A user-centric view of a Demand Side Management program: from surveys to simulation and analysis

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***Abstract*—Residential Demand Side Management (DSM) strategies increase the efficiency of the smart grid. However, the efficacy of these strategies relies on the participation of customers in DSM programs, an issue usually neglected in the analysis. To encompass all aspects, we tried to identify what are the drivers for the user engagement, focusing on the social and psychological behaviour of the user in order to simulate and analyse a residential DSM program with a centralised approach. In particular, the DSM program minimises costs taking into account different energy sources and performing load shifting considering and learning users' acceptance of requests. The results show the advantage of a preferences-aware approach, highlighting the importance of user satisfaction on participation.**

***Index Terms*—Demand Side Management, Energy Community Participation, Multi-Agent System, Users' Preference, Linear Programming, Social and Behavioural Sciences**

NOMENCLATURE

Abbreviations

ALA	Acceptance Learning Algorithm
att	Attitude Toward the Behaviour
b	Behaviour
bi	Behavioural Intention
DOI	Diffusion of Innovation Theory
DR	Demand Response
DSM	Demand Side Management
EC	Energy Communities
ESS	Energy Storage System
ISTAT	Italian National Institute of Statistics
M2A	Market Agent to Aggregator Agent
MAS	Multi-Agent System
MILP	Mixed Integer Linear Programming
OPT	Optimisation
P2A	Prosumer Agent to Aggregator Agent
P2P	Prosumer Agent to Prosumer Agent
pbc	Perceived Behavioural Control
PV	Photovoltaic Panel
RA	Relative Agreement
RES	Renewable Energy Sources
sn	Subjective Norm
SWN	Small World Network
TPB	Theory of Planned Behaviour

Indices

i	appliances, $i \in$ {1,2,3}
j	households (prosumers), $j \in$ {1,2,..,N}
t	time slots, t $\in$ {1,2,..96}
f_i	interval "allowed" for i, $f_i \in \{\mathrm{low_i},..,\mathrm{upper_i}\}$

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Data

δ	time interval duration (h) $\rightarrow$ 1/4
$capacity$	battery capacity [kWh]
$Cdisch_t$	discharging price of the battery at time t [€/ kWh]
$Cfrom_t$	market price at time t (buying) [€/ kWh]
$Cmax/Dmax$	max charge/discharge rate [kW]
Cpv_t	PV price at time t [€/ kWh]
Cto_t	market price at time t (selling) [€/ kWh]
$Ebat\_init$	battery initial condition [kWh]
eff	battery efficiency [%]
$Lshift_{i,j}{}^{f,t}$	cycle matrix for each appliance, for each user
$minCharge$	min stored energy [kWh]
$NOTshift_t$	power needed by not shiftable i at time t [kW]
PV_t	PV generated at time t [kW]
$request_{i,j}$	there is/not a request for appliance i from user j (1/0)

Decision Variables

$\mathrm{Ebat_t}$	amount of energy in the battery at time t [kWh]
$\mathrm{PCbat_t}$	charging power of the battery at time t [kW]
$\mathrm{PDbat_t}$	discharging power of the battery at time t [kW]
$\mathrm{PDon_t/PCon_t}$	binary variable that indicates if the battery is discharging or charging at time t
$\mathrm{Pfrom_t}$	amount of power from the grid at time t [kW]
$\mathrm{Pto_t}$	amount of power given to the grid at time t [kW]
$\mathrm{x_f}^{\mathrm{ij}} \in \{0,1\}$	binary variable that selects the day load profile of the appliance i of the customer j

I. INTRODUCTION

In the energy transition towards a sustainable economy, the presence of smart grids and the newly formed Energy Communities (EC) play an important role, enabling Renewable Energy Sources (RES) usage, CO_2 and energy cost reduction [1]. To enhance energy savings and energy management, Demand Side Management (DSM) strategies might be adopted [2]. DSM comprises everything done on the demand side of an energy system, from energy efficiency to Demand Response (DR), with different timing and user involvement [3]. Hence, the willingness of the users plays a pivotal role in this context and should be emphasised. Needless to say, that without user consensus, none of these DSM strategies is applicable.

Regrettably, several studies concentrate on technical and economic aspects only, addressing this problem in the future, e.g. [4]. Instead, other works deal with the problem of user's discomfort without including upstream cognitive processes. Indeed, a copious amount of works does not consider that before accepting a program event request, the customers must decide first whether to sign up for a DSM program, e.g. "Customers are assumed to enrol in the price-based DR program of the Service Provider" [5].

On the one hand, several studies on resource optimisation, i.e. RES and loads, exist. On the other hand, diverse research projects survey what factors affect the decision to participate in EC and DSM programs employing regression analysis [6], [7], however, they are not used in simulations.

Thus, besides optimising costs applying Mixed Integer Linear Programming (MILP), w.r.t. previous works,nspecial attention is given to the analysis of prosumers' behaviour, their mutual influence and the individual response to requests at different shifts in time. Therefore, we adopt a user-centric view where the needs of the users and their experiences are taken into account to try building a long-lasting customer relationship. Indeed, many prior articles that use Linear Programming consider the time slots allowed for the shift fixed and established a priori. Instead, we tackle this problem by mixing the MILP formulation with an algorithm that learns the time slots accepted by the simulated users without any prior knowledge. In particular, since it emerges that a significant portion of users wants to have control of the appliances [8], we propose to ask consumers for confirmation. This information - acceptance or refusal of the proposed shift - increases the knowledge of users acceptance.

The analysis was performed thanks to a dynamic framework obtained coupling a co-simulator platform, i.e. MOSAIK [9], and a Multi-Agent System (MAS) called AIOMAS [10]. MASs are composed of autonomous agents that operate in a networked environment. Large MASs comprise Smart Grids [11], as in our case. Our framework allows changing simulators effortlessly, resulting in a tool to test the diffusion of different DSM programs besides the proposed one.

Given the chosen context, we focus on residential loads shifting in EC through a centralised approach. Thus, in our simulated EC, we selected three main entities that became the Agents for our simulations: i) the Aggregator, which is responsible for the DSM program and manages the shared resources - i.e. the Energy Storage System (ESS) and the RES, ii) the Prosumer - producer and consumer at the same time and iii) the day-ahead Market.

The remainder of this paper is organised as follows. Section II reviews surveys and related works in literature. A quick overview of the psychological theories that have been used in our work is given in Section III. Then, Section IV introduces our methodology, presenting the agents and the models, describing the formulation of the MILP problem and the algorithm for learning the maximum delay tolerated by users. Section V shows the results obtained and Section VI provides a final discussion on the results. Finally, Section VII discusses concluding remarks.

II. Related Works

Since our study tries to consider and accurately model certain aspects of the user, we wanted to identify the key factors that drive people to participate in DSM programs. Indeed, the recommendations from the European projects focusing also on this topic (e.g. INVADE, STORY, GOFLEX) are to understand the consumers and keep them "happy and engaged", without affecting "their initial comfort and satisfaction" [23].

