



A review of demand response in an efficient smart grid environment

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ARTICLE INFO

Keywords:

Demand response
Smart grid
Energy management systems
Pricing schemes

ABSTRACT

As the electricity system shifts from a conventional operating system into a smart grid system, the paper proposes an efficiency-enhancing mechanism comprised of communication-based demand response (CBDR) and a customer-friendly inclining block tariff (IBT) that takes into consideration customers' income and consumption profiles.

1. Introduction

The management of the electricity market is currently undergoing drastic changes in its structure and operations as it is transformed from a conventional system into a smart and decentralized system with added contributions from renewable sources (Ketter et al., 2016; Yang et al., 2017). The smart grid emphasizes maintaining interactions with users, including power consumption and dynamic pricing; that in turn is achieved through the deployment of various demand-side management programs. By the definition of the U.S. Department of Energy, the smart grid (SG) is an electricity delivery system enhanced with communication facilities and information technologies to enable more efficient and reliable grid operations with improved customer service and a cleaner environment (U.S. Dept. of Energy, 2009). Demand response takes advantage of two-layer communications and information networks in SGs and make the grid multi-layer-intelligent by realizing intelligent demand response.

According to the DOE's definition, demand response is a program established to incentivize end use customers to change their normal consumption patterns in response to changes in electricity prices (U.S. Dept. of Energy, 2006). Through electricity DRs, SGs can achieve energy saving measures, peak load shaving, improve the efficiency of the grid system, and reduce the need for power investments.

Existing literature has thoroughly discussed DR as a measure for curtailing peak demand and increasing grid reliability, networking, marketing policies, and integrated technology in power systems. The work done by Callaway and Hiskens (Callaway and Hiskens, 2010) hypothesized that a DR program should primarily focus on increasing information processing requirements in the smart grid system. They argue that the DR system will incur massive volumes of data that may lead to an inherent internal security problem. There are many contributions in the literature about the architecture and components of a

DR system. For instance, Palensky and Dietrich (Palensky and Dietrich, 2011) constructed a web-based energy information system and named its typical components. Tan (Tan et al., 2012) proposed a high-level design of a decision support system for demand-side management. Sui and Sun (Sui et al., 2011) provided a high-level overview on how to utilize smart metering to establish a DR system. Ghazvini (Ghazvini et al., 2017) used an optimization-based HEMS model that was applied under the pricing schemes of RTP and TOU. Many authors in the literature studied incentive-based DR schemes as inputs and scheduled electricity consumption based on DRs and price signals. The DR system of Huang (Huang et al., 2015) used a controller on all electrical appliances, including interruptible, deferrable, and multi-operational controllers. Dan and Kushler (Dan and Kushler, 2005) reviewed the effect of DRs on energy efficiency and found that DR programs generally yielded energy savings. Zareen (Zareen et al., 2015) focused their research on the profit maximization of customers and the revenue maximization of the utility provider.

This paper conducts an extensive literature review of DR programs and proposes a communication and computation-based DR program (CBDR) for future grid systems. The study further enhances the DR program through the deployment of a customer-friendly and cooperative tariff. The objectives are fourfold: to monitor users' consumption behavior by installing home displays and smart meters connected with the grid; to minimize peak demand by employing an inclined-block tariff (IBT) on power volume distribution; to maintain a responsive communication interaction for data sharing between users and the power grid through the (HAN, WAN and NAN) networks. Both, the smart communications and smart tariff will propagate DR intensively among users and utility providers. In this work, CBDR is introduced in order to convey the price and incentive updates to customers through a speedy and secure communication network.

The structure of this paper is organized as follows. Section 2

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provides an extensive overview and categorization of demand response. Section 3 elaborates on the objectives of DR and its significance in the power market. Section 4 describes the different demographic and economic factors that directly influence the true applications of DR. Section 5 demonstrates the future directions for an efficient and customer-responsive DR. Section 6 underlines future limitations and opportunities for DR in the electricity market. Section 7 concludes.

2. Background and classifications

Demand response can be defined as changes in electricity usage by end-use customers from their usual consumption pattern in response to changes in prices. Price-dependent DR refers to the financial incentives or penalties to motivate customers to provide load flexibility (Torriti et al., 2010). Demand response facilitates the reduction of power consumption and saves energy. In addition, it maximizes capacity utilization of the distribution system’s infrastructure by reducing or eliminating the need to build new lines and expand the system. The two-way communication capability in the smart grid allows for the widespread deployment of DR technologies and programs, thereby allowing load to adjust to supply variations.

In the US, as of 2015, DR programs alone were estimated to have the potential of 31,754 MW, accounting for 6.6% of total peak demand of all ISO/RTO, and it was estimated that demand response would probably shave 38,000 MW off the country’s peak demand in the year 2019 (Wright et al., 2011). The actual peak demand savings was approximately 12,000 MW, equivalent to the total generation capacity of Bulgaria or Denmark in 2012 (CIA: The World Factbook: Denmark, 2001) (Fig. 1).

