DECENTRALIZED, AGENT-BASED PARTICIPATION OF LOAD APPLIANCES IN ELECTRICITY POOL MARKETS

Dimitrios PAPADASKALOPOULOS
Imperial College London – UK
d.papadaskalopoulos08@imperial.ac.uk

Goran STRBAC
Imperial College London - UK
g.strbac@imperial.ac.uk

ABSTRACT

Challenges towards the achievement of direct participation of the demand side in electricity markets are examined in this paper. A decentralized market mechanism, dealing effectively with computational, communicational and consumers' privacy concerns is developed, based on Lagrangian Relaxation and an original price update algorithm. A novel agent-based scheme enables automated participation of load appliances in the decentralized market with minimum human users' engagement and accurate representation of the complex, inter-temporal users' preferences, appliances operational constraints and flexibility patterns. Domestic wet appliances have been used in order to exemplify this scheme and benefits realized through the proposed models are analyzed and quantified through suitable case studies.

INTRODUCTION

In the liberalized electricity sector, realizing the significant potential of the inherent flexibility at the demand side [1] needs to be coupled with integration schemes driven by competitive market dynamics and the individual consumers' interests. Among such schemes, the direct participation of consumers in electricity pool markets has recently attained increased research interest [2]-[4] but still exhibits outstanding challenges.

First of all, small (e.g. domestic) consumers have neither the knowledge nor the will to negotiate themselves in the market. Thus, this scheme requires the deployment of suitable automation technologies; in this context, the novel concept of smart load appliances [5] seems promising and deserves further examination.

Another challenge is the accurate representation of the demand flexibility in the bidding process. Moving from manually- to automatically-facilitated demand participation will require a comprehensive demand flexibility model, able to express the complex, inter-temporal operational constraints, flexibility patterns and users' preferences of load appliances; this complicated modeling task cannot be carried out through the price elasticity approaches adopted in the relevant literature [2]-[4].

Finally, most of the related work (including [2]-[3]) has focused on centralized market mechanisms. It is evident that the potentially participating load appliances are characterized by a large number of diverse constraints and physical parameters. Transmission of all these characteristics to the central clearinghouse will not only be hard to achieve through a standardized bid form, but will also create information collection and communication problems; furthermore, the vast number of decision variables and constraints will create a massive computational burden to the market operator. Even if these techno-economical problems are adequately resolved, the consumers are likely to raise significant privacy constraints, related to the disclosure of sensitive information during the bidding process.

In the next sections, these challenges are addressed in an integrated fashion. On the one hand, a decentralized pool market mechanism resolving the above limitations of centralized designs is proposed; in contrast with previous work [4], this mechanism captures interdependencies between the different time periods of the market horizon and encompasses an original price update algorithm, based on Broyden's method, which reduces significantly the computational burden. On the other hand, a novel agent-based demand participation scheme, able to keep the human users' engagement at the minimum level is incorporated in the decentralized market model; this scheme involves software agents, embedded in users' appliances and acting as their market representatives by taking into account their detailed operational features.

DECENTRALIZED MARKET MECHANISM

The examined pool market is a day-ahead market with hourly resolution (24 commodities, representing the active power in each hour of the next day, are traded simultaneously). In a centralized market design, the market operator derives the market participants' cost and benefit functions from their respective bids and determines the clearing dispatch and prices by solving a problem of daily social welfare (sum of all participants' individual surpluses) maximization:

$$\max_{\substack{\boldsymbol{d_i}, i=1,2,..,I \\ \boldsymbol{s_k}, k=1,2,..,K}} \left(\sum_{i=1}^{I} B_i(\boldsymbol{d_i}) - \sum_{k=1}^{K} C_k(\boldsymbol{s_k})\right) \quad (1)$$

$$\text{s.t. } \boldsymbol{e} = \sum_{i=1}^{I} \boldsymbol{d_i} - \sum_{k=1}^{K} \boldsymbol{s_k} = \boldsymbol{0} \quad (2)$$

$$\boldsymbol{ld_i}(\boldsymbol{d_i}) \le \boldsymbol{0}, i = 1,2,..,I \quad (3)$$

$$\boldsymbol{ls_k}(\boldsymbol{s_k}) \le \boldsymbol{0}, k = 1,2,..,K \quad (4)$$