Thus, we undertook an exhaustive review of the surveys on factors affecting participation in energy-related projects.

The main reason for participating in DR programs is reducing the overall spending on energy, i.e. the financial reward [8], [24]–[26]. Secondary motivations include avoiding malfunction in the smart grid and supporting the transition to RES [25].

Moreover, it emerges that participants in DR programs proactively find ways for reducing the bill and have an awareness of energy use and existing programs [24]–[26]. Thus, energy-related education favours or hinders participation.

Therewith, it emerges that those who have a low energy consumption - i.e. families with a few members, using appliances a few times - perceive it as an obstacle in participating [26], e.g. they receive few requests and have little savings.

In a survey on Direct Load Control of appliances such as air conditioner and water heater involving 600 people [8], the 46% would prefer paying a flat monthly fee, while the others would choose "per interruption" payment. Among the latter group, 74% would prefer to have the possibility to override the interruption. Indeed, it appears that the user wants to feel that it is in control of its energy usage. Furthermore, 72% would prefer to receive notifications of control events, ideally, 24h in advance. Customer satisfaction might translate into user willingness to enrol more appliances. Certain users claim that they would use the washing machine before or after the Direct Load Control event. The suggestion of an overriding option to reduce the concerns about losing control is underlined by [27], too. Only 25% of respondents would accept Direct Load Control for the washing machine (22% maybe, 53% no), and only 23% for the dishwasher (27% maybe, 51% no).

Many participants pointed out that bills are unclear and user-hostile that is perceived as a lack of transparency from the retailer [26]. Thus, trust is needed.

Furthermore, the majority of users of a DR program [24] was not satisfied with the rewards and communications. Thus, utility providers should improve communications to increase awareness, understanding and acceptance [24], bearing in mind that people expressed a desire for learning to save energy [26].

We used this information for the prosumer characterisation. Moreover, we examined how related works consider users' preferences to find out what solutions have already been proposed. These have been divided based on the way used to consider user preference in: *i) Fixed* - the appliance usage-times are equal and established for all users, i.e. predefined; *ii) Communicated by the user* - the users specify explicitly their preferences; *iii) Trade-off between cost and satisfaction* - costs and user satisfaction are weighted properly; *iv) Objective choice* - the user selects what it wants to minimise (e.g. CO_2 emissions or costs); *v) Survey based* - users' preferences are learnt through a survey. In the following, we provide an overview of the literature solutions for each of these categories.

i) Fixed. Solar panels and ESS are considered in a building with 30 houses in [20]. Both costs and CO_2 emissions are minimised. Similarly, [21] considers the same technologies but it uses a MAS to model the chosen entities. The optimisation problem minimises costs for consumers satisfying their needs.

ii) Communicated by the user. In [12], authors formulate the problem as Mixed Integer Programming. The 250 users express the level of preference for each period where each ap-

TABLE I
COMPARISON AMONG OUR FRAMEWORK AND THE ANALYSED LITERATURE SOLUTIONS

	User preference	HHs no	Time slots	RES	ESS	Agents	Co-Simulation Framework	Behavioural & Social Theories
[12]	*Communicated by the user*	250	1 hour	✗	✗	✗	✗	✗
[13]	*Trade-off between cost and satisfaction*	1	15 min	✗	✗	✗	✗	✗
[14]	*Trade-off between cost and satisfaction*	1	15 min	✗	✓	✗	✗	✗
[15]	*Trade-off between cost and satisfaction*	1 (x3HHs)	1 hour	✓	✓	✗	✗	✗
[16]	*Trade-off between cost and satisfaction (Learnt)*	1	1 hour	✗	✗	✗	✗	✗
[17]	*Objective choice*	1	1 hour	✓	✓	✗	✗	✗
[18]	*Survey based*	427 real user for the survey +1000 for the simulation	30 min	✓	✗	✗	✗	✗
[19]	*Survey based*	Ekbatan residential complex	15 min	✓	✓	✗	✗	✗
[20]	*Fixed*	30	30 min	✓	✓	✗	✗	✗
[21]	*Fixed*	4 groups of residential/small commercial users + 25 houses, each represented by an agent.	1 hour	✓	✓	✓	✗	✗
Our previous work [22]	*ALA (Learnt)*	1011	15 min	✓	✓	✓	✓	✗
Proposed solution	***ALA (Learnt)***	**10046**	**15 min**	✓	✓	✓	✓	✓

pliance may be used. The user does not have to communicate preference every single day, but only if they change.

iii) Trade-off between cost and satisfaction. In [13], authors minimise electricity costs and maximise user convenience at the same time. The homeowner chooses between three levels of priority for each appliance, giving the highest priority to the period in which the appliance is desirable to be turned on, and the lowest level to the lowest priority time interval. The solution proposed in [16] uses iterative learning to set parameters in the objective function, keeping a proper trade-off between consumption expense and user satisfaction. The consumer communicates if it feels satisfied with the proposed schedule plan. The load scheduling algorithm is based on a linear programming relaxation technique. Wei et al. [14] proposed a multi-objective optimization model for residential DR based on day-ahead electricity price solved thanks to a genetic algorithm. It considers non-flexible deferrable loads (e.g. washing machines), flexible deferrable loads (e.g. electric vehicles) and thermal loads (e.g. air conditioners). In the objective function, it uses a weighting factor representing the proportion of power consumption cost and discomfort cost. The scenario with both power consumption and discomfort costs - equally weighted - is compared with a second scenario with consumption cost only. Authors in [15] presented a multi-objective DR optimization model to manage the scheduling of home appliances minimizing both electricity consumption costs and dissatisfaction of the user while considering RES and ESS. It uses the constrained many-objective non-dominated sorted genetic algorithm to solve the multi-objective model.

iv) Objective choice. In [17], authors consider RES - PV, wind turbine and combined heat and power - and ESS for one house. The user selects whether it wants to minimise costs, CO_2 or user comfort, i.e. appliances start when decided by the user. Moreover, [17] employs Artificial Neural Networks to predict energy demand and RES production.

v) Survey based. In [18], authors follow a Quality of Experience driven approach. First, [18] surveys 427 people without finding any correlation between users' data and appliances usage habits. Thus, [18] classifies consumers using the k-means algorithm, relying on preferences expressed on a scale ranging from 1 (minimum annoyance) to 5 (maximum annoyance), obtaining various profiles. As an example, for certain users the appliance, e.g. dishwasher, may be turned on only at the nearest hours to the favourite time, i.e. the level of annoyance increases with the amount of delay. Meanwhile, others are willing to shift the appliance's usage at any time (in ± 3 hours). Although their level of annoyance is always the minimum one in ± 3 hours, the effects of a larger shift on the annoyance level are not investigated. New customers do not need to complete a questionnaire. Indeed, they only have to answer to some annoyance rating questions due to task shifting for a brief testing period to assign to the new customer one of the obtained profiles. Then, two different algorithms are proposed to assign an optimal time interval to the load. [19] presents a new formulation for electrical appliances, such as washing machines, dishwashers and heating/cooling systems. The maximum time for load shifting considers the consumers' welfare extracted from a survey. The loads are shifted to a time-period when the difference between load and RES power generation is maximum, by considering also the welfare of consumers.

