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ABSTRACT

In this paper, we survey 82 papers related to revenue management and dynamic pricing of electricity and lists future research avenues in this field. Dynamic pricing has the potential to modify electric load profiles by charging different prices at different demand levels and hence can act as an effective demand side management tool. There are different forms of dynamic prices that can be offered to different markets and customers. Forecasting of demand, and demand price relationship play an important role in determining prices and helps in scheduling load in dynamic pricing environments. Consumers' willingness-to-pay for electricity services is also necessary in setting price limits. Elasticity of demand is an indication of the demand response to changing prices. Market segmentation can enhance the effects of such pricing schemes. Appropriate scheduling of electrical load enhances the consumer response to dynamic tariffs.

Keywords: Dynamic prices, forecasting, demand elasticity, willingness-to-pay, market segmentation, scheduling of load.

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Introduction

Electricity markets generally offer a flat tariff structure to consumers. Implementation of dynamic pricing of electricity is mostly restricted to block pricing in which the per unit rate of electricity increases or sometimes decreases after the consumption of a certain amount (block) of electricity. Electricity prices typically do not experience the full effects of market forces and hence do not reflect the true costs of generation and distribution. Peaks in load profiles are a result of unregulated demand, and huge capacity addition is required to meet peak load. This peak-load capacity stays idle during off-peak periods resulting in a loss of opportunity cost and system efficiency. Although flat rates offer uncertainty-free electricity bills to customers, it may require costly capacity additions, most of which are environmentally harmful. Dynamic tariff structures have the potential to flatten demand profiles and thus help power suppliers to reduce expenditure on capacity addition and efficiently plan electricity generation and distribution. Dynamic tariffs also provide each consumer with an opportunity to reduce his/her electricity bill at a constant consumption level just by shifting load. Knowledge about the demand-price relationship for electricity, consumers' willingness-to-pay for electricity, and demand forecasts are necessary for suppliers to plan their supply and tariff structures. Effective scheduling of electrical load can help consumers to reduce their electricity bills by increasing consumption when prices are low and reducing consumption when prices are high. Demand patterns and elasticity of demand vary from consumer to consumer and thus segmentation of the electricity market can prove to be helpful. Suppliers can offer suitable pricing schemes in properly segmented markets to boost their revenue. Supporting technologies can further bridge the demand-supply gaps in electricity markets. Published literature review on the multiple aspects of dynamic pricing of electricity is not available. We try to address this gap by surveying 82 published works in this field.

This paper is organized as follows. Review of studies on experiments using dynamic pricing in electricity is followed by discussions on works on various issues relating to dynamic prices in electricity. These include retail electricity pricing, wholesale market pricing, forecasting of price and demand, elasticity of demand, customers' willingness-to-pay for electricity, the effect of enabling technologies, electricity market segmentation and consumption scheduling. Thereafter, future avenues of research in this field are discussed followed by a conclusion. A list of references used in this survey paper is provided in the end. While we have looked into several publications in open literature, we do not claim the survey to be an exhaustive literature search.

Experimentations with Dynamic Pricing in Electricity

Dynamic tariffs are implemented in the electricity sector at different geographical locations through pilot projects. These experiments highlight a number of interesting insights about the nature of consumers regarding their response to electricity price signals. It is evident from most of these experiments that the price and income elasticity of demand for residential electricity is low, but other lifestyle and behavioral factors can significantly impact the same. A list of some research works based on such experiments and their important deductions are presented below.

Reference	Summary of Research Works
Faruqui & Sergici, 2014	The authors observe a large variation of demand response in data from 163 pricing treatments in 34 projects across 7 countries in an international database 'Arcturus'. They also find that the demand response depends on ratio of the peak and off-peak prices. The response curves are nonlinear. Consistent results show that dynamic pricing can modify load profiles.
Faruqui et al., 2009	Based on various experimental studies, the authors note that sampling should consider an estimate of net benefit of implementation, cost of experimentation, good probability of making the right decision, and internal and external validity of collected data. They propose the Gold standard of experimental design which includes control group and treatment group/s and pre and post data. They propose simple, revenue neutral and cost reflecting rate design, short peak period, strong price signal, and opportunity for significant bill saving.
Faruqui et al., 2014	The authors observe that customers' response to dynamic prices increases with enabling technology. Price responsiveness is higher in hotter climates. Residential customers respond better to dynamic prices than commercial and small industrial customers. "Hardship Low Income Customers" respond less than others mainly because their consumption is low and indispensible, leaving them no opportunity to reduce their consumption further.
Filippini & Pachauri, 2004	The authors analyze data from 30000 households in India and develop three electricity demand functions one each for winter, monsoon, and summer seasons. Their work demonstrates that electricity demand is price and income inelastic but varies with household, demographic, and geographical variables.