Where B_i and $\boldsymbol{d_i}$ are the daily benefit function and the vector of hourly demand functions respectively of the ith participating consumer (I in total), while $C_k(\cdot)$ and $\boldsymbol{s_k}(\cdot)$

are the daily cost function and the vector of hourly supply functions respectively of the kth participating generator (K in total). (1) is subject to both coupling constraints (2) (coupling the consumption and production of all market participants) and local constraints (3)-(4) (each one related to an individual participant). By relaxing the coupling constraints through a vector of Lagrangian multipliers $\boldsymbol{\lambda}$ [6], the Lagrange function is derived:

$$L(\boldsymbol{d_i}, \boldsymbol{s_k}, \boldsymbol{\lambda}) = \sum_{i=1}^{I} B_i(\boldsymbol{d_i}) - \sum_{k=1}^{K} C_k(\boldsymbol{s_k}) - \boldsymbol{\lambda^T}\left(\sum_{i=1}^{I} \boldsymbol{d_i} - \sum_{k=1}^{K} \boldsymbol{s_k}\right) \quad (5)$$

Since this function is additively separable with respect to each market participant for certain $\boldsymbol{\lambda}$, the initial problem (1) can be decomposed into $I + K$ independent sub-problems, each one corresponding to a surplus maximization problem for an individual consumer (6) or generator (7) and parameterized by the value of $\boldsymbol{\lambda}$:

$$max_{\boldsymbol{d_i}}(B_i(\boldsymbol{d_i}) - \boldsymbol{\lambda^T d_i}) \quad (6)$$
$$max_{\boldsymbol{s_k}}(\boldsymbol{\lambda^T s_k} - C_k(\boldsymbol{s_k})) \quad (7)$$

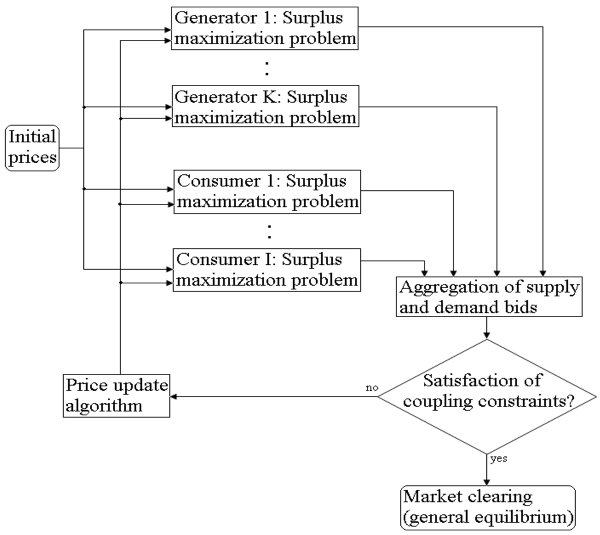

Fig. 1: Model of decentralized market mechanism

Each of the elements of $\boldsymbol{\lambda}$ represents the electricity price at the respective hour and the decentralized market mechanism can be modeled through a two-level iterative algorithm (Fig. 1). In the local level, each market participant solves separately their individual surplus maximization problem for certain prices and bid their optimal consumption/generation vector to the market operator. In the global level, the market operator updates the prices according to the received bids and sends them back to participants until the aggregation of the participants' bids leads to the satisfaction of the coupling constraints. Thus, the market operator's task can be mathematically modeled as a problem of solving a system of non-linear equations [4] and more specifically of determining the 24 elements of $\boldsymbol{\lambda}$ which satisfy (simultaneously) the 24 equations (2).

The simplest and most general method of solving this kind of problems is the Newton-Raphson algorithm [7]; starting from some initial prices $\boldsymbol{\lambda^0}$, the prices sent to the market participants in each iteration are calculated as:

$$\boldsymbol{\lambda^{r+1}} = \boldsymbol{\lambda^r} - \beta * \boldsymbol{J^{-1}}(\boldsymbol{\lambda^r}) * \boldsymbol{e^r}(\boldsymbol{\lambda^r}) \quad (8)$$

where r is the iteration index, β is the step size and J is the Jacobian matrix, each element of which is defined as:

$$\mathrm{J}_{t\tau} \equiv \frac{\partial e_t}{\partial \lambda_\tau} = \sum_{i=1}^{I} \frac{\partial d_{i,t}}{\partial \lambda_\tau} - \sum_{k=1}^{K} \frac{\partial s_{k,t}}{\partial \lambda_\tau} \quad (9)$$

