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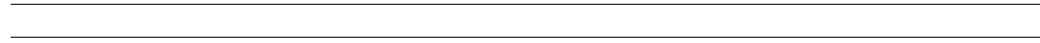
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Decentralized Neighbourhood Energy Management Considering Residential Profiles and Welfare for Grid Load Smoothing

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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

1 Nomenclature

- | | | |
|---|------------------------------|---|
| 2 | α^h | Sensitivity of consumer h towards price, REN, or confort |
| 3 | \mathbb{A}^h | Appliance set of consumer h |
| 4 | a | Appliance index |
| 5 | $\mathbb{A}_{fi/cy/oo/fl}^h$ | Respectively: fixed-, cycle-, on-off-, and flexible-appliance set of user h |
| 6 | eq | Dummy for equilibrium in the algorithm (equal 1 if no change occurs between |
| 7 | | two rounds) |

8	\mathbb{H}	Set of the H consumers
9	h	Index for users
10	H	Number of consumers
11	K	Number of time steps
12	k	Time step index
13	\hat{k}_a^s, \hat{k}_a^e	Forecasted departure and end time for appliance a
14	k_a^{\min}, k_a^{\max}	Allowed departure and end time for appliance a
15	L	Total load on the grid
16	$\phi_{..}$	Instant ratio of the factor cost or environnement
17	ψ	Price function over the day
18	P_c^h	Contract power of user h
19	ρ^h	Satisfaction function of consumer h
20	τ	Time step duration
21	U^h	Objective function of consumer h
22	ξ	Renewable energy power ratio produced
23	X	$K \times H$ matrix containing the consumption of the H households
24	\mathbb{X}^h	Strategy set of consumer h
25	x_k^h	Power of consumer h at k
26	X^h	Power profile of consumer h
27	$x_{a,k}^h$	Power of appliance a of consumer h at k

28	$\hat{x}_{a,k}^h$	Forecasted power of appliance a of consumer h at k
29	X^{-h}	Power profile of all consumers except consumer h
30	X^{h*}	Optimal strategy of consumer h

31 1. Introduction

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

42 For this purpose, Demand Side Management (DSM), and especially Demand Response
43 (DR) [2] are used to control the load at the household level depending generally on the price
44 level [3, 4]. Dynamic pricing is therefore getting increasingly studied in recent publications
45 [5, 6, 7, 8]: it aims to limit the consumption at critical peak hours to avoid congestion,
46 encouraging the consumers to reduce their bill by lowering their demand or shifting their
47 consumption over the day, or by guiding price-based automated load scheduling [9]. However,
48 as previously mentioned, usual DR programs neglect the complexity of consumers profiles by
49 only considering price signal to regulate the load: as the need for control increases, involve-
50 ment and sensitivities of stakeholders should be taken into account through more complete
51 management programs [10, 11]. Aiming for sustainable cities where the stakeholders are
52 more responsible for the production, the consumption, and the share of electricity means
53 indeed to consider each one of them while sharing the pay-off, to encourage and ensure their

54 engagement. Multidisciplinary approaches involving electrical engineering together with hu-
55 manities and social sciences must be therefore considered, in order for the profiles to be
56 understood and then included in the DR program. From a technical point of view [12]
57 suggests for example a segmentation of consumers' lifestyles based on their electricity con-
58 sumption, while relying on surveys, [13] shows the heterogeneity of consumers' engagement
59 through six profiles.

60 Concrete examples of the involvement beyond the financial aspect are to be found in
61 [14] or [15]: showing the pluralism of possible trigger for consumers contribution in energy
62 management. Simply by giving feedback and relying on awareness, therefore letting the
63 households manage their consumption according to their own values, reduction of energy
64 consumption equivalent to a price increase of 11-20% are observed. The core problem of
65 DR programs is to optimise the load of various consumers given their constraints and their
66 objectives, while ensuring the required balance on the grid. To address this challenge, several
67 methods are used: either considering households loads as only continuous [16, 11] or only
68 shiftable [8], or a mix between loads types [10]. The weakness of the first approaches is
69 their inability to encompass the full complexity of dwelling consumption and to retrieve
70 the complete flexibility of residential users. Furthermore, regardless of the method, the
71 optimisation process is either centralized or decentralized. Centralized management reaches
72 better results but requires a higher investment for the communication infrastructure [17]
73 and raises the questions of privacy and acceptance by the users, as it means letting an other
74 entity interfere with their consumption. Thus, residential DR program tend to decentralized
75 approaches [4], enabling the users to autonomously manage their consumption. The next
76 step is then to incorporate the users preferences.

