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# A Survey on Demand Side Management Techniques in Smart Grids

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*Abstract:* New generation electricity network called Smart Grid is a vision for a cleaner, more efficient and cheaper electricity generation, transmission and distribution system. One of the major challenges of Smart Grid is to incorporate renewable energy resources: the uncertainty of these sources cannot be compensated by the control of fossil generators because of their large time constants. One solution to this problem is influencing the demand side by controlling the consumption and incorporating energy storages like batteries of electric or hybrid vehicles. Balance between demand and supply is crucial since oversupply means waste of energy, while undersupply causes performance degradation of the grid parameters (e.g. phase, voltage level, etc.). In this paper new Demand Side Management techniques will be surveyed, which are algorithmic solutions to the new challenges and are successful candidates to increase the efficiency of the Smart Grid. The new strategies can be grouped as direct control of smart appliances, price-based methods and scheduling of charging electric vehicles.

*Keywords:* Smart Grid, Demand Side Management, Demand Response

## 1 Introduction

Power needs of our modern society are growing day-by-day. For example hybrid and electric vehicles make extra load to the existing electric power network. The traditional approach to solve this problem was expanding supply by installing new capacity. Recently the cost of new capacity became higher, and environmental issues came to the fore [1]. Going to a greener World, renewable power resources are playing more and more important role, however incorporating them into the grid increases the uncertainty of the generated power because of their hard-to predict nature. Traditionally there are uncertainties in the load side, which rise severe problems to the energy supply system: undersupply and oversupply. Both of them should be avoided to maintain operational stability and financial efficiency. Electricity storage technologies could solve the balance problem of the network (supply and load should be equal for every moment), but they are still not in a mature state. The rapid control of the supply side is impossible due to the physical parameters of the traditional power plants. As a consequence the only possible solution could be the control of the consumption side. In Smart Grid and energy management literature the influence of consumers' behavior is called Demand Side Management (DSM), Demand Response (DR), and load management. DSM is a very broad set of actions such as applying

- intelligent appliances (which can be controlled by the network operator),
- complicated electricity pricing strategies to motivate consumers to change their load profiles,
- scheduling of large and shiftable consumers (e.g. charging of batteries of electric vehicles).

Demand Response is a subset of DSM programs which relies on price signals as main motivations for changing consumer electricity usages [1]. The common objective of the above mentioned methods is increasing the reliability, the stability and the economic efficiency of the of electric power network.

The basis of the new DSM techniques is smart metering and two-way communication channel between smart meters and the network operator agent, which are fundamental components of the

| | **start time** | **duration of operation** | **stop time** | **load** | **usage pattern** | **control** | **intermit** |
|---|---|---|---|---|---|---|---|
| **ALWAYS ON** | stochastic | stochastic | stochastic | not constant | can be learned | no | no |
| **BATTERY** | latest is stopTime-duration | depends on load | can be predefined | constant | can be learned or predefined | yes | any time |
| **TIMED ON** | latest is stopTime-duration | fixed mini-mum | can be predefined | pattern | can be learned or predefined | yes | yes (if time left to finish > duration) |
| **CYCLIC** | | >minONTime | | semi constant | | yes | yes (if ONTime > minONTime) |

Table 1. Characterization of consumer classes

future electric power network, the smart grid. In this paper the most promising DSM techniques will be surveyed.

## 2 Control of Smart Appliances

In Smart Grid, Smart Appliances (controlled and supervised by an agent) can provide real-time consumption information. Balancing demand with supply is feasible by controlling flexible devices, whereas devices are controlled by an agent with supervisor commands (e.g. on/off policy) initiated by a system, running sophisticated algorithms. The investigation on control strategies can focus on the residential, commercial and industrial sectors as well. Basic component of the Smart Grid is the Smart Meter. A Smart Meter has the ability to disconnect and reconnect remotely and control the user Smart Appliances to manage loads and demands within a HAN – Home Area Network. HANs of Smart Meters collect most critical data: total energy consumption and production, individual consumption from home appliances, indoor environmental parameters (related to user comfort), other user oriented data like thresholds and policies for efficient equipment operation.

### 2.1 Goals of Direct Control

Expected results by implementing an algorithm for controlling Smart Appliances are overall cost reduction, load balancing and energy savings. Beside these most important goals we must also consider fairness and comfort. Fairness means DSM should be financially good choice for both the providers and the customers. Comfort is an individual factor, which has different metrics. For instance thermal comfort is highly investigated in the DSM literature [2].

