Distributed Demand Response and User Adaptation in Smart Grids

Zhong Fan, Senior Member, IEEE

Abstract—This paper proposes a distributed framework for demand response and user adaptation in smart grid networks. In particular, we borrow the concept of congestion pricing in Internet traffic control and show that pricing information is very useful to regulate user demand and hence balance network load. User preference is modeled as a willingness to pay parameter which can be seen as an indicator of differential quality of service. Both analysis and simulation results are presented to demonstrate the dynamics and convergence behavior of the algorithm.

Index Terms—Smart grid, demand response, pricing, utility.

I. INTRODUCTION

A smart grid is an intelligent electricity network that integrates the actions of all users connected to it and makes use of advanced information, control, and communication technologies to save energy, reduce cost and increase reliability and transparency. Recently, many countries have started massive efforts on research and developing smart grids. For example, the smart grid is a vital component of President Obama's comprehensive energy plan: the American Recovery and Investment Act includes 11 billion USD in investments to “jump start the transformation to a bigger, better, smarter grid”.

In electricity grids, demand response (DR) is a mechanism for achieving energy efficiency through managing customer consumption of electricity in response to supply conditions, e.g., having end users reduce their demand at critical times or in response to market prices. In the future smart grid, the two way communications between energy provider and end users enabled by advanced communication infrastructure (e.g., wireless sensor networks and power line communications) and protocols will greatly enhance demand response capabilities of the whole system. In contrast to the current simple time-of-use (TOU) pricing (e.g. peak time vs. off-peak time), it can be envisaged that a more dynamic, real-time adaptation to market prices would not only enable consumers to save more energy and money, as well as manage their usage preferences more flexibly, but also facilitate the grid move closer towards its optimal operating point. For a recent overview of challenges and issues of enabling communication technologies in this area, please refer to [1].

The authors of [2] argue that demand response and distributed energy storage can be seen as distributed energy resources and are main drivers of smart grid. While DR can help the industry to achieve market efficiency and operational reliability, there are also challenges ahead in implementing DR under smart grid and market paradigms.

There are a few papers recently on smart grid DR using load scheduling. In [3], user preferences are taken into account with the concept of discomfort level and an optimization problem is formulated to balance the load and minimize the user inconvenience caused by demand scheduling. Several ideas from the distributed computing area such as makespan have been introduced to energy consumption optimization. Similarly, in [4], an energy consumption scheduling problem is established to minimize the overall energy cost. Techniques similar to those used in wireless network resource allocation have been applied here to solve the underlying optimization problem. In both works, the user demands are known beforehand and the optimization problem is solved in numerical iterations.

In this paper, we consider a fully distributed system where the only information available to the end users is the current price which is dependent on the overall system load. Based on this information, the users try to adapt their demands so as to maximize their own utility. There is no central control entity. Inspired by the well-established work on congestion pricing in IP networks, we propose a simple adaptation strategy based on price feedbacks and show that it is very effective in achieving demand response.

The rest of the paper is organized as follows. Section 2 introduces our DR model and the adaptation algorithm. We present some simulation results in Section 3. Conclusions and future work are presented in Section 4.

II. DEMAND RESPONSE MODEL

A. Congestion pricing background

In this paper we propose to apply the principle of congestion pricing in IP networks to demand response in the electricity grid. In their seminal paper [5], Kelly et al. have proposed the proportionally fair pricing (PFP) scheme in which each user declares a price per unit time that he is willing to pay for his flow. In that sense the network capacity is shared among the flows of all users in proportion to the prices paid by the users. It has been shown in [5] that in a weighted proportionally fair system where the weights are the prices the users pay per unit time, when each user chooses the price that maximizes the utility she gets from the network, the system converges to a state where the total utility of the network is maximized. In other words, in an ideal environment, the PFP proposal is able to decentralize the global optimal allocation of congestible resources. Another important result of [5] is that rate control (such as TCP) based on additive increase and
multiplicative decrease achieves proportional fairness. It has been proved in [5] that the decentralized congestion control mechanism is stable even under arbitrary network topologies and heterogeneous round trip times (feedback delays).

