A Gaming and Social Networking Platform for Evolving Energy Markets' Operation and Educating Virtual Energy Communities

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Initial version of GSRN platform functionalities

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Glossary of Acronyms

Acronym	Definition
API	Application Programming Interface
AUW	Aggregated Users’ Welfare
BMC	Business Model Canvas
BR	Behavioral Reciprocity
B-RTP	Behavioral Real Time Pricing
CDF	Cumulative Distribution Function
C&I	Commercial & Industrial
CIS	Customer Information System
CRM	Customer Relationship Management
C-RTP	Community Real Time Pricing
CW	Community Welfare
DMP	Data Management Plan
DMS	Distribution Management System
DR	Demand Response
DoA	Description of Action
DSM	Demand Side Management
DSO	Distribution System Operator
EC	Energy Community
ECFA	Energy Community Formation Algorithm
ECC	Energy Consumption Curve
EC-RTP	Energy Community Real Time Pricing
EE	Energy Efficiency
EIDaaS	Energy Information distribution as a Service
EMS	Energy Management System
EP	Energy Program
ESCO	Energy Services Company
ESP	Energy Services Provider
EV	Electric Vehicle
FC	Flexibility Curve
GDPR	General Data Protection Regulation
GSMaaS	Gamified Social Marketing as a Service
GSRN	Green Social Response Network
HVAC	Heating Ventilation and Air Conditioning
InEC	Innovation & Exploitation Committee
IBR	Inclining Block Rates
ICT	Information and Communications Technology
IPR	Intellectual Property Rights
KPI	Key Performance Indicator
LCMS	Learning Content Management System
LO	Learning Object
M&V	Measurement & Verification

NE	Nash Equilibrium
OSN	Online Social Network
PAR	Peak Average Ratio
PC	Price Controller
PP	Peer Pressure
P-RTP	Personalized Real Time Pricing
QoE	Quality of Experience
RAT	Research Algorithms Toolkit
RTP	Real Time Pricing
SEM	Strategic Energy Management
SEP	SOCIALENERGY Points
SSO	Single Sign-On
S/W	Software
SW	Social Welfare
TE	Transactive Energy
ToU	Time of Use
TSO	Transmission System Operator
VEC	Virtual Energy Community
VPC	Value Proposition Canvas

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Document History

This deliverable includes the first version of GSRN platform functionalities together with all S/W modules of SOCIALENERGY's real world. It also includes the first version of research algorithms' results as well as the technical application programming interfaces' design for the S/W integration of the individual subsystems of SOCIALENERGY's real world.

Table 1: Document History Summary

Revision Month	File version	Summary of Changes
13/12/2017	v0.1	Draft ToC circulated to the entire consortium.
15/01/2018	v0.2	Final ToC circulated to the entire consortium.
14/02/2018	v0.6	First round of ICCS contributions.
15/03/2018	v0.8	INTELEN and SU-NIS contributions.
16/03/2018	v0.9	ICCS integrates all required material and provides the pre-final version for internal review.
27/03/2018	v0.95	SU-NIS reviews the report and provides comments for quality enhancement before submission.
30/03/2018	Final	Coordinator addresses comments from internal review and submits the final version in ECAS portal.

Executive Summary

This report presents the initial version of SOCIALENERGY S/W platform's functionalities. It elaborates on the previous deliverables D2.2 and D6.1, which mainly dealt with the: a) SOCIALENERGY system's architecture design and technical specifications, b) research problems to be addressed (i.e. scientific algorithms) and intelligence to be integrated at the platform's backend, and c) market analysis about related existing products and services in today's retail electricity markets.

In chapter 1, an overview of SOCIALENERGY S/W platform's position in the current market, its main functionalities, valuable assets and expected impact is provided.

Chapters 2 and 3 present the most important research results so far regarding the intelligence that SOCIALENERGY S/W platform embeds at its backend (i.e. behavioural demand response framework, proposed algorithms and performance evaluation results). We describe how novel energy programs in the retail electricity sector can help towards behavioral change of the end users. We clarify how all this research work is closely/directly inter-related with SOCIALENERGY platform's services. In particular, chapter 2 deals the design of novel personalized energy programs that can be used by utility companies/energy service providers (ESPs) and generally retailers in the electricity market. A wide family of Personalized Real Time Pricing (P-RTP) energy programs is presented together with performance evaluation results.

Chapter 3 follows a similar structure presenting the design of novel Community Real Time Pricing (C-RTP) energy programs. Scientific algorithms for creating efficient Virtual Energy Communities (VECs) are also studied and respective performance evaluation results for several case studies are demonstrated. Finally, the research results are closely inter-related with the SOCIALENERGY S/W platform's functionalities (i.e. virtual currency and credit distribution policies) and the respective intelligence provided by the proposed scientific algorithms.

In chapters 4 and 5, the SOCIALENERGY's "real world" functionalities are presented via the use of indicative screenshots from the core Green Social Response Network (GSRN) platform (cf. chapter 4) and the Research Algorithms' Toolkit (RAT) subsystem (cf. chapter 5). For each S/W module, there is extensive description and explanation of the services that it provides to the end users.

In chapter 6, there is a high-level description of all Application Programming Interfaces' (APIs) structure. More specifically, the following interactions (APIs) and data exchanges among the various S/W components are described: a) MDMS-GSRN API, b) GSRN-RAT API, c) GSRN-GAME API, and d) GSRN-LCMS API.

Finally, chapter 7 concludes the report and summarizes the major action points of the consortium for the upcoming months.

1 Introduction

Progressive electric utilities are continuously seeking for new business and technology-driven innovations to create new revenue streams and be sustainably competitive in the liberalized electricity markets. This digitization era for utilities is tightly coupled with the development of inter-disciplinary software (S/W) platforms such as SOCIALENERGY aiming at establishing much more efficient communication pathways with their clientele and other smart grid market stakeholders. SOCIALENERGY is a user engagement, social networking, gamification and business management platform aiming at evolving energy markets' operation and educating virtual energy communities. The proposed business model is targeted on electric utilities' customer segment. The proposed system is modular by design incorporating several subsystems from various disciplines, such as ICT, energy efficiency, behavioral economics, socio-economic sciences, online social networks, education, serious games and gamification. The diversified combined functionalities described in this report facilitate the easy, rich and deep communication among individual energy consumers, virtual energy communities, utilities, policy makers, and other less direct stakeholders (such as electric appliance retailers and building renovators). This communication will allow them to: i) discover each other, ii) educate themselves so as to understand the difficulties and challenges each of them faces, and iii) finally interact and trade with each other.

According to several recent surveys undertaken by independent world-known consultancy companies and policy makers the high-level business strategy objectives of a progressive utility (or else ESP) are summarized in Table 2 and each one of them is directly mapped to one of the five main SOCIALENERGY subsystems.

Table 2: Mapping of ESP's Business Objectives With SOCIALENERGY Subsystems

ESP's Business Objectives	Expected outcome	SOCIALENERGY subsystem
Obj. #1: Build and strengthen a strong core of digital trust with clientele	Maximize customer satisfaction, minimize churn rate, cope up with high competition in the market.	Core GSRN platform
Obj. #2: Move from services to experiences via a cohesive personalization strategy	Customers are better and more efficiently engaged, because they deeply comprehend the services that are being offered.	GAME, LCMS
Obj. #3: Innovative value propositions and pricing algorithms able to trigger investments in energy efficiency.	Automated algorithms (investment planning and pricing) able to maximize profits and end users' welfare.	RAT
Obj. #4: Exploit the deep insight into energy use consumption to engage customers on cross-sell options that fit their needs	New revenue streams via collaborations with stakeholders from sectors other than/not directly related with energy.	Virtual Marketplace/ EIDaaS
Obj. #5: Use rapid prototyping (i.e. modular and customizable S/W platform)	Cope with various, diverse, volatile and dynamically changing needs of the liberalized electricity market and customer segmentation.	APIs among all sub-systems (modularity-by-design)

1.1. Overview of SOCIALENERGY's architecture design and proposed S/W platform

Taking into consideration the above-mentioned objectives of ESP's business, the proposed SOCIALENERGY S/W platform has been designed in such a way that it:

- Is 'modular by design', in order for each ESP/utility to be able to customize its own S/W platform based on the business strategy and the type of its customer portfolio's needs (cf. Obj. #5).
- Can be used by multiple types of users and stakeholders (i.e. end consumers/prosumers, VEC leaders, ESP user, ESCO user, etc.) in order to facilitate the easy, rich and deep interaction among all involved stakeholders.
- Allows the user to be seamlessly educated in the virtual world (i.e. game) and then apply the lessons learned in the real world (cf. Obj. #2).
- Educates the user based on a competence-based education framework that progressively and sustainably engages the user via the use of Individual Learning Plans (ILPs).
- Allows users to interact with each other, create VECs with a bottom-up manner, purchase various community energy programs (EPs) and other innovative products at a community level.
- Supports intelligent functionalities for the automation of the various complex processes via the operation of algorithms (e.g. artificial intelligence, dynamic pricing, machine learning, big data analytics, context-aware recommendations, etc.).
- Secures the insight needed to help customers make smart energy use choices and offers new products and services that help customers optimize their bills.
- Combines automation with manual interaction with the user. Therefore, social and behaviour analytics considerations will periodically inform social innovation and guide technology-oriented activities.
- Facilitates a virtual/online marketplace, where a diversified set of products and services can be purchased by the end user. For example, a residential consumer can use his/her SOCIALENERGY credits to purchase a more energy efficient electric appliance or upgrade/renovate his/her home (cf. Obj. #4).
- Is interoperable with a DSO's distribution management system (DMS) taking into consideration the physical underlying network's needs and constraints. It can also be upgraded to a transactive energy (TE) platform for peer-to-peer energy trading in the future.

The following figure presents a high-level architecture design of SOCIALENERGY system, which comprises of six S/W components (subsystems), namely: 1) Meter Data Management System (MDMS), 2) the core GSRN S/W platform or else SOCIALENERGY's real world, 3) Energy Efficiency GAME or else SOCIALENERGY's virtual world, 4) Research Algorithms' Toolkit (RAT), 5) Learning Content Management System (LCMS), 6) Energy Information Distribution as a Service (EIDaaS) or else virtual marketplace.

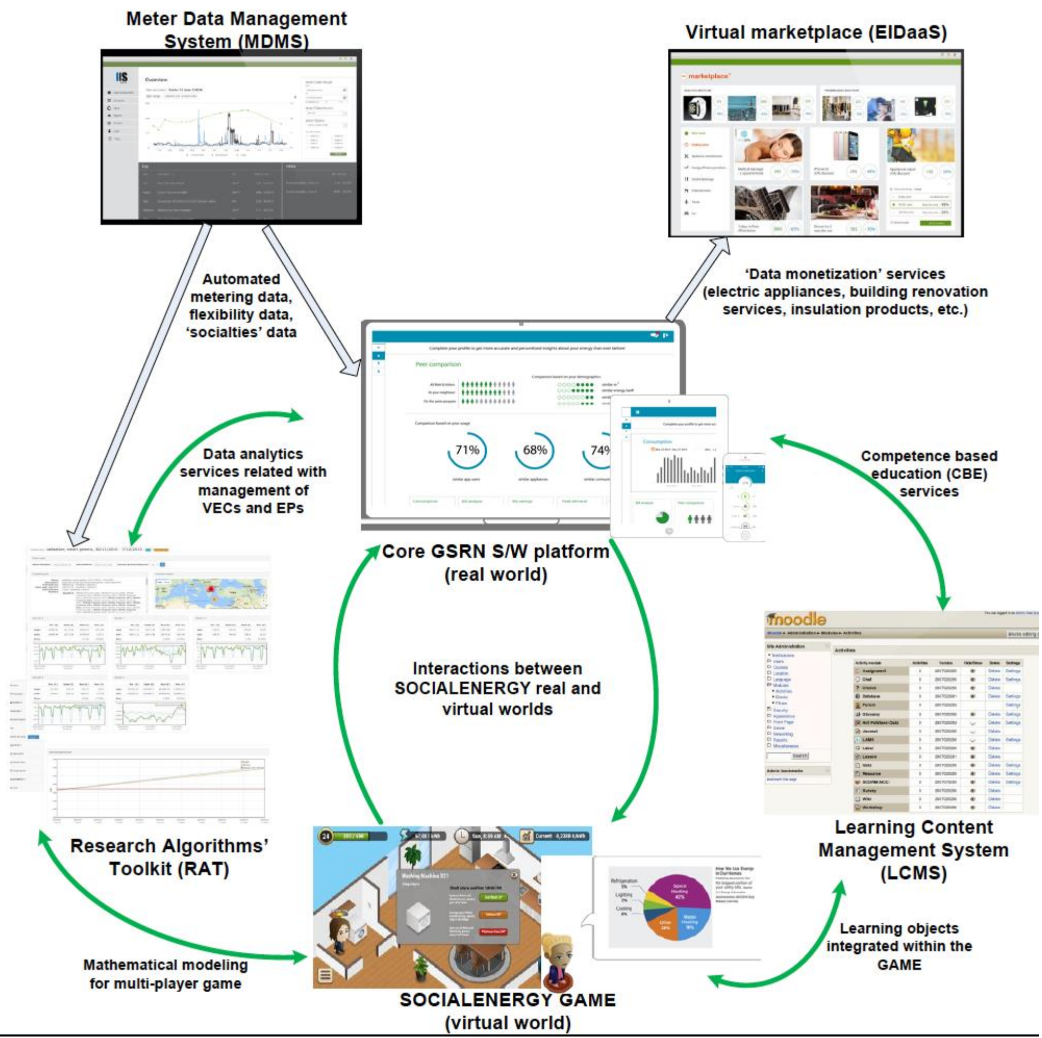


Figure 1: High-level architecture design of SOCIALENERGY system

1.2. Purpose and role of SOCIALENERGY's real world

By the term "SOCIALENERGY's real world", we mean the web-based S/W platform with all the respective services offered to an electric utility company in order for the latter to provide advanced and competitive services for its energy consumers in the retail market. On the other hand, by the term "SOCIALENERGY's virtual world", we mean the Game application for energy efficiency, in which the users can enhance the Quality of Experience (QoE) being simultaneously educated in good practices regarding energy efficiency with the aid of LCMS.

In MDMS, all energy consumption related data is collected. MDMS actually serves as SOCIALENERGY's database, where all energy-related data models are also available (e.g. electric appliance consumption models). The datasets that will be used for SOCIALENERGY purposes come from real energy consumers of various types (e.g. residential vs. commercial, high vs. low educational level, different locations/countries, etc.). This energy consumption data is made available in various time granularities (i.e. monthly, daily, hourly, 15-min).

The GSRN is the core S/W platform of the SOCIALENERGY system, in which all types of SOCIALENERGY users (e.g. individual consumers, VEC leaders/managers, electric utility/retailer user, ESCO user, etc.) are able to log in and visualize/experience many innovative functionalities. GSRN has technical interfaces with all other five (5) subsystems integrating several multi-disciplinary functionalities ranging from the scientific/research sector (cf. RAT) to the gaming/gamification sector (cf. GAME) and the educational sector (cf. LCMS). GSRN is also being fed with real-life energy consumption data from MDMS. It also offers Energy Information Distribution as a Service (EIDaaS) services to various targeted stakeholders such as building renovation companies and electric appliance vendors/retailers, who aim at indirectly exploiting SOCIALENERGY system's operation towards realizing new revenue streams for their businesses, too.

The RAT subsystem is very important for SOCIALENERGY's operation, because it provides all the intelligence that is required towards making SOCIALENERGY S/W platform competitive enough and commercially successful in a sustainable manner. It provides "data analytics" services mainly to GSRN. Various research algorithms are executed regarding the dynamic pricing models that are adopted in the various innovative Energy Programs (EPs) and the Virtual Energy Communities' (VECs) creation and dynamic adaptation algorithms, which are required for the online management of the virtual energy communities. RAT also provides context-aware recommendations to GSRN and is also a toolkit to be used by the system administrator for business/strategy analysis by running various simulations (i.e. 'what if' scenarios).

LCMS is the subsystem, where the user educates herself both online and offline to consolidate the new knowledge about good practices on energy efficiency. LCMS interacts with GSRN. Thus, the latter can provide recommendation services to the user according to the educational content that is mostly keen on watching next based on her/his current educational profile and experiences in both SOCIALENERGY's real and virtual worlds. The role of the LCMS is important because it provides the user the opportunity to better comprehend the new concepts in the liberalized smart grid markets and inter-relate the "lessons learned" from the GAME with the real-life conditions in order to be able to efficiently interact with her/his electric utility/retailer.

Finally, via the EIDaaS S/W component, SOCIALENERGY bridges the gap between energy consumers and companies as well as among multiple other stakeholders related to the energy efficiency sector. Using the SOCIALENERGY platform, the profile of each energy consumer is created (e.g. energy consumption history, social networking activities, commercial actions' history, etc.). This profiling information could be exploited from stakeholders in order to: i) design energy efficiency products and services more appealing to their audience, ii) allow VECs to participate in the design by giving their opinions, iii) exploit VECs as cells within which they will enable group trading, and iv) generally sell Energy Information Distribution as a Service (EIDaaS) to whom it may concern in the long-term future. SOCIALENERGY has created an API through which it can commercialize this idea of "data monetization" service. Moreover, the virtual marketplace module can host products and services from electric appliance vendors/retailers, building renovation companies, etc., so the user can have an end-to-end experience towards achieving his/her energy efficiency targets.

1.3. Summary of SOCIALENERGY's business model and value propositions

Figure 2 summarizes the business modelling work for SOCIALENERGY S/W platform as a whole. It presents the Business Model Canvas (BMC), which is extensively analysed in D6.2 (M15). We focus on one customer segment that is progressive electric utilities (or else Energy Service Providers - ESPs). We also consider five distinct value propositions (or else business cases) for SOCIALENERGY S/W platform's commercial exploitation, namely:

1) Digital user engagement, marketing and gamification platform
2) Business analysis and intelligence tool
3) Administrative tool for Virtual energy communities' management
4) Virtual/Online marketplace for energy efficiency products and services
5) SOCIALENERGY Game application for entertainment, education and social inclusion

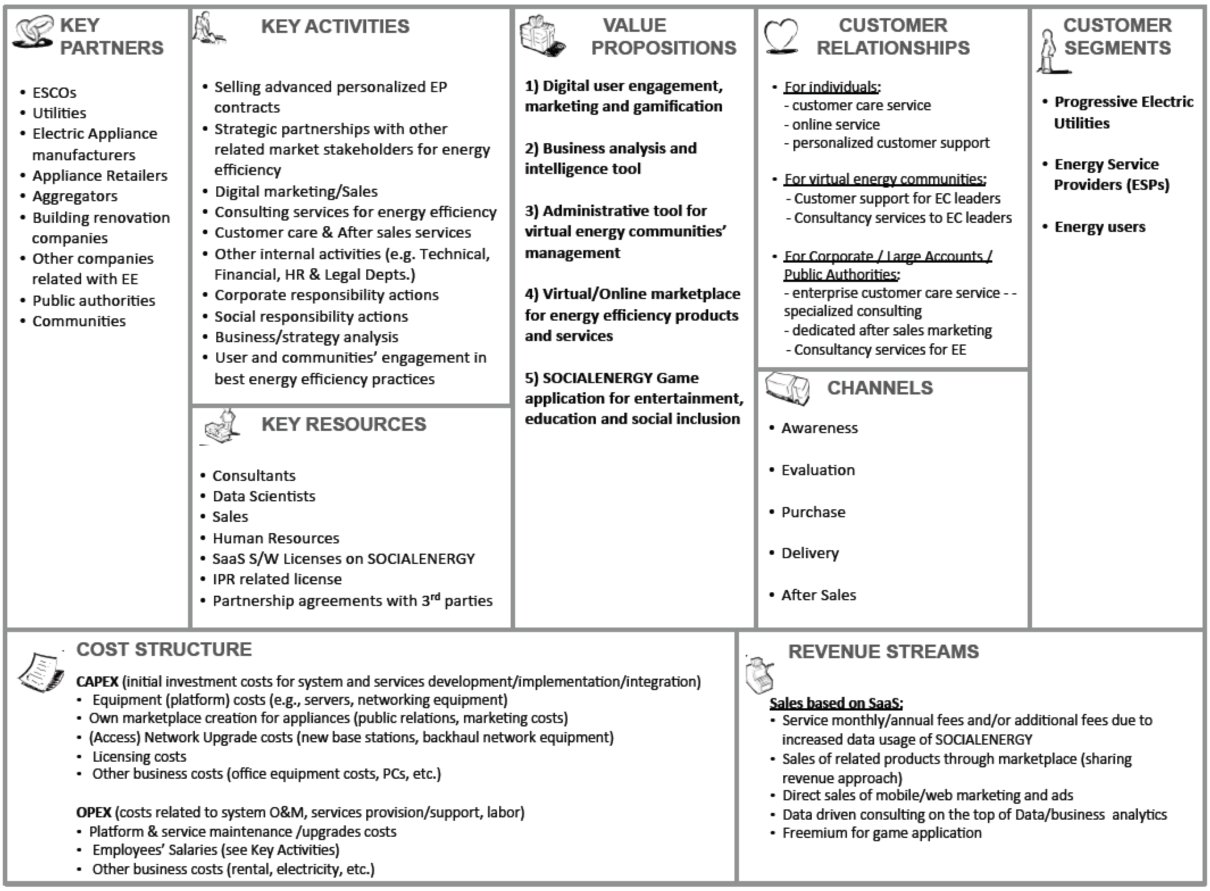


Figure 2: A high-level business model analysis of SOCIALENERGY (updated BMC version in D6.2)

Extensive analysis and technical details about the above-mentioned BMC and Value Proposition Canvases (VPCs) can be found in SOCIALENERGY deliverable D6.2 (March 2018).

2 Novel personalized energy programs' design and dynamic pricing algorithms

To design a new Energy Program (EP) that incentivizes behavioral change towards the desired energy efficiency targets, a dynamic pricing model and algorithm are required. Let us consider a system, which consists of an electric utility company (or else Energy Service Provider - ESP) and its N clients/energy consumers. Without harm of generality, in the retail market, the utility provides electricity to its clients in order to cover their demand. Thus, utility participates in wholesale electricity markets and purchases the required amount of energy at a certain cost, which is time-variant and also a non-linear function of the aggregated consumption of all N end users (i.e., each incremental energy unit purchased costs more). Generally, the utility can minimize the cost of the energy that it purchases in the wholesale electricity market (i.e., the system cost) by giving incentives to its end users to "harmonize" the aggregated Energy Consumption Curve - ECC (i.e. the demand curve of its entire customer portfolio) with the wholesale market prices. Utilities and end users (energy consumers) can mutually benefit from this system's cost reduction and the stability improvement that behavioral changes in the energy consumption can bring (see figure below). Modern pricing schemes (or else EPs) should be able to trigger these behavioral changes (e.g., by motivating users to consume less during peak hours and more during non-peak hours). For example, in Real Time Pricing (RTP), prices are analogous to the dynamic ratio between the total energy production cost (i.e. supply) and the total amount of consumption (i.e. demand) [1] [2]. A pricing scheme has to achieve an attractive trade-off among the following requirements (or else Key Performance Indicators - KPIs): i) the end user's satisfaction, ii) the stability of the energy production/ transmission/consumption system, iii) the utility's financial profitability, and iv) fairness in allocating the incurred flexibility benefits to all users. The first requirement is also referred to as '*user's welfare*' and is formulated as the difference between a utility function that expresses how much an end user values a specific consumption pattern and the cost of energy that s/he consumes. In the context of comparing different pricing schemes, the user's welfare expresses which pricing scheme leads to more competitive services in the open electricity market [3] [4]. The second requirement is also denoted as '*behavioral efficiency*' and expresses the capability of a pricing scheme to achieve the objectives that motivated it in the first place (e.g. load curtailments and shifts). Intuitively, behavioral efficiency of a pricing scheme expresses how friendly it is to a TSO/DSO (addressing issues related to energy network stability, efficiency and costs) and implicitly affects several financial metrics (e.g. investments in RES, energy storage and network upgrades). Usually, it is linked with minimizing the system's energy cost, as in [5] [6]. The third requirement is also referred to as '*profit dynamics*' and represents the profit percentage per energy unit and the total revenues of the utility company. In other words, it expresses the financial growth potential of the company that exploits a specific pricing scheme (or else EP) [1] [7]. Finally, the fourth requirement is fairness KPI and it refers to how fairly the system's energy savings resulting from the behavioral changes of the participating users are allocated among them. Authors in [8] propose a pricing model based on the principle that the users' bills should be analogous with their contribution to the system's energy cost reduction.

A wide range of innovative EPs are integrated in SOCIALENERGY platform and more specifically in the RAT subsystem. In particular, SOCIALENERGY conducts research on the improvement of the behavioral efficiency of the EPs without sacrificing the rest of the aforementioned KPIs. For example, as shown in **Figure 3**, a behavioral change in the aggregated Energy Consumption Curve (ECC) can provide reduced energy cost for the system without sacrificing users' welfare due to the fact that some of them are flexible enough to undertake the changes in their individual ECCs and in return get reimbursed by the utility company. Through SOCIALENERGY platform, the administrative user can perform exhaustive system-level simulations before deciding to release a new EP in the retail market (see more details in chapter 5 regarding RAT subsystem operation). Similarly, an end user can also exploit SOCIALENERGY platform to dynamically invest (if it is beneficial for her/him) on a new EP that fits his/her updated needs. Finally, an end user can also play the SOCIALENERGY GAME in order to comprehend the optimal behavior that one should have towards harvesting the maximum benefits from a certain EP.

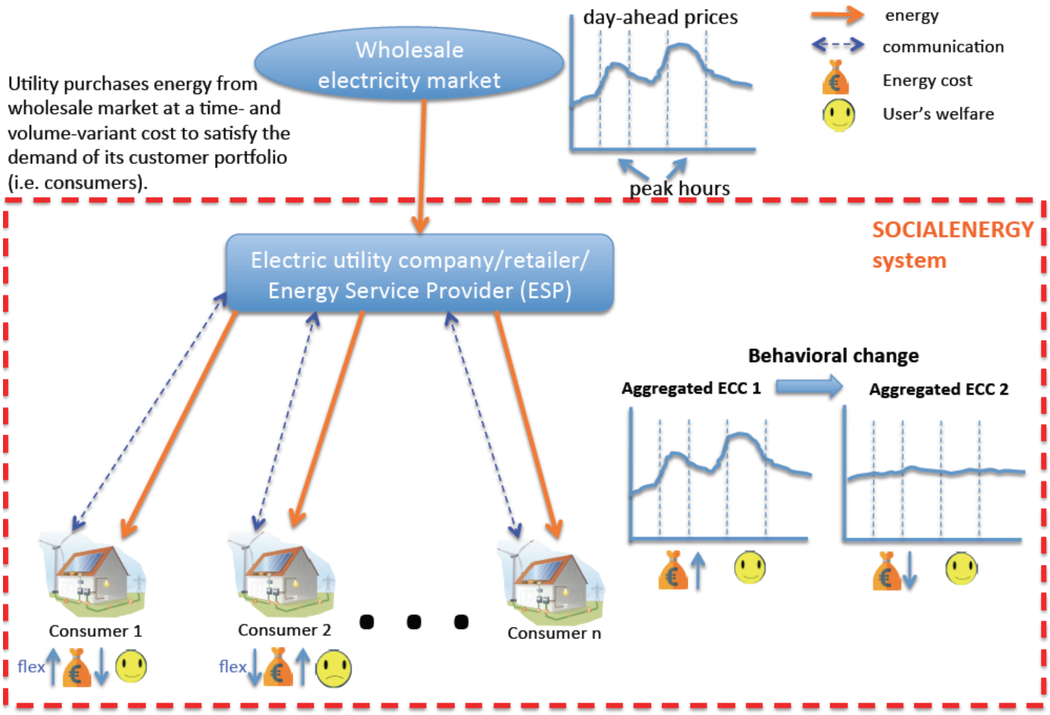


Figure 3: Advanced Energy Programs design for behavioural change

Complementarily to the above-mentioned business model of an electric utility company/ESP, another similar business model is illustrated in the figure below. **Figure 4** explains the role and use of the proposed SOCIALENERGY's EPs for facilitating the trading of Demand Side Management (DSM) units (i.e. as commodity units) in emerging flexibility markets. In the assumed business model, as previously mentioned, the ESP purchases energy from the wholesale electricity market at a time- and volume-variant cost G in order to satisfy the demand of its customer portfolio (i.e. energy consumers). On the other hand, aggregated users' flexibility (i.e. behavioral changes) can create a cost reduction ΔG. Subsequently, the ESP can trade its ability to control the demand (e.g. reduce energy cost) as a commodity in various types of flexibility markets (e.g. congestion, balancing, voltage control, frequency control markets, etc.). This amount of ΔG can be fully returned back as a reimbursement/discount to the end users or a fraction of ΔG can also be used to increase the ESP's profits. The premise of the proposed Personalized Real Time Pricing (P-RTP) scheme is that it can considerably decrease the energy system's cost without deteriorating the users' quality of experience (or else the aggregated users' welfare - AUW). Moreover, P-RTP fairly allocates the cost reduction benefits among the users that create them, which is very important for the commercial success of SOCIALENERGY product and services.

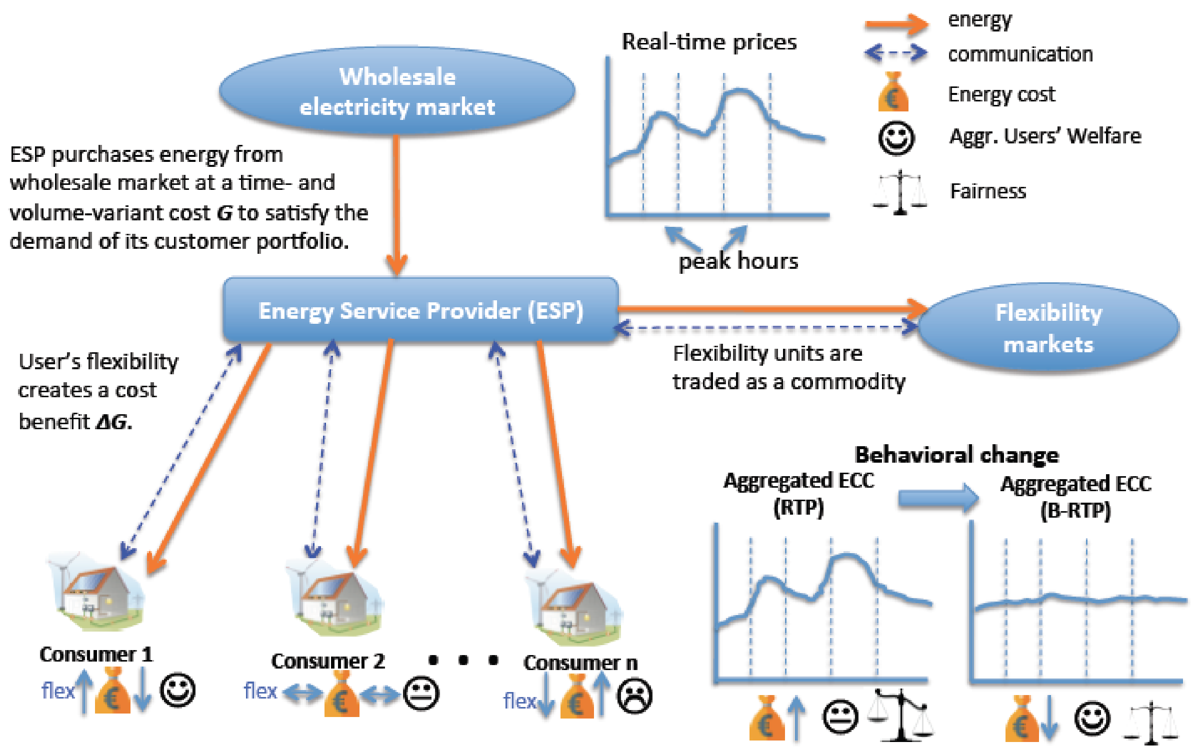


Figure 4: ESP's business model for energy flexibility units trading in flexibility markets

There are two types of buildings/environments that participate in DSM programs: i) Fully automated smart houses/buildings/industries, where users automatically/electronically control their electric appliances by setting their preferences online and an Energy Management System (EMS) controls their operation, ii) Less automated houses, in which only the user's current consumption can be monitored. Therefore, the research community has to design pricing schemes for both of the above- mentioned use cases. The first use case assumes an a priori known user's "base" ECC (before the behavioral changes that P-RTP will incentivize) and the second one an unknown "base" ECC. By "base", we mean the natural/voluntary (unforced) consumption behavior of a user, in the absence of incentivized time varying penalties or rewards. In this report, we focus on a *personalized energy billing mechanism*, referred to as Personalized - Real Time Pricing (P-RTP), which applies to the first use case, and motivates energy consumers to efficiently schedule their flexible loads in order to adopt a more energy-efficient ECC. In the next version of this report (i.e. D3.2), research results and respective comparative study regarding the second use case will also be provided.

2.1. Overview of existing pricing schemes in today's retail electricity markets and SOCIALENERGY proposals

Nowadays, the majority of residential energy consumers in Europe area continue to receive their electricity bills (most probably every month or two/three/four months) with a *flat price rate*. This means that every energy unit (e.g. KWh) costs a fixed price independently of the time, the type of user, network state, market state, location, etc. The follow-up model of *Inclining Block Rates (IBR)* charges a higher per unit price of electricity to users with high consumption profiles. For example, in Greece, for a 4-month energy consumption up to 1600 KWh, the price per KWh is the lowest possible, while each energy unit above the pre-mentioned threshold costs considerably higher. This model is an effective motivator towards lower consumption, but it does not address the issue of making the end user's profile more convenient with respect to the time of consumption (i.e. load shifts).

As a result, *Time-of-Use pricing (ToU)* models were introduced, where a generally different per-unit price was applied for each hour of the day (e.g. peak load pricing). For example, during morning hours (e.g. 07:00-10:00) and late afternoon (e.g. 17:00-20:00), when electricity demand is high, the prices are high, too. Therefore, users are motivated to shift loads into low pricing hours. However, ToU programs drawback is that it is still static and the respective prices are not: i) reflecting the real-time needs of the grid, thus often resulting in congestion problems during the low-priced hours, and ii) acting as effective motivators towards load shifting. To cope with these shortcomings, a more dynamic version of ToU model is Real Time Pricing (RTP) model, in which the prices are fluctuating every hour or even every 15 minutes according to the respective time granularity. However, the problem with the RTP model is that it is not practically feasible for the end user to continuously monitor the dynamic energy prices and perform respective load reduction and shift actions within the day.

The most beneficial aspect of RTP model is that it can directly connect the generation, transmission and distribution costs to the charging price and harmonize in this way production with consumption. Towards the realization of RTP (enabling demand side management actions by the end user's side), the first step is the development of a two-way communication system between the utility company/ESP and the end users. Then, through a limited number of message exchanges, prices are derived in real time resolving the trade-off between pricing requirements, which are:

- The minimization of electricity cost (electricity cost varies in time according to the way that the energy is generated and the aggregated energy consumption or else demand).
- The maximization of user's comfort because of the fact that load shifts and cuts increase user's discomfort.
- The fair distribution of the costs to the participating users (each user should be billed according to the cost of its consumption and the discomfort that load shift and load shedding introduces to her/him)
- The utility company/ESP should be able to realize some profits from the whole procedure in order for innovative services to be commercially sustainable.

In SOCIALENERGY project, we incorporate all the above-mentioned existing pricing schemes (or else energy programs) in the Research Algorithms' Toolkit (RAT), which is currently under development. The baseline model for SOCIALENERGY (or else benchmark) is the RTP model (DR-enabled), which is analyzed in the following subsection 2.2. SOCIALENERGY's proposals and research results for even better performing pricing schemes (EPs) are: i) Personalized RTP programs, which are analyzed in subsection 2.3, and ii) Community RTP (C-RTP) programs, which are analyzed in section 3.

2.2. Real Time Pricing (RTP) with demand response

In this subsection, we describe a basic model for the proposed SOCIALENERGY system, which incorporates the state-of-the-art RTP scheme, in order to have a competitive benchmark for the demonstration of the outperformance of the novel SOCIALENEGRY EPs (i.e. P-RTP and C-RTP energy programs).

