Real-Time Scheduling of Time-Shiftable Loads in Smart Grid with Dynamic Pricing and Photovoltaic Power Generation

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Abstract—**Time-shiftable loads, also known as deferrable loads, such as charging of electric vehicles, washing machines, dryers, are able to provide scheduling flexibility for demand response. This can help to reduce the energy cost under the condition of dynamic electricity pricing. It can also facilitate deeper integration of renewable generation by absorbing variability. According to the environmental conditions and real time market price of electricity in Singapore, two real-time price-based scheduling algorithms are proposed and studied in this paper. Simulations were conducted with different percentages of deferrable loads and solar penetration levels, with about 1 million devices participating in the demand side management program. The results show that the proposed algorithms schedule tasks resulting in a significant reduction in electricity bill cost. The algorithm was further modified to include demand and renewable generation forecasts to mitigate the problem of variability, which resulted in deeper possible renewable penetration and better system stability.**

Index Terms—**Demand response, real-time pricing, renewable energy resources, scheduling algorithms.**

I. INTRODUCTION

Smart grid consists of a physical power system and information system that links various equipment and assets and incorporates some new technologies in communications, automation, distributed systems, advanced metering, safety and security [1]. It allows increase in reliability and robustness of the power network and in turn reduces the energy costs. With the development of smart grid, residents can reduce their electricity cost by scheduling the pattern of their home electricity usage, based on the real-time electricity prices.

At the same time, to combat environmental pollution and natural resource depletion, many countries have committed to substantially increase the percentage of renewable energy used to serve their demand. Singapore as one of the most industrialized and urbanized countries in South-East Asia relies heavily on imported oil and natural gas [2]. Due to its geographical conditions, renewable energy sources for power generation are limited. The photovoltaic power generation is widely seen as the sole viable option as renewable energy, and the percentage of solar energy penetration in the distribution network has been steadily increasing in Singapore [3].

Although solar energy resources are plentiful in raw energy availability, the inherent variability in their power output will pose serious challenges to their deep integration to the electrical grid. These variable generations exhibit large fluctuations, which are random and cannot be dispatched according to demand [4]. The current approach replies on operating reserve to absorb variability of renewable generation. This works for modest penetration levels, but will not scale for the future when we have 30% or more of energy generation from renewable sources. As shown in a recent study in California [5], to accommodate 33% renewable energy penetration, large increases in reserve capacities are required.

Demand Response (DR) plays an important role in both improving electricity bill savings and mitigating the variability of renewable energy. Time-shiftable loads have received increasing attention due to their ability to create load flexibility and enhancing demand response program. Time-shiftable loads, a.k.a. deferrable loads with deadlines, is a task that requires consuming a certain total amount of energy to finish, but its operation can be scheduled any time before the given deadline. Some examples of such loads include: charging electric vehicles [6], intelligent pools [7], irrigation pumps [8], water heaters [9], batch processes in data centers and computer servers [10], [11], industrial equipment in process control and manufacturing [12], [13], and various home appliances such as washing machines, dryers, and dishwashers [14]-[17]. In recent years, the research on modeling and utilizing time-shiftable loads in demand side management has emerged.

The problem of scheduling time-shiftable loads under different electricity pricing conditions is addressed in [15], [17] for home appliances, and in [18] for charging of electric vehicles. Simulation results show significant reduction in electricity payments by using the proposed energy consumption scheduling designs. However, they did not

This work was supported by National Research Foundation under Grant R-712-000-032-281

consider the case when renewable generations are introduced to the grid. In [19], the authors proposed a method that uses dynamic programming to optimally supplying renewable energy to deferrable demands in order to mitigate variability of renewable generation. But the algorithm cannot make decisions in real-time due to high computational complexity, which takes minutes to complete.

The authors of [20] proposed a real-time deferrable loads scheduler that can coordinate with current demand forecast to make proper short-term scheduling to mitigate variability of deep renewable penetration and create savings on reserve costs. The paper adopted the direct load control (DLC) approach where a centralized Cluster Manager (CM) coordinates operation of the various resources in a cluster. The CM involves in ex-ante markets to procure generation to meet load requirements and schedules the deferrable loads in real-time. Three different causal heuristic scheduling algorithms were studied, which are Earliest Deadline First (EDF), Least Laxity First (LLF), and receding Horizon Control (RHC).