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

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

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

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

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

107 Studying the contribution of a game theory approach enhanced by a blockchain imple-
108 mented energy management, [20] study as well the PAR reduction and the cost savings for
109 the grid and the household by relying on individual appliances flexibility. However, only the
110 shifting sensitivity per consumers is taken into account. Similarly, the cost minimization
111 is considered through a real time pricing strategy in [21] using a game theory approach,

112 once again to decrease the cost and the PAR, here with one participation parameter. User
113 preferences are the focus of [22], with a preferred time interval considered for each con-
114 sumers during the optimisation of the cost. The centralized approach requires nevertheless
115 that each user gives its details of preferences and consumption to the central entity. Lastly,
116 the comfort notion is discussed in [23] by defining different strategies for the consumers
117 and indicating a favoured one. The deviation from the aforementioned is considered as a
118 *discomfort*. The number of users deviating from their preferred strategies is considered as
119 a measurement of the community discomfort, and considered in the optimisation process,
120 which aim at reducing the cost for the entire community. The limitation of this approach is
121 that individual discomfort is neither evaluated nor scaled.

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

126 In this paper, we present therefore a complete management system aiming to lower the
127 PAR and the fluctuation of the neighbourhood's load while considering the diversity of load
128 (fixed, discrete, continuous, cycle) and profiles. The local optimisation is performed au-
129 tonomously by the dwellings using multi-pass Dynamic Programming (DP). Additionally,
130 we incorporate whole consumers profiles along three sensitivities: financial, environmental,
131 and comfort. The focus is on the corresponding energy management strategy, discussing how
132 to work with these sensitivities found in the literature that can be taken into account in such
133 context. The value of the parameters used in this research can be adjusted or defined by
134 numerical functions according to the results of local studies in a given population. Further-
135 more, keeping the consumers reacting to DR programs incentives over time is also an other
136 issue that is not in the technical scope of the present paper, as it requires sociological, psy-
137 chological and economic approaches to grasp and propose an appropriate environment. For
138 this purpose, day ahead shifting possibilities and their influence on measurable factors (paid
139 price, renewable consumption, and comfort as we defined it) are incorporated. The cost
140 (both economic and environmental) of technical solutions being long term considerations,

141 it needs to be studied on long term energy management program, together with economic
142 model to grasp the best of such flexibility, and therefore not considered in this work. Seven
143 profiles are thus presented in this paper, but they can be then split into the wide variety
144 of real observed profiles in a given population. The aim of this paper is therefore to give
145 a critical perspective using three scenarios stemming from the presented approach, through
146 their application to a modelled population. Results should indeed be assessed from a grid
147 point of view, but also from the users' perspective, as their inclusion is essential to enhance
148 acceptance first and then their involvement [24].

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

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

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

166 **2. Methodology**

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

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

172 *2.1. Socio-economic approach*

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

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

190 Resulting from this first step, three main sensibilities are to be found amongst residential
191 consumers, from which ensue the different profiles: sensitivity toward the energy environ-
192 mental impact, the energy cost, and the shifting effort required to react to the first two
193 sensitivities. Knowing the existing profiles, defining them in a given population or in a lim-
194 ited space can be achieved through various means: either by survey [13], by self-statement

195 of the households (declared or registered through smart appliances manager [27]), or by
196 statistical analysis if the relevant data are available [28].

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

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

217 2.2. Demand Response approach

218 Considering the context presented in the introduction, the following decentralized prob-
219 lem formulation is drawn from the pursuit of the best compromise between privacy, data
220 flow, computing power, embedded preferences, and grid equilibrium, compared to central-
221 ized methods. Working a day ahead, an aggregator, as a central entity, is in charge of
222 collecting and gathering the total load on the grid, and sending this information to each of

223 the consumers in order for the optimisation to be performed.