2.1. Price-based DR (PBDR)

The price based DR program depicts the actual cost for the electricity from production to the distribution in a system. As Fig. 1 shows the different dynamic pricing schemes that provide insight for the customers shifting their consumption pattern from high cost interval to the lower price interval.

2.1.1. Time-of-use (TOU)

The time-of-use scheme is split into two periods of peak and off-peak with high and low rates, respectively. However, the tariff can motivate customers to reduce electricity consumption from peak to off-peak order to balance the interaction between supply and demand. The tariffs are frequently combined with a separate charge for peak usage, which means that customers pay a given price per kilowatt for their maximum demand in the billing period. These demand charges are levied irrespective of whether the system is constrained or not (Borenstein et al., 2002). TOU-pricing-based schemes are effective in reducing peak electrical consumption by incentivizing consumers to use more electricity at cheaper hours and reduce demand in peak hours.

2.1.2. Critical peak pricing

In critical peak pricing (CPP), a normal tariff, which generally belongs to the TOU family, is valid for most of the days of the year. However, a small number of days are subject to a price change. These occurrences correspond to periods of very high demand (peak loads) during which the generating utilities could not provide a sufficient quantity of electricity if prices were flat (Andrey and Haurie, 2013). It charges higher prices during extreme peak periods or emergency situations, while the rates on other periods remain the same (Fischer, 2008). Both the critical peak periods and the critical peak rates are not fixed. The critical peak periods may be only a few days or a few hours in a year (Mohagheghi et al., 2010).

2.1.3. Peak-time rebate

Critical peak rebate programs are usually offered to residential and small commercial customers without any form of automated control technology, such as via a programmable communicating thermostat (PCT). In a few jurisdictions across the U.S., residential customers are by default enrolled in this program, but otherwise they comprise a relatively limited amount of the national potential peak load reductions (Wright et al., 2011).

2.1.4. Real-time pricing

The RTP scheme reflects the marginal value of continuous electricity according to real-time supply and demand situations. Prices are not predetermined and are subject to hourly changes. There are two common forms of RTP. One provides the 24-hour price schedule a day in advance (DA-RTP) and the other provides the hourly price within 60 min after consumption has already occurred (RT-RTP). In the smart grid infrastructure, the devices that are installed in homes usually show the price signals of utilities during peak hours and the customer instantly reacts by reducing the peak and taking part in the competitive electricity market in an off-time interval so that the RTP prices can become more efficient (Ahn et al., 2011).

2.2. Incentive-based DR (IBDR)

The program includes direct load control (DLC), behavioral demand response (BDR), demand bidding, buyback and ancillary and regulation services. These schemes provide customers with peak shaving incentives. IBDRs are needed and requested when customer demand significantly increases more than supply and system reliability is at risk.

2.2.1. Direct load control (DLC)

Demand response programs have been around for decades and have been proven an effective means for utilities to manage system peaks by controlling customer loads. In DLC programs, the utility directly controls the customers’ appliances such as air conditioning systems, hot water heaters, and pumps, by regulating their frequency. The utility benefits from a better ability to manage demand and supply, while the customer benefits from financial incentives for program participation. In the DLC program, customers agree to allow their utilities to directly access some of the selected appliances or equipment during peak time interval in order to shut down or cycle them. In some cases, the utility charges penalties for overrides by users in peak times (Dan and Kushler, 2005).

2.2.2. Behavioral DR

Extensive research has studied the timely feedback to consumers to reduce peak demand of electricity or shifts the demand to off-peak periods (Darby, 2006) (Faruqui et al., 2010). However, some problems have been identified with feedback, including problems with engagement over the long term after the novelty has worn off (Houde et al., 2013) (Sintov and Schultz, 2015). Behavior-based DR programs rely on behavioral changes to produce a change in electricity consumption but are voluntary and do not provide any explicit performance-based

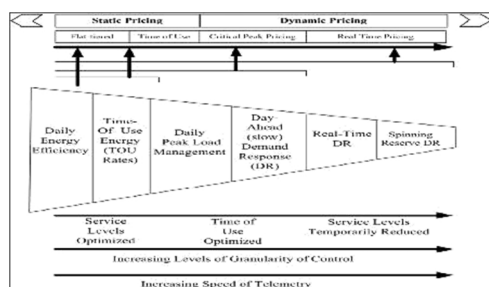


Fig. 1. Conceptual representation of efficiency and the demand response. Adopted from (U.S. Dept. of Energy, 2006).

payments.

2.2.3. Demand bidding and buyback

Demand-bidding programs encourage large customers to provide load reductions where they agree to curtail the amount of consumption based on a settled price. These programs encourage customers to trade electricity with the utility market and depict the price responsiveness as the time when the prices begin to increase (Khajavi et al., 2011). Under sponsor pricing, the utilities predefine the prices and the quantity to the customers. Then, the customers are paid accordingly against the reduced amount by the system operators (Inc, 2003).

