted in time rather than modifying the nominal power consumption trajectory, this is because motor based loads have power constraint which needs to be respected.

A. Shifting Load in Time

The end user uses flexible loads to alter the aggregate consumption trajectory in order to minimize the total cost of consumption. In this subsection we consider the end-user QoS is achieved if the power consumption trajectory is shifted in the flexible window of operation set by consumer. In a real time scenario load disaggregation techniques based on past consumption patterns can be used to understand the nominal power consumption trajectories. This mechanism of shifting flexible loads in time takes as input the window of flexibility (z), the starting time of the device (t_s), consumption vector

(D_{L_f}) and the end of time horizon (t_e). Using the flexible load parameters, V_x, the load shift matrix is developed as:

$$A_x = \begin{bmatrix} D_1 & D_2 & D_3 & - & D_k & 0 & - & 0 & 0 \\ 0 & D_1 & D_2 & - & D_{k-1} & D_k & - & 0 & 0 \\ 0 & 0 & D_1 & - & D_{k-2} & D_{k-1} & - & 0 & 0 \\ 0 & 0 & 0 & - & D_{k-3} & D_{k-2} & - & 0 & 0 \\ - & - & - & - & - & - & - & - & - \\ 0 & 0 & 0 & - & - & - & - & D_k & 0 \\ 0 & 0 & 0 & - & - & - & - & D_{k-1} & D_k \end{bmatrix}$$

The size of the load shift matrix for flexible load L_f^x is given as A_x for the flexibility parameter given by V_x. The order of load shift matrix, A_x is $(z_x - k) \times (z_x - 1)$, where k is the length of period of operation of the flexible load. Note if $t_e < z_x$ then the size of load shift matrix will be $(t_e - k) \times (t_e - 1)$. The index for optimal starting of the flexible load x is

$$i_{\text{opt}}^x = \arg\min A_x p_x = \arg\min A_x \begin{bmatrix} p_{i_s^x} \\ p_{i_s^x+1} \\ p_{i_s^x+2} \\ - \\ p_{i_s^x+z_x/h-2} \\ p_{i_s^x+z_x/h-1} \end{bmatrix} \quad (4)$$

The optimal time to start the flexible device L_f^x is given as $t_{\text{opt}} = t_s^x + i_{\text{opt}}^x h - 1$. The optimal power consumption vector of flexible load x is given as

$$(L_f^x)_{\text{opt}} = [\text{Nom}(i_s + i_{\text{opt}} - 1) \quad D_{L_f^x} \quad \text{Nom}(i_s + i_{\text{opt}} + k : t_e/h)], \quad (5)$$

where Nom represents the nominal consumption vector of the flexible device which is not shiftable. For example, pool pumps consume a constant power over the whole time. The total optimal flexible load is given as $L_f^{\text{opt}} = \sum_{x=1}^{m} (L_f^x)_{\text{opt}}$. The optimal load is denoted as $L_{\text{opt}} = \sum_{x=1}^{m} (L_f^x)_{\text{opt}} + L_{nf}$. Deviation from the nominal is denoted as $L_\Delta = L_{\text{opt}} - L$. For devices operated multiple times in the time horizon, the algorithm `OptimalDR` is implemented multiple times and the output matrix is concatenated to form the optimal power consumption trajectory for the entire time horizon.

Algorithm 1 `OptimalDR`(t_s^x, z_x, L_f^x, t_e)

Inputs: t_s^x, z_x, t_e
Function: Performing price based demand response
Initialize: Set device threshold, c

1: Find $w_x = \min(z_x, t_e)$
2: Find $D_{L_f^x}$
3: Consider w_x and create A_x and p_x.
4: Find $i_{\text{opt}} = \arg\min A_x p_x$
5: Find $(L_f^x)_{\text{opt}}$
6: Calculate L_{opt}
7: Deviation from the nominal is L_Δ

B. Profile Steering

For some loads like electric vehicle, energy storage device, the overall power consumed in the nominal scenario if match then the QoS is achieved and the exact trajectory is not a concern for the consumers.

Prior work in load consumption profile steering shows that profile steering assists in power quality improvements and reduction in distribution losses [20].

In our work we propose appliance based local optimization to identify the power consumption trajectory subject to device constraints of power consumption, total energy and available window of operation. The optimization problem is represented as $\sum_{i=t_S^x}^{z_x} D_{L_f^x}^*(i) p_i$, subject to, $\sum_{i=t_S^x}^{z_x} D_{L_f^x}^*(i) = \sum_{i=t_S^x}^{z_x} D_{L_f^x}(i)$, s.t. $D_{L_f^x}^*(i) \in [D_{L_f^x}^{\min}, D_{L_f^x}^{\max}] \quad \forall i$. Note: Profile steering can be used for devices with flexible power consumption trajectory. For example motor based loads like washing machines, pool pumps cannot differ their power consumption trajectory drastically because of the requirements of power.

