Decentralized Neighbourhood Energy Management Considering Residential Profiles and Welfare for Grid Load Smoothing

Abstract

Managing electricity in the grid is a key point to reach energy efficiency while enabling an increased use of renewable energies. To take stakeholders into account, they need to be understood regarding their consumption behaviour. Part of a multidisciplinary approach introducing the involvement of stakeholders in an energy supervisor, this paper introduces a day-ahead energy management system (EMS) incorporating seven consumers profiles along three sensitivities. Aiming to smooth consumption, the developed decentralized optimisation process is presented comparing three different scenarios relying on the variation of a proposed objective function. A critical review using relevant metrics on the presented strategy, the form of the function, as well as the proposed algorithm is developed over the simulation. Hence, this paper aims to validate a consistent method to incorporate predefined consumers profiles together with the grid objectives in grid management.

Keywords: Demand response, Energy management, Decentralized load management, Consumers profiles, Consumers preferences, Game Theory

Nomenclature

$\alpha^h_{\dots}$	Sensitivity of consumer h towards price, REN, or confort
$\mathbb{A}^h$	Appliance set of consumer h
a	Appliance index
$\mathbb{A}^h_{\text{fi/cy/oo/fl}}$	Respectively: fixed-, cycle-, on-off-, and flexible-appliance set of user h
eq	Dummy for equilibrium in the algorithm (equal 1 if no change occurs between two rounds)

$\mathbb{H}$	Set of the H consumers
h	Index for users
H	Number of consumers
K	Number of time steps
k	Time step index
$\hat{k}_a^{\mathrm{s}}, \hat{k}_a^{\mathrm{e}}$	Forecasted departure and end time for appliance a
$k_a^{\min}, k_a^{\max}$	Allowed departure and end time for appliance a
L	Total load on the grid
$\phi_{\dots}$	Instant ratio of the factor cost or environnement
ψ	Price function over the day
P_c^h	Contract power of user h
ρ^h	Satisfaction function of consumer h
τ	Time step duration
U^h	Objective function of consumer h
ξ	Renewable energy power ratio produced
X	$K \times H$ matrix containing the consumption of the H households
$\mathbb{X}^h$	Strategy set of consumer h
x_k^h	Power of consumer h at k
X^h	Power profile of consumer h
$x_{a,k}^h$	Power of appliance a of consumer h at k

$\hat{x}_{a,k}^h$	Forecasted power of appliance a of consumer h at k
X^{-h}	Power profile of all consumers except consumer h
X^{h*}	Optimal strategy of consumer h

1. Introduction

Environmental concerns such as, amongst other, greenhouse gas emissions or resource depletion energy sources led to an steadily increased integration of renewable energy sources in the electricity mixes of countries around the world [1]. As the main concern for grid operators, the production-consumption equilibrium is therefore challenged by the growing part of less controllable productions capacities: to tackle this issue, the first step is to improve forecast models accuracy of the grid load, and the second step considered nowadays is to increase the manageability of the loads. From this new requirement, together with the development of the Information and Communication Technologies (ICT), the smart-grids emerged through improved automation and the implementing of sensor networks enabling a monitoring at every level of the grid.

For this purpose, Demand Side Management (DSM), and especially Demand Response (DR) [2] are used to control the load at the household level depending generally on the price level [3, 4]. Dynamic pricing is therefore getting increasingly studied in recent publications [5, 6, 7, 8]: it aims to limit the consumption at critical peak hours to avoid congestion, encouraging the consumers to reduce their bill by lowering their demand or shifting their consumption over the day, or by guiding price-based automated load scheduling [9]. However, as previously mentioned, usual DR programs neglect the complexity of consumers profiles by only considering price signal to regulate the load: as the need for control increases, involvement and sensitivities of stakeholders should be taken into account through more complete management programs [10, 11]. Aiming for sustainable cities where the stakeholders are more responsible for the production, the consumption, and the share of electricity means indeed to consider each one of them while sharing the pay-off, to encourage and ensure their engagement. Multidisciplinary approaches involving electrical engineering together with humanities and social sciences must be therefore considered, in order for the profiles to be understood and then included in the DR program. From a technical point of view [12] suggests for example a segmentation of consumers' lifestyles based on their electricity consumption, while relying on surveys, [13] shows the heterogeneity of consumers' engagement through six profiles.

Concrete examples of the involvement beyond the financial aspect are to be found in [14] or [15]: showing the pluralism of possible trigger for consumers contribution in energy management. Simply by giving feedback and relying on awareness, therefore letting the households manage their consumption according to their own values, reduction of energy consumption equivalent to a price increase of 11-20% are observed. The core problem of DR programs is to optimise the load of various consumers given their constraints and their objectives, while ensuring the required balance on the grid. To address this challenge, several methods are used: either considering households loads as only continuous [16, 11] or only shiftable [8], or a mix between loads types [10]. The weakness of the first approaches is their inability to encompass the full complexity of dwelling consumption and to retrieve the complete flexibility of residential users. Furthermore, regardless of the method, the optimisation process is either centralized or decentralized. Centralized management reaches better results but requires a higher investment for the communication infrastructure [17] and raises the questions of privacy and acceptance by the users, as it means letting an other entity interfere with their consumption. Thus, residential DR program tend to decentralized approaches [4], enabling the users to autonomously manage their consumption. The next step is then to incorporate the users preferences.

In [10], a distributed algorithm based on a sub-gradient method manages three types of appliances, minimizing the cost and including delay and energy gap sensitivities while achieving Peak to Average Ratio (PAR) decrease. However the comfort is there an objective on the same level as the cost and the weighting parameters have no physical meaning (between 1 and infinity), thus offering no guarantee on the resulting load shift, unless randomly setting high weight values.

Relying on multi-objective mixed integer linear programming technique, [18] reduces the PAR as well as the energy cost for consumers and the system operator. Nevertheless, it solely incorporates the cost reduction objective without distinguishing their sensitivities. Even while allowing appliances schedule preferences of consumers, it implies that the price is the only motivational factor for involvement influencing consumers in the same manner.

Using a game theory approach with totally flexible household's load (applicability with heterogeneous appliances type is not insured), [11] incorporates two sensitivities with a unique weighting coefficient. The resulting problem is that the price sensitivity is consequently directly constrained by the comfort preferences, thus unable to acknowledge real profiles such as high flexibility-low cost sensitivity.

An other interesting decentralized approach is presented by [4], aiming to increase local renewable energy penetration through storage unit control and shiftable appliances contribution using Genetic Algorithm. It succeed in decreasing the PAR and the electricity bill of the users, but does not incorporate any preferences or involvement parameter concerning the households.

Finally, [19] proposes an optimisation using a PL-Generalized Benders algorithm also to solve a multi-residential electricity load scheduling problem with multi-types appliances. The focus is therefore on the mathematics to obtain a near optimal solution regardless of the convexity of the problem. Same as observed previously, two factors are weighting the sensitivities of the user toward the cost or the consumed energy, thus restraining the model to incorporate real consumers' profiles. It is nonetheless interesting to notice that the consumer's utility function is defined not globally but for each appliance: an agent is therefore not the entire household but each appliance individually, decentralising the energy management one level lower.

Studying the contribution of a game theory approach enhanced by a blockchain implemented energy management, [20] study as well the PAR reduction and the cost savings for the grid and the household by relying on individual appliances flexibility. However, only the shifting sensitivity per consumers is taken into account. Similarly, the cost minimization is considered through a real time pricing strategy in [21] using a game theory approach, once again to decrease the cost and the PAR, here with one participation parameter. User preferences are the focus of [22], with a preferred time interval considered for each consumers during the optimisation of the cost. The centralized approach requires nevertheless that each user gives its details of preferences and consumption to the central entity. Lastly, the comfort notion is discussed in [23] by defining different strategies for the consumers and indicating a favoured one. The deviation from the aforementioned is considered as a *discomfort*. The number of users deviating from their preferred strategies is considered as a measurement of the community discomfort, and considered in the optimisation process, which aim at reducing the cost for the entire community. The limitation of this approach is that individual discomfort is neither evaluated nor scaled.

Resulting from this literature review is a lack of consumers consideration: the complexity of their profiles is not taken into account, and as only the grid state improvement is under focus, the resulting users pay-off for the proposed management strategies is not evaluated besides the cost.

In this paper, we present therefore a complete management system aiming to lower the PAR and the fluctuation of the neighbourhood's load while considering the diversity of load (fixed, discrete, continuous, cycle) and profiles. The local optimisation is performed autonomously by the dwellings using multi-pass Dynamic Programming (DP). Additionally, we incorporate whole consumers profiles along three sensitivities: financial, environmental, and comfort. For this purpose, day ahead shifting possibilities and their influence on measurable factors (paid price, renewable consumption, and comfort as we defined it) are incorporated. The cost (both economic and environmental) of technical solutions being long term considerations, it needs to be studied on long term energy management program, together with economic model to grasp the best of such flexibility, and therefore not considered in this work. Seven profiles are thus presented in this paper, but they can be then split into the wide variety of real observed profiles in a given population. The aim of this paper is therefore to give a critical perspective using three scenarios stemming from the presented approach, through their application to a modelled population. Results should indeed be assessed from a grid point of view, but also from the users' perspective, as their inclusion is essential to enhance acceptance first and then their involvement [24].

