Integration of Consumers' Sensitivities and Preferences in Demand Side Management

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Abstract To address the new challenges arising from the higher penetration of renewable energy in electrical grid, Demand Side Management (DSM) and Demand Response (DR) aim to involve the residential as well as industrial consumers in the grid equilibrium. Ensuring benefits for both utility and users requires the consumers sensitivities to be understood and then included in the Energy Management System (EMS). For this purpose, the cost is the predominant and most often only factor taken into account in the literature, although in the residential sector other concerns influencing electricity consumption behaviour has been observed. This paper presents an EMS based on a neighbourhood of consumers modelled at the level of their appliance and incorporating 6 consumption profiles along three sensitivities: cost, environment and appliances shifting comfort. A multi-agent optimization is lead by a central aggregator but performed locally by the household using multi-pass Dynamic Programming (DP), thus ensuring privacy protection for the stakeholders.

1 Introduction

Environmental concerns lead to an increasing part of renewable energies in the energy mix, therefore challenging the production-consumption equilibrium of the electrical grid.

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To address this issue, reconsidering the way electricity is managed is a necessity: to balance the uncertainties on the production side, the focus is nowadays on the consumption through DSM and especially DR [1]. It aims therefore to reduce the relative unforeseeable character of the load, either with (e.g., [2]) or without storage. The incentives are most often monetary and many DR programs focus therefore on minimizing the households' electricity bills (e.g., [3]). However, it should not be the only mean considered: solely through diffusion of good practices alert during peaks in the south of France for example, the Ecowatt project mentioned in [4] shows the pluralism of possible trigger for involvement.

The necessity of taking into account this multiplicity of consumers' sensitivities beyond the scope of economics consideration is underlined by the feedback on smart-grids project in Europe over the past 14 years [5]. Consumer's engagement is particularly under focus, as their role definition is observed to be unclear - the cost-benefit share for each is imprecise - thus reducing their involvement in new grid model. The challenge is not only technical but also requires a multi disciplinary approach relying on electrical engineering as well as sociology and economy. Segmentation of consumers profiles is therefore of primary importance and underlined by the diversity of research on this particular subject: relying on surveys, [6] shows the heterogeneity of consumers' engagement through 6 profiles, [7] suggest a segmentation of consumers' lifestyles based on their electricity consumption, to cite but two. Once understood, sensitivities and preferences need to be included in an energy supervisor [8]. To tackle the problematic of privacy for the consumers, the most suitable approach is decentralized: Each household is then in charge of calculating its own optimized consumption through the smart-meter [3, 9–11]. Following up with this type of approach, [9] suggests a two level game between utilities and consumers, including a global involvement parameter. Also relying on game theory, [11] tested various pricing scheme while studying the impact of temporal preferences, incorporating a weighting coefficient for the optimization to focus on the cost or on the shifting time. [10] proposes a multi-objectives optimisation aiming to minimize the cost and the delay of appliances in a Peak to Average Ratio (PAR) constrained grid, while incorporating consumers sensitivities on delay acceptance. If one or two factor is taken into account, the literature does not offer any research on the consideration of whole profiles, to imagine a more complete representation of the socially observed sensitivities.

The aim of this article is therefore to investigate a new day-ahead supervisor for residential consumption, incorporating three sensitivities: economics, environment, and shifting comfort. Firstly are presented the mathematical framework and the function used to perform the optimisation, as well as the relevant indicators. The study case on which the simulation is based and the corresponding algorithm are then described. The last part introduces the simulation of the interaction between the different profiles, focusing on 6 stakeholders. Finally, after a brief summary, we present an overview on the remaining challenges.

2 Proposed approach

2.1 Problem formulation

The objective of the presented EMS is, for a day ahead, to calculate the adequate electricity consumption of the stakeholder considering his objectives and taking into account his constraints (technical as well as social). In this paper, the management is decentralized and the households are therefore assumed to be able to manage their consumption either in a manual (as proved efficient in [12] for example) or an automatic way through their smart home appliances.