This paper proposes modified EDF and LLF scheduling algorithms with deferrable loads to better meet the deadline of each load and to incorporate real-time pricing. The paper first analyzes how scheduling would affect the total electricity bill cost at different levels of deferrable loads with dynamic pricing schedules. It then incorporates increasing solar power penetration levels, and examines how the proposed scheduling algorithms can further reduce the cost while reducing the effects of variability of solar energy generation. Actual electricity price data and solar generation forecast from Singapore was used in the simulations with about 1 million devices participating in the demand side management program. The average power of these devices is between 80-3000 W, and operating time in the range of 0.75 to 3 hours.

The rest of paper is organized as follows: section II models various loads and generation resources, and then formulates the scheduling problem. Section III proposes the task scheduling algorithms implemented in the paper. Section IV presents the simulation results and section V concludes the paper.

II. Problem Formulation

The fundamentals to grid voltage stability are to have proper balancing of power generation and load over the operating time window [*0, T*]. Suppose the balancing is performed N times within this window at times indexed by $k \in \{1, 2, ..., N\}$. The Cluster Management (CM) performs scheduling to meet the loads requirements as well as to balance the demand and supply.

The solar power generated neglecting its initial setup cost is thought to have negligible operating cost, hence when cost optimization is considered, the use of power generated through solar can be expected to be favored over the use of power generated using traditional means. Traditional resource scheduling is however required to anticipate shortfalls when shadowing and passing clouds over solar panels happens so that it could effectively mitigate non-desirable effects of voltage fluctuation occurring in the form of voltage sag or voltage drop due to supply-demand imbalances.

A. Generation Modeling

We make assumption that CM procures generation to meet load requirements from two sources:

1) Solar Power Generation s_k: This refers to variable generation from distributed rooftop photovoltaic system. We assume it has negligible cost, but exhibits significant variability as illustrated in Fig. 1. But due to its zero marginal cost assumed it will always be used first.

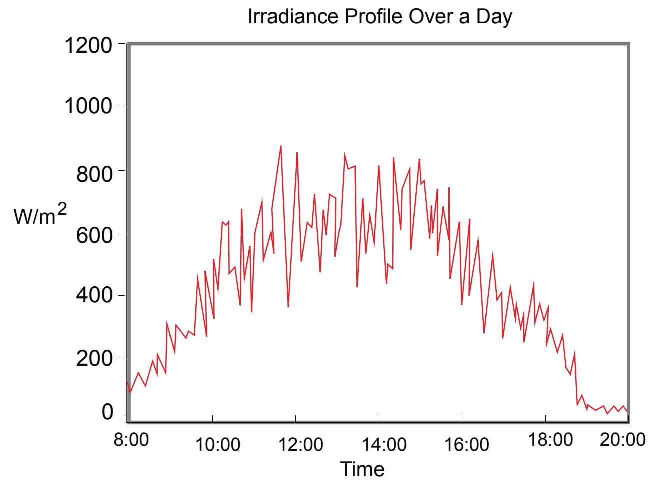

Figure 1. Irradiance profile during a typical day with high variability in tropical Singapore; Source: SERIS meteorological station.

2) Grid Generation g_k: This refers to the power purchased in conventional electricity market at market price [21] through the transmission system. As shown in Fig. 2, the market price from Energy Market Company (EMC) in Singapore varies over the day. We denote the price at time index *k* as λ_k. The grid generation is assumed to be available and sufficient when demanded by the CM. For simplicity, we use the same price data for different markets. Compared with variable generation from the renewable energy sources, the availability of grid power is certain but costlier.

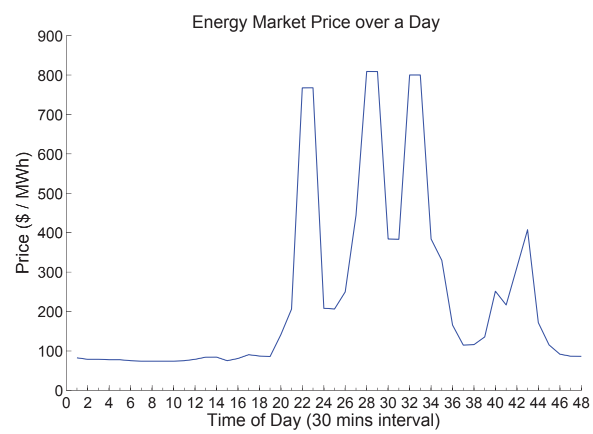

Figure 2. Price data in 30 mins interval over a random day from Energy Market Company, Singapore.