The problem arising is that the derivatives of the individual demand and supply functions in (9) are private to the respective participants. Since the knowledge of the exact Jacobian is not critical for the convergence of the Newton-Raphson algorithm, this problem can be resolved by approximating numerically these elements through finite differences and regression techniques, using observations from past $(\boldsymbol{\lambda}, \boldsymbol{e})$ pairs [4]. However, such techniques require large computational time and storage. In this context, quasi-Newton (or secant) methods [7] seem particularly appealing; in each iteration, instead of calculating these elements one-by-one, such methods provide directly an approximation $\boldsymbol{A}$ of the whole Jacobian, based on the most recent changes in $\boldsymbol{\lambda}$ and $\boldsymbol{e}$:

$$\boldsymbol{\delta\lambda^r} = \boldsymbol{\lambda^{r+1}} - \boldsymbol{\lambda^r} \quad (10)$$
$$\boldsymbol{\delta e^r} = \boldsymbol{e^{r+1}} - \boldsymbol{e^r} \quad (11)$$

In this work, we have deployed the most popular of them, Broyden's method [7]. Starting from some initial approximation $\boldsymbol{A^0}$, $\boldsymbol{A}$ is updated based on:

$$\boldsymbol{A^{r+1}} = \boldsymbol{A^r} + \frac{(\boldsymbol{\delta e^r} - \boldsymbol{A^r} * \boldsymbol{\delta\lambda^r}) * (\boldsymbol{\delta\lambda^r})^T}{(\boldsymbol{\delta\lambda^r})^T * \boldsymbol{\delta\lambda^r}} \quad (12)$$

and the price update is carried out according to:

$$\boldsymbol{\lambda^{r+1}} = \boldsymbol{\lambda^r} - \beta * (\boldsymbol{A^r})^{-1} * \boldsymbol{e^r} \quad (13)$$

The solution is reached when the coupling constraints are satisfied and it constitutes a general equilibrium since i) each participant maximizes their own surplus at the prevailing prices (surplus optimum and fair solution) and ii) the coupling constraints are satisfied. This equilibrium is a Pareto optimal allocation of the commodities (no alternative allocation makes any participant better off without making another one worse off) and a solution to the initial centralized problem (1) [8].
In such a market design, consumers' privacy constraints are respected and the information collection and communication burdens get significantly mitigated since the market negotiations are carried out through simple price and demand/supply signals; moreover, the market operator's computational task is simplified since he/she does not deal with individual participants' constraints, but

the latter are encapsulated into the respective bids.

AGENT-BASED DEMAND PARTICIPATION

As discussed in the Introduction, small consumers are neither willing nor able to employ themselves in the bidding process. Under the proposed scheme, such consumers wishing to participate in the market install dedicated software programs in their load appliances - called smart appliance agents in this work- to act as their market representatives. In each iteration of the market clearing process of Fig. 1, these agents determine the optimal bidding consumption of their appliance, by solving the optimization problem (6), given the 24 electricity prices at this iteration; this problem is subject to a number of local constraints (3), associated with the users' preferences (related to their habits and comfort levels), the operational constraints and the flexibility patterns of the respective appliance. In order to limit further the required engagement by the user, these agents could also direct the control of the appliances in real time, according to the outcome of the market (Fig. 2).

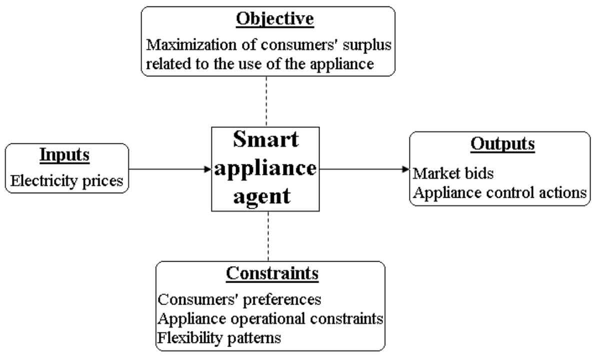

Fig. 2: Abstract model of smart appliance agent

The domestic load appliances considered in this paper are the so-called wet appliances, namely dishwashers (DW) washing machines (WM) and integrated washing/drying machines (IWD). As discussed in [5], the shiftability of the operational cycle of such appliances is their most well-proven flexibility potential. Under this scenario, the users determine the process initiation time t_{start} (i.e. the time they will load the clothes or dishes and switch the appliance on) and the latest time t_{end} by which the washing/drying process should be ended (or equivalently the maximum delay δ_{max} in the start of the consumption cycle, measured from t_{start}) and the appliance can start its operation at any time after t_{start} as long as it will complete the process by t_{end}. This operational cycle is modeled by a cycle demand curve, giving the duration and the power consumption at each time step of the process [5].