2.2.4. Emergency demand response

In case of insufficient capacity, the utilities are apt to establish a contingency program at the transmission level and necessitate load reductions. In such cases, utilities have two options. Their first option is to call on the interruptible program that targets large commercial and industrial customers who have the capability of shutting down their operations for short periods or who can switch to their own backup generation to meet their needs. Their second option is to resort to bulk load shedding to maintain system stability and avoid large-scale system failures (Tyagi and Black, 2010).

2.2.5. Regulation services

The regulation service is a real-time service to balance load and power generation so that the frequency will be maintained within a specific range of the nominal frequency. The frequency deviates from its nominal value when there is a mismatch between load and electricity supply. Regulation service refers to the capacity to respond to random deviations from the net scheduled load (Tulabing et al., 2016) (Fig. 2).

2.3. Communication-based DR (CBDR)

2.3.1. Communication and computation infrastructure

Smart meters, bidirectional communication, advanced metering infrastructure (AMI), home automation, and home area network (HANs) are the techniques and technologies presented by researchers in the literature (Erol-Kantarci and Mouftah, 2011). Smart grid technology has applications in energy generation, transmission, distribution, and consumption (Khan et al., 2013). Smart grid technology provides a viable environment for DR programs in the electricity market and enables customers to curtail their peak loads that are aligned with financial incentives. Fig. 2 depicts the proposed model of effective and efficient DR in making possible the customer participation for changing consumption behavior at real-time intervals. In a CBDR program, all home-used appliances are linked with smart meters, thus establishing easy connections between subscribers and utilities in receiving and transferring the data and prices, respectively. The Fig. 3 thoroughly demonstrates the functions of different devices, networks, and domains that are coordinated with the utility control center. AMI can be viewed as a communication and control link between a meter data management agency (MDMA) and a collection of metered facilities.

The FERC defines AMI as “meters that measure and record usage data at hourly intervals or more frequently, and provide usage data to both consumers and energy companies at least once daily. Data are used for billing and other purposes.”

The AMI architecture consists of various integrated technologies and applications including smart meters, wide-area networks (WAN), neighborhood area networks (NANs), meter data management systems (MDMS), and home (local) area networks (HANs). The home area network (HAN) is a house-specific network that creates a network link among the demand responsive appliances, such as smart thermostats and HVAC, controllable washers/dryers, or even electric vehicle chargers.

HANs connect various smart devices to achieve optimum energy

usage and to implement demand response (DR) and advanced metering infrastructure (AMI). NANs fulfill the gap between HANs and WANs. A wide area network (WAN), which usually centralizes all the neighborhood area networks with a central command system (Meng et al., 2014), is shown in Fig. 3. It actually forms the backbone of the communication links between NANs and the utility control centers (Yu et al., 2011). The wide area network bridges the utility and field area networks and provides all communication links between the control center and the substations. It mostly combines the received data from the lower domain, NAN, and sends it to the utility (Mohagheghi, 2012). A smart grid neighborhood area network (NAN) is deployed within the distribution domain of the grid to form a communication facility between the high-domain WNA and the lower-domain smart meters and smart homes in a distribution system. Smart grid NANs offer distribution domains with the capability of monitoring and controlling electricity delivery to each household according to user demands and energy availability. It also connects the users in the domain area with higher domains levels to form a centered power grid that can determine the efficiency of the whole grid system (Meng et al., 2014). As one of the core technological advancements, the advantages of AMI include the cost savings of AMR, and prospects for increased customer control, including demand responses.

2.4. Energy management and monitoring infrastructure

2.4.1. Home energy management system (HEMS)

A smart home can be defined as a house that consists of a highly advanced communication network between different devices and appliances that are installed in the home and allow for the controlling, monitoring, and remote access of all applications and services of the management system (Fernandes et al., 2014). In fact, it is an easy way to obtain the consumption profile of different home appliances and devices as is shown in Fig. 4 through a proper resource management that could balance the load among the appliances. A fully equipped smart home area network (HAN) can have the ability to access the smart appliances deployed in the user's side through direct load control devices that are connected directly to large appliances, programmable communicating thermostats (PCT) to manage the heating and cooling system, and in-home displays (IHDs) to provide near-real-time energy usage information. These in-home displays can also inform the consumer of critical electricity pricing events that are part of a utility's demand response program (Lemay et al., 2008) (Fig. 4).

2.4.2. Building energy management system (BEMS)

The building industry is a growing factor in energy consumption. According to the European Union (EU), building energy consumption reaches up to 40–45% of total energy consumption and is responsible for 50% of greenhouse gas (GHG) emissions ((Wilkin, 1988) Smart buildings (SBs) are usually equipped with smart and other cutting-edge technologies in order to provide salient facilities such as providing comfort to customers, minimizing consumption, and reducing greenhouse gas (GHG) emissions. Alternatively buildings have some electricity loads that can be controlled for demand response purposes and fall into a miscellaneous category (Motegi et al., 2007). Meanwhile, the buildings that are already equipped with BEMS have the potential to be part of the DR system by contributing to the effective role of making the energy power system more reliable and efficient and maximizing the profits for the building owners as well (Cui et al., 2017).