B. Resource Modeling

In our case, two different types of loads are considered. They include:

1) Static Loads l^s: offer no scheduling flexibility. The energy management system must ensure that adequate generation is present to meet this load requirement at each time k within the operating interval. The aggregated power requirement of all static loads is modeled as a power demand profile $l^s = \{l_k^s\}_{k=1}^N$ that must be satisfied at each scheduling time k. Fig. 3 shows the power demand over a random weekday.

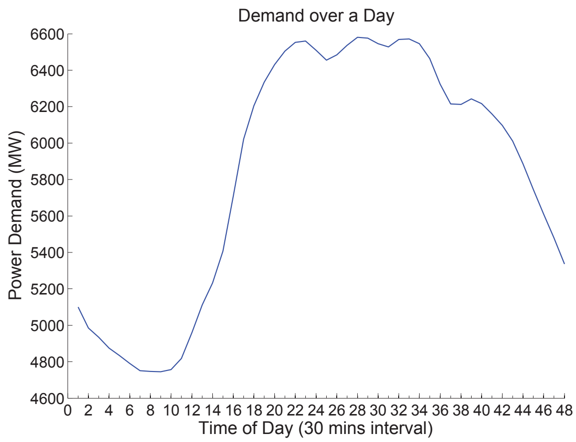

Figure 3. 24-hour demand data from Energy Market Company, Singapore.

2) Time-Shiftable Loads/Deferrable Loads T_i: require a certain amount of energy to be delivered within a deadline. Detailed modeling of loads to varying degrees of accuracy is an active research area. In general, such loads can be modeled as a lump model while their energy needs can be modeled as separate tasks.

Each task T_i is parameterized by (E_i, m_i, a_i, d_i). These parameters capture the degree of flexibility of deferrable loads. Where E_i is the total energy demand of the task, m_i is the power transfer rate limit, $\{a_i, \ldots, d_i\}$ is the service interval of task over which a quantity of energy E_i must be delivered with a maximum power transfer rate m_i. Therefore, the task requirement can be defined as:

$$\sum_{k=a_i}^{d_i} p_{ik}\Delta t = E_i, 0 \le p_{ik} \le m_i, \forall k \in \{a_i, ..., d_i\} \qquad (1)$$

The energy state e_{ik} of a task at time k is defined as the remaining energy requirement for the task at the end of the k^{th} time-step. A task T_i is active at time k if $a_i \le k \le d_i$, and $e_{ik} > 0$. The set of active tasks at time k is written as A_k.

C. Rules of Scheduling

As defined previously, it is expected that all load requirements are to be met over the operating window. At each scheduling interval, the energy management algorithm will first assigned renewable power fully or partially with grid power when renewable power is insufficient to firstly meet the static load demands. At time interval k, we define the available solar generation as s_k, required grid generation as g_k, static load demand as l_k^s, the amount of power allocation to task T_i as p_{ik} The generation and load balancing equation can then be expressed as:

$$s_k + g_k = l_k^s + \sum_{i \in A_k} p_{ik} \qquad (2)$$

After the static load demands are met, the scheduling policy will determine the set of power allocations $p_k = \{p_{ik}\}_{i \in A_k}$ at time k to all active tasks. If there is remaining solar power available, solar power is first used. Otherwise, grid power with real-time varying price is used to satisfy the deferrable load demands. In addition to load requirement, the price information will also be used to determine the scheduling of active tasks.

III. Task Scheduling Algorithms

This paper proposes modified versions of two casual heuristic methods namely Earliest Deadline First (EDF) and Least Laxity First (LLF) to incorporate dynamic pricing information. We study how the scheduling policy affects the total cost and the amount of grid generation g_k required over the operation window using the proposed modified EDF and LLF scheduling algorithms. Simulations with varying degrees of deferrable loads are conducted to better meet the deadline of each load and incorporate dynamic pricing schedules. Further simulations are carried out to incorporate increasing solar power penetration levels to examine how the proposed scheduling algorithms can further reduce the cost while reducing the effects of variability of solar energy generation.