Bose & Shukla, 1999	The authors examine the econometric relationship between electricity consumption and other variables at a national level in India with more than 9 years data. They find that electricity consumption in commercial and large industrial sectors is income elastic, while in the residential, agricultural, and small and medium industries, it is income inelastic.
Tiwari, 2000	The author analyzes household survey data from Mumbai in India for short-run income and price elasticity. The residential sector, a major contributor to demand, comprises mainly lighting and comfort applications. Demand is found to be both price and income inelastic and the upper middle class responds the most to price signals.
Zhou & Teng, 2013	The authors find that the price and income elasticity of demand are low for urban residential demand in China. They argue that lifestyle and demographic variables play a significant role in explaining electricity demand.
Abreu et al., 2010	The authors observe 15 households for 270 days in an interdisciplinary study about residential electricity consumption using electronic meters. They emphasize the need for knowledge about customer characteristics and behavior. Although the sample size is small, the authors find potential for improvement of energy efficiency from large consumer appliances.

Issues Related to Dynamic Pricing in Electricity

There are several issues related to dynamic pricing of electricity that are important in the event of a practical application of the concept. This section includes retail and wholesale pricing, demand and price forecasting, demand elasticity, consumers' willingness-to-pay, enabling technologies, market segmentation, and consumption scheduling.

Retail Electricity Pricing

The retail price of electricity commands the demand profile of the retail electricity sector. Any demand side management effort involves appropriate designing of price schemes. This section describes the various possible pricing schemes and the importance of dynamic tariffs.

Electricity Pricing Schemes

Electricity prices can be broadly categorized into two types - static prices that do not change with a change in demand and dynamic prices that change with changing demand situation. (Faruqui & Palmer, 2012), (Simshauser & Downer, 2014), (Desai and Dutta, 2013) and (Quillinan, 2011) describe various pricing schemes as mentioned below.

a. *Flat tariffs*: Price remains static even though power demand changes. Consumers under such a scheme don't face the changing costs of power supply with a change in aggregate demand. Thus, consumers have no financial incentive to reschedule their energy usage. They don't face any risk of high value electricity bills for any unavoidable or unplanned electricity consumption. Hence this scheme is often used as a welfare pricing scheme.
b. *Block Rate tariffs*: This scheme differentiates between customers based on the quantity of electricity consumption. The scheme consists of multiple tiers characterized by the amount of consumption. Inclining rate schemes increase the per-unit rate with increasing consumption and declining schemes do the opposite.
c. *Seasonal tariffs*: These schemes observe different rates in different seasons to match the varying demand levels between seasons. Energy is charged at a higher rate during high demand seasons and the price lowers during low demand seasons.
d. *Time-of-use (TOU) tariff*: These are pre declared tariffs varying during the different times of the day, that is, high during peak hours and low during off-peak hours. Such schemes can stay effective for short or long terms. This is also known as time-of-day (TOD) tariff.
e. *Super peak TOU*: It is similar to TOU but the peak window is shorter in duration (about four hours) so as to give a stronger price signal.
f. *Critical peak pricing (CPP)*: This is a pricing scheme in which consumers are charged a high fixed rate during a few peak hours of the day and a discounted rate during the rest of the day. It gives a very strong price signal and enhances the reduction of excessive peak load.

g. *Variable peak pricing (VPP)*: This is quite similar to CPP with the only difference that the peak prices are not fixed, and vary from day to day. The consumers are informed about such peak prices beforehand.

h. *Real time pricing (RTP)*: This is the purest form of dynamic pricing and the scheme with the maximum uncertainty or risk involved for the consumers. Here the prices change at regular intervals of one hour or less and the consumers are made aware of the prices beforehand as per the design of the scheme. The change in prices in small intervals increases the efficiency of the pricing scheme in reflecting the actual costs of supply, but such schemes require advanced technology to communicate and manage these frequent changes.

The diagram below shows the relative risk-reward positions of the schemes described above from the consumers' point of view.