In Kelly’s approach, the philosophy is that users who are willing to pay more should get more. As the network makes no explicit promises to the user, there is no need for over provisioning in the core of the network. One implementation of PFP is to give control to end systems (users). In this scheme, the TCP algorithm is modified to incorporate congestion prices by means of protocols like explicit congestion notification (ECN) [7]. Upon receiving feedback signals, f(t), which are related to shadow prices (in terms of packet marks), the users are free to react as they choose, but will incur charges when resources are congested. An end system can adjust its rate using a willingness to pay (WTP) parameter w:

\[ x(t + 1) = x(t) + \alpha(w - f(t)), \]

where \( \alpha \) affects the rate of convergence of the algorithm.

In [8], explicit prices instead of marks are fed back to the end users as incentives and users adapt their rates accordingly. It has been shown that the system converges to an optimal allocation of bandwidth: the users’ price predictions converge to the actual price and their bandwidth allocations converge to levels which equalize their marginal utility of bandwidth to the price of bandwidth.

B. The DR model and user adaptation

We consider a discrete time slot system where \( N \) users share some energy resources. In each time slot \( n \), user \( i \) has a demand of \( x_i(n) \) (e.g. hourly energy consumption if the time granularity is one hour). The unit price of energy in a time slot is a function of the aggregate demand:

\[ p(n) = f(\sum_{i=1}^{N} x_i(n)). \]

The price function (spot market price) can be of the following form [3,9]:

\[ f(x) = a(x)^k, \]

where \( a \) and \( k \) are constants, and \( C \) is the capacity of the market.

Each user \( i \) is associated with a utility function \( u_i(x_i(n)) \) in time slot \( n \), which is a concave, non-decreasing function of its demand. A typical logarithmic utility function is given by [3]:

\[ u_i(x) = w_i \log x, \]

where \( w_i \) is the willingness to pay parameter. Hence user \( i \) chooses its demand \( x_i(n) \) in time slot \( n \) to seek to maximize

\[ u_i(x_i(n)) - x_i(n)p(n). \]

Here the adaptation of \( x \) can be seen as an action of load scheduling: for example, re-scheduling a dryer operation from time slot \( n = 1 \) to slot \( n = 3 \) leads to \( x(1) \) reduced by 2.50 kW per hour and \( x(3) \) increased by 2.50 kW per hour. Secondly, how to characterize user preference is an open issue. For instance, a user may prefer his washing done at 6pm which is a typical peak time. To some extent, this preference can be reflected in the WTP parameter \( w \) in [4]: when a user is willing to pay more, he/she can have a higher demand. However, the delay (or waiting time) incurred due to rescheduling is not considered in this model. Thirdly, as pointed out in [3], logarithmic utility functions lead to proportional fairness. There are other types of utility functions available corresponding to different fairness criteria, e.g. \( u_i(x) = w_i x^{\beta} - 1, \beta < 1 \) as proposed in [8]. How to choose a most suitable utility function in DR applications is an open issue, e.g. how to factor in the waiting time and user discomfort level [3].

User \( i \) adapts its demand according to the following equation:

\[ x_i(n + 1) = x_i(n) + \alpha_i(w_i - x_i(n)p(n)), \]

where \( \alpha_i \) is a parameter that controls the rate of convergence of the algorithm. It is clear that the user adjusts her demand according to the price information \( p(n) \) and her own willingness to pay preference \( w_i \).