The simulation is based on a whole set of real appliances, divided into four groups : Flexible, On-Off, cycle, fixed. The framework of multi-agent system is used here with an aggregator from one side, and the users (consumers) on the other side, communicating through smart-meters. The convergence of the optimization process is assured by the form of the objective function and the strategy space, representing all the possible strategies for a given user. In the context of a game theory approach shown in a previous work [13], provided that the strategy space is closed, bounded, and convex, the optimization will converge to the Nash equilibrium if the function is convex. Due to type cycle appliances, this set is still closed and bounded, but not convex: the uniqueness of the equilibrium is not assured, thus requiring a stop criterion. In this study, the Peak-to-Average Ratio (PAR) is used as objective for the grid and its evolution serves as stop criterion.

Given the information sent by the aggregator -here the grid load over the day- a household n minimizes its objective function (1) that incorporate its sensitivities (through the function ρ^n, as explained in the subsection 2.2) as well as the objective of the grid. The consumption of this dwelling for a time step t is noted x_t^n and the peak reduction goal is integrated through the minimization of the quadratic total load of the neighbourhood.

$$\min U^n(X) = \sum_{t=1}^{T} (1-\rho^n(t)) \left(x_t^n + \sum_{j=1, j\neq n}^{N} x_t^j \right)^2 \tag{1}$$

Furthermore, social and technical constraints linked to the use of each appliance are taken into account. For type cycle appliances, the consumption is defined over a fixed amount of time step, and its beginning is optimized within an allowed time interval set by each user. On-Off and flexible appliances are also optimized in an allowed time interval, the only difference being the possible power steps at each time step, only constraint by the fixed daily energy amount associated to the considered appliance. Finally, the last constraint is the power limit, set for each user during the modelling phase, that can not be exceeded by the total load.

2.2 Sentivities

According to socio-economic studies [6, 14], consumers are not all engaged in the same way in energy management. Their involvement depends on different motivational factors. To achieve a representation of this diversity, three main motivating factors has been defined through social sciences. They answer the following questions: Is the user bill reduced? (Cost) Is the user ecological footprint reduce? (Environment) Is the user comfort preserved? (Comfort). These are translated in the previous equation (1) through functions ϕ^n and weighing coefficients α^n balancing their predominance according to each user's profile. The global preference ρ^n is therefore expressed, for a time step t, as:

$$\rho^n(t) = \alpha^n_{\text{price}} \cdot \phi^n_{\text{price}}(t) + \alpha^n_{\text{Env}} \cdot \phi^n_{\text{Env}}(t) + \alpha^n_{\text{Comf}} \cdot \phi^n_{\text{Comf}}(t) \tag{2}$$

with,

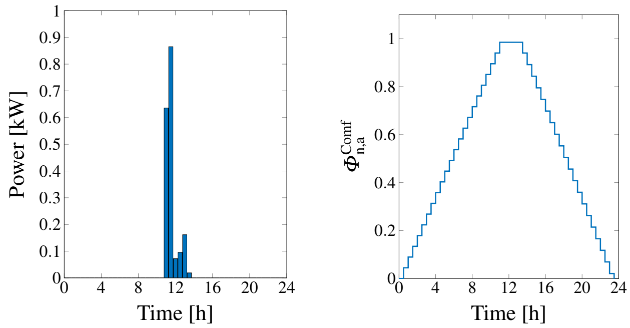
$$\begin{cases} \forall n \in [\![1,N]\!], & \alpha^n_{\text{price}} + \alpha^n_{\text{Env}} + \alpha^n_{\text{Comf}} = 1 \\ \forall n \in [\![1,N]\!], & \{\alpha^n_{\text{price}}, \alpha^n_{\text{Env}}, \alpha^n_{\text{Comf}}\} \in [0,1] \end{cases} \tag{3}$$

Each motivational factor ϕ is defined over time, according to grid information such as the price of the energy, $\psi(t)$, for ϕ_{Price}, and the ratio of renewable energy in the production Part^{REN} for ϕ_{Env}. The values are normalised between 0 and 1 to make them consistent with the definition of the preference. As only a small cluster of users is considered, cost of energy, production of renewable energy and comfort are assumed to be uncorrelated.