In summary, the main contributions of this work compared to the previous literature review are threefold:

- Multi-objective residential energy management is proposed, introducing consumers objectives alongside the peak reduction goal of the grid.
- We take into account real observed consumers profiles considering three sensitivities. Moreover, the flexibility, as an image of the user comfort, is here defined as independent of the two other objectives (e.g. low flexibility does not necessarily imply low cost sensitivity) and each sensitivities parameter is kept meaningful, being bounded between 0 and 1.
- The impact of integration level of consumers sensitivities in the management of the grid (three simulated scenarios) is analysed, from a grid and a user point of view, through the introduction of 6 six different metrics.

This paper is arranged as follows: Section 2 introduces the methodology, concentrate on the decentralized energy management and the then mathematical context. The case study including the modelling of the consumers and the simulated scenarios are explained in Section 3. Section 4 presents the output of the simulation. Results are then discussed in Section 5 and further perspectives in Section 6.

2. Methodology

This research is part of a three steps methodology answering the three following questions:

1. What are the existing involvement-profiles in terms of electricity consumption/production?
2. How to model these profiles?
3. How to use these models in an energy management strategy?

2.1. Socio-economic approach

In order to include and actively engage consumers sensitivities and preferences in the management of the grid, understanding them is essential. The first step of the methodology is therefore a multidisciplinary approach, using sociology and economic to carve the profiles in a given population.

Today's most used leverage for DR is the price [25], therefore implicitly assuming a global economic sensitivity of the stakeholder. Among price schemes, [25] indicates for example Critical Peak Pricing (CPP) models to be the most efficient. However, this economic approach is expandable on an other level by differentiating profiles by sensitivities. In this regard, the micro-economy studies the behaviour of individuals in their decision-making process of resources' allocation. In the presented methodology, we rely on the neoclassical economy. Practically, the model is a mathematical set of functions correlating, for each good, the price of the good, the prices of the others good (market prices), and the total individual income, besides other socio-demographics characteristics [26]. Coupled with sociological studies to determine the energy consumption behaviour of a population, it enables to retrieve their different profiles. As we focus here on the integration of these consumers profiles in the management of energy, this part is developed parallel to the work presented here and is not in the scope of this paper.

Resulting from this first step, three main sensibilities are to be found amongst residential consumers, from which ensue the different profiles: sensitivity toward the energy environmental impact, the energy cost, and the shifting effort required to react to the first two sensitivities. Knowing the existing profiles, defining them in a given population or in a limited space can be achieved through various means: either by survey [13], by self-statement of the households (declared or registered through smart appliances manager [27]), or by statistical analysis if the relevant data are available [28].

However, as stated in the first section, this prior step is essential for DR program, shifting the paradigm in order to actively engage the consumer and overall stakeholders in the smart grid equilibrium, to enable each profile to be considered in a way both the grid and the stakeholder can profit.

Another important aspect of consumers involvement and preferences is their evolution over time. Various programs focused on residential consumers do not tackle this issue, although the observed energy consumption reduction can diminish in the long term due to a disinterest, a return to previous practices [29, 30], or because of users moving between different life stages [31]. This issue is particularly pointed out while studying new technologies for DR, as technical issues or loss of autonomy may cause distrust [32], or while investigating feedback efficiency, as improvements often tend to fade. This fading is observed for example once novelty wears off [33], or as *householders realise the limits to their energy saving potential and become frustrated by the absence of wider policy and market support* [34]. [35] also raises the complexity of this issue requiring in depth and focused study on the phenomena, given that changing deep-rooted habits takes time. Concerning this aspect, the parameters representing the involvement in this paper are fixed, but with the functioning presented approach, incorporating them will not be of trouble, as they can be changed regarding field observation. The difficulty lies namely on how to incorporating them (as tackled in this paper) and on the framework of such program (namely the feedbacks, the price evolution, etc.) that needs to be addressed on field.

2.2. Demand Response approach

Considering the context presented in the introduction, the following decentralized problem formulation is drawn from the pursuit of the best compromise between privacy, data flow, computing power, embedded preferences, and grid equilibrium, compared to centralized methods. Working a day ahead, an aggregator, as a central entity, is in charge of collecting and gathering the total load on the grid, and sending this information to each of the consumers in order for the optimisation to be performed.

The properties of a non-cooperative N-person game, presented in [36], are used in this context. It is defined as follows: The set of players $\mathbb{H}$ is the set of the H consumers; the strategy set $\mathbb{X}^h$ gather the possible power profiles X^h of each consumers; the utility function is the objective function U^h of each household incorporating its sensitivities, and is discussed in the next section. This game is therefore written as $\mathcal{J} = \{\mathbb{H}, \{\mathbb{X}^h\}_{h\in\mathbb{H}}, \{\mathbb{U}^h\}_{h\in\mathbb{H}}\}$

If the players optimise their consumption in an asynchronous way, the convexity of the used objective function guarantees the convergence of the algorithm and the uniqueness of the Nash equilibrium, provided the strategy space to be compact and convex [36]. A Nash equilibrium is a state between all the players where none of them can improve its pay-off by deviating unilaterally from its equilibrium strategy [37]. Therefore, this equilibrium is defined as:

Definition 1. *Noting X^{-h} the strategy of all the players except the player h, a strategy vector $[X^{h*}, X^{-h*}]$ is a Nash equilibrium if and only if $\forall h \in \mathbb{H}$ and $\forall X^h \in \mathbb{X}^h$*

$$U^h(X^{h*}, X^{-h*}) \geq U^h(X^h, X^{-h*}) \tag{1}$$

As non-intrusive load monitoring (NILM) in households is developing [38] identification, estimation and forecasting of equipment consumption as well as their potential for energy conservation are assumed to be available locally for the day-ahead management. Therefore, the underlying hypothesis is the existing ability of the consumers to manage their load either manually, or automatically though smart home appliances [27], both from a technical as well as an awareness point of view. To account for the diversity of devices' flexibility and their potential for participation in the proposed EMS, the formulation incorporates therefore the home appliances under four categories. As presented in the introduction, the households optimise their consumption according to their sensitivities: the cost, the environmental impact and the accepted flexibility.

2.3. Objective function and sensitivities

As explained previously, the consumers energy management is performed locally. Each household have its own constraints as well as its own objectives embedded in the objective function used for the optimisation. From a grid point of view, one of the most interesting possibilities for a grid manager setting up a DR program, is to be able to limit the peak on the grid and flatten the consumption. Beyond the prevention of energy congestion in the grid, it limits also the use of polluting and expensive means of production on a short term, and to delay the building of bigger infrastructures on a longer term. The mathematical formulation developed here aims therefore not only to include the peak reduction objective but also to take into account the sensitivities of the consumers. The starting point of the formulation aims therefore to reduce the peaks by minimizing the squared load, which is then weighted by the sensitivity parameters of the considered consumer. The household is indeed able to decide to participate or not in the equilibrium process, and to do so given its objective. The notation used in this paper are: X is a $K \times H$ matrix containing the consumption of the H households (set $\mathbb{H}$) for each of the K steps of time dividing the day (set $\mathbb{K}$). Thus, the consumption of the household h over the day is noted $X(:,h) = X^h = [x_1^h, \cdots, x_k^h, \cdots, x_K^h] \in \mathbb{X}^h$, with $\mathbb{X}^h$ the set of all reachable consumption pattern over the day, given the possessed appliances and their constraints. The objective function for h is then expressed according to (2), and will serve as basis for the different scenarios presented in Section 3.4.

$$\min_{\forall X^h \in \mathbb{X}^h} U^h(X^h) = \sum_{k=1}^{K} \left((1 - \rho^h(k))[x_k^h + \sum_{j=1, j \neq h}^{H} x_k^j] \right)^2 \tag{2}$$

In (2), $\rho^h(k)$ represents the satisfaction function containing the users' preferences regarding the cost and the environmental impact, as defined by 3. It is important to note that the satisfaction considered in this paper is set to reflect the services ensured for the user, not a physiological or psychological factor. It is the satisfaction regarding the use of the household electric flexibility to reach both grid and user objectives.

$$\rho^h(k) = \alpha_{\text{cost}}^h \cdot \phi_{\text{cost}}(k) + \alpha_{\text{env}}^h \cdot \phi_{\text{env}}(k) \tag{3}$$