2.2.1. Demand Side Management (DSM) model

We consider a smart community, which consists of electricity users and a utility company/ESP. An electricity consumer can be a single smart home or a group of smart homes acting as a single unit. Each user $i \in \boldsymbol{N}$ is equipped with advanced smart meters that monitor her appliances' Energy Consumption Curves (ECCs) and an Energy Management System (EMS) that schedules her energy consumption over the scheduling horizon according to the preferences that are set by the electricity consumers. We do not consider price-taking consumers as in [9], but, on the contrary, users interact with the ESP in order to reach an agreement on the energy consumption schedules and the energy prices. A communication network lies on top of the electric grid, enabling the message exchange between the users and a Price Controller (PC) installed at ESP's premise. The PC receives each user's *i* aggregate consumption and sends back to the users' EMSs their energy bills. As we later analyze, our proposed architecture includes limited information disclosure from the energy consumers and thus preserves their privacy by following the same data exchange model as in [10]. Next, we present the user model and the energy generation cost model that is widely adopted in the literature in order to facilitate the evaluation of the proposed P-RTP billing scheme and the comparison between P-RTP and RTP. Note that P-RTP is also applicable to other user and energy generation cost models. Finally, without harm of generality, we consider a discrete-time model with a finite horizon that models the scheduling period ***H***. Each period is divided into *T* timeslots of equal duration.

Each user $i \in N$ owns a set D_i of household devices, and each device $d \in D_i$ consumes energy $x_{i,d}^t$ at time $t \in H$. The total amount of energy that all devices in $\boldsymbol{D_i}$ of user *i* consume at time t is denoted as x_i^t. According to the literature [2] [9] [11], user's devices can be categorized into three categories with respect to their load flexibility: *curtailable*, *shiftable* and *non-adjustable*.

2.2.1.1. Modeling the curtailable loads

This category of loads includes appliances such as: heating, ventilation, and air conditioning (HVAC) system, building lights with adjustable volume, etc. We denote by $D_{c,i} \subseteq D_i$ the set of curtailable appliances of user *i*. For each device $d \in D_{c,i}$, each user $i \in N$, according to her preferences, a priori declares a desired consumption schedule $\widetilde{x_{i,d}} = \{\widetilde{x_{i,d}^t}, t \in H, d \in D_{c,i}\}$ and a minimum consumption level $\underline{x_{i,d}^t}$ $, t \in H, d \in D_{c,i}$ (see Eq. 1). User's satisfaction in every time slot *t* depends on the amount of energy that a curtailable device actually consumes, denoted as $x_{i,d}^t$ and on how close it is to the desired consumption $\widetilde{x_{i,d}^t}$. Therefore, user *i* attains a utility $U_{i,d}^t(x_{i,d}^t)$ in time interval *t* when her device *d* consumes $x_{i,d}^t$, which varies according to her lifestyle and preferences.

$$\underline{x_{i,d}^t} \leq x_{i,d}^t \leq \widetilde{x_{i,d}^t} \qquad (1)$$

In order to have a benchmark for the evaluation of P-RTP, we use the concept of utility function, drawn from the fields of Microeconomics [12], to model the end users' preferences regarding the operation of a device. In the case of curtailable devices, it is reasonable to assume that the users' utility function is increasing (i.e. the more a user consumes, the more utility she perceives) and concave (i.e. the more a user consumes, the less the incremental added utility is). This approach is also in line with the vast majority of the literature (e.g. [1] [13] [14]), where a quadratic form is usually considered for the utility function, expressed as:

$$U_i^t(x_i^t, \omega_i^t) = \begin{cases} \omega_{i,d}^t \cdot x_i^t - \frac{a}{2} \cdot (x_i^t)^2, & if\ \ 0 < x_i^t < \frac{\omega_{i,d}^t}{a} \\ \frac{(\omega_{i,d}^t)^2}{2 \cdot a} & ,\ if\ \ x_i^t > \frac{\omega_{i,d}^t}{a} \end{cases} \tag{2}$$

In Eq. (2), a and ω_i^t are predetermined parameters, and ω_i^t denotes the responsiveness of user *i* to financial incentives (i.e. *flexibility*) at time interval *t* in terms of reduction of her energy consumption, while parameter a expresses how the rate of change of user's utility is changing as consumption changes. Another utility function that is used by the literature [15] makes use of $\widetilde{x_i^t}$:

$$U_i^t(x_i^t) = \begin{cases} -\left(x_i^t - \widetilde{x_i^t}\right)^2, & if\ 0 \leq x_i^t \leq \widetilde{x_i^t} \\ 0, & if\ x_i^t > \widetilde{x_i^t} \end{cases} \tag{3}$$

In order to combine the advantages of the two aforementioned functions, we use a utility function, which is mathematically expressed as:

$$U_{i,d}^t\left(x_{i,d}^t\right) = \begin{cases} U_{\max,i,d}^t - \omega_{i,d}^t \cdot \left(x_{i,d}^t - \widetilde{x_{i,d}^t}\right)^2, & if\ 0 \leq x_{i,d}^t \leq \widetilde{x_{i,d}^t} \\ U_{\max,i,d}^t \quad , & if\ x_{i,d}^t > \widetilde{x_{i,d}^t} \end{cases} \tag{4}$$

$U_{\max,i,d}^t$ is the maximum user satisfaction concerning appliance d, the one achieved when she consumes her desired load. The proposed utility function of Eq. (4) is a composition of the two aforementioned functions and is able to: i) model the heterogeneity in the flexibility among participating users that Eq. (2) is also able to model through ($\omega_{i,d}^t$), and ii) explicitly correlate the maximum user's satisfaction with her desired consumption $\widetilde{x_{i,d}^t}$ as the utility function of Eq. (3) is also able to do. In Eq. (4), $\omega_{i,d}^t$ is again a predetermined parameter that captures the flexibility of user *i* concerning appliance d in time slot *t*. More specifically, the lower the value of parameter $\omega_{i,d}^t$, the more tolerant will be the user towards a certain change in her desired energy schedule of device *d*. Figure 5 depicts user's *i* utility at time slot *t* as a function of $x_{i,d}^t$ for a given $U_{\max,i,d}^t$ and different values of $\omega_{i,d}^t$.

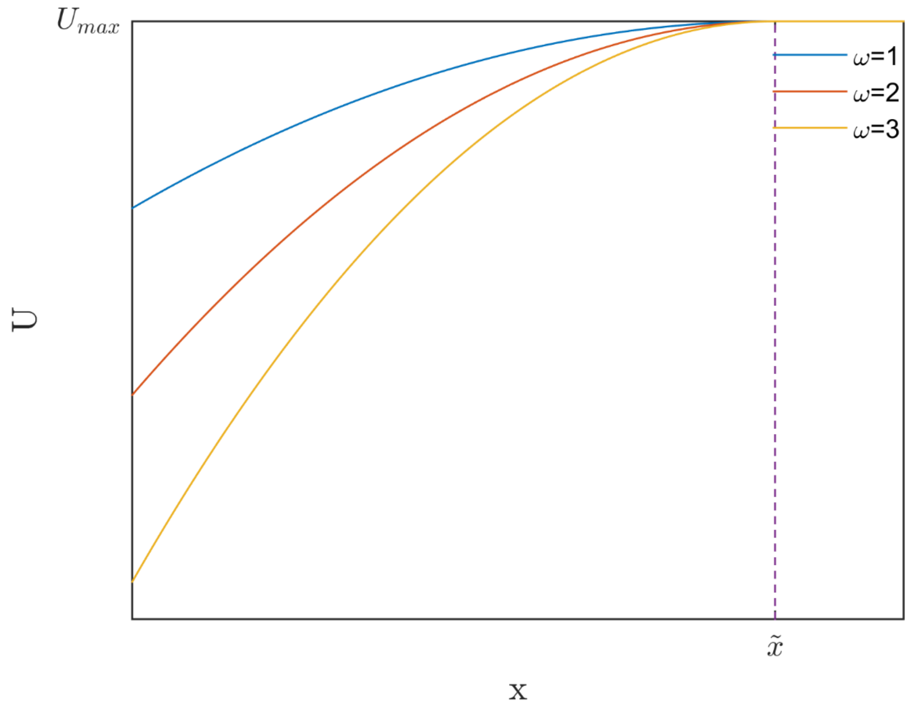


Figure 5: User's *i* utility in timeslot *t* as a function of her/his energy consumption for various flexibility levels

2.2.1.2. Modeling the shiftable loads

This category of loads includes appliances that can shift their consumption according to user's preferences. Appliances such as: Electric Vehicles (EVs), the dishwasher, the washing machine and the clothes' dryer can be considered available for consumption shift. We denote by $D_{s,i}$ the set of shiftable appliances of user *i*. For this type of appliances, the energy consumer sets a desired operating schedule $\widetilde{x_{i,d}^t}, t \in \widetilde{H_s}$, where $\widetilde{H_s} = [\widetilde{t_{i,d}^a}, \widetilde{t_{i,d}^b}]$ is a time interval where $\widetilde{t_{i,d}^a}$ is the timeslot at which it is desirable for the device to start and $\widetilde{t_{i,d}^b}$, is the timeslot at which *d* normally finishes its task if it starts operation at $\widetilde{t_{i,d}^a}$. Additionally, user *i* sets a deadline $t_{i,d}^l$, which is the latest time by which the task of device *d* should be completed. Thus, regardless of the shifts that will take place, the total energy consumption of device $d \in D_{s,i}$ of user $i \in N$ must reach a certain energy threshold $E_{i,d}$ by $t_{i,d}^l$, that is,

$$0 \le x_{i,d}^t \le E_{i,d}\ , \quad \forall t \in \left[\widetilde{t_{i,d}^a}, t_{i,d}^l\right] \tag{5}$$

$$\sum_{t=\widetilde{t_{i,d}^a}}^{t_{i,d}^l} x_{i,d}^t = E_{i,d}, \quad \forall i \in N, d \in D_{s,i} \tag{6}$$

Therefore, regarding user's *i* shiftable loads, we can define a feasible scheduling set X_i that is,

$$\begin{aligned} X_i = \{x_i | \sum_{t=\widetilde{t_{i,d}^a}}^{t_{i,d}^l} x_{i,d}^t = E_{i,d}, \quad & \forall d \in D_{s,i}, \\ 0 \le x_{i,d}^t \le E_{i,d}\ , \quad & \forall t \in \left[\widetilde{t_{i,d}^a}, t_{i,d}^l\right], \\ x_{i,d}^t = 0, \quad & \forall t \in H \backslash \left[\widetilde{t_{i,d}^a}, t_{i,d}^l\right] \} \end{aligned} \tag{7}$$

We assume that each user is fully satisfied when the operation of her device $d \in D_{s,i}$ does not deviate from her desired energy schedule $\widetilde{x_{i,d}} = \{\widetilde{x_{i,d}^{t}}, t \in \widetilde{H_s}\}$, where $\widetilde{H_s}$=$[\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}]$ $\subseteq H_s$ and $H_s = [\widetilde{t_{i,d}^{a}}, t_{i,d}^{l}] \subseteq H$. The degree (monetary value) of each user's *i* dissatisfaction for every unit of energy that a shiftable device d consumes in any other time slot ($t \in H_s \setminus \widetilde{H_s}$) depends on user's individual lifestyle and preferences. In the international literature, this particular behavior of users is modeled by a disutility function [2] [3] [16] [17] [18] [19]. We assume that user's dissatisfaction increases as her shiftable devices consume more energy at later hours in H_s, which intuitively means that her waiting time increases. Thus, we exploit the utility function used in [16], where user's *i* dissatisfaction for her/his device is given by:

$$DU_{i,d} = \sum_{t \in \boldsymbol{H_s}} \frac{(\delta_{i,d})^{t-\widetilde{t_{i,d}^{b}}} \cdot x_{i,d}^{t}}{E_{i,d}}, \tag{8}$$

In Eq. 8, $\delta_{i,d} \geq 1$ is an adjustable control parameter. The higher the value of $\delta_{i,d}$ the higher will be the dissatisfaction of user *i* for a given change in her desired energy schedule of device *d*. In other words, the lower the value of parameter $\delta_{i,d}$, the more responsive will user *i* be to price incentives. As we did in the case of curtailable loads, we again note that this utility function is used only for evaluation purposes and the proposed P-RTP scheme is transparent to any convex utility function that may be used in the real-life business.

2.2.1.3. Modelling the non-adjustable loads

Each user *i* a priori declares which of her devices fall into this category. These loads have predetermined consumption schedules and are not adjustable by the EMS. We denote by $\boldsymbol{D_{f,i}}$ the set of the devices that user *i* categorize as non-adjustable. Examples of this category of appliances are: refrigerator, freezer, TV, etc. and their load is not curtailed or shifted at all. For non-adjustable loads, we should have:

$$x_{i,d}^{t} = \widetilde{x_{i,d}^{t}}, \forall i \in \boldsymbol{N}, t \in \boldsymbol{H}, d \in \boldsymbol{D_{f,i}}. \tag{9}$$

2.2.2. Energy Cost Model

In the literature [1] [2] [7], in order to evaluate pricing models, an increasing convex function *G(x)* is often adopted to (approximately) model the cost of energy that comes from conventional generation. Piece-wise linear functions and quadratic functions are two example cost functions. In our study, we use a quadratic energy cost function, the mathematical expression of which is given by:

$$G^t = G(\sum_{i=1}^{N} x_i^t) = a \cdot (\sum_{i=1}^{N} x_i^t)^2 + b \cdot (\sum_{i=1}^{N} x_i^t) + c, \tag{10}$$

where $a > 0$, $b, c \geq 0$ are predetermined parameters that depend on the energy generators characteristics. This cost function models either the cost of the ESP to purchase the necessary energy units from the wholesale electricity market, or the actual cost of the utility company/ESP to produce energy by operating its own generation units.

2.2.3. Proposed system model

We consider electricity consumers (users) that participate in a DSM program (which is modeled as a game) with the objective to maximize their payoff. User's *i* payoff is defined as her individual welfare, which equals the total utility attained when her schedulable appliances consume a certain amount of energy (as analyzed in the previously) minus her energy bill B_i given by Eq. (11). Thus, each user's EMS calculates her energy consumption schedule by solving Eq. (12), and then informs ESP about the updated consumption schedule x_i. ESP, in turn, sets the energy prices so as to achieve an attractive trade-off among the requirements that have been described at the beginning of section 2. Its primary goal is to motivate consumers to change their ECCs through a *fair* billing scheme in order to reduce the *total energy cost* without sacrificing efficiency in terms of *social welfare.* Social Welfare (*SW*) is defined as the aggregate users' comfort minus the total energy cost (Eq. 13). Users and ESP repeat the aforementioned steps until the process converges to the Nash Equilibrium (NE).

$$W_i = \sum_{d=1}^{D_{c,i}} \sum_{t=1}^{T} U_{i,d}^t \left(x_{i,d}^t\right) - \sum_{d=1}^{D_{s,i}} \left(DU_{i,d}\left(\widetilde{t_{i,d}^a}, \widetilde{t_{i,d}^b}, t_{i,d}^l, x_{i,d}^t\right)\right) - B_i \quad (11)$$

$$x_i = \arg\max W_i \quad (12)$$

subject to (1), (7), (9)

$$SW = \sum_{i=1}^{N} \left(\sum_{d=1}^{D_{c,i}} \sum_{t=1}^{T} U_{i,d}^t \left(x_{i,d}^t\right) - \sum_{d=1}^{D_{s,i}} DU_{i,d}\left(\widetilde{t_{i,d}^a}, \widetilde{t_{i,d}^b}, t_{i,d}^l, x_{i,d}^t\right)\right) - \sum_{t=1}^{H} G^t \quad (13)$$

In what follows, we present the RTP scheme (i.e. benchmark) and follow with the description of our proposed P-RTP scheme. The RTP scheme will be used in section 2.3 as a benchmark, in order to compare it with P-RTP.

2.2.4. State-of-the-art Real Time Pricing (RTP) algorithm

In the initial phase of the RTP algorithm, ESP collects the desired schedule $\widetilde{x_i}$ of each user *i* from their EMSs, and calculates their nominal energy bills $\widetilde{B}_{i,RTP}$, $\forall i \in \boldsymbol{N}$. In order to do so, ESP exploits Eq. (14) to calculate the price (average cost) per unit of energy at each time interval *t* as:

$$\rho^t = \frac{G\left(\sum_{i=1}^{N} x_i^t\right)}{\sum_{i=1}^{N} x_i^t} \quad . \quad (14)$$

The ESP, through the communication infrastructure, informs its customers about the energy bills, calculated by:

$$B_{i,RTP} = \sum_{t=1}^{N} \rho^t \cdot x_i^t \quad (15)$$

Eq. (14) corresponds to a non-profit version of RTP [2] [20]. In [2], it is proved that social welfare is maximized when ρ^t is set to the marginal cost of energy, (i.e. $dG\left(\sum_{i=1}^{N} x_i^t\right)/d\left(\sum_{i=1}^{N} x_i^t\right)$). However, in this case, social welfare maximization comes with a budget revenue, which violates the budget-balance of the business models described at the beginning of this section. Thus, in order to evaluate P-RTP, we exploit a non-profit RTP version according to Eq. (14). The algorithm of RTP scheme is summarized in the table below. Convergence is proved in Theorem 2 of [21].

Table 3: Algorithm for the calculation of the energy bills and the energy consumption schedules in RTP

Initialization: $k = 1$, $x_i^k = \widetilde{x_i^k}$, $B_{i,RTP}^k = \tilde{B}_{i,RTP}$
Repeat
$k \rightarrow k+1$
For each user $i \in \boldsymbol{N}$
Receive $B_{i,RTP}^k$ from ESP
Repeat
Update x_i^k
ESP updates $B_{i,RTP}^k$ using (14), (15)
Calculate W_i^k using (11)
Until Reach solution of (12)
End for
Calculate $divergence = max\left\|x_i^{t,k+1} - x_i^{t,k}\right\| \quad \forall i \in \boldsymbol{N}, t \in \boldsymbol{H}$
Until $divergence < desired\ accuracy$
End

2.3. Personalized Real Time Pricing (P-RTP) model

The P-RTP model is a hybrid billing mechanism that is able to take full advantage of users' flexibility. This is achieved through a personalized billing policy, which rewards in a fair way the behavioral change (i.e. ECC adjustment) of consumers. In more detail, they receive a discount in their energy bill, which is equal or proportional to their contribution in the total energy cost reduction. Users that do not change their ECCs do not receive similar treatment and may even be penalized in cases of emergencies requiring energy cost reduction (e.g. network congestion, lack of energy in islanded mode, etc.). In these cases, as our evaluation results show, ESPs using P-RTP are able to participate in various types of flexibility markets [22] [23] without sacrificing user's welfare and fairness.

Identically with RTP, in the initialization phase of P-RTP, users set their desired consumption schedules $\widetilde{x_i}$ (desired ECC) and, based on them, ESP calculates $\tilde{B}_{i,RTP}$, $\forall i \in \boldsymbol{N}$, using Eqs. (14) - (15), and communicates them to the users. Repeating the assumption that users are rational and their objective is to maximize their individual welfare given by Eq. (11), each user determines her ECC (energy schedule) by solving Eq. (12). This process is repeated (as depicted in Table 3), until its convergence to the final (actual) ECCs and energy bills. As it is obvious from the above, the valuation of an ECC for a specific user *i* (e.g. the evaluation of RTP price from Eq. (14) is not a standalone process. The bill of each user *i* depends on the ECCs of the other users in set *N*, as Eq. (15) depicts for RTP. RTP scheme, as well as other DSM algorithms considers that users determine their ECCs sequentially and the ESP determines sequentially the valuation of the ECCs, until the convergence of this iterative process. In more detail, a user *i* is implicitly, but adequately informed (through the billing system) about the decision (ECCs) of the other users (in every iteration of the aforementioned process) and afterwards updates her x_i^t.

In the case of P-RTP, as far as the shiftable loads are concerned, this creates an advantage for the users who act first over those who act later. For example, two equally flexible users with similar ECCs would be similarly responsive to a specific financial incentive given by the ESP. However, the one that acts first may shift a shiftable load from a peak-hour to a low-cost time interval, and this will prevent the second user to do the same, as that would lead to a reverse peak. Thus, the first user will get a discounted energy bill, while the second user will not. Consequently, the users' order of action plays a major role in the final energy schedules and energy bills. To overcome this problem, we exploit and enhance [21], in which users act in parallel and therefore users decide their actions without knowing what the others do in each iteration of the aforementioned process. Thus, in every iteration *k* of P-RTP, users calculate their energy schedule by solving Eq. (12) simultaneously. This approach, may temporarily create reverse peaks, since every user, in order to achieve a larger total cost reduction and receive a larger discount in her energy bill, shifts her shiftable loads to low–cost hours. In order to overcome this problem, in each iteration *k*, we impose a restriction in the changes that users are allowed to make in their energy schedules. In more detail, the updates are done so that shifts are done in an incremental way, satisfying,

$$\left|x_i^{t,k} - x_i^{t,k-1}\right| < \theta^k \cdot x_i^{t,k-1}, \qquad (16)$$

where $\theta^{\kappa} < 1$ is a parameter that sets the upper bound of the volume of shift that a user can make in a certain step *k* of P-RTP. If after the users' decisions, there is a reduction in total energy cost (i.e. no peak shifting), θ^{k+1} will remain the same as in iteration *k*. Otherwise, P-RTP will continue in the next step with a smaller $\theta^{k+1} = \theta^k \cdot \zeta$, where $0 < \zeta < 1$ in order to approach the equilibrium more accurately. The iterations continue until θ gets sufficiently small (i.e. users are allowed to change a negligible fraction of their energy schedules). At step *k* of P-RTP, each user *i* alters her desired/initial energy schedule $\widetilde{x_i}$ into x_i^k, according to her flexibility and the P-RTP's billing. This leads to a total energy cost reduction:

$$\Delta C^k = \sum_{t=1}^{T} \left(G\left(\sum_{i=1}^{N} \widetilde{x_i^t}\right) - G\left(\sum_{i=1}^{N} x_i^{t,k}\right) \right) \qquad (17)$$

for the ESP. Through P-RTP, ESP rewards each user *i* for her contribution to total energy cost reduction, by an energy bill discount:

$$\Delta B_i^k = \frac{\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1 \\ j\neq i}}^{N} \left(x_j^{t,k-1} + \widetilde{x_i^t} \right) \right) - G\left(\sum_{\substack{j=1 \\ j\neq i}}^{N} \left(x_j^{t.k-1,} + x_i^{t,k} \right) \right) \right)}{\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1 \\ j\neq i}}^{N} \left(x_j^{t,k-1} + \widetilde{x_i^t} \right) \right) - G\left(\sum_{\substack{j=1 \\ j\neq i}}^{N} \left(x_j^{t,k-1} + x_i^{t,k} \right) \right) \right) \right)} \cdot \Delta C^k \qquad (18)$$

In Eq. (18), the numerator represents the energy cost reduction that user's *i* behavioral change generated in step *k* of P-RTP. Note that each user acts knowing only what the rest of the users have done in the previous iteration *k-1* of P-RTP and having no knowledge of their actions in the current iteration. The denominator equals to the summation of each user's analogous contribution and thus we have $\sum_{i=1}^{N} \Delta B_i^k = \Delta C^k$. Therefore, the energy bill discount that each user receives is a fraction of the total energy cost reduction, and equal to her contribution.

In order to combine the volume-aware pricing that RTP proposes and the incentives that P-RTP offers, we designed a hybrid billing mechanism which, in every iteration *k*, calculates the $B_{i,B-RTP}^k$ of each user *i* according to:

$$B_{i,B-RTP}^{k} = \tilde{B}_{i,RTP} - \gamma \cdot \Delta B_i^k - (1-\gamma) \cdot (\tilde{B}_{i,RTP} - B_{i,RTP}^{k}) \quad (19)$$

Here, $B_{i,RTP}^{k}$ denotes the energy bill of user *i* in step *k* of the algorithm in the case that ESP applies the RTP model (according to Table 3). By studying Eq. (19), we observe that for $\gamma = 0$, P-RTP reduces to the RTP model, while for $\gamma = 1$, the total cost reduction that is derived from the behavioral change of a user is converted into an equivalent reduction in her energy bill. In case $0 < \gamma < 1$, a fraction γ of the cost reduction derived from the behavioral change of a user is converted into discount in her bill and the remaining fraction *1-γ* is allocated to all participating users according to RTP. In case that $\gamma > 1$, P-RTP actually penalizes the set of users who are more reluctant to deviate from their desired energy schedule, in order to further favor the flexible users.

By replacing Eqs. (18) and (15) into Eq. (19) for ΔB_i^k and $B_{i,RTP}^{k}$, respectively, one can easily prove that $\sum_{i=1}^{N} B_{i,B-RTP}^{k} = G\left(\sum_{i=1}^{N} x_i^{t,k}\right)$, which means that our scheme is budget-balanced and does not generate surplus or deficit of money. P-RTP is summarized in the table below.

Table 4: Algorithm for the calculation of energy bills and the energy consumption schedules in P-RTP

1	**Initialization**: $k = 0$, $x_i^k = \widetilde{x_\iota}$, $B_{i,B-RTP}^{k} = \widetilde{B_{\iota,RTP}}$, $\forall i \in \boldsymbol{N}$, $\theta = \theta^0$,θ_{min},ε, ζ
2	**While** $\theta^k > \theta_{min}$ do
3	Calculate G^k
4	$k \rightarrow k+1$
5	**For** each user $i \in \boldsymbol{N}$
6	Receive B_i^k
7	**Repeat**
8	Update x_i^k
9	Update $B_{i,B-RTP}^{k}$ using (16), (17) and(19)
10	Calculate W_i^kusing (13)
11	**Until** reach solution of (14)
12	**End for**
13	Calculate G^{k+1}
14	**If** $G^{k+1} > G^k * (1-\varepsilon)$
15	$\theta^{k+1} = \theta^k * \zeta$
16	**Else**
17	$\theta^{k+1} = \theta^k$
18	**End**

2.4. Performance evaluation results of the P-RTP energy programs

We evaluate our proposed P-RTP scheme using the state-of-the-art RTP scheme as a benchmark. We consider a system consisting of *N* = 10 energy consumers, each of whom operates two curtailable and four shiftable devices. More specifically, each energy consumer may conserve energy through the curtailment of the operation of an A/C and a lighting system, and additionally shift the operation of an oven, a washing machine, a spin dryer and the charging of an Electric Vehicle (EV). Moreover, every user characterizes some appliances as non-adjustable loads. In more detail:

- **Lights**: We assume that each household is illuminated by 14 bulbs, which can be either LED (8W), CFL (14W) or incandescent bulbs (60W), and that users want the lights on from 18:00 until 24:00. Thus, user's i total desired lighting energy consumption is randomly selected over the interval [0.672 – 5.040 kWh]. We assume that in every time slot, equal energy amounts are consumed.
- **A/C**: Each user operates an A/C system from 14:00 until 22:00. Single A/C units come in different sizes and use from 500 to 1500 watts. User's i total desired A/C energy consumption is randomly selected over the interval [4.0-12.0 kWh]. As we did with the lights, we assume that equal energy amounts are consumed in every time slot.
- **Oven**: We consider that users classify the oven as a shiftable device. Ovens use 1000 to 5000 watts and are assumed to require at most one hour to complete their task. Therefore, user's i total desired oven's energy consumption is randomly selected over the interval [1.0 – 5.0 kWh]. Users' desired oven plug-in times vary from 17:00 to 19:00.
- **Washing Machine**: It falls into the category of shiftable appliances. Washing machines use 400 to 1300 watts and finish their task in less than an hour. User's i total desired washing machine energy consumption is randomly selected over the interval [0.4-1.3 kWh]. Users' desired plug-in times vary from 09:00 to 12:00.
- **Spin Dryer**: Is also accounted as a shiftable device. The energy use of a spin dryer varies between 1800 and 5000 watts and it takes less than an hour for them to finish their task. User's i total desired energy consumption is randomly selected over the interval [0.4-1.3 kWh]. Users' desired plug-in times vary from 13:00 to 18:00.
- **EV**: The battery capacity is randomly chosen over the interval [5.5-6 kWh] and the maximum charging rate is 2 kW. Thus, the minimum time that an EV demands in order to be charged is 3 hours. We assume that users desire the charging to start somewhere between 00:00 and 05:00 or 18:00 and 21:00, and to be finished ideally in 3 hours.
- **Non-adjustable loads**: We assume that users categorize as nonadjustable loads devices, such as the refrigerator, the TV, the freezer, the Wi-Fi Router, etc., which are meant to be ON whenever requested. Thus, users' aggregate energy consumption of critical loads is randomly chosen from [3.6-11.4 kWh] at each timeslot.

The above datasets are derived from [24] [25] [26] and are summarized in Table 5. The aggregate desired ECC is presented in the following figure. The scheduling horizon consists of T = 24 time slots of hourly duration. For the step size, we set $\theta^0 = 0.95$, $\zeta = 0{,}50$, $\varepsilon = 0.001$ and $\theta_{min} = 0.01$ throughout the simulations. Regarding the parameters of energy cost function in Eq. (10), b and c are usually set to 0, while the value of parameter a varies from 10^{-4} to 0.05 [7] [13] [27]. In this study, parameters b and c are also set 0, while a is chosen to be 0.01, 0.02 or 0.03, which is the usual case in the aforementioned works, too. Moreover, in [28], parameter δ of Eq. (8) is set to 1 implying perfectly flexible energy consumers. In order to evaluate P-RTP in scenarios of various flexibility classes of end users, δ varies from 1 to 1.5. For the same reason, we choose ω of Eq. (4) to vary from 0.1 to 6.

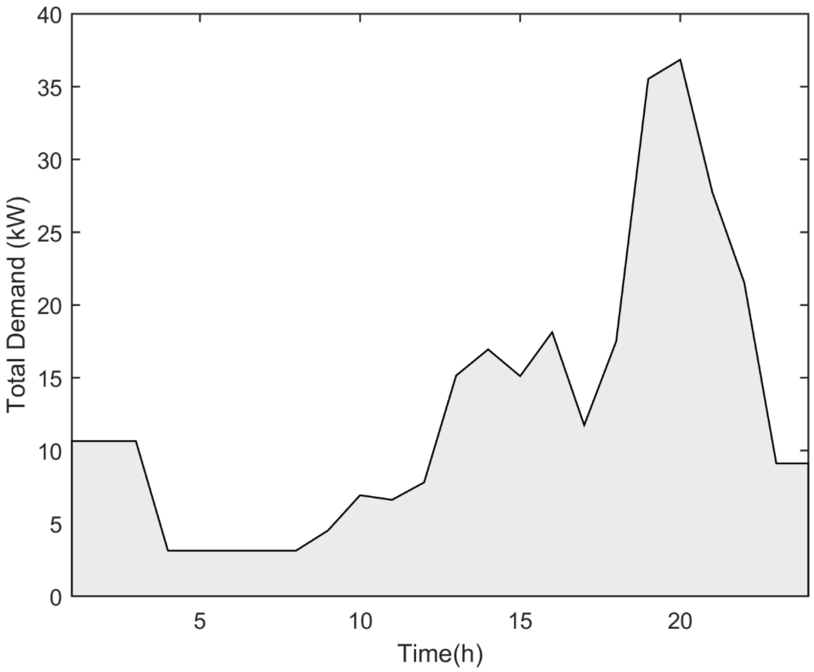


Figure 6: Aggregate daily users' Energy Consumption Curve

Table 5: Electricity consumption of a typical household's appliances

Appliance	Power (kW)	Type of device	$\widetilde{t_{i,d}^{a}}$	Duration (h)	$\widetilde{t_{i,d}^{b}}$	Energy (kwh)
-	-	Non-adjustable	00:00	24	24:00	[3.6-11.4]
Lighting	[0.008-0.060]	Curtailable	18:00	6	24:00	[1.2-5.0]
A/C	[0.5-1.5]	Curtailable	14:00	8	22:00	[4.0-12.0]
Oven	[1.0-5.0]	Shiftable	[17:00-19:00]	1	[17:00-19:00]	[1.0-5.0]
Washing Machine	[0.4-1.3]	Shiftable	[10:00-13:00]	1	[10:00-13:00]	[0.4-1.3]
Spin Dryer	[1.8-5.0]	Shiftable	[14:00-19:00]	1	[14:00-19:00]	[1.8-5.0]
EV	[0.0-2.0]	Shiftable	[00:00-05:00,18:00-21:00]	3	[03:00-08:00,21:00-24:00]	[5.5-6.0]

In order to demonstrate the performance of the P-RTP model for different classes of energy consumers (or else ESP's customers), we consider three cases:

a) <u>Low Flexibility</u>: Energy consumers are reluctant to change their energy consumption habits. Parameter $\delta_{i,d}$ for each user $i \in N$ and $d \in D_{s,i}$ is randomly selected over [1.20-1.50], while parameter ω_i is randomly chosen over [3,6]. Finally, in this use case, we consider users that set relatively strict deadlines, i.e. they allow their EMSs to schedule their shiftable loads not more than one to two hours after $\widetilde{t_{i,d}^{b}}$.

b) Medium Flexibility: Energy consumers are more price-sensitive than in the 'Low Flexibility' use case. Parameter $\delta_{i,d}$ is randomly selected over [1.10-1.20] $\forall\, i \in N, d \in D_{s,i}$. Parameter ω_i is randomly chosen over [1.0,3.0]. Users set their deadlines two to four hours after their $\widetilde{t_{i,d}^{b}}$.

c) High Flexibility: In this use case, energy consumers are most willing to participate in DSM programs, even for a relatively small repayment. Parameter $\delta_{i,d}$ is randomly selected over [1.00-1.10] $\forall\, i \in N, d \in D_{s,i}$. Parameter ω_i is randomly chosen over [0.1,0.5]. Users set their deadlines two to six hours after their $\widetilde{t_{i,d}^{b}}$.

Without loss of generality, in all of the above cases, parameter U_{max} in the utility function for curtailable loads is set to 0. Moreover, $\underline{x_{i,d}^{t}}$ is set to 0 $\forall i \in N, d \in D_{c,i}$. In order to assess the performance of P-RTP algorithm, the following Key Performance Indicators (KPIs) are used:

- Energy Cost (*G)*, as defined in Eq. (10), which is the cost of ESP to acquire the electricity needed to fulfill the requirements of its customers. This is an index of how energy-efficient a pricing scheme is, that is, how successful it is in incentivizing customers to adopt energy-efficient habits.
- Aggregate Users' Welfare (*AUW)* is a KPI that expresses the competitiveness of an ESP that adopts a billing strategy in an open electricity market:

$$AUW = \sum_{i=1}^{N}\left(\sum_{d=1}^{D_{c,i}}\sum_{t=1}^{T} U_{i,d}^{t}\,(x_{i,d}^{t}) - \sum_{d=1}^{D_{s,i}}\sum_{t=1}^{T} DU_{i,d}^{t}\left(\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}, t_{i,d}^{l}, x_{i,d}^{t}\right) - B_{i,RTP}\right) \quad (20)$$

- Fairness (F_i) is a KPI that indicates the percentage of user's *i* contribution to system cost reduction that she will be rewarded in terms of energy bill discount:

$$F_i = \frac{D_i^R}{D_i^A}, \forall i \in N, \quad (21)$$

where

$$D_i^R = \frac{\widetilde{B_{i,RTP}} - B_i}{\sum_{i=1}^{N}(\widetilde{B_{i,RTP}} - B_i)}, \forall i \in N \quad (22)$$

represents the discount that user *i* receives in his energy bill as a fraction of the total discount in all users' bills, and

$$D_i^A = \frac{\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1\\ j\neq 1}}^{N} x_i^t + \widetilde{x_i^t}\right) - G\left(\sum_{i=1}^{N} x_i^t\right)\right)}{\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1\\ j\neq 1}}^{N} x_i^t + \widetilde{x_i^t}\right) - G\left(\sum_{i=1}^{N} x_i^t\right)\right)\right)} \quad (23)$$

represents the discount achieved by user *i*, i.e. her contribution to system cost reduction, as a fraction of the summation of all users' contributions. This is calculated employing the concept of Shapley value in cooperative games [29]. In this regard, user's impact in the reduction of system cost is measured through the comparison of the total energy cost in: 1) the case in which user *i* performs the alterations in her ECC, 2) the case in which user *i* follows her desired ECC. Values of F_i close to 1 indicate a fairer correlation between the behavioral change of user *i* and the reward that she gets for it.

In SOCIALENERGY context, the adaptability of the Hybrid P-RTP (γ) scheme gives the ESP the opportunity to select its own strategy with respect to users' reward, by adjusting properly the value of γ. According to the price elasticity of its customers and the DR services it has to provide to the various smart grid market stakeholders, ESP will select a certain value of 'γ' in order to achieve an attractive trade-off among the above KPIs. Ultimately, this means that there is a whole family of P-RTP energy programs that the ESP may select according to its business needs, the type of its targeted users, etc., and it does so by just selecting the optimal value of parameter 'γ'. This automated business analytics service is provided by RAT subsystem.

