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Abstract

To address the new challenges arising from the higher penetration of renewable energy in electrical grid, Demand Response (DR) aims to involve the residential consumers in the grid equilibrium. Ensuring benefits for both utility and users requires the consumers sensitivities to be understood and then included in the Energy Management System (EMS). For this purpose, the cost is the predominant and most often only factor taken into account in the literature, although in the residential sector other concerns influencing electricity consumption behaviour have been observed. This paper presents a two levels EMS applied to a neighbourhood of consumers mathematically modelled at the level of their appliances and incorporating 5 consumers profiles along three sensitivities: cost, environment and appliances shifting comfort. The first level is a day ahead supervision based on a multi-agent optimisation lead by a central aggregator but performed locally by the household using Dynamic Programming (DP), thus ensuring privacy protection for the stakeholders. The second level is a real time supervision using the same de-

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centralized structure and based on fuzzy logic. Both level are evaluated in this paper, with a focus on the balance between grid and consumers objectives.

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

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1. Introduction

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

The necessity of taking into account this multiplicity of consumers' sensitivities beyond the scope of economics consideration is underlined by the feedback on smart-grids project in Europe over the past 14 years [4]. Consumer's engagement is particularly under focus, as their role definition is observed to be unclear - the cost-benefit share for each is imprecise - thus reducing their involvement in new grid model. The challenge is not only technical but also requires a multi disciplinary approach relying on electrical engineering as well as sociology and economy. Segmentation of consumers profiles is therefore of primary importance and underlined by the diversity of research on this particular subject. For example, relying on surveys, [5] shows the heterogeneity of consumers' engagement through 6 profiles, [6] suggest a segmentation of consumers' lifestyles based on their electricity consumption. Once understood, sensitivities and preferences need to be included in an energy supervisor [7]. From this specific literature [8], the three main parameters defining involvement profiles of consumers are the following: sensitivities toward cost, environmental impact and comfort (modelled either as thermal comfort or shifting delay of appliances operations). One of the important aspect of these profiles is the feeling of control, reflected by the acceptance (or not) of an external control of the *invisible loads*, namely the ones whose shifting during the day does not lead to a discomfort for the user. The two main appliances considered as *invisible loads* are the hot water cylinder (HWC) and the electrical vehicle (EV): as long as hot water is available during the day or the EV is sufficiently charged at departure time, their times of energy consumption do not matter for the user.

From the literature on day ahead (DA) energy management, to tackle the problematic of privacy for the consumers, the most suitable approach is decentralized: Each household is then in charge of calculating his own optimised consumption through the smart-meter [2, 9, 10, 11]. Following up with this type of approach, [9] suggests a two levels game between utilities and consumers, including a global involvement parameter. Also relying on game theory, [11] tested various pricing scheme while studying the impact of temporal preferences, incorporating a weighting coefficient for the optimisation to focus on the cost or on the shifting time. [10] proposes a multi-objectives optimisation aiming to minimize the cost and the delay of appliances in a Peak to Average Ratio (PAR) constrained grid, while incorporating consumers sensitivities on delay acceptance. If one or two factors are taken into account in the literature, no research combines interdisciplinary approaches to consider socially observed sensitivities in the definition of stakeholders profiles introduced in the proposed EMS.

The same observation is made for the real time (RT) energy management in residential sector. The bill minimisation is the main and only considered objective for the users [12, 13]. However, the inclusion of this objective is interesting to investigate, and especially the modelling of the involvement of the consumer. Using linear programming for example, the thermal comfort is set as a constraint in [12], while considering the bill reduction as only goal for the consumers and introducing a penalty/reward price scheme. The same approach is used in [14] with a dynamic pricing aiming to increase the renewable energy (REN) penetration in the grid. Two recent studies focus on residential profiles: [15] investigates the accepted extra cost consumers are willing to pay to consume REN and bill reduction is considered in parallel. The problem is that if not enough users are involved, the REN production is not consumed. [16] introduces consumers profiles with their flexibility (low/medium/high), and manages it using incentive based price, here optimising the consumption aiming at reducing the bills.

The main critic about the aforementioned literature, for DA as well as RT energy management, is that the sensitivity toward cost and/or comfort, when considered, is not scaled nor evaluated a posteriori. Thus, the proposed models do not incorporate real involvement profiles observed through humanities and social sciences approaches on energy. However, with the growing need of flexibility in electrical grids, this consideration of consumers objectives is indeed an important factor to ensure their acceptance and their involvement [17].

The aim of this article is therefore to propose a new day-ahead (DA) supervision followed by a real time (RT) adjustment for residential consumption, incorporating three sensitivities retrieved from a prior interdisciplinary study: economics, environment, and shifting comfort. The main contributions of this work compared to the previous literature review are fourfold:

- Consideration of real observed residential consumers involvement profiles, taken into account introducing meaningful sensitivity parameters modelling their preferences;
- Mathematical modelling of these profiles in DA energy management, aiming to optimise the consumption to increase consumers satisfaction while reducing the load fluctuation on the grid;
- Introduction of these profiles in RT energy management relying on the prior DA optimisation, aiming to ensure the balance between grid and consumers objectives while reacting to forecast errors;
- Assessment of the overall consistency of the two levels of supervision, observed through a detailed residential study case and the comparison of four scenarios: unsupervised, DA-supervised, RT-supervised, and successive DA and RT supervised.

The first part of this paper presents firstly the mathematical framework and the function used to perform the DA-optimisation, then the fuzzy logic approach for the RT-adjustement and finally the relevant indicators. The study case on which the simulation is based is then described. The last part introduces the simulation of the interaction between the different profiles, focusing on 5 stakeholders. Finally, after a brief discussion and summary, we present an overview of the remaining challenges.

2. Proposed approach

2.1. Day ahead optimisation

2.1.1. Problem formulation

The objective of the first supervision stage is, for a day ahead, to calculate the adequate electricity consumption of the stakeholder considering his objectives and taking into account his constraints (technical as well as social). In this paper, the management is decentralized and the households are therefore assumed to be able to manage their consumption either in a manual (as proved efficient in [18] for example) or an automatic way through their smart home appliances.

The simulation is set to work at constant energy over the day (before/after optimisation) and is based on a whole set of real appliances, divided into four groups : Flexible, On-Off, cycle, fixed. Therefore, the power profile of appliances involved in the optimisation process will only be shifted to adequate time with respect to the consumer sensitivities, but the total energy consumed over the day will be the same. The framework of multi-agent system is used here with an aggregator from one side, and the appliances of each users (consumers) on the other side, communicating through smart-meters. The convergence of the optimisation process is guaranteed by the form of the objective function and the strategy space, representing all the possible strategies for a given user. In the context of a game theory approach shown in a previous work [19], provided that the strategy space is closed, bounded, and convex, the optimisation will converge to the Nash equilibrium if the function is convex [20, 21], a state where there is no incentive for a player to deviate unilaterally from his strategy. By being non-intrusive and without having a central entity calculating a global optimum with a complete control over the consumptions of each one of the players, it enables to achieve an interesting equilibrium between grid and consumers objectives, that helps improve both the grid and the users satisfaction.