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

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

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

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

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

247 *2.3. Objective function and sensitivities*

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

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

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

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

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

$$\begin{cases} \forall h \in \mathbb{H}, \alpha_{\text{cost}}^h + \alpha_{\text{env}}^h = 1 \\ \forall h \in \mathbb{H}, \{\alpha_{\text{cost}}^h, \alpha_{\text{env}}^h, \alpha_{\text{flex}}^h\} \in [0, 1] \end{cases} \quad (4)$$

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

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

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

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

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

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

289 For each appliance of a user h , this flexibility is linked to the forecasted and preferred time
 290 schedule considering α_{flex}^h . The allowed time interval to shift the appliances when optimising
 291 the consumption is therefore defined as a percentage of the maximum possible time over the

292 day (midnight-midnight), according to (7). The same process is used for all appliances of h
 293 taking part in the flexibility and this allowed period will then serve during the optimisation
 294 to define the possible time slots to evaluate. The forecasted time is referred to as $[[\hat{k}_a^s, \hat{k}_a^e]]$
 295 and the allowed time to shift it $[[k_a^{\min}, k_a^{\max}]]$ will be defined with α_{flex} .

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

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

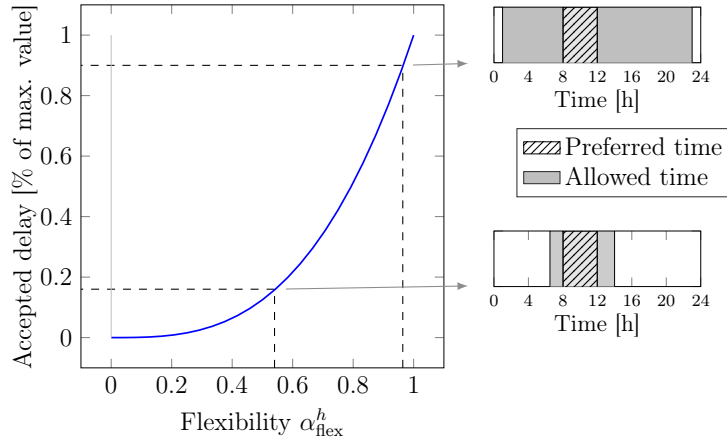


Figure 1: Flexibility modelling regarding the corresponding sensitivity

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

303 2.4. Constraints

304 To account for the technical limits (due to the type of appliances) and also for the
 305 constraints linked to the owners schedules and habits in every day appliances use, constraints
 306 concerning the users consumption are mathematically added to the model. It should be also

307 reminded that the optimisation preserves the total energy consumed by each user and only
 308 shifts part of it. From the consumption model presented thereafter in Section 3.1, the 33
 309 appliances of the model are considered here, with the addition of electrical vehicles. Their
 310 characteristics are gathered in Table 1. They are divided in four types, each with its own
 311 constraints. The set of appliances for a user h is defined as \mathbb{A}^h , and the power consumed
 312 by an appliance a at a step k as $x_{a,k}^h$. Furthermore, the \hat{x} account for the forecasted (or
 313 preferred) power prior optimisation. By increasing flexibility order, the four specific sets of
 314 appliances are:

- 315 • The fixed consumption (e.g. lighting), hereinafter referred to as subscript _fi , does
 316 not take part in the optimisation process and the appliances' constraints are therefore
 317 expressed as:

$$\forall a \in \mathbb{A}_{\text{fi}}^h, \forall k \in \mathbb{K}, x_{a,k}^h = \hat{x}_{a,k}^h \quad (8)$$

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

$$\forall a \in \mathbb{A}_{\text{cy}}^h, k_a^s \in [[k_a^{\min}, k_a^{\max} - \tau_a]] \quad (9)$$

- 322 • The consumption of an on-off appliance (e.g. Hot water cylinder), hereinafter referred
 323 to as subscript _oo , with a rated power P_a is constrained by:

$$\forall a \in \mathbb{A}_{\text{oo}}^h \left\{ \begin{array}{l} x_{k,a} \in \{0, P_a\} \\ [[k_a^s, k_a^e]] \subset [[k_a^{\min}, k_a^{\max}]] \\ \sum_{k=1}^K x_{k,a} = \sum_{k=1}^K \hat{x}_{k,a} \end{array} \right. \quad (10)$$

