An Agent Based Model for Optimal Generation Mix based on Price Elasticity of Aggregated Consumer Demand

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Abstract. This work has its interests in the relation between the generation mix within a power system and the elasticity of demand based on the prices emerging from the short term electricity market. The paper starts by describing a new agent-based modelling framework that involves electricity producers, consumers and suppliers as agents participating in a market environment. The framework allows for investigating the effect of demand elasticities on bidding of generators in the short term market and its influence on their revenue in the long term. We focus on the increasingly important issue of renewable technology such as wind generation and the volatility it brings into the electricity market. Specifically we investigate three scenarios with varying mix of generating technologies such as coal, gas and wind turbines and measure the aggregate demand response to signals such as the System Buy Prices (SBP) emerging out of the balancing market.

Key words

Optimal Generation Mix, Agent Based Model, Short Term Electricity Prices, Wind Power, Elasticity.

1. Introduction

The evolution of the modern electricity grid into a smart and responsive one is dependent on evolution of its features such as demand response, supplier participation, generator operation and bidding strategies, market structures and the like. Participation of demand sites such as large commercial consumers, hospitals, schools, community of households is becoming imperative for the success of demand response programs in new market structures. In such a scenario, we need to assess the effect of large scale participation of these loads on the generator behaviour in the market. The generators are themselves active in the short term electricity markets such as power exchanges, balancing markets, ancillary services and the like. While the response of loads is dependent in some way on the prices in such markets and in turn on the strategies and technologies employed by the generators, conversely the strategies and more importantly the technology mix is dependant to an extent on the response of these demand sites. Hence the need to assess the relation between the generation mix and the response of demand via price signals. Demand elasticity then becomes a predominant factor in modelling the response of demand to price signals from the market. Demand elasticity or price elasticity in this context means the percentage change in the demand due to a percentage change in the price as seen by this demand. The objectives of this work therefore are to investigate the effective utilization of different generation technologies through aggregated demand response of varying elasticities, and also to bring to a wider audience an Agent Based Modelling (ABM) framework for probing such issues. Given the complexity surrounding the operation and functioning of a smart grid, ABM methodology enables investigation of issues such as the above in a dynamic framework. The main contributions of this work are to our understanding of the effect of price elasticity of demand on the optimal mix of generation technologies in a competitive short term electricity market. To begin with, we introduce an agent based modelling framework incorporating generation and aggregated demand models along with a model of the UK short term electricity market. We then investigate the effect of demand elasticity on the sustainability of an optimal mix of generation technologies in a competitive electricity market.

The effect of demand response programs as observed through feedback of price signals to the consumers has been widely observed in various pilot projects [1]. Different types of pricing schemes such as Real Time Pricing (RTP), Time Of Use pricing (TOU), Critical Peak Pricing (CPP) and the like have been experimented in these pilot projects and have shown to yield good results in varying circumstances. For instance, Sioshansi and Short [2] demonstrated the effectiveness of RTP on demands of varying elasticities under different scenarios of generation mix, predominantly focusing on wind power. They showed that constraints on operation of conventional power generators could result in wind power being under-utilized and that RTP, even with low elasticities, could increase both the percentage of load served by wind power and the amount of power utilized from wind generation in real time. However, their model does not take into account all aspects of electricity market such as market power and learning schemes to bid and offer power in the market.

The processes within a market structure provide the participating agents, especially the producers of electricity, with opportunities to game the system in order to secure a large share of the market at the expense of the overall efficiency of the market. Such market power has typically been related to lower elasticity of consumer demands [3]. Therefore it is imperative to engage consumers for achieving increased market efficiency at least in the short-term. This could be done by means of designing a participatory tariff or price signal that engages the consumers especially those who are capable of influencing the behaviour of trading entities in the balancing or short term electricity markets. The potential candidates for such price signals could be the System Sell and System Buy Prices that are a result of the balancing market.

2. Agent Based Modelling Framework

The framework for probing the issues surrounding demand response programs, and in turn its effect on the generator side of the grid would largely comprise of a market model and a model for demand participation. Our modelling approach is to combine the features of an electricity market with the models of generators and demand that are actively participating in this market. The framework focuses on the operation of the short term electricity market prevalent in the UK. Price signals arising out of the short term market provide a useful indicator of the level of participation of generators and demand sites in balancing the power requirement of the system. Additionally, it could act as a basis for demand to respond to variations in the market.