Given the information sent by the aggregator -here the grid load over the day, the price and the REN production- a household n, for an appliance a amongst the A^n possessed ones, minimizes his objective function on the strategy space $\mathbb{X}_a^n$. His sensitivities are incorporated through the function ρ^n (explained in the subsection 2.1.2) together with the objective of the grid. The consumption of this dwelling for a time step t is noted x_t^n, the consumption of a specific appliance a referred as $x_{t,a}^n$, and the peak reduction goal is integrated through the minimization of the quadratic total load of the neighbourhood. The problem is therefore formulated as:

$$\min_{\forall X_a^n \in \mathbb{X}_a^n} U_a^n(X_a^n) = \sum_{t=1}^{T}(1-\rho^n(t))\left(x_{t,a}^n + \sum_{b=1,b\neq a}^{A^n} x_{t,b}^n + \sum_{j=1,j\neq n}^{N} x_t^j\right)^2 \tag{1}$$

Furthermore, social and technical constraints linked to the use of each appliance are taken into account. For type cycle appliances, the consumption is defined over a fixed amount of time step, and its beginning is optimised within an allowed time interval set by each user. Mathematically, these time bounds are defined with, D the duration time of the appliance cycle, t^{s} its start time and $[\![\hat{t}^{\mathrm{s}}, \hat{t}^{\mathrm{e}}]\!]$ the allowed time interval, the constraint is then $t^{\mathrm{s}} \in [\![\hat{t}^{\mathrm{s}}, \hat{t}^{\mathrm{e}} - D]\!]$.

On-Off and flexible appliances are also optimised in an allowed time interval, the only difference being the possible power steps at each time step, only constraint by the fixed daily energy amount associated to the considered appliance. Finally, the last constraint is the subscribed power limit P_s, set for each user during the modelling phase, that can not be exceeded by the total load of each dwelling.

2.1.2. Sentivities

According to socio-economic studies [5, 22], consumers are not all engaged in the same way in energy management. Their involvement depends on different motivational factors. To achieve a representation of this diversity, three main motivating factors have been defined through social sciences. They answer the following questions: Is the user bill reduced? (Cost) Is the user ecological footprint reduce? (Environment) Is the user comfort preserved? (Comfort). These are translated in the problem formulation (1) through functions ϕ^n and weighting coefficients α^n balancing their predominance according to each user's profile. The global preference ρ^n is therefore expressed, for a time step t, as:

$$\rho^n(t) = \alpha_{\mathrm{price}}^n \cdot \phi_{\mathrm{price}}^n(t) + \alpha_{\mathrm{env}}^n \cdot \phi_{\mathrm{env}}^n(t) \tag{2}$$

with the following constraints to keep each one of the sensitivity coefficient meaningful and to include them in a coherent manner [23]:

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

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

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

$$\phi^n_{\text{env}}(t) = \frac{\xi(t) - \xi_{\min}}{\xi_{\max} - \xi_{\min}} \tag{5}$$

In the literature, the comfort of the user is proportional to the amount of energy consumed at a time t defined prior to optimisation, as in [11]. However, this definition is incomplete. Indeed for storage appliance, the comfort is linked to the time at which the power can be consumed by the user, not at which the power is stored. E.g. for the electrical vehicle (EV), the comfort is linked to its state of charge at a chosen hour. This definition of the comfort is also source of problem when several appliances are aggregated. A washing machine may consume as much power as a dryer but switching them in time is cause for discomfort. In this paper, the comfort is therefore related to the shifting of cycle appliances within the accepted period $[\![\hat{t}^{\text{s}}_a, \hat{t}^{\text{e}}_a]\!]$. The corresponding sensitivity α^n_{comf} is used to define this allowed time interval relying on the forecasted time $[\![\underline{t}_a, \bar{t}_a]\!]$ and the last possible time step T according to (6) (but can be otherwise declared by the user though their energy management system or on the appliance itself if technically feasible) for each appliance a of a user n (here the forecasted time resulting from section 3.1.1). Furthermore, the sign of α^n_{comf} is used to differentiate the consumers willing to make their *invisible load* (here the EV and HWC) available to participate to the flexibility (positive sign), from those who do not (negative sign).

$$\begin{cases} \hat{t}^{\mathrm{s}}_a = \underline{t}_a \cdot (1 - {\alpha^n_{\mathrm{comf}}}^2) \\ \hat{t}^{\mathrm{e}}_a = \bar{t}_a + (T - \bar{t}_a).{\alpha^n_{\mathrm{comf}}}^2 \end{cases} \tag{6}$$

2.1.3. Algorithm

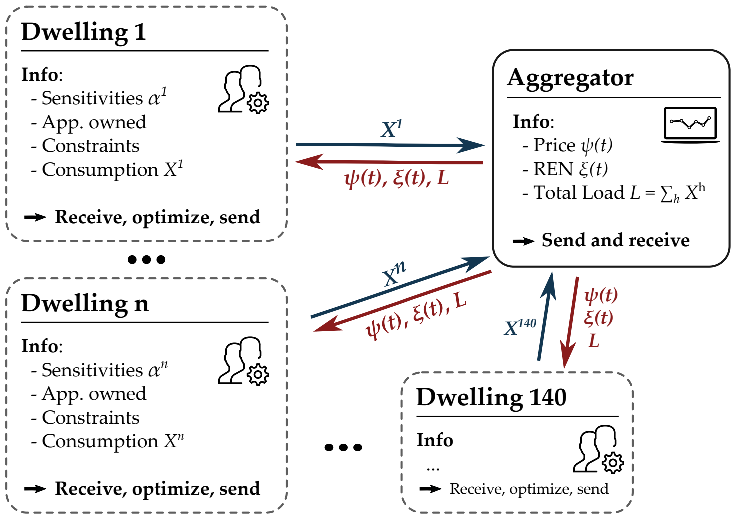


Figure 1: Decentralized approach for day ahead energy optimisation

As introduced in section 2.1.1, the stakeholders calculate their optimal consumption path in a sequential and asynchronous way, therefore interacting only with the aggregator. For writing simplicity in this paper, X is a $T \times N$ matrix containing the consumption of the N player for each of the T step of time $X(:,n) = [x_{1,n}, \cdots, x_{t,n}, \cdots, x_{T,n}] = \sum_{a=1}^{A^n} X^n_a$. The process of interaction between the households and the aggregator is the two stage algorithm 1: On the upper level, the aggregator is in charge of calculating the total load on the grid after each local optimisation and sending it to the next household until the stop criterion is fulfilled, meaning the equilibrium is reached. This state is achieved when all the households do not change their consumption simultaneously during one round, i.e. they have no incentive to shift their consumption anymore. On a local level, the stakeholder optimises his consumption using dynamic programming (DP) according to his utility function and with respect to his constraints, before sending it back to the aggregator. For an appliance in the allowed time period, the DP optimisation proceeds as follows:

1. Considering the total energy to be consumed on the allowed time range, the possible power step of the appliance, and the duration of the time step τ, the algorithm evaluates the required cost (with respect to the problem formulation) to reach each achievable energy level after the first step.
2. For each further time step and for each achievable energy level, every possible path (i.e. the required power to reach the energy level) is evaluated based on the cost stored at the previous energy level and the required power. From the possible path, the one minimising the objective function is stored together with the corresponding cost.
3. When attaining the last time step at the desired energy level (i.e. the total energy to be consumed), the algorithm proceeds backwards by following the stored path at each hit energy level. The obtained power curve is the one minimizing the objective function.