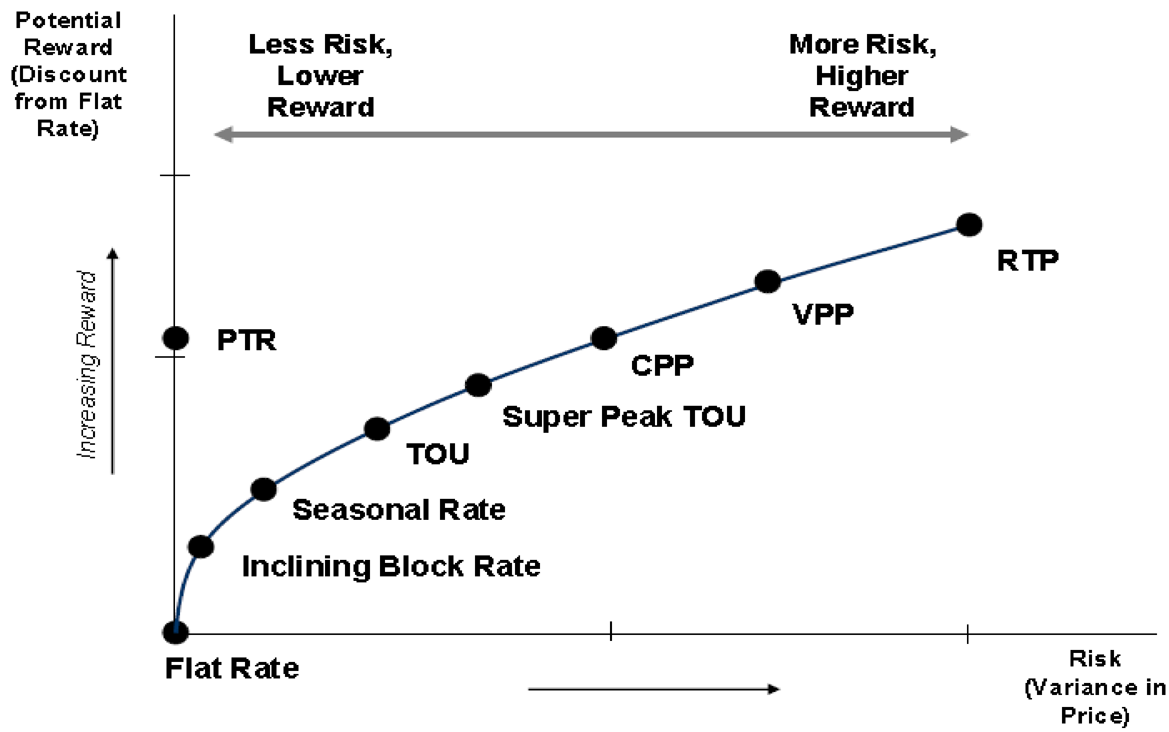

Fig. 1 - Risk-Reward mapping of dynamic tariff types. Image source: (Faruqui et al. 2012).

There can be various hybrid schemes by combining the basic schemes described earlier, based on situational requirements. Peak time rebates (PTR) also fulfill the objective of flattening the demand profile. These rebates are just the opposite of CPP schemes - they are provided for consuming below a certain pre-determined level during peak hours, and can be redeemed at a later time.

Pricing in Retail Electricity

Pricing in competitive markets generally depends on customers' perceived value and producers' supply cost and tends to be dynamic in nature. However, regulated markets generally experience flat tariffs that do not reflect the supply costs. (Desai and Dutta, 2013) prove that dynamic pricing is more efficient than traditional flat rate tariffs as it utilizes the consumer surplus and reduces peak loads. Various processes of developing price are studied which are as follows. (Harris, 2006) describes a way of deriving the price of electricity by indexing it against a weighted average of present and past wholesale rates. (David & Li, 1993) state that both concurrent prices and prices at other times affect the demand response to dynamic tariffs, thus demonstrating cross-elasticity of demand. They develop theoretical frameworks that address the price formation problem with cross elasticity of demand under certain conditions. (Skantze et al., 2002) show that delay of information flow between different markets causes price variations. Prices are correlated only if the markets are connected by transmission lines which are not congested.

(Stephenson et al., 2001) mention that variations in electricity pricing schemes may depend on several factors like thermal storage, combined heat and power generation, auto-producers, photovoltaic, net metering, small hydropower plants, dynamic tariffs, renewable energy, green tariffs, and consumer characteristics like consumption pattern. (Garamvölgyi & Varga, 2009) show that prices can be designed by using artificial intelligence techniques to classify consumers based on procurement costs. (Holtschneider & Erlich, 2013) develop mathematical models based on neural networks for modeling consumers' demand response to varying prices. Their model is used to identify an optimal dynamic pricing by Mean-Variance Mapping Optimization method.