The α-coefficients represent the sensitivity of the user towards the corresponding factor and are defined during the first step of the methodology, presented in Section 2.1. In order to keep them in a contained range that can easily be interpreted (between 0% and 100%, from insensitivity to fully sensitive), the following imposed constraints are added:

$$\begin{cases} \forall h \in \mathbb{H}\ ,\ \alpha^h_{\text{cost}} + \alpha^h_{\text{env}} = 1 \\ \forall h \in \mathbb{H}\ ,\ \{\alpha^h_{\text{cost}}, \alpha^h_{\text{env}}, \alpha^h_{\text{flex}}\} \in [0, 1] \end{cases} \tag{4}$$

Furthermore in (3), the functions ϕ represent the instant ratio regarding each factor for each time step, also bounded between 0% and 100%. These ratio reflect the achievable factor values depending on its maximum and minimum rates during the considered day:

- Considering the price $\psi(k)$ at time step k over the day, the instant price ratio is defined as:

$$\phi_{\text{cost}}(k) = \frac{\max_k \psi(k) - \psi(k)}{\max_k \psi(k) - \min_k \psi(k)} \tag{5}$$

- The environmental impact is considered to be directly linked to the rate of consumed renewable energy (REN). Therefore, with $\xi(k)$ the renewable energy power ratio produced at a time step k compared to the total production, the instant environmental ratio is calculated as:

$$\phi_{\text{env}}(k) = \frac{\xi(k) - \min_k \xi(k)}{\max_k \xi(k) - \min_k \xi(k)} \tag{6}$$

The last sensitivity α^h_{flex} concerns the accepted flexibility by the household h. The concept of comfort in this paper is not introduced as its physiological meaning, but as the realisation of a task (to have enough hot water, clean laundry, ...) before a given time. Thus, accepting a discomfort is translated as setting a larger time period for the completion of a required service.

For each appliance of a user h, this flexibility is linked to the forecasted and preferred time schedule considering α^h_{flex}. The allowed time interval to shift the appliances when optimising the consumption is therefore defined as a percentage of the maximum possible time over the day (midnight-midnight), according to (7). The same process is used for all appliances of h taking part in the flexibility and this allowed period will then serve during the optimisation to define the possible time slots to evaluate. The forecasted time is referred to as $[\![\hat{k}^{\text{s}}_a, \hat{k}^{\text{e}}_a]\!]$

and the allowed time to shift it $[\![k_a^{\text{min}}, k_a^{\text{max}}]\!]$ will be defined with α_{flex}.

$$\begin{cases} k_a^{\text{min}} = \hat{k}_a^{\text{s}} \cdot (1 - \alpha_{\text{flex}}^3) \\ k_a^{\text{max}} = \hat{k}_a^{\text{e}} + (K - \hat{k}_a^{\text{e}}).\alpha_{\text{flex}}^3 \end{cases} \tag{7}$$

This modelling is graphically presented on Figure1, and then included as a constraint in the solver, for each appliance.

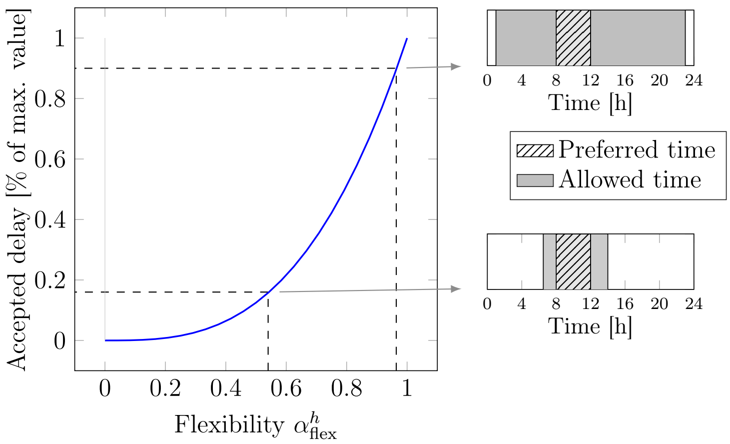


Figure 1: Flexibility modelling regarding the corresponding sensitivity

It is to be noted that the form of the curve is here to simulate the fact that low flexible stakeholders are more reluctant to be involved and to introduce variability in the involvement as we defined the profile group arbitrarily to test the approach on relevant groups. However, the comfort sensitivity is to be declared by the household themself, and therefore, a real study case will not required such model.

2.4. Constraints

To account for the technical limits (due to the type of appliances) and also for the constraints linked to the owners schedules and habits in every day appliances use, constraints concerning the users consumption are mathematically added to the model. It should be also reminded that the optimisation preserves the total energy consumed by each user and only shifts part of it. From the consumption model presented thereafter in Section 3.1, the 33 appliances of the model are considered here, with the addition of electrical vehicles. Their characteristics are gathered in Table 1. They are divided in four types, each with its own constraints. The set of appliances for a user h is defined as $\mathbb{A}^h$, and the power consumed by an appliance a at a step k as $x^h_{a,k}$. Furthermore, the $\hat{x}$ account for the forecasted (or preferred) power prior optimisation. By increasing flexibility order, the four specifics sets of appliances are:

- The fixed consumption (e.g. lighting), hereinafter referred to as subscript $\_{\mathrm{fi}}$, does not take part in the optimisation process and the appliances' constraints are therefore expressed as:

$$\forall a \in \mathbb{A}^h_{\mathrm{fi}}, \forall k \in \mathbb{K},\ x^h_{a,k} = \hat{x}^h_{a,k} \tag{8}$$

- Cycle appliances (e.g. dishwasher), hereinafter referred to as subscript $\_{\mathrm{cy}}$, have a fixed consumption sequence over their operating time τ_a, thus the optimisation affects only their schedule, depending on the user's sensitivity (Section 2.3). The start time of the appliance k^{s}_a must therefore comply with the allowed time interval $[\![\hat{k}^{\mathrm{s}}_a, \hat{k}^{\mathrm{e}}_a]\!]$ following:

$$\forall a \in \mathbb{A}^h_{\mathrm{cy}},\ k^{\mathrm{s}}_a \in [\![k^{\min}_a, k^{\max}_a - \tau_a]\!] \tag{9}$$

- The consumption of an on-off appliance (e.g. Hot water cylinder), hereinafter referred to as subscript $\_{\mathrm{oo}}$, with a rated power P_a is constrained by:

$$\forall a \in \mathbb{A}^h_{\mathrm{oo}} \begin{cases} x_{k,a} \in \{0, P_a\} \\ [\![k^{\mathrm{s}}_a, k^{\mathrm{e}}_a]\!] \subset [\![k^{\min}_a, k^{\max}_a]\!] \\ \sum_{k=1}^{K} x_{k,a} = \sum_{k=1}^{K} \hat{x}_{k,a} \end{cases} \tag{10}$$

- The most flexible appliances (e.g. Electrical Vehicle), hereinafter referred to as subscript $\_{\text{fl}}$, are constrained by their power step $P_{\text{a,step}}$ and rated power P_a:

$$\forall a \in \mathbb{A}^h_{\text{fl}} \begin{cases} x_{k,a} = n.p_{\text{step}} \leqslant P_a, \ n \in \mathbb{N} \\ [\![k^{\text{s}}_a, k^{\text{e}}_a]\!] \subset [\![k^{\min}_a, k^{\max}_a]\!] \\ \sum_{k=1}^{K} x_{k,a} = \sum_{k=1}^{K} \hat{x}_{k,a} \end{cases} \tag{11}$$

Lastly, the constraint reflecting the contract power P_c for each user is expressed as:

$$\forall (h,k) \in \mathbb{H} \times \mathbb{K}, \sum_{a \in \mathbb{A}^h} x^h_{k,a} \leqslant P^h_c \tag{12}$$

2.5. Algorithm

The optimisation process is a two stage algorithm. The aggregator in charge of dispatching the information of the total load on the grid L runs Algorithm 1 until it converges: The total load L on the grid is calculated and sent to each dwelling, one at a time, together with price and REN information. At the local level, when receiving the total load and if it has change since the last round, each dwelling optimises its consumption using Algorithm 2 and sends it back to the aggregator. Locally (Algorithm 2), the fixed consumption is stored by the user h, and for each appliance (Cycle first, then on-off, then flexible appliances) the dwelling solves (2) using dynamic programming and according to its preferences, its constraints and the state of the grid received from the aggregator. Once done, the grid load information is stored as L^* in order to compare the change at the next iteration. When a dwelling has no more interest to shift its consumption, its corresponding equilibrium dummy is set to one. Therefore, when all the users indicate one, the algorithm stops as the equilibrium is reached. Indeed, by optimising their consumption, the pay-off of the household either decreases or remains the same: as the objective function is non-negative, therefore bounded below, the global optimisation converges to a fixed point.The objective function (2) of each user being quadratic (therefore convex) and given the linear constraints (9), (10), (11) and (12) presented in Section 2.4, the strategy space is compact and convex: as

