D2S: Dynamic Demand Scheduling in Smart Grid Using Optimal Portfolio Selection Strategy

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***Abstract*—In this paper, we propose a dynamic demand scheduling (D2S) scheme — an effort towards cost-effective energy consumption at customers' end. The theory of *Optimal Portfolio Selection* is adopted to generate customers' expected day-ahead energy demand graph called the *weight graph*, based on past days' history — energy demand, profit return, and corresponding risk. In such a scenario, the *weight graph* of energy ensures that the expected profit return and the corresponding risk to the customers are optimized. Consequently, we evaluate the dynamic scheduling scheme for optimizing the energy cost to the customers using the *weight graph*. Furthermore, the proposed scheme also assists in relieving the peak-demand on the grid, which, in turn, implies that the grid is capable of providing service to the scheduled appliances. The performance of the proposed scheme is evaluated with different performance metrics — peak-demand, demand variation, energy-cost, and utility of the customers. Simulation results show that the proposed dynamic scheduling scheme, D2S, yields improved performance than that with the existing ones — *no scheduling* and *static scheduling*. It also shows that the utility of the customers increases approximately** 28.2% **over the existing ones.**

***Index Terms*—Portfolio, Energy Management Unit (EMU), Dynamic Scheduling, Optimization, Smart Grid**

Nomenclature

$\mathcal{P}_d^{exp}$	Expected profit return of a day
$\mathcal{R}_d^{exp}$	Expected risk of a day
$\mathcal{X}_t^{exp}$	Expected energy demand in the t^{th} time-slot
$\mathcal{X}_t$	Actual demand in the t^{th} time-slot
$\mathcal{K}_t$	Set of appliances served in the t^{th} time-slot
$\mathcal{L}_t$	Set of appliances requested in the t^{th} time-slot
$\mathcal{M}_t$	Set of appliances requested and served in the t^{th} time-slot
$\mathcal{N}_t$	Set of appliances deferred from previous periods but served in the t^{th} time-slot
$\mathcal{P}_t^{exp}$	Expected profit return in the t^{th} time-slot
$\mathcal{R}_t^{exp}$	Risk in the t^{th} time-slot
E_{rem}^{exp}	Remaining required energy
P_t^{rtp}	Real-time profit return in the t^{th} time-slot
R_t^{rtp}	Risk with real time price in the t^{th} time-slot

I. Introduction

A smart grid is envisioned to support cost-effective energy management with the help of bi-directional communication and electricity flows. To support cost-effective energy management, different technologies such as demand response, dynamic pricing, and demand scheduling are presented in the literature [1], [2]. In a smart grid, the customers play an important role in minimizing their energy consumption cost with different strategies such as energy consumption scheduling and presence of storage devices [3]. Appliance scheduling is one of the promising smart grid technological approaches which has the potential to minimize *peak-to-average* ratio of demand to the grid, while concurrently minimizing the energy cost to the customers [4], [5]. In such an approach, the appliances are categorized into two types — *shiftable*, and *non-shiftable*. *Shiftable* appliances such as washing machine and fridge can be used in any time of the day. On the contrary, *non-shiftable* appliances such as light and air-conditioner must be used in real-time to meet the requirements. Therefore, in the peak hour, the customers can schedule their shiftable appliances to relieve the extra load from the grid, so as to minimize the energy consumption cost. Consequently, with the implementation of the scheduling scheme, a well-balanced energy management scheme can be established in smart grid. However, an adequate and adaptive scheduling process needs to be implemented in order to achieve cost-effective energy management.

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A. Motivation

Erol et al. [6] discussed a static scheduling scheme for reducing the energy consumption cost to the customers. In such a scheme, different time-slots have different associated pricing tariffs (i.e., pre-defined static price). Using their scheme, the entire demand of a customer may be shifted from one time-slot to another, so as to minimize the load on the grid during peak hours. Consequently, if most of the customers schedule their appliances in the same time-slot (off-peak period), then the corresponding time-slot may be changed to on-peak. Accordingly, the grid increases the real-time price of energy to maintain the supply-demand curve, which, in turn, results in cost-expensive energy consumption for the customers, rather than a cost-effective one. Therefore, there is a need to deploy a scheduling strategy, which can deal with the dynamic behavior of energy requests from customers.

B. Contribution

In this paper, a dynamic appliance scheduling scheme, named as D2S, is proposed in order to reduce the energy consumption cost of the customers in the smart grid architecture. The theory of *Optimal Portfolio Strategy* [7] is applied in order to calculate the expected energy price to optimize the energy cost, while considering the corresponding risk involved in it. Conversely, customers' day-ahead energy demand — *weight graph* — in different time-slots is also evaluated. Accordingly, we present a dynamic scheduling algorithm for energy consumption, which conforms with the *weight graph* of energy. It may be clarified at this juncture that the concept of weight graph has been adopted from the theory of Optimal Portfolio Strategy, on which the proposed solution is based. We consider that the appliances are flexible and non-flexible in nature, i.e., the flexible appliances are shiftable, while the real-time price and the corresponding risk are high. In summary, the *contributions* of this work are as follows:

- We propose a dynamic appliance scheduling scheme for cost-effective energy management in smart grid.
- The concept of *weight graph* of energy is introduced for day-ahead energy consumption of a customer.
- The theory of *Optimal Portfolio Strategy* [7] is adopted to evaluate the expected energy price in different time-slots. With the integration of weight graph and optimal portfolio strategy, we evaluate the expected energy demand of the customer for which his/her expected profit return is maximized, while the risk is minimized.
- Algorithms for *weight graph* evaluation and dynamic scheduling are presented.