- 324 • The most flexible appliances (e.g. Electrical Vehicle), hereinafter referred to as sub-

325 script $_fl$, are constrained by their power step $P_{a,step}$ and rated power P_a :

$$\forall a \in \mathbb{A}_{fl}^h \begin{cases} x_{k,a} = n \cdot p_{step} \leq P_a, \quad n \in \mathbb{N} \\ \llbracket k_a^s, k_a^e \rrbracket \subset \llbracket k_a^{\min}, k_a^{\max} \rrbracket \\ \sum_{k=1}^K x_{k,a} = \sum_{k=1}^K \hat{x}_{k,a} \end{cases} \quad (11)$$

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

$$\forall (h, k) \in \mathbb{H} \times \mathbb{K}, \quad \sum_{a \in \mathbb{A}^h} x_{k,a}^h \leq P_c^h \quad (12)$$

327 2.5. Algorithm

328 The optimisation process is a two stage algorithm. The aggregator in charge of dispatch-
 329 ing the information of the total load on the grid L runs Algorithm 1 until it converges: The
 330 total load L on the grid is calculated and sent to each dwelling, one at a time, together
 331 with price and REN information. At the local level, when receiving the total load and if it
 332 has change since the last round, each dwelling optimises its consumption using Algorithm 2
 333 and sends it back to the aggregator. Locally (Algorithm 2), the fixed consumption is stored
 334 by the user h , and for each appliance (Cycle first, then on-off, then flexible appliances) the
 335 dwelling solves (2) using dynamic programming and according to its preferences, its con-
 336 straints and the state of the grid received from the aggregator. Once done, the grid load
 337 information is stored as L^* in order to compare the change at the next iteration. When a
 338 dwelling has no more interest to shift its consumption, its corresponding equilibrium dummy
 339 is set to one. Therefore, when all the users indicate one, the algorithm stops as the equi-
 340 librium is reached. Indeed, by optimising their consumption, the pay-off of the household
 341 either decreases or remains the same: as the objective function is non-negative, therefore
 342 bounded below, the global optimisation converges to a fixed point. The objective function
 343 (2) of each user being quadratic (therefore convex) and given the linear constraints (9),
 344 (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

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

347 the decentralisation is presented in figure 2.

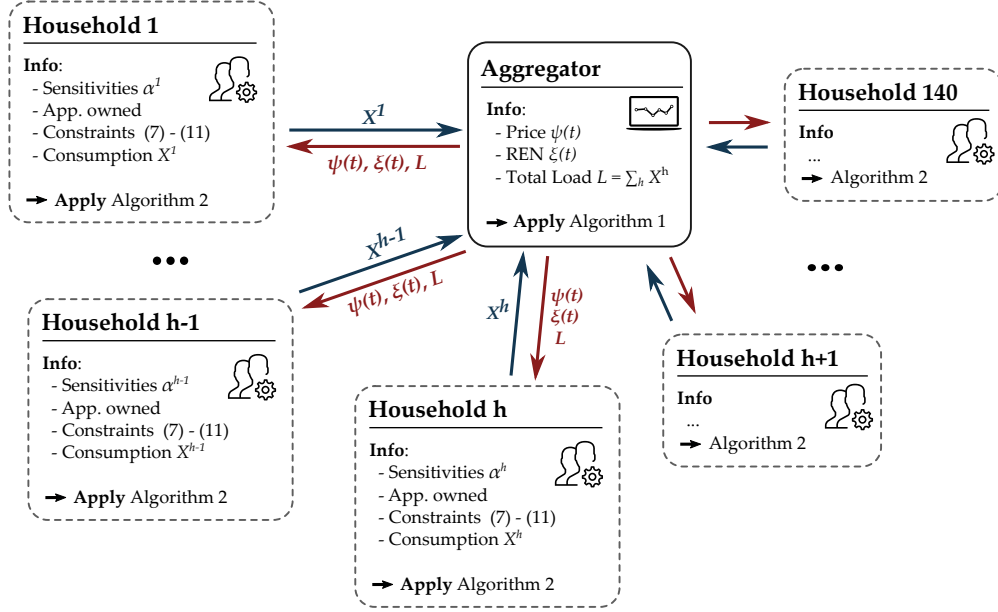


Figure 2: Possessed and circulating informations for the proposed decentralized scheme