3. Objectives and applications

3.1. Improve the grid reliability and reduce the costs

Demand response (DR) is an effective and efficient tool or a set of activities to reduce or shift electricity use in order to improve electric grid reliability, manage electricity costs, and ensure that customers

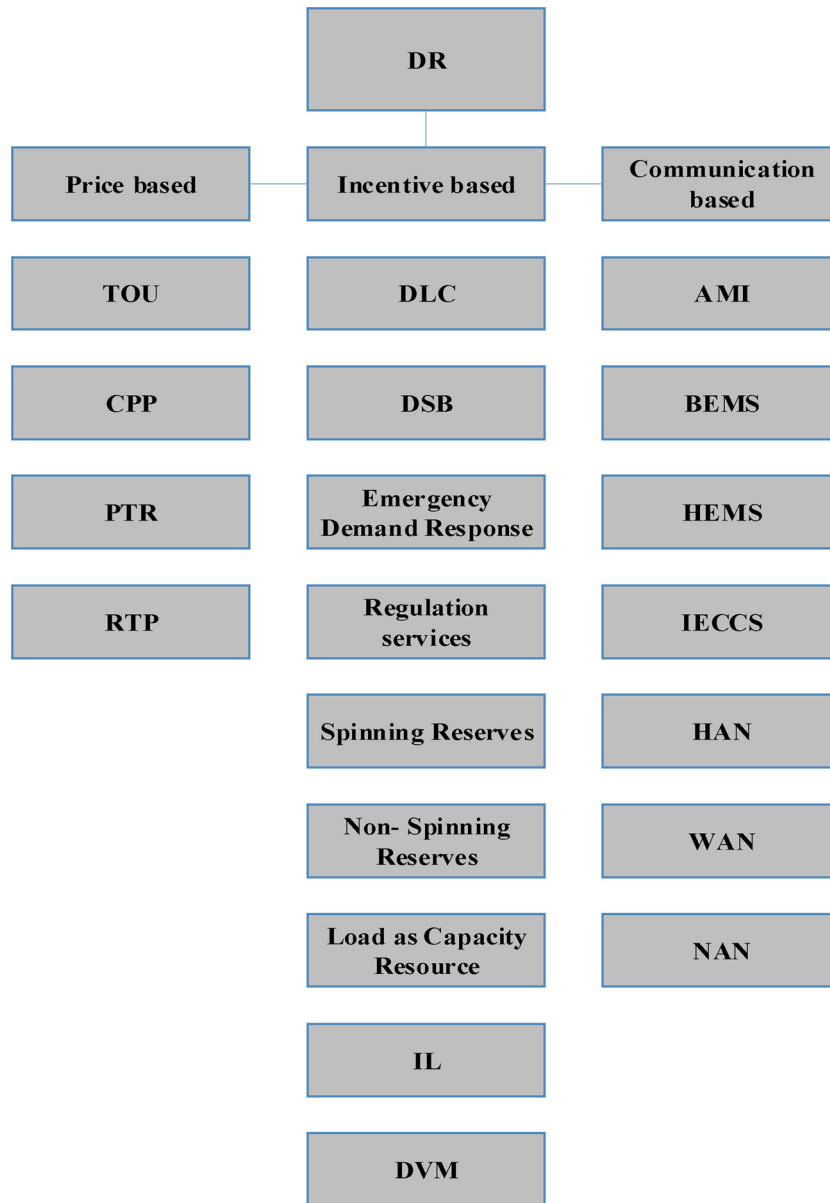


Fig. 2. Proposed demand response classifications.