The rest of the paper is organized as follows. Section II presents a brief overview of the current state-of-the-art for real-time energy management in smart grid. The overview of the system architecture is elaborated in Section III. Subsequently, the optimal portfolio selection and corresponding algorithms are presented in Section IV. Performance of the proposed scheme is discussed in Section V. Finally, we summarize the contributions of this work in Section VII, while throwing light on some future research directions.

II. Related Works

In smart grid, several schemes are discussed in the literature in the context of cost-effective and reliable energy management [1], [3], [6], [8]–[15]. In a recent study [1], implementation of energy consumption scheduling (ECS) devices in the smart meter is studied in order to schedule home appliances automatically. In such a setting, several buildings share a common energy source. Similarly, Rad et al. [3] also proposed a demand scheduling scheme to minimize energy consumption cost to the customers. Briel et al. [4] proposed a distributed appliance scheduling scheme, in which, the appliances are scheduled in a randomized basis. A load controller schedules the appliances according to their bounded running time (e.g., an appliance must be used within 8 a.m. to 4 p.m.). In [5], demand scheduling scheme is studied in the presence of time-shiftable loads. In such a scheduling scheme, demand bidding to the day-ahead and real-time markets is proposed in order to minimize energy consumption cost. The author showed that the proposed scheme is useful for different practical bidding scenarios. Static energy scheduling scheme was advocated by Erol et al. to minimize the energy consumption cost to the customers [6]. In such a scheduling scheme, an energy scheduler checks all time-slots, and accordingly, schedules the appliances for which the energy consumption cost is minimized. A two stage demand response scheduling scheme is proposed in [9]. In the first stage, a convex optimization problem is formulated to minimize the utilities' generation cost. On the other hand, Vickrey auctions strategy is evaluated in different time periods to maximize social-welfare of the customers, which is presented as stage two. In such a strategy, the utility provider schedules the customers' energy requests as a maximization of social welfare. Koutsopoulos et al. [10] proposed a centralized energy scheduling method, in which the utility provider serves requested energy from the customers up to a threshold value. Consequently, remaining energy requests are queued, and serviced in the next time-slots.

Kim and Lavrova [11] proposed a demand response scheduling scheme, which is based on the priority of individual loads. Additionally, they considered the availability of local storage of energy to the customers. However, the effect of real-time pricing is not considered in the proposed scheme. Chen et al. [12] proposed a scheme for household appliance scheduling based on time-varying real-time price from the grid to minimize energy consumption cost to the customers. The uncertainty of appliances' starting times and intermittent behaviors of renewable energy sources are also considered. However, the authors assumed that the real-time price is static, and all the time-slots have pre-defined pricing tariff. Adika et al. [13] proposed a multi-objective appliance scheduling algorithm in the presence of renewable energy sources. The energy scheduler installed at the customers' end schedules the energy sources (such as conventional and modern renewable energy grids) to the appliances automatically. However, the proposed scheduling scheme may not be cost-effective, as the objective is to solely schedule the energy sources. A repeated energy scheduling game is demonstrated by Song et al. for minimizing energy consumption cost [16]. To model the proposed scheme, two types of customers are considered — *self-interested* and *fore-sighted*.

The proposed scheduling schemes in the literature only focus on the static behavior of energy demands from the customers. Therefore, there is need to propose an adaptive scheme, which can schedule the demands of appliances dynamically. In this paper, we propose a dynamic demand scheduling scheme, which is cost-effective and reliable.

III. System Model

Let us consider a system consisting of T time-slots, and denoted by a set $\mathcal{T}$, where $\mathcal{T} = \{1, 2, ..., T\}$. An energy scheduler is implemented at each of the customers' homes for scheduling appliances according to the real-time price, so as to minimize the energy consumption cost. In such a setting, we consider two types of appliances — *shiftable* such as washing machine and fridge, and *non-shiftable* such as light and fan. Shiftable appliances can be scheduled at any time-slot throughout a day. On the contrary, non-shiftable appliances cannot be scheduled to any other time-slot from the current time-slot in which the demand is generated. Let us also consider that there are A number of appliances at a customer's home, which is denoted by a set $\mathcal{A}$, where $\mathcal{A} = \{1, 2, ..., A\}$. Therefore, each customer has his/her appliances and consume energy according to his/her requirements. In such a scenario, the scheduler schedules the appliances in such a manner that the overall energy consumption cost to the customer is minimized. As discussed before, in this work, we consider both shiftable and non-shiftable appliances. Additionally, if total demand from the customers is greater than the total supply to the grid, the customers' energy consumption activities can be interrupted by

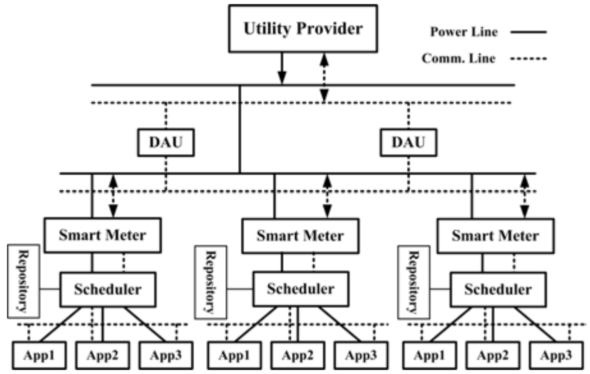

Fig. 1: Schematic smart grid architecture used in this work

the grid. Figure 1 shows the communication architecture of the smart grid considered in this work. The data aggregator units (DAUs) act as relays between the customers and the service provider. All the appliances, which communicate for consuming electricity are connected to the scheduler. According to the real-time price and requested energy, the scheduler schedules the appliances.