(Seetharam et al., 2012) develop a real-time self-organizing pricing scheme, called Sepia, to compute the unit price of electricity based on consumption history, grid load, and type of consumer. This pricing scheme is decentralized and a grid frequency is used for grid load measurement in smart meters for determining the subsequent unit price of electricity. (McDonald & Lo, 1990) mention that an appropriate social basis of price designs for retail electricity includes welfare considerations for both consumers as well as suppliers. (Li et al., 2003) express the price-deriving objective as a non-linear optimization problem leading to welfare, yet reflecting the competitive relations among generation companies, utilities, and customers.

Wholesale Market Pricing

Electricity is traded in a wholesale market for industrial customers and electricity retailers. The market price for a future time frame is discovered through a bidding process in the bulk electricity markets. (Kirschen et al., 2000) illustrate a method of determining market price through bidding. The lowest bid price is set by the supplier based on its costs of supplying a quantity of electricity for a future time period. Then a pool of bid prices is accepted from bulk buyers. The selection of the bids is done from the highest priced one, in the order of decreasing prices, till the cumulative demand matches the supply. The last accepted bid price from the pool of selected bids sets the market price. However, the key price design decisions can depend on factors like contract pricing or compulsory pool pricing, one-sided or two-sided bids, firmness of bids or offers, simple or complex bids, price determination timing with respect to actual delivery, capacity payments, geographically-differentiated pricing and price capping.

(David and Wen, 2000) conduct a review of literature to discuss bidding by individual participants for individual profit maximization. They also discuss the role of regulators in limiting possible market abuse by some participants. The survey reveals that oligopoly exists in the market, instead of perfect competition, due to the several characteristics of the electricity market that restrict the number of suppliers. Different methods and ideas are used to model bid prices as follows. (Li et al., 1999) represent electricity trade as a two level optimization process. A priority list method through a “Centralized Economic Dispatch” (CED) is used in the top level.

The lower level has sub-problems of decentralized bidding. Here, hourly bid curves are developed for the CED by using self-unit scheduling based on parametric dynamic programming. Both the levels focus on revenue maximization rather than on cost minimization. (Zhang et al., 2000) develop bidding and self-scheduling models using probability distributions and Lagrangian relaxation respectively. (Weber and Overbye, 1999) use a two-level optimization problem to determine the optimal power flow considering social welfare. They determine a Nash equilibrium along with a market price with all participants trying for individual profit maximization.

(Krause and Andersson, 2006) use agent-based simulators to demonstrate different congestion management schemes such as market splitting, locational marginal pricing, and flow-based market coupling. The welfare aspects of different pricing schemes are analyzed in these methods to arrive at suitable market power allocations. (Zhao et al., 2010) explain that the 'bid cost minimization' technique, generally used in the wholesale market, actually provides a much higher cost than the minimum bid cost. The authors use game theoretic approaches and propose that 'payment cost minimization' is a better technique from the consumer welfare point of view as it directly minimizes the payment made by consumers. (Zhao et al., 2008) further introduce transmission constraints in the problem, making it complicated but more realistic. (Han et al., 2010) use CPLEX's MIP for this problem to find low efficiencies. They overcome this problem by 'objective switching method' in which the feasible region is reduced by performance cuts to minimize infeasibilities and improve efficiency.

Forecasting

Forecasting is an integral part of revenue management. Designing of dynamic prices requires forecasts of future demand and scheduling consumption requires forecasts of future prices. Forecasting thus provides a platform for planning for the future in case of dynamic tariffs for all concerned parties. This section describes works on price and demand forecasting in the electricity sector.

Price Forecasting

Retail price forecasts help consumers to preplan their consumption in a dynamic pricing environment whereas wholesale price forecasts assist buyers and sellers in planning for bidding strategies. (Nogales et al., 2002) develop forecasting models based on dynamic regression and transfer function approaches. The authors use data from Spain and California with high levels of accuracy. However, (Contreras et al., 2003) find reasonable errors with the application of ARIMA models on the data from the same markets. (Zareipour et al., 2006) use ARIMA models to forecast Ontario's hourly prices from publicly available market information with significant accuracy, failing only to predict unusually high or low prices. (Mandal et al., 2006) observe improved forecasting accuracy by using the artificial neural network computing technique based on similar days approach. They identify time factors, demand factors, and historical price factors that impact price forecasts. (Catalao et al., 2006) note that neural networks for next day price forecasting display sufficient accuracy for supporting bidding strategy decisions. (Kekatos et al., 2013) examine the Kernel-based day-ahead forecasting method and prove its market worthiness.