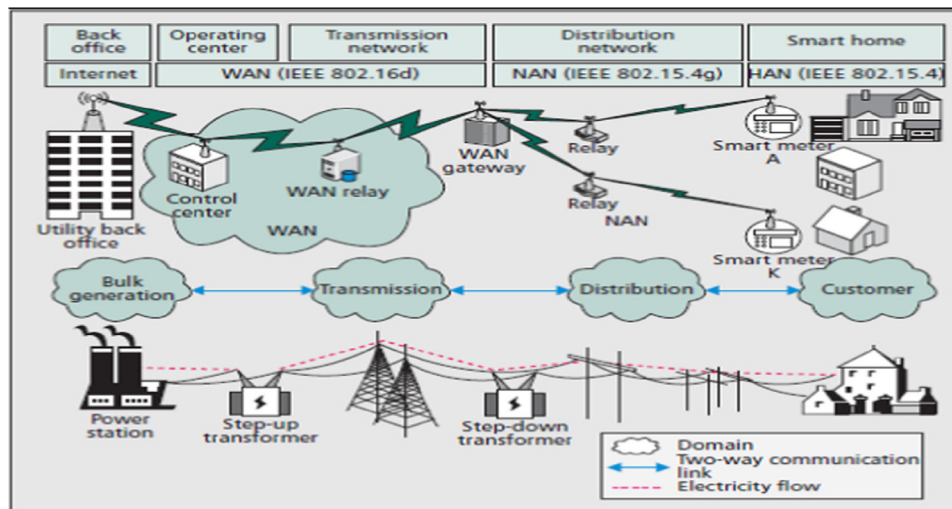


Fig. 3. Smart grid communication and networking infrastructure. Adopted from (Meng et al., 2014).

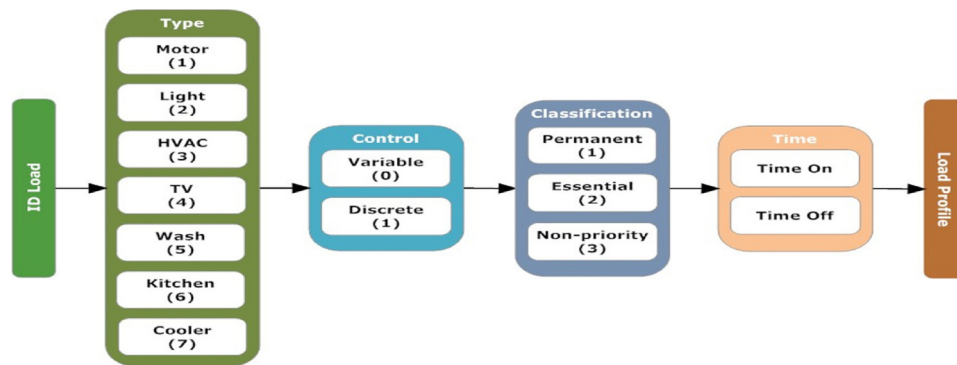


Fig. 4. Characteristics of the load in the management event. Adopted from (Fernandes et al., 2014).

receive signals that encourage load reductions. The program further ensures the system's security by reducing the generating plant load. It is required only if generators are providing spinning reserves since this allows them to either increase or decrease power output as required. The maintenance of grid reliability depends upon balancing the supply and demand through the application of demand-side management programs. However, the regulatory framework of the electricity industry is encouraging more smart solutions that typically rely on the active participation of customers in DR in order to mitigate both social and capital costs (Morgan, 2010).

3.2. Smart in reduction of pollutant emissions

It is well known that DRs are able to reduce conventional generation capacity, maximize low-carbon generation, contribute to short-term system balancing, and defer the network's reinforcements (Briefing, 2008). In China, the electric power system often has to rely on small coal-fired generators and diesel generators to provide peaking electricity. The utilization of DR resources can reduce the use of these high-carbon peak generators (Yang, 2017).

If demand response is used to shift electricity use from on- to off-peak, it may cause a net reduction (or increase) in air emissions. The environmental impacts of a demand-response-driven load shift will be determined by local utilities and the regional generation portfolios used during peak and off-peak periods (e.g., nuclear, coal) and actual operations during the demand response.

If a demand response is used to integrate intermittent renewable generation in the future, it can have a net environmental benefit because the additional wind, solar, and other renewable sources are likely to displace fossil fuel-fired generation with higher emissions of pollutants such as nitrous oxides, sulfur oxides, and carbon dioxide.

As smart grid technologies, widespread energy price and use information, and dynamic rates become more accessible for consumers, these tools that facilitate demand responses will also enable customers to become more energy-efficient and deliver greater overall environmental benefits from this synergy (Goldman et al., 2010).

3.3. Load management through curtailment and shifting

Electricity load management has drawn wide attention from both academia and industry. A DR strategy (Dugan et al., 2003) can be used to change the time invariant consumption behaviors to time variant by shifting peak loads to off-peak periods, as reported in Fig. 5(b). The application of DR utilities can manage the load by shifting or curtailing the energy consumption, as shown in Fig. 5(a), and the proper implementation of information communication and technology (ICT) in more than one device that is accountable for the flow of large amounts of data [6]. In fact, the SG has the capacity to manage energy flows from renewable sources while ensuring the integration and involvement of distributed energy resources by implementing reasonable approaches

to manage the loads during high electricity demand (Fera et al., 2016). The benefits of effective electricity load management are two-fold. First, it can help customers curtail their electricity costs by strategically adjusting the consumption modes. Second, it can relieve the unbalanced situation between electricity demand and supply to improve grid reliability and thus reduce the investments required for construction of new peak power plants specifically run during extreme peak periods that only occur a few hundred hours per year (Ahn et al., 2011) (Fig. 5).