Table 1: Set of modelled appliances

Appliance	**Standby** [W]	**Type**	**Nominal Power** [W]	**Penetration** [rate]
Lightning	0	Fixed	-	1.000
Chest freezer	0	Fixed	190	0.000
Fridge & freezer	0	Fixed	190	0.692
Fridge	0	Fixed	110	0.327
Upright freezer	0	Fixed	155	0.523
Answerphone	1	Fixed	0	0.900
CD player	2	Fixed	15	0.900
Clock	2	Fixed	0	0.900
Phone	1	Fixed	0	0.871
HIFI	9	Fixed	100	0.540
Iron	0	Fixed	1000	0.900
Vacuum	0	Fixed	2000	0.900
Fax	3	Fixed	37	0.200
PC	5	Fixed	141	0.811
Printer	4	Fixed	335	0.665
TV1	3	Fixed	124	0.963
TV2	3	Fixed	124	0.440
TV3	3	Fixed	124	0.003
VCR & DVD	2	Fixed	34	0.699
Receiver	15	Fixed	27	0.592
Hob	1	Fixed	2400	0.463
Oven	3	Fixed	2125	0.616
Microwave	2	Fixed	1250	0.890
Kettle	1	Fixed	2000	0.975
Small cooking	2	Fixed	1000	1.000
Dish washer	0	Cycle	1131	0.608
Tumble Dryer	1	Cycle	1500	0.305
Washing machine	1	Cycle	406	0.964
Washer & Dryer	1	Cycle	792	0.100
DESWH	0	On-Off	3000	0.419
Inst. water heater	0	Fixed	3000	0.010
Electric shower	0	Fixed	9000	0.003
Electric heater	0	Fixed	3000	0.360
Electrical vehicle	0	Flexible	-	0.150

presented in Section 2.2, this proves that this point is a Nash equilibrium and is unique according to [36, 39]. A summary of the possessed and circulating informations implied by the decentralisation is presented in figure 2.

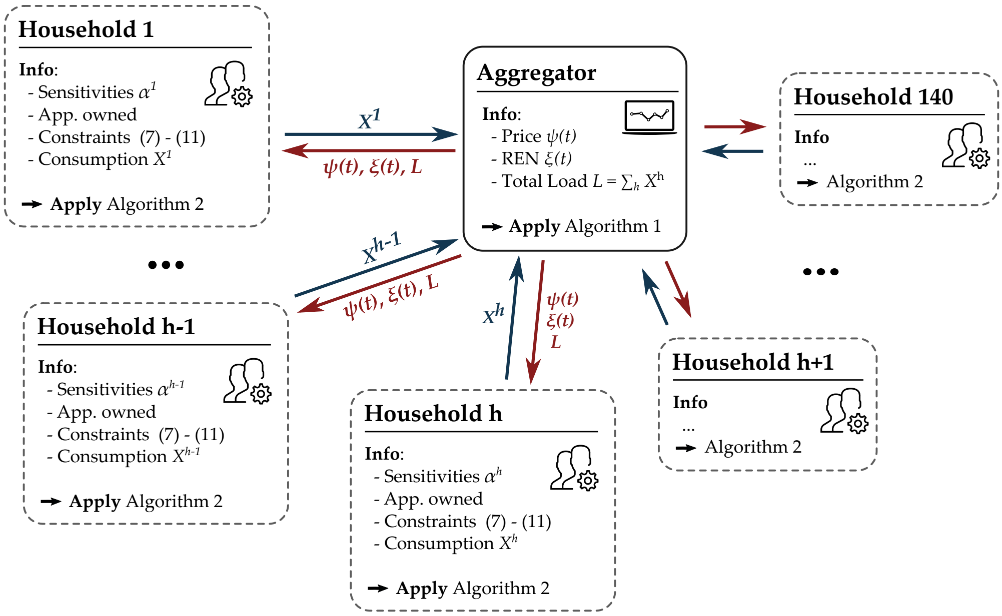


Figure 2: Possessed and circulating informations for the proposed decentralized scheme

Algorithm 1 Aggregator level

eq $\leftarrow 0$ ▷ Dummy for equilibrium
$L \leftarrow \sum_{h=1}^{H} \hat{X}^h$
while $eq \neq 1$ **do**
    for $h \leftarrow 1$ **to** H **do**
        send L to h
        Household h apply algorithm 2
        receive X^h
        $L \leftarrow \sum_{h=1}^{H} X^h$
    end for
end while

2.6. Metrics

In order to evaluate the proposed formulation, a relevant metric needs to be considered. For the grid, two indicators are calculated: the PAR and the Euclidean Square Distance (ESD), according to (13) and (14) respectively.

$$\mathrm{PAR} = \frac{\max_k L}{\overline{L}} \tag{13}$$

Algorithm 2 Household level

User h receive L
eq(h) $\leftarrow 0$
if $L \neq L^*$ **then**
  GridState $\leftarrow L - X^h$
  Fixed consumption is stored as X^h
  for each type cycle appliance **do**
    for each possible time slot (X) **do**
      h evaluates (2) with (9) and (12)
    end for
    h add the best reply to X^h
  end for
  for each type on-off then flexible appliance **do**
    for $k = 1$ **to** K **do** h solve (2) with (10), (11) and (12) using DP.
    end for
    h add the best reply to X^h
  end for
else
  eq(h) $\leftarrow 1$
end if
$L^* \leftarrow L$
send X^h and eq(h)

$$\mathrm{ESD} = \sum_{k=1}^{K} (x_k - \bar{x})^2 \tag{14}$$

For the consumers, four metrics are observed toward the evolution of the price paid (15), their consumption of renewables (16), their shifting effort (17) and a global one concerning their satisfaction, comparing theses values before and after the optimisation.

$$\gamma^h_{\mathrm{cost}} = \frac{\sum_{k=1}^{K} x^h_k \psi(k)\tau - \sum_{k=1}^{K} \hat{x}^h_k \psi(k)\tau}{\sum_{k=1}^{K} \hat{x}^h_k \psi(k)\tau} \tag{15}$$

$$\gamma^h_{\mathrm{env}} = \frac{\sum_{k=1}^{K} x^h_k \epsilon(k)\tau - \sum_{k=1}^{K} \hat{x}^h_k \epsilon(k)\tau}{\sum_{k=1}^{K} \hat{x}^h_k \epsilon(k)\tau} \tag{16}$$

In (16), $\epsilon(k)$ stands for the renewable energy production rate. The third indicator represents, in hours, the mean shifting delay of all the appliances contributing to the flexibility that are not transparent for the user (in contrast to those whose shifting is invisible, e.g. the hot water cylinder).

$$\gamma^h_{\mathrm{flex}} = \frac{\sum_{a \in \mathbb{A}^h_{\mathrm{cy}}} (k^s_a - \hat{k}^s_a)}{\mathrm{card}(\mathbb{A}^h_{\mathrm{cy}})} \tag{17}$$

Finally, the global satisfaction, or welfare, is measured according to the preferences of the user. As the perceived benefit depends indeed on the objective, the satisfaction (18) is therefore the ratio between the satisfied energy (using function ρ^h defined in Section 2.3) and the total consumed energy, introducing the time step duration τ.

$$\gamma^h_S = \frac{\sum_{k=1}^{K} x^h_k \cdot \rho^h(k) \cdot \tau}{\sum_{k=1}^{K} x^h_k \cdot \tau} \tag{18}$$

In addition, the evolution of the standard deviation σ for each metrics will be calculated.

3. Modelled scenarios

3.1. Consumption

To test the approach, the simulation is based on the model developed in [40]. It enables to simulate any given number of consumers in their daily energy consumption and to have a realistic scenario incorporating real problematic of the grid. Most of all, a detailed set of appliances (presented in Table 1) with their power consumption is incorporated and distributed given a probability linked to daily households activities. Details of the model can be found in the open source code provided by the authors [41]. The original model was adapted to account for the situation in France, based on data from the French national housing survey (Enquête National Logement) achieved by the National Institute of Statistics and Economic Studies (Institut National de la Statistique et des Études Économiques) [42]. The last column of Table 1 presents therefore the penetration rate for each appliance in France.

In addition, electrical vehicle (EV) where also added to the model in the same manner as [43]. The aim is to have a realistic approximation of possible EV contribution for the grid management. The first hypothesis are [44]: a penetration rate of 0.15 in France for the coming decades, and a modelling reduced to the four type of vehicles with the highest market share in France (gathered in Table 2), distributed amongst the population proportionally to those market shares. Then, the two type of charge (3.7 kW and 7.4 kW) available for private dwellings and compatible with the subscribed power and the daily simulation are distributed with a probability of 0.75 and 0.25 respectively. A conversion loss of 10% is considered for the consumption on the grid during the recharge.