Demand Forecasting

Electricity suppliers can better plan their supply and generating capacities with appropriate demand forecasts. Demand can be forecasted daily, weekly, monthly or annually. Short-term load forecasts from minutes to several hours ahead are required for controlling and scheduling of power systems. Long term forecasts help in planning investments, overhauls, and maintenance schedules. (Taylor et al., 2006) compare the accuracy of six univariate methods for forecasting short-term electricity demand and find that simple and more robust methods (i.e. exponential smoothing) outperform more complex alternatives. The complex methods are seasonal ARIMA, neural networks, double seasonal exponential smoothening, and principal component analysis (PCA). (Taylor, 2003) implements double seasonal Holt-Winters exponential smoothening for within-day and within-week seasonality. This method proves to be more effective than ARIMA and the standard Holt-Winters method for short-term demand forecasting. They correct the residual autocorrelation by using a simple autoregressive model. (Taylor, 2010) incorporates within-year seasonal cycle as an extension of the double seasonal model. This triple seasonal model performs better than the double seasonal model and the univariate neural network approach. (Wang et al., 2009) demonstrate reduced errors in forecasts done by feeding a single order moving average smoothened data to a ε-SVR (ε -insensitive loss function support vector regress) model.

(Mirasgedis et al., 2006) incorporate weather influences in the medium-term electricity demand forecasts that can range up to 12 months. Meteorological parameters, like relative humidity and temperatures that affect the electricity demand are used along with autoregressive model to reduce serial correlation for four different climatic scenarios. (Zhou, Ang and Poh, 2006) show that the trigonometric grey model (GM) prediction approach, by combining GM(1,1) with trigonometric residual modification technique, can improve the forecasting accuracy of GM(1,1). (Akay and Atak, 2007) predict Turkish electricity demand using grey prediction with the rolling mechanism approach that displays high accuracy with limited data and little computational efforts. (Hyndman and Fan, 2010) use semi-parametric additive models that estimate relationships between demand and other independent variables and then forecast the density of demand by simulating a mixture of these variables. (McSharry et al., 2005) provide probabilistic forecasts for magnitude and time of future peak demand from simulated weather data, as real data is unavailable. (Saravanan et al., 2012) apply multiple linear regression and artificial neural networks with principle components for forecasts made in India. They use eleven input variables and show that the second method is more effective.

Elasticity of Electricity Demand

A clear idea of the demand-price relationship or elasticity is helpful for effective demand side management (DSM). (Borenstein et al., 2002) explain that elasticity of demand can be short-run as well as long-run. In Short-run elasticity we describes the price-response from the system with its current infrastructure and equipment. In long-run elasticity, we consider the investments that can be made in response to higher prices during a longer time span. (Wolak, 2011) observes that electricity markets mostly have low elasticity of demand, at least in the short-run. Dealing with low demand elasticity leads to the implementation of large price spikes in spot pricing markets. He concludes that consumer response is roughly similar for short hourly peaks and longer periods of high price. (Ifland et al., 2012) reveal a steep slope of the demand curve from a study of the German electricity market. However, this field test proves that dynamic tariffs can increase demand elasticity and demand curves are more elastic during winter and less elastic during summer. (Kirschen, 2003) also observes that implementation of dynamic pricing definitely increases the elasticity of demand. He further notes that demand curves are steep, and shift, depending on the time of day or day of week. (Shaikh & Dharme, 2009) explain the seasonal variation of load curve with TOU tariffs in the Indian context.

(Kirschen et al., 2000) study the short term price response in the electricity market of England and Wales. In this case half-hourly prices are announced 13 hours in advance. The authors study cross-elasticity of demand along with self-elasticity. Cross elasticity is measured as the rate of change of demand for one time period with respect to change in the price of another time period. They form a 48 by 48 matrix of elasticity coefficients. They further establish that the consumer reaction to a price increase in the short-run is rare unless the price increase is significantly high. This low demand response can be because of consumption scheduling that involves some relatively cumbersome technology. The authors observe that consumers respond more to short-term price hikes than to short-term price drops. They develop a non-linear elasticity function from this study. However, (Braithwait, 2010) explains that there can be no particular formula for determining the amount of demand response, which varies across customer types, events, and types of price structures.

Willingness-To-Pay for Electricity

Designing any dynamic pricing scheme requires knowledge about the consumer's willingness-to-pay (WTP) for electricity and associated infrastructure. (Devicienti et al., 2005) study a TERI report that uses the contingent valuation method to determine the WTP for additional service features like reliability of supply. However, a portion of the respondents do not believe in the possibility of the improved scenario projected by the hypothetical market used in this process.