Note: The proposed *hybrid P-RTP(γ)* scheme is also mentioned as *B-RTP (Behavioral RTP)* in order to outline the whole family of P-RTP energy programs that the ESP may select according to the business context. These two terms are used interchangeably throughout the text and have the same meaning.

2.4.1. Low Flexibility Case

In the Low Flexibility case, ESP needs to provide its customers with more generous financial incentives in order to motivate them towards more energy-efficient ECCs, as they are not so price-sensitive. Figure 7 depicts the ratio between the energy cost G (across the whole time horizon) with hybrid P-RTP and the energy cost G with RTP as a function of *γ*. The graphs in the figure below, represent the cases of energy with low generation cots (*c* = 0.01), medium-cost energy (*c* = 0.02) and high-cost energy (*c* = 0.03). We notice that even in the low flexibility case, B-RTP is able to bring (for *γ*=2) a cost reduction of 10% in comparison with RTP, in case of low- and medium-cost energy (*c*=0.01, *c*=0.02) and 13% in case of high-cost energy (c = 0.03). As cost of energy rises, it is reasonable for *G* to further decline, since the energy bills are higher and thus customers are more willing to exploit their schedulable loads.

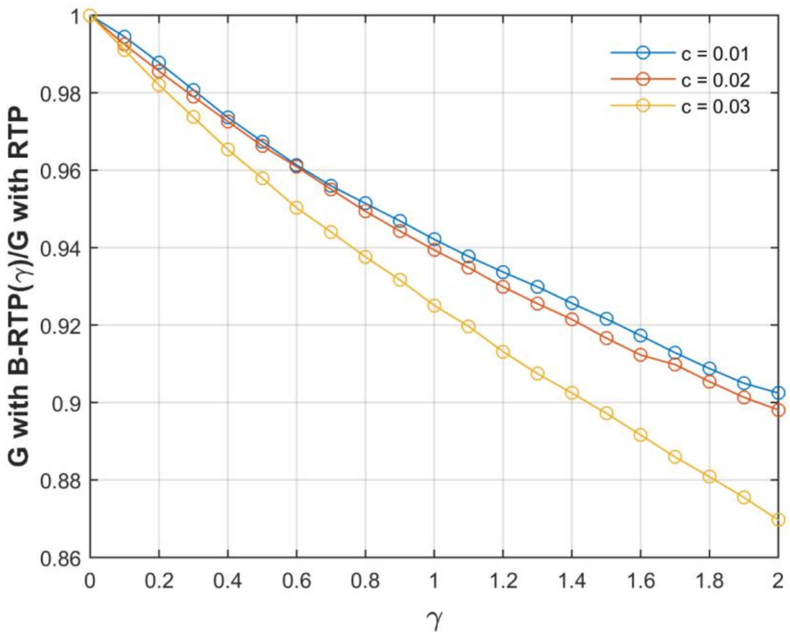


Figure 7: Ratio between *G* with B-RTP (*γ>0*) and *G* with RTP (γ=0) as a function of *γ* in Low Flexibility case

These results are expected for *γ* = 2, which could correspond to a case, for example, of an imminent congestion event in a certain area of the grid. As it is inferred from Eq. (19), values of *γ* greater than 1 imply that ESP over-rewards the more flexible users for their DSM actions, while it imposes a monetary penalty to the less flexible ones.

Figure 8 presents the ratio between *AUW* with B-RTP and *AUW* with RTP scheme as a function of *γ*. According to it, the aforementioned energy cost reduction does not come with any significant users' welfare decrease even in low flexibility case. In fact, ESP could select *γ* to be up to 1.8 and *AUW* would not be lower than that under RTP scheme. This is explained firstly by the fact that a load shift or a load cut, which are the reasons of the decrease of a user's comfort, are higher compensated by the ESP, when $\gamma > 1$. Moreover, even the more flexible users in this inelastic set of energy consumers manage a relatively small cost reduction *ΔC*. Thus, the penalties in the energy bills of the less energy efficient users are too small compared to their RTP bills to justify a large decrease in *AUW*. In other words, given that ESP's customers are a set of inelastic users, increasing *γ* diminishes *AUW* by a slow rate. Hence, B-RTP (comparing to RTP), manages to reduce energy costs by 9-12%, depending on conventional energy generation cost level (c), without sacrificing at all the aggregate users' welfare (AUW). ESP could continue increasing *γ* in order to further motivate users to shift or shed their loads and therefore achieve even higher energy cost reduction. However, this would be done at the expense of users' welfare. Finally, we note in the following figure that *AUW* reaches its peak for *γ* = 0.8 independently of the value of c. Apparently, in case of high-cost energy (*c* = 0.03), the gap between *AUW* under B-RTP and *AUW* under RTP is larger, since the financial motivation for the users is larger. This incurs more energy efficient actions (load shifts and cuts) and hence lower energy bills and finally higher AUW. In other words, the bill discounts are greater than their marginal utility, which they may opt to sacrifice in order to get the discount.

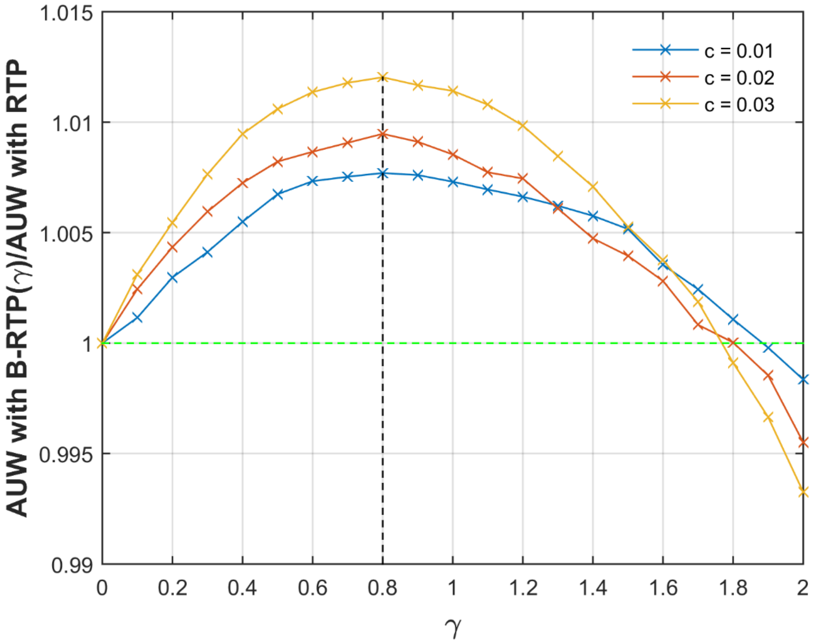


Figure 8: Ratio between *AUW* with B-RTP (γ>*0*) and *AUW* with RTP (γ=0) as a function of γ in Low Flexibility case

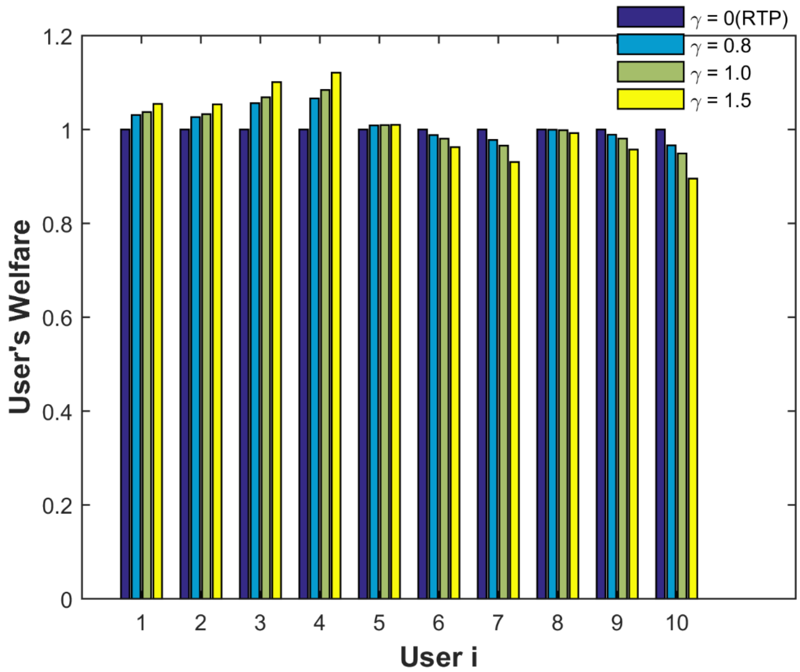


Figure 9: Ratio between users' welfare for various values of γ and users' welfare for γ = 0 (RTP) in Low Flexibility case

Table 6: Average users' welfare for different values of 'γ' in low flexibility case

γ	0 (RTP)	0.8	1.0	1.5
$\mathbf{AUW(B-RTP(\gamma))}/\boldsymbol{AUW(RTP)}$	1	1.0094	1.0085	1.0039

In order to examine the impact of γ on users' welfare in more detail, we depict in Figure 9 the ratio between users' welfare in case of $\gamma \in [0\,,0.8\,,1,1.5]$ and in case of RTP for every user $i \in N$ and *c* = 0.02. Ten users are sorted based on their flexibility, with *i*=1 denoting the most flexible user and *i*=10 the least flexible one[1]. Studying **Figure 8**, we observe that, as we expected, W_i of the less price inelastic users *i* increases with γ. On the other hand, RTP is in the best interest of price inelastic users, since not being willing to change their energy consumption patterns, it provides them with financial benefits that others have created. Like in **Figure 8**, in Table 6, we establish the preference of users for B-RTP(γ=0,8) on average. Also, we note that in B-RTP(γ=1,5), even if price inelastic users are penalized in order for the flexible users to receive a generous bonus for their behavioral change, users' welfare is marginally higher on average than in RTP in this low flexibility case.

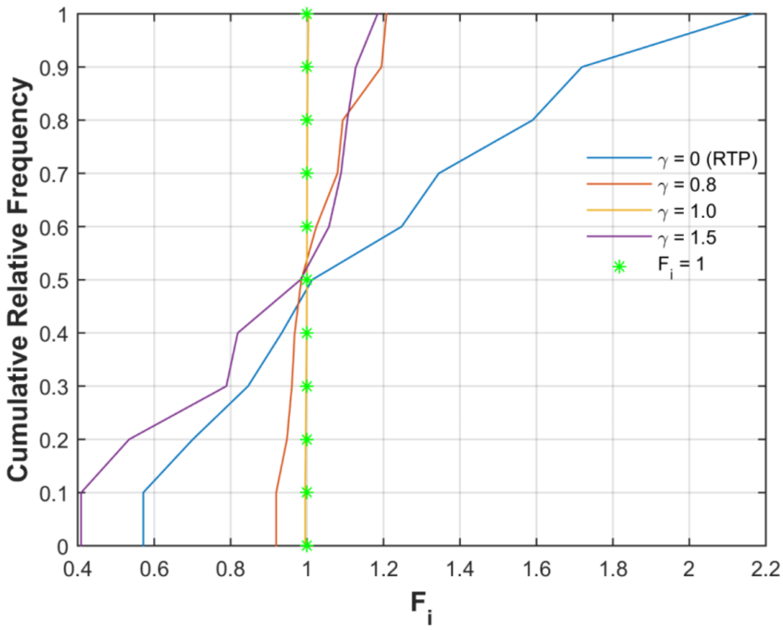


Figure 10: CDF of F_i among participating users under P-RTP for various values of 'γ' in Low Flexibility case

Table 7: Mean values of F_i for different values of 'γ' in low flexibility case

γ	0 (RTP)	0,8	1	1,5
$\boldsymbol{F_i}$	1.2131	1.0379	1	0.9097

Figure 10 depicts the Cumulative Distribution Function (CDF) of F_i for different values of γ. Cost parameter *c* is set to 0.02. As analyzed above, F_i is an index of how fairly the energy cost reduction is allocated to users. The fairest way of distributing energy savings among the users is represented by $F_i = 1$. The figure shows that B-RTP (γ=1) is the fairest billing mechanism. This was expected as it incentivizes users towards an energy-efficient behavior so that they receive a generous discount in their bills. Under RTP (γ = 0), inflexible users benefit from the others' actions and thus are not motivated to change their energy consumption behavior, while demand responsive customers see their actions not being

[1] Flexibility is a function of parameters ω and δ, used in Eqs. (4) and (8), respectively, and also $\widetilde{t_{i,d}^{a}}$, $\widetilde{t_{i,d}^{b}}$, $t_{i,d}^{l}$ (i.e. users' desired ECC). Thus, sorting users based on their flexibility is not a straightforward task and has been done approximately. This is why there is not a continuity in the variation of users' welfare for a certain value of γ. This is also observed in corresponding graphs for the other flexibility cases.

sufficiently compensated. This discourages users to deviate from their desired ECC. For gradually increasing γ, the distribution of users around $F_i = 1$ gets narrower (i.e. fairer billing) and for γ=0.8 (which maximizes *AUW*), it is much closer to $F_i = 1$. For values of γ greater than 1, the distribution of users around $F_i = 1$ starts getting wider again as we can see in case of γ = 1.5. Still, the mean value of F_i (see Table 7) is closer to 1 than RTP, meaning that the whole family of P-RTP energy programs (or else B-RTP) is a fairer billing scheme than RTP on average. If ESP chooses to impose the fairest possible pricing scheme, B-RTP will manage a cost reduction of 6-7.5% comparing to RTP and a slightly higher *AUW*.

2.4.2. Medium Flexibility Case

In this medium flexibility case, the concept of Figure 11 Figure 12 Figure 13 Figure 14 is similar to that of the respective 4 figures of the previous low flexibility case. In this use case, several of the ESP's clients represent energy consumers with DR capability. They are more price-sensitive than in the former case, but still not eager to change their energy behavior without a significant financial reimbursement. Thus, in Figure 11, we observe that B-RTP achieves a larger energy cost reduction comparing to RTP scheme. Similarly to the low flexibility ucase, as γ increases the cost reduction declines in almost linear fashion. However, for $\gamma > 1.3$, this happens at the expense of *AUW* (see Figure 12), which declines as the less flexible users are penalized so that the more flexible ones achieve a quite generous bonus. In this case, users seem to be less tolerant to the increase of γ above 1. This is because users, being more price-elastic comparing to the low flexibility case, create a larger cost reduction, which translates into stricter penalties for the less DR-active users. Nevertheless, in case of *c* = 0.02, B-RTP reduces energy cost by up to 16% compared to RTP without sacrificing AUW ($\gamma = 1{,}3$). In case of higher or lower cost of energy, this cost reduction is larger (21%) or smaller (11%) respectively. Here, we observe a larger gap between the 3 plots of Figure 11, when we compare them with those of Figure 7, since users are more price-responsive and higher energy costs leads them to even more load shifts and cuts in order for them to benefit from B-RTP.

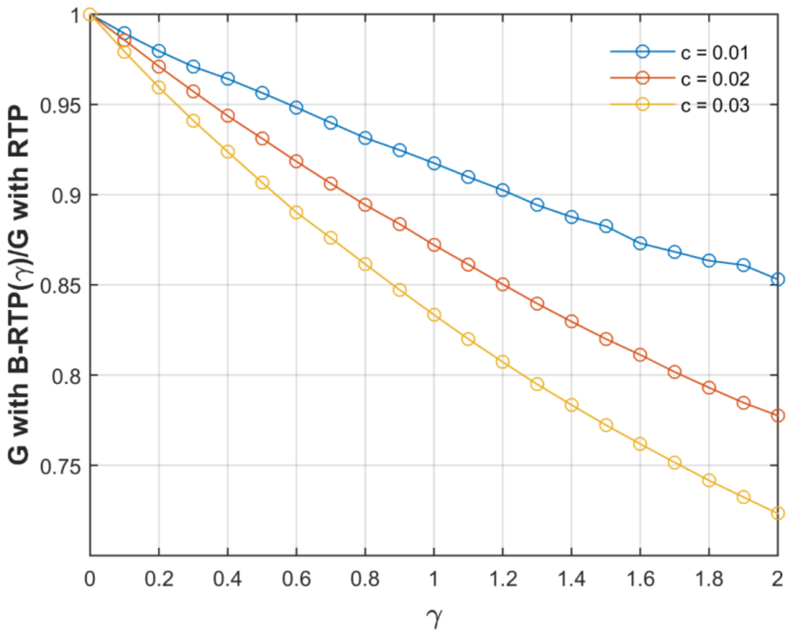


Figure 11: Ratio between *G* with B-RTP (γ>0) and *G* with RTP (γ=0) as a function of γ in Medium Flexibility case

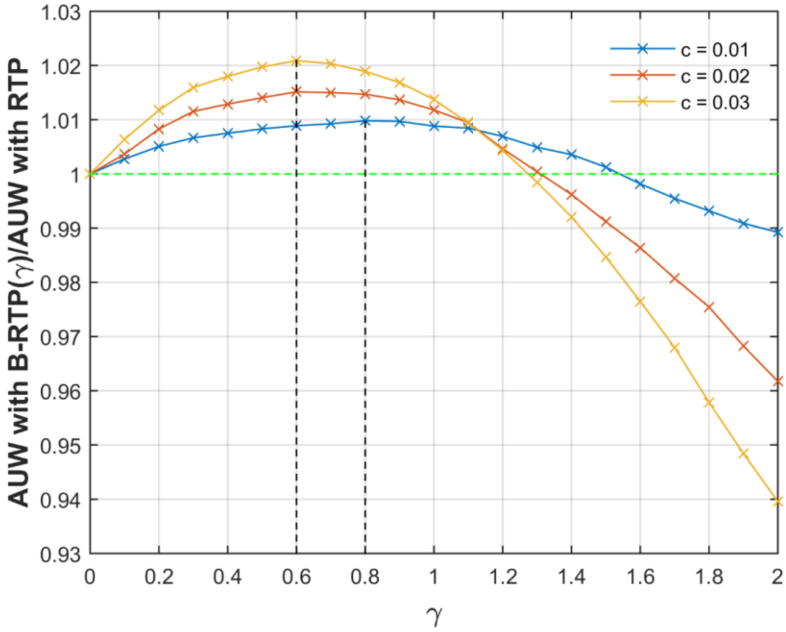


Figure 12: Ratio between *AUW* with B-RTP (γ>0) and G with RTP (γ=0) as a function of γ in Medium Flexibility case

In Figure 13 and Table 8, we can see that, as in the low flexibility case, increasing '*γ*' benefits the more price elastic users, who take advantage of the billing mechanism and receive a high discount in their energy bills. On the other hand, the rest of the users experience a steeper downfall in their Welfare as *γ* increases compared to the previous case. This can be interpreted, not only by the higher penalties that these users have to pay, but also by the fact that they are not totally price inelastic energy consumers as in the low flexibility case.

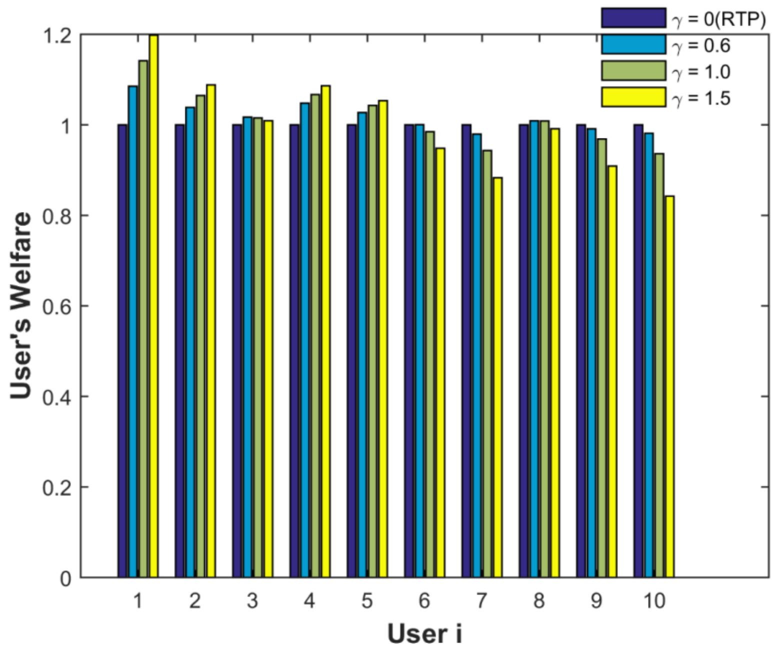


Figure 13: Ratio between users' welfare for various values of γ and users' welfare for γ = 0 (RTP) in Medium Flexibility case

Table 8: Average users' welfare for different values of 'γ' in Medium Flexibility Case

γ	0 (RTP)	0,6	1,0	1,5
$\mathbf{AUW(B-RTP(\gamma))}/\boldsymbol{AUW(RTP)}$	1	1.0149	1.0117	0.9911

As in the low flexibility case, we observe in Figure 14 and Table 9 that B-RTP (γ=1) is the fairest billing mechanism, while RTP is the least fair among B-RTP schemes with parameter $0 \leq \gamma \leq 1$. Even B-RTP (γ=1.5) compensates in a fairer way more users than RTP does. So, ESP can choose *γ*=1 to efficiently incentivize its customers to alter their ECCs and achieve a cost reduction of 6.5, 12.5 or 17% over RTP, according to the energy generation cost parameter *c*. Alternatively, ESP could choose *γ*=0.6 to maximize *AUW* in cases of medium-cost and high-cost energy and achieve a 7.5 and 11% respectively larger cost reduction than RTP in a fairer manner. In case of low-cost energy (*c* = 0.01), ESP, in order to maximize *AUW,* should select *γ* = 0.8, which results in a 5% cost reduction over RTP.

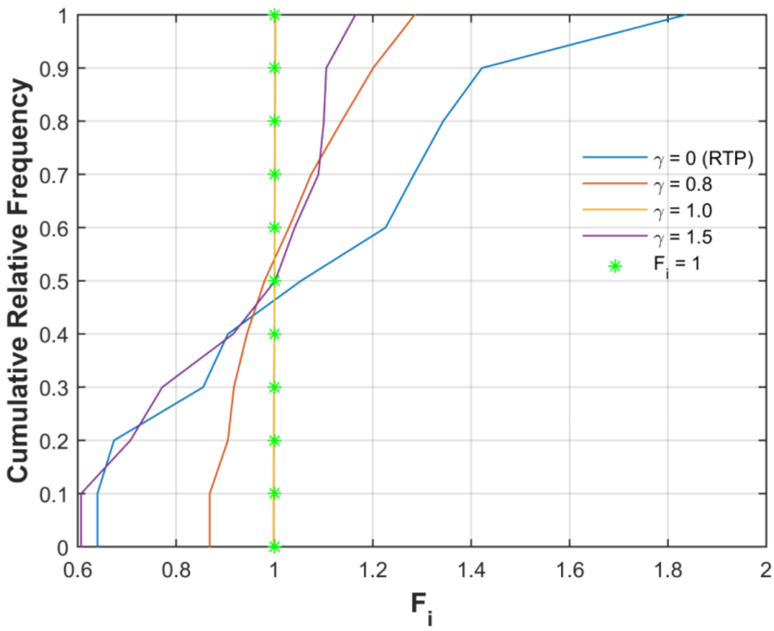


Figure 14: CDF of F_i among participating users under B-RTP for various values of 'γ' in Medium Flexibility case

Table 9: Mean values of F_i for different values of 'γ' in medium flexibility case

γ	0 (RTP)	0,6	1	1,5
F_i	1.1239	1.0341	1	0.9504

2.4.3. High Flexibility Case

In this subsection, we examine the case when ESP's customers are a set of highly price-sensitive users, who are eager to exploit their schedulable loads in order to gain discounts in their energy bills. In this high flexibility case, Figure 15, Figure 16, Figure 17, Figure 18 are again similar with the corresponding four figures for the previous two use cases.

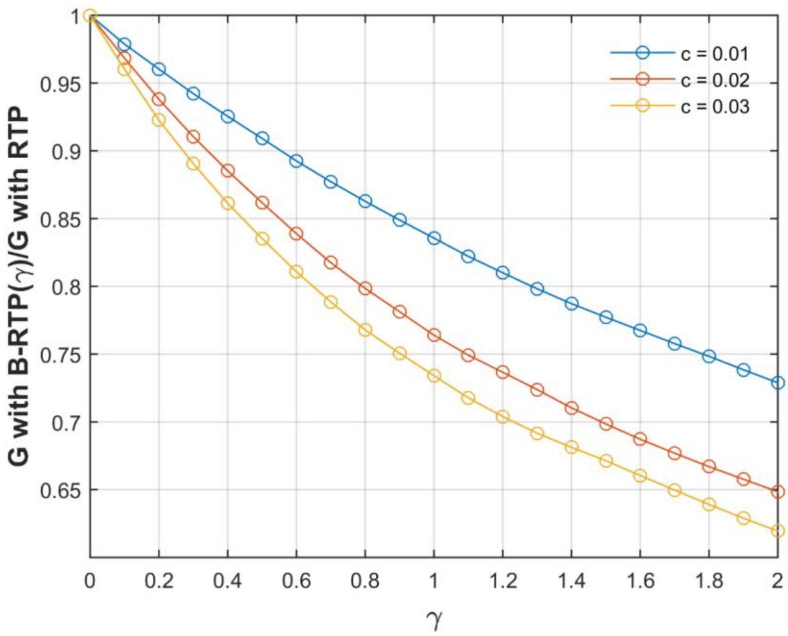


Figure 15: Ratio between *G* with B-RTP (γ>0) and *G* with RTP (γ=0) as a function of γ in High Flexibility case

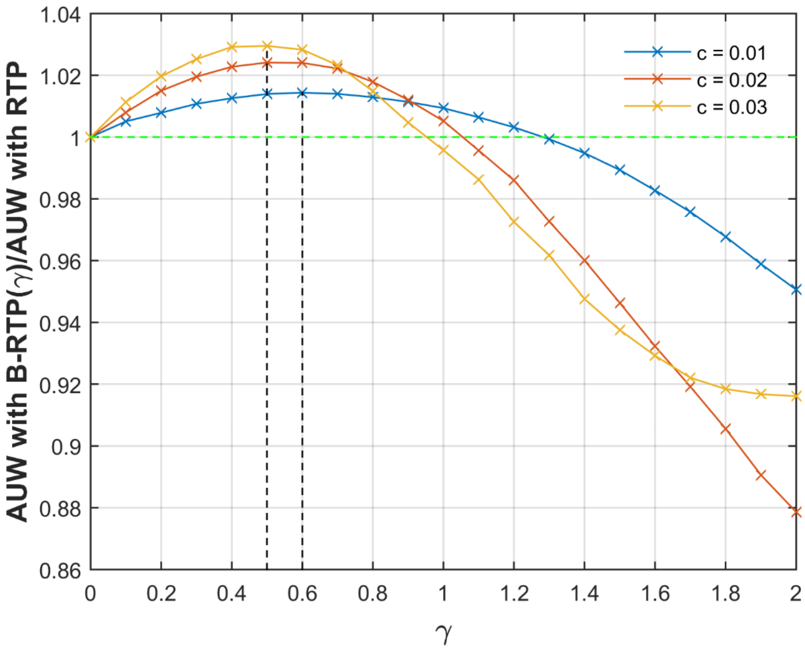


Figure 16: Ratio between *AUW* with B-RTP (γ>0) and *AUW* with RTP (γ=0) as a function of γ in High Flexibility case

Thus, Figure 15 illustrates a downturn in energy cost comparing to RTP scheme. However, increasing *γ* diminishes *AUW* in much steeper fashion in comparison to the two former use cases (see Figure 16). This is because B-RTP (γ>1) penalizes users, who are much more willing to provide flexibility services in order for them to get financially rewarded and not users who are price-inelastic. This result is very interesting from the ESP's business perspective in case it participates in various types of flexibility markets, where DSM units can be sold in really competitive prices (e.g. to solve an imminent congestion problem). In the latter case, users would be more tolerant to a fine imposed to their energy bills. This is illustrated in Figure 17 and Table 10 (*c* = 0.02), in which it is clear that the welfare of less flexible users decreases for γ=1.5. Conclusively, B-RTP reduces energy cost by 16 % over RTP when c = 0.01, by 24% when c = 0.02 and even by 27% when c = 0.03, while simultaneously managing to keep *AUW* above that of RTP. In case of B-RTP (γ=0,5) which maximizes *AUW* for c = 0.02 or c = 0.03, the energy cost reduction reaches 14% and 17%, respectively. In case of low-cost energy (c = 0.01) *AUW* is maximized for γ = 0.6 and the equivalent cost reduction is 10.5% in comparison with RTP.

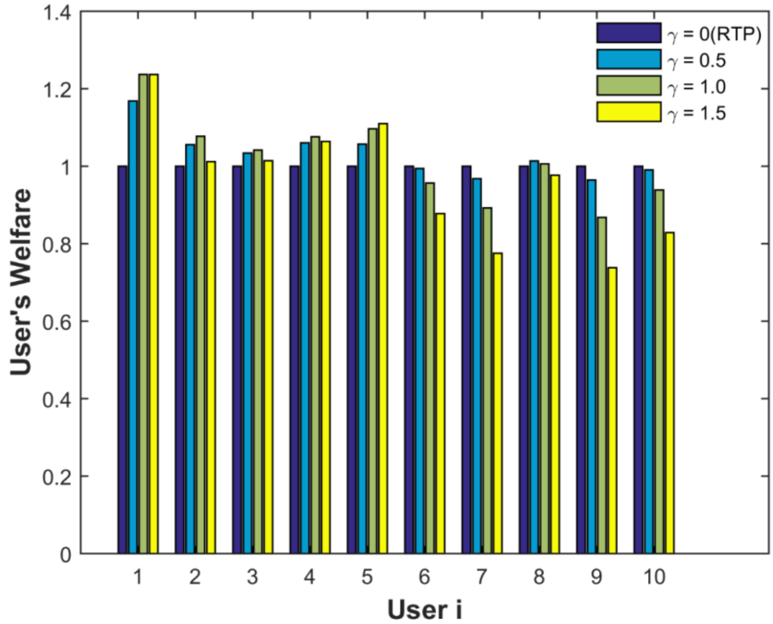


Figure 17: Ratio between users' welfare for various values of γ and users' welfare for γ=0 (RTP) in High Flexibility case

Table 10: Average users' welfare for different values of γ in High Flexibility Case

γ	0 (RTP)	0,5	1,0	1,5
$\mathbf{AUW(B-RTP(\gamma))} / \boldsymbol{AUW(RTP)}$	1	1.0236	1.0052	0.9432

In the CDF of F_i (see Figure 18), we re-establish that B-RTP (γ=1) is the fairest billing mechanism, while RTP the least fair one. By gradually increasing γ and as it approaches to value 1, the distribution of users gets narrower (fairer pricing), until γ surpasses 1 and the users' distribution starts widening again. We also notice that even B-RTP with γ=1.5 allocates the energy cost reduction to the users in a fairer way than RTP (see table below). In more detail, B-RTP with γ=1.5 overcharges some users for their energy consumption, although it charges users more fairly and thus it is a stronger motivator towards energy-efficient ECCs than RTP. This policy would bring a large cost reduction (e.g. 30% for c = 0.02) although it would decrease *AUW* (e.g. 6% for c = 0.02). This policy could be selected in the case of emergency situations (e.g. congestion issues in a specific network location, governmental policies to cope with energy poverty issues, etc.), when energy cost is requested to severely decrease at any cost.

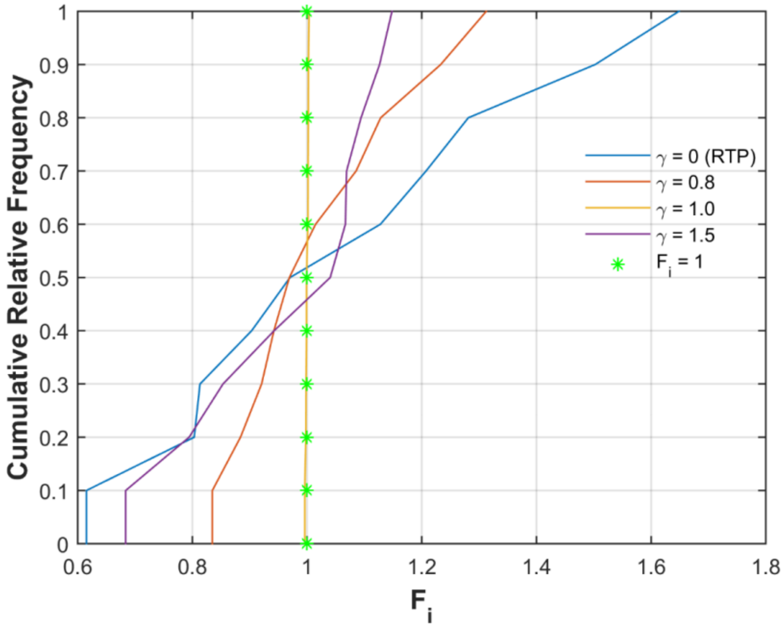


Figure 18: CDF of F_i among participating users under B-RTP for various values of γ In High Flexibility case

Table 11: Mean values of F_i for different values of 'γ' in High Flexibility case

γ	0 (RTP)	0.5	1	1.5
$\mathbf{AUW(B-RTP(\gamma))}/\boldsymbol{AUW(RTP)}$	1.0873	1.0325	1	0.9819

Note: More technical details and performance evaluation results about the family of P-RTP energy programs is provided in several journal and international conference publications, such as [30] [31] [32] [33] [34].

2.5. Integration in SOCIALENERGY S/W platform

In the 3 use cases examined above, we demonstrated that B-RTP offers a much more attractive trade-off between widely accepted KPIs than the RTP scheme for all levels of energy generation cost and all levels of the end users' elasticity (i.e. flexibility). Based on these results, we consider B-RTP a very useful tool in the hands of an ESP, which can exploit it in order to participate in several types of flexibility markets (i.e. balancing, congestion management, voltage control, frequency control, N-1 adequacy) with efficient DSM services, while being fair towards its customers and without sacrificing the level of eligibility of its services in an open and competitive retail market. In emergency circumstances, where the stability of the system is at risk and the energy cost is about to increase dramatically (e.g. congestion market), an ESP making use of B-RTP, can carry through the task with a relatively smooth reduction of users' welfare.

In SOCIALENERGY context, all the above-mentioned algorithms and performance evaluation results regarding the family of P-RTP energy programs have been integrated in the RAT subsystem. Therefore, the administrative user (e.g. CEO or business analyst of a utility company or ESP) is able to run exhaustive "what-if" scenarios in order to decide the best pricing policy according to the types of users, its business plan and the KPI that it wants to *optimize. Via the GUI of RAT subsystem (see more details in section 5), the admin user is able to easily customize all above-mentioned parameters. The results are also illustrated in the core GSRN platform via the deployment of GSRN-RAT API. The individual (energy consumer) user of the SOCIAENERGY platform will also be able to run instant simulations in order to realize which P-RTP energy program is the most beneficial for him/her.*

3. Novel community energy programs' design and energy communities' creation algorithms

In SOCIALENERGY system, we use the term "Virtual Energy Communities" (VECs). VECs can be created in a bottom-up (and thus manual) way from the users themselves just like in traditional social network platforms. A VEC leader may also be the one that initiates and coordinates the process just like in web forums and other web 2.0 tools. However, VECs can also be created and dynamically adapted in an automated way via the use of clustering algorithms in order for both users and the utility company/ESP to optimally exploit the benefits of VEC concept. In particular, a utility's portfolio can be categorized in several VECs based on qualitative characteristics such as demographics, geographical, socio-economic and other social norms-based metrics [35] [36] [37]. Given an already existing social graph, the goal of a clustering algorithm may also be to find such VECs that the total power consumption in each group of users achieves minimum variance [38]. VECs can also be created in a way that users' satisfaction, social network dynamics and the peer pressure that VEC members induce to each other are taken into consideration [39]. Other algorithms may take into account quantitative metrics for VEC creation problem. For example, the dominant VEC creation criterion can be the similarity factor of Energy Consumption Curves (ECCs) and/or the Flexibility Curves (FCs) of the users. In other words, users with similar ECCs and FCs increase the probability of performing better in a community-based EP. Another criterion would be to put together users that have the minimum deviation between their forecast and real consumption in order to minimize the imbalance penalties of a utility's portfolio, as we propose in our prior works [40] [41]. Finally, for billing purposes, there are also intra-clustering algorithms, which can allocate the costs among the members of a certain VEC by applying various policies as shown in the work of some of the authors in [42].