$$\phi^n_{\text{price}}(t) = 1 - \frac{\psi(t) - \psi_{\min}}{\psi_{\max} - \psi_{\min}} \tag{4}$$

$$\phi^n_{\text{Env}}(t) = 1 - \frac{P^{\text{REN}}(t) - P^{\text{REN}}_{\min}}{P^{\text{REN}}_{\max} - P^{\text{REN}}_{\min}} \tag{5}$$

In the literature, the comfort of the user is proportional to the amount of energy consumed at a time t defined prior to optimisation, as in [11]. However, this definition is incomplete. Indeed for storage appliance, the comfort is linked to the time at which the power can be consumed by the user, not at which the power is stored. E.g. for the electrical vehicle (EV), the comfort is linked to its state of charge at a chosen hour. This definition of the comfort is also source of problem when several appliances are aggregated. A washing machine may consume as much power as a dryer but switching them in time is cause for discomfort. In this paper, the comfort is therefore related to the shifting of cycle appliances, in a comparable manner to [15]. The motivational factor $\phi^{\text{Comf}}_{n,a}$ is defined for each appliance a of a user n: equal to 1 during the preferred execution of the appliance (here the forecasted time resulting from section 3.1.1) and is set to decrease linearly around this time interval, as shown in Fig. 1. For storage appliance the motivational factor is equal to 0, as the time constraints set by the user are already taken into account by the algorithm presented in section 3.2.



(a) (b)

Fig. 1 Preference construction for one appliance, with (a) the preferred power vector, (b) the corresponding motivational factor $\phi^{\text{Comf}}_{n,a}$.

2.3 Indicators

2.3.1 Global satisfaction of the user

The satisfied energy is defined, for the non-fixed appliances ($_{\text{nf}}$), the product of the energy with the preference: it is therefore higher for energy consumed when his preference is higher. The ratio of the satisfied energy and the total energy consumed by one user represent its satisfaction S^n. Its evolution δS^n is then calculated, with S^n_0 the satisfaction before optimisation.

$$\begin{cases} S^n = \dfrac{\varepsilon^n_{\text{nf}}}{E^n_{\text{nf}}} = \dfrac{\sum_t \sum_a \rho^n_a(t) \cdot x^n_{t,a} \cdot \tau}{\sum_t \sum_a x^n_{t,a} \cdot \tau} \\ \delta S^n = S^n - S^n_0 \end{cases} \tag{6}$$

2.3.2 Relative difference of the electricity bill

Assuming the price of energy $\psi(t)$ is not constant, the daily bill of one user is defined as C^n. Its evolution after optimisation is measured through δC^n , with C^n_0 the electricity bill before optimisation. The relative difference is positive for a lesser bill after optimisation.

$$\begin{cases} C^n = \sum\limits_{t=1}^{T} \psi(t) \cdot \left(\sum\limits_{a=1}^{A} x^n_{t,a} \right) \\ \delta C^n = \frac{C^n_0 - C^n}{C^n_0} \end{cases} \tag{7}$$

2.3.3 Relative difference of renewable consumption

The part of renewable energy consumed by one user, $\varepsilon^n_{\text{REN}}$, is assumed to be proportional to the part of renewable energy on the grid, Part_{REN}. Then the relative difference $\delta\varepsilon^n_{\text{ENR}}$ is defined to measure the evolution of the renewable energy consumed by each user after optimisation.

$$\begin{cases} \varepsilon^n_{\text{REN}} = \sum_{t=1}^{T} \sum_a \text{Part}^{\text{REN}}(t) \cdot x^n_{t,a} \cdot \tau \\ \delta\varepsilon^n_{\text{ENR}} = \dfrac{\varepsilon^n_{\text{ENR}} - \varepsilon^n_{\text{ENR},0}}{\varepsilon^n_{\text{ENR},0}} \end{cases} \tag{8}$$

2.3.4 Evolution of shifting delay

As previously stated, the comfort is relevant only for the A^{cycle} shifting appliances. To measure the satisfaction regarding the comfort, the mean shifting delay after optimisation is therefore computed:

$$\Delta t^n_{\text{shift}} = \frac{\sum_a (t^{\text{start}}_a - t^{\text{start},0}_a)}{A^{\text{cycle}}} \tag{9}$$