Consumers find it difficult to comprehend electricity consumption in terms of KWh. Thus the study phrases consumption in terms of 'appliance capacity' or 'hours of use' of each appliance. Stated choice experiments can be helpful in this case. (Twerefou, 2014) uses the contingent valuation method in Ghana and discovers that consumers' WTP is 1.5 times more than the market price of electricity. The author identifies significant factors that influence households' WTP through an econometric analysis of the data from this study. (Ozbafli and Jenkins, 2013) study 350 households in North Cyprus using the choice experiment method. They indicate that the electricity industry can experience an annual economic benefit of 16.3 million USD by adding 120 MW capacity, since consumers are ready to pay more for uninterrupted power supply.

(Gerpott and Paukert, 2013) estimate the WTP for smart meters using responses from 453 German households through online questionnaires. The authors use variance-based 'Partial Least Squares' Structural Equation Modeling and find that 'trust for data protection' and 'intention to change usage behavior' are the most influential factors for WTP. (An et al., 2002) calculate Chinese consumers' WTP for shifting from firewood to electricity. They use stated preference data from personal interviews to estimate the parameters of a binary logit model from a random utility model. The authors calculate the probabilities of adopting electricity at different prices. (Oseni, n.d.) explains that the ownership of a backup generator significantly increases the WTP for reliable grid supply in Nigeria. The author uses event study methods and discovers that the higher cost of backup generation with respect to the stated WTP amount causes this behavior.

Dynamic Price Enabling Technology

Dynamic pricing enabling technologies help in dealing with price and quantity signals. These technologies provide effective communication of the signals to consumers and sometimes also provide a suitable automated response from them. Technology helps in speeding up operations and enables efficient implementation of dynamic prices. (Ifland et al., 2012) conduct a field test in a German village that represents 50% of German living conditions. Consumers respond to flexible prices even without the aid of home automation but automation technology is required to increase night-hour consumptions. (Faruqui and Sergici, 2009) examine evidences from 15 dynamic pricing experiments and reveal that the magnitude of response of retail electricity customers to pricing signals depends on factors like 'extent of price change', 'presence of central air conditioning ', and 'availability of enabling technologies'. (Thimmapuram and Kim, 2013) note that consumers overcome technical and market barriers by using Advanced Metering Infrastructure (AMI) and smart grid technologies that improve price elasticity. (Kaluvala and Forman, 2013) state that smart grid technologies can transfer load from peak to off-peak and reduce overall consumption without reducing the level of comfort. (Quillinan, 2011) elaborates that information communication technology (ICT) in a smart grid system increases the electric grid's efficiency. Applications like 'appliance control', 'notification', 'information feedback', and 'energy management' make enabling technologies essential in demand response programs.

A typical electricity supply curve is nonlinear concave with positive slopes. The benefit of demand response measures can be best observed at the steeper parts of the supply curve. (Faruqui & Palmer, 2012) analyze the data of 74 dynamic pricing experiments and find that the amount of reduction in peak demand increases with the increase of the peak to off-peak price ratio, but at a decreasing rate. They derive a logarithmic model and check the variation of demand response with several factors like the effects of time period, the length of the peak period, the climate, the history of pricing innovation in each market, the pattern of marketing dynamic pricing designs and the use of enabling technologies. They find that variation in the price ratio and the effect of enabling technologies are responsible for almost half of the variation in demand response. (Wang et al., 2011) study several smart grid enabled pricing programs and find that technology and greater price differentials enable better demand response. (Roozbehani et al., 2012) mention that demand response technologies and distributed generation increase the price elasticity of electricity along with the volatility of the system.

Segmentation of Electricity Markets

Segmentation of the electricity market helps in differentiating customers based on various attributes. Attributes of market segments are helpful in setting the range of prices or the time span for maintaining a certain price in a dynamic pricing environment. This section describes works on the basis of electricity market segmentation and focuses on the use of consumption level for segmentation. We also discuss low income groups as an important segment.