All the above-mentioned multi-parametric approaches for VECs' creation can be easily customized and integrated in SOCIALENERGY platform. A few clustering examples that we currently use in the SOCIALENERGY platform are illustrated in the figure below. What's more interesting is that the administrative user can set specific thresholds based on which an end consumer can be recommended to switch to a different VEC that better fits his/her updated interests and needs. Users can also play the multi-player mode of the GAME in order to be seamlessly educated about the potential benefits and operation of community-based EPs.

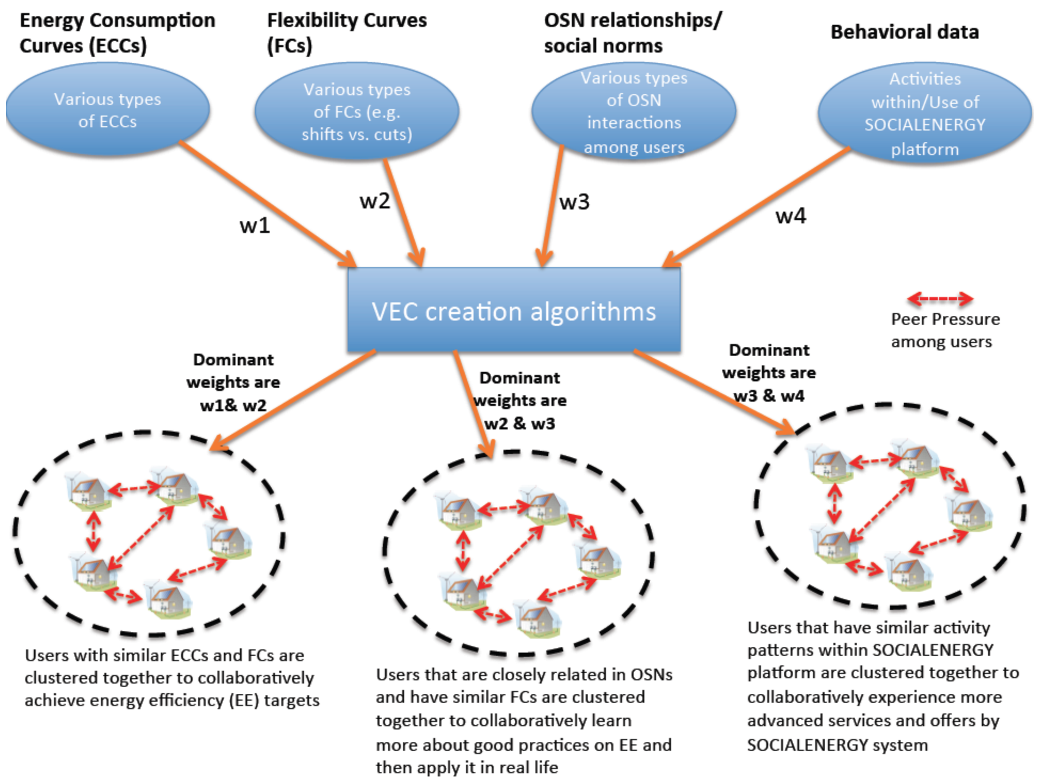


Figure 19: Multi-parametric VEC creation and dynamic adaptation process in SOCIALENERGY

The proposed business model for the utility company/ESP is similar to the one presented in section 2 (see **Figure 3** and **Figure 4**). However, the ESP is now able to offer community energy programs and related services to its customers (i.e. end users). Given that the end consumers have a certain aggregated Energy Consumption Curve (see ECC_1 in the figure below), the objective of the ESP is to change the energy consumption behavior of its portfolio by 'flattening' the aggregated ECC (cf. ECC_2), or more generally modifying it so as to a be closer to a desired (supply) curve. As a result, the end consumers will also be better satisfied as they will experience reductions in their electricity bills without any increase in their discomfort levels. It should be noted that it is possible in this paper for the monetary gains arising from the reduction of system's energy cost to be fully returned back to the users, or the ESP may take a certain percentage in order to increase its profits. In the proposed C-RTP system model that follows, and without lack of generality, we assume the former case for the sake of being specific.

In **Figure 20**, three VEC formation examples are illustrated. In VEC_1 case, the correlation of flexibility curves is high (i.e. highly flexible users are grouped together, low flexibility users also grouped together, etc.) and the correlation of social connections is also high (i.e. VEC_1 members are friends in social networks and have many common friends, too). We will see that VEC_1 results in the highest possible decrease of energy cost, the best aggregated users' welfare (AUW) and a fair distribution of incurred gains among the VEC_1 members. In contrast, in the VEC_2 case, users are pretty much socially connected, but the similarity factor of their flexibility curves is pretty low. We will see that this results in an unfair distribution of energy cost and welfare among the users, as the less flexible VEC_2 members will get an equal price for each DR unit offered to the ESP with the more flexible users (i.e. flexible users will be frustrated).

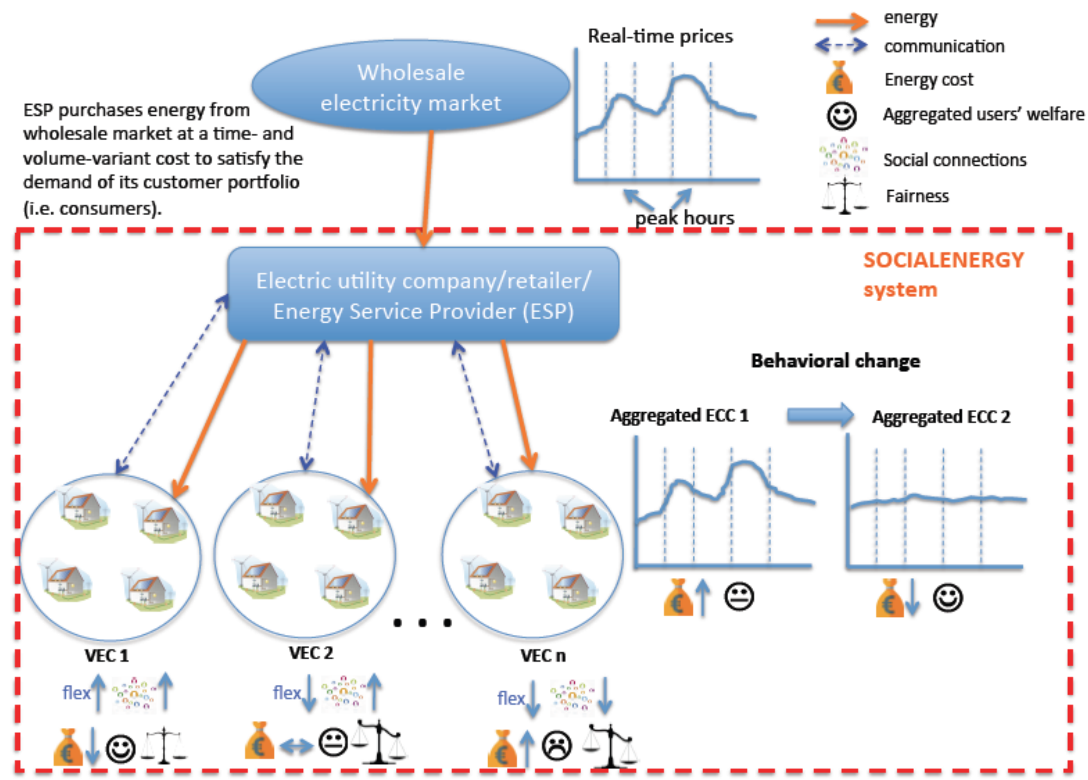


Figure 20: Business exploitation of VECs and community energy programs

In SOCIALENERGY system, VECs can also be created and dynamically adapted in an automated way via the use of clustering algorithms in order for both users and the utility to optimally exploit the benefits of VEC concept, such as:

- *Users are recommended to participate in beneficial communities/groups of users towards achieving collaborative goals by realizing individual benefits, too.*
- *Utilities are able to use automated procedures for business intelligence purposes (e.g. dynamically classify users and recommend specific tips, EPs, offers to them).*
- *VECs can be dynamically adapted easily in order to achieve new goals that set as a community.*
- *VECs can employ the C-RTP scheme to realize a local/peer-to-peer electricity market.*

3.1. Overview of state-of-the-art and related works on energy communities

In recent years, many electric utilities, ESPs and regulators around the globe increasingly rely on behavior change programs, as essential parts of their DSM portfolios and innovative business planning. Based on [43], existing behavior change programs are classified in three main categories, depending on whether they are based on: 1) information, 2) social interactions, or 3) education programs. *Information* programs include home energy reports (HERs), real-time feedback via web platforms and dashboards, energy audit programs and personalized or community-level recommendation services.

Social interaction programs include competitive/collaborative gamification solutions and games as well as community-based programs via community social marketing. *Education* programs include strategic energy management (SEM), training for community members, K–12, adult and campus programs. The achievements of these programs are to generate energy savings on their own, increase participation in existing programs and enhance user engagement and loyalty (minimize churn rate) in specific web platforms and associated products and services. The SOCIALENERGY S/W platform combines characteristics from all three above-mentioned categories, promising really innovative services to its end users.

Regarding the related works in energy communities' creation and management towards improving energy efficiency, our recent work in [41] deals with the value of energy prosumers' aggregation, the value of flexibility and the value of ECCs' correlation to mitigate the problems of RES unpredictability and volatility in the near-real-time balancing market context. In another recent work [40], we proposed a spectral clustering algorithm to reduce the energy system's cost. We cluster together users that have the minimum deviation between their forecast and real prosumption in order to minimize the imbalance penalties of an ESP's portfolio. In the proposed C-RTP model, we extended the algorithm to include flexibility and social network metrics and modified the key performance indicator (KPI). Moreover, via the introduction of the proposed C-RTP scheme, we can now have more quantitative performance evaluation results.

Authors in [44] discuss on the use of Online Social Network (OSN) communities and the pre-qualification criteria for a user to be included in a community, but no clustering algorithm to automate the process is proposed. [45] defines a set of criteria that can be used for the energy community formation problem. It clusters users with similar energy behavior, but only considering the range of the actual consumption and not the whole pattern of energy consumption. The same hold for [36]; the focus is more on the various goals that a goal-oriented community may have and different ways to achieve these goals, but it does not deal with the other issues needed (i.e. mathematical model, evaluation, etc.). [46] provides a more complete work than [36] regarding the mathematical modeling and criteria of clustering. Given a social graph, the clustering algorithm aims at finding groups of users so that the total power consumption in each group (who are socially connected) achieves minimum variance. The goal is to reduce the peak-to-average-ratio (PAR). However, no pricing model is proposed and user utility functions play no role in the problem formulation. [47] introduces the VEC concept giving emphasis on the OSN interactions that the users should have in order to participate in the same VEC. However, the ECCs and the flexibility parameters are not taken into consideration. [48] proposes a clustering algorithm, too, but there is no mathematical model supporting the user's utility function, the energy cost, the pricing and the flexibility of each user. [37] considers personality characteristics and social networks, which can be embedded in dynamic pricing and DR models. It simulates the user satisfaction, the social network dynamics and the peer pressure that members of a group induce to each other. Other related works that have coarsely quantified the impact of peer/social pressure in behavioral change towards energy efficiency are [49] and [50]. The results from these studies are based on theoretical data and methodologies from the social sciences sector and were used as input parameter to our proposed system. Finally, [51] deals with the market-bidding problem of a cluster of price-responsive consumers of electricity that participate in the wholesale electricity market. But, no specific way of clustering is used and no VEC concept is utilized (i.e. all users belonging to an ESP's portfolio are aggregated in just one group).

3.2. Community Real Time Pricing (C-RTP) with demand response

Our objective is to design an efficient and automated Demand Side Management (DSM) system in the form of an innovative pricing scheme able to exploit online social relationships. In this section, the proposed system model is presented in a high-level approach. In the next subsections, we elaborate more on the proposed system by providing the mathematical modeling and algorithmic operation.

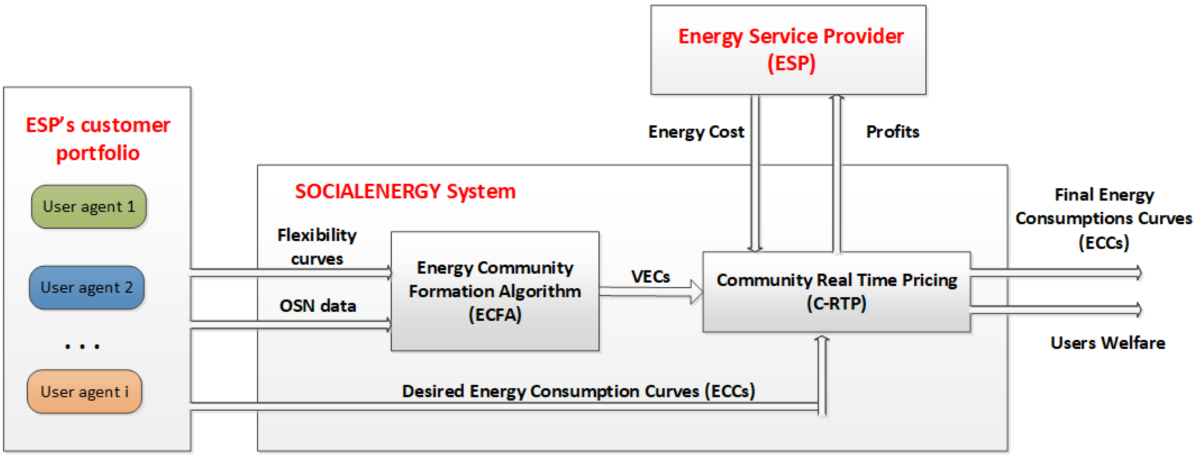


Figure 21: Proposed system architecture for VECs' management

Figure 21 depicts the two main components of the proposed framework, which are C-RTP and the Energy Community Formation Algorithm (ECFA). The ECFA module takes as input offline information (which could be updated periodically), namely: 1) the flexibility curves of the participating users, which can be declared or measured from historical data, 2) an online social network graph representing the social connections among all possible combinations of users (cf. OSN data). The objective of ECFA is the creation of a set of communities C= {VEC_1, VEC_2 , … , …}. ECFA module employs a multi-objective spectral clustering algorithm, which is analyzed extensively below. The objectives of the clustering algorithm are to minimize the inter-coherency among different clusters (i.e. VECs) and simultaneously maximize the intra-coherency of the members of each single VEC. Moreover, conventional clustering techniques like the k-means algorithm cannot handle the variation and complexity of a VEC's structure, especially when multiple criteria are considered for its creation and dynamic adaptation. From a behavioral efficiency, social dynamics and educational point of view, and based on recent findings from real-life surveys and pilots it is rational to put together users with similar social connections, because this would intrinsically incentivize them to be more engaged in improving their own performance as well as help their community to achieve its objectives [52]. By taking into consideration the social relationships among all pairs of users (cf. OSN fully-connected graph), we aim at increasing the peer pressure among the members of a VEC. When the members of a VEC have strong personal relationships and continuously interact with each other by using OSNs we expect a more positive "social network synergy" effect [49] [50] [53]. All the above-mentioned historical datasets are fed into the ECFA module and the outcome of the algorithm is the formation of VECs. It should be noted that the ECFA execution can be done periodically and the timeframe depends on the business policy of the ESP's administrative user. For example, in a real-business scenario, the VECs could be adapted on a daily, weekly or even monthly basis. VECs formations are then fed into the C-RTP module. The other input parameters of C-

RTP are: a) energy cost at time *k* which is a function of the total demand at time interval *k*, b) the desired energy consumption curves (ECCs) of each user, and c) the ESP profits. The output of the proposed C-RTP is: a) the final (actual) ECC of each user, and b) the welfare of each user.

3.2.1. Proposed system model

The mathematical modeling and the operation of ECFA and C-RTP are presented. In more detail, we initially present: i) a widely accepted user model and a well-known energy cost model in order to evaluate the proposed framework, ii) the proposed Community – Real Time Pricing (C-RTP) scheme, iii) the criteria for the design of ECFA according to the requirements that are derived from C-RTP, and iv) the proposed novel Energy Community Formation Algorithm (ECFA).

The end users (energy consumers) participating in the system form set $N = \{1,2,\dots,N\}$. Each user i disposes a smart meter, which is able to monitor her ECC. We consider a finite time horizon of time intervals $H = \{1,2,\dots,H\}$. Each time interval k has equal but arbitrary length. Each user i belongs to exactly one community *c* and the set of the communities are forming the set *C*. In each time interval k, user i has a desired energy consumption $\overline{x_i^k}$, which is generally different for each user and timeslot. We assume that the desired consumption of user i at time interval k is modified to the actual consumption x_i^k, through its participation to an EP (C-RTP with ECFA in this case) We then have for the desired and the actual consumption of community *c* at interval k that:

$$\overline{x_c^k} = \sum_{i\in c} \overline{x_i^k} \qquad x_c^k = \sum_{i\in c} x_i^k \ . \tag{24}$$

3.2.2. Modelling the users

The convenience of user i at a time interval k is expressed through a utility function $u_i^k(x_i^k,\omega_i^k)$. This is a function of user's consumption x_i^k and her flexibility parameter ω_i^k. Intuitively, the $u_i^k(x_i^k,\omega_i^k)$. expresses how much user i values (in monetary terms) consumption x_i^k at time k. The utility function that is used here towards the evaluation of C-RTP is adopted from microeconomics theory and it is a widely accepted method for the evaluation of pricing models in smart grids (see related references in subsection 2.2). The form of the utility function is the same for each i, *k*, but parameter ω_i^k distinguishes different user and time preferences. A concave and increasing utility function of x_i^k and ω_i^k with a constant maximum value after a saturation point (related to $\overline{x_i^k}$) is widely adopted:

$$u_i^k\left(x_i^k,\omega_i^k\right) = -\omega_i^t \cdot \left(x_i^t - \overline{x_i^k}\right)^2 . \tag{25}$$

For the scope of the current work and without loss of generality, we assume only one continuous, dispatchable and positive load for each user i, representing the sum of the dispatchable/curtailable consumptions of all the electric appliances of user i at time k. Finally, we note that the aforementioned utility function is used only for evaluation purposes (for comparing C-RTP with state-of-the-art RTP), while C-RTP does not make any assumption on its form.

3.2.3. Modelling the energy cost

The modelling of energy cost is the same with the one presented in subsection 2.2.

3.3. Community Real Time Pricing (C-RTP) model

As mentioned earlier, the state-of-the-art RTP model does not incentivize efficiently changes (i.e. cuts and shifts) in the ECC of the users. When a user decreases energy consumption, s/he does not only cause a reduction in the total cost of energy G_k but she also reduces the price of energy as depicted in Eq. (10), due to the convexity of G_k. With RTP, these benefits of the actions of a specific user are distributed to all users proportionally to their actual consumption. In this way, a user may gain from the behavioral changes of other users, even if she did not perform any change in her behavior (ECC modification). In order to avoid this phenomenon, our proposed C-RTP/ECFA framework factorizes the desired and the actual consumption of the participating users in order to enhance RTP with behavioral efficiency.

Moreover, in order to generate a degree of peer pressure to the participating users and increase in this way their flexibility (modelled through parameter ω_i^k), users are grouped into communities. Thus, we are able to charge them in each time instant k according to the aggregated desired energy consumption $\overline{x_c^k}$ and the aggregated actual energy consumption x_c^k of community c. According to these, the aggregated bill $B_c^k$of community c for time interval k is given as:

$$B_c^k = \overline{p^k}\overline{x_c^k} - \gamma \frac{\left(\overline{x_c^k} - x_c^k\right)}{\sum_{c\in C}\left(\overline{x_c^k} - x_c^k\right)}\left[G\left(\sum_{c\in C}\overline{x_c^k}\right) - G_k\right] - (1-\gamma)\left[\overline{p^k}\overline{x_c^k} - \frac{x_c^k}{\sum_{c\in C} x_c^k} G_k\right], \quad (26)$$

where $\overline{p^k}$ is the price of energy that users would have paid if their consumptions were their desired ones (no energy sheds). Parameter γ quantifies the level of incentives that C-RTP provides, as described next.

In case γ=0, C-RTP (γ=0) is identical to RTP model, which sees communities as "virtual" users. Our performance evaluation results show that in this case, the pricing scheme suffers from behavioral efficiency, as it charges communities only according to the actual consumption without factorizing at all their behavioral changes:

$$B_c^k(\gamma = 0) = \frac{x_c^k}{\sum_{c\in C} x_c^k} G_k \quad (27)$$

In case γ=1, the C-RTP(γ=0) pricing model becomes behaviorally efficient by distributing all the financial benefits $G\left(\sum_{c\in C}\overline{x_i^k}\right) - G\left(\sum_{c\in C} x_c^k\right)$ derived from the energy sheds to all the communities in a way proportional with the sheds $\overline{x_c^k} - x_c^k$ each of them performed, and thus equal to the proportional financial benefits they offered to the system.

$$B_c^k(\gamma = 1) = \overline{p^k}\overline{x_c^k} - \frac{\left(\overline{x_c^k} - x_c^k\right)}{\sum_{c\in C}\left(\overline{x_c^k} - x_c^k\right)}\left[G\left(\sum_{c\in C}\overline{x_\iota^k}\right) - G\left(\sum_{c\in C} x_c^k\right)\right]. \quad (28)$$

When 0<γ<1, the C-RTP(γ) model follows a hybrid strategy between the two aforementioned cases. Finally, in case where γ>1, C-RTP constitutes a more aggressive policy, in terms of behavioral efficiency, by even penalizing communities that are not performing energy sheds, thus incentivizing more communities to participate in demand response actions. In the performance evaluation of the proposed framework (see the next subsection), we look into the performance of C-RTP for various values of γ and elaborate on the capabilities offered by the appropriate choice of this parameter.

The first step of C-RTP operation is the calculation of the community bills B_c^k for all $c \in C$ and the calculation of the x_c^k. Thus, an iterative process between the ESP and each community in C takes place. In each step m of this process, the ESP takes the new energy consumption of a community c at k, denoted as $x(m)_c^k$ with $x(0)_c^k = \overline{x_c^k}$, and calculates the new bills for all communities in C according to Eq. (28). Then each community, updates its consumption $x(m+1)_c^k$ aiming to maximize its welfare. The Community Welfare (CW) of a community c at time interval k is defined as:

$$CW_c^k = \sum_{i\in C} u_i^k\left(x(m)_i^k, \omega_i^k\right) - B_c^k. \quad (29)$$

In Eq. (29), each $x(m)_i^k$ (which is the energy consumption of user i at k in the m^{th} iteration of C-RTP) is $\delta_c(m)\overline{x_\iota^k}$ where $\delta_c(m)$[0,1] is equal for all the participating users in a community c. As it is analyzed in the next subsection, in order to preserve the fairness properties that this architectural decision introduces, the formation of communities takes into account the flexibility parameters of the users, so as to place in each community, users with similar flexibility levels.

After a number of interactions of the two aforementioned steps, C-RTP converges and its outputs are the bills B_c^k and actual consumptions x_c^k for all $c \in C$. In order to achieve this in each steps *m,* it adjusts x_c^k by solving Eq. (30) to compute $\delta_c(m)$ value as follows:

$$\delta_c(m) = \arg\max_c\{CW_c^k\} \;. \quad (30)$$

After the calculation of the final community bills, the next process is the calculation of the bill of each participating user. In our model, users participate in the bill of their community in a way proportional to their actual consumption x_i^k. Thus, the bill B_i^k for user i in time interval k is given by:

$$B_i^k = \frac{x_i^k}{\sum_{\iota\in C} x_i^k} B_c^k \quad (31)$$

More advanced policies that distribute the bill of each community to its members has been already described in our previous work [42] and are outside the scope of this work. C-RTP is transparent to these policies and can be combined with any of them.

3.4. Energy community creation algorithms

3.4.1. Criteria that determine the formation of the Virtual Energy Communities

Based on the philosophy of the C-RTP scheme, which is to incentivize communities, exploit social interactions, but also be fair, we derive two criteria as the most appropriate ones to play a role towards the creation of the VECs. The first criterion is the flexibility similarity levels (apart from the desired and actual energy consumption) of the participating users, which is modeled here through flexibility parameter ω_i^k. In view of Eq. (28), users with similar flexibilities perform similar energy sheds. Thus, ECFA will have to group users with similar flexibilities towards the development of a fair pricing model, especially given that the distribution of profits among the members of the community (Eq. (31)) is based on their consumption and not on their individual contribution. In addition, as the performance evaluation subsection describes, the optimization of the community welfare (Eq. (29)) is much more behavioral efficient (maximization of energy sheds and users' welfare) in this case.

The second criterion that influences the formation of the communities is the social correlation of the participating users. The VECs' formation according to social correlation among its members has been found to result into effective behavioral changes. In more detail in [49], the results on a social network peer pressure show that the influence is not only related to its connectivity, but it is also strongly affected by node-to-node social weights. Energy savings reported in [49] start from 5.64% and reach up to 25%. Related research findings in [54], found the effect of group-level feedback and peer education on energy reductions to be in the range from 4% to 7%. Thus, in the energy efficiency sector, there are already some initial attempts to exploit social networks (peer pressure) in order to achieve a behavioral change in the energy consumption. On the other hand, there is no pricing model yet able to automate and exploit these phenomena. In addition, there are no experimental studies and results from other areas/sectors in order to quantify through simulations the expected improvements. We should note here that criteria other than flexibility and social connections could also be used to form Virtual Energy Communities (and define associated Energy Programs), such as geographic location, age group, income level, etc. As a result, updated research results will be provided in D3.2 (M24), once real behavioural data from the SOCIALENERGY S/W platform is available.

3.4.2. Proposed Energy Community Creation Algorithm (ECFA)

The implementation of ECFA is done through the use of spectral clustering [55], which is one of the most widely used algorithms for clustering, thanks to their ease of implementation, simplicity, efficiency, and empirical success. According to ECFA, the set N of consumers is clustered into a set of communities $\boldsymbol{C} = \{\boldsymbol{c_1}, \boldsymbol{c_2}, \dots, \boldsymbol{c_{|C|}}\}$. ECFA takes into account the flexibility of each consumer and his/her connections in online social networks (OSNs, such as Facebook, Twitter, etc.) and according to their factorization, produces a distance between a consumer $\boldsymbol{i}$ and a consumer $\boldsymbol{j}$ which is:

$$d(i,j) = w_1 \cdot \Big(1 - \big((\omega_i - \omega_j)/\max(\omega_i, \omega_j)\big)\Big) + (1 - w_1) \cdot f(i,j). \qquad (32)$$

Parameter $w_1 \in [0,1]$ can be used to obtain a trade-off between the similarity in flexibility and in social connections, as described later, while ω_i and ω_j express user flexibilities. User flexibility could be declared by the users and monitored/validated in practice, or be measured through historical data (e.g. user's recent behavior). Parameter $f(i,j) \in [0,1]$ represents the level of social connection between i and j and is defined as:

$$f(i,j) = 0.5 \cdot Fr(i,j) + 0.5 \cdot Cf(i,j)/Tf(i,j) \qquad (33)$$

In Eq. (33), $Fr(i,j)$ is 1 if i is socially connected with j in OSNs, $Cf(i,j)$ is the number of common social connections between i and j in OSN and $Tf(i,j)$ is the sum of the social connections of i and j in OSNs. The definition of Eq. (33) is motivated from observations from field trials [49] [50] [56] [57]. Other definitions of $f(i,j)$ could have been used in our proposed framework, and the specific definition is used only in our performance evaluation results.

The objective of ECFA is to group consumers into VECs, in a way that consumers in the same VEC are similar to each other, with the index of similarity given by Eq. (32). This distance metric among consumers is the input value to similarity matrix, and the spectral clustering technique is then used to group consumers in a predefined number of clusters. The table below describes the execution steps of ECFA.

Table 12: Energy Communities Formation Algorithm (ECFA)

Energy Communities Formation Algorithm (ECFA)	
Input: A set of consumers $N = \{1,2, \dots, N\}$	
Output: A partition $C = \{c_1, c_2, \dots, c_{\|C\|}\}$	
Step 1.	Compute similarity matrix *W* such that $W(i,j) = d(i,j)$, for all *i,j*$\in N$
Step 2.	Compute diagonal matrix: $D_{ii} = \sum_j W_{ij}$ for all *i*$\in N$
Step 3.	Compute Laplacian matrix: *L* = *D* – *W*.
Step 4.	Compute Normalized Laplacian matrix: $\mathcal{L} = D^{-1/2} L D^{1/2}$
Step 5.	Compute the first *k* eigenvectors of $\mathcal{L}$, denote as U.
Step 6.	Consider the rows of *U* as data points, use k-means to cluster them into *k* VECs.
Step 7.	Assign user *i* to VEC $c_{\|}$, if row *i* of matrix *U* was assigned to community $c_{\|}$.

The optimal value of w_1 in Eq. (32) according to which ECFA takes place is dataset dependent and it also depends on the impact that social connections have on the modification of the flexibility levels of the consumer. One last thing that has to be modelled is the effect peer pressure (pp) from socially connected users on a specific user i. Based on relevant field trials [49] [50] [56] [57], we assume that the peer pressure impact is quantified as a reduction of the flexibility parameter (increase in flexibility) from the a priori value ω_i to an a posteriori (after the peer pressure) value of ω_pp_i given by:

$$\omega\_pp_i = \omega_i(1 - max\_pp \cdot f(i,j)) \qquad (34)$$

Thus, ω_pp_i is the flexibility parameter of consumer i after the peer pressure caused by community formed by ECFA. Here, $max\_pp \in [0.1]$ is the maximum percentage in which peer pressure effect is able to modify flexibility of consumers.

3.5. Performance evaluation results of the C-RTP energy programs

In this subsection, we evaluate the performance of the proposed C-RTP scheme, by using the RTP scheme as a benchmark. More details about the operation of RTP are provided in section 2.2.4. We consider a system consisting of *N = 64* energy consumers and simulate a period of one day. Unless otherwise stated, we set *c*=0.02 in the energy cost generation function of Eq. (10), and use ECFA to form $|C|$=16 VECs.

To evaluate the proposed system, we use the following Key Performance Indicators (KPIs), also widely accepted in the literature:

- Energy Cost *G*, as defined in Eq. (10), which is the cost of ESP to acquire the electricity needed to fulfil the requirements of its customers. This is an index of how energy-efficient a pricing scheme is in terms of incentivizing its customers to adopt energy-efficient habits.
- Aggregate Users' Welfare (*AUW)* is a KPI that summarizes UW and expresses the competitiveness of an ESP that adopts a billing strategy in an open retail electricity market.
- Behavioral Reciprocity *BR*i of user i is the degree of correlation between the behavioral change of i and the reward that i gets for it:

$$BR_i = \frac{D_i^A}{D_i^R}, \forall\, i \in N \qquad (35)$$

where D_i^A (Eq. (36)) represents the discount achieved, i.e. the system cost reduction, for user i and D_i^R (Eq. (37)), represents the discount received by i, i.e. the difference between user i's bill with the original system's state ($x_i^t = \widetilde{x_i^k}\ \forall i \in N$) and the actual user i bill (after applying RTP or C-RTP). Values of BR_i close to 1 indicate a better trade-off between *AUW* and *G*, and thus a fairer pricing mechanism.

$$D_i^A = \left(\widetilde{x_i^k} - x_i^k\right) \cdot \frac{\left[G\left(\sum_{i=1}^N \widetilde{x_i^k}\right) - G\left(\sum_{i=1}^N x_i^k\right)\right]}{\sum_{i=1}^N \widetilde{x_i^k} - \sum_{i=1}^N x_i^k} \qquad (36)$$

$$D_i^R = \widetilde{x_i^k} \cdot \left[\frac{G\left(\sum_{i=1}^N \widetilde{x_i^k}\right)}{\sum_{i=1}^N \widetilde{x_i^k}}\right] - x_i^k \cdot p_i^k \qquad (37)$$

In the rest of this section, we present five case studies. The first observes the performance of C-RTP under various values of *γ* and energy generation cost models (Eq. (10)) in order to justify the importance of the design of a pricing scheme to motivate behavioural changes to the end users. The second studies how C-RTP reacts under various levels of user's flexibility in order to prove that the proposed system is not data-dependent. The third evaluates the performance of C-RTP under different assumptions on the number $|C|$ of VECs and different peer pressure levels (Eq. (34)) in order to demonstrate their impact in promoting behavioral change towards energy efficiency. The fourth compares C-RTP with ECFA to C-RTP without ECFA in order to justify the necessity of the interaction of these two components. Finally, the fifth compares an ECFA that takes into account multiple criteria, namely the user's flexibility and the user's social connections, with two ECFAs that take into account only one of them in order to justify our decision to design VECs with multiple criteria.

3.5.1. Study for varying generation cost of energy in the wholesale electricity market

Figure 22 depicts the ratio between the consumed energy cost *G* under C-RTP and also under RTP as a function of *γ*, for three different choices of the energy generation cost parameter, *c* =0.01, 0.02 and 0.03. The total percentage of energy cost reduction for *γ*=1 varies from 8% for low generation cost of energy (*c*=0.01) to 24% for high generation cost of energy (*c*=0.03) for a given number |*C*|=16 of VECs. It is apparent from this figure that in all scenarios, *γ* parameter highly affects the system's energy cost *G*. It should be noted that large values of *γ* (e.g., *γ*>1) reduce AUW and thus ESPs using C-RTP have to select a value of *γ* that gives an attractive trade-off between *G* and *AUW*.

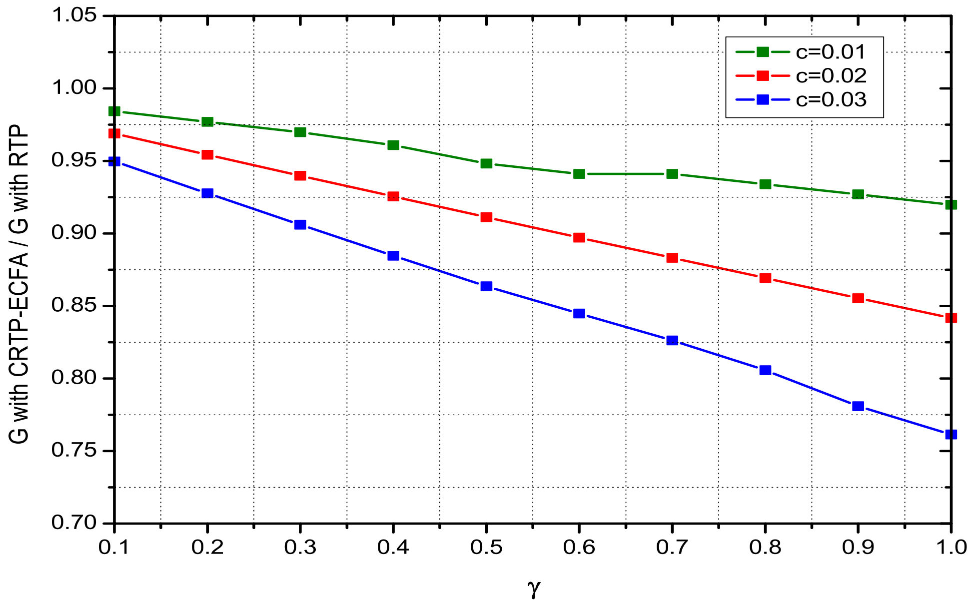


Figure 22: Ratio between G under C-RTP/ECFA and G under RTP, as a function of γ for various energy generation cost parameters c.

Figure 23 depicts the ratio between AUW under C-RTP and AUW under RTP again as a function of *γ*. The scenarios that depicts are the same with **Figure 22** (*c* takes values 0.01, 0.02 and 0.03). As it can be observed, the AUW under C-RTP is also higher than AUW in RTP and this increase ranges from 2% to 5%. Low values of *γ* favor inflexible users, while high values favor flexible ones. In the zone of *γ* around 0.6 to 0.8, there is an attractive trade-off between the welfare of both flexible and inflexible users. On the other hand, the value of *γ* that maximizes AUW depends on parameter *c*, the ECCs of the consumers and their flexibility levels. Thus, it is infeasible to calculate it analytically and ESPs have to adjust *γ* empirically through software tools for business analytics like these that SOCIALENERGY project proposes.