2.2. Real time energy management

2.2.1. Approach and structure of real time supervision

First introduced by [24] as an extension of boolean logic, fuzzy logic authorises an assumption to be true or false to a certain degree between 0 and 1. This tool of artificial intelligence is of particular interest as the approach enables to mathematically model the *fuzziness* of human representation in the decision making process. Furthermore, it has been proved efficient for energy management in [25] or [26].

The structure of the present fuzzy logic based supervisor is described for one household on figure Fig. 2. The decentralized approach of the DA supervision is kept, but here, only one additional information is exchanged from the aggregator to the household, namely ΔP_{adjust}, calculated as the ratio between the difference of forecasted and the effective total consumption and the maximum reachable power (here the sum of all the consumers subscribed power). The objective is still to limit the load fluctuation while allowing consumers to increase their satisfaction and taking into account the three sensitivities (price, environment and comfort). The principle is that the supervisor aims to find a suitable balance between grid and users objectives, allowing deviation from DA optimised users strategies as long as ΔP_{adjust} is low, otherwise using the flexibility of consumers to reduce the offset.

In order to limit the complexity of the system and the number of rules in the next steps, the input number must be kept as low as possible. Therefore,

Algorithm 1 Global algorithm

eq $\leftarrow 0_{\mathbb{R}^N}$ ▷ Dummies for equilibrium
TotalLoad $\leftarrow \sum_{n=1}^{N} X(:, n)$
TotalLoad* $\leftarrow 0_{\mathbb{R}^{T\times N}}$
while $\sum_{n=1}^{N} eq(n) \neq N$ **do**
    for $n \leftarrow 1$ **to** N **do**
        $eq(n) \leftarrow 0$
        if TotalLoad $\neq$ TotalLoad$^*(:, n)$ **then**
            for each type cycle applicance **do**
                GridState $\leftarrow$ TotalLoad $- X_a^n$
                n uses DP to solve (1) within $[\![\hat{t}_a^{\text{s}}, \hat{t}_a^{\text{e}}]\!]$ depending on GridState
                n gets the best reply X_a^{n*}
                TotalLoad $\leftarrow$ GridState $+ X_a^{n*}$
            end for
            if $\alpha_{\text{comf}}^n > 0$ **then**
                GridState $\leftarrow$ TotalLoad $- X_{HWC}^n$
                n uses DP to solve (1) for the HWC depending on GridState
                n gets the best reply X_{HWC}^{n*}
                TotalLoad $\leftarrow$ GridState $+ X_{HWC}^{n*}$

                GridState $\leftarrow$ TotalLoad $- X_{VE}^n$
                n uses DP to solve (1) for the VE depending on GridState
                n gets the best reply X_{VE}^{n*}
                TotalLoad $\leftarrow$ GridState $+ X_{VE}^{n*}$
            end if
        else $eq(n) \leftarrow 1$
        end if
        TotalLoad$^*(:, n) \leftarrow$ TotalLoad
        n sends $X(:, n) = \sum_{a=1}^{A^n} X_a^{n*}$ to the aggregator
    end for
end while

besides the construction of ΔP_{adjust}, the inputs describing the interest and behaviour of a consumer are expressed as follows (see also Fig. 2) for each time step:

- Interest in shifting his consumption regarding his DA optimised strategy, $\Delta P_{\text{interest}}$: Price and REN ratio values are capped using DA extrema (as the real extrema are not known over the day) and compared to their forecasted values (DA values), before being standardized (for the price) and then weighted by the corresponding dwelling sensitivity parameters α.

- Shift in dwelling consumption ΔP_{consu}: The shift between the DA optimised strategy and the one observed in real time is calculated and then standardised using the dwelling subscribed power P_s^n.

For these three first inputs, the following formalism is applied:

- $\Delta P > 0$ indicates either: a need for the grid to increase the overall consumption (ΔP_{adjust}), an interest of a user to increase his consumption ($\Delta P_{\text{interest}}$), or a higher user's consumption than the DA optimised one (ΔP_{consu});

- $\Delta P = 0$ indicates either: no specific need of the grid to decrease or increase the overall consumption (ΔP_{adjust}), no interest for a user to shift his consumption ($\Delta P_{\text{interest}}$), or no observed shift between the user's DA optimised strategy and the current one (ΔP_{consu});

- $\Delta P < 0$ indicates either: a need for the grid to decrease the overall consumption (ΔP_{adjust}), an interest of a user to decrease his consumption ($\Delta P_{\text{interest}}$), or a lower user's consumption than the DA optimised one (ΔP_{consu}).

The last three inputs are flexibility indexes of the involved appliances, computed using: their nominal power P_a; the accepted start and end time $[\![\hat{t}_a^{\text{s}}, \hat{t}_a^{\text{e}}]\!]$; for cycle appliances, their cycle duration time D^a; The consumed energy by the appliance up to the present time step and the total energy the appliance must consume over the day, respectively E_{consu}^a and E_{total}^a. These indexes help to maximize the remaining flexibility over the day during the energy supervision:

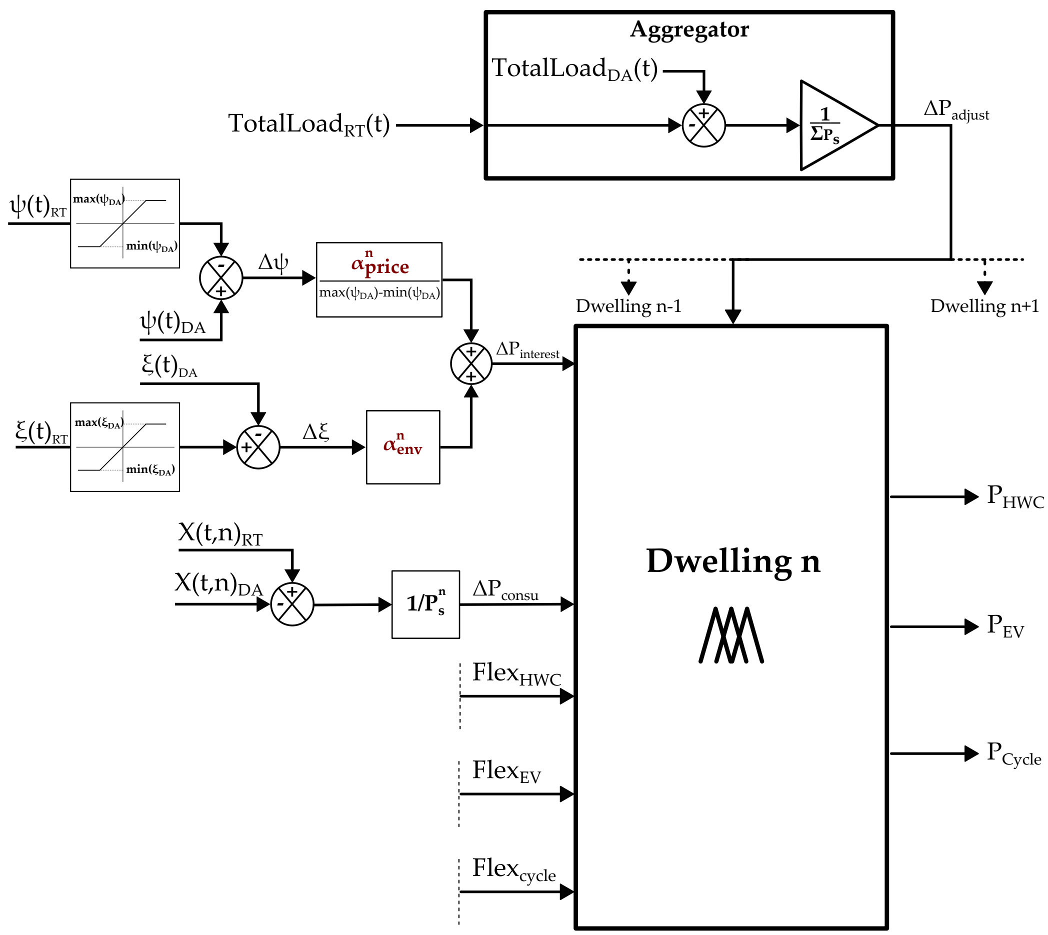


Figure 2: Architecture of the decentralized supervision based on fuzzy logic

- Flex_{HWC} for the hot water cylinder, and Flex_{EV}, for the electrical vehicle, see algorithm 2;

- $\text{Flex}_{\text{cycle}}$ for each of the type cycle appliances, see algorithm 3. If several cycle appliances are used, the supervisor relies on the one with the earliest accepted end time $\hat{t}_a^{\text{e}}$.

For the outputs, three signals are designed for the control (ON/OFF) of the involved appliances: P_{HWC}, P_{EV}, and P_{cycle}.

Algorithm 2 Flexibility parameter for flexible and On-Off appliances

if $t \in [\![\hat{t}_a^{\mathrm{s}}, \hat{t}_a^{\mathrm{e}}[\![$ **then**

$$\mathrm{Flex}_a = 1 - \frac{(E^a_{\mathrm{consu}} - E^a_{\mathrm{total}})/P_a}{\hat{t}_a^{\mathrm{e}} - t}$$

else

$\mathrm{Flex}_a = 1$

end if

Algorithm 3 Flexibility parameter for cycle appliances

if $t \in [\![\hat{t}_a^{\mathrm{s}}, \hat{t}_a^{\mathrm{e}}[\![$ **and** OFF **then**

$$\mathrm{Flex}_a = 1 - \frac{D^a/P_a}{\hat{t}_a^{\mathrm{e}} - t}$$

else

$\mathrm{Flex}_a = 1$

end if

2.2.2. Application to a non DA-optimised scenario

To test the approach, a RT supervised scenario without prior DA optimisation is simulated: inputs need therefore to be adapted for this case. This supervision will aim to follow the forecasted values of consumption, price and REN ratio, considering the grid operation plan to be adjusted for these values.

The major difference is that the consumers do not have any visibility over the day and react only to real time values. The inputs are therefore:

- $\Delta P_{\mathrm{adjust}}$: the calculated variation is performed relatively to forecasted value and not the DA optimised consumption;
- $\Delta P_{\mathrm{interest}}$: capping is performed as previously, but standardisation is performed to centre the signal around zero, based on the forecasted mean value;
- $\Delta P_{\mathrm{consu}}$: user consumption shift is based on the forecasted value and not on the prior optimised DA value.

2.2.3. Fuzzyfication

Once the inputs and outputs have been defined and adapted, the choice of membership function parameters is done empirically through the knowledge of the system. Membership functions are the functions defining the degree of membership to a fuzzy value, and their form is here chosen as trapezoidal.

For ΔP_{adjust}, five membership functions are considered, set regarding the peaks tolerated by the grid: **Z**ero, **S**mall **N**egative, **B**ig **N**egative, **S**mall **P**ositive, and **B**ig **P**ositive. $\Delta P_{\text{interest}}$ and ΔP_{consu} are divided into three membership functions: **N**egative, **Z**ero and **P**ositive. Finally the appliance flexibility is divided into only two membership function: **S**mall and **B**ig. Outputs membership functions are their **ON** and **OFF** states.

These membership functions for the inputs and the outputs are presented respectively on Fig. 3 and Fig. 4.