Various Bases of Segmentation

Electricity utilities generally segment their markets based on geographic boundaries. (Moss and Cubed, 2008) argue that segmentation schemes for residential customers should typically focus on attitudes and motivations. (Yang et al., 2013) refer to four consumer segments based on socio-demographic variables and attitude towards adoption of green electricity in Denmark. A majority of consumers in all segments are ready to pay a higher price for green electricity. The authors observe that electricity market segmentation became ineffective because of three reasons - lack of comprehensive data, emphasis on technological solutions alone for demand side management, and a tendency to stay within the traditional broad industry segments of industrial, commercial, and residential customers. (Simkin et al., 2011) mention that a 'bottom-up' analysis of customer attitudes, usage patterns, buying behavior and characteristics can be useful to develop segments. They develop a directional policy matrix from variables that represent market attractiveness and business capability, and prioritize segments. Other factors like consumer service, green credentials, innovative tariffs, and guarantee of no price inflation for a certain period also characterize energy market segments. (Ifland et al., 2012) develop a lifestyle typology and create three market segments based on consumption behavior, attitude towards energy consumption and enabling technologies, values, and leisure time activities of consumers.

Segmentation Based On Consumption Data

Segments can be based on consumption data. (Panapakidis et al., 2013) describe segmentation based on load patterns - high level and low level. The high level segment includes geographical characteristics, voltage level, and type of activity. The low level segment is based on demographic characteristics, regulatory status, price management, universal service, fuel labeling supply and metering resolution. Clustering algorithms are required for further detailed categorization of segments. (Varga & Czinege, 2007) use discriminant analysis to characterize and classify consumers based on their load profiles. (Hyland et al., 2013) use smart meter data from Ireland and register the difference in gross margin earned by electricity suppliers from different types of consumers. This data is helpful in identifying different possible market segments and the characteristics of the most profitable segmentation.

Low Income Group as a Market Segment

A low income group can be a market segment where the welfare viewpoint gains priority. These groups can be the worst affected in case of improper dynamic pricing implementation. (Wood and Faruqui, 2010) observe the effect of different pricing schemes on low income consumers and find that Critical Peak Pricing (CPP) is most effective in reducing bill amounts. They propose that the percentage of consumers benefiting from the schemes depends on the rate design itself. (Faruqui et al., 2012) study practical experiments of CPP and note that low income groups reduced their electricity bills more than higher income groups. (Wolak, 2010) also finds that low income consumers are more sensitive to price signals than high income ones. However, (Wang et al., 2011) state that low income customers have low price responsiveness. This is because they have fewer opportunities to reduce consumption due to unavailability of specific home appliances in which the energy consumption can be controlled. Governments need to take up the primary role in creating the conditions for segmentation both in regulated and deregulated markets. (Sharam, 2005) notes that unethical welfare motives or improper administrative and regulatory control can bring out the ills of segmentation in electricity markets. He identifies these ill-effects as redlining, that is, discrimination of consumers in the market, and residual markets, that is, suppliers misusing too much market power, leading to exclusion and exploitation of some customers on financial or other bases.

Consumption Scheduling under Varying Prices

Proper scheduling of electricity consumption in a dynamic pricing environment can flatten the load curve to a large extent. The scheduling problem is addressed in different ways as described below. (Agnetis et al., 2013) identify various types of appliances with varying load types like shiftable, thermal, interruptible, and non-manageable, and then schedule their operations. The authors use a Mixed Integer Linear Programming (MILP) model and a heuristic algorithm to solve the NP-hard problem. The objective functions are cost minimization and comfort maximization through scheduling preferences and climatic control. (Hubert & Grijalva, 2012) incorporate electricity storage provisions in the scheduling problem by classifying loads as energy storage system, non-interruptible loads, and thermodynamic loads. They use MILP for robust optimized consumption scheduling to minimize the impact of stochastic inputs on the objective function. The objective function integrates electric, thermodynamic, economic, comfort, and environmental parameters.

(Liu et al., 2012) emphasize the maximum use of renewable resources in a load scheduling problem. Their model depends on weather forecasts. They classify appliances based on type of energy consumption and assign dynamic priority in the scheduling process. (Dupont et al., 2012) state that the renewable energy tariff scheme can be used to increase renewable energy consumption during periods of high renewable energy generation. They use integer linear programming to optimize this scheduling problem taking into account customer preferences. This paper also emphasizes the use of automation in households for consumption scheduling over the year. (Hu et al., 2010) incorporate both active and reactive power demand and generation in the scheduling problem. The authors use a non-linear load optimization method in a real-time pricing environment. The scheduling of consumption is studied for three customer groups – industrial, commercial, and residential, and for three load periods – peak load, flat load, and off-peak load periods.