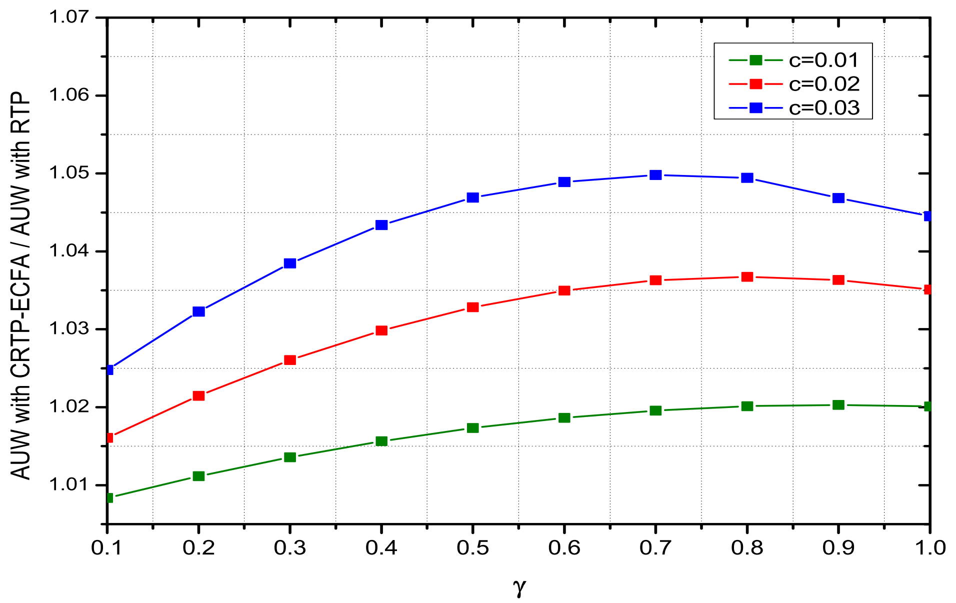


Figure 23: Ratio between AUW with C-RTP/ECFA and AUW with RTP, as a function of γ

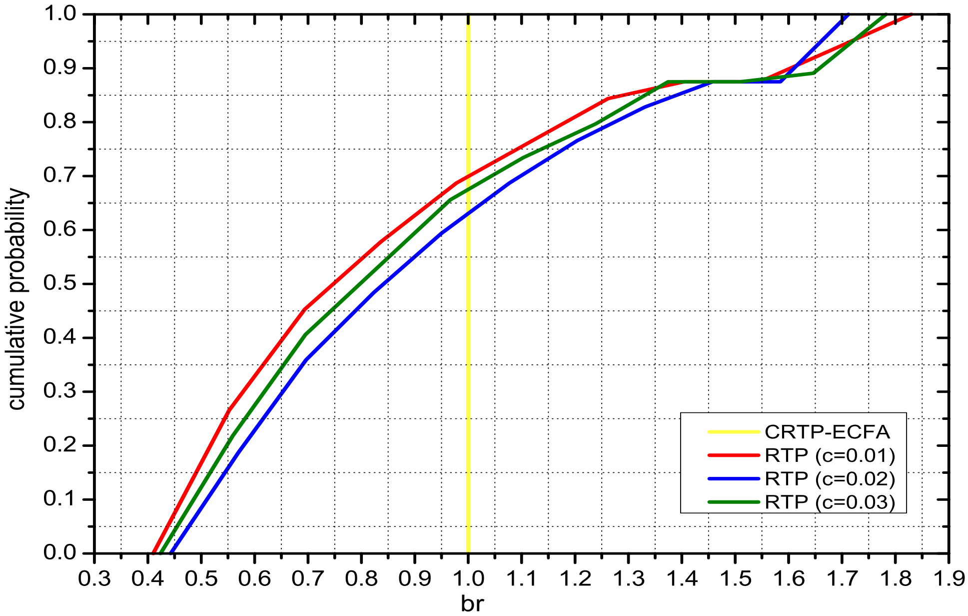


Figure 24: CDF of BR in RTP and C-RTP for different energy generation costs

In **Figure 24**, the Cumulative Distribution Function (CDF) of the BR under RTP and under the proposed C-RTP/ECFA is presented for various choices of the energy generation cost parameters c. As observed in the figure above, C-RTP is capable to fairly distribute the financial benefits that are caused by the behavioral changes taking place to the VECs that perform these behavioral changes. On the contrary, RTP is a volume-aware pricing, which does not incentivize behavioral changes. In particular, there is high variance of *BR* among the participating users. For example, there are some users (i.e. highly flexible users) that are rewarded less than 50% of their contribution to the system's energy savings, while some others (i.e. low flexibility users) get much more rewarded than what their contribution is worth. In contrast, the yellow line obtained for C-RTP shows that all users get reimbursed exactly based on each one's contribution to the system's energy cost reduction.

3.5.2. Study for varying levels of users' flexibility

Figure 25 presents the ratio between the consumed energy cost G with C-RTP/ECFA and with RTP as a function of γ for various average level of user flexibility [parameter ω in Eq. (25)]. Three different scenarios were executed based on user's flexibility ω, which are noted as 'LOW', 'MEDIUM' and 'HIGH'. In these scenarios, the elasticity parameter ω of each user is chosen randomly in the interval [9,17] for 'LOW' flexible users, in the interval [4,10] for 'MEDIUM' flexible, and in the interval [0.5,7] for 'HIGH' flexible users. As we observe, significant cost reductions are achieved starting with ~11% for inflexible users and reaching up to 35% for flexible users without sacrificing at all the user's welfare.

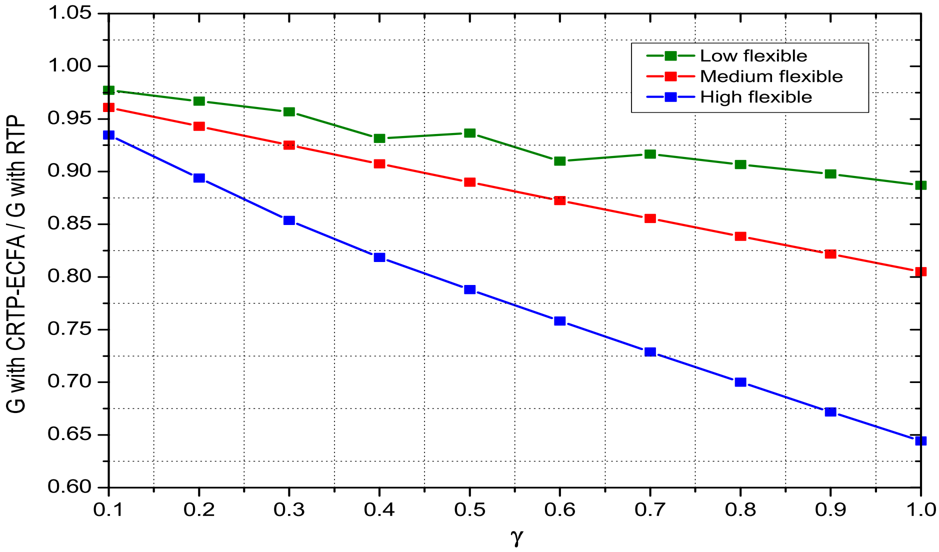


Figure 25: Ratio between energy generation cost G with C-RTP/ECFA and G with RTP as a function of γ, for different user flexibility levels

Figure 26 depicts the ratio between aggregated users' welfare *AUW* with C-RTP/ECFA and *AUW* with RTP, again as a function of γ for the same three scenarios (LOW, MEDIUM, HIGH). C-RTP/ECFA achieves better results in all scenarios, which range from 3% (LOW) to 6% (HIGH). In the latter case, the increase of AUW with C-RTP is higher than that with RTP because higher flexibility allows C-RTP more options to use this trade-off more efficiently.

Figure 27 depicts the Cumulative Distribution Function (CDF) of BR with RTP and with C-RTP/ECFA, for different levels of the users' flexibility. We see that C-RTP is able to fairly distribute the financial benefits among all the users. Moreover, the level of unfairness in RTP increases when users have higher flexibility levels (cf. blue line). In these cases, RTP fails to reward flexible users and thus we observe even higher variance in *BR*.

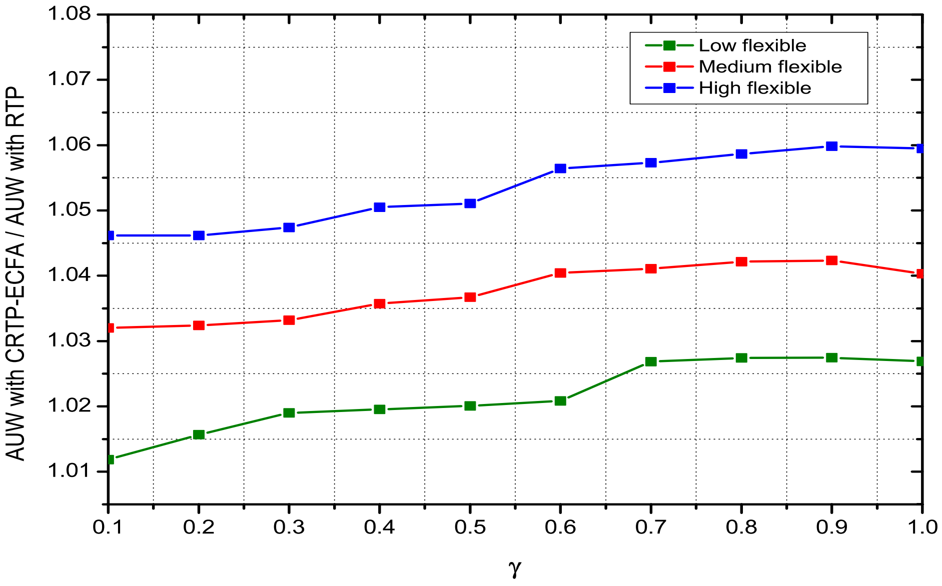


Figure 26: Ratio between AUW with C-RTP/ECFA and AUW with RTP as a function of γ, for multiple user flexibility levels

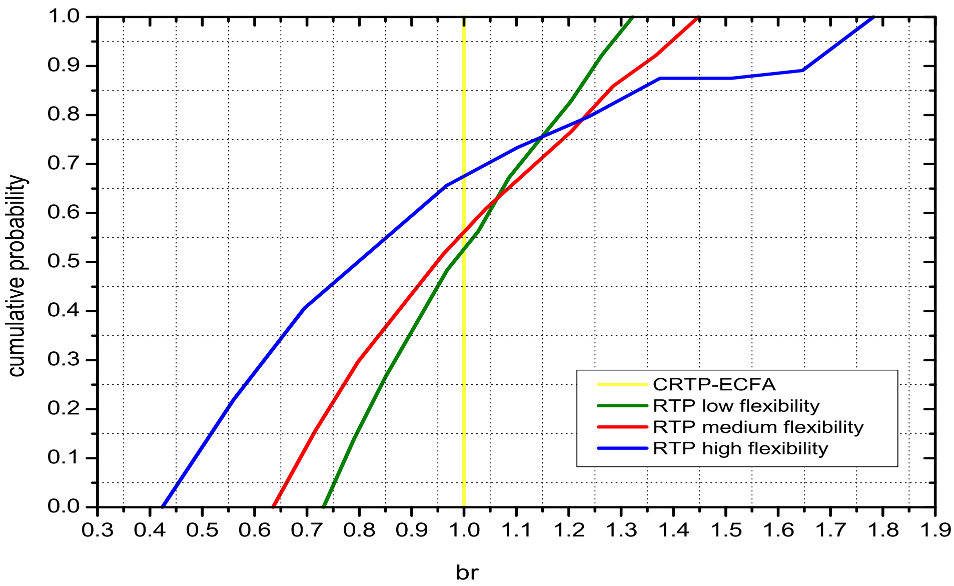


Figure 27: CDF of BR in RTP and C-RTP/ECFA for various user flexibility levels

3.5.3. Study for varying average size of VECs and peer pressure factor

Figure 28 depicts the ratio between the generation cost *G* with C-RTP/ECFA and *G* with RTP as a function of maximum peer pressure effect [parameter *max_pp* in Eq. (34)] for multiple numbers of VECs (or else multiple average VEC size). Additionally, the figure presents the ratio between *G* under C-RTP/ECFA and *G* under RTP as a function of *max_pp* for multiple numbers of VECs. In this case, three case scenarios were validated: 64 users were divided into 16 VECs for the first scenario, into 24 VECs for the second scenario, and finally into 32 VECs. As *max_pp* increases, the total cost reduction ranges from 15% to 20% depending on the number of VECs. In addition, as expected, as *max_pp* increases AUW also increases (around 2%), which means that the exploitation of the peer pressure effect improves both KPIs.

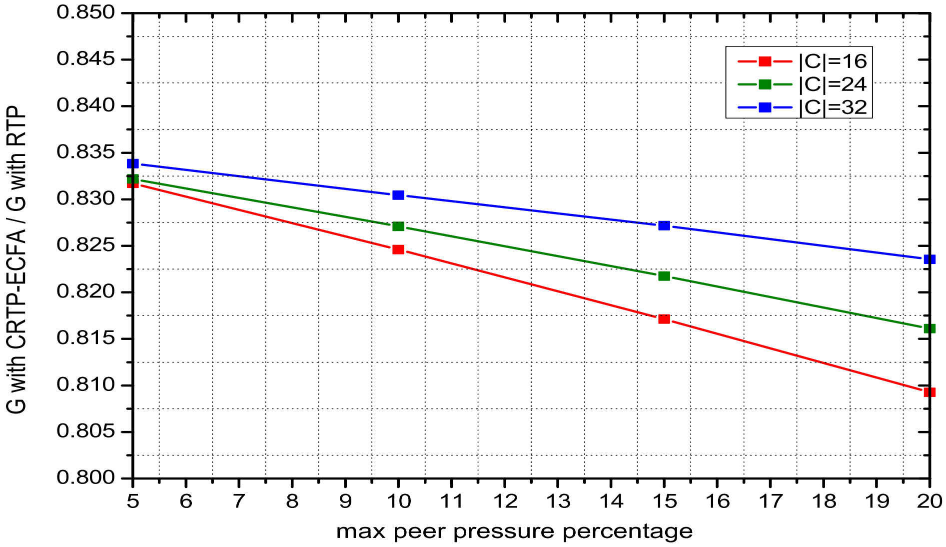


Figure 28 : Ratio between energy generation cost G with C-RTP/ECFA and G with RTP as a function of maximum peer pressure effect for multiple VEC formations

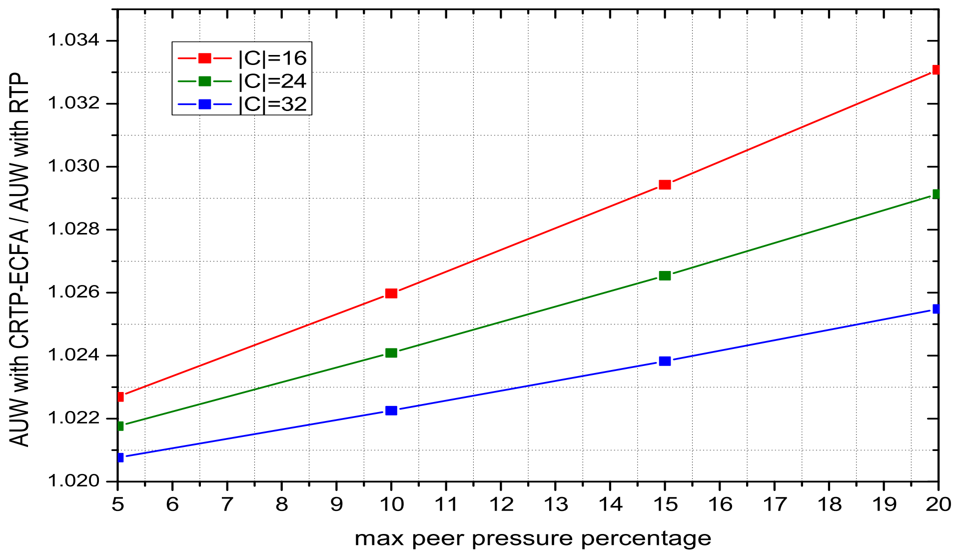


Figure 29: Ratio between AUW under C-RTP/ECFA and AUW under RTP, as a function of maximum peer pressure effect for different sizes |C| of the VEC formations

3.5.4. Outperformance of ECFA and spectral clustering technique

In **Figure 30**, we present the ratio between the energy cost *G* with C-RTP in case that VECs are generated through the use of ECFA and the energy cost *G* with C-RTP in case that VECs are generated randomly; this ratio is depicted as a function of the flexibility level of the participating users. Results indicate a significant reduction in *G*, between 5% for users with low flexibility and up to 35% for users with high flexibility, through the use of ECFA in C-RTP. This is rational because the proposed C-RTP/ECFA intelligently groups the users in the most appropriate VECs compared to the case that VECs are randomly created. In **Figure 31**, we depict the ratio between the *AUW* under C-RTP in case that VECs are generated through the use of ECFA and the *AUW* under C-RTP in case that VECs are generated randomly this ratio is again who as a function of the flexibility level of the participating users. According to this figure, there is a considerable increase in *AUW* that starts from 3% in case of low flexibility and $|C|$=8 and reaches 15% in case of high flexibility and |C|=16. These two figures prove the importance of the combination of C-RTP with ECFA towards an efficient design of community energy programs.

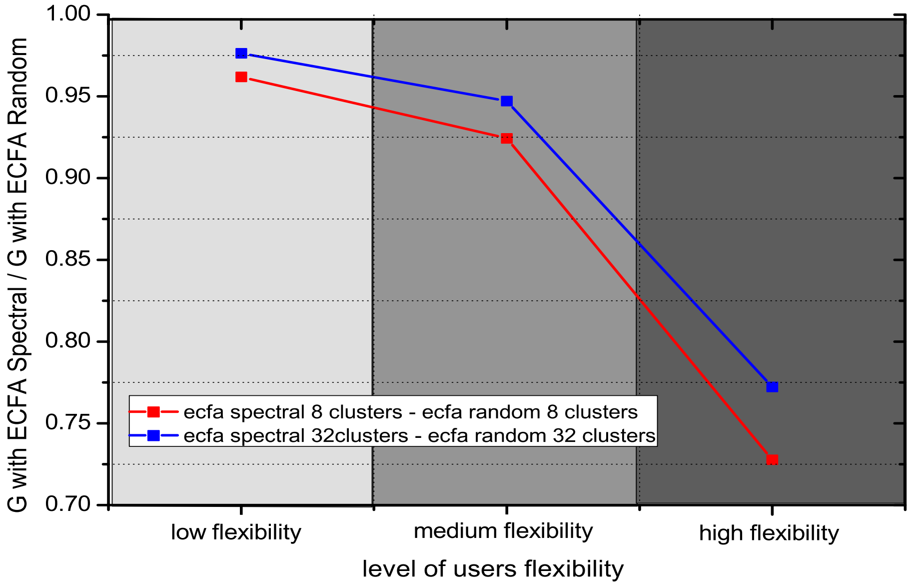


Figure 30: Ratio G (C-RTP/ECFA)/ G (C-RTP/random VECs) as a function of user's flexibility

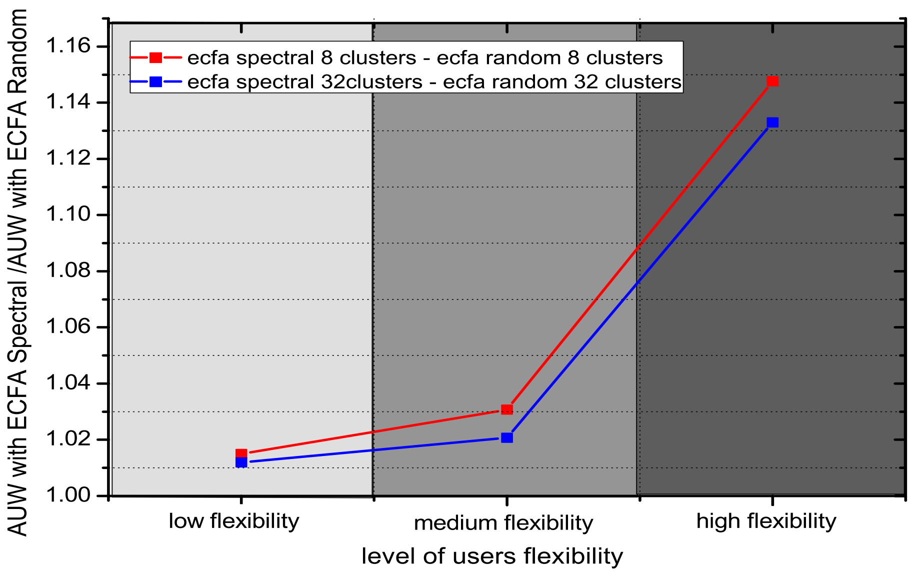


Figure 31: Ratio AUW (C-RTP with ECFA)/AUW (C-RTP with random VECs) as a function of users' flexibility

3.5.5. Study of the multi-parametric objective function for VECs' creation

Table 13 presents the ratio between G under C-RTP/ECFA and G under RTP, while **Table 14** presents the ratio between AUW under C-RTP/ECFA and AUW under RTP, for various values of the weighting parameter w_1 used in Eq. (32). In column 2 (or 4) of these tables, scenarios in which ECFA takes into account only flexibility levels (or only social connections, respectively) for the formation of VECs are presented. On the other hand, column 3 presents a multi-criteria scenario, where both flexibility in energy consumption and social connections were equally taken into account through the use of ECFA. As we observe from these tables, for each scenario (regardless the flexibility level of consumers), the use of multiple criteria provides the maximum behavioral change (minimum cost), while at the same time AUW is increased.

Table 13: The ratio between G in C-RTP and G in RTP under various values of w1 in ECFA (trade-off between flexibility and social factor)

G(C-RTP)/G(RTP)	*flexibility only (w_1 =0)*	*social & flexibility factors (w_1 =0.5)*	*social factor only (w_1 =1)*
low flex users	0,882357083	0,86590362	0,917851501
medium flex users	0,786386355	0,766113567	0,815745019
high flex users	0,690906852	0,657595769	0,766077134

Table 14: The ratio between AUW in C-RTP and AUW in RTP under various values of w1 (trade-off between flexibility and social factor)

AUW(C-RTP)/AUW(RTP)	*flexibility factor only(w1=0)*	*social & flexibility factors (w_1 =0.5)*	*social factor only (w1=1)*
low flex users	1,009411053	1,037985595	1,012341827
medium flex users	1,030316886	1,060829799	1,036837756
high flex users	1,022028129	1,040631129	0,941376169

<u>Note:</u> More technical details and performance evaluation results about the family of C-RTP energy programs is provided in several journal and international conference publications written by ICCS partner, such as [40] [41] [42] [58] [59] [60].

3.6. Dynamic adaptation of energy communities, profiling, recommendation engines and their commercial applicability in SOCIALENERGY's business

The following figure illustrates the process of VECs' dynamic adaptation and its close inter-relation with the innovative services offered by SOCIALENERGY. This process includes 4 main steps and the technical details are analyzed in chapter 5 of the current report. Initially, the business objective should be defined by the SOCIALENERGY administrator user (e.g. the CEO or business analyst of an electric utility company/ESP). Then, all energy consumers that meet the specific business criteria are selected and subsequently several virtual energy communities (VECs) are created. For example, one VEC could be comprised by all energy consumers, who have the same EP or belong to the same VEC or have similar flexibility levels, etc. During the dynamic VEC adaptation process, significant changes in the users' profiling information may be realized and subsequently the VECs' structure should be adapted. Finally, the final step is to automate the recommendation process by creating specific rules for each business objective case and then send the required messages to end users (i.e. community members). The end users are then able to see the messages in the form of notification in their web interface.

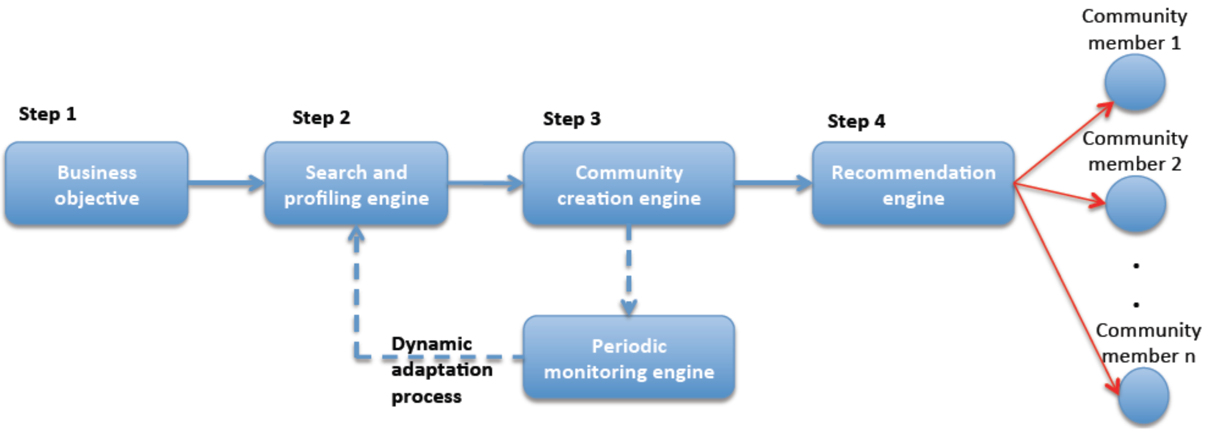


Figure 32: Overview of the reporting/recommendation services offered by SOCIALENERGY S/W platform

More technical details about the SOCIALENERGY reporting/recommendation mechanism are provided in chapter 5. The design rationale of the proposed framework allows the scale-up to hundreds or thousands of business objectives that an electric utility company may have in the future. Within SOCIALENERGY project's context, the following 6 cases will be implemented and demonstrated, namely:

- Match user's/community's profile with the most suitable Energy Program
- Switch to another more beneficial Energy Program
- Switch to another more beneficial Energy Community
- Instructions to follow the DR signals
- Recommendation for new electric appliances and other energy efficiency products
- Match user's learning profile with the most suitable learning material from LCMS

3.6.1. Match user's/community's profile with the most suitable Energy Program

In this business case, the ESP's objective is to run the scientific algorithms proposed in chapters 2 and 3 in order to decide which is the most suitable EP for each end user of its commercial portfolio.

3.6.2. Switch to another more beneficial Energy Program

Here, the service is to provide the incentives and the required knowledge to the end user to switch to another EP that may be more beneficial according to his/her updated needs. For example, an energy consumer may switch to a "holiday EP" for just one month that the house will be vacant and earn extra discount in his/her electricity bill.

3.6.3. Switch to another more beneficial Energy Community

This recommendation service is similar with the previous one. The difference is that this one refers to the family of C-RTP energy programs, while the previous one refers to the family of P-RTP energy programs.

3.6.4. Instructions to follow the DR signals

In this business case, the utility company/ESP may engage a specific portion of its portfolio in a DR event. During a DR event, the end user is guided via reporting/recommendation messages about the exact actions that should take place in order to gain more discounts in her electricity bill.

3.6.5. Recommendation for new electric appliances and other energy efficiency products

This case refers to the collaboration of the electric utility with other market stakeholders, who are related with energy efficiency sector (e.g. electric appliances' vendors/retailers, insulation material companies, building construction/renovation companies, etc.).

3.6.6. Match user's learning profile with the most suitable learning material from LCMS

Finally, this case is part of the user engagement and education services offered by SOCIALENERGY platform. In particular, there is an Individual Learning Plan (ILP) for each end user, which is dynamically monitored. Once an end user reaches a learning milestone, s/he is recommended the most suitable learning material to continue.

3.7. Integration in SOCIALENERGY S/W platform and credit distribution policies

C-RTP family of energy programs allocates the demand response gains fairly among the users and promotes behavioral change towards energy efficiency. The average energy cost savings are about 10-20%, while they even reach 30% under certain scenarios, where users are very flexible. Moreover, the proposed Energy Community Formation Algorithm (ECFA) can be used by a utility company's/ESP's business to automatically form efficient VECs that achieve high behavioral change via the use of the proposed SOCIALENERGY S/W platform. VECs can be used as input to various business analytics functionalities such as user profiling, reporting and recommendation mechanisms towards achieving higher and sustainable user engagement in ESP's products and services.

In SOCIALENERGY context, all the above-mentioned algorithms and performance evaluation results regarding the family of C-RTP energy programs have been integrated in the RAT subsystem. Therefore, the administrative user (e.g. CEO or business analyst of a utility company or ESP) is able to run exhaustive "what-if" scenarios in order to decide the best VEC formation and respective pricing policy according to the types of users, its business plan and the KPI that it wants to optimize. Via the GUI of RAT subsystem (see more details in section 5), the admin user is able to easily customize all above-mentioned parameters. The results are also illustrated in the core GSRN platform via the deployment of GSRN-RAT API. The *individual (energy consumer) user of the SOCIAENERGY platform will also be able to run instant simulations in order to realize which P-RTP energy program is the most beneficial for him/her (see more details in section 6).*

3.7.1. The SOCIALENERGY Point System and how it works

SOCIALENERGY's Point System represents the mechanism, which defines when, in which way and how many SEP points the user will gain, by using the GSRN platform. SOCIALENERGY Points (SEPs) represent the way that a user watches, ranks, and guides his/her experience in the whole S/W platform. Every action that a player undertakes within the system entails a specific amount of SEPs earned. The proposed SOCIALENERGY Point System and respective mechanisms are the most important features in order to provide a base for the gamified application development. SEPs are also useful for comparing users. Moreover, it gives user the feeling of progress and as s/he tries to win more points, s/he visits more often the S/W platform. Levels serve as a marker for players to know where they stand in a gaming experience (thus experience points) over time. In the game design and all other gamification features of SOCIALENERGY platform, level difficulty is not linear. In other words, it does not take 100 SEPs to get to level one, 200 for level two, 300 for level three, and so on. Instead, difficulty increases in an exponential form. In our project, the following SEP formula will be used:

SEP Formula: SEP = a*Level*(1+Level) (38)

Constant 'a' in eq. (38) represents the ease of achieving an increase in one level up. In most games this type of mathematical formulas are determined only after play-testing and trying out several options. In our case, we should find balance between SEP points assigned to each user's action and constant 'a'. In order to find the most fitted value for 'a', we calculate the total SEP points that the user will gain on his/her first GSRN visit (on boarding) in the app. We keep in mind that through on boarding, user should experience one level up.

For example, GSRN Registered user's first visit can be calculated as follows:

Welcome	5
Daily reward	15
Read GSRN announcement	10
Read GSRN tips and energy curves	4
Engage with GSRN EP or DR or Efficiency targets	5
Play the SOCIALENERGY Game or purchase Marketplace devices	4
Engage with LCMS courses	8
Total:	**51**

These 51 points must be more than 1 level. Thus, we set a=15 and according to eq. (38), we have the curve shown in the figure below:

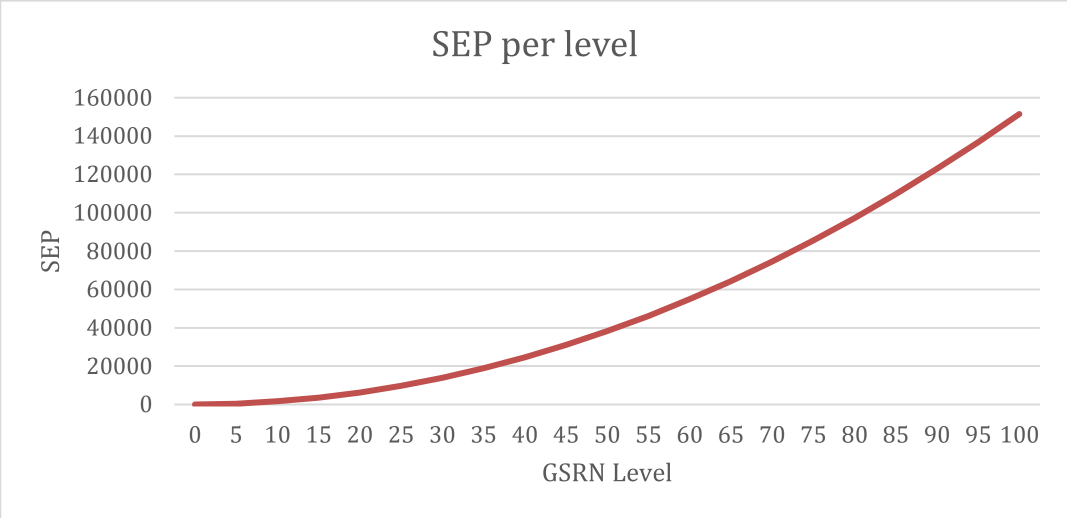


Figure 33: Indicative structure of SOCIALENERGY's Point System for an indicative value of a=15

Alternatively, the respective matching of the GSRN levels with the SEPs is provided below:

GSRN Level	SEPs
Level 1	0-29
Level 2	30-89
Level 3	90-179
Level 4	180-299
Level 5	300-449
Level 6	450-629
…	…

Subsequently, the various GSRN levels are matched with the various user descriptions as shown below:

Description	Levels
Novice	Levels 1-3
Beginner	Levels 4-9
Player	Levels 10-18
Challenger	Levels 19-30
Experienced	Levels 31-45
Energy geek	Levels 46-63
Master	Levels 64-84
Guru	Levels 85-108

In the figure below, an indicative hierarchical structure is depicted for the matching of user characterizations with the various levels:

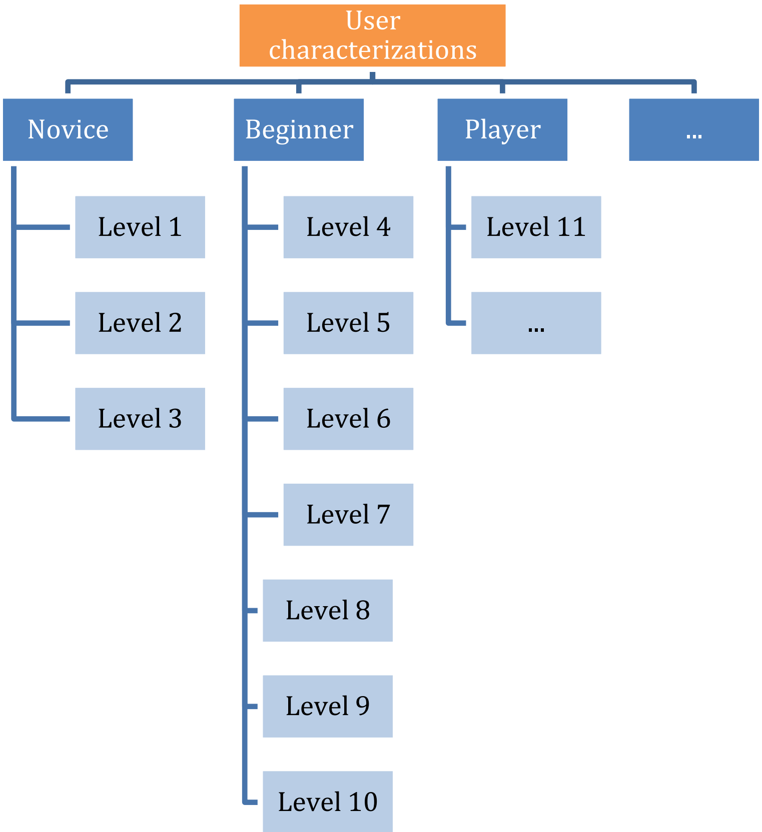


Figure 34: Structure and description of levels within SOCIALENERGY S/W platform

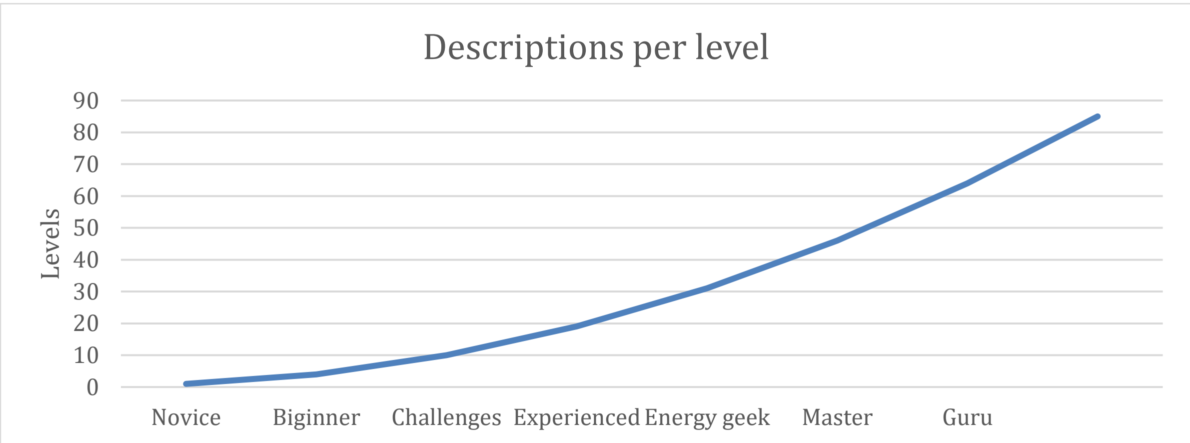


Figure 35: Indicative structure of SOCIALENERGY's levels for an indicative value of a=15

3.7.2. SOCIALENERGY Coin System

Based on our literature review and on similar gamification applications, we recommend the following currency equivalent between virtual currency (i.e. SOCIALENERGY Coin (SEcoin)) and Euro currency.

$$\textbf{SEcoins / Euro = 1 / 3} \qquad \textbf{(39)}$$

This means that each Euro is equal to 3 SEcoins. The redemption mechanism should be easy. The detailed mechanism can be described as follows:

a. User gets into the marketplace inventory. The prizes/offers that the user can redeem are marked differently than the ones s/he cannot redeem.

b. The option of further investigating such prize is available to the user, by clicking in the prize/offer description.

c. The user can then select the option Redeem Prize.

d. The user can either select the prize for himself or for a gift.

e. If the user selects the prize for himself/herself, then a message indicating the shipping address that we have in the database appears. The user can also add another shipping address if needed.

f. If the user continues with the redemption, then a summary of the prize and the address is shown with a confirm button. Upon confirming, an email is sent to the user and to the supplier with the details and the expected delivery and the process, which, for each prize, has been determined with the supplier.

g. If the user introduces a new address, a message with a summary of the prize and the new address is shown and (f) step is repeated after confirmation.