Table I summarises this literature review highlighting the main features for each solution. The main difference between our solution and previous works resides in modelling also social and behavioural theories (see column "Behavioural & Social Theories" in Table I). Indeed, "social interactions do not just happen alongside energy behaviour - the two are intrinsically linked" [28].

For the sake of completeness, we want to point out that other approaches might be used to investigate the response from the users. As an example, Rahmani-andebili [29] modelled the reaction of the responsive load for different DR programs with both linear and nonlinear responsive load behavioural models. Different levels of participation of the responsive load in DR programs - i.e. 40% and 100% - are investigated in several power markets, noticing that sometimes the DR programs might not be beneficial. In [30], nonlinear emergency DR program and nonlinear time of use program are applied in the Unit Commitment problem. Simulated annealing algorithm is used to solve the optimisation problem. It demonstrates the advantages of including residential customers in the Unit Commitment problem.

W.r.t. [16], we consider time preference in the dynamic constraints of the MILP formulation thanks to the developed framework, including ESS and PV. Some literature solutions, e.g. [20], [21], that exploit these two technologies and a MILP formulation, used only a *Fixed* or *Objective choice* method.Their formulation turns loads on exactly once per day. Instead, in pursuit of reality, our users decide whether to use an appliance daily. This dynamism has been achieved thanks to the proposed framework, resulting from the combination of MOSAIK - a co-simulation platform that provides for synchronisation - with AIOMAS - an agent-based model that allows having a distributed system. Due to the heterogeneity of the agents, a MAS is the right solution to model independent entities with different objectives. MOSAIK enables more complex simulations can be performed, even distributed across different internet-connected computational resources (i.e. servers and computers). Instead, w.r.t. the problem analysed, from the literature it does not emerge that other solutions consider all the above mentioned heterogeneous aspects combined in a single simulation framework. Thus, the scientific contribution of the paper is twofold: i) a novel agent-based framework to evaluate day-ahead DSM strategies following a co-simulation paradigm; ii) modelling social and psychological theories of a realistic population and evaluating the acceptance of prosumers to a DSM program and its possible diffusion. Concerning the first contribution, the framework has been designed to be agnostic to the specific DSM strategy to be simulated. Hence, it can be seen as a virtual environment (or virtual box) where DSM strategies can be easily replaced one with another. As for the second contribution in our view, there is a gap in the simulation tools in literature in modelling the user social and psychological behaviour, which would contribute to a greater understanding of the forthcoming distribution network and the evaluation of possible business models.

As highlighted in Table I, this work is a significant extension of our previous work [22], as detailed in the following. Cognitive processes have been modelled thanks to social and behavioural theories, which include Relative Agreement (RA), Theory of Planned Behaviour (TPB), Small World Network (SWN) and Diffusion of Innovation Theory (DOI). To apply these theories, we characterised each prosumer by a larger number of parameters. Therefore, the factors that affect the sign of the contract discovered in the surveys have been considered in the TPB. Furthermore, the influence that people have on the behaviour of other users has been considered either in the sign of the contract or - to a lesser extent - in everyday behaviour. To simulate realistic interactions, the SWN has been considered since a prosumer meets with major probability who lives in the nearby area, but it is also a friend with distant people. Then, the possible effects of the diffusion of a DSM program have been studied by comparing results with DOI. Last but not least, the number of families considered for the optimisation has been increased from 1011 to 10046 to perform more realistic simulations and evaluate the impact in a wider and more lifelike scenario.

To sum up, w.r.t. the literature solutions, we did exhaustive research of existing surveys to model upstream cognitive processes as realistically as possible. Thus, we simulated the sign of the DSM contract to test the consequences of a pleased or unappreciated program in the EC. Following what was discovered, we proposed a program where on a virtual application the prosumers communicate the day before when they want to use certain appliances and the aggregator can shift these loads in liked time slots after confirmation from prosumers. We try to join the user needs, i.e., [8], with the Acceptance Learning Algorithm (ALA) presented in our previous work [22] that learns user accepted shifts based on the answer it collects when there is a request. The users' acceptance has been modelled considering the user profiles identified in the survey conducted in [18].

In a nutshell, the main contribution of the paper is to provide a tool that includes the psychological and social aspects to simulate future smart grids. To achieve this goal, the parameters that influence the behaviour of the user had been first identified and then modelled in the framework. The framework has been tested using our previously proposed DSM program [22].

III. Social and Behavioural theories

With the aim of modelling properly the user, we selected social-psychological theories widely used to explain people behaviours. In our view, those selected in [31] represent a comprehensive subset of the theories used for agent based modelling, which are particularly suitable for the problem faced in this article since they simulate well the psychological mechanisms described in the surveys. The rest of this section gives a brief overview of these theories.

A. The Theory of Planned Behaviour

Mengolini et al. [32] suggest that the Theory of Planned Behaviour is one of the most influential attitude-behaviour model, easily expressible with a mathematical model.

According to TBP, the way of acting of each individual depends on three independent attributes: i) Attitude Toward the Behaviour (*att*) - "the degree to which a person has a favourable or unfavourable evaluation or appraisal of the behaviour in question" [33], thus, people approval/disapproval in acting in a certain way; ii) Subjective Norm (*sn*) - "the perceived social pressure to perform or not the behaviour" [33] and iii) Perceived Behavioural Control (*pbc*) - "the perceived ease or difficulty of performing the behaviour" [33], factors that increase or reduce the perceived difficulty of performing a behaviour. The relative importance of the attributes in predicting the intention varies according to the situations and personal beliefs. Thus, *att* is influenced by behavioural beliefs and *sn* is affected by normative beliefs. Control beliefs have impact on the *pbc*. The weighted linear combination of *att*, *sn* and *pbc* forms the Behavioural Intention (*bi*, Eq. 1).

$$bi = w_{att}att + w_{sn}sn + w_{pbc}pbc \quad (1)$$

It indicates how much a person is ready to take action. Indeed, from *bi* derives the actual Behaviour (*b*) in Eq. 2.

$$b = w_{bi}bi + w_{pbc'}pbc \quad (2)$$

B. The Relative Agreement

Relative Agreement well simulates opinion dynamics thanks to two parameters:

- *opinion* y_i with a value between [-1,1], where the positive extreme may represent a person wholly in favour of a certain idea, while the negative one an opposite view.
- *uncertainty* u_i - the level of confidence in the opinion in (0,2), the smaller the values, the higher the confidence.

These parameters can be visualised as a segment with the opinion value plus/minus the uncertainty. When individual i interacts with another one, depending on how much the confidence intervals overlap, i may influences individual j.

$$h_{ij} = min(y_i + u_i, y_j + u_j) - max(y_i - u_i, y_j - u_j) \quad (3)$$

If the overlapping part h_{ij} (Eq. 3) is larger than u_i, x_j and u_j are modified (Eq. 4-5):

$$y_j = y_j + \mu[(h_{ij}/u_i) - 1](y_i - y_j) \quad (4)$$

$$u_j = u_j + \mu[(h_{ij}/u_i) - 1](u_i - u_j) \quad (5)$$

A high value of the "learning rate" μ increases the speed of population convergence.