Algorithm 1 Aggregator level

```

1: eq ← 0 ▷ Dummy for equilibrium
2:  $L \leftarrow \sum_{h=1}^H \hat{X}^h$ 
3: while eq ≠ 1 do
4:   for  $h \leftarrow 1$  to  $H$  do
5:     send  $L$  to  $h$ 
6:     Household  $h$  apply algorithm 2
7:     receive  $X^h$ 
8:      $L \leftarrow \sum_{h=1}^H X^h$ 
9:   end for
10: end while

```

348 2.6. Metrics

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

$$\text{PAR} = \frac{\max_k L}{\bar{L}} \quad (13)$$

Algorithm 2 Household level

```
1: User  $h$  receive  $L$ 
2:  $\text{eq}(h) \leftarrow 0$ 
3: if  $L \neq L^*$  then
4:    $\text{GridState} \leftarrow L - X^h$ 
5:   Fixed consumption is stored as  $X^h$ 
6:   for each type cycle appliance do
7:     for each possible time slot (X) do
8:        $h$  evaluates (2) with (9) and (12)
9:     end for
10:     $h$  add the best reply to  $X^h$ 
11:   end for
12:   for each type on-off then flexible appliance do
13:     for  $k = 1$  to  $K$  do  $h$  solve (2) with (10), (11) and (12) using DP.
14:     end for
15:      $h$  add the best reply to  $X^h$ 
16:   end for
17: else
18:    $\text{eq}(h) \leftarrow 1$ 
19: end if
20:  $L^* \leftarrow L$ 
21: send  $X^h$  and  $\text{eq}(h)$ 
```

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

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

$$\gamma_{\text{cost}}^h = \frac{\sum_{k=1}^K x_k^h \psi(k) \tau - \sum_{k=1}^K \hat{x}_k^h \psi(k) \tau}{\sum_{k=1}^K \hat{x}_k^h \psi(k) \tau} \quad (15)$$

$$\gamma_{\text{env}}^h = \frac{\sum_{k=1}^K x_k^h \epsilon(k) \tau - \sum_{k=1}^K \hat{x}_k^h \epsilon(k) \tau}{\sum_{k=1}^K \hat{x}_k^h \epsilon(k) \tau} \quad (16)$$

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

$$\gamma_{\text{flex}}^h = \frac{\sum_{a \in \mathbb{A}_{\text{cy}}^h} (k_a^s - \hat{k}_a^s)}{\text{card}(\mathbb{A}_{\text{cy}}^h)} \quad (17)$$

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

$$\gamma_S^h = \frac{\sum_{k=1}^K x_k^h \cdot \rho^h(k) \cdot \tau}{\sum_{k=1}^K x_k^h \cdot \tau} \quad (18)$$

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

364 **3. Modelled scenarios**

365 *3.1. Consumption*

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

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

386 Meanwhile, a normal distribution regarding the daily departure and arrival time is used
387 to estimate the consumption of each vehicle once connected to the grid. The parameters of
388 the corresponding probability density (esperance and standard deviation) are presented in
389 Table 3 [45]. The steps for the modelling of the EV fleet, proceeding for each user in turn,
390 are the following: 1. Assignment of a VE or not. 2. Assignment of a type VE and a type
391 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