A. Earliest Deadline First(EDF)

In Processor Time Allocation (PTA), EDF is a commonly used method to schedule a set of computational task such that the deadlines of which could be met in specific intervals. It is useful in our case as the available generation can be thought as an analogous comparison to the available processing time. Subtle difference can be highlighted; available generation could be adjusted while processing time is fixed. Hence, one degree of freedom is relaxed when applying to our case. Task rate limitation is prevalent in TCL loads and this will add restriction to service particular task. Finally, unlike in PTA, generally static load and deferrable loads can be served in the same time without requirement of dedicated intervals. The aforementioned conditions make the EDF a highly suitable heuristic method for the available generation problem when introduced with some modification.

The modified EDF will run at each time interval k in the following 4 steps:

1) Allocate all available s_k to l_k^s, if $l_k^s > s_k$, the rest will use g_k.

2) Find the list of active tasks, which must be scheduled in order to meet its deadline. Allocate available s_k to them. If s_k is not enough, use g_k for the rest.

3) If there is still s_k available, allocate it to the task with the earliest deadline, then to the task with next earliest deadline, until all the s_k is consumed.

4) To further exploit dynamic pricing for cost saving, if the current price λ_k is less than the price threshold λ_c, more active tasks are scheduled.

Compared to the previously published works, such as [20] which do not guarantee meeting all the task deadlines, the approach proposed in this paper gives priority to the tasks which must be served to meet deadlines. These deadlines are to be met using available solar power and grid generation. In addition, we incorporate dynamic pricing to the algorithm to achieve further savings.

B. Least Laxity First (LLF)

In step 3 of EDF, resources are allocated on the basis of task deadlines. LLF is another causal heuristic that also incorporates remaining task requirements in making the allocation decisions. The laxity for each task T_i at time k is defined as:

$$\phi_{ik} = (d_i - k) - e_{ik} / m_i \tag{3}$$

The modified LLF operates in the same way as EDF in the first two steps and for the last step. It differs only in the third step, where the task with the least laxity is scheduled first.

C. Scheduling with Demand and Solar Generation Forecasts

To achieve deep penetration of solar generation, we have to reduce the variability by using better demand and solar generation forecast. Step 4 of EDF and LLF proposed previously can be further modified to make use the generation forecasts. At each scheduling interval, instead of using the market price threshold λ_c to determine which active task should be scheduled, more active tasks are scheduled if the sum of static load and scheduled load has not reached the forecast load at that time interval.

IV. Simulations and Results

Extensive simulations were carried out using solar electricity generation and electricity price data obtained from the Energy Market Company in Singapore. Simulations were conducted with different percentages of deferrable loads and solar penetration levels, with about 1 million devices participating in the demand side management program. The simulation results presented below first demonstrate how EDF scheduling would impact on different levels of deferrable loads and solar power generation over one day. It then compares the cost saving using the EDF and LLF scheduling algorithms.

The demand and real-time price data were selected from the Energy Market Company on a random weekday as shown in Fig. 2 and Fig. 3. The data is in 30-minute-interval form. As our scheduling algorithm runs every 15 minutes, we assume the price and power demand does not change over the 30 minutes.

The solar power generation data was from a 5MW solar power plant in Singapore on a randomly selected day. The data is scaled for different levels of solar power penetration.

For deferrable loads, a random task arrival profile was formulated as shown in Fig. 4 to illustrate the arrival time a_i. For a task T_i, the deadline $d_i = a_i + E_i / m_i + \Delta$, where Δ is randomly generated from 15 – 120 minutes to represent flexibility of a task. We assume the average power of a task is between 80-3000W, and requires 0.75 to 3 hours according to the data from NREL; the parameters for each task are randomly generated in the pre-defined range. For 5% deferrable load penetration level, there were around one millions of devices (tasks) generated.