C. The Small World Network

Small-world networks model well real-world networks. As pointed out in [34], the properties of a SWN graph are: *i)* high clustering coefficient - sub-networks with edges between almost all vertices - and *ii)* small characteristic path length - the small average distance between two nodes.

This network topology lies in between a completely random topology - small path length and small clustering coefficient - and one fully regular - large path length and large clustering coefficient. To obtain a SWN, starting from a regular topology, some edges should be rewired randomly with probability p.

D. The Diffusion of Innovation Theory

The Diffusion of Innovation Theory (DOI) developed by Rogers explains how an idea perceived as new by people spreads through the population [35], i.e. the time at which different people adopt a "new" idea. Besides the concept of innovation, other key terms are the communication channel, the time aspect, the social system.

Each individual follows a 5-step process: i) it becomes aware of the idea; ii) it develops a positive/negative attitude towards the idea; iii) it may adopt the innovation; iv) the innovation is "used"; v) it evaluates the choice made, confirming or not its decision.

The population is split into groups sorted by time of adoption. The rate of adoption is the "speed with which an innovation is adopted by members of a social system" [35]. The cumulative distribution is an S-shaped curve.

IV. Multi-Agent System Implementation

In this section, we examine in-depth the selected agents, the interactions among each pair of agents and the models.

A. The agents and interactions

Agents - the entities endowed with intelligence - are responsible to manage the resources (e.g. ESS, load), which are treated like models. Therefore, the proposed system is made up of three agents as follows:

i) **Prosumer Agent**. All the *Prosumer Agents* belong to the EC benefitting from the usage of PV and ESS. At its core, the *Prosumer Agent* implements the TPB (that models the sign of the contract) and the RA, talking only to its friends, selected thanks to the SWN (see Section III). Thus, each *Prosumer Agent* has its own opinion on the proposed DSM program. The heterogeneity of the population has been considered thanks to a set of attributes that assumes different values for different prosumers. Indeed, the user is also characterised by a certain level of education and by the family size from which the related energetic load profile is derived. Therefore, each *Prosumer Agent* owns a fair amount of appliances. Moreover, different *Prosumer Agents* have different tolerances to delay an appliance that depends on the discomfort perceived;

ii) **Aggregator Agent**. The *Aggregator Agent* manages the battery banks and the PV generation, which are considered as resources owned by the whole community. It implements the DSM program. Thus, for those who signed the DSM contract, it optimally shifts the appliances of the *Prosumer Agents*. In order to have a win-win situation for both prosumers and aggregator, it learns prosumers' tolerance thanks to the ALA (see Section IV-E);

iii) **Market Agent**. It has no intelligence and it just knows the day-ahead market price of the energy.

The possible interactions are:

i) Prosumer Agent to Prosumer Agent (P2P). They exchange opinions on the DSM program via the RA. Thus, they can influence the acquaintances with their opinions, fostering or hindering the diffusion of the DSM program;

ii) Prosumer Agent to Aggregator Agent (P2A). *Prosumer Agents* - who sign the contract - communicate the planning of shiftable loads for the day after. They also respond to the request from the *Aggregator Agent* to shift the loads. It is supposed that the total load profile curve of all *Prosumer Agents* is known one day in advance;

iii) Market Agent to Aggregator Agent (M2A). The *Market Agent* communicates one day in advance the next 24-hours energy prices to the *Aggregator Agent*.

B. The available resources

The models have been implemented for the resources listed in the following:

i) **Prosumers' Loads**. The load curves of each *Prosumer Agents* have been generated using the model developed by Bottaccioli et al. [36], which generates both the load profile for the single appliance and the total demand curve. Moreover, the appliances have been divided into *shiftable* - if their use can be delayed - and *not-shiftable*. We considered *shiftable* the washing machine and the dishwasher. Instead, appliances such as the television or lights are *not-shiftable*;

ii) **Expected PV**. The PV production is estimated following the methodology developed in our previous work [37]. For simplicity, we suppose that the forecast is 100% correct;

iii) **Battery**. For simplicity, batteries are considered as a single virtual battery with a total capacity equal to the sum of capacities of all the batteries in the systems. A simplified empirical model with a constant efficiency has been used as done in [20], [21];

iv) **Market**. Market information is available online as open data. Then, taxes, system and network charges can be added.

C. The EC simulation

In this Section, we present the main steps performed during a simulation to better understand the working principle of the system, see Fig. 1.

STEP-1: The first day of the month, the Aggregator Agent asks the Prosumer Agents whether they want to sign the DSM contract for one year. The answer of Prosumer Agents is modelled with TPB. If Prosumer Agents join the program, they undertake to use an imaginary application where if they want to use a *shiftable* appliance they have to send the hour (time slot) at which the appliance should be turned on the next day. Instead, all the appliances belonging to those who did not sign the contract will be switched on by the users according to preferences. This step determines which appliances will be considered as potentially shiftable by the aggregator. It is a *P2A* interaction.

STEP-2: At 9 p.m. the *Aggregator Agent* is informed on the market price (*M2A* interaction), the foreseen production of PV panels and load curves of prosumers (*P2A* interaction). The *Prosumer Agent* who signed the contract send both the total load curve and the dis-aggregated curves of the shiftable appliances.

STEP-3: At 11 p.m. two optimisations are performed. The first one (*1' OPT*) is computed considering the total load curves, thus turning on the appliances exactly when users want to. The objective is to minimise the cost considering the different sources (PV, ESS, from/to the grid). The obtained cost represents the worst case. The second optimisation (*2' OPT*) gives the opportunity to shift loads in the best time slot allowed, according to the information known up to that moment. Then, each *Prosumer Agent* evaluates the proposal and communicates the decision to the *Aggregator Agent* (*P2A* interaction). If it accepts, its loads are turned on according to *Aggregator Agent* decisions. Otherwise, the loads are turned on exactly when the *Prosumer Agent* wants. Each appliance is considered individually. This step increases the information of the *Aggregator Agent* on user acceptance.

STEP-4: A third optimisation (*3' OPT*) - with the load curves decided in Step-3 - i.e. according to the answer of prosumers - is performed. This step determines the actions to be taken during the day after, e.g. when to charge the battery. This optimisation computes also the actual cost.

STEP-5: The *Prosumer Agents* may talk to each other during the day, fostering or hindering the diffusion of the DSM program. The exchange of opinion is simulated thanks to RA. Therefore, it is a *P2P* interaction. It has been supposed that they talk about the DSM program experience twice a week, but this value can be easily configured.