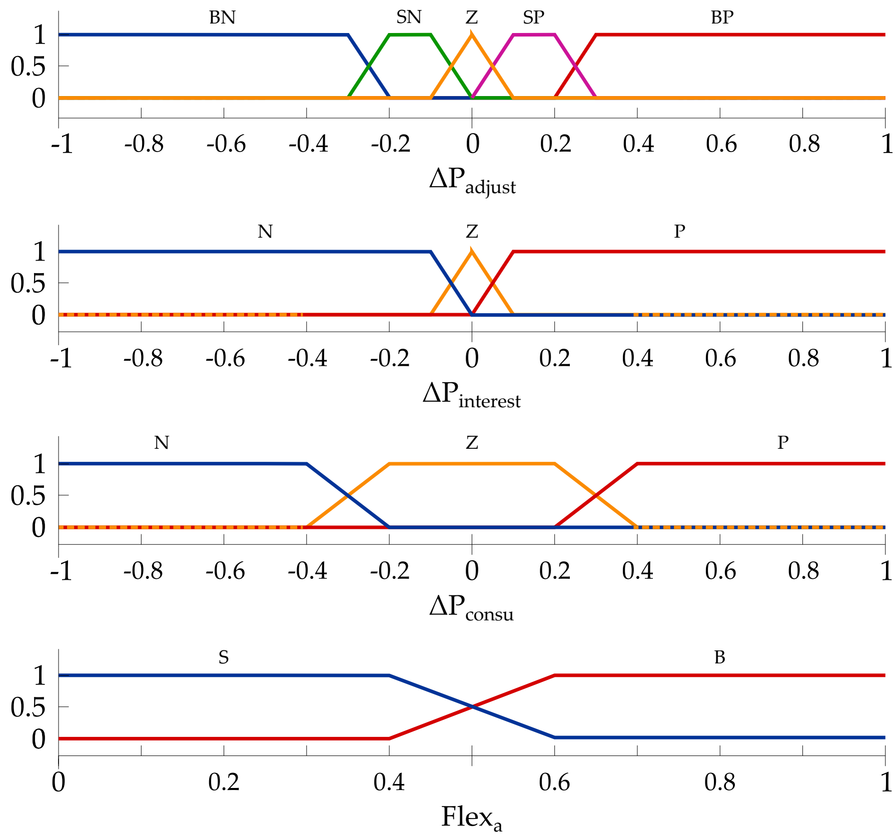


Figure 3: Membership function for the supervisor intputs

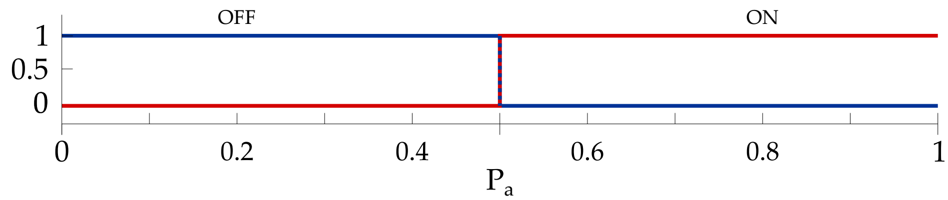


Figure 4: Membership function for the supervisor outputs

2.2.4. Rules

Based on the fuzzyfication step and the supervisor objectives, the defined rules for the supervisor are gathered in Tab. 1.

Table 1: Fuzzy rules of the real-time supervisor

N1	N1.1	N1.1.1	**If** ΔP_{adjust} is Z	**and**	$\Delta P_{\text{interest}}$ is Z	**and**	ΔP_{consu} is N	**and**	$\text{Flex}_{\text{cycle}}$ is S					**then**	P_{Cycle} is ON
			If ΔP_{adjust} is Z	**and**	$\Delta P_{\text{interest}}$ is Z	**and**	ΔP_{consu} is N	**and**	$\text{Flex}_{\text{cycle}}$ is B	**and**	Flex_{HWC} est S			**then**	P_{HWC} is ON
			If ΔP_{adjust} is Z	**and**	$\Delta P_{\text{interest}}$ is Z	**and**	ΔP_{consu} is N	**and**	$\text{Flex}_{\text{cycle}}$ is B			**and**	Flex_{VE} is S	**then**	P_{VE} is ON
			If ΔP_{adjust} is Z	**and**	$\Delta P_{\text{interest}}$ is Z	**and**	ΔP_{consu} is P			**and**	Flex_{HWC} est B			**then**	P_{HWC} is OFF
			If ΔP_{adjust} is Z	**and**	$\Delta P_{\text{interest}}$ is Z	**and**	ΔP_{consu} is P					**and**	Flex_{VE} is B	**then**	P_{VE} is OFF
		N1.1.2	**If** ΔP_{adjust} is Z	**and**	$\Delta P_{\text{interest}}$ is P			**and**	$\text{Flex}_{\text{cycle}}$ is S					**then**	P_{Cycle} is ON
			If ΔP_{adjust} is Z	**and**	$\Delta P_{\text{interest}}$ is P			**and**	$\text{Flex}_{\text{cycle}}$ is B	**and**	Flex_{HWC} est S			**then**	P_{HWC} is ON
			If ΔP_{adjust} is Z	**and**	$\Delta P_{\text{interest}}$ is P			**and**	$\text{Flex}_{\text{cycle}}$ is B			**and**	Flex_{VE} is S	**then**	P_{VE} is ON
		N1.1.3	**If** ΔP_{adjust} is Z	**and**	$\Delta P_{\text{interest}}$ is N					**and**	Flex_{HWC} est B			**then**	P_{HWC} is OFF
			If ΔP_{adjust} is Z	**and**	$\Delta P_{\text{interest}}$ is N							**and**	Flex_{VE} is B	**then**	P_{VE} is OFF
	N1.2	N1.2.1	**If** ΔP_{adjust} is SP	**and**	$\Delta P_{\text{interest}}$ is P			**and**	$\text{Flex}_{\text{cycle}}$ is S					**then**	P_{Cycle} is ON
			If ΔP_{adjust} is SP	**and**	$\Delta P_{\text{interest}}$ is P			**and**	$\text{Flex}_{\text{cycle}}$ is B	**and**	Flex_{HWC} est S			**then**	P_{HWC} is ON
			If ΔP_{adjust} is SP	**and**	$\Delta P_{\text{interest}}$ is P			**and**	$\text{Flex}_{\text{cycle}}$ is B			**and**	Flex_{VE} is S	**then**	P_{VE} is ON
			If ΔP_{adjust} is SP	**and**	$\Delta P_{\text{interest}}$ is Z			**and**	$\text{Flex}_{\text{cycle}}$ is S					**then**	P_{Cycle} is ON
			If ΔP_{adjust} is SP	**and**	$\Delta P_{\text{interest}}$ is Z			**and**	$\text{Flex}_{\text{cycle}}$ is B	**and**	Flex_{HWC} est S			**then**	P_{HWC} is ON
			If ΔP_{adjust} is SP	**and**	$\Delta P_{\text{interest}}$ is Z			**and**	$\text{Flex}_{\text{cycle}}$ is B			**and**	Flex_{VE} is S	**then**	P_{VE} is ON
		N1.2.2	**If** ΔP_{adjust} is SP	**and**	$\Delta P_{\text{interest}}$ is N	**and**	ΔP_{consu} is N	**and**	$\text{Flex}_{\text{cycle}}$ is S					**then**	P_{Cycle} is ON
			If ΔP_{adjust} is SP	**and**	$\Delta P_{\text{interest}}$ is N	**and**	ΔP_{consu} is N	**and**	$\text{Flex}_{\text{cycle}}$ is B	**and**	Flex_{HWC} est S			**then**	P_{HWC} is ON
			If ΔP_{adjust} is SP	**and**	$\Delta P_{\text{interest}}$ is N	**and**	ΔP_{consu} is N	**and**	$\text{Flex}_{\text{cycle}}$ is B			**and**	Flex_{VE} is S	**then**	P_{VE} is ON
	N1.3	N1.3.1	**If** ΔP_{adjust} is SN	**and**	$\Delta P_{\text{interest}}$ is N					**and**	Flex_{HWC} est B			**then**	P_{HWC} is OFF
			If ΔP_{adjust} is SN	**and**	$\Delta P_{\text{interest}}$ is N							**and**	Flex_{VE} is B	**then**	P_{VE} is OFF
			If ΔP_{adjust} is SN	**and**	$\Delta P_{\text{interest}}$ is Z					**and**	Flex_{HWC} est B			**then**	P_{HWC} is OFF
			If ΔP_{adjust} is SN	**and**	$\Delta P_{\text{interest}}$ is Z							**and**	Flex_{VE} is B	**then**	P_{VE} is OFF
		N1.3.2	**If** ΔP_{adjust} is SN	**and**	$\Delta P_{\text{interest}}$ is P	**and**	ΔP_{consu} is P			**and**	Flex_{HWC} est B			**then**	P_{HWC} is OFF
			If ΔP_{adjust} is SN	**and**	$\Delta P_{\text{interest}}$ is P	**and**	ΔP_{consu} is P					**and**	Flex_{VE} is B	**then**	P_{VE} is OFF
	N1.4		**If** ΔP_{adjust} is BP					**and**	$\text{Flex}_{\text{cycle}}$ is S					**then**	P_{Cycle} is ON
			If ΔP_{adjust} is BP					**and**	$\text{Flex}_{\text{cycle}}$ is B	**and**	Flex_{HWC} est S			**then**	P_{HWC} is ON
			If ΔP_{adjust} is BP					**and**	$\text{Flex}_{\text{cycle}}$ is B			**and**	Flex_{VE} is S	**then**	P_{VE} is ON
	N1.5		**If** ΔP_{adjust} is BN							**and**	Flex_{HWC} est B			**then**	P_{HWC} is OFF
			If ΔP_{adjust} is BN									**and**	Flex_{VE} is B	**then**	P_{VE} is OFF