2.3.5 Grid indicators

As the objective for the grid is the peak reduction, two corresponding indicators are measured before and after optimisation: The PAR and the Square Euclidean Distance (SED) using (10), where $X_k = \sum_{n=1}^{N} x^n_t$.

$$\begin{cases} \text{PAR} = \dfrac{\max_t(X_t)}{\bar{X}_t} \\ \text{SED} = \sum_{t=1}^{T} (X_t - \bar{X}_t)^2 \end{cases} \tag{10}$$

3 Study case

3.1 Modelled population

3.1.1 Load modelling

As explained in section 2.2, information on each appliance is needed to perform the optimisation according to the comfort of each user. The demand of the population must therefore be modelled with a sufficient temporal resolution to encompass them all. Among the reviewed models [16], the bottom-up approach is selected as it gives access to the contribution of each appliance. In this category, the model CREST V.2 [17] is chosen. This model builds the load curve of one user by summing the demands due to each appliance at a timestep of 1 min, for the UK residential sector. The gas demand due to heating is also modelled. In addition, an open-source tool is provided by the authors. This model has been used in a demand-side management context to build input data in [15] for example. For this paper, the model has been slightly modified, for the French residential electrical demand is more thermosensitive than the English one. In fact, in France [18], 50% of the dwellings use electricity to heat water, and 36% use electricity to heat the house. To account for this difference, part of the power flow due to heating (air and water) is therefore rerouted to the electrical demand. Furthermore, the statistical data are updated using data from the French national housing survey (ENL - Enquête National Logement) carried out by the National Institute of Statistics and Economic Studies (INSEE).

Since the CREST does not consider electrical vehicles (EV) and to add more flexibility to the load curve, a fleet of electric vehicles has been modelled. Normal distributions of travels and of arrival time were used for the modelling, as proposed in [19], and the loads due to the fleet were added to the output of the CREST using french statistical data on EV ownership.

3.1.2 Sensitivity modelling

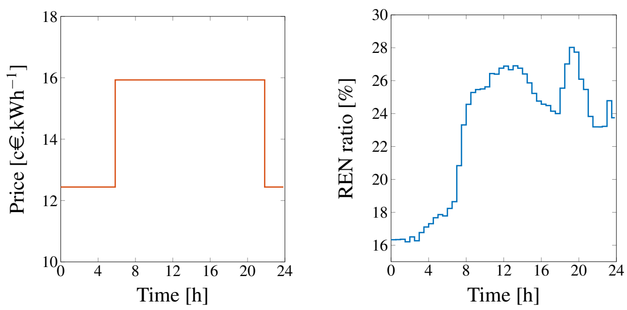
The goal of this work is to demonstrate the effectiveness of a new approach to differentiate users' utility based on their sensitivities towards factors. Therefore, 6 main profiles have been modelled and described in Tab. 1. Each sixth of the total population ($N = 100$) is given a different profile. To achieve diversity in each sub-population, randomness around the target value is performed (+/-10% around 50%, and 20% below 100%). To ensure a realistic comparison between the different profiles, one dwelling among the modelled population has been duplicated 6 times, one in each profile group. For the simulation, there are therefore six dwelling with the same appliances, and same consumption but with different sensitivities.

Table 1 Profile distribution of the 100 households

Profile	Cost	Envir.	Comf.	Size
1 - Cost	80-100%	-	-	17
2 - Environment	-	80-100%	-	17
3 - Comfort	-	-	80-100%	17
4 - Cost & Envir.	40-60%	40-60%	-	17
5 - Cost & Comfort	40-60%	-	40-60%	16
6 - Envir. & Comfort	-	40-60%	40-60%	16

3.1.3 External factors

The external factors influencing the consumption included in this paper are the price and the production of renewable energy. Their evolution over the considered day is presented on Fig. 2(a) and Fig. 2(b) respectively. The price is an actual two-step Time Of Use pricing currently used in France, and the ratio of REN in the total electrical production feeding the grid is retrieved from the french electricity transmission system operator RTE [20].