D. The Prosumer Agent

In line with what was reported in the surveys [8], [24]–[26], the key parameters chosen to characterise the prosumers are:

i) **Opinion.** Each *Prosumer Agent* has its own opinion on whether it considers more important comfort or price. This coefficient is strictly linked to an opinion in favour of the DSM or not, since a prosumer who cares more about money is prone to join the DSM program. The opinion assumes a value between [-1,1], where the positive extreme represents a *Prosumer Agent* that only cares about price, while "-1" means that the *Prosumer Agent* is only interested in its comfort. A zero value means that it is neutral. The opinion of an individual Prosumer Agent can change according to the virtual discussion with other Prosumer Agents, modelled through the RA. The individual opinion can also evolve if the *Prosumer Agent* likes the proposed shift or not - i.e. the opinion becomes more favourable or more contrary, respectively. Indeed, if a rational user joins the DSM program, it answers affirmatively when it is not bothered, thus it cuts down on the energy costs and it should be satisfied. The opinion is the primal motivation that drives people to take part in a DSM program. It is the *att* parameter in TPB and has a great influence;

ii) **Level of Confidence.** It is the uncertainty or level of belief in the opinion of the RA. It is difficult that who has a neutral opinion on the DSM program, strongly believes in it. According to Schiera et al. [31], the level of confidence is formulated as:

$$-2 \cdot (opinion^2 - 1) \tag{6}$$

iii) **Price.** The *Opinion* is translated into a price coefficient in the range [0,1].

$$price_{coeff} = (opinion - (-1)) \cdot 0.5 \tag{7}$$

iv) **Comfort.** It is complementary to the *Price*;

v) **Geographic Coordinates**. They are the x and y coordinates of the house where the *Prosumer Agent* lives in. They influence the creation of the Social Circle. Basically, if prosumers live in the same area, they have major opportunities to meet and chat. The coordinates of the centroids of buildings can be used for calculating the distance among all apartment blocks as:

$$dist = \sqrt{(x_{home} - x_j)^2 + (y_{home} - y_j)^2} \tag{8}$$

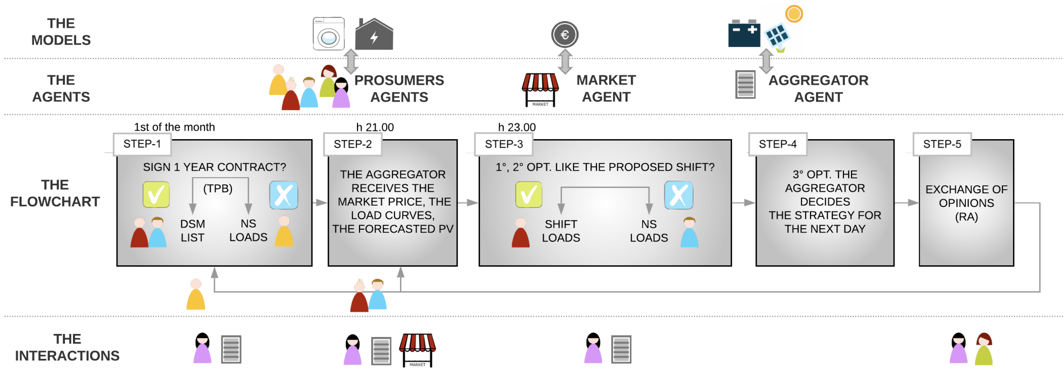

Fig. 1. The agents, the models, the flowchart (with a brief description) and the interactions that take place at each step.

where x_{home} and y_{home} are the latitude and the longitude of the considered home, while x_j and y_j are those of the j-family;

vi) **Social Circle.** It is composed of friends and acquaintances who the *Prosumer Agent* can meet under the SWN;

vii) **Family Size.** It is one of the *pbc* inputs for TPB. Following the logic described in Section II, large families have a better chance to save up. Theoretically, on average, they have more appliances that could be shifted. Thus, they might be more interested in participating in the DSM program. The coefficients used are shown in Table II

viii) **Trust**. It is a binary value to indicate the *Prosumer Agent* trust (1) or un-trust (0) in the energy provider. It favours or hinders participation. It is a *pbc* input.

ix) **Education.** It is the *sn* input. The possible values it can assume are shown in Table III. We supposed that those who have a higher level of education have also a higher education on energy. Moreover, it is more informed about environmental problems and possible strategies to contribute, or it has a higher knowledge of its energy consumption and interest in reducing energy costs. Furthermore, it could have a strong propensity towards technology and new ideas related to it. In other words, being more conscious means being more influenced by government/local action plans and news;

TABLE II
FAMILY SIZE

No.	Normalised
1	0.00
2	0.25
3	0.5
4	0.75
⩾5	1

TABLE III
EDUCATION

Education	Normalised
Primary School	0.00
Middle School	0.33
Secondary School	0.66
University	1

x) μ. It is the learning rate of the RA. It is equal for everyone. It weights the influence that a *Prosumer Agent* has on the others in exchanging opinions;

xi) **Acceptance.** It indicates the maximum acceptable delay. Many previous works, e.g. [38], [39], use a dis-utility function to model the dissatisfaction derived from the delay of the usage of an appliance. The increase of the shift from the desired time slots translates into an increase in value of the dissatisfaction, similarly to what emerges for some users of the survey in [18]. In [40], it is modelled as a convex, but not strictly convex function. Thus, there might be no dissatisfaction at all for small shifts, but then significant dis-utility for larger shifts. We model it as the square difference between the desired and the proposed start time normalised following Eq. 9.

$$Dissat(t_{prop}) = \left(\frac{t_{des} - t_{prop}}{96}\right)^2 \tag{9}$$

where the difference between *desired* and *proposed* is in number of time slots, while 96 is the number of slot in a day. The level of tolerance after which the user cannot stand the delay and refuses the proposal made by the *Aggregator Agent* is modelled as a threshold *T*- different for each *Prosumer Agent* - w.r.t the dissatisfaction function, i.e. high level of annoyance in [18]. Before that value, which corresponds to a certain amount of delay, the user accepts the proposal made by the *Aggregator Agent*. Moreover, we took the following assumption. For each *Prosumer Agent*, the threshold *T* is not static: it varies a little depending on the opinion on the DSM program (Eq. 10), where T_{base} is the fixed part of *T*.

$$T = T_{base} + opinion \cdot 0.01 \tag{10}$$

The terms introduced above are graphically represented in Fig. 2.

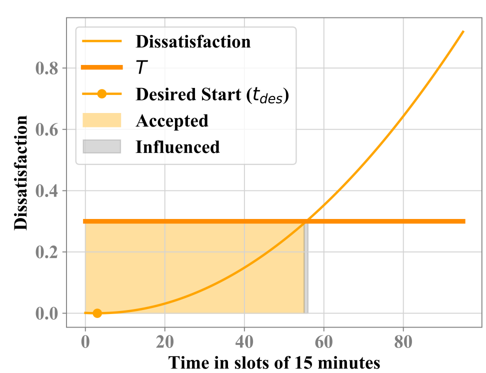

Fig. 2. The dissatisfaction curve and the related terms

When the user realises that the DSM program is rewarding it, the prosumer may be more prone to make a little effort.