3. Study case

3.1. Modelled population

3.1.1. Load modelling

As explained in section 2.1.2, information on each appliance is needed to perform the optimisation according to the comfort of each user. The demand of the population must therefore be modelled with a sufficient temporal resolution to encompass them all. Among the reviewed models [27], the bottom-up approach is selected as it gives access to the contribution of each appliance. In this category, the model CREST V.2 [28] is chosen, to obtain daily load curves for 140 dwellings. This model builds the load curve of one user by summing the demands due to each appliance for the UK residential sector, enabling to obtain a representative residential consumption over two weeks for the following simulation, with a timestep of $\tau = 10\,\mathrm{min}$. The gas demand due to heating is also modelled. In addition, an open-source tool is provided by the authors. This model has been used in a demand-side management context to build input data in [29] for example. For this paper, the model has been slightly modified, for the French residential electrical demand is more thermosensitive than the English one. In fact, in France [30], 50% of the dwellings use electricity to heat water, and 36% use electricity to heat the house. To account for this difference, part of the power flow due to heating (air and water) is therefore rerouted to the electrical demand. Furthermore, the statistical data are updated using data from the French national housing survey (ENL - Enquête National Logement) carried out by the National Institute of Statistics and Economic Studies (INSEE).

Since the CREST does not consider electrical vehicles (EV) and to add more flexibility to the load curve, a fleet of electric vehicles has been modelled. Normal distributions of travels and of arrival time were used for the modelling, as proposed in [31], and the loads due to the fleet were added to the output of the CREST using french statistical data on EV ownership.

3.1.2. Sensitivity modelling

The goal of this work is to demonstrate the effectiveness of a new approach to differentiate users' utility based on their behaviour towards external factors. It should be noted that the term *profile* used in this paper refers to the way consumers react to given external factors, these profiles should be therefore distinguished from traditional *consumption profiles*, depicted by power curves. From the mentioned humanities and social sciences literature in the introduction, different energy sensitivities are observed to cover the possible involvement of residential consumers. Therefore, 5 main profiles relying on those sensitivities are modelled and described in Tab. 2. Each fifth of the total population ($N = 140$) is given a different profile. To achieve diversity in each sub-population, randomness around the target value is performed (+/-10% around 50%, and 20% below 100%).

Table 2: Profile distribution of the 140 households

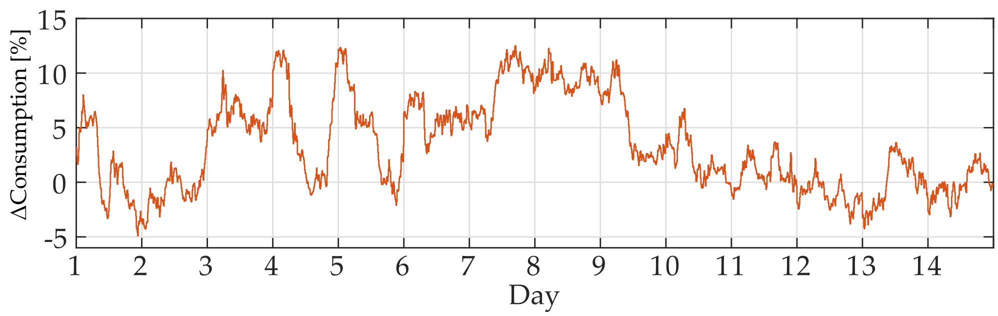
Profile	**Size**	**Cost** α_{price}	**Envir.** α_{env}	**Comf.** α_{comf}
1. Cost sensitive	28	80%	20%	75..100%
2. REN sensitive	28	20%	80%	75..100%
3. Technophiles	28	50%	50%	80..100%
4. Indifferents	28	50%	50%	0..20%
5. Disengaged	28	50%	50%	-20..0%

3.2. External factors

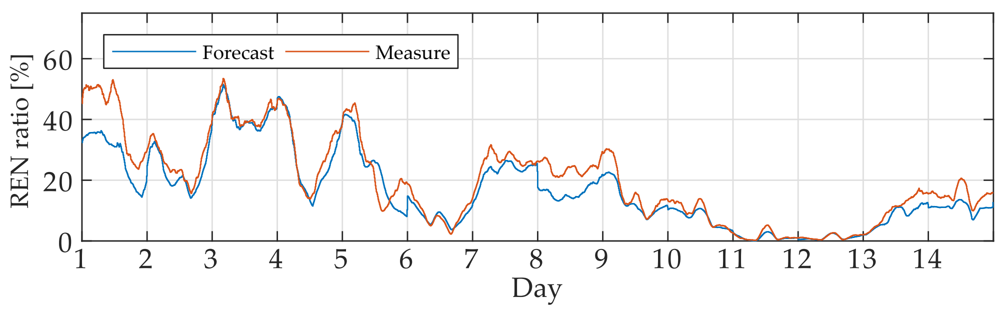
In order to test the approach, the external factors influencing the consumption, namely the price and the production of renewable energy should be introduced, as well as the forecast errors on these factors and the global consumption. To model a realistic study case, data are collected from the German grid, as the three values of interest are available in parallel over the first two weeks of 2018:

- The forecast error of the total grid consumption and the forecast and measured REN ratio are retrieved from the German TSO Amprion [32]. These data, available at a 15min-step, are presented on Fig. 5(a) and Fig. 5(b) respectively.

- For the price, DA-data (*Day-Ahead Fixing*) and RT-data (*Intraday Fixing*) for Germany are market data retrieved from European Power Exchange, EPEX SPOT [33]. Available at a hourly time step, these data are presented on Fig. 5(c).