To show that the above adaptation converges to the user optimum, let us assume that the equilibrium price is \( q \). Then by solving \( u_i'(x_i(n)) = q \), we have the optimal demand \( x_i^* \) as

\[ x_i^* = \frac{w_i}{q}. \]

Given (6), the error of demand estimate, \( e_i(n + 1) \), is given by

\[ e_i(n + 1) = x_i(n + 1) - x_i^* = x_i(n) + \alpha_i(w_i - x_i(n)q) - \frac{w_i}{q}. \]

Then it follows that

\[ e_i(n + 1) = (1 - \alpha_i q)(x_i(n) - \frac{w_i}{q}) = (1 - \alpha_i q)e_i(n). \]

Therefore \( e_i(n) \) is a geometric series, and when \( 1 - \alpha_i q < 1, \lim_{n \to \infty} e_i(n) = 0 \). This has established that with properly chosen \( \alpha_i \), the adaptation will converge to the optimum. Following [5], it is also straightforward to establish the global stability of the algorithm in a differential equation form [10] using an appropriate Lyapunov function.

\[ \frac{d}{dt} x_i(t) = \alpha_i(w_i - x_i(t)p(t)). \]

C. Implementation considerations

In a residential energy management scenario, we envisage that each user in our model is represented by an entity or software agent called home energy manager (HEM) at a consumer’s home. Appliances in the home are equipped with smart meters, and they communicate with HEM via low power wireless such as ZigBee. HEM is further connected to the grid (supplier) via either wired or wireless links. Based on the price information it receives, HEM calculates demand in the next
time slot and distributes it to different appliances. The overall architecture is shown in Figure 1.

We note that some appliances like refrigerator and heating have hard consumption scheduling requirements, while others such as washing machine have soft requirements [4]. When HEM has to shift the demand to another time slot, it may apply only to soft appliances. For example, HEM obtains $x(n+1)$ based on (6) with WTP parameter $w$. If it can satisfy the demand from the hard appliances (denoted by $h$), it can re-schedule the demand from some of the soft appliances (denoted by $s$) so that $x(n+1) = h(n+1) + s(n+1)$. On the other hand, if it cannot meet the demand from the hard appliances, HEM may have to increase $w$ and recalculate $x(n+1)$.

III. SIMULATION RESULTS

In this section, we use simulations to study the behavior and dynamics of the proposed algorithm. There are $N = 10$ users and without loss of generality we assume that the capacity $C$ is 1. For the price function (5), $a = 1, k = 4$.

A. Basic simulation

Here all the users initiate their demands at 0.02, and their willingness to pay parameters range from 0.11 (user 1) to 0.20 (user 10). All the users have the same adaptation parameter $\alpha$ of 0.1. Figure 2 shows the demand changes with time for 10 users. After a short transient period, each user demand converges to a stable value (determined by different $w$ values). It is also evident that $w$ is a crucial factor in determining how aggressive a user should be responding to the price signals. Figure 3 clearly shows that the price converges to the optimal value. When the system reaches its equilibrium (assuming $\alpha = 1, C = 1$), we have

$$x_i = \frac{w_i}{(\sum_{i=1}^{N} x_i(n))^k},$$  \hspace{1cm} (11)

Summing over $i$ on both sides of (11), it is easy to verify that the price at equilibrium is

$$p = \left( \sum_{i=1}^{N} w_i(n) \right)^{\frac{1}{k}}.$$  \hspace{1cm} (12)

In this case, $p = 1.42$ as shown in Figure 3.

B. The effect of $\alpha$

In this simulation experiment we study the effect of $\alpha$ on system performance. Figure 4 and Figure 5 depict the demand and price evolution versus time respectively for $\alpha = 0.17$. Compared with Figure 2 and Figure 3, it can be seen that with a larger $\alpha$, it takes much longer to converge. Therefore $\alpha$ is an important system parameter that controls the convergence speed of the process.