Due to the difficulties in quantifying the daily benefit function, we have assumed without lack of generality that it does not depend on the power consumed by the appliance at each hour of the day and has a large constant value compared to the energy payment as long as δ_{max} is not violated and a large negative value otherwise. This assumption converts the surplus maximization problem (6) to an energy payment minimization problem:

$$min_{\boldsymbol{d}_i} \boldsymbol{\lambda}^T \boldsymbol{d}_i \qquad (14)$$

which is subject to local constraints defined by a) the users' preferences (the appliance cannot start its operation cycle before t_{start} and needs to complete it by t_{end}) and b) the operational characteristics of the appliance (the whole operation cycle can be shifted in time but not altered e.g. interrupted, prolonged or shortened). This problem can be formulated as an integer optimization problem, where the decision variable is the delay δ_{shift} in the start of the process, solved based on a simple algorithm of complete enumeration of all delay options ($\delta_{shift} = 0, \delta_{shift} = 1, .., \delta_{shift} = \delta_{max}$).

CASE STUDIES

The examined case studies involve the application of the proposed model in the UK system on a typical winter day. Since this paper emphasizes on the demand side of the market, the whole generation system is modeled as one equivalent generator without inter-temporal constraints and fixed costs, which bids according to its linearly increasing marginal cost function.

Different scenarios regarding the penetration and the flexibility of smart wet appliances are examined (Table 1). The figures in the low, medium and high penetration scenarios are derived by assuming that 5%, 10% and 20% of the total number of wet appliances of each type respectively are characterized by smart functionality and participate in the pool market. Their flexibility is quantified by δ_{max}, typical values of which are based on consumer surveys presented in [5]. The same surveys give the percentage of appliances of each type initiated at each hour of an average day, capturing the diversity regarding t_{start}. The base case corresponds to a scenario without load flexibility, where all wet appliances start their operation cycle at t_{start}.

Table 1: Smart wet appliances scenarios

	Penetration (thousand appliances)			Flexibility (δ_{max} in hours)		
	Low	Medium	High	Low	Medium	High
DW	375	750	1,500	1 to 4	1 to 6	1 to 8
WM	563	1,125	2,250	1 to 2	1 to 3	1 to 4
IWD	710	1,420	2,840	1 to 2	1 to 3	1 to 4

The shift of the appliances from more expensive (peak) to cheaper (off-peak) hours of the day results in a reduction of the demand during the former and an increase during the latter and consequently a similar impact on market prices. In other words, the flexibility at the demand side tends to flatten the demand and price profiles (Fig. 3-4). As expected, increasing the number of smart appliances enhances this effect as more demand migrates from peak to off-peak periods (Fig. 3). The same holds for the flexibility of those appliances (Fig. 4); as the consumers allow higher δ_{max}, the range of shifting options for the smart appliance agents is increased and thus more appliances migrate towards more favorable hours of the day and the profile flattening effect is enhanced.

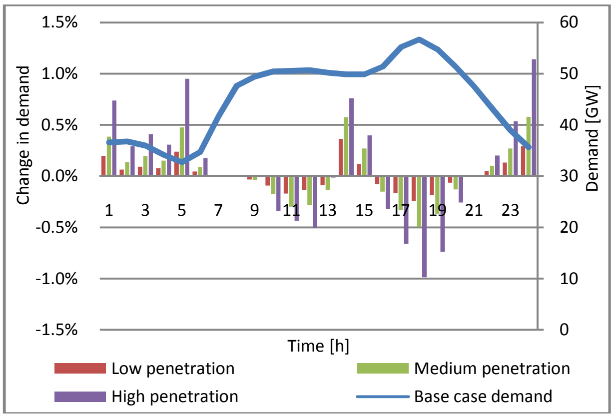

Fig. 3: Impact on demand profile (medium flexibility case)