(a)



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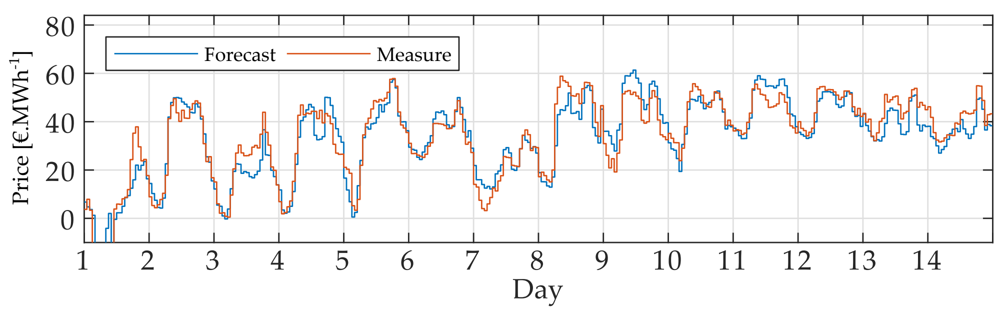


(c)

Figure 5: Forecast errors of the consumption Fig. 5(a), forecast and actual REN ratio Fig. 5(b) and price Fig. 5(c)

3.3. Indicators

3.3.1. Global satisfaction of the user

The satisfied energy is defined, for the non-fixed appliances ($_{\text{nf}}$), the product of the energy (using the power x and the timestep τ) with the preference: it is therefore higher for energy consumed when his preference is higher. The ratio of the satisfied energy and the total energy consumed by one user represent his satisfaction S^n. Its evolution δS^n is then calculated, with S_0^n the satisfaction before optimisation.

$$\begin{cases} S^n = \dfrac{\epsilon_{\mathrm{nf}}^n}{E_{\mathrm{nf}}^n} = \dfrac{\sum_t \sum_a \rho_a^n(t) \cdot x_{t,a}^n \cdot \tau}{\sum_t \sum_a x_{t,a}^n \cdot \tau} \\ \delta S^n = S^n - S_0^n \end{cases} \tag{7}$$

3.3.2. Relative difference of the electricity bill

Assuming the price of energy $\psi(t)$ is not constant, the daily bill of one user is defined as C^n. Its evolution after optimisation is measured through δC^n , with C_0^n the electricity bill before optimisation. The relative difference is positive for a lesser bill after optimisation.

$$\begin{cases} C^n = \sum\limits_{t=1}^{T} \psi(t) \cdot \left(\sum\limits_{a=1}^{A} x_{t,a}^n \right) \\ \delta C^n = \frac{C_0^n - C^n}{C_0^n} \end{cases} \tag{8}$$

3.3.3. Relative difference of renewable consumption

The part of renewable energy consumed by one user, ϵ^n, is assumed to be proportional to the part of renewable energy on the grid, $\xi(t)$. Then the relative difference $\delta\epsilon^n$ is defined to measure the evolution of the renewable energy consumed by each user after optimisation.

$$\begin{cases} \epsilon^n = \sum_{t=1}^{T} \sum_a \xi(t) \cdot x_{t,a}^n \cdot \tau \\ \delta\epsilon^n = \dfrac{\epsilon^n - \epsilon_0^n}{\epsilon_0^n} \end{cases} \tag{9}$$

3.3.4. Grid indicators

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

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

4. Simulation and results

4.1. Scenarios

Simulations are performed in order to compare four cases over the two weeks period, with the 10-minutes time step: a non-supervised scenario, *Initial*, used as baseline to evaluate the results; a DA-supervised scenario, *DA*, optimising the consumption a day ahead without any further adjustment in real time; a RT-supervised scenario, *RT*, without a prior DA optimisation; and finally the whole supervisor, *DA+RT*, adjusting the consumption in real time based on the results of the prior optimisation.

4.2. Global results

Global results of these simulations are presented on Fig. 6(a) for the grid, and Fig. 6(b) for the mean values regarding the whole population. These results are very positive regarding the validity of the approach, as seen on Fig. 6 where a balance between grid and users objectives is observed. Indeed, the *DA+RT* supervision achieves a 68.0% reduction of the grid load fluctuation and a 17.5% peak reduction while increasing the mean consumers satisfaction up to 34.0%.

In the meantime, *DA* and *RT* decrease the PAR by -14.0% and -7.5% respectively, and a SED reduction of 59.5% and -31.5% respectively. For the consumers mean metrics on Fig. 6(b), the increase in satisfaction is explained by the better results of the *DA+RT* supervision concerning the price reduction 19% and the REN consumption increase 26.6%, followed by the *DA* supervision with a satisfaction increase of 23.4%, while the *RT* supervision reaches only a 9.4% increase in satisfaction due to a very limited shift in bill and REN consumption.

4.3. Profile groups results

This observed balance is also to be found on metrics results by consumers profiles (see Fig. 7) as each group increases its payoff regarding its main objective. Furthermore, the observed regulation achieved by the consumers to increase their satisfaction regarding the main objective is done on the weakest sensitivities (e.g. the lowest increase of REN consumption observed for *Cost-sensitive* profiles who decrease the most their bill).

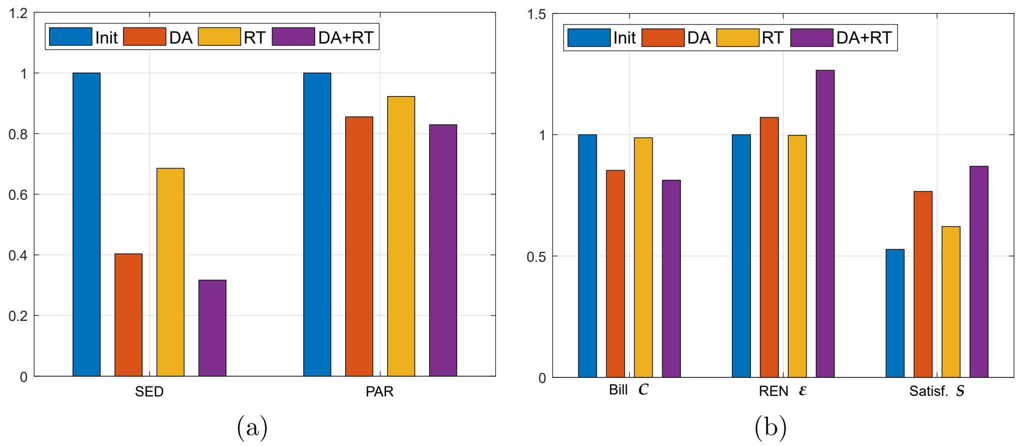


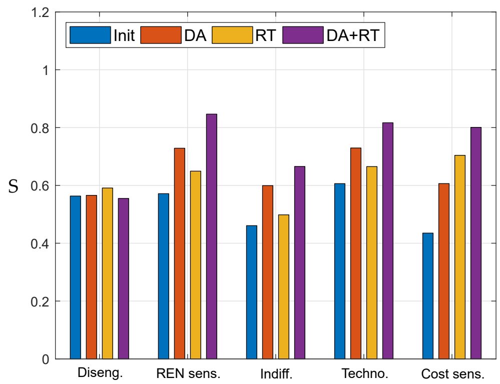
Figure 6: Global metrics of the case study: Grid indicators 6(a), consumers indicators 6(b)