Instead, if the mechanism is not working, it is less willing to contribute. Indeed, the user experience may affect user behaviour. Furthermore, since the opinion is influenced by the RA, the prosumer's friends have a little weight in the decision of the single individual, i.e. a social pressure.

E. The Aggregator Agent

The *Aggregator Agent* is the central entity responsible for battery and PV systems. It learns the acceptance of users and performs the three optimisations described in Section IV-C.

1' OPT and *3' OPT* find the minimum cost without shifting loads. Thus, they take into account the Levelised Cost of Energy (used to compare different methods of electricity generation) of the PV (Cpv), the battery (Cdisch), the cost of buying energy from the grid (Cfrom), the gain derived by the sale of the surplus of energy to the grid (Cto) and P, which is the corresponding amount of power. This is formalised in Eq. 11, which aims at finding the best strategy for the day after. Thus, it suggests the amount of power that must be taken from or given to the grid at time t ($Pfrom_t$ and Pto_t, respectively) and discharging power ($PDbat_t$) of the battery at time t.

$$\begin{aligned} \min \quad & \sum_{t=1}^{96} \delta \cdot [Cpv_t \, PV_t + Cfrom_t \, Pfrom_t \\ & + Cdisch_t \, PDbat_t - Cto_t \, Pto_t] \end{aligned} \tag{11}$$

where δ is the time interval duration. Since the *2' OPT* has the formulation of the other two with more constraints, the MILP formulation will be described once for the *2' OPT* optimisation.

◊ *ESS Constraints:*

$$\begin{aligned} Ebat_t \quad &= Ebat_{t-1} + \delta \cdot eff \cdot PCbat_t \\ & -PDbat_t \cdot \delta / eff \;\; \forall t > 0 \end{aligned} \tag{12}$$

$$PCon_t + PDon_t \leqslant 1 \;\forall t \tag{13}$$

$$PCbat_t \leqslant PCon \cdot C_{max} \forall t \tag{14}$$

$$PDbat_t \leqslant PDon \cdot D_{max} \forall t \tag{15}$$

$$Ebat_t \leqslant capacity \;\forall t \tag{16}$$

$$Ebat_t \geqslant minCharge \;\forall t \tag{17}$$

$$Ebat_{t=1} = Ebat\_init \tag{18}$$

$$Pto_t \leqslant M \cdot (1 - PDon_t) \;\forall t \tag{19}$$

Equation 12 models the behaviour of the battery. $Ebat_t$ is the amount of energy in the battery at time t, that depends on $Ebat_{t-1}$, $PDbat_t$ and $PCbat_t$, i.e. the charging power of the battery at time t. The battery cannot be simultaneously charged and discharged (Eq. 13), where $PC\textit{on}_t$ and $PD\textit{on}_t$ are binary variables indicating if the battery is charging or discharging at time t, respectively. The ESS must fulfil the maximum charge/discharge rate (Eq. 14-15, respectively). The energy stored in the battery must be lower than the maximum capacity and higher than the minimum charge (Eq. 16-17, respectively). The energy stored at the beginning of a new day (t=1) must be equal to the energy stored at the end of the previous day (t=96, Eq. 18). Moreover, it cannot be discharged to sell its energy to the grid (Eq. 19).

◊ *User request:*

$$\sum_{f=low}^{up} x_f^{ij} = request_{ij} \;\forall i, j \tag{20}$$

In Eq. 20, *Low* and *Up* bounds for each appliance usage are defined. Without the prosumer request (i.e. $request_{ij}$=0) the appliance is not turned on. x_f^{ij} is a binary variable that selects the daily load profile of the appliance *i* of the customer *j*.

◊ *Balance Constraint:*

$$\begin{aligned} & NOTshift_t + \sum_{i=1}^{3}\sum_{j=1}^{N}\sum_{f=1}^{M} x_f^{ij} Lshift_{ij} = \\ & = PV_t + Pfrom_t - PCbat_t + PDbat_t - Pto_t \;\forall t \end{aligned} \tag{21}$$

Power balance must be respected (Eq. 21). $Lshift_{ij}$ is a dictionary that contains the possible allocation of the consumption vector of each shiftable appliance *i*, of each prosumer *j*. It can be viewed as a cycle matrix.

In Eq. 20, the lower and upper time slots allowed for the shift, dynamically change thanks to ALA, the algorithm presented in our previous work [22]. ALA learns the acceptance of the user based on the household's answer using an explore-exploit mechanism. According to this algorithm, there are 25 possible actions, including "0" when no shift is needed, "± 1" when the shift is between plus/minus one hour, "± 2" and so on up to "± 24". ALA goes through the following steps (see Fig. 3):

Pre-action: A decreasing ϵ-greedy algorithm has been chosen to select the pre-action. Therefore, *2' OPT* receives in input a vector containing time slots in between a number randomly large for a fraction ϵ of the requests (*Explore*). Otherwise, if the algorithm *Exploits*, the vector in between the shift (action) that gives the major reward is chosen as input (Fig. 3, top-left).

Action: *2' OPT* decides the shift that will be proposed to the *Prosumer Agent*. It is the "action" that is evaluated (Fig. 3, top-right).

Prosumer evaluation: Each *Prosumer* informs the *Aggregator Agent* of the decision according to its own threshold (Fig. 3, bottom-right).

Update: In case of a refusal, the action is penalised. Otherwise, that action is rewarded proportionally to the introduced delay in such a way that larger time shifts receive higher rewards *R* (Fig. 3, bottom-left). New answers are weighted more w.r.t. previous since the prosumer's opinion is not static. Thus, information on the chosen action is updated according to Eq. 22.

$$Q_{n+1} = Q_n + \alpha(R_n - Q_n) \tag{22}$$

where Q_n is the estimated value after its n-1 selections, α is a constant step-size parameter and R_n is the n^{th} reward [41].

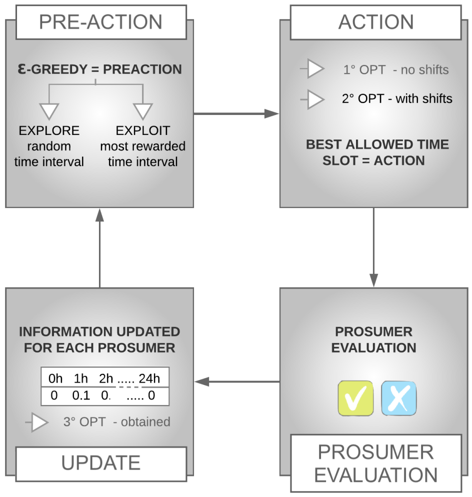

Fig. 3. The Acceptance Learning Algorithm

V. Case Study and Results

To test the whole structure and analyse the proposed algorithm, the city of Turin - a city in the north of Italy - has been chosen as our case study. Specifically, part of the neighbourhood "Center" has been considered (Fig. 4).