392 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

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

396 3.2. External inputs

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

401 3.3. Sensitivities and Profiles distribution

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

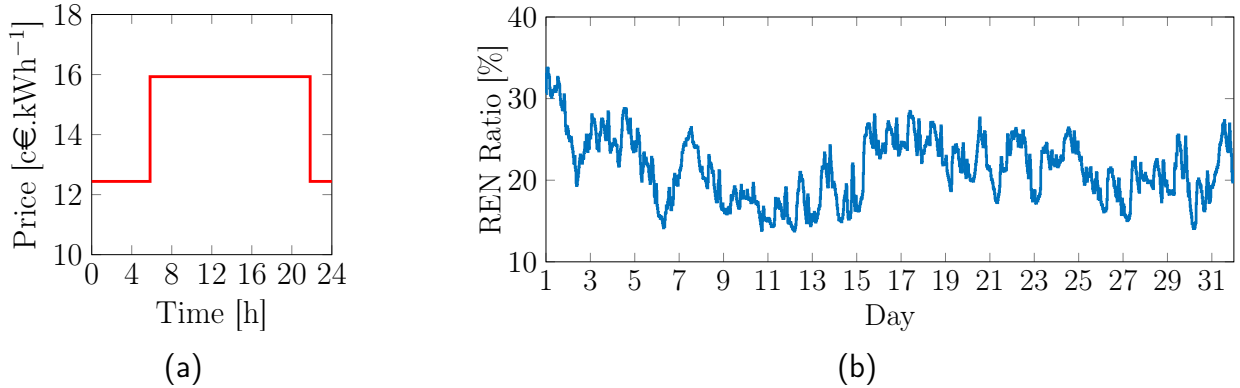


Figure 3: Evolution of (a) the electricity price over the day and (b) the hourly ratio of REN in the production over the month.

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

Table 4: Profile distribution of the 140 households

Profile	Population	Cost	REN	Flexibility
		α_{cost}	α_{env}	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%

412 3.4. Scenarios

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

417 **Sc2 - Mixed approach DR** The second scenario is a mixed objective-oriented-coordination
 418 scenario. The grid goal in each is balanced with the sensitivities of the consumers. The

419 households will be therefore able to participate or not, according to their sensitivities
 420 and constraints, thus using the first presented objective function (2).

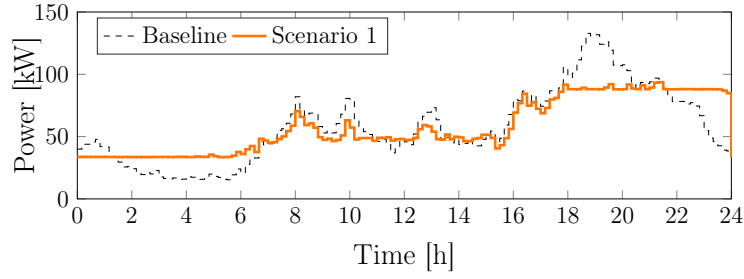
421 **Sc3 - Consumer centered DR** The last scenario is a non coordinated scenario set to
 422 observe the effect of a unilateral conduct of the consumers. Users have the possibility to
 423 manage their consumption according solely to their preferences, given their constraints
 424 and the grid information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

427 4. Simulation results

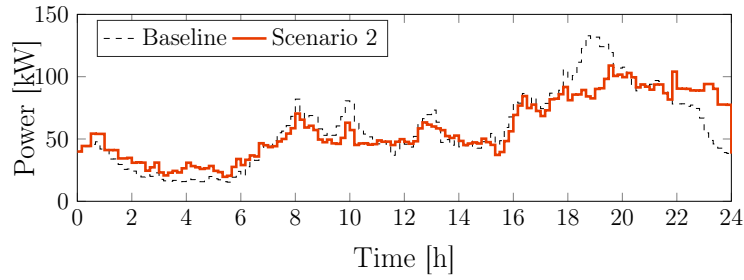
428 The output of the simulations, in terms of consumption power, is presented for the first
 429 day in Fig. 4 and the associated metrics in Table 5. For each scenario, the results (Table
 430 7, 8 and 9) are compared relatively to the baseline, whose absolute values are gathered in
 431 Table 6.

Table 5: Grid Metrics

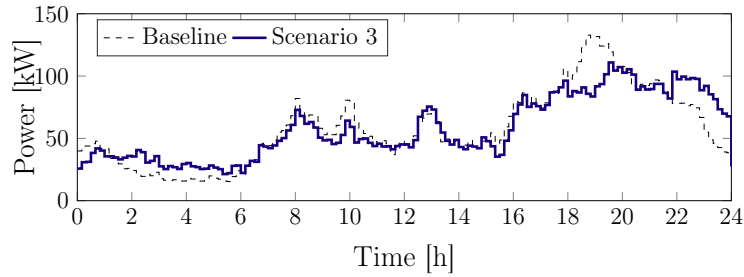
Metric	Baseline	Sc1	Sc2	Sc3
PAR [-]	2.43	-31%	-23%	-21%
ESD [10^{10} kW ²]	13.5	-48%	-37%	-31%