A. Market Model

The main stay of the framework is an Agent-based Short Term Electricity Market (A-STEM) model that was developed as part of an EPSRC funded project CASCADE (Complex Adaptive Systems Cognitive Agent and Distributed Energy) [4]. In this model we represent a day-ahead power exchange employing a simple double discriminatory auction mechanism and a UK based balancing mechanism market that operates in real-time. The trading parties engage in the markets through bids and offers that are updated in real-time. These bidding strategies are largely based on the imbalance between supply and demand and also on the technical characteristics and economic models of the generating units.

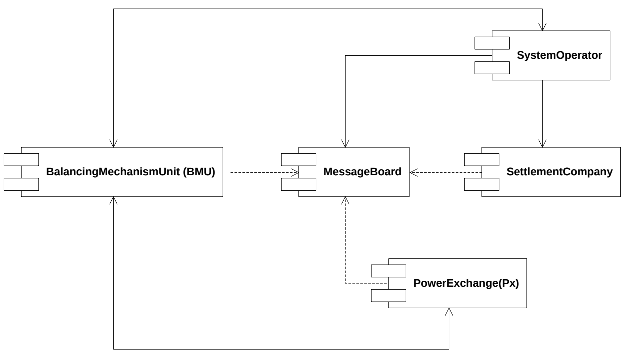

Fig. 1. Schematic of the short term electricity market used in the framework. The arrows indicate the flow of information.

While the power exchange operates without much supervision, the balancing mechanism is monitored and delivered by the system operator, which in the UK is the National Grid. The Balancing Mechanism Units (BMUs) are nothing but the generating units and the load entities that are parties in the trading. Figure 1 shows the different entities of the market model and interactions between them.

These entities are modelled as agents behaving in a predefined manner but adaptable to the environment in which they are interacting. This approach allows the BMUs to alter their bidding strategies given the revenue that they earn over time. The system operator accepts and rejects bids based on reliability and cost-effectiveness. The system operator also has to make sure that the physical constraints of the grid are satisfied while accepting these bids. The bids and offers might be in the form of increase or decrease in either generation or demand. The settlement company then calculate the System Sell and System Buy Prices (SSP/SBP) which are forwarded on to those BMUs who aggregate demand sites. The SBP and SSP are as shown in Figure 2. The prices are plotted over five days, each day being made up of 48 settlement periods.

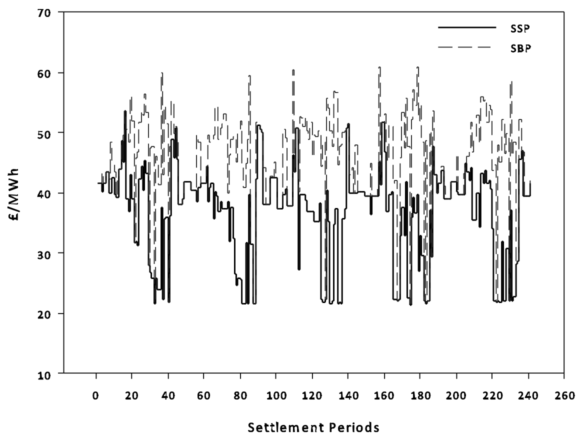

Fig. 2. A plot of the System Sell and System Buy Prices of the Balancing Market [4]. Each Settlement Period is of ½ hour duration.

B. Generator and Aggregated Demand Models

The framework consists of generators of different technologies such as Coal, CCGT (Combined Cycle Gas Turbine), offshore and onshore Wind turbines. The capacities for each of the generating plant are fixed based on the prevalent UK standard values taken from the National Grid's database. For example the capacity of a coal plant is fixed at 1200MW with an operating load factor of 40%. Similarly, CCGT plants have a capacity of 800MW with a load factor of 60%, whereas a typical wind farm is assumed to have a capacity of 150MW with a load factor of about 25%. The details of the generator characteristics are given in [4].

The aim of the generating units is to minimize their operating costs, as given in equation (1), while increasing the profits through improvised bids and offers in the market.

$$Min_{Cost} = \sum_{i} FC_i * Cap_i + \sum_{i,j} VC_i * G_{ij} \quad (1)$$

(where, *FC* and *VC* are the fixed and variable costs of the

i^{th} generators, *Cap* is the Capacity of the generators and G is the actual generation of the i^{th} unit in j^{th} hour.) As a result, the flexibility of the demand profile is crucial for generating units to develop strategies for participation in the market [3]. Such models have predominantly been based on optimization principles [5], [6]. However, such models suffer from not taking into account the adaptive dynamic behaviours of generating and demand units in a competitive market. They usually assume similar bidding strategies for all generators. Estimates of the various costs associated with the running of generating plants of specific types are given in Table I.