(a) (b)

Fig. 2 Evolution of (a) the electricity price and (b) the ratio of REN in the production over the day

3.2 Algorithm

As introduced in section 2.1, the stakeholders calculate their optimal consumption path in a sequential and asynchronous way, therefore interacting only with the aggregator. For writing simplicity in this paper, X is a $K \times N$ matrix containing the consumption of the N player for each of the K step of time $X(:,i) = [x_{1,i}, \cdots, x_{k,i}, \cdots, x_{K,i}]$. The process of interaction between the households and the aggregator is the two stage algorithm 1: On the upper level, the aggregator is in charge of calculating the total load on the grid after each local optimization and sending it to the next household until the stop criterion is fulfilled. On a local level, the stakeholder receives the total load on the grid and then optimizes his consumption according to his utility function and with respect to his constraints, before sending it back to the aggregator.

Algorithm 1 Global algorithm

round ← 0 ▷ Round counter
eq ← 0 ▷ Dummy for equilibrium
par ← 0 ▷ Peak to Average Ratio
TotalLoad ← $\sum_{n=1}^{N} X(:,n)$
while $eq \neq 1$ **and** par $\neq$ PAR(X) **and** round $\leq$ $r_{\max}$ **do**
    par ← PAR(X)
    for $n \leftarrow 1$ **to** N **do**
        $eq(n) \leftarrow 0$
        if TotalLoad $\neq$ TotalLoad* **then**
            GridState ← TotalLoad $- X(:,n)$
            Fixed consumption is stored as $X(:,n)$
            for each type cycle, on-off, then flexible appliance **do**
                n uses DP to solve (1) for the K time slots depending on GridState
                n adds the best reply to $X(:,n)$
            end for
        else $eq(n) \leftarrow 1$
        end if
        TotalLoad* ← TotalLoad
        $X^*(:,n) \leftarrow X(:,n)$
        TotalLoad ← $\sum_{i=1}^{N} X(:,n)$
    end for
    round ← round + 1
end while

4 Simulation and results

4.1 Grid perspective

The results concerning the evolution of the total load on the grid are presented on Fig. 3(a), and the related indicators are gathered in Tab. 2. The PAR is effectively decreased (-20%), and it is noticeable how the fluctuation of the load is drastically attenuated (-79%). It is therefore interesting to analyse the other part of the objective, i.e. the evolution of the consumers satisfaction.

Table 2 Simulation results for the grid

Indicator	Initial	Optimized	Evolution
PAR [1]	2.18	1.74	-20%
SED [10^{10} kW^2]	25.1	5.33	-79%

4.2 Consumers perspective

The indicators per group of consumers and per observed dwelling are respectively gathered in Tab. 5 and Tab. 4. During the optimisation, the mean satisfaction amongst consumers increased of 17.2%. An example of the evolution of the load of one dwelling, for which the cost sensitivity is 0.99, is represented in Fig. 3(b): the observed decreased in expenditure (6.6%) is the highest amongst the consumers. Each group of consumers increases its indicators with respect to its main objective (bold emphasis). Furthermore, on both tables, the observed consumers who do not improve their satisfaction are the ones with the highest comfort sensitivity (profile 3) and therefore leaving their consumption practically unchanged, as requested.

Table 3 Indicators evolution for the 6 groups of consumers

Group	Satisfaction δS^n [%]	Cost δC^n [%]	REN $\delta \varepsilon^n_{\mathrm{ENR}}$ [%]	Comfort $\Delta t^n_{\mathrm{shift}}$ [h]
Profile 1	50.8	**5.8**	-24.3	2.41
Profile 2	15.5	-1.0	**7.0**	1.97
Profile 3	-0.4	1.9	-18.8	**0.04**
Profile 4	23.2	**6.5**	**-17.5**	6.03
Profile 5	10.2	**3.0**	0.0	**2.25**
Profile 6	2.7	-0.6	**0.0**	**0.60**