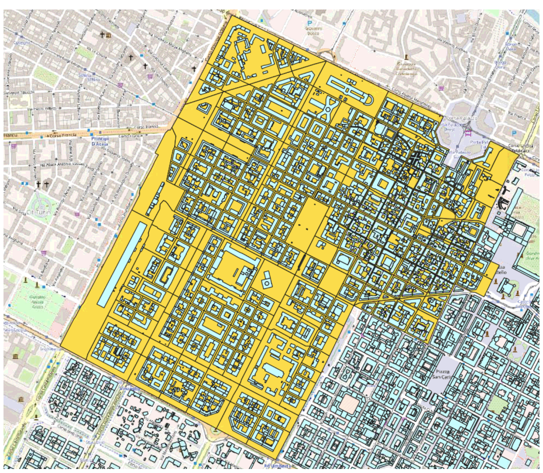

Fig. 4. The selected area

Using the cadastral map, the centroids containing the latitude and longitude of each building have been extracted from a shapefile. In addition, using data provided by the Italian National Institute of Statistics (ISTAT) [42], the number of families per building has been distributed proportionally to the square meters of the buildings. Non-residential buildings have been excluded. 10046 residential households have been considered.

Using ISTAT data, each household has been given a certain level of education and family size. Based on the family size, a load profile [36] has been associated. Different load profiles contain a diverse number of appliances. Thus, a prosumer may own a washing machine or a dishwasher or both. Since all the *Prosumer Agents* belong to the EC, we supposed that only very few of them have the trust coefficient equal to 0, i.e. 4%.

At the beginning of the simulation, each *Prosumer Agent*'s opinion is picked from a normal distribution truncated to the range [-0.6,0.6] (μ=0, σ=1/3). We made this assumption since it is uncommon that people have a really strong opinion on a new DSM program just introduced. Thus, too strong opinions, either favourable or contrary, have been excluded.

The amount of shifts accepted has been modelled with a normal distribution (μ=3, σ=1) truncated to the range [1,5] hours. As already mentioned, for a small shift there could be no dissatisfaction at all, but a significant discomfort for larger shifts. Since we have information on real users only up to $\pm$3 hours, we do not know if the user profile that is not bothered at all in $\pm$3 would behave as described in [40] or would be comfortable in shifting the appliance usage at any time during that day. Thus, in this scenario, we imagined users that accept up to 5 hours of delay.

To select *Prosumer Agent*'s friends, *Prosumer Agents* have been first "connected" to the spatially closest *Prosumer Agents*, then the local connections have been replaced with random individuals with probability p.

Table IV lists the value chosen for the coefficients of the different social theories. We chose reasonable values consistent with the information found in the surveys.

TABLE IV
COEFFICIENTS

Coeff.	Theory	Value	Motivation
μ	RA	0.1	avoid that opinions converge too fast
b	TPB	$\geq$ 0.67	arbitrary
w_{att}	TPB	0.75	primary motivation
w_{sn}	TPB	0.15	secondary motivation
w_{pbc}	TPB	0.1	secondary motivations
w_{bi}	TPB	0.9	major factor
$w_{pbc'}$	TPB	0.1	secondary factor
p	SWN	0.06	inside the range for the rewiring

The day-ahead market prices have been taken from Gestore Mercati Energetici - the Italian Power Exchange - of 2013 (NORTH) [43], adding system and network charges [44] and fees (excise tax and VAT [45]). The period goes from January 1st, 2013 to December 31st, 2013. We supposed that each *Prosumer Agent* is equipped on average with a 1 kW photovoltaic system. The Levelised Cost of Energy has been set to 0.13 €/kWh [46], while the photovoltaic energy in surplus is plausibly sold to the grid for 0.1 €/kWh. The ESS cost is 0.12 €/kWh.

We simulated an entire year with a 15 minutes time step. Results are presented in Fig. 5-11.

At the beginning of both simulations, 20,42% of prosumers sign the contract. Later on, if ALA is not used, i.e., if the shifts asked do not take into account the preferences of the users, the participation reaches only 21.08% in the first months and then no further increase in the level of participation is observed. Instead, with ALA the participation curve has a shape similar to the one described by Roger (Section III-D). With ALA, 98.36% had signed the DSM contract by the end of the year.

This is also highlighted in the opinion trend in Fig. 6. With ALA when an *Exploration phase* for a new customer starts,

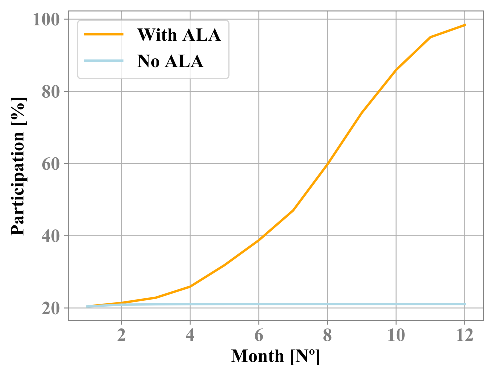

Fig. 5. Participation evolution

the opinion coefficient may decrease a little bit, but it increases shortly after towards a positive one.

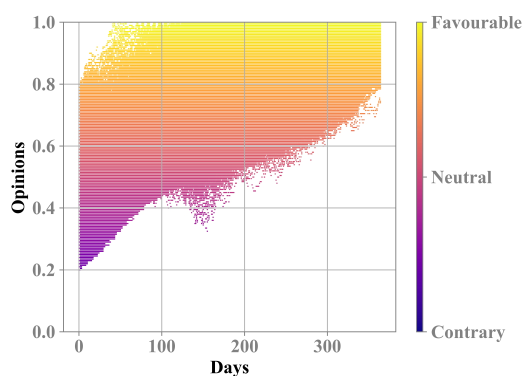

Fig. 6. Opinions. Preference-aware

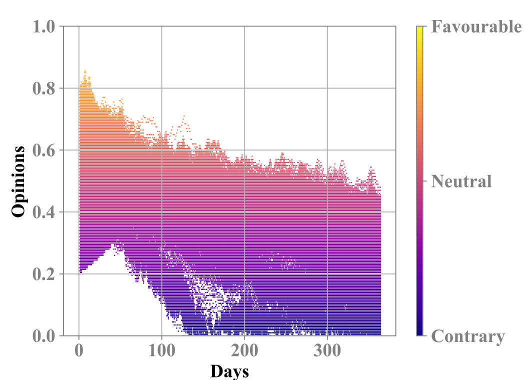

Fig. 7. Opinions. Preference-unaware

Starting from the same situation, Fig. 7 shows that during the first months *Prosumer Agents* are uncertain, while at the end the opinion is in between neutral and a contrary one.

Fig. 8 reports the acceptance rate. Each month new people join the program, and a *Learning phase* starts for them. At first, the DSM subscriptions do not increase that much, thus ϵ (the amount of exploration) for those who joined at the beginning decreases down to 10% from the 5th month and *Prosumer Agents* receive more and more requests for shifting the appliance usage of an amount they like. Then, the majority starts to sign up - and their strong *Exploration phase* starts as well. In any case, the acceptance rate oscillates around 80%. In the end, when few prosumers still have to sign the contract, this rate increases. Without ALA, the acceptance rate decreases since *Prosumer Agents* are getting annoyed and they are unwilling to make an effort.