TABLE I. – Estimates of Generation Costs, Department of Energy and Climate Change, UK 2012.

Costs (£/MWh)	CCGT	Coal	Onshore Wind	Offshore Wind
Capital	9	22	73	97
Fixed O&M	3	5	17	37
Variable O&M	0	1	3	-
Fuel	48	28	-	-
Carbon costs	19	45	-	-
Total	80	102	93	134

The demand is broadly classified into two groups, namely *SMALL_DEM* and *LARGE_DEM* sites of capacities 200MW and 1000MW respectively. An estimation of the demand curve for each of these demand sites is done based on the national grid's generic demand profile. An estimate of the daily total demand curve is as shown in Figure 3. The *SMALL_DEM* for example would be an *AGGREGATOR* of a community of households supplied by the same supplier. In such a case the aggregator is said to have commercially aggregated the loads. We consider three broad categories of aggregated demand profiles – residential, commercial and industrial. The values for elasticity (Table II) are average and are derived by aggregating over individual consumer units. This avoids the complexity of modelling consumers such as households. For testing the framework we consider elasticities of 10% and 30%. However the framework has the capability to run over a range of elasticities as given in Table II below.

TABLE II. – Estimates of Electricity Price Elasticity based on Day-Ahead RTP [7], [8].

	Price Elasticity
Residential	-0.05 to -0.12
Commercial	-0.01 to -0.28
Industrial	-0.01 to -0.38

3. Methodology

The generators and demand sites as described above are allowed to participate in the A-STEM market model. The settlement period is used as the unit time step for all market operations. This period is equal to ½ hour in the present UK system, i.e., the billing, metering and balancing of power is done predominantly at ½ hour time intervals. The generators and demand aggregators bid into the market along with an estimate of their generating and demand profiles. The system operator then settles the market by accepting preferable bids and conveys this information to the trading parties who in turn make changes to their generation or demand accordingly. The sustainability of a particular power plant depends not only on its bids/offers being accepted but also on its operating cost as determined by the technology of generation. We calculate the cost of operating each of the generating plants and the revenue it makes through accepted bids/offers, based on which the bid/offer prices are altered. This in turn affects the System Sell and System Buy Prices.

The demand aggregators would respond to real time price signals from the short term electricity market according to their respective price elasticities [9]. These price signals could either be the System Sell or System Buy Prices of the Balancing Mechanism market (Fig 2) or a combination thereof. The System Buy Price (SBP) is the price paid by the generator BMU if it generates less than what it bid, and paid by the demand BMU if it consumes more than what it offered. This is sufficient enough reason for choosing SBP as the price signal for which the aggregated demand BMU responds. This would encourage the demand BMUs to reduce their actual consumption and in turn reduce the imbalance between supply and demand.

This change in the demand profiles proliferates into the total imbalance between supply and demand as seen by the market, which in turn influences the bidding strategies of the players in the market. The market players such as generating units would then alter their bids based on their previous bidding experience and a goal to minimize their operating costs. The consequence of the above processes would give rise to the right proportion of a mixture of generation technologies in a competitive electricity market based on the price elasticity of aggregated demand sites.

An estimate of the aggregated demand is supplied by each demand BMU to the system operator who in turn evaluates the total imbalance of the system for the next day. Suppose that D_0 is the baseline demand which is an estimate of the next-day demand. This estimate is largely based on the present day demand. Each demand BMU is now allowed to respond to a price signal P which is supplied by the A-STEM model. This price signal is nothing but the SBP. This price signal is compared with the reference price signal P_0, which is an average of the SBPs taken over N number of days. Therefore the reference price for the i^{th} settlement period is

$$P_0[i] = \frac{\sum_{j=1}^{N} SBP_j[i]}{N} \tag{2}$$

The new demand is given by

$$D = D_0 \frac{(1+a)}{(1-a)} \tag{3}$$

where $a = e\frac{(P - P_0)}{(P + P_0)}$ and e is the price elasticity of that particular demand BMU.