A. Energy Consumption Profile

In the scheduling approach, some of the appliances are scheduled from one time-slot to another one. Therefore, the energy request in a particular time-slot is a combination of energy requests generated in that time-slot and the scheduled ones from previous time-slots. Let $\mathcal{K}_t$ be the set of appliances whose energy requests are to be served at time-slot, t, where $\mathcal{K} \in \mathcal{A}$. In such a case, $\mathcal{K}_t$ is the combination of the set of appliances $\mathcal{M}_t$, which are scheduled at time-slot, t, from the previous time-slots, and the set of appliances $\mathcal{N}_t$, whose demand is generated at time-slot, t. Therefore, $\mathcal{K}_t$ is represented as $|\mathcal{K}_t| = |\mathcal{M}_t| + |\mathcal{N}_t|$. If the energy consumption of any appliance, k, is x_t^k, for unit time, and its running time is τ_t^k, then the total energy consumption by $\mathcal{K}_t$ appliances at time-slot, t, can be represented as follows. $\mathcal{X}_t^{\mathcal{K}} = \sum_{i=1}^{M} x_{i,t}^k \tau_{i,t}^k + \sum_{j=1}^{N} x_{j,t}^k \tau_{j,t}^k$, where $i, j \in \mathcal{A}$ where M and N are the number of appliances in the set $\mathcal{M}_t$ and $\mathcal{N}_t$, respectively. Consequently, the objective of the customer is to minimize the total energy consumption cost with real-time pricing, p_t, which is formulated as follows.

$$\text{Minimize} \sum_{t=1}^{T} p_t \left(\sum_{i=1}^{\mathcal{M}_t} x_{i,t}^k \tau_{i,t}^k + \sum_{j=1}^{\mathcal{N}_t} x_{j,t}^k \tau_{j,t}^k \right)$$

subject to

$$\sum_{t=1}^{T} x_{i,t} \geq \mathcal{X}_t^{req}, \tag{1}$$

$$p_t^{min} \leq p_t \leq p_t^{max} \tag{2}$$

In the optimization problem, Equation (1) illustrates that the total energy consumed by the customers must be greater than or equal to the energy required. The real-time price, p_t, has both minimum and maximum values, as shown in Equation (2). Therefore, the optimization problem is formulated in such a way that the overall energy consumption cost to the customers is minimized, while considering all the constraints. Consequently, it is necessary to schedule the appliances in an optimal manner, so that the total energy requirements of the customers are fulfilled with minimum cost.

B. Registration of Appliances with Scheduler

All the appliances installed at the customers' end undergo a registration process with the scheduler. The appliances communicate with the scheduler with the following message format: *<ID, Req, Prio>*, where *ID* is the appliance ID, *Req* is the required energy, and *Prio* is the priority of the appliance. The priority of the appliances is considered as *shiftable* and *non-shiftable*, where, as discussed in Section I, the shiftable appliances can be scheduled to next time-slots, whereas the non-shiftable ones cannot be.

C. Repository

We consider a database for maintaining the history of the past data for $\mathcal{D}$ days. It also contains all information about the appliances, i.e., *ID*, required energy, time, and real-time price of energy. Therefore, the repository maintains the following information:

- Real-time price of energy for last $\mathcal{D}$ days in each time-slot, t. It fetches the information from smart meter at the completion of every time-slot.
- It saves a customer's day-ahead energy demand at different time-slots.
- It also contains the *priority* of the appliances and required energy to run a particular appliance per unit time.

D. Use of Optimal Portfolio

The objective of this work is to optimize the energy consumption cost to the customers, while meeting all the constraints discussed in Section III-A. The customers schedule their appliances in different time-slots, for which their utility increases. However, in general, risk (i.e., price uncertainty) to the customers may be higher, while expecting higher utility value (i.e., profit return), which, in turn, maximizes the customers' energy consumption cost. Therefore, all the appliances are to be scheduled in such a manner that the total profit return and the corresponding risk involved in the scheduling process are moderate. Consequently, an optimization technique needs to be incorporated, which can estimate the expected demand and the profit return at different time-slots to optimize both the cost and risk to the customers. The theory of Optimal Portfolio Selection [7] is useful to design a cost-effective energy consumption scheme in the smart grid architecture in order to schedule the appliances optimally in different time-slots. In general, optimal portfolio theory ensures optimal investment of assets with maximum profit return. In this work, we use the concept of optimal portfolio to compute optimal distribution of demands of a customer over different time-slots, while considering the expected profit return and the associated risk.

IV. Optimal Portfolio Selection

As discussed before, in order to optimize the energy consumption cost to the customers, we use the theory of *Optimal Portfolio Selection Strategy* [7] in the context of smart grid architecture, as discussed in Section III-D.

A. Prerequisites

Optimal portfolio selection strategy determines the optimal weight vector, which helps to calculate the expected optimal energy demands of a customer in different time-slots throughout a day. It takes the real-time price information of last $\mathcal{D}$ days with the weight graph of energy, and calculates the expected profit return and risk. Therefore, if p_t^d denotes the real-time price of energy at time-slot, t, of the d^{th} day, then the profit return of that time-slot is expressed as: $\mathcal{P}_t^d = \frac{p_t^{max} - p_t^d}{p_t^{max}}$, where p_t^{max} is the maximum price of energy. Therefore, the expected profit return, $\mathcal{P}_t^{exp}$, for time-slot, t, is expressed as follows.

$$\mathcal{P}_t^{exp} = \frac{\sum_{d=1}^{\mathcal{D}} \mathcal{P}_t^d}{\mathcal{D}} \tag{3}$$

1) Expected Demand: Let E_d be the total actual demand of energy of the d^{th} day of a customer. Therefore, the expected total demand, E_d^{exp}, of the d^{th} day of the customer is computed from the history of the last $\mathcal{D}$ days, as $E_d^{exp} = \frac{\sum_{d=1}^{\mathcal{D}} E_d}{\mathcal{D}}$. Therefore, the expected demand is the average daily power profile of a customer, so that his/her energy requirement for the day is fulfilled.