4. Demography and economic variations in DR

4.1. Household energy consumption behavior

The individual household energy consumption behaviors are based on different factors such as, individual income, rewards, punishments, and the social and physical infrastructure that cause the variability of the DR program. The average household user feels comforted by installing and using more electric appliances, air conditioners, heating stoves, lighting, fans in each and every room, dishwashers, clothes washers, dryers, and heating pumps. After having complete information, customers rationally analyze the costs and benefits of their quantity demand and set a time frame for utilizing home appliances (Lutzenhiser, 1993; Simon, 1953). The reward and punishment appear in the application of dynamic prices and incentives for peak shaving. Therefore, in localities, the application of rewards against a reduced or curtailed amount of energy leads to a significant improvement in consumer behavior compared to the punishment group that is more nervous and remain passive in taking part in DR programs (Finger, 1942).

However, a survey regarding public knowledge and attitudes about energy issues implied that environmental concerns tend to play an increasingly important role in varying household consumption behaviors during peak hours (Tapscott, 2011). For instance, a reduction in electricity consumption by 2.5% has been achieved by changing user behaviors in the U.S. (Siano, 2015) (Fig. 6).

4.2. Tariff structure and household income

The income level of the households, the physical size of the building, the age level of family members, the type and quality of the dwelling, and the appliances used at home are factors that determine demand-side energy consumption (Wu et al., 2014). Income differentiation among households affects DR in two ways. First, customers with high income that remain inelastic at peak times enjoy the incentives provided by the utility company. Second, low-income households are sensitive to price changes. Fig. 7 shows different behavioral demand curves (1 and 2, respectively). Curve 1 depicts a small change in quantity demand (ΔD) with respect to the change in price (ΔP) that is, $\% \Delta P > \% \Delta D$ demonstrates that income variability directly impacts the customer demand curve during peak hours. Similarly, curve 2

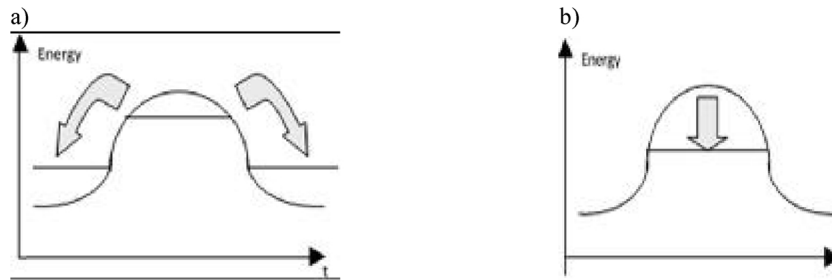


Fig. 5. (a). The energy decrease. Adopted from (Fera et al., 2016) Fig. 5(b). The energy shift. Adopted from (Fera et al., 2016).

shows the elastic nature of customer demand as $\% \Delta P < \% \Delta D$. Sun and Lin (Sun and Lin, 2013) found that 45% of subsidies were given to higher-income groups (accounting for 27% of the population) while the lower-income groups (accounting for 22% of the population) only received 10.1% of the subsidies. The DR program is primarily based on pricing mechanisms and promoting financial incentives for consumers to reduce peak use and provide load flexibility (Torriti et al., 2010).

5. Future direction to efficient DR

5.1. Increasing-block tariff (IBT) and DR

The aim of DRs in smart grids is to reduce or shift the electricity consumption pattern through direct and indirect control of home appliances or providing financial incentives such as TOU, RTP, TOD, and block tariffs (Wallin et al., 2005). Financial incentives contribute to peak reductions and provide system reliability when electricity consumption is below the threshold level. Since a larger the incentive size results in lower household consumption, the “fair allocation” incentive could be interpreted as a “reward” for a household’s conservation