4.4. Payoff sensitivity

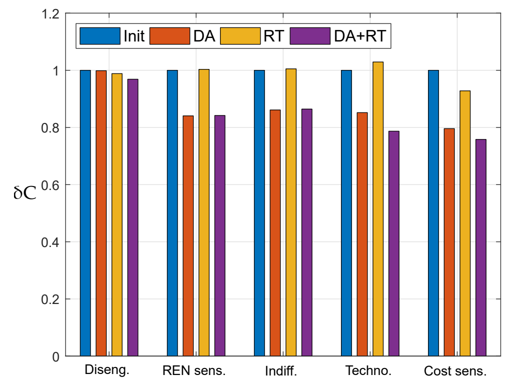
To complete this study, the involvement of consumers is reviewed regarding their sensitivity parameters for the *DA+RT* supervision. The responsiveness of the consumers payoff (Bill decrease δC^n, and REN consumption increase $\delta\epsilon^n$) is studied as a function of their corresponding sensitivity (α_{price} and α_{env}, respectively) weighted by their flexibility involvement α_{comf}. Low flexibility with high sensitivity profiles will thus be differentiated from high sensitivity with high flexibility profiles. The type of possessed appliances is also graphically reflected and a linear regression is performed in order to test the ability of the model to incorporate this complexity. For the bill metric, the results are presented on Fig. 8(a), and for the REN consumption, on Fig. 8(b).

5. Discussion

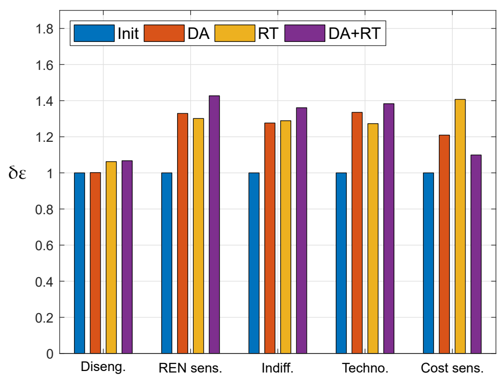
The aforementioned results highlight the adequacy of the approach to integrate real consumers profiles to increase grid flexibility while helping them to increase their satisfaction. The benefit of coupling a prior DA optimisation with RT adjustment appears clearly when studied simultaneously with each supervision step independently. The best balance between grid and consumers objectives is indeed observed for the whole supervision, while the weakest performance is achieve by the RT supervision alone. It should be



(a)



(b)



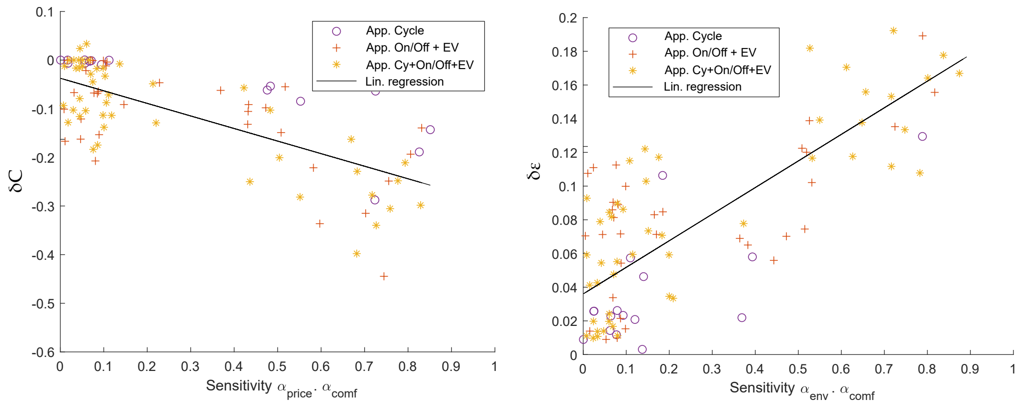
(c)

Figure 7: Metrics by consumers profiles of the case study: Satisfaction 7(a), bill 7(b), REN consumption 7(c)

borne in mind that this RT supervision can still be optimised, but does not have the perspective over the entire day. Furthermore, optimising the membership functions means to arbitrarily weight the grid or consumers objective. However, this question is more politic and societal than technical.

Concerning the detailed results by profile group, if each profile increases its payoff regarding its main sensitivity, it may be noted that the profiles *indifferent* reach a high satisfaction (+20%) (Fig. 7(a)). This is explained by the high contribution of HWC to global flexibility compared to other appliances, especially for RT management.

Apart from high grid imbalance period, the interaction between the two stages of supervision is worth further investigation, as each one of the three



(a) (b)

Figure 8: Payoff responsiveness towards: price 8(a), REN consumption 8(b)

supervised case performs better than the inital unsupervised case scenario. Discussion must therefore address the temporality of each stage (here DA supervision on 24h period and TR supervision on 10 minutes time steps) in order to increase the performance.

The payoff responsiveness study presented on Fig. 8 shows that for the low sensitivities, consumers obtain an unreliable payoff, but that this observed discrepancy declines with the increase of the sensitivity. This result emphasizes the adequacy of the model: a payoff is only ensured for the most sensitives and involved consumers. However, this findings should be tempered with the type of flexibility (types of appliances) possessed by each dwelling: the ones possessing only cycle appliances have little to gain from this EMS, whichever their involvement sensitivity.

6. Conclusion and perspectives

This paper proposes a decentralized EMS taking into account the consumers preferences and sensitivities while participating to the grid objective that is to reduce the load peak and fluctuation. This present study proposes a modelling for 5 different consumers involvement profiles stemming from interdisciplinary literature, based on a set of 3 sensitivities: price, environment and shifting comfort. The mathematical modelling of the consumers is developed through the construction of a two stages energy supervisor optimising the residential consumption a day ahead using a game theory approach, before adjusting these energy flows in real time in response to forecast errors. Each step of this management system is then evaluated, and the best results are observed for the two successive stages, with an interesting balance between grid and consumers objectives by profile.

Considering four appliances types (fixed, On/Off, cycle, flexible), the observed PAR and SED reduction are indeed of 17.5% and 68.0% respectively, while the mean satisfaction for the consumers increases up to 34.0%. These results shows the possibility of achieving a higher flexibility for the grid without diminishing the consumers' satisfaction if their sensitivities, objectives and constraints are properly considered - a way to ensure their involvement in the grid equilibrium.

It will be therefore interesting to investigate the influence of the parameters on each other and furthermore, to look at the distribution of the effort through the modelled population given the stated profile repartition. In this study, the decrease of the PAR is assumed to be the only goal of the grid manager, however, the final state of the grid in terms of voltage plan obtained through this kind of EMS is worth further investigation. Furthermore, the question of computational time, short in the simulation, is to be tackled in a real neighbourhood application, as it will depend on the existing communication infrastructure and the computing capacity of each consumer.

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

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