2) Expected Profit Return: Let x_t^{exp} be the part of energy consumed from the grid at t^{th} time-slot. Therefore, x_t^{exp} is expressed as follows $x_t^{exp} = \frac{\mathcal{X}_t^{exp}}{E_d^{exp}}$, while maintaining the constraint $\sum_{t=1}^{T} x_t^{exp} = 1$, where $\mathcal{X}_t^{exp}$ is the expected demand at time-slot, t. Therefore, the expected total profit return of the d^{th} day is calculated as:

$$\mathcal{P}_d^{exp} = \sum_{t=1}^{T} x_t^{exp} \mathcal{P}_t^{exp} \tag{4}$$

3) Expected Risk: The corresponding risk in the computation of the weight graph is computed from the relative variation between different profit returns in the past $\mathcal{D}$ days, which, in turn, illustrates the variation between the expected and the actual prices to the customer. The expected risk at time-slot t is represented as follows:

$$\mathcal{R}_t^{exp} = \sigma_{ij} x_i^{exp} x_j^{exp}, \qquad i \neq j, \text{ and } i, j \in \mathcal{T} \tag{5}$$

where σ_{ij} is the co-variance between the i^{th} and the j^{th} time-slots, and mathematically,

$$\sigma_{ij} = \frac{\sum_{d=1}^{\mathcal{D}} \left[\left(\mathcal{P}_i^d - \mathcal{P}_i^{exp} \right) \left(\mathcal{P}_j^d - \mathcal{P}_j^{exp} \right) \right]}{\mathcal{D}} \tag{6}$$

Therefore, the total expected risk is expressed as follows.

$$\mathcal{R}_d^{exp} = \sum_{i=1}^{T} \sum_{j=1}^{T} \sigma_{ij} x_i^{exp} x_j^{exp}, \qquad i \neq j \tag{7}$$

4) Utility: With the computation of the expected profit return, $\mathcal{P}_t^{exp}$, and the expected risk, $\mathcal{R}_t^{exp}$, the optimal portfolio searches the optimal pairs of $\mathcal{P}_d^{exp}$ and $\mathcal{R}_d^{exp}$, for which the utility of the customer increases. Therefore, the corresponding utility of the customer at the t^{th} time-slot is computed as $\mathcal{U}_t = x_t^{exp} \mathcal{P}_t^{exp} - x_i^{exp} \mathcal{P}_i^{exp}$. The utility of the customer is the difference between the profit return for the appliances' demand generated at the i^{th} time-slot and the one served at the t^{th} time-slot. Thus, the utility of the customer for a day is computed as $\mathcal{U} = \sum_{t=1}^{T} x_t^{exp} \mathcal{P}_t^{exp} - \sum_{i=1}^{T} x_i^{exp} \mathcal{P}_i^{exp}$.

B. Weight Graph Calculation

Optimal Portfolio Selection Strategy helps in computing the corresponding utility (refer to Section IV-A4) for different time-slots, and determining the weight vector over different time-slots. Therefore, the optimal weight vector is obtained at different time-slots in a day for which the total profit return is maximized, while considering the corresponding risk. Therefore, the weight graph of energy for a day is the aggregation of the expected demand ($\mathcal{X}_t^{exp}$) from a customer for each time-slot $t \in T$. Mathematically,

$$\mathcal{W}_d = [\mathcal{X}_1^{exp}, \mathcal{X}_2^{exp}, \cdots, \mathcal{X}_t^{exp}, \cdots, \mathcal{X}_T^{exp}]$$
$$\text{where } \mathcal{X}_t^{exp} = x_t^{exp} E_d^{exp}, \ \forall t \in \mathcal{T} \tag{8}$$

and x_t^{exp} is the weightage for time-slot t depending on the past days' profit return and the associated risk. The algorithm for weight graph calculation is presented in Algorithm 1.

Algorithm 1: Weight Graph Calculation

Input: Price and demand history of last $\mathcal{D}$ days

Output: *Weight Graph* of energy throughout a day

Calculate expected profit return, $\mathcal{P}_t^{exp}$, according to Equation (3);
Calculate expected risk, $\mathcal{R}_t^{exp}$, according to Equation (5);
Calculate optimal weightage of energy demand, x_i^{exp}, for each time-slots according to $\mathcal{P}_t^{exp}$ and $\mathcal{R}_t^{exp}$;
for $i = 1$ *to* T **do**
    $\mathcal{X}_i^{exp} \leftarrow x_i^{exp} E_d^{exp}$;

C. Pricing policy

In the proposed scheme, we consider multiple customers consume energy from a single utility provider. The customers form a group among themselves, and can be treated as 'community' users. Depending on the demand from the customers to the grid, the on-peak, mid-peak, and off-peak hours are estimated. We adopt an usage-based dynamic pricing policy [17] to determine the real-time price of energy which is used just as proxy to update the price signal throughout the day in response to customers' energy consumption. We also consider that the real-time price in a particular time-slot remains same throughout the entire time-slot, as considered in [6]. Therefore, the energy price is set in real-time based on the demand from the customers, and it also rolls throughout the day.