If the user selects the prize as a gift, a message with space to insert the name and the new address is shown and after inserting it, step (f) is followed again.

4. Green Social Response Network (GSRN) platform

GSRN is considered the central SOCIALENERGY dashboard and system that users interact with (login, logout, etc.). The user can be easily navigated into the GAME, LCMS and RAT subsystems via the GSRN dashboard (i.e. front-end system). GSRN interacts with all other SOCIALENERGY subsystems and provides all the corresponding results via user-friendly GUIs. In the following subsections, indicative screenshots are provided from the 1st version of GSRN (mainly using mock-up datasets) for each individual S/W module.

4.1. Meter Data Management System functionalities

"My energy profile" module provides real consumers' energy consumption data. The user can select the meter installed and then s/he can visualize with nice graphs his/her Energy Consumption Curves (ECCs) for various time granularities and periods. This module gives users the ability to monitor their energy consumption, and learn about environment and energy efficient practices affecting their daily energy usage.

Figure 36: Indicative screenshot from "My energy profile" tab

4.2. Core GSRN S/W functionalities

There are some core GSRN S/W functionalities, which support the administrative user towards managing and customizing the whole S/W platform. For example, GSRN administrator can create notifications (mostly in the form of tips) and post them to specific user groups. Groups are generated via EC creation algorithms in RAT subsystem and tips are trigged upon date / time definition. The notifications are visualized to the end user and can represent DR events, EP suggestions, learning material suggestions, or even offers from the virtual marketplace. As shown in the figure below, notification tips displayed on the header bar of GSRN.

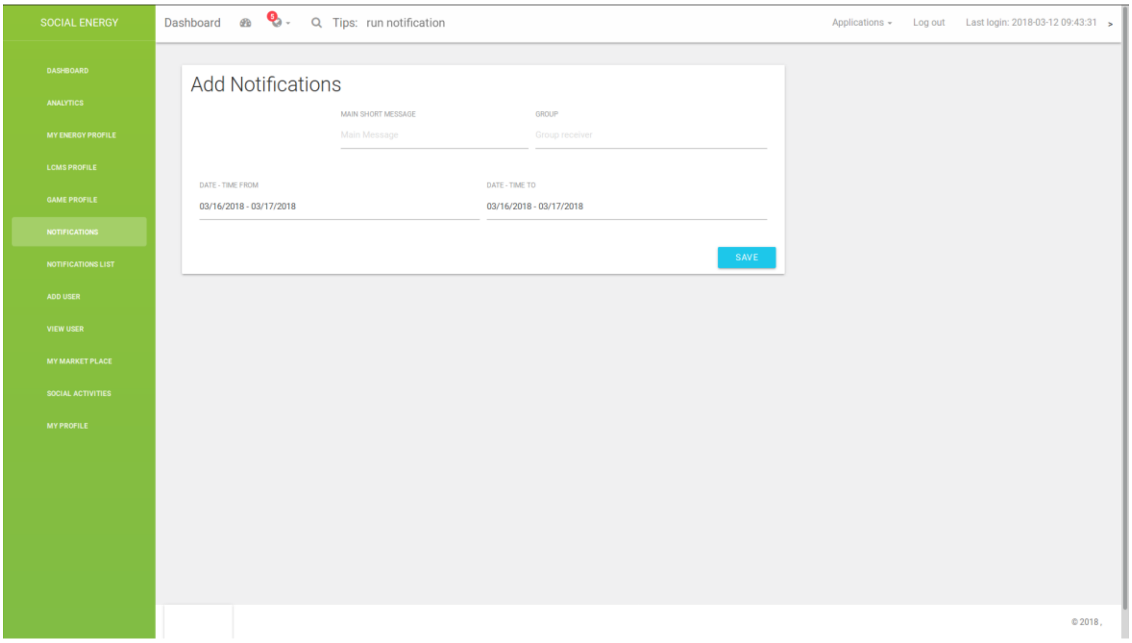


Figure 37: Indicative screenshot for notifications on GSRN platform

Furthermore, the administrative user can add new users to GSRN. Upon user creation, GSRN communicates to other sub-modules (RAT / LCMS) about new user registration, by posting a new token. Hence, all GSRN modules are synchronised for the new user creation (see more technical details in section 6 about the OAuth2.0 global authentication procedure). End users can edit and manage their account through GSRN Add/Edit user as shown in the figure below.

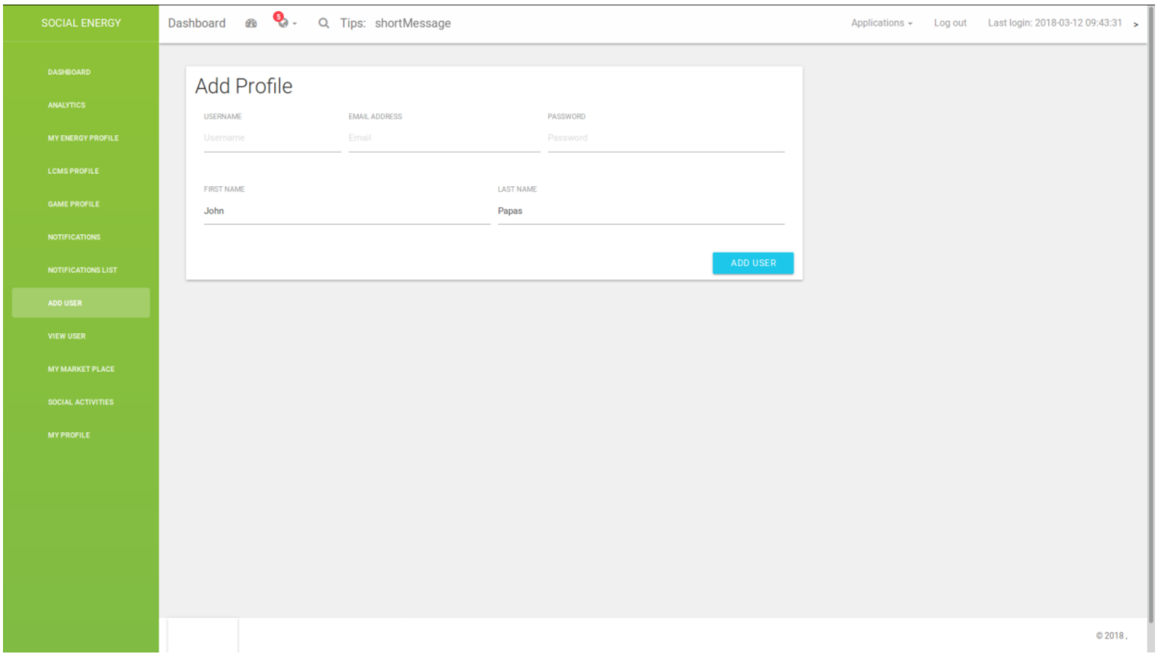


Figure 38: Edit / Add end users on GSRN

GSRN also provides the ability to the end user to update – view his/her profile data.

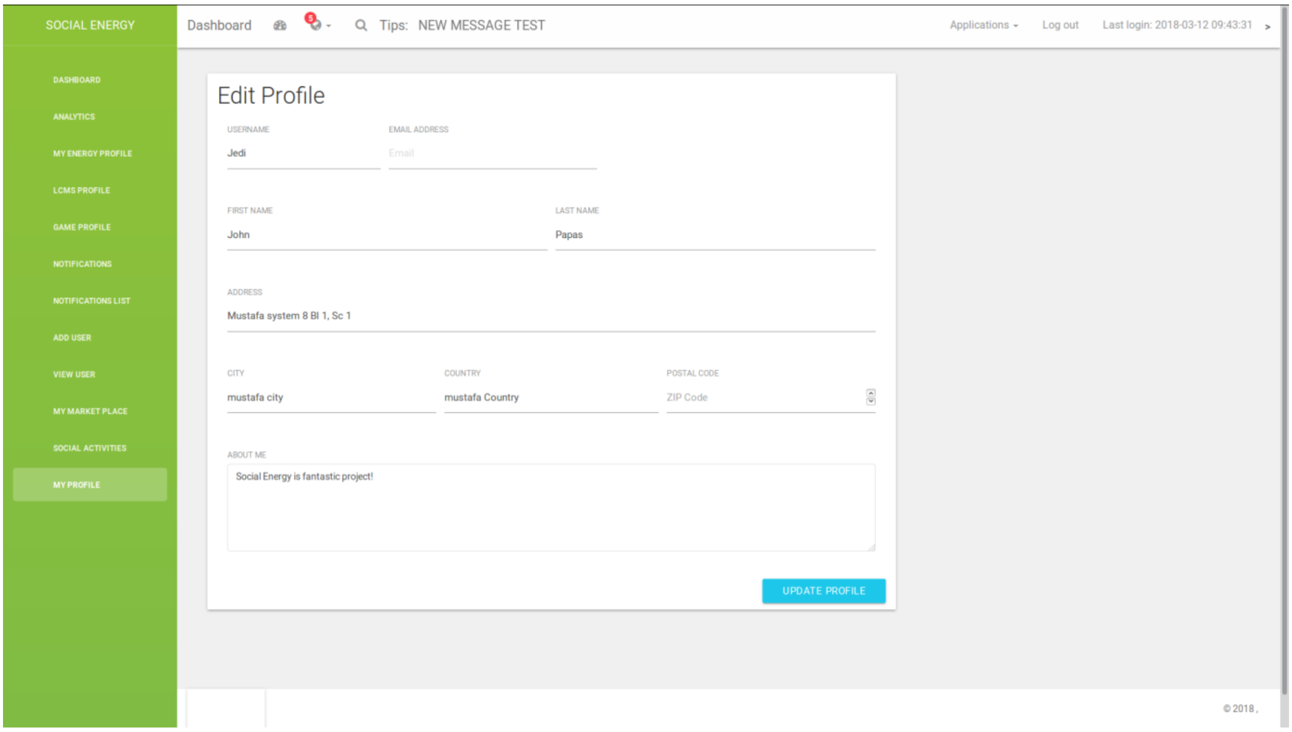


Figure 39: Edit users profile on GSRN

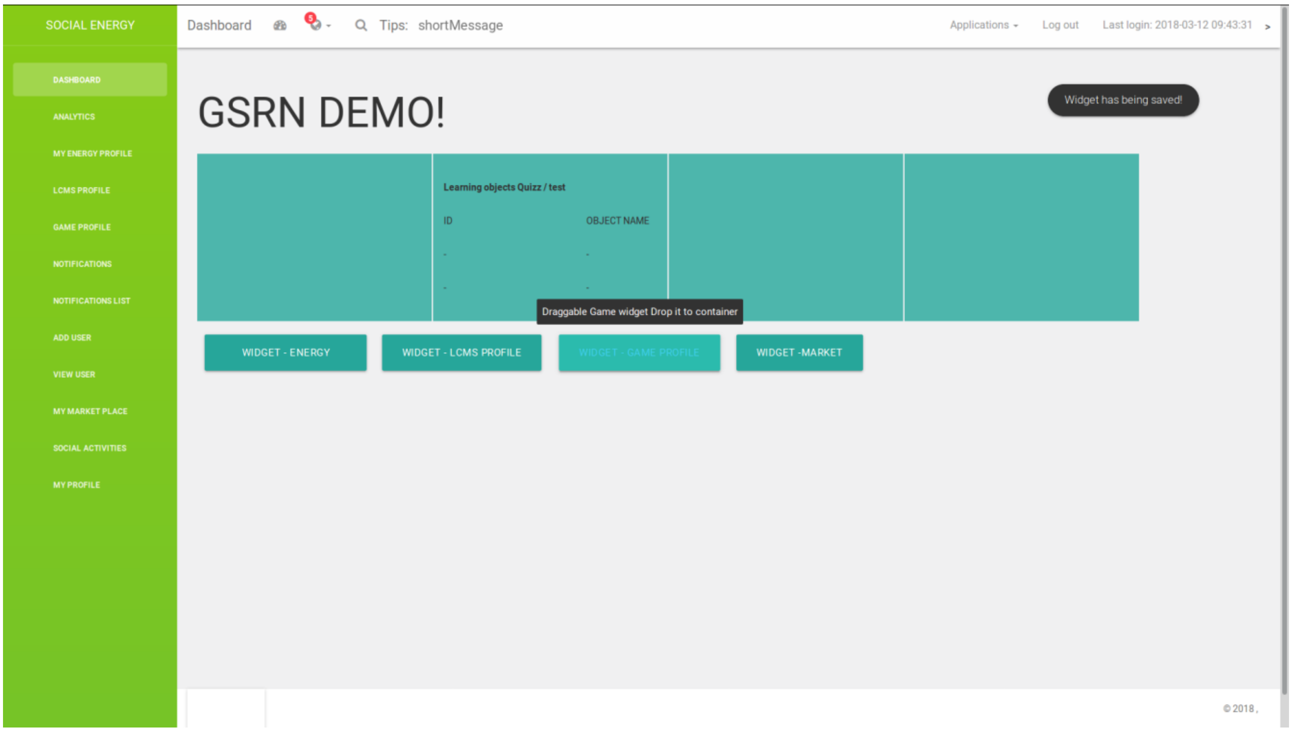


Figure 40: GSRN Dashboard

GSRN Dashboard module allows admin users to drag 'n' drop modules latest news, for a quick update upon login. The user has full visibility on all GSRN modules and s/he can select or click the ones that s/he is interested in the most.

Moreover, upon initial successful user's registration, a questionnaire is being displayed to user, to complete it electronically. Inputs from the questionnaire define the initial competence level and the results are being communicated to the LCMS, RAT and GAME subsystems. Once this questionnaire is being successful submitted, it is not being displayed again in the future.

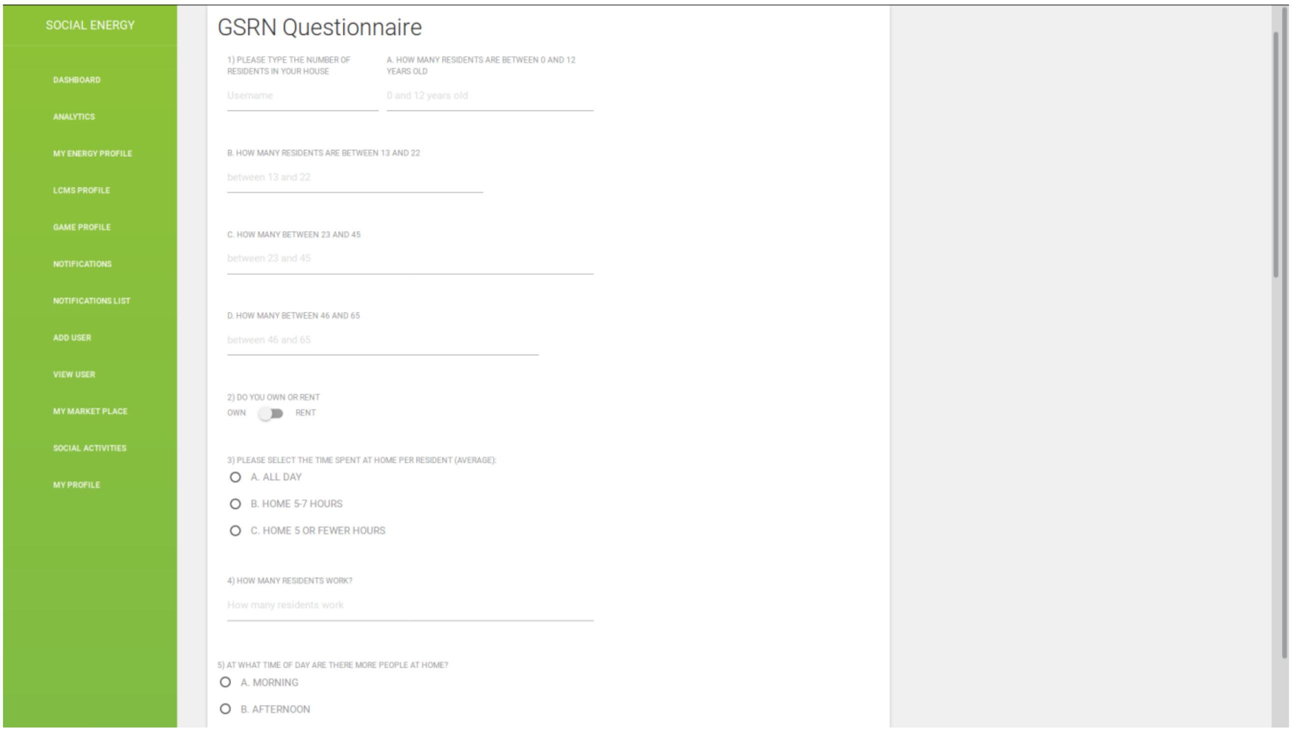


Figure 41: Snapshot of GSRN Questionnaire

4.2.1. E-learning/training S/W module

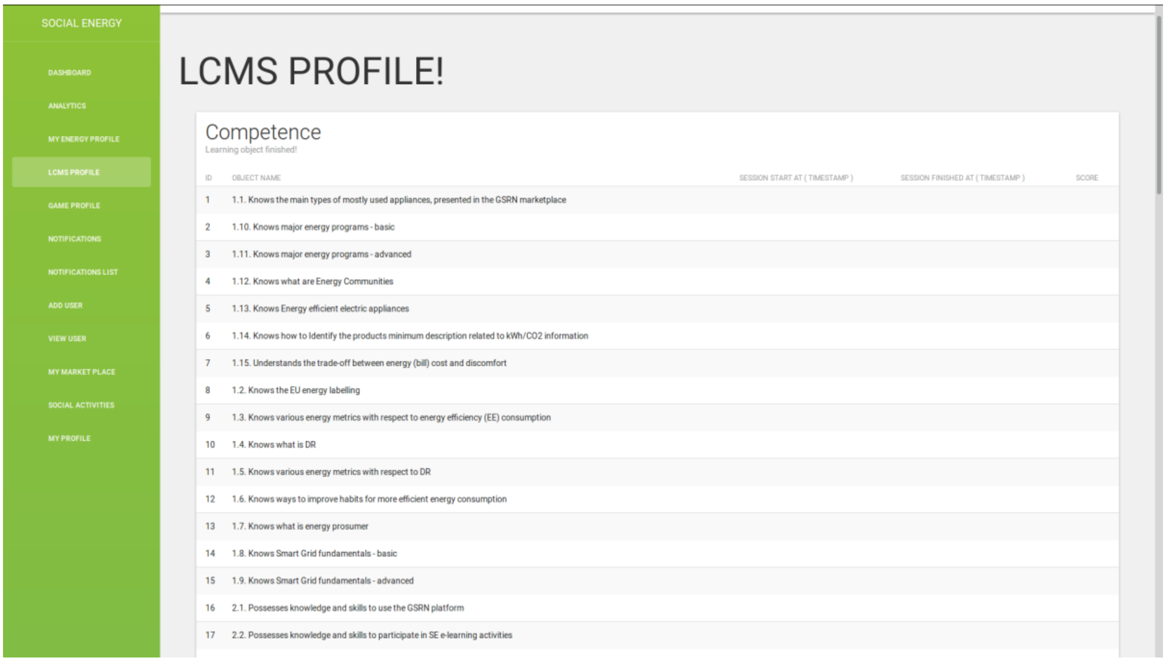


Figure 42: Indicative screenshot from "LCMS profile" tab

GSRN's E-learning/LCMS visualization module is responsible for the integration and visualization of all educational material and relevant interactions coming from the GSRN-LCMS API. The training module visualizes all on-line courses taken from the user, the grades, the difficulty and the relevant connections with the actual subjects (efficiency, recycling, etc.). The module is connected with the individual User Profile so that users will be informed of/recommended for all available courses and related educational actions. Moreover, users can visualize actions they did in LCMS subsystem, courses taken and grades/performance. They can overview competencies acquired or list badges - courses they did in the past. GSRN keeps history of related actions that users do into the LCMS. In the figure below, an indicative snapshot of *"LCMS profile"* tab is depicted.

4.2.2. Rewarding mechanism S/W module

SOCIALENERGY's Point System represents the mechanism, which defines when, in which way and how many SEP points (i.e. SOCIALENERGY Points) the user will gain, using the GSRN platform. SEPs represent the ways that a user watches, ranks, and guides his/her SOCIALENERGY experience. Everything a player does within the system will earn SEP. SEP never maxes out. They are the most needed and basic feature to add in order to provide a base for a gamified application development. The rewarding mechanism is a backend module that calculates the points and the rewards, based on the description of subsection 3.7 above.

4.2.3. Data analytics S/W module

GSRN's Data Analytics module will visualize all GSRN-RAT outputs and will provide a visualized KPIs dashboard to the users to check their overall performance. Most important results from dynamic pricing and EC creation/dynamic adaptation algorithms are visualized to the end user. Via the RAT functionalities, the "data analytics" module can run multiple scenarios based on a variety of parameters and algorithms; users can change values using a web form, providing different input parameters for the various algorithms' execution. The algorithms' results are being drawn automatically into graphs for a better user experience.

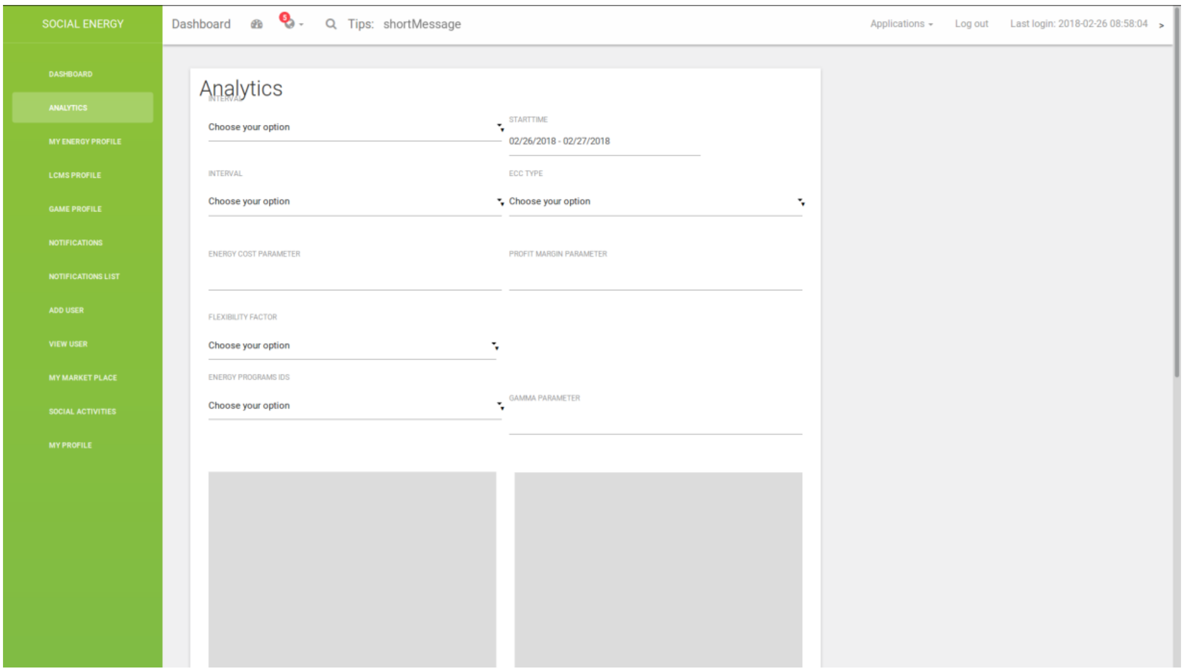


Figure 43: Data Analytics dashboard

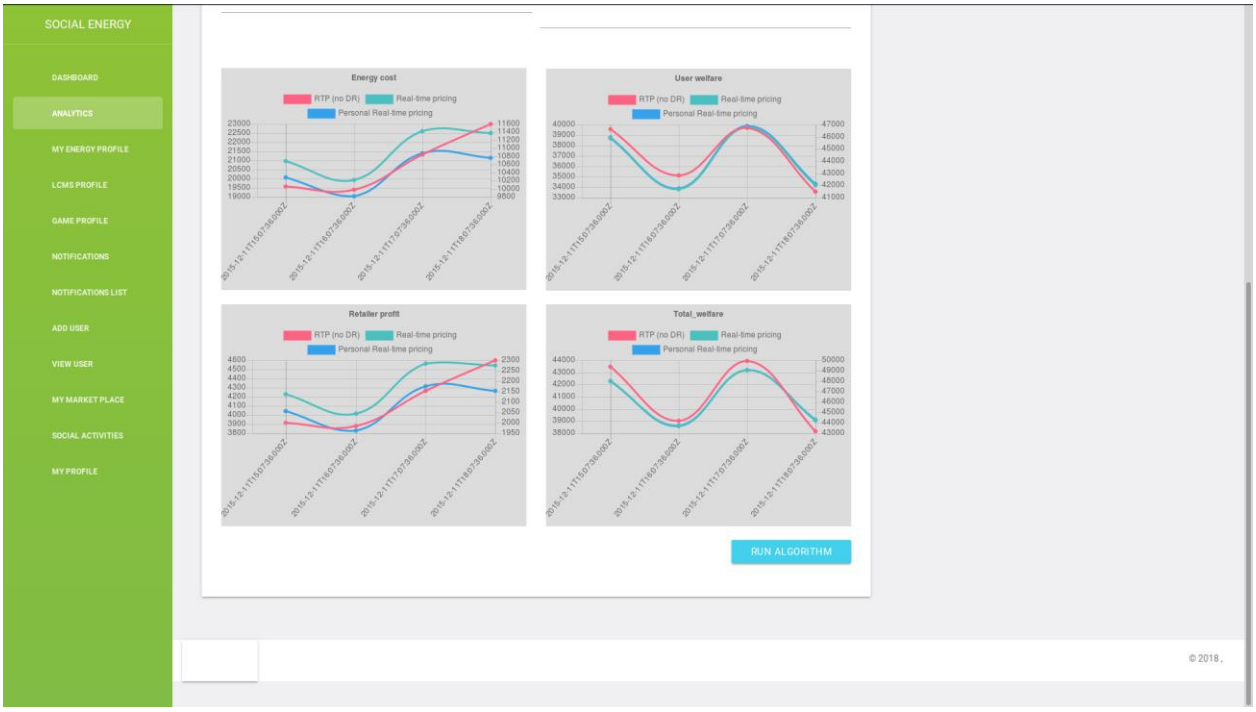


Figure 44: Indicative screenshot from data analytics dashboard graphs (retrieved from RAT via GSRN-RAT API)

4.2.4. Gaming and Social Profile S/W module

GSRN's Gaming profile module connects directly to the GAME-API and gets all relevant details from the game, regarding each specific user. The end user gets badges, leader board, performance, stages, points and all available GAME-API inputs. The Game profile will inform the user how s/he is performing in the game and how his/her performance is compared with others. GSRN's Social module is also working at the backend and will be used to get user info from social networks, as the user logs in the system. "Social" module will be combined with all other modules to provide personalization and further data analytics.

As shown in the figure below, GSRN gives the ability to the end user to keep track of his performance in the game. S/he can preview scores, level game that s/he finished, time period played, a variety of information's, aiming to help and train him/her to have a more energy-efficient behavior.

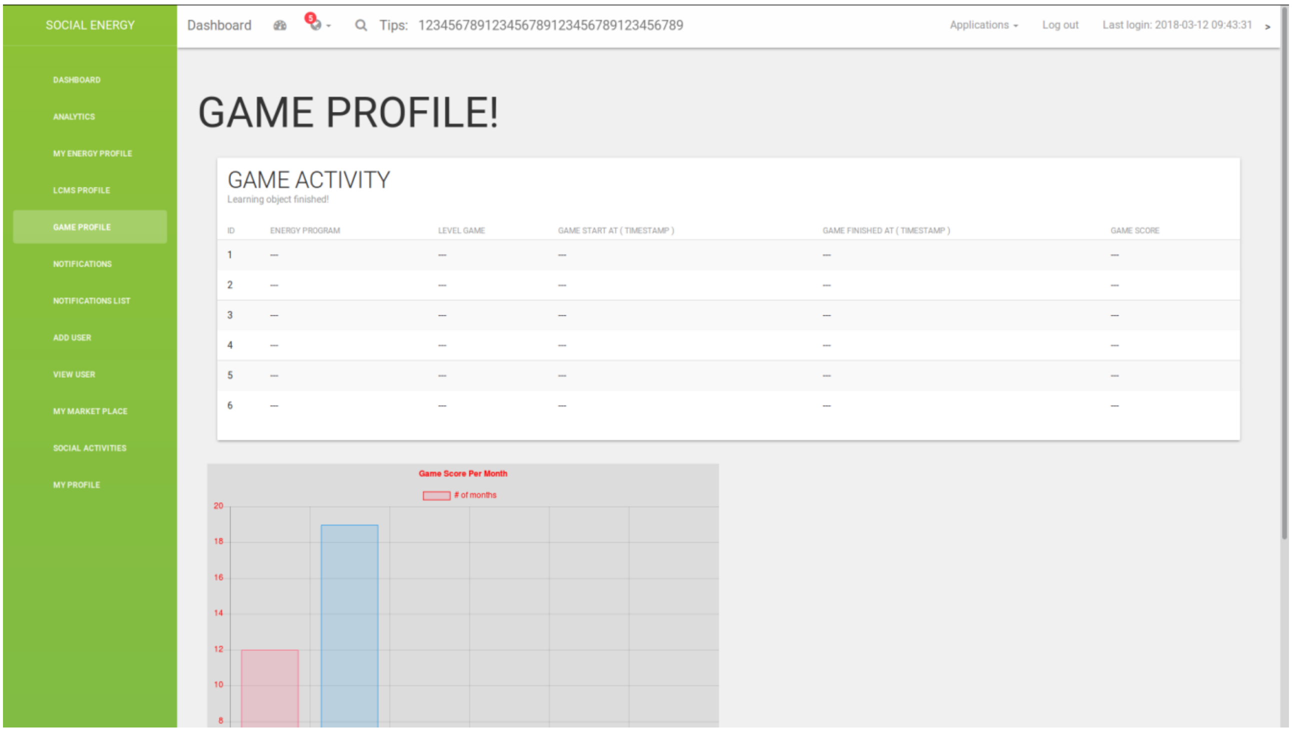


Figure 45: Indicative screenshot from GSRN's "Game Profile" tab

4.3. Virtual Marketplace functionalities

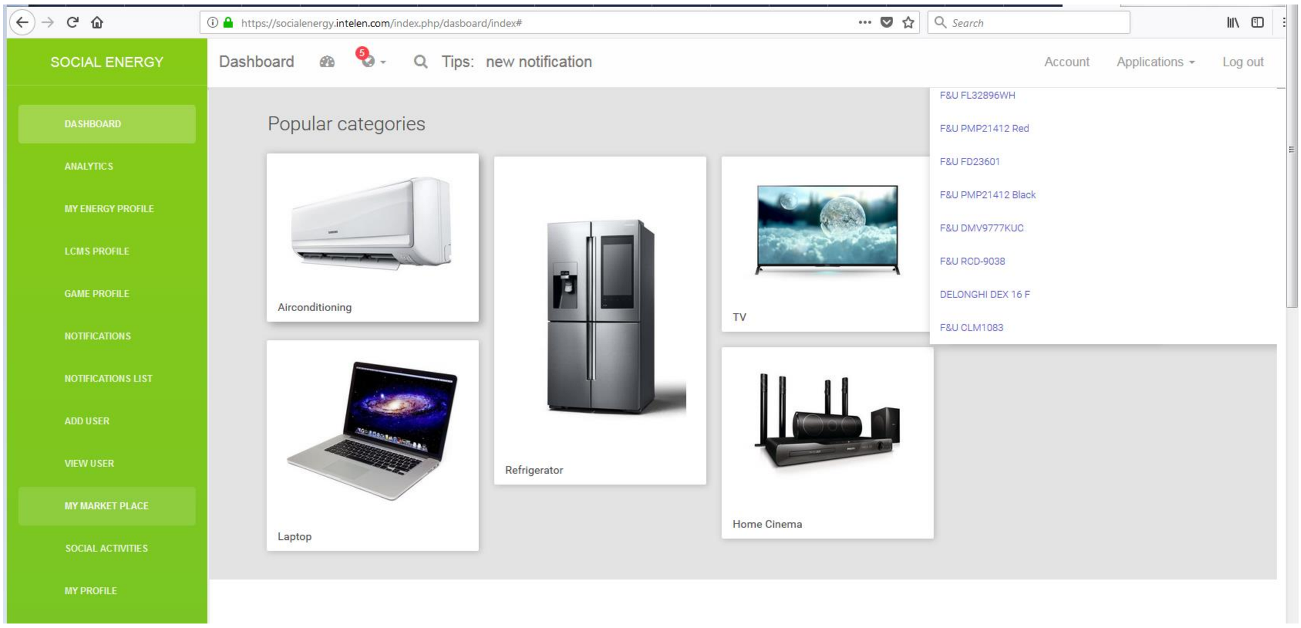


Figure 46: GSRN Marketplace with various Class A++ devices and offers for the users

GSRN's *"My Marketplace"* module is responsible for the electric appliances' database that will be uploaded onto the system, through the Marketplace CMS sub-module and will be available to the users through the rewarding scheme (redeem prizes). Various electric appliances will have details such as kWh, Class, C02 emissions, price, discounted price, etc., so that the user will be able to choose and proceed with an online payment gateway. Various appliances will be pushed to the User Profile, based on personalization and RAT-API or LCMS-API or GAME-API in order to map user performance with rewards. In the figure below, an indicative screenshot of GSRN's virtual marketplace tab is depicted.

The redemption mechanism should be easy. The following describes the mechanism in a sententious manner:

a. User gets into the marketplace inventory. The prizes/offers that the user can redeem are marked differently that the ones s/he cannot.
b. The option of further investigating such prize is available to the user, by clicking in the prize/offer description.
c. The user can then select the option Redeem Prize.
d. The user can either select the prize for himself/herself or for a gift.
e. If the user selects the prize for himself/herself, then a message indicating the shipping address that we have in the database appears. The user can also add another shipping address if needed.
f. If the user continues with the redemption, then a summary of the prize and the address is shown with a confirm button. Upon confirming, an email is sent to the user and to the supplier with the details and the expected delivery and the process which (for each prize/discount), has been determined with the supplier.
g. If the user introduces a new address, a message with a summary of the prize and the new address is shown and step (f) is repeated after confirmation.

If the user selects the prize as a gift a message with space to insert the name and the new address is shown and after inserting it, step (f) is followed again.

4.4. Next S/W implementation steps

During the next few months (M16-M19), the focus will be on the S/W integration activities in order for a 1st stable SOCIALENERGY S/W platform to be released and communicated to the potential customer segment and 3rd party stakeholders (cf. milestone 5 and D5.2 to be delivered in M18). At the same time, the core GSRN functionalities will be enhanced towards releasing the final version of SOCIALENERGY functionalities (cf. milestone 6 and D3.2 to be delivered in M24).

5. Research Algorithms' Toolkit – RAT

5.1. Introduction

In a nutshell, the RAT's functionalities are provided like data analytics as a service to the other two main subsystems of SOCIALENERGY, namely the core GSRN platform and the GAME. Especially for the GAME, RAT provides the mathematical equations that derive the game's structure and operation. Some main functionalities that RAT offers to its users are the following:

- Run research algorithms and compare them with state-of-the-art (mainly applicable to the system administrator user and potentially researchers that will use RAT for their experimentations).
- Run simulations to identify/define various business strategies from the utility's/ESCO's perspective.
- Provide data analytics services to utilities/ESCOs such as reporting, recommendations, profiling, virtual energy communities' management, dynamic pricing and calculation of various key performance indicator's related with the online execution of various energy programs.
- Provide sophisticated mathematical modelling to support the operation of serious games related with energy efficiency.