### 2.2 Categories of Power Loads

To be able to define adequate and feasible control strategies we should first categorize our appliances and determine the main parameters of their operation. Several papers in the literature focus on controlling low power consumption appliances. Others papers emphasize the control of high power consumption devices, which have more significant impact on overall consumption of a household or building. Our proposed categorization of devices is based on the available literature [5, 6] and it is described in the following section (main parameters are collected in Table.1).

ALWAYS ON - Appliances that can be switched on any time (e.g. lighting, cooking stove, microwave oven, computing and network devices). They provide information on energy usage (helps to schedule other devices) instead of offering the possibility of controlling them.

BATTERY – Defines the total amount of time, the device should be turned on and starting time has to be given, so that a certain state of charged level can be reached (e.g. laptops and Electric Vehicles that need recharging). These devices typically have constant load during operation.

TIMED ON - Devices that are scheduled to be ready with a certain job on time. They have a fixed duration and are required to start and finish at given moments (printer, clothes dryer, dishwasher, washing machine.).

CYCLIC - These devices are always in running state during a long period of time and must be operated cyclically (HVAC: Heat Ventilation Air Conditioning, refrigerator, water heater).

### 2.3 Control Techniques

There are different opportunities to define control strategies. One of the most simple and feasible is the on/off policy [3-6], where maximum allowable load and duration signals come from the Smart Grid. To control flexible devices, decision is made locally according to the incoming load and duration data, the measured consumption values and the policies associated with appliances. Comfort is related to parameters like physical values, threshold values, the minimum time needed to reduce discomfort metric, and the time needed the discomfort metric to reach an upper limit. Based on the literature [4] the total consumption (power load) of a building with controllable appliances can be modeled with the followings (NApp is the number of appliances):

$$Control\ goal: P_{Total} \leq P_{Allowable} \tag{1}$$

$$P_{Total} = \sum_{n=1}^{NApp} P_{Consumption}(n) \tag{2}$$

$$P_{Consumption} = P_{Rated} * Signal_{Control}$$
$$Signal_{Control} = \begin{cases} 0, & if\ OFF \\ 1, & if\ ON \end{cases} \tag{3}$$

A more sophisticated model could provide the ability to control appliances in a continuous policy. Dynamic scheduling of the operation of appliances can be performed with different approaches. The objective function of a scheduling algorithm can be the minimum energy consumption or the price paid for all consumed electricity [6]. In the work of [5] the load control is solved with an online scheduling technique (adopted from a real-time computing systems scheduling algorithm). To solve the optimization problem as a different approach a priority queue with the Breadth-Fist Search is implemented in [6]. In most of the papers the control of real appliances in realistic environment is relatively rare [4], most of the sources deal with simulations [3-5].

# 3 Price-based DSM

Price-based demand response programs aim to motivate the consumers to change their consumption responding the actual purchase price of electricity. Rescheduling the consumption to low-price-hours results in saving cost for the end-users. At the same time service providers can increase their profit and satisfy higher quality of service, and authorities can satisfy lower level of environmental load. The main goals of the service provider side are (i) load shaping (peak shaving – i.e. reducing the peak load power, load shifting and valley filling), and (ii) balancing the supply and consumption in every moment in order to satisfy the stability of the grid (frequency, voltage, etc.).

Price-based demand side management programs (instead of conventional flat-pricing) can be categorized as follows:

- Time-of-use (TOU) tariffs: there are predefined prices for different periods of the day (typically peak hours and non-peak hours); the prices are related to the estimated average cost of generating and distributing energy in the given period [9,11];
- Real Time Pricing (RTP): for RTP the price can be changed in short periods of time (hourly or 15 minutes resolution); price is advertised in an hour-ahead basis; the price reflects the instantaneous cost of generating and distributing of power. [11-14]
- Critical peak pricing (CPP) is a mixture of TOU and RTP: The basic program is TOU which is modified in the case of critical situations like critical peak loads, or stability problems of the grid caused by outages. The main drawback of CPP is coming from its hard-to-implement nature. [11]

Another important and intensively discussed issue regarding demand response programs is mandatory or voluntary participation. Nowadays all the running programs are mostly voluntary [11]. The major benefit of voluntary participation is that only collaborating consumers want to take part in the program, but unfortunately economically and environmentally aware end-users are in minority, that is why mandatory programs are waited to be more efficient.

## 3.1. Time of Use (TOU) programs

TOU based programs are relatively easy to implement and customers can easily understand the benefit of participation. However it is shown, that the efficiency highly depends on the behavior of the users and the load shaping effects of TOU are poor. For example in a pilot project in Italy (with ca. 1000 end-users and one-year assessment of load data [9]), the energy cost of the consumers decreased 2%, but the energy usage increased 15%. The morning peak has been decreased and shifted as well, but the afternoon peak neither could be shifted nor could be shaved [9].