IV. Numerical Results

For numerical evaluation we use real consumption data from Pecan Street [1] and electricity price data from ERCOT [2]. We use data for home ID 5357 for 3rd and 4th January 2017 and consider the wholesale market prices from ERCOT. Note the residential prices are often less volatile, implying lower incentives for the users to deviate. Therefore, for this numerical experiment we use wholesale market price. The information fed by user is listed in Table II. For this numerical example we consider electric car, pool pump, dishwasher and water heater as flexible devices. These devices comprise approximately 28% of total load, as shown in Table I. For this numerical example the power consumption trajectories meeting QoS for the user are assumed to be known a priori. The nominal power consumption trajectory is then shifted in time depending the flexibility window and price variations.

TABLE II
User Input based on Nominal Consumption

	Window (z_x)	Start Time (t_S)	End Time (t_e)
Electric Car	10 hours	21	48
Pool Pump	12 hours	[11,35]	[31,48]
Dishwasher	6 hours	[19, 43]	[32,48]
Waterheater	6 hours	[5, 17, 29, 41]	[16, 28, 40,48]

The nominal load consumption trajectory is shifted in time using the proposed algorithm. For devices being operated multiple times, the same algorithm is applied and the output vectors are concatenated.

Fig. 2 shows the nominal and optimal operation of flexible devices considering price variations, the window of flexibility and end-time. Table III lists the profits the consumer makes by deviating consumption in time. Fig. 3 shows the deviation from the nominal operation. Note L_Δ is a zero mean signal. Fig. 4 shows the new steered profile for EV charging. The new profile is calculated by solving the optimization profile described in Section III.B. The end user profit is \$0.0586, higher than shifting the power consumption trajectory in time (see Table III). Note the charging of battery has various modes: constant current charging is when the bulk charging happens

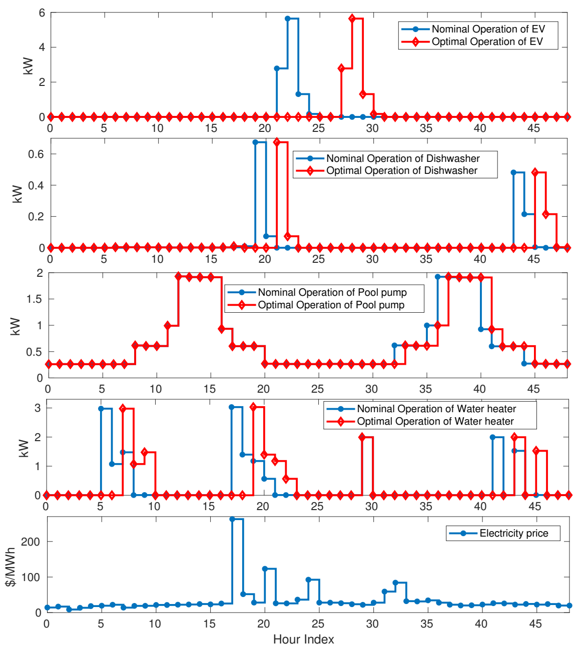

Fig. 2. The nominal operation versus the optimal operation considering electricity price

TABLE III
PROFIT FOR USER

device	Electric Car	Pool Pump	Dishwasher	Water heater
Profit($)	0.0425	0.0166	0.0086	0.6886

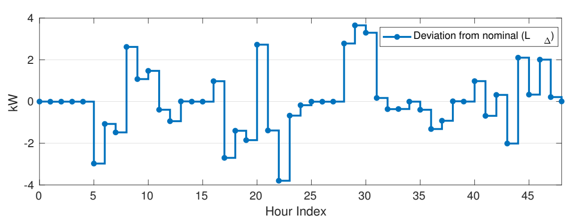

Fig. 3. Deviation from the nominal operation

till state of charge of the battery reaches to a level ($\approx 80-90\%$ for Li-Ion) and then the battery is charge at constant voltage (slow rate of charging). In profile steering for EV we didn't consider these modes of operation.

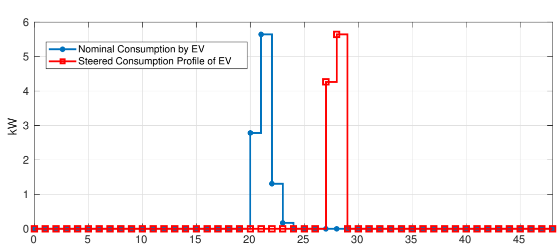

Fig. 4. Profile steering for EV

V. CONCLUSION

We propose a framework to shift loads in time to perform price based demand response using consumer fed preferences and considering price variations. We present two different ways in which consumers can use their flexibility to minimize their cost of consumption: shifting load in time and profile steering of power consumption trajectory. We present numerical results for a representative home.

In future work we will consider stochasticity in parameters and model load flexibility as virtual batteries performing grid based services to maximize consumer benefits.

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