D. Dynamic Appliance Scheduling Algorithm

After calculating the expected demand, risk, and profit return, we present an algorithm for dynamically scheduling the appliances in an optimal manner, so that the corresponding energy consumption cost is minimized. The proposed scheme uses the dynamic behavior of energy demand, profit return and risk to the customers, and schedules the appliances dynamically.

The proposed algorithm dynamically changes the *weight graph* in the beginning of each time period and schedules the

Algorithm 2: Dynamic scheduling of the appliances at time-slot t

Input: Weight-graph from Algorithm 1, Expected profit return, $\mathcal{P}_t^{exp}$, and Expected risk, $\mathcal{R}_t^{exp}$.

Output: Scheduling of appliances at time-slot t

Calculate remaining required energy, $E_{rem}^{exp} = \sum_{i=t}^{T} \mathcal{X}_i^{exp}$;
Calculate profit, $\mathcal{P}_t^{exp}$, and risk, $\mathcal{R}_t^{exp}$;
if $\mathcal{P}_t \geq \mathcal{P}_t^{exp}$ *and* $\mathcal{R}_t \leq \mathcal{R}_t^{exp}$ **then**
    Increase expected profit and risk;
    Change expected demand as $\mathcal{X}_t^{new}$;
    Calculate variance, $\sigma_t = \mathcal{X}_t^{new} - \mathcal{X}_t^{exp}$;
    for $i = t+1$ *to* T **do**
        $\mathcal{X}_i^{exp} = \mathcal{X}_t^{exp} - \sigma_t \frac{\mathcal{X}_i^{exp}}{E_{rem}^{exp}}$;
if $\mathcal{P}_t < \mathcal{P}_t^{exp}$ *and* $\mathcal{R}_t > \mathcal{R}_t^{exp}$ **then**
    Decrease expected profit and risk;
    Change expected demand as $\mathcal{X}_t^{new}$ by deferring low-priority appliances;
    Calculate variance, $\sigma_t = \mathcal{X}_t^{exp} - \mathcal{X}_t^{new}$;
    for $i = t+1$ *to* T **do**
        $\mathcal{X}_i^{exp} = \mathcal{X}_t^{exp} + \sigma_t \frac{\mathcal{X}_i^{exp}}{E_{rem}^{exp}}$;
Schedule deferred demand, $\mathcal{X}_t^{\mathcal{N}}$, from previous time-slots;
Calculate remaining demand, $\mathcal{X}_t^{rem} = \mathcal{X}_t^{exp} - \mathcal{X}_t^{\mathcal{N}}$;
Calculate total demand generated at t^{th} time-slot, $\mathcal{X}_t^{\mathcal{L}}$;
if $\mathcal{X}_t^{\mathcal{L}} \leq \mathcal{X}_t^{rem}$ **then**
    $\mathcal{X}_t = \mathcal{X}_t^{\mathcal{N}} + \mathcal{X}_t^{\mathcal{L}}$, Schedule all appliances;
else
    Schedule the set of appliances, $\mathcal{M}_t$, at time-slot t, such that $\mathcal{X}_t^{\mathcal{M}} \leq \mathcal{X}_t^{rem}$, and $\mathcal{X}_t = \mathcal{X}_t + \mathcal{X}_t^{\mathcal{M}}$;
    Compute remaining number of appliances, A_{rem};
    for $i = 1$ *to* A_{rem} **do**
        if $\mathcal{X}_t^i \leq \mathcal{X}_j^{exp}$, $\forall j \in [t+1, T]$ **then**
            Reschedule i^{th} appliance to j^{th} time-slot;
Send final demand, $\mathcal{X}_t$, to grid at time-slot t;

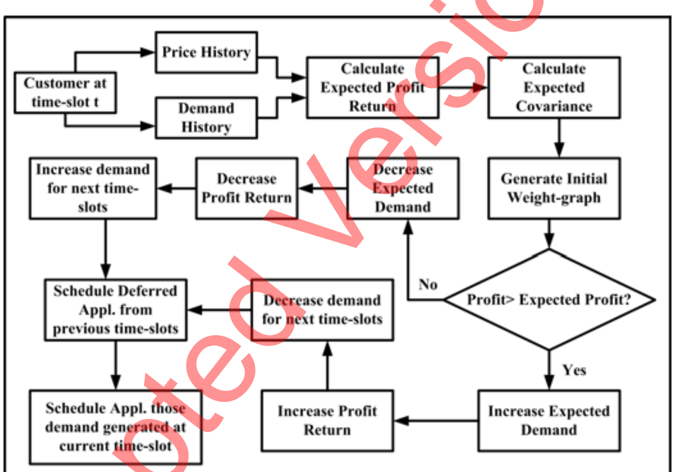

Fig. 2: Flow-chart of the proposed scheme

appliance's demand according to the changed *weight graph*. The scheduler gets the real-time price from the smart meter and increases/decreases the expected demand of that time-slot, by calculating the expected price and risk with the announced price and risk, respectively. The proposed algorithm is presented in Algorithm 2. According to the weight-graph, the scheduler schedules the requested demands in different time-slots. Therefore, the customers and utilities need to collect the price and demand information, respectively. The utilities decide the real-time price of energy according to the requested demand from the customers. After collecting the pricing information, the customers schedule their appliances accordingly to minimize the energy consumption cost and the associated risk. Therefore, a particular customer is independent from other customers, as the proposed approach completely schedule the appliances according to real-time price, energy cost, and the associated risk. Consequently, the customer is not affected by other customers' scheduling strategies. The proposed scheme schedules the appliances in a cost-effective manner, while maintaining fairness among the customers. Additionally, we present the flow-chart of the proposed scheme in Figure 2 for individual customers.