## 3.2. Real Time Pricing

Real Time (or adaptive) Pricing (RTP) is shown to be a more powerful tool than TOU. RTP is capable to influence subscribers to consume wisely, and at the same time allows retailers to maximize their profit with possible lowest risk [12]. Residential customers can reduce their electrical energy cost by scheduling their power need to hours of lower prices. This behavior results in peak load clipping and valley filling which is the basic interest of retailers and power generators as well, because wholesale prices in the case of large peak loads are very expensive due to inefficiency of marginal oil-fired generators. This fact is illustrated by Fig.1 [10]: one can see the very steep slope of the offered price vs. generated power

| paper | Objective function | Constraints | Optimization method | Type of RTP | distribut-ed |
|---|---|---|---|---|---|
| **[11]** | profit of the retailer | maximum limit of load reduction; price cap; | non-linear programming | day-ahead | no |
| **[12]** | profit of the retailer as a function of a composite demand response function of prices (different type of customers) | price cap | Q-learning | day-ahead | no |
| **[13]** | profit of the retailer as a function of the demand response function of prices | consumer's benefit, max. and min. demand; min. daily consumption, price cap, network constraints | non-linear programming | day-ahead | no |
| **[14]** | utility minus cost | - | differentia equation | hour-ahead | yes |
| **[19]** | aggregate utility of all subscribers and minimizing the cost of the retailer | limit of total energy consumption | convex pro-gramming | hour-ahead | yes |

Table 2. Comparison of optimal RTP algorithms

function in a given hour in Alberta, USA. Furthermore, as a result of the flat load curves, the usage of the marginal generators can be reduced, and the role of environmentally friendly renewable resources can be increased.

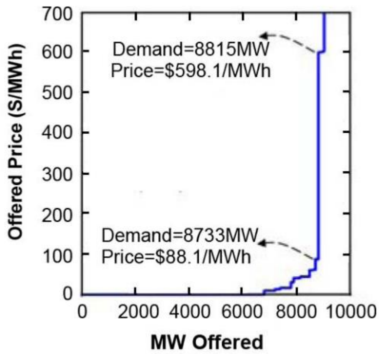


Fig.1. Alberta Supply curve [10]

From an economical point of view electricity markets have a special feature: supply and demand have to be balanced at every moment since the very limited facilities for storing electrical energy. As a result, well elaborated economic indicators, such as utility, welfare, discomfort and price elasticity cannot be used in the original form, but their time varying nature has to be taken into consideration [7,8]. The most important findings are

- voluntary participation in RTP programs has insufficient efficiency, mandatory participation is needed;
- RTP needs smart metering (not only to deliver detailed and on-line consumption data to the service provider, but for giving information for the subscribers to motivate them);
- Regulatory system is needed regarding licensing, controlling and monitoring user's activities;
- The whole risk of spot prices cannot be pushed to subscribers: cap price has to be introduced in real systems.

Recently some papers [10-14] aim to contribute to optimal algorithms to calculate real time prices. The suggested methods often substantially differ from each other, because of the differences in the used models and objective functions.

Real time prices are considered both in a day-ahead fashion (e.g. in [11-13]), or in an hour-ahead fashion (e.g. in [14,19]). In the case of the day-ahead approach, for every hour of the next day retail prices are calculated based on the day-ahead wholesale prices and using forecast of the demand. Since demand depends on the price, an iterative process is applied to reach an optimal equilibrium (see [11-13]). In the case of the hour-ahead real time pricing algorithms, the price of the next hour will be advertised directly before the upcoming hour. In this case the goal is to allocate the supplied energy among competitive consumers. The basic idea is borrowed from the method of congestion pricing used originally for internet traffic control [14, 19]. User preference is modeled by willingness to pay parameter. In other words the philosophy is that users who are willing to pay more should get more. The initial step of the algorithm is advertising an initial price calculated by demand forecast. The consumers react to the initial price by their capacity needs that maximize their utility function. The retailer sums the capacity needs and updates the price offer, resulting in an iterative process. It is shown in [14] that the algorithm is convergent, furthermore it is shown that local optima leads to global optimum in the sense of user's mean utility.

The number of players of the electricity markets is huge; therefore distributed optimization methods play a crucial role. The hour-ahead algorithms are fully distributed, since users have to optimize locally their capacity needs regarding the actual price offer and their willingness to pay parameter.