(a)



(b)



(c)

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

432 *4.1. Results Sc1*

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

437 *4.2. Results Sc2*

438 The best compromise is reached in the second scenario. The peak reduction and flatten-
 439 ing 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	σ
	[%]		[€]		[kWh]	
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	σ	Cost	σ	REN	σ	Shift	σ
	γ_S [%]		γ_C [%]		γ_E [%]		γ_{Sc} [h]	
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

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

444 For this scenario, a focus is made on the first day in order to observe the impact of
445 the optimisation on a dwelling and the specific role of each appliance taking part in the
446 flexibility. On this period, the price evolution is given in figure 3a and the REN ratio in
447 figure 5. The shifting of the total load of the first dwelling (a price sensitive consumer
448 ($\alpha_{\text{cost}} = 0.94, \alpha_{\text{flex}} = 0.95$)) is illustrated in figure 6, where it can be noticed that the
449 consumption peaks during the day are shifted to low price period during the night. Amongst
450 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

451 presented graphically in figure 7, broken down with the shifting of the entire set of appliances
452 in figure 7a, of cycle appliances in figure 7b, of HWC in figure 7c, and of the EV in figure
453 7d.

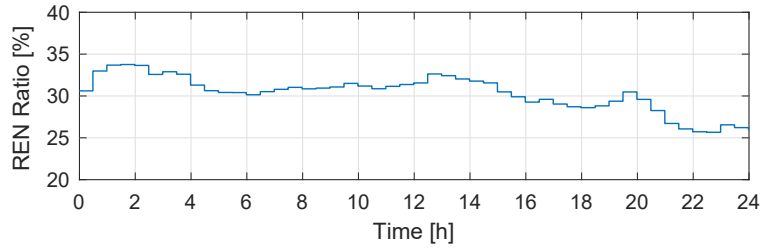


Figure 5: Evolution of the hourly ratio of REN in the production over the first day.

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

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

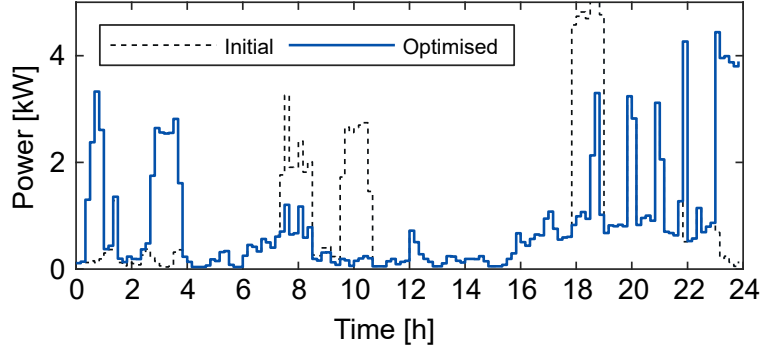


Figure 6: First day evolution of the consumption of a price sensitive dwelling ($\alpha_{\text{cost}} = 0.94, \alpha_{\text{flex}} = 0.95$).

464 4.3. Results Sc3

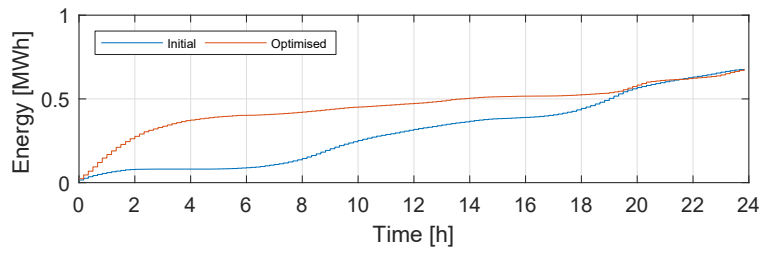
465 The last scenario shows similar results to the second one: PAR and ESD reduction of 21%
 466 and 31% respectively, as well as a global satisfaction increase of 12.7% (Table 9). Similarly,
 467 the evolution of metrics for each profile group is of the same order, showing no significant
 468 differences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

469 This result is interesting as it shows a strong involvement of consumers, even when
 470 reducing the information exchange with the aggregator. It therefore demonstrates that an
 471 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.