V. Simulation and Results

To simulate the proposed dynamic scheduling scheme, we used the MATLAB simulation software. All the parameters used in the simulation process are presented in Table I. We consider multiple customers in the proposed scheme. However, we present the demand related parameters for individual customers.

TABLE I: Simulation Parameters

Parameter	**Value**
Energy price	7.0-15.0 cents/kWh
Energy demand per day	$20-50$ kWh
Number of time-slots	24
Number of days in database ($\mathcal{D}$)	50
Maximum delay	6 hours
High peak	12.0 cents/kWh
Mid peak	9.0 cents/kWh
Appliance flexibility rate	10% - 100%

A. Benchmark

The performance of the proposed dynamic appliance scheduling algorithm (D2S) is evaluated by comparing it with the existing state-of-art, i.e, the iHEM appliance scheduling algorithm [6], proposed by Erol-Kantarci and Mouftah. The benchmark algorithm, iHEM, is a wireless sensor network-based appliance scheduling algorithm, in which the generated appliance demands are scheduled in off-peak time periods by considering delay up to a possible extent. The authors also proposed the concept of scheduling the appliances in mid-peak, if the delay is more than the threshold delay for the off-peak period. Additionally, the authors also considered the flexibility of the appliances, in which the appliances can be served if both the off-peak and mid-peak are far than the possible extent considered. Therefore, once the appliances are scheduled in a time-slot, they cannot be scheduled in other time-slots, even though the real-time price is high in that time-slot.

Conversely, the proposed scheme schedules the appliances dynamically with dynamic pricing policy. Therefore, all the customers schedule their appliances, while considering the expected profit return and corresponding risk as well. Consequently, the appliances can be rescheduled from one time-slot to another, if the real-time price in that time-slot is high, i.e., profit return is low. We evaluate the performance of the proposed scheme (D2S) with the following performance metrics discussed below.

B. Performance Metrics

Different metrics are used to analyze the performance of the proposed scheme. We elaborate all the performance metrics as follows.

1) Demand Scheduled in Peak-hours: The energy demand can be scheduled in three different hours — *on-peak*, *off-peak*, and *mid-peak*. It is cost-expensive to the customers if the demand is scheduled in the on-peak hours, which in turn, increases energy load on the grid. Consequently, we compute the percentage of demand scheduled in the on-peak hours, which can be treated as the ratio of energy consumed in the peak-hours and the total demand from the customers. Mathematically, $\frac{\mathcal{X}^{\mathcal{D}}_{peak}}{\mathcal{X}^{\mathcal{D}}} \times 100\%$.

2) Demand Scheduled with High-risk: As in Section V-B1, energy demand from the appliances may be scheduled with different risk values. Customers always want to consume energy with low-risk, while concurrently minimizing the energy consumption cost (as in general, the profit return is low with low-risk). Therefore, the percentage of energy demand scheduled with high-risk is evaluated, which increases the uncertainty to the customers about the minimization of energy consumption cost. Mathematically, $\frac{\mathcal{R}^{\mathcal{D}}_{high}}{\mathcal{R}^{\mathcal{D}}} \times 100\%$.

3) Variation in Demand Distribution: Variation of demand is calculated as the mean demand distributed from one time-slot to reduce the energy consumption cost. We take the mean value for the distributed demand throughout the day-ahead energy demand of the customers. Therefore, the variation in demand distribution is represented as: $\mathcal{X}_t - \tilde{\mathcal{X}}_t$, where $\mathcal{X}_t$ and $\tilde{\mathcal{X}}_t$ are the served energy and mean energy, respectively.

4) Cost of energy: Cost of energy is calculated as the cost incurred by the customer for the day-ahead energy consumption. Therefore, the cost of energy is represented as $\mathcal{C}_d = \sum_{t=1}^{T} \mathcal{X}_t p_t$.

5) Utility: The utility of customers is shown as their profit gain over the no scheduling and the static scheduling [6] schemes. Therefore, the utility of the customers is represented as:

$$\mathcal{U} = \begin{cases} \mathcal{C}_{no\_sch} - \mathcal{C}_{dyn\_sch}, & \text{over no scheduling} \\ \mathcal{C}_{iHEM} - \mathcal{C}_{dyn\_sch}, & \text{over iHEM} \end{cases} \tag{9}$$

where $\mathcal{C}_{no\_sch}$, $\mathcal{C}_{dyn\_sch}$, and $\mathcal{C}_{iHEM}$ are the energy cost incurred by the customers with no scheduling, dynamic scheduling (proposed), and static scheduling, respectively.

C. Results and Discussion

According to the performance metrics discussed above, we show the performance of the proposed approach compared with the iHEM [6] and "no scheduling" schemes. We evaluate the results for multiple customers. We adopt the use of *confidence interval* (95%) to show the effectiveness of the proposed scheme. In such a setting, the confidence interval shows the variance of specific performance metrics for the customers, while depicting the upper and lower values. Therefore, the specified interval demonstrates that the value for the particular metric is bounded by the upper and lower values for all customers. Consequently, we are able to show that the proposed scheme (D2S) outperforms the existing schemes with multiple customers, as shown in the subsequent sections.

1) Weight Graph: Figure 3 shows an example of the weight graph of energy obtained after computing the expected profit return and risk for a particular day. Different weights of the *weight graph* are differentiated by different values of profit return and risk (variations in profit return). Higher profit return with satisfactory risk depicts higher weight in any time period and vice-versa. We assume that the satisfactory risk for a time-slot is the expected risk at that time-slot. However, higher profit return and higher risk outputs moderate the amount of energy weight in that time period.