The retailer sums the capacity need and updates the price offer. Day-ahead RTP algorithms generally needs a central computer that globally optimize the given cost function. The objective function of the optimization in the case of the day-ahead methods is mainly related to the profit of the retailer. In the case of hour-ahead algorithms the goal is the maximization of the utility of the consumers. In Table 2. the optimal RTP algorithms founded in the literature [11-14,19] are characterized by the applied objective function, optimization technique, and some other features.

# 4 Scheduling-based DSM

Main goals of scheduling-based DSM could be maximizing the economic benefit, maximizing the use of renewable energy resources, or reducing the peak load demand. Another challenge in scheduling-based DSM is to fulfill consumer demands while avoiding infrastructure overloads. Scheduling-based DSM is able to yield the desired load curve according to the preferred objective function. The desired objective of the DSM strategy can be achieved bringing the final load curve as close to the objective load curve as possible when scheduling-based DSM alters customers' electricity consumption.

Common ways to shape demand profile can be shifting, scheduling, or reducing customers' demand. The goal is to achieve a smoothed demand profile instead of the initial profile with sharp peaks; or reduce peak demand of the total energy demand; or reduce the peak-to-average ratio [5-7]. A new challenge can be to reduce novel arising costs of imbalance as unpredictable changes in production and consumption yield to a cost for repairing the balance. Fixed settlement periods are used in organizing load schedule varying per country in length between 15 and 60 minutes. Figure 2 shows a typical daily load profile of a residential consumer before and after scheduling-based DSM.

Some of typical appliances in industrial, commercial or residential consumers' load profile are shiftable consumption devices (e.g. washing machine, air conditioner) giving an opportunity to reach the effective load shaping. Unfortunately this is still not sufficient to balance the unreliable output of RES power generators (e.g. solar panels and wind turbines). Meanwhile new challenges and new opportunities for scheduling-based DSM are emerging with fully electric vehicles and plug-in hybrid electric vehicles launched to market in a rapidly growing number [14-18]. In most cases electric vehicles need to be charged after their batteries deplete. The increasing penetration levels of uncoordinated electric vehicle charging will significantly reduce power system performance and efficiency, and even result in overloading the grid system. One possible solution for mitigation of the impact of this effect is to optimize their charging profile. It means that we need to keep the peak power demand as small as possible, taking into account the extra power consumption of vehicle charging. This can be achieved by coordination of their charging. A more highlighted impact of electric vehicles is that they provide a new way to store and supply electric power. It is easy to recognize that the key question is to determine the appropriate daily charge and discharge time periods of these vehicles, taking into account the requirements of both vehicle owners and their utility. An electric vehicle can only deliver power to the grid or can charge its batteries when it is parked and connected to grid which property results in a higher uncertainty of the power supplied or consumed by any electric vehicle. This problem leads to a need for using appropriate analytical tools, enabling an investigation of a large-scale electric vehicle stochastic behavior.

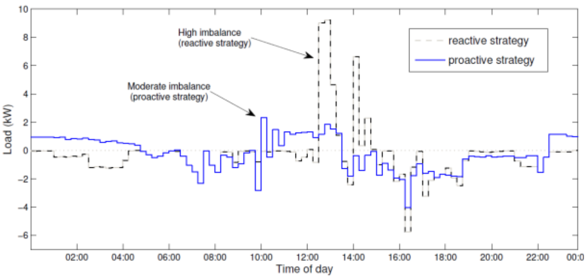


Fig.2: Typical daily load profiles

Easy to understand why a hot topic in smart grid literature is the role and impact of electric vehicles on the power grid. Several distributed frameworks are proposed in the literature to coordinate electric vehicle charging using stochastic programming [14], quadratic optimization [16, 17], particle swarm optimization [15], dynamic programming, and other resource allocation methods based on multi-agent system [18]. To increase the fraction of electricity supplied from today's widespread utilized RES having a fluctuating output, we must learn to maintain a balance between demand and supply.

The final goal of investigations in the field of scheduling-based DSM is the development of methods and techniques to ensure this balance.

It is expected that the DSM solutions in practice will base on utilizing storage capacity of electric vehicles to support this balance. As an addition this solutions will greatly support a reduce in overall $CO_2$ emissions.

# 5 Conclusion

In this paper, Demand Side Management and Demand Response Techniques have been surveyed, which allow system operators to control electricity network in a more stable and financially feasible way. Different approaches such as Control of smart appliances, pricing strategies and load scheduling have been presented, which are able to enhance grid efficiency and hence leading to a Smart Grid.

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