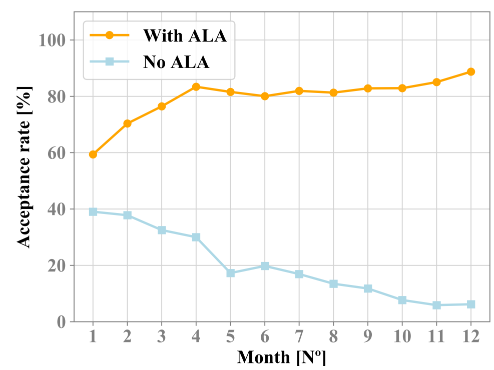

Fig. 8. Acceptance rate comparison

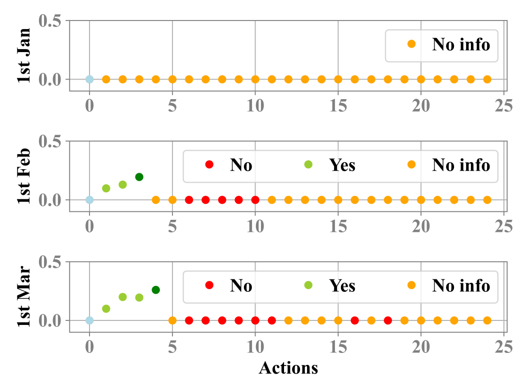

Fig. 9. Information on a user in January, February and March

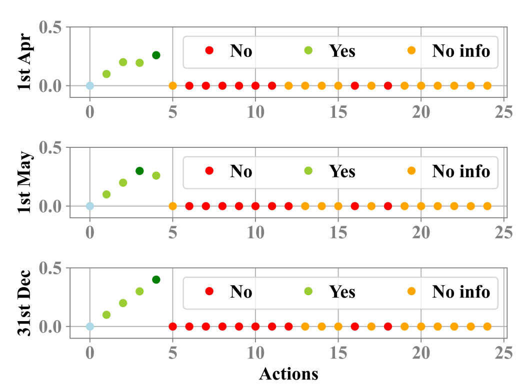

Fig. 10. Information on a user in April, May and December

To understand how ALA works, Fig. 9-10 report an example of a prosumer that signed the contract on the 1st of January. At the beginning, there is no information on the user preference (yellow dots in both figures). During the first months, ALA collects information on the user. If the user gives a negative answer the state is penalised with a very small negative reward (not visible in scale, see red dots in both figures). If a positive answer is given, that action increases its value (green dots in both figures). If ALA is in the *Exploitation phase*, the MILP problem receives as input the action with the highest value, i.e. dark green dots in both figures.

The costs obtained per month in different situations are compared in Fig. 11. The pink curve is obtained before the implementation of the DSM program. If a preference-unaware strategy is applied the light blue curve is obtained. Thus, only very few of those who signed accept the shift and there are almost no savings. When ALA is not applied, if the possibility to refuse the proposed shift is not given to the *Prosumer Agents*, the results show that the obtained savings are lower than the one obtained if we adopt a preference-aware strategy, i.e. grey curve. Thus, it is possible to see, that from July savings are greater when ALA is used. For the sake of completeness, the best obtainable cost is also plotted (green curve). It represents the case where all prosumers have signed the DSM contract on the 1st of January and cannot refuse the proposed shift. Considering the selected appliances, it is an unrealistic case, but it represents the optimal lower bound.

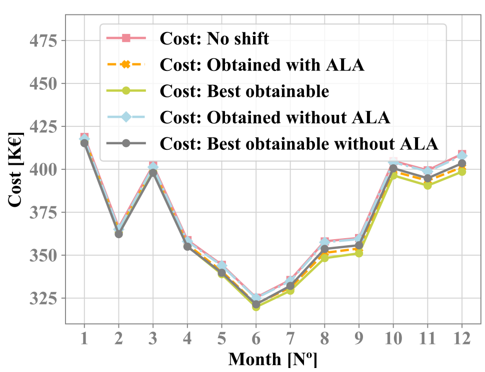

Fig. 11. Savings comparison

VI. Discussion

The proposed co-simulation framework does not just focus on technical and economical aspects, it also looks at the evolution of a DSM program and the social-psychological factors to cover the discussed gap in the literature, testing different DSM strategies in the future smart grids.

W.r.t. our proposed solution, the obtained results depend on the input parameters and the assumptions taken. Thus, we are not claiming that the proposed program would please all real users. Rather, we provide a tool that links the energy behaviour to the social dimension, realistically simulating the possible effects of DSM programs on the population. When the aggregator starts asking for shifts into the tolerated interval, the *Prosumer Agents* - that signed the contract during the first months of the year - start to be satisfied, influencing the others positively, who in their turn sign the contract as well. This mechanism boosts the diffusion of the DSM in the Energy Community.

However, social interaction might also disincentive the diffusion of DSM programs. Indeed, the failure of a program that ignores the preferences is not only the consequence of requests not liked by the *Prosumer Agents*, but also by the negative influence of the few who signed the DSM contract.

The comparison of cost savings in Fig. 11 underlines the importance of taking into account the preference of users. Indeed, the preference-aware strategy, i.e. the trend in orange in Fig. 11, is more profitable than the trend in grey where the aggregator decides the optimal shifts. Moreover, as shown in Fig. 6, the *Prosumer Agents* have all a favourable opinion, thus they will sign the DSM contract also the year after.

VII. Conclusion

Thanks to the existing surveys in literature, we consider upstream cognitive processes that may lead to the signing of a DSM program and we model accurately some aspects of the *Prosumer Agent*. In particular, we investigate in our simulated EC the effectiveness of the proposed strategy that results from the information discovered in the surveys.

The participation, the effects of positive or negative word-of-mouth on *Prosumer Agents* and savings for the selected parameters have been shown for one year. Results demonstrate the strong impact of the opinion on participation. It has been stressed the importance of keeping in mind user acceptance. Indeed, there could be a segment of the population that is comfortable with a central entity in full control of appliances, thanks to which the maximum savings (considering only users who signed the DSM contract) are obtained. But, if another large amount of individuals does not appreciate this mechanism, we will end up saving much less than if almost all the community participate with less flexibility. Thus, it might happen to have a higher initial financial gain if we consider only the utility profits, but this will translate into lower economical benefits in time. We tried to achieve a win-win situation where the aggregator maximises its profit and the prosumers maximise their utility, which is a combination of monetary gain and comfort.

The presented results are obtained from a realistic simulation scenario where the population has a quite neutral opinion at the beginning and, then, it is influenced by those who are in the DSM program. By changing the composition of the population, different types of convergence would be given. But, the importance of the user preferences is still valid. *Prosumer Agents* are simplified models of people, but the whole analysis paraphrases well the EU recommendations [23].

In future works, the initial annoyance created to the user will be avoided and grid constraints will be added.

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