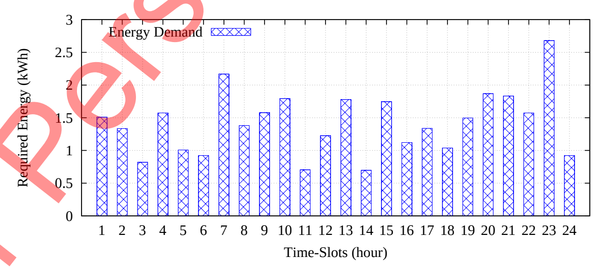

Fig. 3: Weight Graph

2) Demand Scheduled in Peak-hours: Figure 4 shows the percentage of demand scheduled in peak-hours with different schemes. The proposed approach yields better performance than that of the other schemes. Therefore, we can infer that the peak-demand is also relieved from the grid with the implementation of the proposed scheme, which is one of most useful characteristics of the smart grid. In case of iHEM, the customers schedule their appliances in the subsequent time-slots, if the current time-slot is on-peak or mid-peak and the appliance is shiftable. However, due to the static scheduling of appliances without considering the corresponding risk, the off-peak hours transform into on-peak hours. Therefore, the percentage of peak-demand is quite high for the iHEM scheduling scheme. Similarly, in case of "no-scheduling", the customers consume energy according to the generated demand, which, in turn, produces on-peak hours in the smart grid. On the contrary, D2S schedules the appliances dynamically over different time-slots, while considering the profit return and the associated risk. Therefore, the use of D2S leads lower on-peak hours than that of the iHEM and no-scheduling schemes.

3) Demand Scheduled with High-risk: The proposed scheme schedules the appliances, while concurrently considering the expected profit return and risk, as discussed in Section IV. We show that the risk involved in the scheduling process in the proposed scheme in comparison with iHEM and "no scheduling" in Figure 5. From the figure, we observe that the risk to the customers in the scheduling scheme is also lower

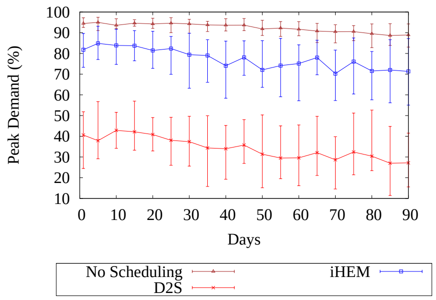

Fig. 4: Total load in peak-hour

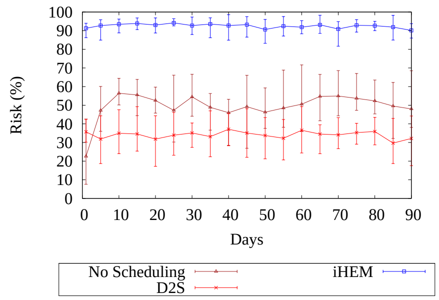

Fig. 5: Total load with peak-risk

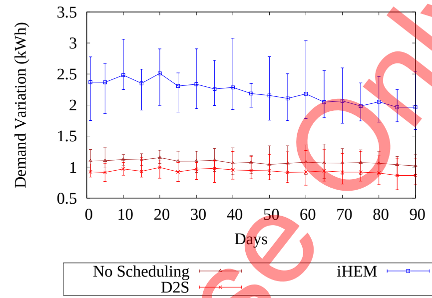

Fig. 6: Mean demand distribution

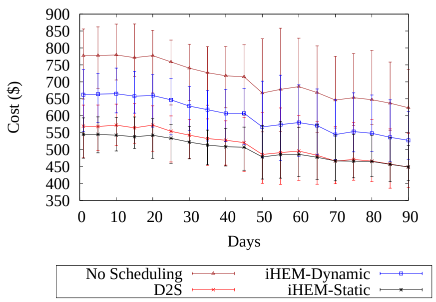

Fig. 7: Energy cost to the customers

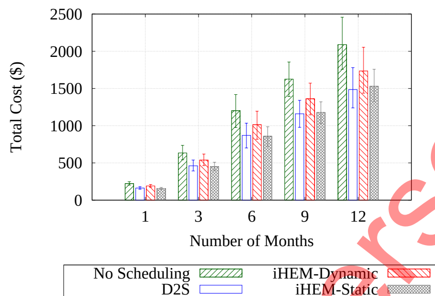

Fig. 8: Total cost to the customers

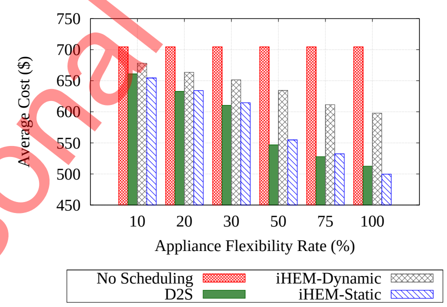

Fig. 9: Energy cost with different appliance flexibility rate

with D2S than the other existing schemes. As the percentage of generation of on-peak hours is low for the proposed scheme (refer to Figure 4), the corresponding risk is also low to the customers. In contrast, the customers incur high risks in using the iHEM scheme due to the high percentage of on-peak demand.

4) Mean demand distribution: Figure 6 shows the variation in demand distribution with different schemes. The higher mean demand distribution influences higher variability in scheduled demand in consecutive time periods and vice-versa. In case of iHEM, variability is more, as demand is scheduled according to off-peak period and threshold delay. Average mean demand distribution value of 3 months in case of the iHEM algorithm is 2.2 kWh. In the "no scheduling" case, the average mean demand distribution value is 1.08 kWh, and using the proposed scheme, it is 0.93 kWh.