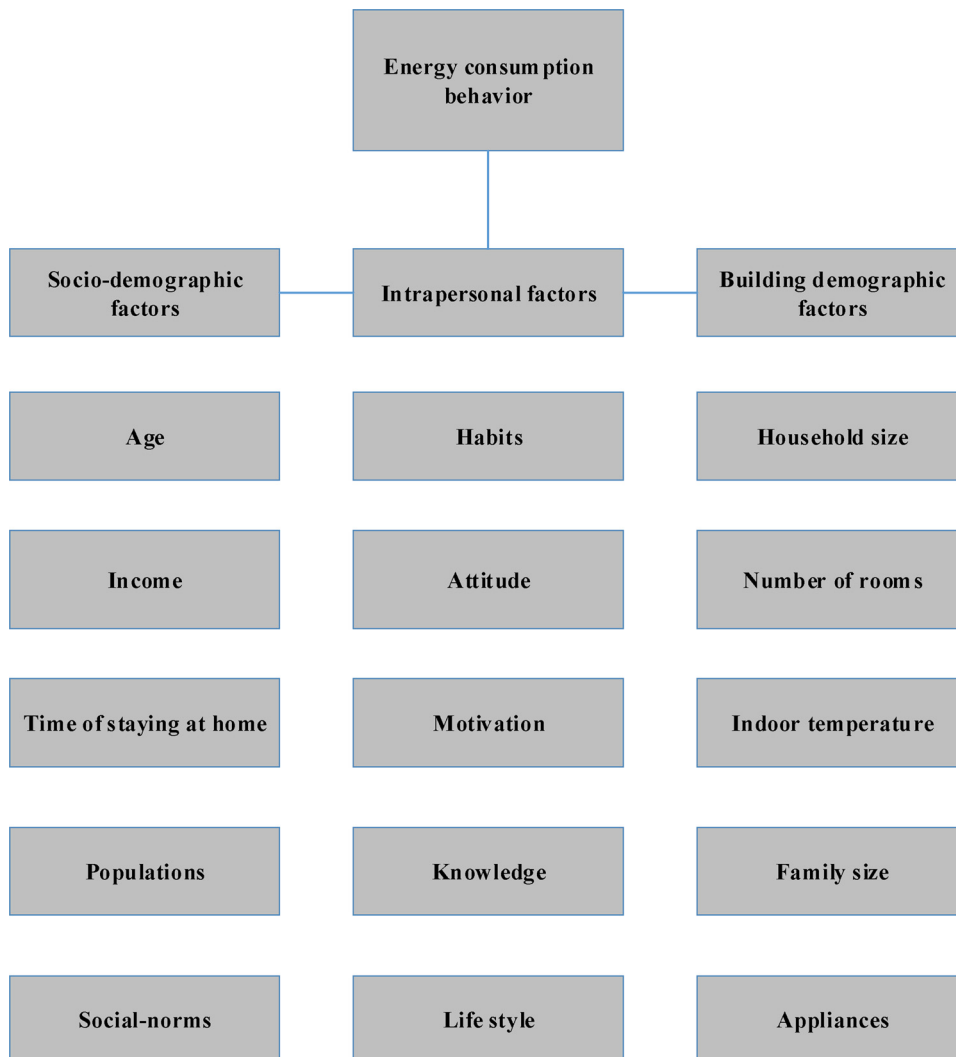


Fig. 6. Portrait of consumer consumption behavior.

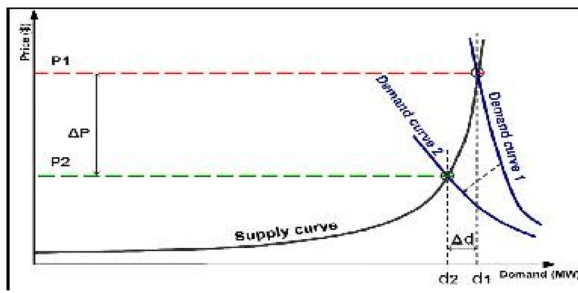


Fig. 7. Effect of demand variation on the electricity price. Adopted from (Baboli et al., 2012).

efforts (Sibly and Tooth, 2014).

By charging marginal costs to customers, the increasing-block tariff (IBT) has three characteristics: economic efficiency, system reliability and environmental friendliness. Due to income differentiation, users that do not actively participate in the DR program may later increase the grid’s volatility through their higher demand for electricity.

The focus of the paper is to make DR program more effective and efficient in the grid’s infrastructure through the application of customer-friendly tariffs that equitably charge customers based on users’ consumption limit. In the IBT tariff, users will be charged when a predetermined electricity consumption threshold is exceeded from the volumetric charge, so that consumers using a lower amount of electricity pay proportionally less, while households exceeding the initial subsidy block will receive extra charges (Lin et al., 2007). The user classification makes it easy for utilities to measure household consumption patterns in order to charge reasonable prices. Fig. 8 shows the blocks assigned according to consumption within the given power volume and price. The first block is allocated to customers with limited incomes and limited consumption capacities. They are charged a subsidized price that is committed to customers. The second block targets customers with moderate consumption capacities that are demand-responsive. They are charged more than the subsidized rates. The third block targets customers with high income and consumption who are always charged high prices (Lin and Jiang, 2012). The tariff has been promoted as a solution to address social equity, cost recovery, efficiency, and environmental concerns (Lin and Liu, 2013).

- The new tariff is financially effective, cost-reflective with an acceptable risk and appropriately influences customer behavior. The

mechanism behind the tariff is that, once it is set, the power units and rates for the participants in blocks is subject to reducing peak demand and providing system reliability.

- It relieves the pressure on low-income households.
- Income would be transferred from the high-income class to the low-income class by cross subsidies.
- It should be socially equitable by presenting appropriate and realistic costs of the service.
- Consumer surplus can be improved through the implementation of the IBT by reducing electricity payments and timing appliance usage to optimal periods.
- The tariff is more applicable for electricity peak shaving and system reliability in the long term for differentiated income level customers.