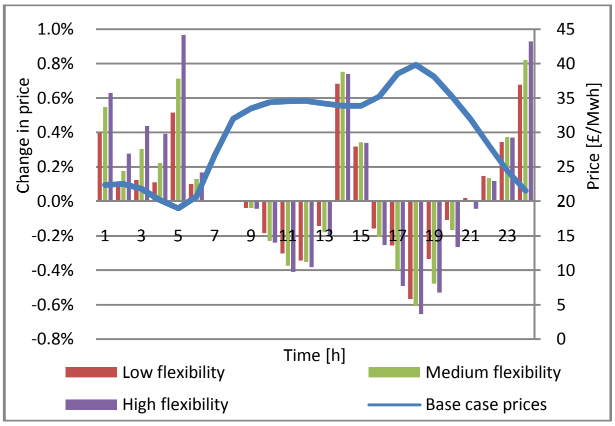

Fig. 4: Impact on price profile (medium penetration case)

The beneficial impacts of smart appliances' market participation on generation costs and consumers' payments are given in Fig. 5. Since the generation costs at each hour increase quadratically with the respective demand (due to the linearly increasing shape of the generation marginal cost function), the total costs are reduced as the demand profile gets flatter; therefore, increasing the penetration and flexibility of smart appliances leads to lower generation costs (and subsequently higher social welfare as the consumers' benefit has been assumed constant). The reduction in consumers' energy payments comprises two components: a) reduction in the expenses associated with the operation of the smart wet appliances (since their operation cycles are moved to cheaper periods of the day) and b) reduction in the payments associated with the rest of the load in the system, driven by the flattening of the price profile (these payments are increased at the off-peak periods and reduced at the peak periods but the overall effect is positive due to the much higher demand at the latter); in other words these flexible load appliances are also beneficial for other, inflexible users (those consuming in peak periods) and not only for their owners. Both components are enhanced as the smart appliances' penetration and flexibility increase and thus the payments savings become more significant.

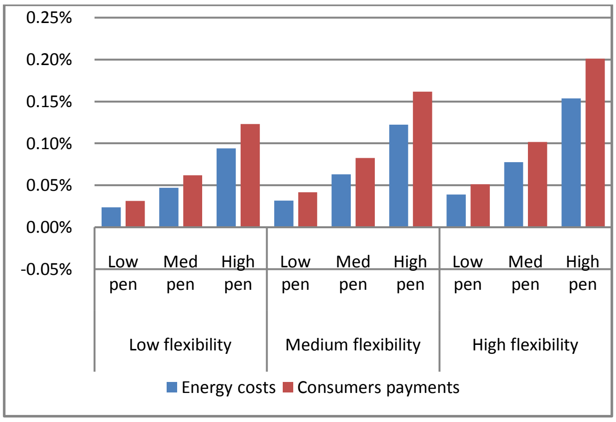

Fig. 5: Reduction of energy costs and consumers payments

REFERENCES

[1] G. Strbac, 2008, "Demand side management: Benefits and challenges", *Energy Policy*, vol.36, issue 12, 4419-4426

[2] C.-L. Su, D. Kirschen, 2009, "Quantifying the Effect of Demand Response in Electricity Markets", *IEEE Trans. on Power Systems*, vol.24, issue 3, 1199-1207

[3] J. Wang, S. Kennedy, and J. Kirtley, 2010, "A new wholesale bidding mechanism for enhanced demand response in smart grids" *Innovative Smart Grid Technologies (IGST)*, Gaithersburg, U.S.A.

[4] A.L. Motto, F.D. Galiana, A.J. Conejo, and M. Huneault, 2002, "On walrasian equilibrium for pool-based electricity markets", *IEEE Trans. on Power Systems*, vol.17, issue 3, 774-781

[5] R. Stamminger, 2009, *Synergy Potential of Smart Domestic Appliances in Renewable Energy Systems*, ed. University of Bonn, Shaker Verlag, Aachen, Germany

[6] H. Everett, 1963, "Generalized Lagrange Multiplier Method for Solving Problems of Optimal Allocations of Resources", *Operations Research*, vol. 11, no.3, 399-417

[7] W. Press, S. Teukolsky, W. Vetterling, and B. Flannery, 1994, *Numerical Recipes in C*, Cambridge University Press

[8] F. Ygge, 1998, *Market-Oriented Programming and its Application to Power Load Management,* Ph.D. Dissertation, Lund University, Lund, Sweeden