5) Cost of energy: We compare the performance of the proposed scheme with the iHEM and the "no scheduling" scheme, as discussed earlier. With no energy scheduling scheme, appliances' requests are serviced in the requested time period without considering profit and risk. On the other hand, using the iHEM scheduling algorithm, the requested energy demands are scheduled depending on the peak price periods and the threshold delay. Figure 7 shows the energy consumption cost incurred by a customer in different days. Therefore, the energy cost to the customers is reduced with the dynamic appliance scheduling scheme than that with the static scheduling and no scheduling scheme. Figure 8 shows the total cost incurred by the customer for different running times. The results show that though iHEM yields almost same performance with the static pricing policy, however, the proposed scheme always does so with the dynamic pricing policy. Figure 9 shows the average cost of energy to the customers with different appliance flexibility rate such as 10%, 20%, 30%, 50%, 75%, and 100%. The energy cost to the customers with lower flexibility rate (such as 10% and 20%) is higher than that with higher flexibility rate (such as 50%, 75%, and 100%). However, the change in the energy cost to the customers is moderate when the flexibility rate is on or above 50%. We see that the proposed scheme, D2S, also performs well than the existing schemes with different appliance flexibility rate.

6) Benefit of Customers: Benefit of the customers is calculated as the profit gain with the proposed scheme over the iHEM and no scheduling scheme, as discussed in Section V-B5. Figure 10 shows the corresponding utility obtained with different schemes. Higher values of utility shows higher benefit to the customer with the proposed scheme over the other existing schemes, when dynamic pricing policy is employed. In case of the iHEM and the "no-scheduling" schemes, the energy consumption cost to the customers is very high, which, in turn, minimizes the customers' benefit. Consequently, we see that the dynamic demand scheduling scheme (D2S) has great impact on cost-effective energy consumption to the customers. Similar to the cost of energy to the customers, we also evaluate benefit to the customers with different appliance flexibility rate, as shown in Figure 11. The percentage of benefit to the customers increases with an increase in the flexibility rate. We see that the benefit to the customers increases on an average only $5-10\%$ with lower flexibility rates (such as 10%, 20%, and 30%). However, the benefit to the customers increases approximately 25% for higher flexibility rate. Additionally, we observe that

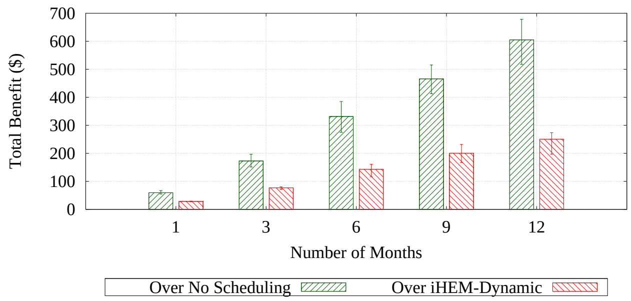

Fig. 10: Benefit of the customers

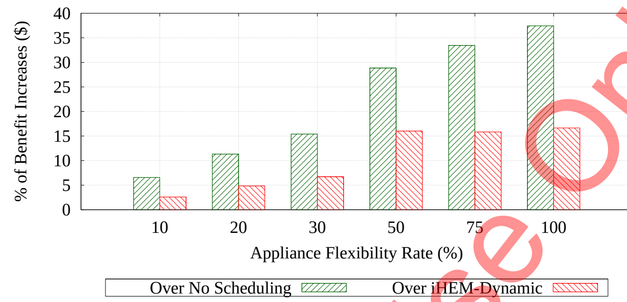

Fig. 11: Benefit increases with different flexibility rate

change in the benefit value is moderate with the proposed scheme, D2S, with higher flexibility rates over the existing scheme, iHEM.

VI. Discussions: Practical Perspective

In this section, we briefly present different applications of the proposed scheme, D2S, from a practical perspective. The main objective of the proposed scheme is home energy management (HEM) in the smart grid environment. Therefore, the primary application of the proposed scheme is residential energy management in a cost-effective manner, which is reflected in the simulation results. Additionally, with the dynamic demand scheduling facility, the peak-load on the grid is also relieved, which, in turn, helps to maintain supply-demand curve. Therefore, the proposed scheme is also capable of implementing the demand response mechanism. In a practical scenario, different customers may have different appliance flexibility rates, i.e., number of flexible appliances, which can be scheduled in different time-slots, varies from one customer to other customers. To address such practical issues, energy cost to the customers is evaluated with different appliance flexibility rates. Therefore, it is evident that the proposed scheme, D2S, is useful in the practical applications.

VII. Conclusion

In this paper, we proposed a dynamic appliance scheduling scheme, D2S, using the theory of *Optimal Portfolio Selection Strategy*. The proposed scheme schedules appliances dynamically in different time periods, while considering the expected profit return and risk factors. The day-ahead energy requirement of a customer is generated in different time-slots using the history of demands, and it is termed as the *weight graph* of energy. After computing the *weight graph*, the scheduler schedules the appliances dynamically in different time-slots, for which the utility of the customer is increased. The simulation results show that D2S always outperforms the existing one with dynamic pricing policy. The average utility of the customer increases approximately 28.2% over the iHEM [6] and "no scheduling" schemes.

In this work, we considered rational customers with different appliances, which may not be true in real-life scenarios. Therefore, we plan to incorporate heterogeneity of the customers' behaviors as the future extension of this work. Additionally, the imbibing of cooperation among customers to improve the reliability of energy supply is also a future extension of this work.

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