6. Opportunities and limitations

6.1. Opportunities/benefits

6.1.1. Economic benefits of DR

In a deregulated power system, load, profiling and time-of-use make it easy to cap the economic benefits by saving marginal costs at peak hours. If dispatch-enabled demand responses become commercial, consumers may be able to earn additional incomes from offering their interruptible loads to DR aggregators. Utility companies offer financial incentives for peak reductions, which are only possible via the implementation of DR in response to consumption. However, in traditional power systems, only flat rates are employed and customers have no incentives to alter their consumption patterns (Kirschen, 2003). The efficiency of time-varying prices keeps customers updated and convinces them to move their electricity consumption from peak to off-peak time slots in order to provide system security and receive financial benefits. According to the report cited in Allcott (Allcott, 2011), time-varying prices increase household welfare by \$10 per year, or about 1–2% of expenditures on electricity, and is insufficient to justify the investments in metering infrastructure.

6.2. Limitations/hurdles

6.2.1. Market and regulatory mechanism

One of the factors that limits the implementation of demand response is the market structure (Cutter et al., 2012). If the power market is state-owned, it is likely that distribution frameworks are designed in a centralized, homogenous manner without a wholesale market

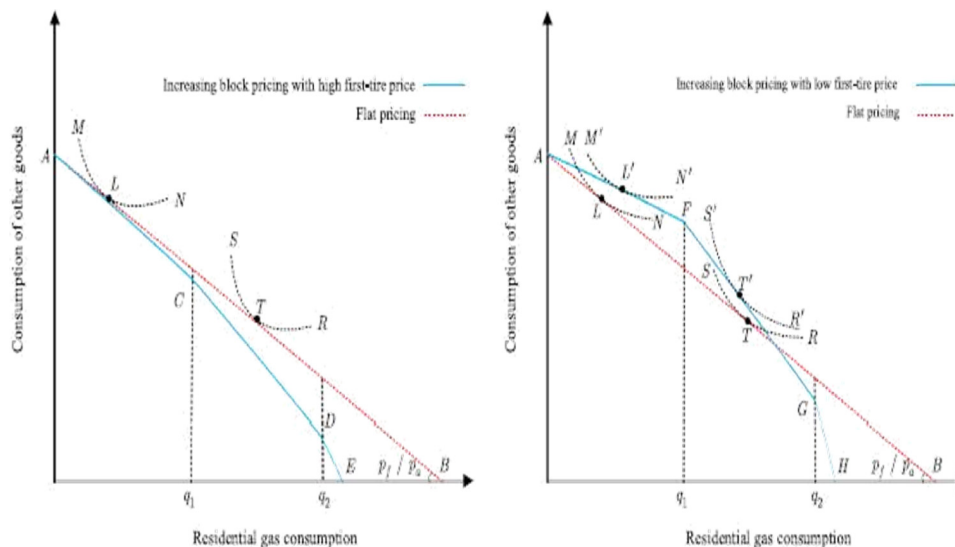


Fig. 8. The impact of block pricing on residential utilities. Adopted from (Gong et al., 2016).

structure. In China, the utilities usually face the lack of a cost recovery mechanism, limiting incentives to make a direct contract with DR aggregators in their dispatch operations (Yang, 2017).

6.2.2. Consumer behavior

The implementation of effective demand response is based on end-user behavior in the power market. Ordinary customers are always focused on minimizing billing, but this is reversed on the supplier's side, where generators aim to maximize profits and establish their economic model. Consumers exhibit asymmetric responses to prices, with limited reductions in demand during peak hours, but a significant increase in consumption during off-peak periods (Allcott, 2011). That shows irrational consumer behavior that need to be considered in the evaluation of effective demand response.

6.2.3. Technological challenges

Technological advancements can increase the deployment of effective demand response in a smart grid system. Smart meters enable more effective demand response by integrating customers with utilities and maintaining a communication network to pass on price signals and send consumption data to the power grid (Romain, 2014). In addition, there also the need of equipment for data retention and reporting infrastructure to work with the meters (Hurley et al., 2013).

7. Conclusion and future perspective

A communication-based demand response is proposed in this paper to implement demand response successfully in the residential market. An advanced communication network and tariffs are the foundation of demand response that is applicable to users. Our work recommends IBT tariffs in different price blocks for power volumes that are based on user consumption. Customers actively link with the utility system by making peak reductions and power shifting based on financial incentives. Therefore, it has been observed that social equity can be an active factor in making DR more effective and successful in future smart grid networks. In existing DR programs, customers are given either flat rates or time-varying tariffs. We suggest the IBT scheme to set the price block for every customer and define power limits for consumption in the smart grid. In this scheme, participants already know the defined price limits in every block with a view to ultimately making DR friendly and acceptable.

Acknowledgements

The National Natural Science Foundation of China (No. 11171221), the Natural Science Foundation of Shanghai (14ZR1429200), and the Innovation Program of Shanghai Municipal Education Commission (15ZZ074), supported this work.

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