5.2. RAT Database

The RAT database stores all the data that is essential input for the operation of the SOCIALENERGY research algorithms. These datasets will include: i) historical data related to the energy consumption/flexibility/performance of each individual consumer and virtual energy communities, ii) behavioural data taken from the core GSRN platform, the game application and LCMS, iii) pricing data from the various markets and research algorithms' results, iv) various results (outputs) from the algorithms' operation, etc.

The database schema that is used in the first version of the RAT subsystem is depicted in the figure below. In particular, we have the following database tables, and corresponding columns:

1. building_types: This table contains the different types of premises, e.g. residential, commercial, public buildings, etc.
2. cl_scenarios: This table contains the execution scenarios for the clustering module.
3. clusterings: A clustering is a collection of communities. Each consumer can belong to only one community in each clustering.
4. communities: It is a collection of consumers, treated as one entity by the utility company for billing purposes.
5. consumer_categories: Each consumer category represents a different dataset of consumers.
6. consumers: A consumer is a single metering entity, e.g. an apartment, office, etc.
7. data_points: A data point is measured amount of energy consumption, and is stored in relation to a consumer, a timestamp, and an interval.

8. ecc_types: These are the types of consumpiton profiles, like “working hours”, “nights”, “weekends”.
9. energy_programs: The different charging policies, e.g. “Real-time pricing”, “Personalized real-time- pricing”, “Time-of-use” etc.
10. flexibilities: The different flexibility models that represent different behaviors related to demand response.
11. intervals: The metering intervals, e.g. “Daily”, “Hourly”, “15-minute”.
12. results: This table contains the results of the scenarios’ execution.
13. roles: This table contains the different role types.
14. scenarios: Each scenario is an execution of a research algorithm.
15. users: The users in the system.

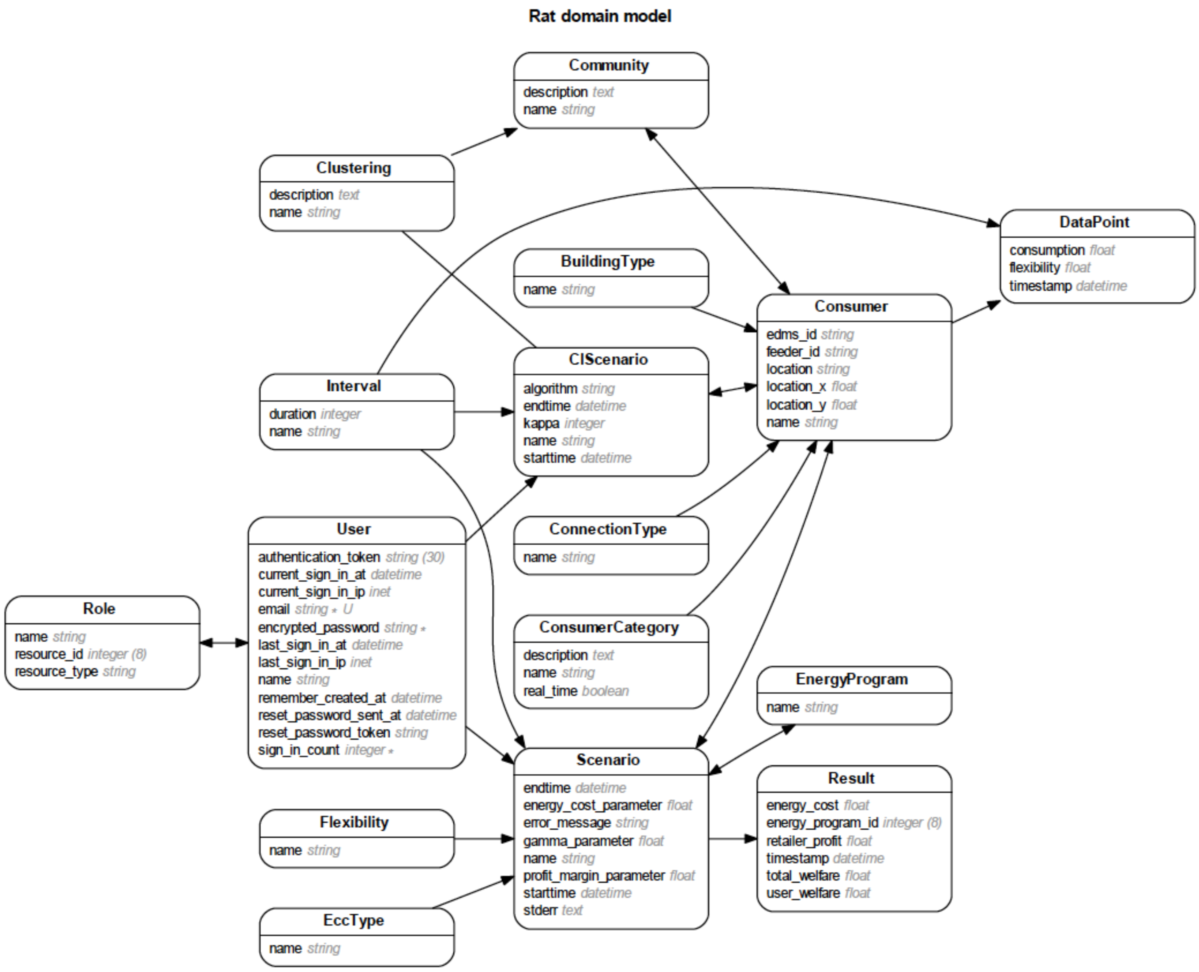


Figure 47: Overview of RAT Database structure and schema

The technical implementation of the database is in PostgreSQL, and is managed through Active Record migrations.

5.3. Data Acquisition Module (DAM)

The Data Acquisition Module (DAM) is responsible for obtaining data from external (to the RAT) sources. The data acquisition is performed either periodically, or on-demand, as required by the algorithms of the RAT. Individual RESTful APIs are implemented for interacting with the SOCIALENERGY subsystems, namely the core GSRN S/W platform, the SOCIALENERGY game and the Meter Data Management System (MDMS).

At the moment, historical datasets from real users and respective meters are used for the RAT algorithm's validation. These datasets are of 15-minute time granularity and refer to various types of energy consumers (approximately 400 smart meters from 400 real users are currently utilized). As the S/W integration work progresses, the next step is for the RAT subsystem to acquire real-time data from real SOCIALENERGY users' activity from all other SOCIALENERGY subsystems.

5.4. Profiling and Searching Module (PSM) including data visualization

Via the Profiling and Searching Module (PSM), the user of RAT is able to request any type of information and then retrieve and visualize it in the RAT's web interface.

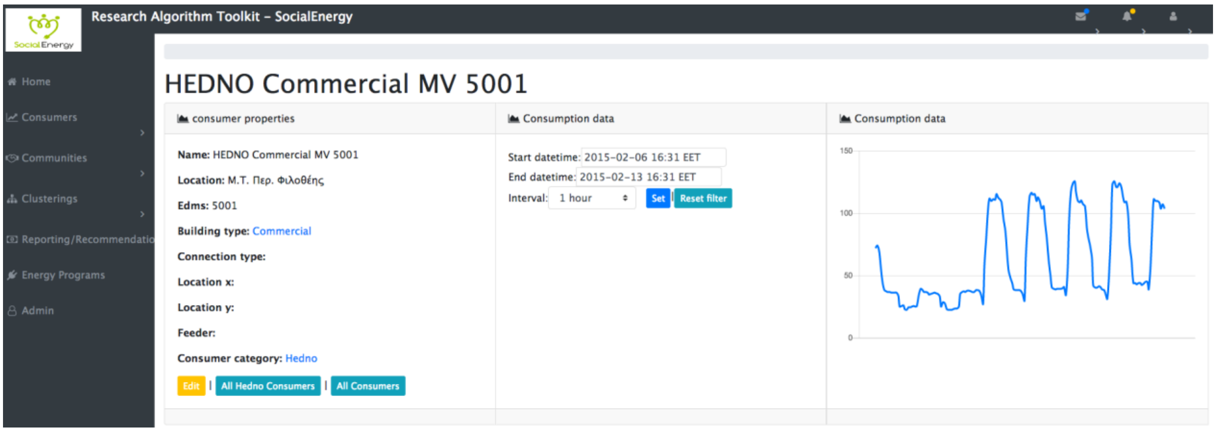


Figure 48: Indicative screenshot for visualization of each user's ECC and profile data

Detailed demonstration of related RAT subsystem's functionalities can be found in SOCIALENERGY project's youtube channel and more specifically in the web links below:

- https://www.youtube.com/watch?v=QAeoyLDRJNI&t=1s
- https://www.youtube.com/watch?v=-1elRHEpyk8&t=18s

5.5. User Admin Dashboard (UAD)

The User Admin Dashboard (UAD) is the interface that the system administrators will use for administering the operation of RAT. A graphical user interface (GUI) is implemented, that allows for setting up the details of each consumer, as well as the parameters that allow for the configuration of the various algorithms that will be implemented in the RAT. An indicative screenshot of the UAD is depicted below:

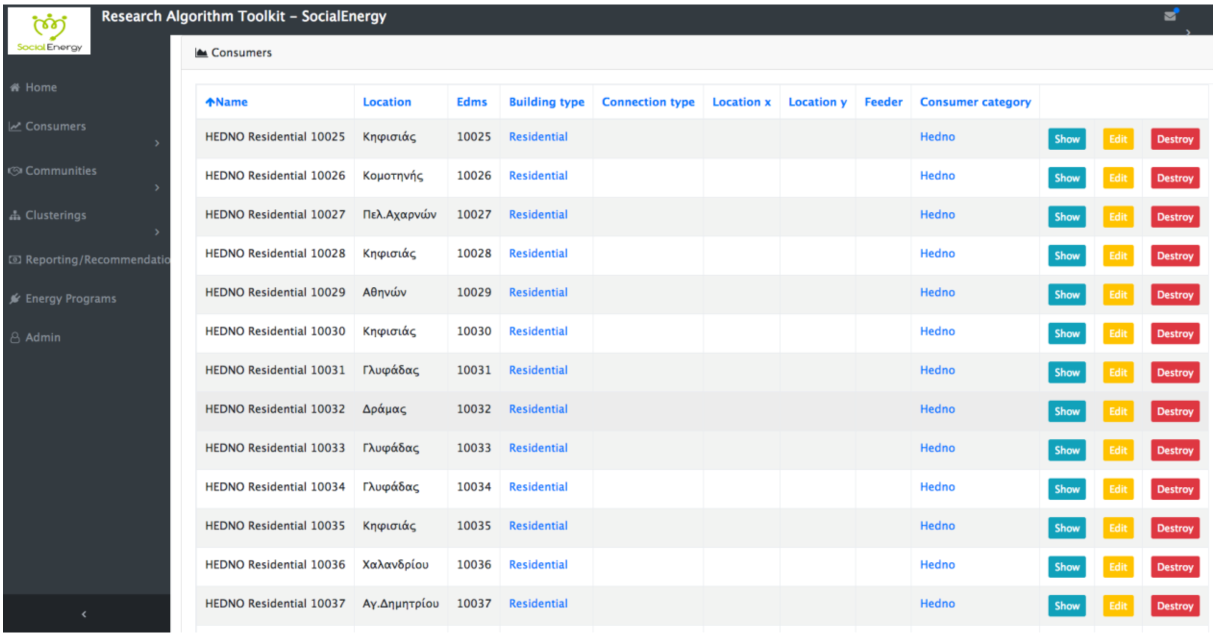


Figure 49: Indicative figure of the User Admin Dashboard

5.6. Configuration Panel (CP)

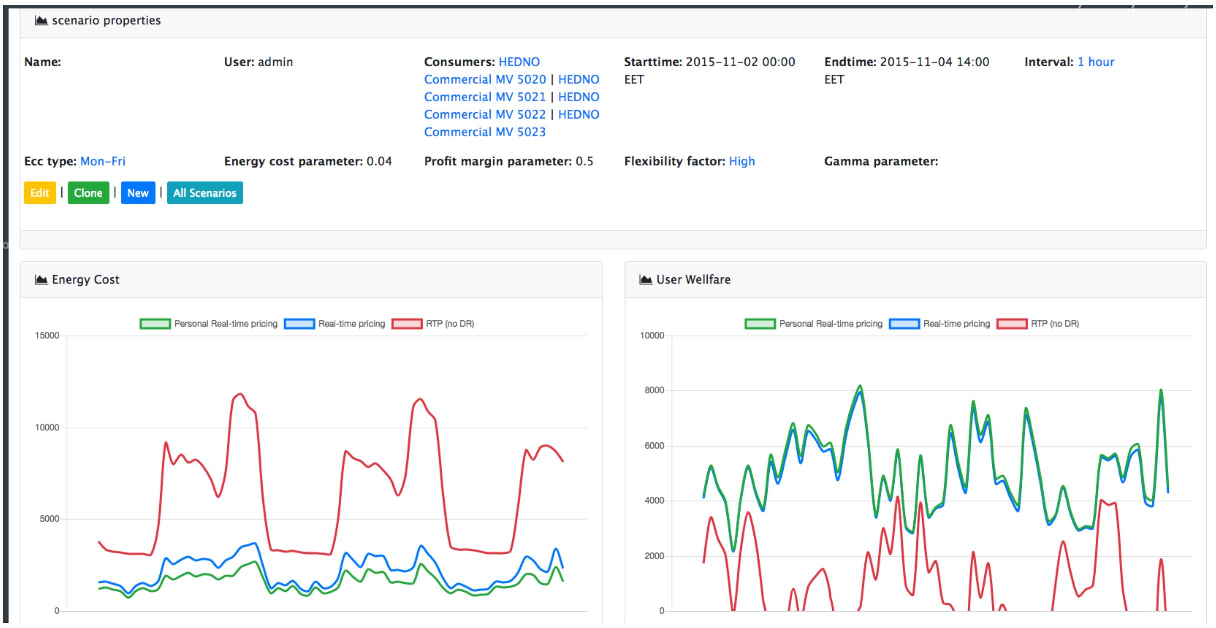


Figure 50: Indicative performance evaluation results from the execution of 3 different Energy Programs

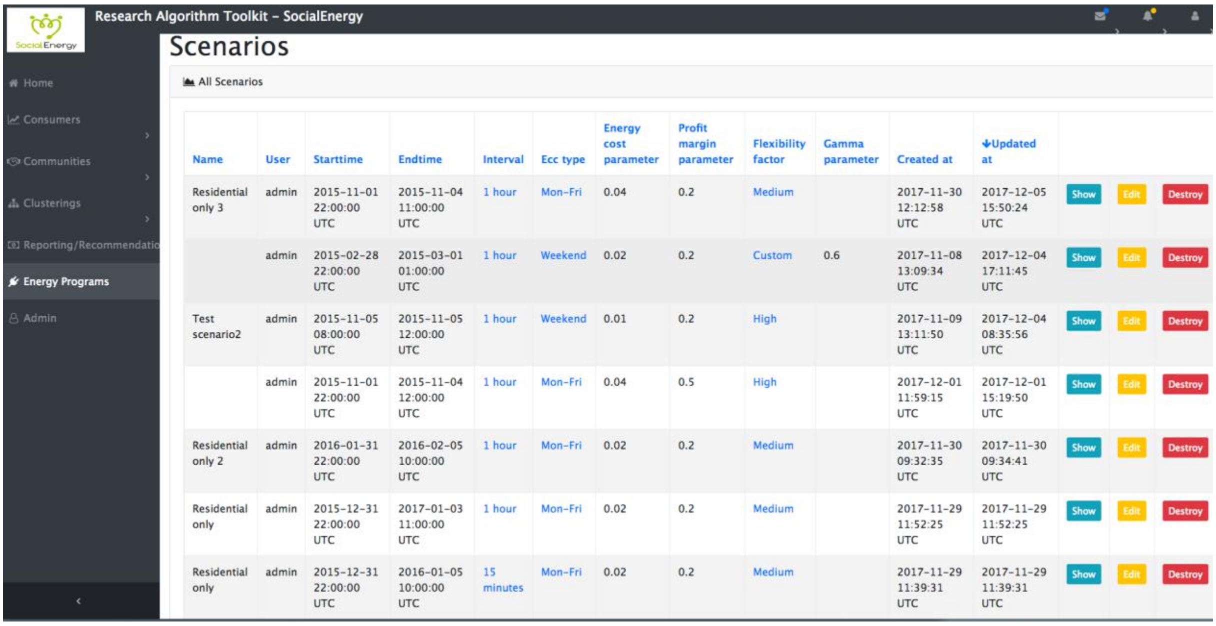
Another GUI is implemented for the users of the RAT to configure their participation and navigate through all the RAT's functionalities. Configuration Panel (CP) incorporates all data visualization capabilities that the users may have on the RAT. It should be noted that this CP may be used by SOCIALENERGY admin user, who will be able to enjoy the SOCIALENERGY system's intelligence and visualize performance evaluation results from the execution of various scientific algorithms. In the figure below, three energy programs (i.e. P-RTP, classic RTP with DR, and RTP with no DR) are compared for a specific set of 4 consumers. The results show that P-RTP outperforms its competitors in terms of less energy cost and greater aggregated users' welfare (AUW). More details about the performance evaluation results are provided in chapters 2 and 3.

5.7. Research Algorithms Module (RAM)

The RAM consists of three basic sets of algorithms that are gradually being integrated, namely the: a) dynamic pricing algorithms (or else Energy Programs), b) EC creation algorithms (or else profiling algorithms), and c) EC adaptation algorithms (or else recommendation algorithms).

5.7.1. Dynamic pricing algorithms or Energy Programs (EPs)

In the "Energy Programs" of RAT subsystem, the administrative user can visualize all simulation scenarios that have already run in the platform. In Figure 51, all parameters for each scenario are presented. The admin user can 'show', 'edit' or 'destroy' a scenario.



Name	User	Starttime	Endtime	Interval	Ecc type	Energy cost parameter	Profit margin parameter	Flexibility factor	Gamma parameter	Created at	Updated at			
Residential only 3	admin	2015-11-01 22:00:00 UTC	2015-11-04 11:00:00 UTC	1 hour	Mon-Fri	0.04	0.2	Medium		2017-11-30 12:12:58 UTC	2017-12-05 15:50:24 UTC	Show	Edit	Destroy
	admin	2015-02-28 22:00:00 UTC	2015-03-01 01:00:00 UTC	1 hour	Weekend	0.02	0.2	Custom	0.6	2017-11-08 13:09:34 UTC	2017-12-04 17:11:45 UTC	Show	Edit	Destroy
Test scenario2	admin	2015-11-05 08:00:00 UTC	2015-11-05 12:00:00 UTC	1 hour	Weekend	0.01	0.2	High		2017-11-09 13:11:50 UTC	2017-12-04 08:35:56 UTC	Show	Edit	Destroy
	admin	2015-11-01 22:00:00 UTC	2015-11-04 12:00:00 UTC	1 hour	Mon-Fri	0.04	0.5	High		2017-12-01 11:59:15 UTC	2017-12-01 15:19:50 UTC	Show	Edit	Destroy
Residential only 2	admin	2016-01-31 22:00:00 UTC	2016-02-05 10:00:00 UTC	1 hour	Mon-Fri	0.02	0.2	Medium		2017-11-30 09:32:35 UTC	2017-11-30 09:34:41 UTC	Show	Edit	Destroy
Residential only	admin	2015-12-31 22:00:00 UTC	2017-01-03 11:00:00 UTC	1 hour	Mon-Fri	0.02	0.2	Medium		2017-11-29 11:52:25 UTC	2017-11-29 11:52:25 UTC	Show	Edit	Destroy
Residential only	admin	2015-12-31 22:00:00 UTC	2016-01-05 10:00:00 UTC	15 minutes	Mon-Fri	0.02	0.2	Medium		2017-11-29 11:39:31 UTC	2017-11-29 11:39:31 UTC	Show	Edit	Destroy

Figure 51: Indicative screenshot of the "Energy Programs" tab in RAT subsystem

There are 4 steps to customize a specific scenario. As shown in the figure below, in step 1, the admin user can select all consumers that participate in the simulation from a list. The 'starttime', 'endtime', 'interval' and 'ECC type' can also be selected.

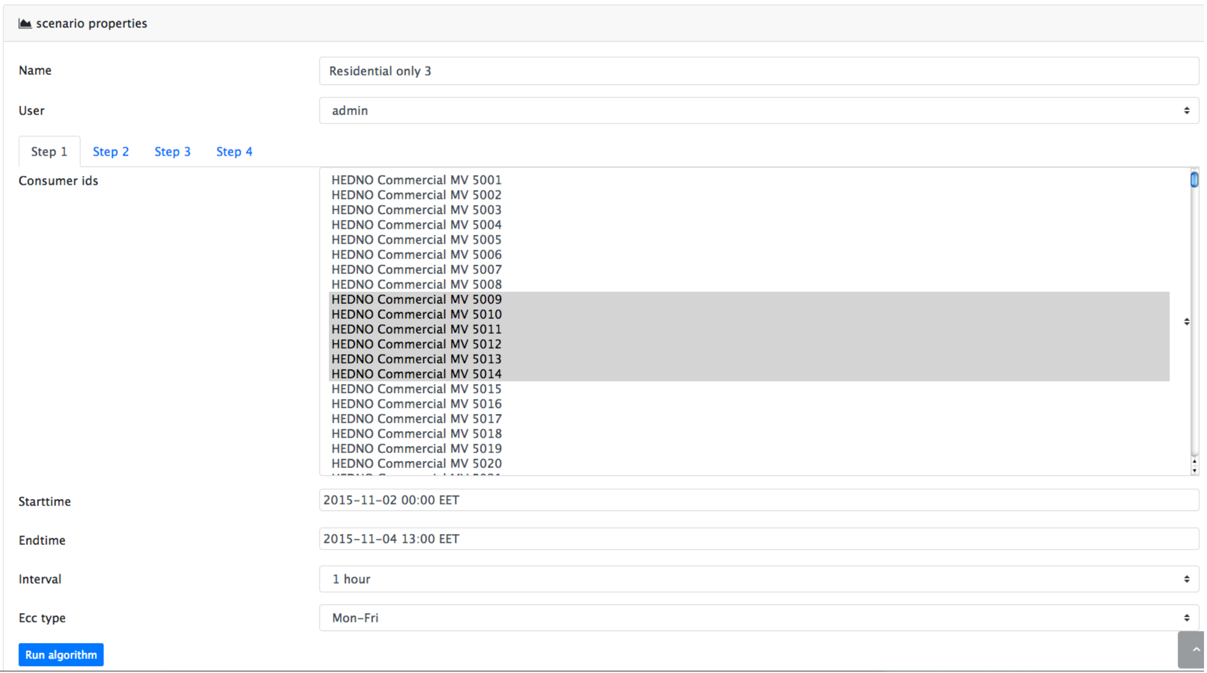


Figure 52: Example for customizing a scenario for comparing Energy Programs (step 1)

In a nutshell, the 4 steps of customizing/editing a specific simulation scenario are:

- Step 1: Defining the aggregated ECC of the simulation scenario
- Step 2: Defining the energy cost model
- Step 3: Defining the user model (i.e. flexibility parameters)
- Step 4: Defining the EP parameters

The final step is to push the "Run algorithm" button and visualize the results as shown in Figure 50.

5.7.2. Energy Community creation algorithms

This module incorporates various algorithms for the creation of ECs based on multiple parameters, meaning that the clustering of consumers is not only made based on their energy consumption curves (ECC)/profiles but also based on: a) their connections in social media, b) their personal habits, character and demographic data, c) their behavior regarding demand response actions (retrieved from GSRN), d) their will for participation/engagement in innovative energy programs and services offered by SOCIALENERGY, e) their learning curve, competences and skills regarding good practices in energy efficiency sector (taken from LCMS and GAME), etc. Via this multi-parametric clustering approach, the ECs that are created can achieve better results in terms of energy efficiency/savings, monetary profits and long-term engagement in good energy efficiency practices. This is achieved via the inherent social-based or else "peer pressure" that takes place among the members of each EC. Within the SOCIALENERGY context, the ESCO/utility user will be able to run various simulations to understand the social dynamics and analyse the behaviour of his/her customer portfolio. An EC leader user will be able to understand whether it is beneficial to add/remove more members to the EC that s/he is leading and realize indicative metrics about which EC members are over- or under-performing.

In Figure 53, an indicative RAT GUI is shown illustrating the way that an administrative/EC leader user can manually create an EC. In Figure 54, it is shown how the admin user is able to choose among various scientific algorithms in order to automatically create ECs.

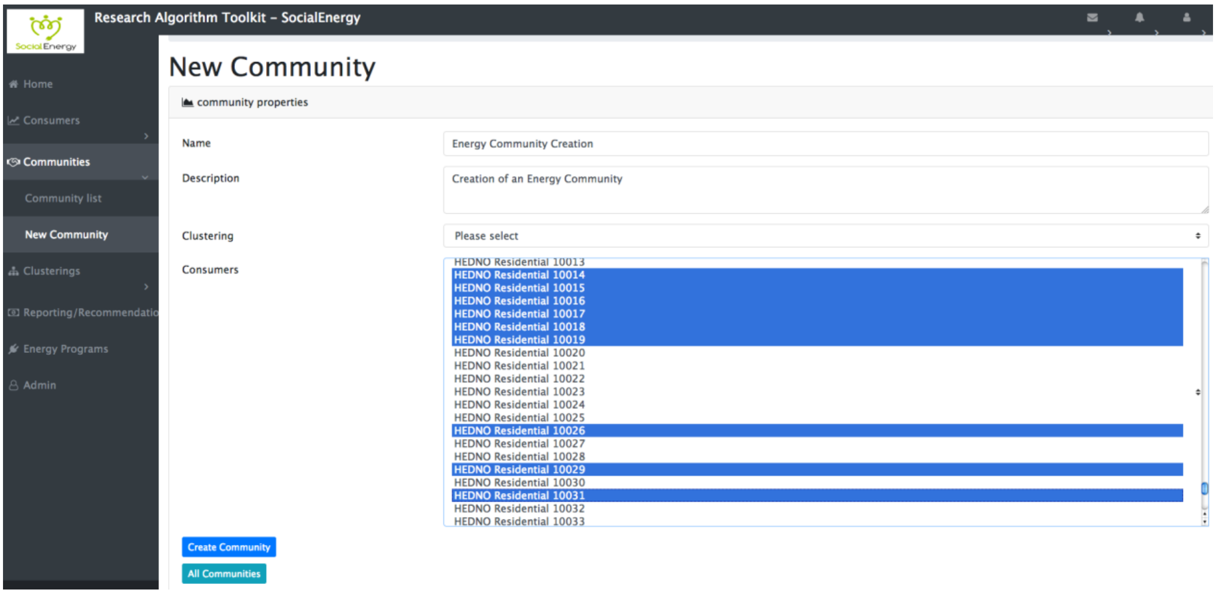


Figure 53: Select users to create an Energy Community in a manual way

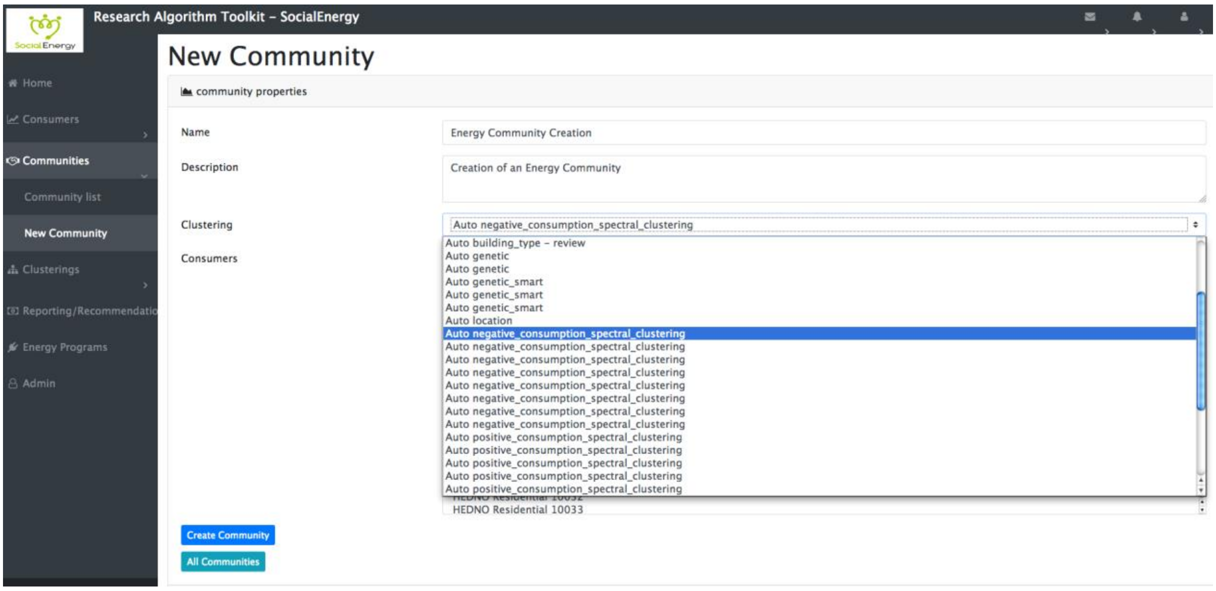


Figure 54: Choose among various algorithms to automatically create an Energy Community (EC)

Figure 55 depicts an indicative list of results after the run of many EC creation algorithms. Once the admin/EC leader user clicks on the "show" button of an EC, then all ECs or else "clusterings" can be visualized as shown in Figure 56 for a spectral clustering algorithm. Finally, in Figure 57, similar results can be visualized after the run of a genetic algorithm. In particular, four ECs have been created (cf. genetic 0, genetic 1, genetic 2 and genetic 3 graphs). For each EC, the aggregated energy consumption curve (ECC) is illustrated with the red font and individual ECCs of the EC members are shown in blue fonts. More technical details are available in several research papers written by ICCS team and can be found in the SOCIALENERGY project's website http://socialenergy-project.eu/index.php/downloads/publications.

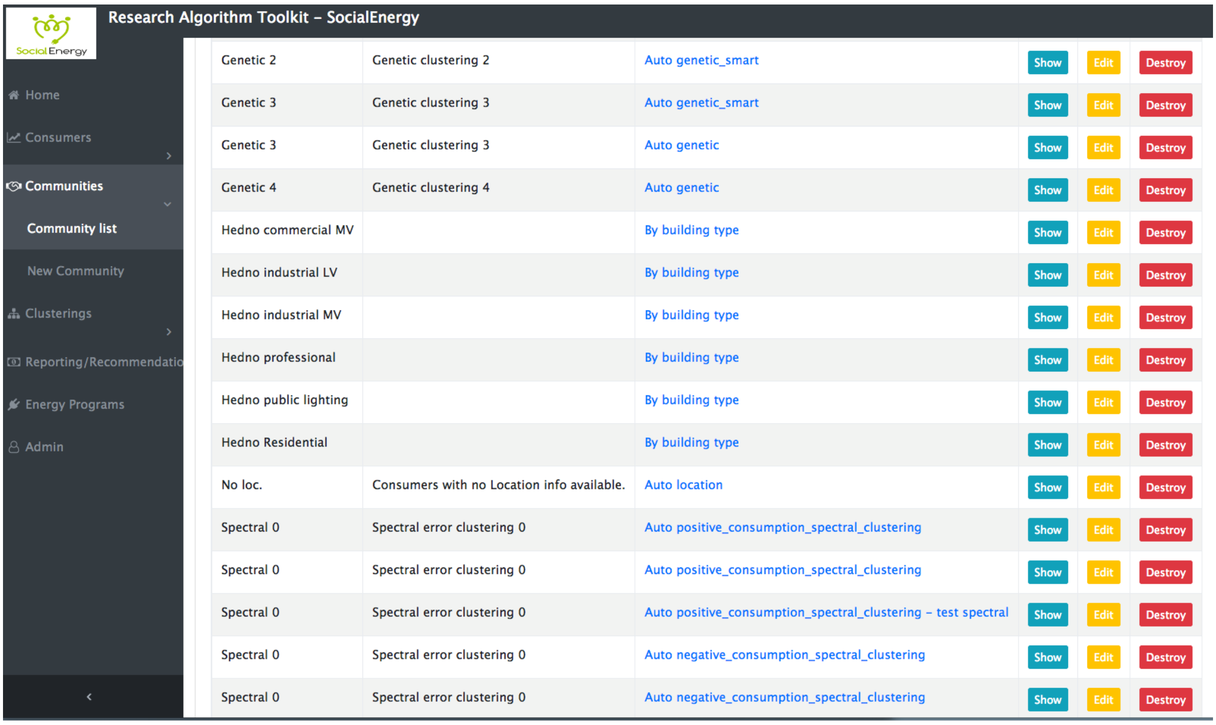


Figure 55: List of results after the run of various EC creation algorithms

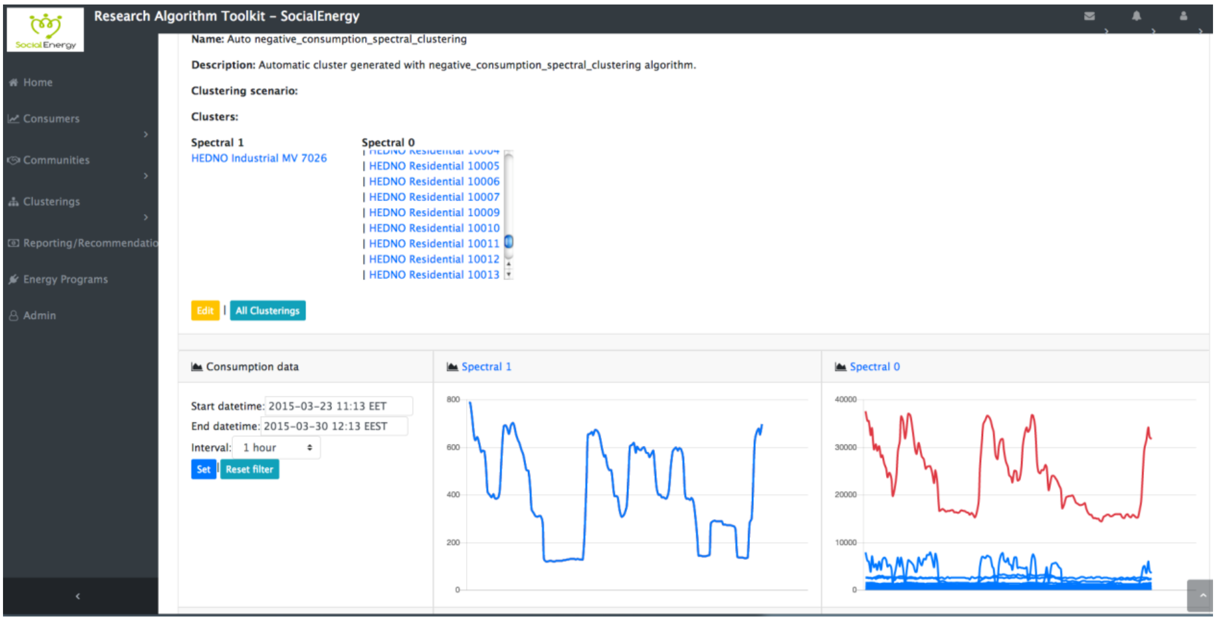


Figure 56: Indicative results after the run of a specific parameterized spectral clustering algorithm

Figure 57: Indicative results after the run of a specific parameterized genetic algorithm

5.7.3. Energy Community adaptation algorithms

In this module, the initial "clusterings" or else ECs, which have been created in the EC creation module, can change in case a pre-defined threshold is being surpassed/violated. In particular, a multi-dimensional space is created in which all consumers are depicted via a point that has multiple coordinates. In this graph, all "distances" between all possible combinations of points are measured and thus based on a constraint that is defined by the administrator (e.g. ESCO/utility/EC leader user), the "clusterings" are created. As the time goes by, the profiles of the energy consumers are continuously changing, so an EC adaptation algorithm should be run in order for the new ECs to be formed. This means that maybe some energy consumers may switch to another more beneficial EC or the administrator or EC leader may choose to add/remove some members from his/her EC. As a result, this sub-module can also be seen as a reporting and recommendation engine, whose results can be retrieved by GSRN and become very useful to the SOCIALENERGY's business scenarios.