The aggregated demand at each i^{th} settlement period of a given day is therefore

$$D[i] = D_0[i]\frac{(1+a_i)}{(1-a_i)} \tag{4}$$

Each of the 5 *LARGE_DEM* and 3 *SMALL_DEM* sites respond to the price signal as given by equation (4). For example, each individual consumer unit is assumed to respond to the price signal and this response is aggregated at the level of a demand BMU such as a *SMALL_DEM* site. The new demand profile is therefore the aggregated responses of the individual units.

4. Results

Using the agent based modelling framework and the methodology as described in sections 2 and 3 respectively, we investigate three scenarios relating to varying proportions of generation technology. The overall capacity of generation and demand remains the same across the three scenarios. In the first instance we consider 4 coal plants, 7 CCGT plants and only 3 wind farms. The training phase for building a reference price signal is 100 days, during which period the demand sites do not respond to the price signal. Once the reference price signal is built, all the 5 *LARGE_DEM* and 3 *SMALL_DEM* sites are allowed to respond to the actual price signal which is the SBP of the previous day. We test the scenario with aggregated elasticity factors of 10% and 30% respectively. The price signals and the total aggregated demand curves are shown in Figure 3. We notice that as the actual price signal varies around the reference price, the demands respond appropriately, i.e., for increase in price from the reference, the demand reduces in volume. This reduction in demand is proportional to the elasticity. We also notice that the reference price is smoother for lesser proportion of wind farms. However the deviation of the actual price from the reference is substantial, thus making a good impact on the responsiveness of the demands.

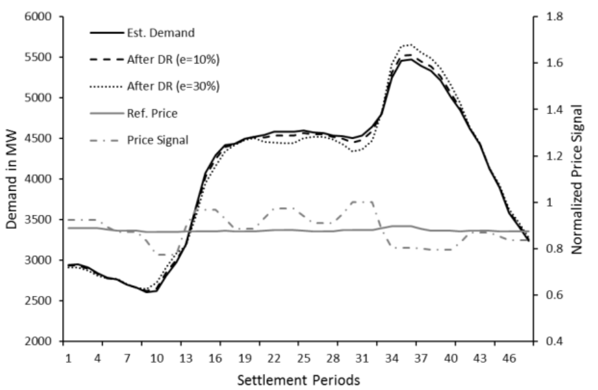

Fig. 3. Case A: Coal plants – 4, CCGT – 7, Wind farms – 3. Aggregate demand response curves for aggregated elasticities of 10% and 30% respectively. The reference price and the actual price signals are normalized between 0 and 1.

In the second case, we increase the proportion of wind power keeping the total capacity constant. The generation mix now has 2 coal plants, 3 CCGT plants and 44 wind farms. We immediately notice a substantial change in the reference price which is the average SBP over 100 days. Additionally, the actual price is closely following the volatile reference price, thereby not allowing for much response from demand aggregators. Only when the elasticity is increased to 30% do we see any noticable change in the total demand.

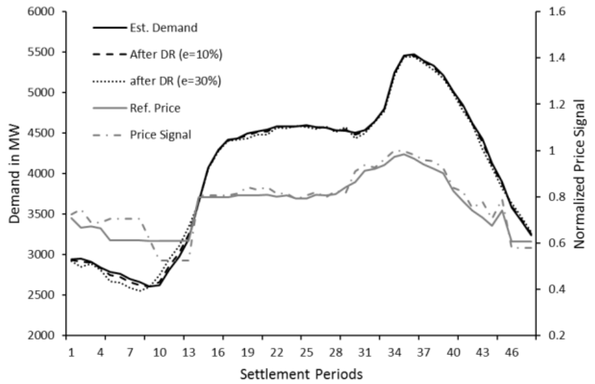

Fig. 4. Case B: Coal plants – 2, CCGT – 3, Wind farms – 44. Aggregate demand response curves for aggregated elasticities of 10% and 30% respectively. The reference price and the actual price signals are normalized between 0 and 1.

Finally, we increase the proportion of wind farms to 64, while number of coal and CCGT plants are reduced to 1 and 2 respectively. With such a high proportion of intermittent source, we once again notice the volatility in the reference price and the respective demand response. These plots show that demand response varies in accordance to the proportion of different technology mix even when the total generating capacity remains the same. Therefore such an agent based framework provides a good basis for testing the evolution of a right proportion of genertion mix for demand response programs to work effectively.