Meanwhile, a normal distribution regarding the daily departure and arrival time is used to estimate the consumption of each vehicle once connected to the grid. The parameters of the corresponding probability density (esperance and standard deviation) are presented in Table 3 [45]. The steps for the modelling of the EV fleet, proceeding for each user in turn, are the following: 1. Assignment of a VE or not. 2. Assignment of a type VE and a type of charge. 3. Assignment of a travel. 4. Computation of the consumption (with an even

Table 2: Main electrical vehicles in France (2018)

Voiture	Capacity [kWh]	Range [km]	Grid consumption [Wh/km]	Rate
EV1	41	300	150	0.39
EV2	22	130	186	0.40
EV3	30	190	174	0.13
EV4	24	160	165	0.07

probability of recharging during the morning or the evening).

Table 3: Model of residential electrical vehicle use [45]

Distance μ [km]	St. dev. σ [km]	Departure μ [h]	St. dev. σ [h]	Arrival μ [h]	St. dev. σ [h]
35	10	8,5	0,5	18,5	0,5

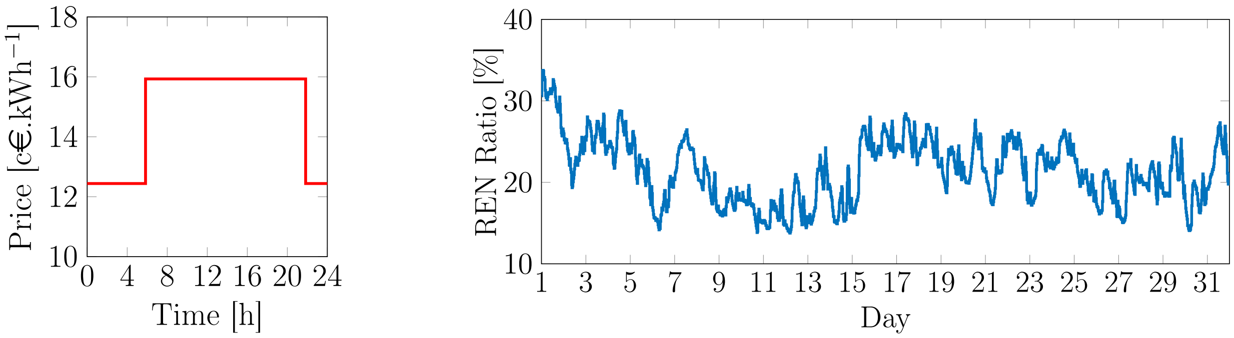
In order to observe a significant grid interaction and to serve as a baseline scenario, consumptions of 140 households were finally modelled over a month (31 days), with a 10-minutes time step.

3.2. External inputs

Evolution of price $\psi(k)$ and renewable energy production $\xi(k)$ are based on french transmission system operator database [46], and shown in Fig. 3. The price is a bi-level Time Of Use pricing (day/night) and the national REN ratio in the electricity production is retrieved from the data of January 2018.

3.3. Sensitivities and Profiles distribution

The most important contribution of this paper hinge on the introduction of consumer sensitivities in the energy management. As discussed in the introduction, various segmentations of the population are found in the literature depending on the chosen approach. In order to account for this heterogeneity, we introduce seven profile groups with a random variation of 20% around defined values of sensitivities, in the boundaries set by (4). This variability enables to keep a disparity while having distinct groups of profile, and the underlying assumption is that each real profile is a combination of these defined ones. We



(a) (b)

Figure 3: Evolution of (a) the electricity price over the day and (b) the hourly ratio of REN in the production over the month.

aim therefore to test and study the impact of the proposed management strategy amongst each group given the defined parameters, in order to validate the model. This distribution is summarized in Table 4.

Table 4: Profile distribution of the 140 households

Profile	**Population**	**Cost** α_{cost}	**REN** α_{env}	**Flexibility** α_{flex}
1	20	80-100%	-	80-100%
2	20	-	80-100%	80-100%
3	20	40-60%	40-60%	80-100%
4	20	80-100%	-	40-60%
5	20	-	80-100%	40-60%
6	20	40-60%	40-60%	40-60%
7	20	-	-	0-20%

3.4. Scenarios

Sc1 - Grid oriented DR The first scenario is a grid-oriented coordinated scenario, considering only the objective of reducing the load fluctuation on the grid. The given objective function is derived from (2) in which the consumers sensitivities are not considered: $\forall(h,k) \in \mathbb{H} \times \mathbb{K},\ \rho_k^h = 0$.

Sc2 - Mixed approach DR The second scenario is a mixed objective-oriented-coordination scenario. The grid goal in each is balanced with the sensitivities of the consumers. The households will be therefore able to participate or not, according to their sensitivities and constraints, thus using the first presented objective function (2).

Sc3 - Consumer centered DR The last scenario is a non coordinated scenario set to observe the effect of a unilateral conduct of the consumers. Users have the possibility to manage their consumption according solely to their preferences, given their constraints and the grid information concerning price and REN production. The limitation of the load fluctuation is considered only in relation to their own consumption. The objective function for a user h is the following: $U^h(X^h) = \sum_{k=1}^{K}[(1-\rho_k^h) \cdot x_k^h]^2$.

4. Simulation results

The output of the simulations, in terms of consumption power, is presented for the first day in Fig. 4 and the associated metrics in Table 5. For each scenario, the results (Table 7, 8 and 9) are compared relatively to the baseline, whose absolute values are gathered in Table 6.

Table 5: Grid Metrics

Metric	**Baseline**	**Sc1**	**Sc2**	**Sc3**
PAR [-]	2.43	−31%	−23%	−21%
ESD [10^{10} kW^2]	13.5	−48%	−37%	−31%

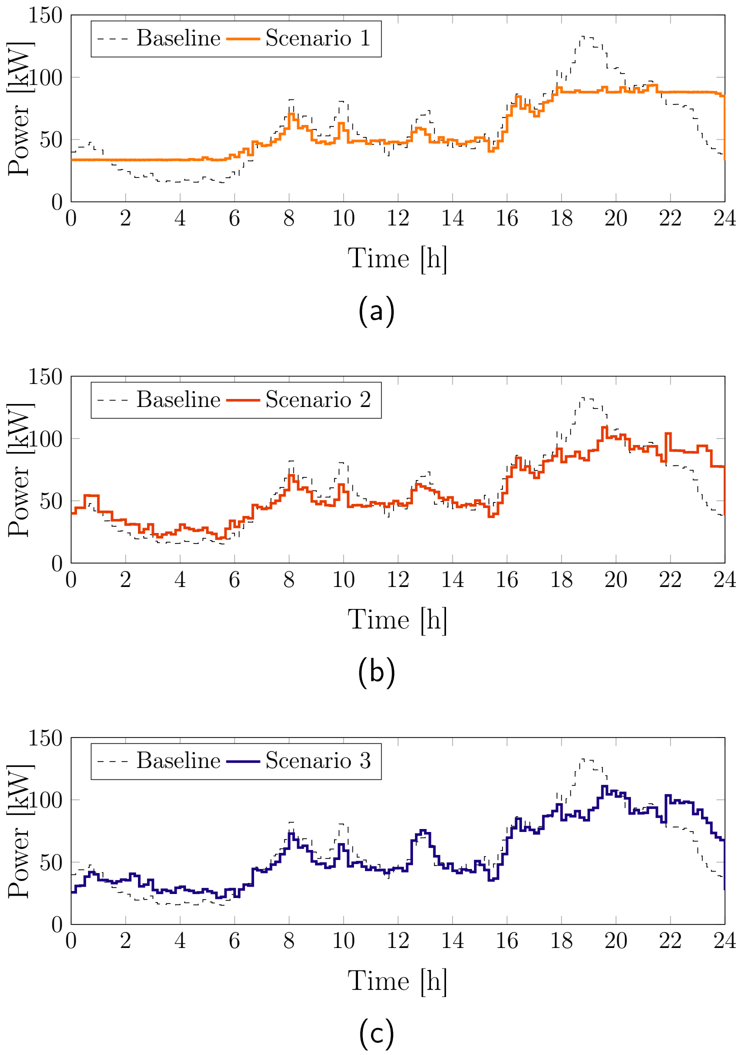


Figure 4: Evolution of the load for the scenario Sc1 (a), Sc2 (b) and Sc3 (c) during the first day.

4.1. Results Sc1

From a grid point of view, this scenario achieves the best results in terms of PAR and ESD reduction (respectively -31% and -48%). Concerning the consumers (Table 7), the global satisfaction increase slightly (5.4%), but the satisfaction of profile groups 2 and 5 decreases. Moreover, the shifting effort is maximum in this scenario.