The following figure presents indicative views of the "Reporting/Recommendation" tab from RAT subsystem. The first screenshot shows the list of recommendations that are available at the administrator's/EC leader's interface. The two depicted recommendations refer to a "switch energy program". In more detail, after the dynamic EC adaptation algorithm is executed, a change in the optimal clustering has been detected, and finally two new recommendations have been generated. For each recommendation, the admin user is able to visualize more specific information as shown in the second part of the figure below:

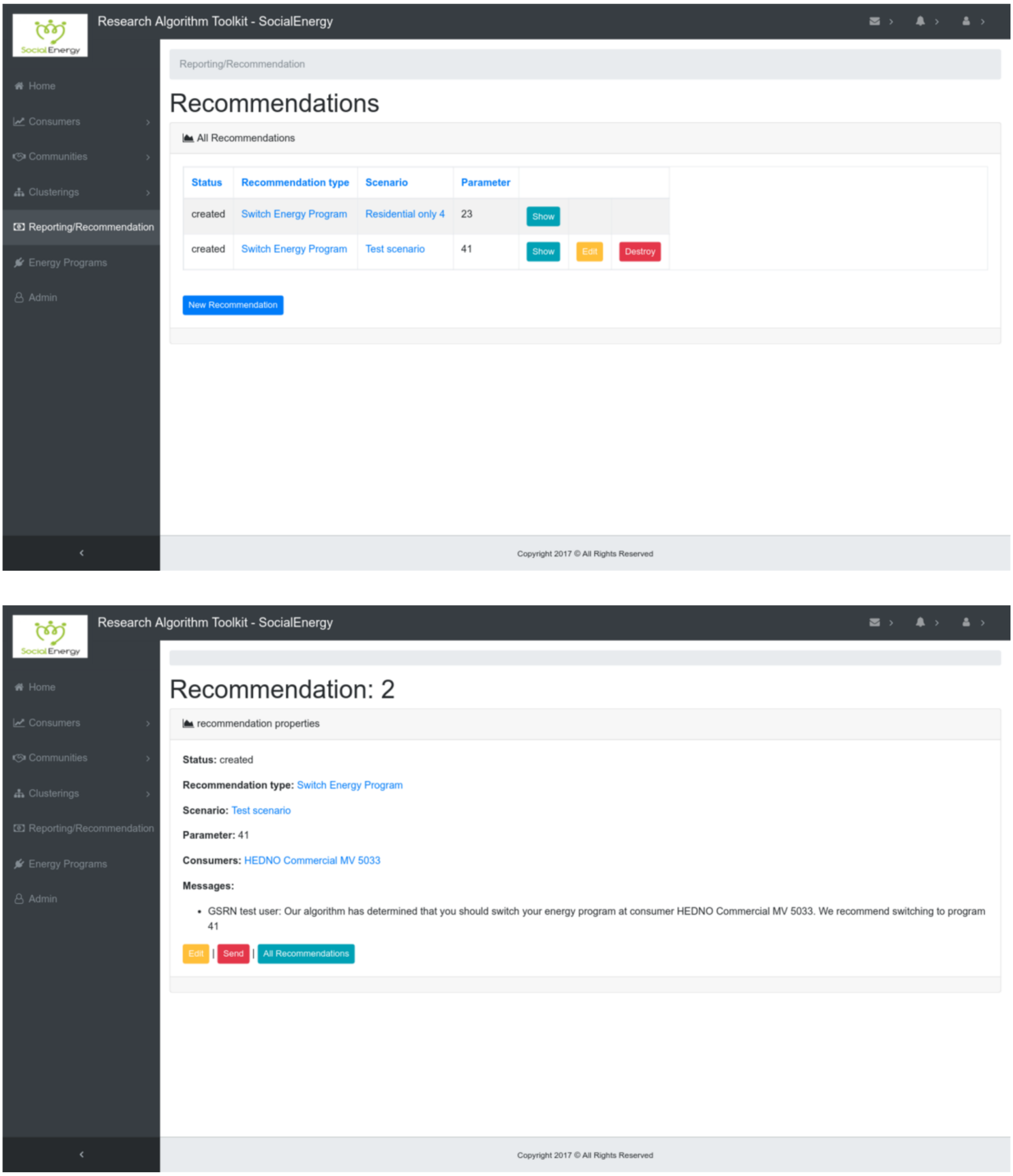


Figure 58: (a) Administrator's/EC leader's view of the entire list of recommendations; (b) detailed view of a single recommendation

After the administrative/EC leader user reviews the recommendation, and possibly edits it, can then send the recommendation, which will create alerts for each affected user that will be delivered to their inbox. After the alerts have been sent, the recommendation cannot be modified, unless the alerts are deleted. When the user logs in the RAT subsystem, a yellow icon will appear in the top-right corner of the screen as shown below, which when clicked, opens a popup with the most recent alerts in the inbox. The user can click on the inbox alert to open it and view it. A list with all alerts that s/he has received is also available.

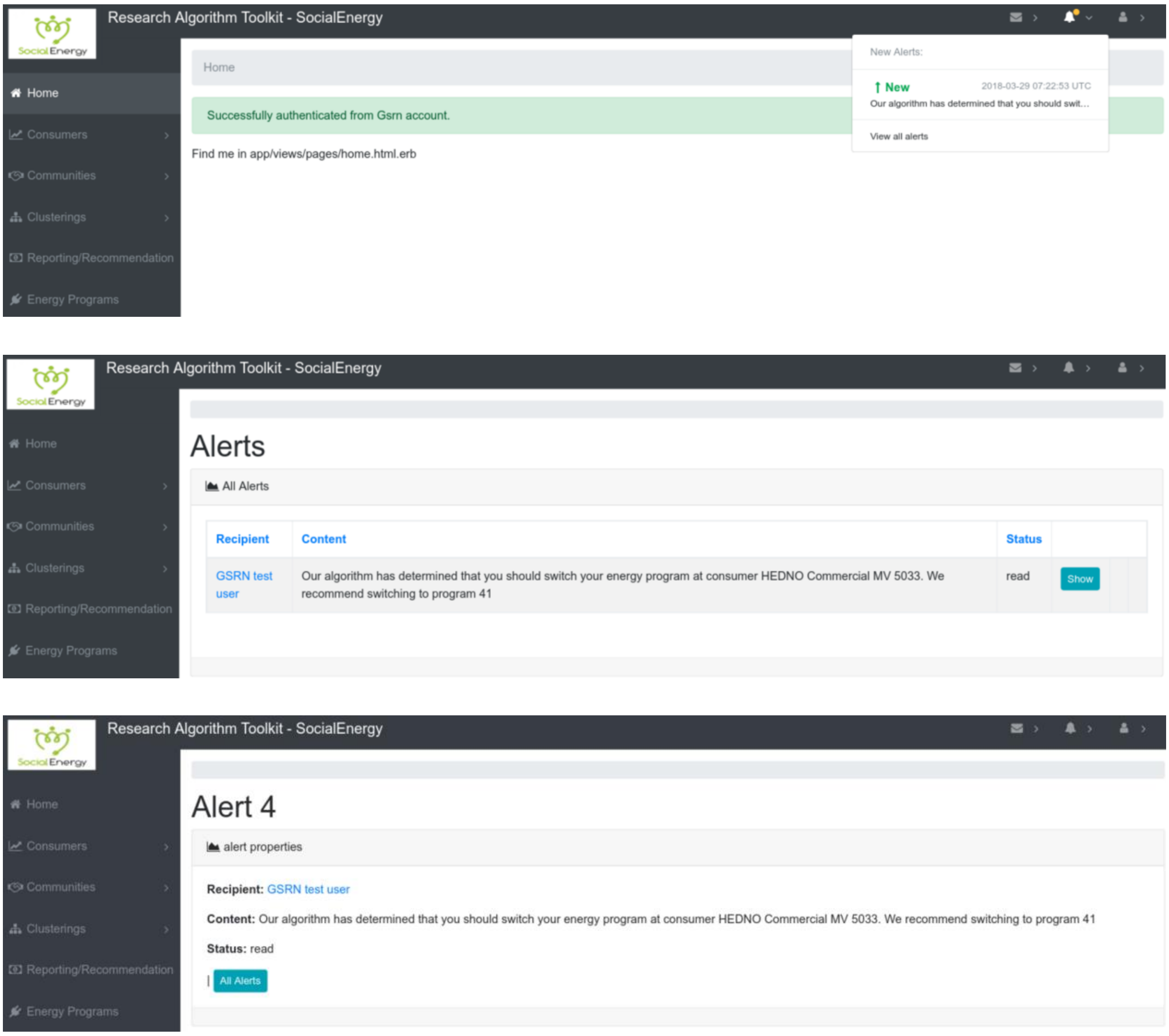


Figure 59: Indicative views of the recommendations received by the end user

5.8. Next S/W implementation steps

During the next few months (M16-M19), the focus will be on the S/W integration activities in order for a 1st stable SOCIALENERGY S/W platform to be released and communicated to the potential customer segment and 3rd party stakeholders (cf. milestone 5 and D5.2 to be delivered in M18). At the same time, the RAT functionalities will be enhanced towards releasing the final version of SOCIALENERGY functionalities (cf. milestone 6 and D3.2 to be delivered in M24). The main S/W implementation tasks can be summarized as follows:

- Test and validate more advanced algorithms for the family of P-RTP energy programs (i.e. more parameters in the system modeling and include storage assets' management)
- Test and validate and then integrate more advanced algorithms for the family of C-RTP energy programs (i.e. integrate more real data from the core GSRN platform to form more sophisticated communities)
- Implement 3 main types of dynamic EC adaptation algorithms (i.e. recommendations) as explained in section 3.5.5.
- Integrate more real users and energy data from real-life pilots

- Integrate more behavioral data from GSRN/GAME/LCMS subsystems as the result of their use by real users during the real-life pilots phase.

6. S/W integration activities

This section provides an overview of the initial S/W integration activities, which are in progress. More technical details about the 1st phase of S/W integration activities will be delivered in the subsequent D5.2 in M18.

The SOCIALENERGY platform has several S/W components. All components are web-based; others could be native in the future, such as mobile apps (e.g. GAME). Moreover, additional third-party applications can be built around this platform in future. Rather than having each S/W component maintain its own user database with usernames and passwords, SOCIALENERGY platform utilizes a Single Sign-On (SSO) Authentication procedure. Therefore, our approach was to identify an SSO strategy and implementation that could support those requirements.

According to Wikipedias' definition: *"A Social login, also known as social sign-in, is a form of single sign-on using existing login information from a social networking service such as Facebook, Twitter or Google+ to sign into a third party website in lieu of creating a new login account specifically for that website. Social login can be also considered as a gateway for authentication and authorization and is often implemented using OAuth standard. OAuth provides a simpler and more standardized solution that simplifies the sign up process".*

OAuth 2.0 [61] is an open protocol for authentication and authorization. There are three main participants in an OAuth transaction, namely: i) the User, ii) the Consumer, and iii) the Service Provider. The relationship between participants is the following: The User uses one application (called Consumer), which requests access to user's private resources from another application (called Service Provider), and the user wants to grant access to the Consumer without giving away the password. From the user's perspective, the process is quite simple – from the Consumer application the user is referred to the Service Provider, where after authentication and granting access to the Consumer application on the requested user's resources is forwarded back to the Consumer application.

Within the SOCIALENERGY project, we **implemented our own SOCIALENERGY OAuth provider** in order to ***meet the privacy requirements for users, who do not want to or cannot (due to legal age restrictions) to join the social networks***. The SOCIALENERGY OAuth provider offers new user registration functionality. Thus, users can authenticate with "SOCIALENERGY" credentials and hence do not need social media in order to use the SOCIALENERGY infrastructure. The SOCIALENERGY OAuth provider does not only create the user locally, but also communicates every account to all other software components within SOCIALENERGY S/W platform.

By communicating these users explicitly, the other S/W components will be aware of these newly created users, even before they logged in the S/W component itself (usually when a user uses an OAuth provider for authentication, the Consumer application creates a user profile in its own user database, when the user logs-in for the first time. Therefore, only creating a user account in the SOCIALENERGY OAuth provider would not enable other S/W components to be aware of the new user till their log-in into it for the first time).

6.1. Interaction between MDMS and GSRN/RAT

This API is responsible for providing all real-time energy consumption data from the real SOCIALENERGY users (or else smart meters) to GSRN and RAT. The POST body parameters and respective response to retrieve energy consumption data from MDMS is the following:

POST body parameter

```
    {
  "usernameID ": "integer",
  "timestampFrom": "integer"
  "timestampTo": "integer"
 }
```

Response:

user_id,
package_id,
user_address : city, region, zip_code,
meter_count,
meter_address : city, region, zip_code,
meter_type,
consumption,
modules : count, timestamp, name, mobile/web,
user_age

Regarding the retrieval of GSRN user's engagement/real activity data in real-time and upon request, the following simple API structure is adopted:

POST body parameter

```
{
  "username ": "string",
  "dateFrom" : "string",
  "dateTo" : "string"
}
```

Response:

```
{
  type_of_action,
  action,
  os,
  browser,
  agent,
  timestamp,
  aggregate_data:{ interval, times_of_visit_page,os,browser,agent,timestamp   }
}
```

6.2. Interaction between GSRN and RAT

The GSRN-RAT API facilitates the data analytics services provided by RAT subsystem to GSRN. The 'POST' body parameters sent from GSRN to RAT are:

```
{
  "name ": "string",
  "consumer_ids": "string",
```

"starttime": "string"
"endtime": "string"
"interval_id": "string"
"ecc_type_id": "string"
"energy_cost_parameter": "string"
"profit_margin_parameter": "string"
"flexibility_id": "string"
"gamma_parameter": "string"
"energy_program_ids": "string"
}

The RAT response back to GSRN in order for the related graphs to be visualized at the user's side in GSRN is the following (indicatively):

energy cost graph data.
Metrics:
RTP (no DR) / timestamp - values
Real-time pricing / timestamp - values
Personal Real-time pricing / timestamp - values

user_welfare graph data.
Metrics:
RTP (no DR) / timestamp - values
Real-time pricing / timestamp - values
Personal Real-time pricing / timestamp - values

retailer_profit graph data.
Metrics:
RTP (no DR) / timestamp - values
Real-time pricing / timestamp - values
Personal Real-time pricing / timestamp - values

total_welfare graph data.
Metrics:
RTP (no DR) / timestamp - values
Real-time pricing / timestamp - values
Personal Real-time pricing / timestamp - values

Please note that in the 2nd release of SOCIALENERGY system's functionalities, more algorithms and respective data analytics services will be supported according to the work WP3 progress.

6.3. Interaction between GSRN and GAME

The GAME needs to authorize user to GSRN, before proceeding with the actual gameplay.

POST body parameter – sent from GAME to GSRN

{

```
 "username ": "string",
 "password": "string"
}
```

Response from the GSRN: token is being generated as follows:

POST body parameter – sent from GSRN to GAME

```
    {
 "token": "string"
}
```

The GAME posts back to GSRN all the players' actions from the actual gameplay and the related features/datasets are indicatively described below:

id_job,
devices: consumption, per_device_time_duration, mode_device,
device_id,points_per_device
total_score,
daily score,
user_id,
game_duration,
timestamp_user_logged_in,
timestamp_user_logged_out,
energy_program,
level_game

6.4. Interaction between GSRN and LCMS

After registering in GSRN, the user completes a questionnaire that assists the process of identifying educational goals and missing competencies. Based on the questionnaire's results, an individual learning plan (ILP) is created in LCMS on behalf of the GSRN covering the missing competencies.

LCMS exposes a user profile to GSRN in a structured type as described below. It should be noted that this is the general structure of the LCMS-GSRN API and it may be enhanced at the 2nd phase of S/W integration (i.e. M19-M27 period).

```
list of (
     object {
          user object {
               id int   //ID of the user
               username string  Optional //the username
               firstname string  Optional //the first name(s) of the user
               lastname string  Optional //the family name of the user
               email string  Optional //an email address
               url string   //profile URL
               firstaccess int  Optional //first access to the site (0 if never)
               lastaccess int  Optional //last access to the site (0 if never)
          }
```

```
        competencies list of (
            object {
                id int  Optional //competence id
                name string   //competence name
                description string   //competence description
                idnumber string   //id number
                proficiency int  Default to "0" //proficiency
                grade int   //grade type
                gradename string   //grade name
            }
        )
        badges list of (
            object {
                id int  Optional //badge id.
                name string   //badge name.
                description string   //badge description.
                url string   //badge URL.
                dateissued int   //date issued.
            }
        )
        courses list of (
            object {
                id int   //id of course
                name string   //long name of course
                description string  Optional //summary
                url string   //the course URL.
                grademin string  Optional //grade min value
                grademax string  Optional //grade max value
                gradepass string  Optional //grade pass value
                grade string  Optional //grade value
                dategraded int  Optional //date issued.
                progress double  Optional //progress percentage
                timespent string  Optional //dedication time of the user to the course
            }
        )
    }
)
```

Figure 60: LCMS user profile and datasets sent to GSRN upon request (general structure)

LCMS supports the OAuth2 authentication strategy chosen as a Single Sign-On Authentication (SSO Authentication) mechanism [61]. The OAuth2 authentication plug-in enables end users to login in LCMS using their credentials from GSRN. Please note that a similar procedure is followed for the authentication among all SOCIALENERGY subsystems.

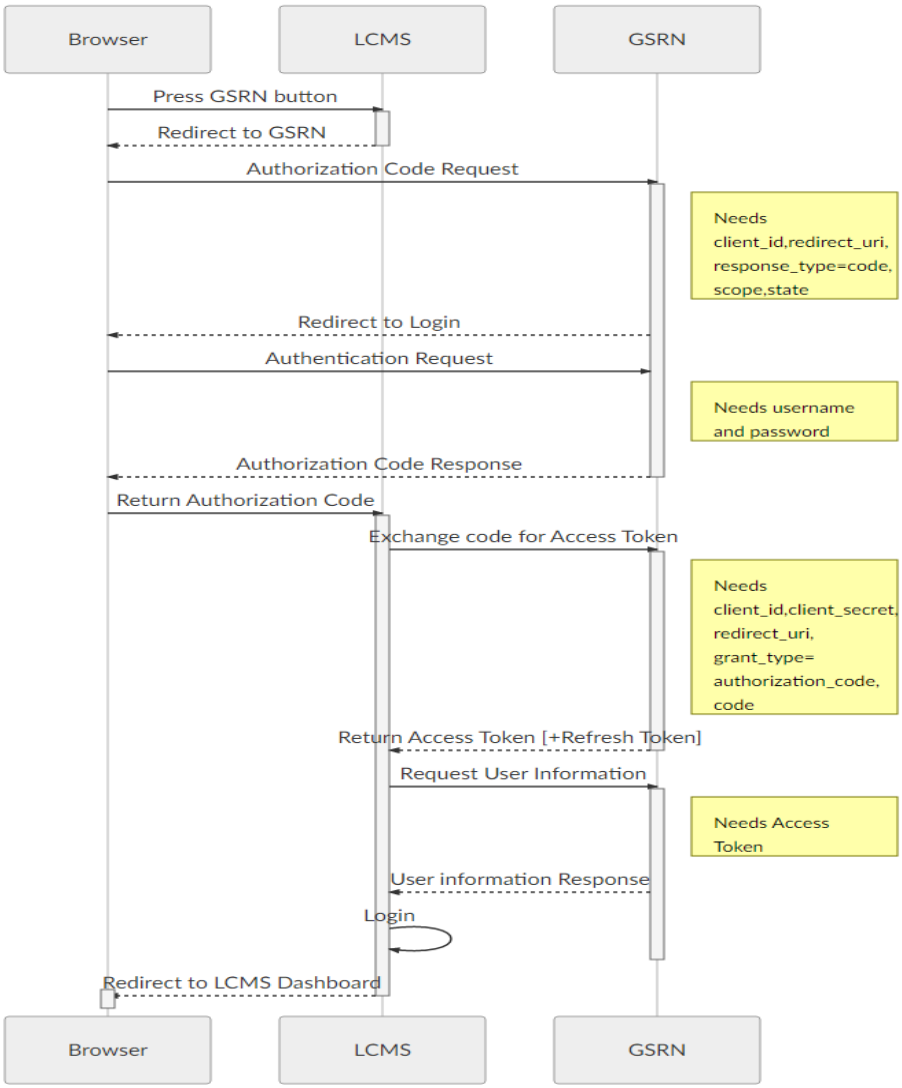


Figure 61: Authentication flow

7. Conclusions

Conclusively, the consortium has now reached Milestone 4, meaning that it has released the initial version of SOCIALENERGY functionalities via the delivery of D3.1 ("Initial version of GSRN platform functionalities") and D4.2 ("Initial version of SOCIALENERGY's virtual world functionalities") in M15. Moreover, via the delivery of D6.2 in M15, the consortium is now focusing the work progress on one unique business model and five value propositions (or else business cases). As a result, the S/W implementation and integration activities are now being focused on the specific set of services according to the respective feedback that the consortium has from its customer segment (i.e. electric utility company/ESP).

The afore-mentioned achievements and work progress give pace to the start of core S/W integration work, which has already begun. Step-wise, the actual work schedule plan is the following:

- The core S/W integration work will take place in the context of technical Work Package 5. Partners will work closely and collaboratively on the APIs for the interaction among the various subsystems during the upcoming 3 months.
- S/W implementation work is continuing by enhancing the existing functionalities and integrating even more research algorithms and intelligence in our system.
- Pilot setup and experimentation plan is under construction in order to start pilot testing activities once a stable SOCIALENERGY S/W prototype version is ready for DEMO.

The goal until the end of the second reporting period is to demonstrate the first stable version of SOCIALENERGY system during the 2nd review meeting in front of potential real customers, too in Athens in September 2018.

References

[1] P. Samadi, A.-H. Mohsenian-Rad, R. Schober, V. W. S. Wong, and J. Jatskevich, “Optimal Real-Time Pricing Algorithm Based on Utiltiy Maximization for Smart Grid”, in Proc. of First IEEE International Conference on Smart Grid Communications (SmartGridComm), Gaithersburg, MD, USA, Oct. 2010.

[2] N. Li, L. Chen, and S. H. Low, “Optimal Demand Response Based on Utiltiy Maximization in Power Networks”, in Proc. of IEEE Power and Energy Society General Meeting, Detroit, MI, USA, Jul. 2011.

[3] N. Yaagoubi, and H. T. Mouftah, “User-Aware Game Theoretic Approach for Demand Management”, IEEE Trans. on Smart Grid, vol. 6, no. 2, pp. 716-725, Mar. 2015.

[4] Z. Wang, and R. Paranjape, “Optimal Residential Demand Response for Multiple Heterogeneous Homes With Real-Time Price Prediction in a Multiagent Framework”, IEEE Trans. on Smart Grid, vol. 8, no. 3, pp. 1173-1184, May 2017.

[5] W. Tang, S. Bi, and Y. J. (A.) Zhang, “Online Coordinated Charging Decision Algorithm for Electric Vehicles Without Future Information”, IEEE Trans. on Smart Grid, vol. 5, no. 6, pp. 2810-2824, Nov. 2014.

[6] S. Althaher, P. Mancarella, and J. Mutale, “Automated Demand Response From Home Energy Management System Under Dynamic Pricing and Power and Comfort Constraints”, IEEE Trans. on Smart Grid, vol. 6, no. 4, pp. 1874-1883, Jul. 2015.

[7] L. P. Qian, Y. J. A. Zhang, J. Huang, and Y. Wu, “Demand Response Management via Real-Time Electricity Price Control in Smart Grids”, IEEE Journal on Selected Areas in Communications, vol. 31, no. 7, pp. 1268-1280, Jul. 2013.

[8] Z. Baharlouei and M. Hashemi, "Efficiency-Fairness Trade-off in Privacy-Preserving Autonomous Demand Side Management," *IEEE Transactions on Smart Grid,* vol. 5, no. 2, pp. 799-808, Mar. 2014.

[9] D. T. Nguyen and L. B. Le, "Joint Optimization of Electric Vehicle and Home Energy Scheduling Considering User Comfort Preference," *IEEE Transactions on Smart Grid,* vol. 5, no. 1, pp. 188-199, Jan. 2014.

[10] C. Clifton, M. Kantarcioglu, J. Vaidya, X. Lin and M. Y. Zhu, "Tools for privacy preserving distributed data mining," *ACM SIGKDD Explorations Newsletter,* vol. 4, no. 2, pp. 28-34, Dec. 2002.

[11] C. Chen, J. Wang, Y. Heo and S. Kishore, "MPC-Based Appliance Scheduling for Residential Building Energy Management Controller," *IEEE Transactions on Smart Grid,* vol. 4, no. 3, pp. 1401-1410, Sept. 2013.

[12] A. Mas-Colell, M. D. Whinston and J. R. Green, Microeconomic Theory, Oxford University Press, 1995.

[13] P. Samadi, H. Mohsenian-Rad, R. Schober and V. W. S. Wong, "Advanced Demand Side Management for the Future Smart Grid Using Mechanism Design," *IEEE Transactions on Smart Grid,* vol. 3, no. 3, pp. 1170-1180, Sep. 2012.

[14] Ma, J. Deng, L. Song and Z. Han, "Incentive Mechanism for Demand Side Management in Smart Grid Using Auction," *IEEE Transactions on Smart Grid,* vol. 5, no. 3, pp. 1379-1388, May 2014.

[15] R. Deng, Z. Yang and J. Chen, "Load Scheduling with Price Uncertainty and Coupling Constrains," in *2013 IEEE Power and Energy Society General Meeting (PES)*, Vancouver , BC, Canada, 2013.

[16] A.-H. Mohsenian-Rad and A. Leon-Garcia, "Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments," *IEEE Transactions on Smart Grid,* vol. 1, no. 2, pp. 120-133, Sep. 2010.

[17] O. M. Longe, K. Ouahada, S. Rimer, A. N. Harutyunyan and H. C. Ferreira, "Distributed Demand Side Management with Battery Storage for Smart Home Energy Scheduling," *Sustainability 2017,* vol. 9, no. 1, Jan. 2017.

[18] W. Shi, N. Li, X. Xie, C.-C. Chu and R. Gadh, "Optimal Residential Demand Response in Distribution Networks," *IEEE Journal on Selected Areas in Communications,* vol. 32, no. 7, pp. 1441-1450, Jul. 2014.

[19] A. Anvari-Moghaddam, H. Monsef and A. Rahimi-Kian, "Optimal Smart Home Energy Management Considering Energy Saving and a Comfortable Lifestyle," *IEEE Transactions on Smart Grid,* vol. 6, no. 1, pp. 324-332, Jan. 2014.

[20] R. Deng, Z. Yang, J. Chen, a, N. R. Asr and M.-Y. Chow, "Residential Energy Consumption Scheduling: A Coupled-Constraint Game Approach," *IEEE Transactions on Smart Grid,* vol. 5, no. 3, pp. 1340-1350, May 2014.

[21] Z. Baharlouei, H. Narimani and M. Hashemi, "On the Convergence Properties of Autonomous Demand Side Management Algorithms," *IEEE Transactions on Smart Grid,* vol. PP, no. 99.

[22] Smart Energy Collective, "An introduction to the Universal Smart Energy Framework," Arnhem, the Netherlands, 2013.

[23] C. Zhang, Y. Ding, N. C. Nordentoft, P. Pinson and J. Ostergaard, "FLECH: A Danish market solution for DSO congestion management through DER flexibility services," *Journal of Modern Power Systems and Clean Energy,* vol. 2, no. 2, pp. 126-133, Jun. 2014.

[24] D. Zhang, N. Shah and L. G. Papageorgiou, "Efficient energy consumption and operation management in a smart building with microgrid," *Energy Conversion and Management,* vol. 74, pp. 209-222, Oct. 2013.

[25] Woodbank Communications Ltd., "Electricity Demand," [Online]. Available: http://www.mpoweruk.com/electricity_demand.htm

[26] "Calculate Electricity Usage," 2017. [Online]. Available: http://energyusecalculator.com/calculate_electrical_usage.htm

[27] Z. Baharlouei and M. Hashemi, "Efficiency-Fairness Trade-off in Privacy-Preserving Autonomous Demand Side Management," *IEEE Transactions on Smart Grid,* vol. 5, no. 2, pp. 799-808, Mar. 2014.

[28] A.-H. Mohsenian-Rad and A. Leon-Garcia, "Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments," *IEEE Transactions on Smart Grid,* vol. 1, no. 2, pp. 120-133, Sep. 2010.

[29] Z. Baharlouei, M. Hashemi, H. Narimani and H. Mohsenian-Rad, "Achieving Optimality and Fairness in Autonomous Demand Response: Benchmarks and Billing Mechanisms," *IEEE Transactions on Smart Grid,* vol. 4, no. 2, pp. 968-975, Jun. 2013.

[30] G. Tsaousoglou, N. Efthymiopoulos, P. Makris, E. Varvarigos, "Personalized Real Time Pricing for Efficient and Fair Demand Response in Communities", under review in Springer Journal of Modern Power Systems and Clean Energy, November 2017.

[31] P. Makris, N. Efthymiopoulos, E. Varvarigos, V. Nikolopoulos, A. Pomazanskyi, B. Irmscher, K. Stefanov, K. Pancheva, " Digitization era for progressive electric utilities: A novel business model through an inter-disciplinary S/W platform and open research challenges", under review in IEEE Systems Journal, November 2017.

[32] K. Steriotis, G. Tsaousoglou, N. Efthymiopoulos, P. Makris, E. Varvarigos, "A Novel Behavioral Real Time Pricing Scheme for the Active Energy Consumers' Participation in Emerging Flexibility Markets", under review in Elsevier Sustainable Energy, Grids and Networks (SEGAN) Journal, January 2018.

[33] P. Makris, N. Efthymiopoulos, D. J. Vergados, E. Varvarigos, V. Nikolopoulos, J. Papagiannis, A. Pomazanskyi, B. Irmscher, K. Stefanov, K. Pancheva, A. Georgiev, "SOCIALENERGY: A Gaming and Social Network Platform for Evolving Energy Markets' Operation and Educating Virtual Energy Communities", under review in IEEE ENERGYCON 2018, Limassol, Cyprus, 3-7 June 2018.

[34] K. Steriotis, G. Tsaousoglou, N. Efthymiopoulos, P. Makris, E. Varvarigos, "Development of Real Time Energy Pricing Schemes that Incentivize Behavioral Changes", under review in IEEE ENERGYCON 2018, Limassol, Cyprus, 3-7 June 2018.

[35] H. Allcott, "Social norms and energy conservation", Elsevier Journal of Public Economics, vol. 95 (9-10), pp. 1082-1095, 2011.

[36] S. N. A. U. Nambi and R. V. Prasad, "Toward the development of a techno-social smart grid," IEEE Communications Magazine, vol. 54, no. 11, pp. 202-209, November 2016.

[37] A. Cassidy, M. Strube and A. Nehorai, "A framework for exploring social network and personality-based predictors of smart grid diffusion," IEEE Transactions on Smart Grid, vol. 6, no. 3, pp. 1314-1322, May 2015.

[38] Q. Huang, X. Li, J. Zhao, D. Wu and X. Y. Li, "Social networking reduces peak power consumption in smart grid," IEEE Transactions on Smart Grid, vol. 6, no. 3, pp. 1403-1413, May 2015.

[39] A. Mani, I. Rahwan, A. Pentland, "Inducing Peer Pressure to Promote Cooperation", Nature Scientific Reports, vol. 3, Article number: 1735, 2013.

[40] D. J. Vergados, I. Mamounakis, P. Makris, E. Varvarigos, "Prosumer clustering into virtual microgrids for cost reduction in renewable energy trading markets", Elsevier Sustainable Energy, Grids and Networks (SEGAN), vol. 7, pp. 90-103, September 2016.

[41] G. Tsaousoglou, P. Makris, E. Varvarigos, "Electricity Market Policies for Penalizing Volatility and Scheduling Strategies: the Value of Aggregation, Flexibility, and Correlation", Elsevier Sustainable Energy, Grids and Networks (SEGAN) Journal, vol. 12, pp. 57-68, December 2017.

[42] N. Doulamis, A. Doulamis, E. Varvarigos, "Virtual Associations of Prosumers for Smart Energy Networks under a Renewable Split Market," IEEE Transactions on Smart Grid, vol. PP, no. 99, 2017.

[43] R. Sussman and M. Chikumbo, "Behavior Change Programs: Status and Impact", Research Report B1601, American Council for an Energy Efficiency Economy (ACEEE), 2016.

[44] A. J. D. Rathnayaka, V. M. Potdar, S. J. Kuruppu "Design of smart grid prosumer communities via online social networking communities", International Journal for Infonomics (IJI), vol. 5 (1/2), pp. 544-556, 2012.

[45] A. J. D. Rathnayaka, V. M. Potdar, T. S. Dillon, O. K. Hussain and E. Chang, "A methodology to find influential prosumers in prosumer community groups," IEEE Trans. on Industrial Informatics, vol. 10, pp. 706-713, 2014.

[46] Q. Huang, X. Li, J. Zhao, D. Wu and X. Y. Li, "Social networking reduces peak power consumption in smart grid," IEEE Tran. on Smart Grid, 6(3), pp. 1403-1413, 2015.

[47] Y. Huang, M. Warnier, F. Brazier and D. Miorandi, "Social networking for smart grid users," IEEE Conference on Networking, Sensing and Control (ICNSC), Taipei, pp. 438-443, 2015.

[48] S. Čaušević, M. Warnier, F. Brazier, "Dynamic, self-organized clusters as a means to supply and demand matching in large-scale energy systems", in Proc. 14th IEEE Intl Conference on Networking, Sensing and Control, Calabria, Italy, May 2017.

[49] F. Du, J. Zhang, H. Li, J. Yan, S. Galloway, K. L. Lo, "Modelling the impact of social network on energy savings", Elsevier Apllied Energy, vol. 178, pp. 56-65, 2016.

[50] R. Jain, R. Gulbinas, J. Taylor, P. Culligan, "Can social influence drive energy savings? Detecting the impact of social influence on the energy consumption behavior of networked users exposed to normative eco-feedback", Elsevier Energy and Buildings, vol. 66, pp. 119-127, 2013.

[51] J. Saez-Gallego, J. M. Morales, M. Zugno and H. Madsen, "A Data-Driven Bidding Model for a Cluster of Price-Responsive Consumers of Electricity," IEEE Trans. on Power Systems, vol. 31, pp. 5001-5011, 2016.

[52] Yu-kai Chou, "Actionable Gamification: Beyond Points, Badges, and Leaderboards", Create Space Independent Publishing Platform, [Online] Available: http://www.amazon.com/Actionable-Gamification-Beyond-Points-Leaderboards-ebook/dp/B00WAOGY4U, 2015.

[53] X. Xua, J. E. Taylor, A. L. Pisello, "Network synergy effect: Establishing a synergy between building network and peer network energy conservation effects", Elsevier Energy and Buildings, vol. 68, pp. 312-320, 2014.

[54] Carrico AR, Riemer M. ,"Motivating energy conservation in the workplace: an evaluation of the use of group-level feedback and peer education", Journal of Environmental Psychology, vol. 31, pp. 1-13, 2011.

[55] U. Von Luxburg, "A tutorial on spectral clustering", Journal of Statisitics and Computing, vol. 17, pp. 395–416, 2007.

[56] R. Castri, V. De Luca, E. Lobsiger-kägi, C. Moser, and V. Carabias, "Favouring behavioural change of households' energy consumption through social media and cooperative play," 2014.

[57] Azar E, Menassa CC., "Evaluating the impact of extreme energy use behavior on occupancy interventions in commercial buildings", Energy and Buildings, vol. 97, pp. 205-218, 2015.

[58] I. Mamounakis, N. Efthymiopoulos, P. Makris, D. J. Vergados, G. Tsaousoglou, E. Varvarigos, " A novel pricing scheme for managing virtual energy communities and promoting behavioral change towards energy efficiency: the SOCIALENERGY project approach", under review in Elsevier Electric Power Systems Journal, January 2018.

[59] I. Mamounakis, D. J. Vergados, P. Makris, E. Varvarigos, N. Doulamis, "*A method for clustering RES prosumers towards creating target aggregated prosumption profiles based on recursive predictions"*, 12th IEEE PES PowerTech Conference, Manchester, UK, 18-22 June 2017.

[60] I. Mamounakis, N. Efthymiopoulos, G. Tsaousoglou, D. J. Vergados, P. Makris, E. Varvarigos, "A Novel Pricing Scheme for Virtual Energy Communities Towards Energy Efficiency", under review in IEEE ENERGYCON 2018, Limassol, Cyprus, 3-7 June 2018.

[61] OAuth 2.0 authentication mechanism, https://oauth.net/2/