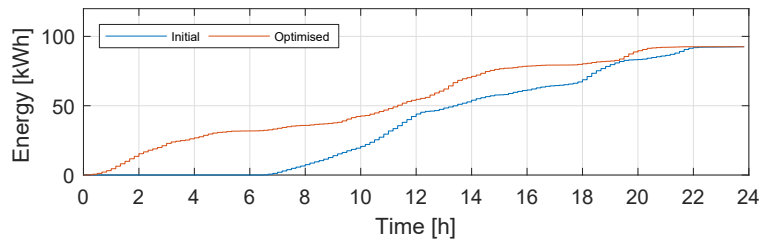
Table 9: Sc3-metrics by profile

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

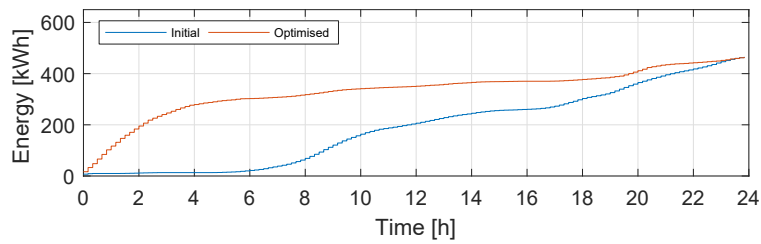
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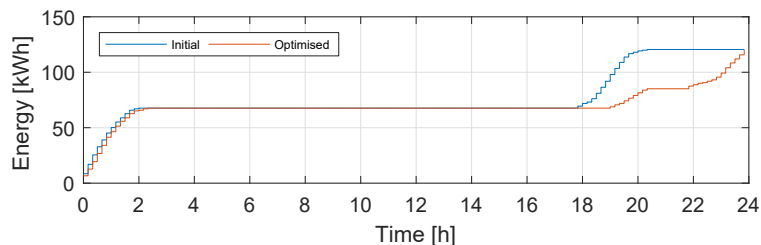
(a)



(b)



(c)



(d)

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)

473 **5. Discussion**

474 To understand these results, it should be borne in mind that the observed increase of
 475 each indicator is limited by the daily baseline load distribution, the evolution of the external
 476 factor (price, REN) over which the consumer does not have control, and the constraints of
 477 the stakeholder (appliances ownership and type, power limit). Knowing this, it is therefore

478 of prior importance to understand and include the different profiles and external factor
479 to understand and model this effect. For example, it is noticeable that the cost sensitive
480 profiles are the less impacted by the level of sensitivities inclusion in the DR program (0.3%
481 difference in percentage of cost reduction between Sc1 and Sc2 for profile 1). It reflects that
482 the price variation is by construction, correlated with the peak reduction objective of the
483 grid, in opposition with the REN production that is by nature, stochastic. Therefore the
484 REN sensitive profiles undergo a substantial decrease in satisfaction (e.g. -25.6% from Sc2
485 to Sc1 for profile 2) if they are not taken into account. This complexity appears clearly
486 with the mixed profiles (3 and 6) for which an increase in satisfaction is ensured, but does
487 not necessarily mean an improvement regarding both objectives, as they may be antagonists
488 over the day. Furthermore, the price sensitive consumers reaching the highest increase of
489 satisfaction can be explained by the two level price being either at its highest or lowest value.
490 Thus, leading to possible high increase in satisfaction with minimum shifting effort. This
491 effect can be reduced either by introducing more dynamic pricing scheme or by descretizing
492 the renewable energy rate input.

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

504 With this approach, same order of PAR reduction as in the presented literature is reached,
505 but here with the evaluation of consumers welfare. This observed balance achieved between
506 both grid and user objectives is of primary importance as it enhances the involvement of the

507 consumers. Indeed, this involvement can only be harnessed by shifting energy management
508 approach from a technocentrism perspective to an interdisciplinary paradigm [47].

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

514 6. Conclusion

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

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

534 incorporated in the objectives function using this framework and depending on the local
535 context, for example to follow a REN production.

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

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