4.2. Results Sc2

The best compromise is reached in the second scenario. The peak reduction and flattening of the load reach 23% and 37% respectively, and not only does the global satisfaction

Table 6: Monthly values of the baseline scenario by profile

Group	Satisfaction [%]	σ	Cost [€]	σ	REN [kWh]	σ
Global	66.2	20.6	48.9	16.5	11.5	14.8
Profile 1	57.3	22.9	49.9	17.3	10.6	13.6
Profile 2	78.4	11.1	44.8	14.4	6.0	5.3
Profile 3	64.6	17.5	51.0	17.2	13.9	17.6
Profile 4	55.4	25.3	47.9	15.0	12.5	15.4
Profile 5	78.5	13.7	44.0	13.9	6.9	9.3
Profile 6	67.3	17.9	46.9	17.6	11.3	15.8
Profile 7	62.1	21.6	58.0	17.7	19.0	19.7

Table 7: Sc1-metrics by profile

Group	Satisfaction γ_S [%]	σ	Cost γ_C [%]	σ	REN γ_E [%]	σ	Shift γ_{Sc} [h]	σ
Global	5.4	-16.1	-1.5	-5.0	-5.1	-5.8	2.3	2.2
Profile 1	32.5	-63.0	-2.0	-4.6	-6.0	-3.1	4.7	2.3
Profile 2	-13.7	49.6	-1.7	-2.0	-9.5	-10.3	4.2	1.7
Profile 3	8.1	-17.6	-2.4	-4.9	-7.1	-4.9	4.1	1.9
Profile 4	6.8	-20.0	-1.2	-7.2	-4.2	-7.7	1.0	0.5
Profile 5	-2.4	11.2	0.0	0.1	-1.0	-0.8	1.0	0.5
Profile 6	0.1	-1.7	-0.7	-4.7	-3.1	-6.3	1.1	0.7
Profile 7	6.4	-44.3	-2.2	-8.2	-5.2	-7.4	0.1	0.1

of consumers increase of 12.7%, but also the satisfaction for each profile group without exception (Table 8). Also to be noted, each profile objective is fulfilled with a corresponding shifting effort proportional to the defined flexibility, thus providing evidence of the relevance of the approach to respect consumers' objective while helping the grid.

For this scenario, a focus is made on the first day in order to observe the impact of the optimisation on a dwelling and the specific role of each appliance taking part in the flexibility. On this period, the price evolution is given in figure 3a and the REN ratio in figure 5. The shifting of the total load of the first dwelling (a price sensitive consumer ($\alpha_{\text{cost}} = 0.94, \alpha_{\text{flex}} = 0.95$)) is illustrated in figure 6, where it can be noticed that the consumption peaks during the day are shifted to low price period during the night. Amongst the whole population, the corresponding shifting of appliances taking part in the flexibility is

Table 8: Sc2-metrics by profile

Group	Satisfaction		Cost		REN		Shift	
	γ_S [%]	σ	γ_C [%]	σ	γ_E [%]	σ	γ_{Sc} [h]	σ
Global	12.7	-19.7	-1.4	-5.0	-2.2	-4.5	1.9	2.0
Profile 1	36.1	-72.2	-2.3	-5.2	-5.0	-2.4	4.5	2.2
Profile 2	11.9	-25.7	-0.1	0.0	7.7	5.3	2.0	0.9
Profile 3	11.8	-24.8	-2.6	-5.6	-5.6	-4.0	4.0	1.8
Profile 4	8.8	-18.0	-1.4	-8.7	-4.7	-7.9	0.9	0.5
Profile 5	7.0	2.1	0.2	0.7	3.9	1.3	0.9	0.4
Profile 6	4.1	-12.7	-0.9	-6.0	-0.7	-5.5	1.0	0.6
Profile 7	9.3	-53.8	-1.8	-5.8	-2.9	-4.0	0.1	0.1

presented graphically in figure 7, broken down with the shifting of the entire set of appliances in figure 7a, of cycle appliances in figure 7b, of HWC in figure 7c, and of the EV in figure 7d.

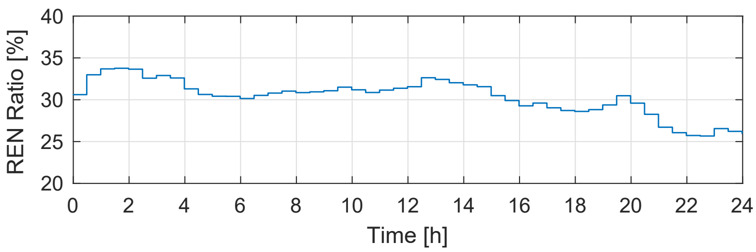


Figure 5: Evolution of the hourly ratio of REN in the production over the first day.

From figure 7, several observation arise. First that cycle appliances and HWC are strongly used for the flexibility at the begining of the day, especially the formers. This shift in time is explained by the high potential of satisfaction due to low price and high REN ratio at the beginning of the day (before 06:00).

Because of the constant energy constraint (this management does not reduce the energy over the day, but only shift the power profiles) and the fact that EV are not available during the day, they are heavily solicited at the end of the day. Indeed, with constant daily energy, it is required to match the total energy level at the end of the day, and they happen to be the last appliances available. If considered negative, this effect can be reduced by adding new constraints in order for the EV to share this responsibility with HWC.

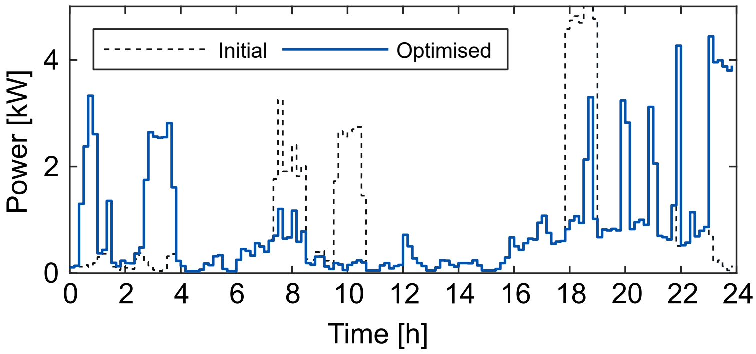


Figure 6: First day evolution of the consumption of a price sensitive dwelling ($\alpha_{\text{cost}} = 0.94, \alpha_{\text{flex}} = 0.95$).

4.3. Results Sc3

The last scenario shows similar results to the second one: PAR and ESD reduction of 21% and 31% respectively, as well as a global satisfaction increase of 12.7% (Table 9). Similarly, the evolution of metrics for each profile group is of the same order, showing no significant differences from the previous scenario.

This result is interesting as it shows a strong involvement of consumers, even when reducing the information exchange with the aggregator. It therefore demonstrates that an adequate information broadcast in the grid, together with an appropriate price scheme, is able to lead the consumption to an adapted power level for the grid equilibrium.

Table 9: Sc3-metrics by profile

Group	**Satisfaction**		**Cost**		**REN**		**Shift**	
	γ_S [%]	σ	γ_C [%]	σ	γ_E [%]	σ	γ_{Sc} [h]	σ
Global	12.7	-18.9	-1.3	-4.8	-1.9	-4.8	1.8	1.8
Profile 1	36.1	-72.3	-2.3	-5.2	-4.8	-3.2	4.2	2.0
Profile 2	11.9	-27.2	0.0	0.0	7.7	5.4	2.0	0.9
Profile 3	11.9	-22.1	-2.2	-4.4	-3.6	-3.9	3.5	1.6
Profile 4	9.0	-18.9	-1.4	-8.7	-4.1	-8.2	0.9	0.5
Profile 5	6.7	9.5	0.1	0.6	3.5	0.0	0.8	0.4
Profile 6	4.3	-12.6	-0.8	-5.0	0.1	-4.3	0.9	0.6
Profile 7	8.6	-51.4	-1.9	-6.5	-3.8	-5.3	0.1	0.1