Scheduling in individual homes must be linked to the aggregate demand situation. Thus it is necessary to model the individual household scheduling incorporating the aggregate demand. (Kishore & Snyder, 2010) point out that shifting the load from peak hours to off-peak hours in each household by means of a same price signal can shift the aggregate peak to the previously off-peak zone. Thus the authors optimize electricity consumption within a home and across multiple homes. The in-home scheduling model attaches the probabilities of start and stop of operation of any appliance in the next time period. It also considers a cost for delay of start of operation. The model minimizes the total cost of electricity in a deterministic dynamic pricing environment. In the neighborhood-level scheduling model, the authors assume a well communicated neighborhood where each household has a minimum guaranteed load at each time slot. The neighborhood however has a maximum limit of energy at each time slot. The idea is to distribute this available power to all households thereby minimizing total costs. A second delay cost is associated in the model to address the delay of starting an appliance after the specified maximum delay time.

(Li et al., 2011) align individual optimality with social optimality by means of a distributed algorithm. Each customer has a utility function and provisions for energy storage. This allows them to forecast their total individual demand for a future time after maximizing their individual benefit. The utility company collects these forecasts from all households and generates a price based on its cost function. This price is then published and the individual households reschedule their consumption. After several iterations, the consumption schedule of each household and the price offered by the utility gets fixed. (Cui et al., 2012) describe how scheduling of household loads helps electricity suppliers to maximize their profits and the global controller to maximize social welfare. The authors use greedy algorithm for the first model with pre-announced dynamic tariffs. They also devise a model for the utilities based on consumers' schedules.

Potential Areas for Future Research

There are interesting future research challenges that evolve from this study. These are noted in this section.

a) Understanding the customers' willingness to adopt dynamic tariffs can be very helpful for further progress in this field. Dynamic prices have never been experienced in many electricity markets. Such markets can provide interesting research opportunities for discovering consumers' willingness-to-pay for electricity within a dynamic pricing environment. Results from such studies can help promote the idea to more number of customers and suppliers.

b) The impact of dynamic pricing increases with the increase of elasticity and hence the most elastic portion of the demand curve in any electricity market is worth identifying. Determination of the demand price relationship for consumers is challenging, especially when such efforts are to be made at the individual household level. Factors influencing electricity demand change from consumer to consumer. Identification of such factors in different markets is necessary for implementing dynamic prices. Experiments to identify electricity market segments and suitable pricing schemes for each segment are necessary to get more benefits from dynamic pricing.

c) Academic research on electricity market segmentation in India and many other economies is rare. Such efforts can open up avenues for better revenue management in electricity markets. Discovery of market segments must be followed by development of suitable pricing schemes. Possibilities need to be analyzed to shift from segment based pricing to individual customized pricing, thereby enabling the markets to better absorb consumer surplus.

d) Carefully designed retail pricing schemes can appropriately link the wholesale and retail markets. Pricing schemes should be researched to form the standard for pricing designs so that neither are the customers exploited nor do suppliers experience loss.

e) Smart grid technology can enable automated scheduling of household loads. Automation is possible with the development of scheduling algorithms. Researchers can keep on developing more realistic scheduling algorithms with different objectives for different customers. On the technological side, the type of enabling technology required in any particular market and the technological and financial feasibility study for the same can be studied.

f) The environmental and social impacts of shifting from a flat rate tariff to a dynamic tariff scheme are worth studying in order to popularize the idea of dynamic pricing. The advantages and disadvantages of introducing dynamic pricing to different classes of society must be studied before practical implementation.

g) Most of the studies referred to in this paper are based on deregulated markets, although regulated markets can also benefit from dynamic prices. This is because dynamic pricing can balance the demand-supply gaps. Future work can be done on the application of dynamic pricing specifically to regulated markets. Factors affecting variations in load profiles need to be identified so as to form segments which are welfare oriented as well as profitable.

Conclusion

The discussions in this paper reveal the importance of dynamic pricing of electricity and its effects on demand response. Experiments show that the elasticity of demand is generally low; however, dynamic pricing has the potential to modify load profiles. We describe several established pricing schemes, many of which have been tested in pilot projects. We also mention works on several forecasting methods and their effectiveness. We study works describing methods of measuring willingness-to-pay for better quality of electricity. The development and testing of enabling technologies is an ongoing process and there are several studies that reveal the usefulness of such technologies. Some studies on electricity market segmentation are studied and several bases of segmentation are discovered. Consumption scheduling in households is studied and several mathematical models for the same are mentioned. We highlight some future research opportunities in this field at the end of our study. This paper can help in drawing the attention of policy makers and electricity market players to the benefits of dynamic and customized pricing, demand mapping, segmentation for electricity markets and automation technologies.

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