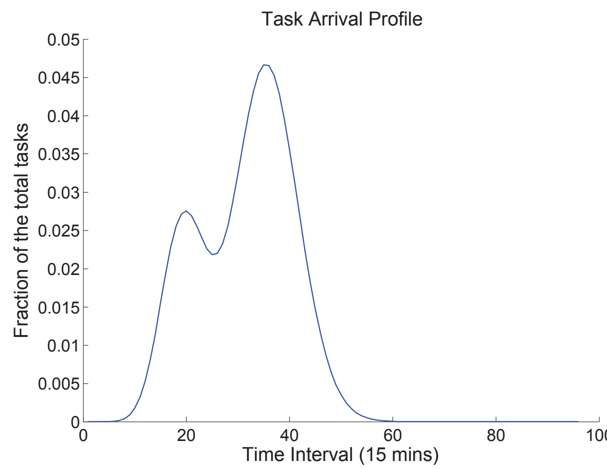

Figure 4. Task arrival profile illustrated by random function.

Fig. 5 compares the load profile before and after EDF scheduling with no solar power generation. We can see that as the price goes up beyond the defined threshold, the loads are reduced to save cost. By introducing solar power generation to the system, the cost can be further reduced.

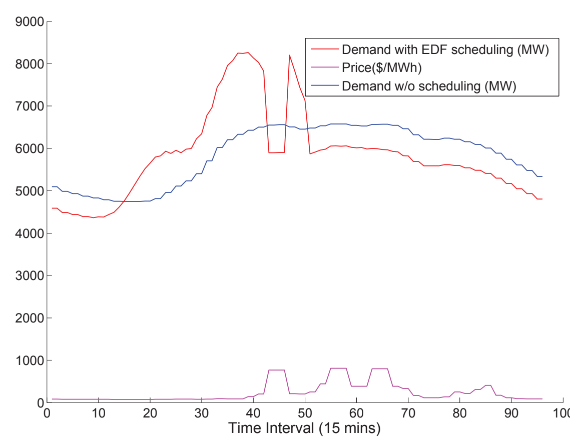

Figure 5. Load profile comparing resource scheduling under EDF with 10% deferrable load penetration without solar power generation.

Fig. 6 shows the scheduling result of using EDF algorithm. Because we do not consider generation forecasts, and we aim to meet all the deadlines of active tasks, therefore, the grid power requirement in our result fluctuates with the solar power generation profile. In addition, we use real-time pricing (RTP) information to schedule the loads. The use of RTP also causes the demand to be shifted to hours with low electricity price, which would lead to a higher peak demand and peak-to-average ratio (PAR) during the low price time [22].

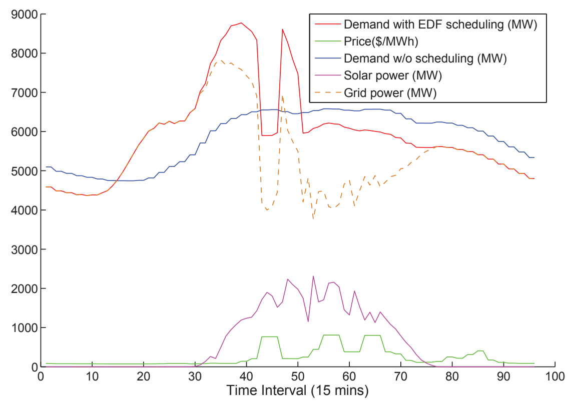

Figure 6. Load profile comparing resource scheduling under EDF with 10% deferrable load and 10% solar power penetration.

Table I shows that by using EDF scheduling algorithm, the total cost over a day can be reduced significantly. The cost also decreases with increasing level of solar and deferrable loads penetration level.

TABLE I. 24-HOUR TOTAL COSTS COMPARISON OVER DIFFERENT SOLAR AND DEFERRABLE LOADS PENETRATION LEVELS FOR SCHEDULING UNDER EDF

	0% deferrable (no scheduling)	1% deferrable	5% deferrable	10% deferrable	15% deferrable
cost with no solar (mil$)	35.9479	35.7665	35.0415	34.1443	33.2481
cost with 1% solar (mil$)	35.3127	35.1317	34.4106	33.5153	32.6110
cost with 5% solar (mil$)	32.7715	32.5908	31.8652	30.9708	30.0710
cost with 10% solar (mil$)	29.5951	29.4137	28.6902	27.7933	26.8910
cost with 15% solar (mil$)	26.4186	26.2377	25.5137	24.6170	23.7150

We also compare the costs for LLF with EDF scheduling algorithm in Table II. Here the deferrable loads level is fixed at 10%. The results show that there is not much difference between the two algorithms in terms of cost savings. The different is below 0.001%, which could be caused by random numbers during different runs in simulation.