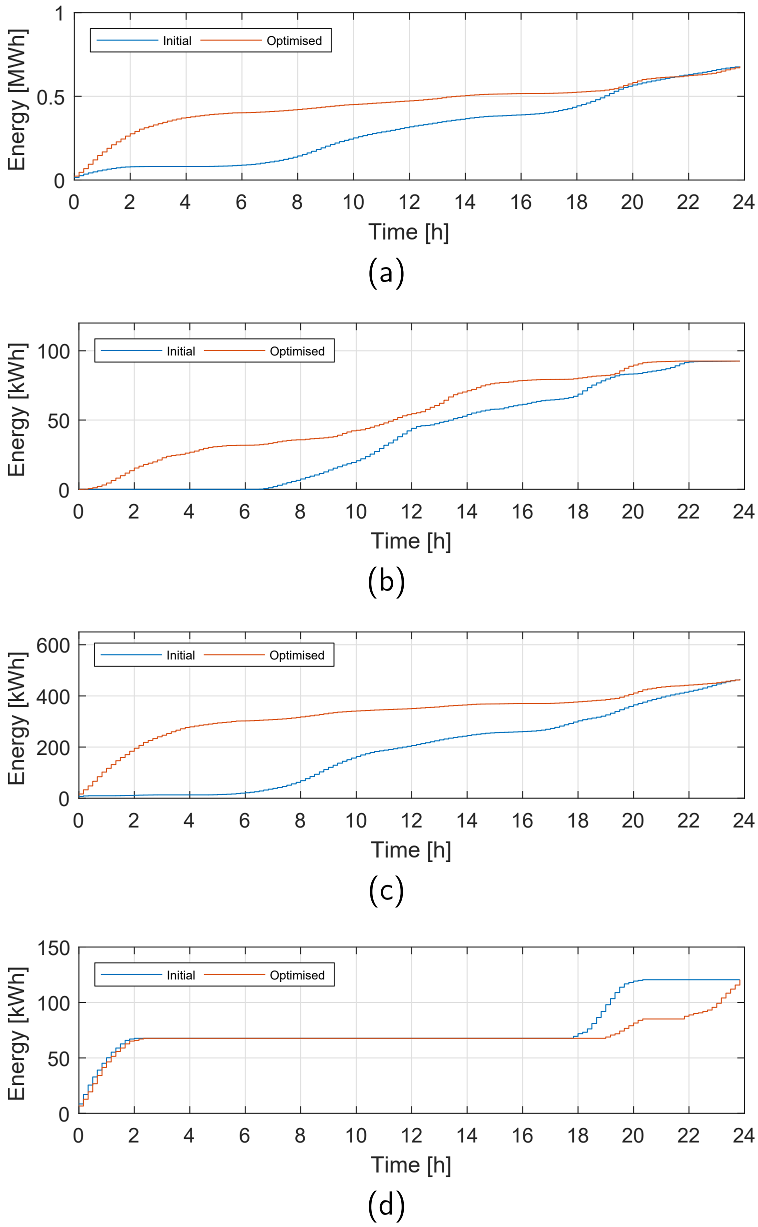


Figure 7: Cumulative energy sum for the appliances taking part in the flexibility, in the case of a REN hazard: entire set of appliances (7a), cycle appliances (7b), HWC (7c), EV (7d)

5. Discussion

To understand these results, it should be borne in mind that the observed increase of each indicator is limited by the daily baseline load distribution, the evolution of the external factor (price, REN) over which the consumer does not have control, and the constraints of the stakeholder (appliances ownership and type, power limit). Knowing this, it is therefore of prior importance to understand and include the different profiles and external factor to understand and model this effect. For example, it is noticeable that the cost sensitive profiles are the less impacted by the level of sensitivities inclusion in the DR program (0.3% difference in percentage of cost reduction between Sc1 and Sc2 for profile 1). It reflects that the price variation is by construction, correlated with the peak reduction objective of the grid, in opposition with the REN production that is by nature, stochastic. Therefore the REN sensitive profiles undergo a substantial decrease in satisfaction (e.g. -25.6% from Sc2 to Sc1 for profile 2) if they are not taken into account. This complexity appears clearly with the mixed profiles (3 and 6) for which an increase in satisfaction is ensured, but does not necessarily mean an improvement regarding both objectives, as they may be antagonists over the day. Furthermore, the price sensitive consumers reaching the highest increase of satisfaction can be explained by the two level price being either at its highest or lowest value. Thus, leading to possible high increase in satisfaction with minimum shifting effort. This effect can be reduced either by introducing more dynamic pricing scheme or by descretizing the renewable energy rate input.

Therefore, this approach succeed in taking into account the grid as well as the consumers objectives. Scenarios 2 and 3 show that both can be fulfilled while respecting the accepted shifting effort. Indeed, reduction of more than 20% of the PAR and more than 30% of the ESD are observed, while increasing the mean consumers satisfaction up to 13%. In this aspect, two of the original contributions of this work while achieving it are, in contrast with the literature: the involvement of consumers is bounded between 0 and 1, therefore easy to grasp and understand, with an introduced flexibility sensitivity ensured to be exploited in the allowed boundaries. Moreover, the similarity between scenarios 2 and 3 results indicates a weak impact, at the dwelling level, of including the grid load (Sc2) or only the dwelling load (Sc3) in the objective function. This interesting finding highlights therefore the possibility to limit the communication with the central entity during normal operation.

With this approach, same order of PAR reduction as in the presented literature is reached, but here with the evaluation of consumers welfare. This observed balance achieved between both grid and user objectives is of primary importance as it enhances the involvement of the consumers. Indeed, this involvement can only be harnessed by shifting energy management approach from a technocentrism perspective to an interdisciplinary paradigm [47].

To conclude, these results demonstrate that taking profiles into account is possible, but their understanding and definition is essential. In order to retrieve the best of the flexibilities, dispatching information (grid state, price, REN production) is therefore required. Thus, if an adequate price should be introduced, it must not be the only information considered in the DR program [48].

6. Conclusion

This paper proposes a day ahead energy management program stemming from a multidisciplinary based methodology. To incorporate three observed sensitivities and constraints of residential consumers, three different scenarios of an original decentralized optimisation process are presented in this paper: A classical DR grid-oriented approach ignoring consumers objectives (**Sc1**), and two others weighting the grid objective with dwellings sensitivities with (**Sc2**) or without (**Sc3**) considering the state of the grid. The **Sc2** scenario reaches the best results: e.g. a satisfaction increase of 12.7% amongst consumers, while respecting their sensitivities, ensuring their accepted comfort level, and achieving a reduction of the PAR and ESD grid metrics of 23% and 37% respectively. The third scenario **Sc3** giving similar results as **Sc2**, this work also introduced the possibility of limiting the information exchange between aggregator and dwellings.

Various perspectives arise from this work. Firstly in the refinement of the model, with the modelling of HWC and the water temperature, battery degradation of EV when used for ancillary services, etc. Secondly concerning the sociological consideration of the users in the management of the energy, if the parameters here are fixed and distributed amongst the simulated population, a real and local case study must be identified in order to test the approach on a given population. Indeed, involvement changes over time must be taken into account, but require on field investigations to observe the full scope of the approach beyond the technical possibilities demonstrated here. Finally, other grid objectives can be incorporated in the objectives function using this framework and depending on the local context, for example to follow a REN production.

To conclude, this work shows the benefit of a decentralized approach of electricity management considering consumers profiles, how to introduce them and how to optimise their load profile to increase their satisfaction using a game theory approach, while helping the grid. Firstly by modelling them and secondly by evaluating the possible pay-off and welfare for both the grid and the consumers while reducing the grid load variation.

Acknowledgement

This research work is funded by the French region Haut-de-France and HEI from Yncréa group.

References

[1] International Energy Agency (IEA). *Statistics: Electricity Information 2018 Overview*. IEA Publishing, 2018. ISBN: 9789264301207.

[2] Pierluigi Siano. Demand response and smart grids—A survey. *Renewable and Sustainable Energy Reviews*, 30:461–478, 2014.

[3] Haider Tarish Haider, Ong Hang See, and Wilfried Elmenreich. A review of residential demand response of smart grid. *Renewable and Sustainable Energy Reviews*, 59:166 – 178, 2016. ISSN 1364-0321.

[4] Berk Celik, Robin Roche, David Bouquain, and Abdellatif Miraoui. Decentralized neighborhood energy management with coordinated smart home energy sharing. *IEEE Transactions on Smart Grid*, 9(6): 6387–6397, 2018.

[5] A.K. Sinha and N. Kumar. Demand response management of smart grids using dynamic pricing. In *proc. 2016 International Conference on Inventive Computation Technologies (ICICT)*, august 2016.

[6] Prosanta Gope and Biplab Sikdar. An efficient privacy-preserving dynamic pricing-based billing scheme for smart grids. In *proc. 2018 IEEE Conference on Communications and Network Security (CNS)*, june 2018.

[7] Meisam Farrokhifar, Farid Momayyezi, Nasser Sadoogi, and Amin Safari. Real-time based approach for intelligent building energy management using dynamic price policies. *Sustainable Cities and Society*, 37:85–92, 2018.

[8] Lazaros Gkatzikis, Theodoros Salonidis, Nidhi Hegde, and Laurent Massoulié. Electricity markets meet the home through demand response. In *proc. IEEE 51st IEEE Conference on Decision and Control (CDC)*, pages 5846—5851, 2012.

[9] Chao Luo, Yih-Fang Huang, and Vijay Gupta. Stochastic Dynamic Pricing for EV Charging Stations With Renewable Integration and Energy Storage. *IEEE Transactions on Smart Grid*, 9(2):1494–1505, 2018.