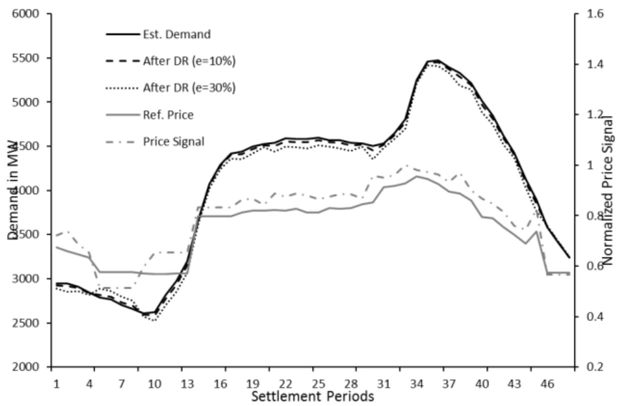

Fig. 5. Case C: Coal plants – 1, CCGT – 2, Wind farms – 64. Aggregate demand response curves for aggregated elasticities of 10% and 30% respectively. The reference price and the actual price signals are normalized between 0 and 1.

5. Conclusions

In the present work we have described an agent-based framework of the UK short term electricity market along with models for generation and aggregated demand sites. These demand sites are allowed to be elastic in response to price signals from the market. Similarly, the generators are allowed to alter their bids and offers in a dynamic market environment. The change in the demand is influenced by its response to system buy price that is a direct consequence of the bids and offers of the generating demand units. The bidding strategies employed by the generators are guided by the operating cost of the generation technology employed. Thus a feedback loop is formed between the demand and the profitability of the generators resulting in some generation technologies prevailing over the others in the longer term. In the present work, we investigate three such scenarios where the mix of generation technology is varied in different proportions resulting in variations in SBPs and consequently variations in the response of aggregated demand sites. From the plots in figures 3 to 5 we notice that a higher percentage of wind powered generation results not only in volatile prices but less than expected response from elastic loads. This is mainly due to the fact that the actual price signal closely follows the reference price signal for higher percentage of wind power. Using the above framework we can therefore assess the effect of varying proportions of generation technology mix on the response of demand aggregators through price signals from the market. This would give us an idea of the right proportion of technology mix for sustaining a required amount of demand response, thereby allowing the generators to put faith in the bidding curves that they submit in the market. In the model we take into account generator characteristics such as generating profiles, market behaviour and cost of generation of individual technologies, while on the demand side, the emphasis is on aggregated demand profiles and price elasticity within a particular range.

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References

[1] A. Faruqui, S. Sergici, and A. Sharif, “The impact of informational feedback on energy consumption- A survey of the experimental evidence” Social Sciences Research Network Working Paper, May 21, 2009.

[2] R. Sioshansi and W. Short, “Evaluating the Impacts of Real-Time Pricing on the Usage of Wind Generation”, IEEE Trans On Power Systems, Vol. 24, No. 2, pp 516-524, May 2009.

[3] E. Bompard, Y. Ma, R. Napoli, and G. Adrate, “The Demand Elasticity Impacts on the Strategic Bidding Behaviour of the Electricity Producers”, IEEE Trans on Power Systems, Vol. 22, No. 1, pp 188-197, Feb 2007.

[4] V. H. Pakka, B. M. Ardestani, and R. M. Rylatt, “Agent-based Modelling of the UK Short Term Electricity Market: Effects of Intermittent Wind Power”, Proc. of 9th Intl Conf. on European Energy Markets, Florence, Italy, May 10-12, 2012.

[5] Cedric De Jonghe, B. F. Hobbs, and R. Belmans, “Optimal Generation Mix with Short-Term Demand Response and Wind Penetration”, IEEE Trans On Power Systems, Vol. 27, No. 2, pp 830-839, May 2012.

[6] Dong Gu Choi and V. M. Thomas, “An electricity generation planning model incorporating demand response”, Energy Policy, Vol. 42, pp 429-441, 2012.

[7] Robert L. Earle, “Demand Elasticity in the California Power Exchange Day-Ahead Market”, The Electricity Journal, Vol. 13, Issue. 8, pp 59-65, Oct 2000.

[8] Energy USDo. “Benefits of demand response in electricity markets and recommendations for achieving them.” A report to the United States congress pursuant to Section 1252 of the Energy Policy Act 2005, 2006.

[9] Roscoe A.J, Ault. G, "Supporting high penetrations of renewable generation via implementation of real-time electricity pricing and demand response," Renewable Power Generation, IET, Vol.4, No.4, pp.369-382, July 2010.