TABLE II. 24-HOUR TOTAL COSTS COMPARISON FOR SCHEDULING UNNDER EDF AND LLF OVER DIFFERENT SOLAR PENETRATION LEVELS

	EDF (10% deferrable)	LLF (10% deferrable)	Difference (EDF-LLF)
cost with no solar ($)	34.1443	34.1463	-0.0060%
cost with 1% solar ($)	33.5153	33.5099	0.0163%
cost with 5% solar ($)	30.9708	30.9701	0.0025%
cost with 10% solar ($)	27.7933	27.7935	-0.0009%
cost with 15% solar ($)	24.6170	24.6190	-0.0079%

The two algorithms were implemented in MATLAB. Their computation time is illustrated in Table III. The results show that the computation time grows as the number of tasks increases. And EDF runs faster than LLF in general. This is because in EDF, the tasks only were only sorted once according to their deadline. However, in LLF the tasks were sorted according to laxity in each scheduling interval as it changes by time.

TABLE III. EDF AND LLF COMPUTATION TIME COMPARISON OVER DIFFERENT DEFERRABLE LOADS PENETRATION LEVELS

	EDF runtime (sec)	LLF runtime (sec)
1% Deferrable	5.73	12.67
5% Deferrable	27.13	61.76
10% Deferrable	53.73	126.09
15% Deferrable	83.09	195.61

Although the simulation result presented above show that the proposed scheduling algorithms can reduce the energy cost, it was noted that they cannot mitigate the effects of intermittency of solar power generation that could lead to higher reserve costs. Hence, further simulations were carried out as described in Section III C, where the generation forecasts are incorporated in the scheduling algorithm. We added Gaussian noise to solar generation data to simulate a synthetic solar generation forecast. The grid generation forecast is the sum of the forecast static and deferrable loads and solar generation data.

Fig. 7 shows the load profile after applying the further modified EDF incorporated with generation forecasts. Compared with the load profile in Fig. 6, the variability is greatly reduced while the demand profile better fits with the generation profile.

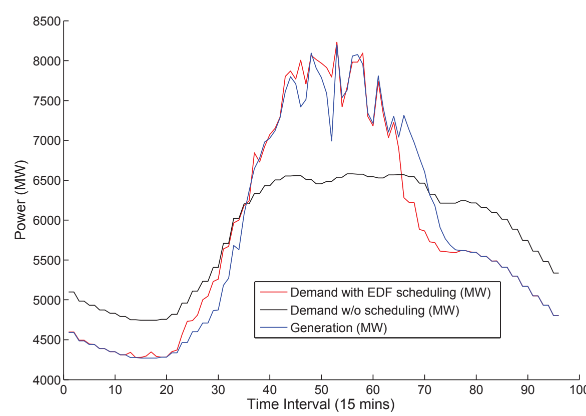

Figure 7. Load profile comparing resource scheduling under the modifed EDF incorperated with generation forecasts. (10% deferrable load and 10% solar power penetration)

V. CONCLUSION

Due to the importance of demand response to achieve increasing levels of renewable penetration, the flexibility that time-shiftable loads provide can be effectively utilized to maximize the cost savings in the future smart grids. This paper proposes scheduling algorithms for scheduling time-shiftable loads/deferrable loads with real-time electricity market pricing, and renewable generation forecasts. We propose the modified versions of two classical processor resource scheduling algorithms EDF and LLF to solve the time-shiftable load-scheduling problem when dynamic market pricing is used. The paper further examines the performance of these algorithms in terms of energy cost savings. The results show a promising decrease in cost as the renewable penetration level and deferrable load percentage increases. The problem of variability introduced by intermittent generation from solar energy forecasts and variable demand forecast was also studied in the paper.

Future improvements can be made by taking into consideration the storage and other facilities cost, and developing more accurate models for different types of time-shiftable loads. More sophisticated price-based scheduling algorithms can also be explored to reduce the peak-to-average ratio of demand so that to reduce variability and improve the stability of the system.

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