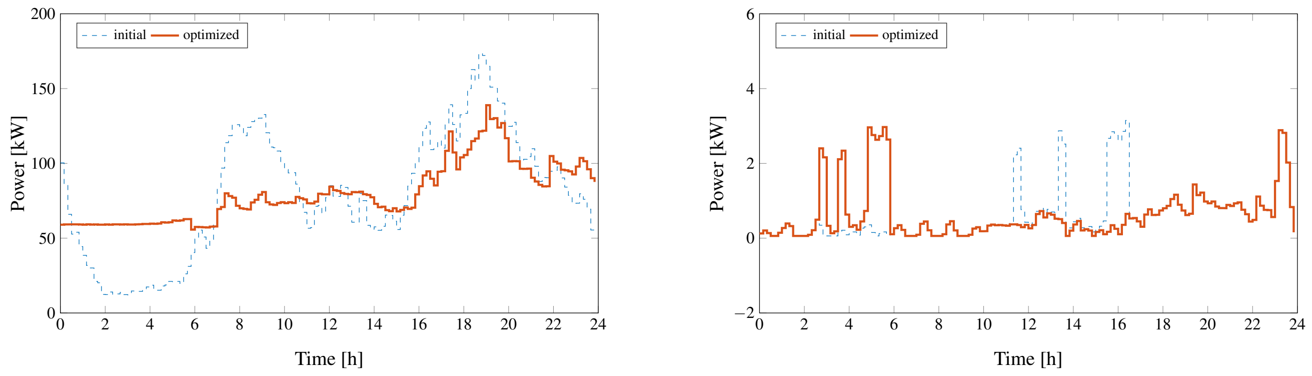
Table 4 Indicators evolution for the 6 observed Dwellings

Profile	Satisfaction δS^n [%]	Cost δC^n [%]	REN $\delta \varepsilon^n_{\mathrm{ENR}}$ [%]	Comfort $\Delta t^n_{\mathrm{shift}}$ [h]
Dwelling 1	99.0	**6.6**	-31.8	9.25
Dwelling 2	10.6	0.0	**4.9**	1.58
Dwelling 3	0.0	0.0	0.9	**0.33**
Dwelling 4	21.0	**5.4**	**-10.9**	8.17
Dwelling 5	0.4	**6.6**	-31.7	**9.17**
Dwelling 6	4.3	0.0	**4.7**	**1.42**

On both the global and local results, it appears therefore that single profiles (1 to 3) are correctly taken into account: the proposed scheme incorporates indeed the various objectives by balancing the load in relation to the sensitivities of the considered stakeholder. The simulation validate therefore the approach to model various profiles but requires further investigation regarding the definition of sensitivities. Indeed, the resulting difficulty concerns the mixed-objectives profiles: with profile 4 and 5, the cost objective displaces the two others (REN and comfort) as most of the forecasted consumption is in a high-price/high-REN-ratio period. Incentive to shift the consumption according to price is therefore considerable, as the following increase in satisfaction will also be substantial, even for low price-sensitive consumers. It requires therefore to include the state of the forecasted consumption regarding external factors while defining the metrics, to account for this effect.

5 Conclusion and perspectives

This paper proposes a decentralized EMS taking into account the consumers preferences and sensitivities while participating to the grid objective that is to reduce the load peak. Through the example of 6 predefined profiles using a set of 3 sensitivities - price, environment and shifting comfort - it achieves a higher flexibility without diminishing the consumers' satisfaction - a way to ensure their involvement in the grid equilibrium. Considering various appliances, the



(a) (b)

Fig. 3 Evolution of the total load on the grid (a) and evolution for the dwelling 1 (b), a price sensitive consumer.

observed PAR reduction is of 20% and the mean satisfaction for the consumers increased up to 17.2%. It will be therefore interesting to investigate the influence of the parameters on each other and furthermore, to look at the distribution of the effort through the modelled population given the stated profile repartition. In this study, the decrease of the PAR is assumed to be the only goal of the grid manager, however, the final state of the grid in terms of voltage plan obtained through this kind of management strategy is worth further investigation.

Other form of utility function are currently under investigation, but in the long run, facing the complexity of real profiles, further study to retrieve them through a socio-economic approach should be conducted in order to have the adequate input for the proposed EMS formulation. With time, knowing the stakeholders and their sensitivities, this could be a methodology to follow in order to get a more accurate prediction. A learning loop would be then adequate to adapt the model to a given population and learn from it. Such approach constitute also an opportunity to change the way electricity is billed and how new contracts are defined, which then requires an adequate economical model to define the financial counterpart for those taking part in the grid equilibrium.

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