[10] Yi Liu, Chau Yuen, Shisheng Huang, Naveed Ul Hassan, Xiumin Wang, and Shengli Xie. Peak-to-Average Ratio Constrained Demand-Side Management With Consumer's Preference in Residential Smart Grid. *IEEE Journal of Selected Topics in Signal Processing*, 8(6):1084–1097, 2014.

[11] Paulin Jacquot, Olivier Beaude, Stéphane Gaubert, and Nadia Oudjane. Demand response in the smart grid: The impact of consumers temporal preferences. In *proc. 2017 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, octobre 2017.

[12] Jungsuk Kwac, June Flora, and Ram Rajagopal. Lifestyle segmentation based on energy consumption. *IEEE Transactions on Smart Grid*, 9(4):2409–2410, 2018.

[13] Accenture. Understanding Consumer Preferences in Energy Efficiency. *Accenture end-consummer observatory on electricity management*, 2010.

[14] J. Naus, G. Spaargaren, B.J.M. Van Vliet, and H.M. Van der Horst. Smart grids, information flows and emerging domestic energy practices. *Energy Policy*, 68:436–446, 2014.

[15] Aira Hast, Behrang Alimohammadisagvand, and Sanna Syri. Consumer attitudes towards renewable energy in China—The case of Shanghai. *Sustainable Cities and Society*, 17:69–79, 2015.

[16] Benoit Durillon, Arnaud Davigny, Sabine Kazmierczak, Herve Barry, Christophe Saudemont, and Benoît Robyns. Demand side management considering consumers sensitivities using a game theory approach. In *proc. 2018 IEEE International Energy Conference (ENERGYCON)*, june 2018.

[17] Luciano C. Siebert, Lucas R. Ferreira, Eduardo K. Yamakawa, Eliane S. Custódio, Alexandre R. Aoki, Thelma S. P. Fernandes, and Kleber Hochwart Cardoso. Centralized and decentralized approaches to demand response using smart plugs. In *proc. 2014 IEEE PES T&D Conference and Exposition*, june 2014.

[18] Bhamidi Lokeshgupta and S. Sivasubramani. Multi-objective home energy management with battery energy storage systems. *Sustainable Cities and Society*, 47, 2019.

[19] Seokjae Moon and Jang-Won Lee. Multi-Residential Demand Response Scheduling With Multi-Class Appliances in Smart Grid. *IEEE Transactions on Smart Grid*, 9(4):2518–2528, 2018.

[20] Sana Noor, Wentao Yang, Miao Guoa, Koen H. van Dam, and Xiaonan Wang. Energy Demand Side Management within micro-grid networks enhanced by blockchain. *Applied Energy*, 228:1385–1398, 2018.

[21] Edstan Fernandez, M.J.Hossain, and M.S.H. Nizami. Game-theoretic approach to demand-side energy

management for a smart neighbourhood in Sydney incorporating renewable resources. *Applied Energy*, 232:245–257, 2018.

[22] Hamed Shakouri and Aliyeh Kazemi. Multi-objective cost-load optimization for demand side management of a residential area in smart grids. *Sustainable Cities and Society*, 32:171–180, 2017.

[23] Tiago Malavazi de Christo, Sylvain Perron, Jussara Farias Fardin, Domingos Sávio Lyrio Simonetti, and Cristina Engel de Alvarez. Demand-side energy management by cooperative combination of plans: A multi-objective method applicable to isolated communities. *Applied Energy*, 240:453–472, 2019.

[24] Iana Vassileva, Fredrik Wallin, and Erik Dahlquist. Understanding energy consumption behavior for future demand response strategy development. *Energy*, 46(1):94 – 100, 2012.

[25] G.R. Newsham and B.G. Bowker. The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: A review. *Energy Policy*, 38(7):3289–3296, 2010.

[26] P.M. Taube and D.N. MacDonald. A Dynamic Almost Ideal Demand System Incorporating Consumer Expectations. *Managerial and Decision Economics*, 12:197–206, 06 1991.

[27] Thamer Alquthami and A. P. Sakis Meliopoulos. Smart House Management and Control Without Customer Inconvenience. *IEEE Transactions on Smart Grid*, 9(4):2553–2562, 2018.

[28] Alexis Bourgeois, Margot Pellegrino, and Jean-Pierre Lévy. Modeling and mapping domestic energy behavior: Insights from a consumer survey in france. *Energy Research & Social Science*, 32:180–192, 2017.

[29] Flavia Gangale, Anna Mengolini, and Ijeoma Onyeji. Consumer engagement : An insight from smart grid projects in Europe. *Energy Policy*, 60:621–628, 2013. ISSN 0301-4215. doi: 10.1016/j.enpol.2013.05.031. URL `http://dx.doi.org/10.1016/j.enpol.2013.05.031`.

[30] Robin Smale, Bas Van Vliet, and Gert Spaargaren. Energy Research & Social Science When social practices meet smart grids : Flexibility , grid management , and domestic consumption in The Netherlands. *Energy Research & Social Science*, 34(June):132–140, 2017. ISSN 2214-6296. doi: 10.1016/j.erss.2017.06.037.

[31] Aimie Hope, Thomas Roberts, and Ian Walker. Energy Research & Social Science Consumer engagement in low-carbon home energy in the United Kingdom : Implications for future energy system decentralization. *Energy Research & Social Science*, 44(November 2017):362–370, 2018. ISSN 2214-6296. doi: 10.1016/j.erss.2018.05.032.

[32] Bryony Parrish, Phil Heptonstall, Rob Gross, and Benjamin K Sovacool. A systematic review of motivations , enablers and barriers for consumer engagement with residential demand response. *Energy Policy*, 138(December 2019):111221, 2020. ISSN 0301-4215. doi: 10.1016/j.enpol.2019.111221.

[33] Muhammad Hussain and Yan Gao. A review of demand response in an e ffi cient smart grid environment. *The Electricity Journal*, 31(5):55–63, 2018. ISSN 1040-6190. doi: 10.1016/j.tej.2018.06.003.

[34] Tom Hargreaves, Michael Nye, and Jacquelin Burgess. Keeping energy visible ? Exploring how householders interact with feedback from smart energy monitors in the longer term. *Energy Policy*, 52: 126–134, 2013. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.03.027.

[35] Kevin Burchell, Ruth Rettie, and Tom C Roberts. Householder engagement with energy consumption feedback : the role of community action and communications. 88(2016):178–186, 2020. doi: 10.1016/j.enpol.2015.10.019.

[36] J. B. Rosen. Existence and uniqueness of equilibrium points for concave n-person games. *Econometrica*, 33(3):520–534, 1965.

[37] Hung Khanh Nguyen and Ju Bin Song. Optimal charging and discharging for multiple phevs with demand side management in vehicle-to-building. *Journal of Communications and Networks*, 14(6): 662–671, 2012.

[38] Yu Liu, Guangchao Geng, Shan Gao, and Wilsun Xu. Non-Intrusive Energy Use Monitoring for a Group of Electrical Appliances. *IEEE Transactions on Smart Grid*, 9(4):3801–3810, 2018.

[39] John C. Goodman. Notes and comments - a note on existence and uniqueness of equilibrium points for concave n-person games. *Econometrica*, 48(1):251, 1980.

[40] E. McKenna and M. Thomson. High-resolution stochastic integrated thermal–electrical domestic demand model. *Applied Energy*, 165:445–461, 2016.

[41] Eoghan McKenna and Murray Thomson. CREST Demand Model. `https://figshare.com/articles/CREST_Demand_Model_v2_0/2001129`. [Accessed december 5, 2018].

[42] Institut national de la statistique et des études économiques (Insee). Enquête nationale sur le logement 2013 (ENL 2013). *National housing survey*, 2013. [On request].

[43] Siyamak Sarabi, Arnaud Davigny, Vincent Courtecuisse, Yann Riffonneau, and Benoit Robyns. Potential of vehicle-to-grid ancillary services considering the uncertainties in plug-in electric vehicle availability and service/localization limitations in distribution grids. *Applied Energy*, 171:523–540, 2017.

[44] European Climate Foundation and Fondation pour la Nature et l'Homme. From cradle to grave: e-mobility and the french energy transition. *Technical report*, 2017.

[45] Anouar Bouallaga, Arnaud Davigny, Vincent Courtecuisse, and Benoit Robyns. Methodology for technical and economic assessment of electric vehicles integration in distribution grid. *Mathematics and Computers in Simulation*, 131:172 – 189, 2017.

[46] RTE. éCO_2mix. `https://www.rte-france.com/fr/eco2mix/eco2mix`. [Accessed july 13, 2018].

[47] Margot Pellegrino and Marjorie Musy. Seven questions around interdisciplinarity in energy research. *Energy Research & Social Science*, 32:1–12, 2017.

[48] Wendy Miller and Manisha Senadeer. Social transition from energy consumers to prosumers: Rethinking

the purpose and functionality of eco-feedback technologies. *Sustainable Cities and Society*, 35:615–625, 2017.