C. Heterogeneous initial demands

In this simulation experiment we study the effect of heterogeneity of initial demands, i.e., ten users start with demands ranging from 0.01 to 0.10 respectively. The results are shown in Figure 6 and Figure 7. We observe that different initial conditions do not affect the system stability and convergence to equilibrium.
D. Heterogeneous initial demands and adaptation rates

In addition to heterogeneous initial demands as in last simulation, here users also have different adaptation rates $\alpha_i$: ranging from 0.11 to 0.20. The results are shown in Figure 8 and Figure 9, where we can see that the system still converges to the equilibrium.

E. Time-varying $w$

To model the situation where users change their WTP $w$ on-the-fly to accommodate their energy needs, we change $w_i$’s at time slot 100 by adding a random number within the region of $(−0.05, 0.05)$. Figure 10 and Figure 11 clearly show that after time 100, the system tracks the change nicely to a new equilibrium.

F. The effect of $C$

The energy provider can influence the price by adjusting the capacity $C$. As shown in Figure 12 and Figure 13 when $C$ is doubled, the price will drop by $1 - C^{-1}$, which is 43%, and each user’s demand will increase accordingly.
G. Inaccurate price signals

The feedback price signals are transmitted via a communication network (e.g., GPRS) to the HEM, during which packet loss and delay could occur. In this case, users may have to adapt their demands based on outdated or inaccurate price information. We model this situation as a small perturbation to the price signal and study its effect on the system behavior. As shown in Figure 14 and Figure 15, the price and demands still converge to the means of the equilibrium values, but with small fluctuations. A more detailed perturbation analysis is part of our future work.

IV. CONCLUSION AND FUTURE WORK

This paper proposes a distributed framework for demand response and user adaptation in smart grid networks. More specifically, we have applied the concept of congestion pricing in Internet traffic control to the DR problem and shown that it is possible that the burden of load leveling can be shifted from the grid (or supplier) to end users via pricing. Individual users adapt to the price signals to maximize their own benefits. User preference is modeled as a willingness to pay parameter which can be seen as an indicator of differential quality of service.
The convergence of the algorithm has been demonstrated by both analysis and simulation results.

This paper is just a first step towards our vision of fully distributed demand response. There are a number of directions for future research. Firstly, the proposed model fits nicely into the game theory framework. In fact, there is already a rich literature in the networking community on game theoretical analysis of congestion pricing, e.g. [10]. In Kelly’s framework, the user and social optima coincide if the prices are right, and the social optimum is a Nash bargaining solution with the logarithmic utility function. More recently, researchers have applied intelligent agents and game theory to micro-storage management for the smart grid [11], in which Nash equilibrium is reached when the agents are able to optimize the energy usage and storage profile of the dwelling and learn the best storage profile given market prices at any particular time. Similarly, based on our model, it would be interesting to study the system dynamics and user interaction in a large scale energy demand game context. There are two types of user strategies: price taking users and price anticipating users [12]. A price taking user assumes that he has no effect on the price of the energy, whereas a price anticipating user realizes that his own choice of \( w_i \) affects the price. An interesting observation is that price anticipating users tend to pay less.

One important element of intelligence in the smart grid is the learning capability of various components. In demand response, if users can learn from past observations (e.g. prices and load profiles), then they can predict the future load and price and adjust their strategies accordingly (e.g. adjusting \( \alpha_i \) and \( w_i \)). In this context, Bayesian networks and reinforcement learning are some of the powerful tools we can leverage to enable learning in this highly dynamic environment.

As mentioned earlier, demand scheduling can be formulated as a typical resource allocation problem, for which a wide range of techniques (many of them have been applied in the networking field) are available. We are currently investigating the feasibility of applying some convex optimization techniques such as water-filling to demand side management, where a certain cost function is to be minimized subject to a number of system constraints.

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Zhong Fan is a Research Fellow with Toshiba Research Europe in Bristol, UK. He received his BSc and MSc degrees in Electronic Engineering from Tsinghua University, China and his PhD degree in Telecommunication Networks from Durham University, UK. His research interests are protocol design and performance analysis of wireless networks, IP networks, and smart grid communications.